CAUSAL ESTIMATION - TP

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PRESENTATION OF THE DATA



- Patients with liver disease hospitalized for encephalopathy
- Treatment of interest: fecal transplantation
- Cohort study that prospectively included patients
- Primary objective: to evaluate the effectiveness of fecal transplantation for the treatment of hepatic encephalopathy
- Primary endpoint: mortality

PACKAGES NEEDED

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DATA IMPORT

```
load("df.RData")
head(df)
```

```
age sex sex.f tobacco tobacco.f alcohol alcohol.f
                                                                        bili hiv
##
          id
  752527
           1 68.50
                         Male
                                     0 Non-smoker
                                                        2 Excessive
                                                                      27.235
                     1 Female
                                     0 Non-smoker
                                                        2 Excessive 288.305
  488554
           2 72.35
                                                                                0
## 67985
           3 48.84
                    1 Female
                                     0 Non-smoker
                                                        2 Excessive 48,427
  250417
           4 62.61
                     1 Female
                                     1
                                           Smoker
                                                        2 Excessive
                                                                      24.315
                     1 Female
                                                           Moderate
  827567
           5 65.46
                                     1
                                           Smoker
                                                                      98.830
  273278
           6 57.39
                     1 Female
                                     0 Non-smoker
                                                                       2.626
                                                           Moderate
##
          hiv.f trt
                        trt.f status status.f
  752527
             Nο
                  0 Unexposed
                                    1 Deceased
  488554
             No
                  0 Unexposed
                                    1 Deceased
## 67985
             No
                  0 Unexposed
                                    1 Deceased
                                         Alive
  250417
             Nο
                  0 Unexposed
##
  827567
             Nο
                  0 Unexposed
                                    1 Deceased
## 273278
             No
                  0 Unexposed
                                         Alive
```

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DEFINITIONS

Variable	Label	Unit/Coding
id	Identification	
	Number	
age	Age	Year
sex	Sex	0: Male, 1: Female
tobacco	Tobacco	0: Smoker, 1: Non-smoker
alcohol	Alcohol	0: Never, 1: Moderate, 2: Excessive
bili	Bilirubin	μ mol/l $^{-1}$
hiv	HIV	0: No, 1: Yes
status	Vital Status	0: Alive, 1: Deceased

Categorical variables have already been recoded as factor (.f at the end of the variable name).

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DESCRIPTION OF THE DATA

```
age sex.f tobacco.f alcohol.f
##
   Min. :35.18 Male : 929 Non-smoker: 803 Never :617
###
   1st Ou.:55.48 Female:1071 Smoker :1197
###
                                         Moderate :962
##
   Median :60.12
                                         Excessive: 421
  Mean :60.05
##
###
   3rd Ou.:64.80
ш
   Max. :85.71
##
  bili hiv.f trt.f status.f
   Min. : 0.214 No :1909 Unexposed:1537 Alive :1113
###
   1st Ou.: 11.079 Yes: 91 Exposed: 463 Deceased: 887
###
###
   Median: 30.498
  Mean : 95.164
##
##
  3rd Ou.: 77.719
   Max. :4542.734
###
```

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DESCRIPTION OF THE DATA

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Characteristic	N = 2,000
age	60 (7)
sex.f	
Male	929 (46%)
Female	1,071 (54%)
tobacco.f	
Non-smoker	803 (40%)
Smoker	1,197 (60%)
alcohol.f	
Never	617 (31%)
Moderate	962 (48%)
Excessive	421 (21%)
bili	95 (263)
hiv.f	91 (4.6%)
trt.f	
Unexposed	1,537 (77%)
Exposed	463 (23%)
status.f	
Alive	1,113 (56%)
Deceased	887 (44%)



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NAIVE ANALYSIS OF THE MORTALITY



EFFECT OF THE TREATMENT ON MORTALITY

 Compare mortality between the 2 treatment groups (using description followed by a simple logistic regression)

Characteristic	Unexposed, N = 1,537	Exposed, N = 463
status.f Alive	845 (55%)	268 (58%)
Deceased	692 (45%)	195 (42%)

```
summary(glm(status ~ trt.f, data = df, family = "binomial"))
##
## Call:
## glm(formula = status ~ trt.f, family = "binomial", data = df)
##
## Coefficients:
             Estimate Std. Error z value Pr(>|z|)
###
## (Intercept) -0.19975 0.05127 -3.896 9.77e-05 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
###
      Null deviance: 2747.0 on 1999 degrees of freedom
##
## Residual deviance: 2745.8 on 1998 degrees of freedom
## ATC: 2749.8
###
## Number of Fisher Scoring iterations: 3
```



EFFECT OF THE TREATMENT ON MORTALITY

■ What do you think?



EFFECT OF THE TREATMENT ON MORTALITY

- What do you think?
- Explore the effect of other variables on mortality

Characteristic	Alive , N = 1,113	Deceased, N = 887
age	58 (7)	62 (7)

```
summary(glm(status ~ age, data = df, family = "binomial"))
###
## Call:
### glm(formula = status ~ age, family = "binomial", data = df)
##
## Coefficients:
               Estimate Std. Error z value Pr(>|z|)
###
## (Intercept) -5.000528  0.434642  -11.51  <2e-16 ***
       0.079212 0.007148 11.08 <2e-16 ***
## age
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
###
      Null deviance: 2747.0 on 1999 degrees of freedom
###
## Residual deviance: 2610.5 on 1998 degrees of freedom
## ATC: 2614.5
##
```

The interpretation of this log odds ratio is: for each additional year, the log odds ratio increases by 0.079.

Number of Fisher Scoring iterations: 4

Characteristic	Alive , N = 1,113	Deceased, N = 887
bili	44 (58)	160 (380)

```
summary(glm(status ~ bili, data = df, family = "binomial"))
###
## Call:
## glm(formula = status ~ bili, family = "binomial", data = df)
##
## Coefficients:
                Estimate Std. Error z value Pr(>|z|)
###
## (Intercept) -0.6770725 0.0588254 -11.51 <2e-16 ***
          0.0064506 0.0006239 10.34 <2e-16 ***
## bili
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
###
      Null deviance: 2747.0 on 1999 degrees of freedom
###
## Residual deviance: 2539.9 on 1998 degrees of freedom
## ATC: 2543.9
##
```

The interpretation of this log odds ratio is: for each additional unit of bilirubin, the risk of death increases by 0.006.

Number of Fisher Scoring iterations: 6

Characteristic	Alive , N = 1,113	Deceased, N = 887
tobacco.f Non-smoker Smoker	494 (44%) 619 (56%)	309 (35%) 578 (65%)

```
summary(glm(status ~ tobacco.f, data = df, family = "binomial"))
##
## Call:
## glm(formula = status ~ tobacco.f, family = "binomial", data = df)
##
## Coefficients:
             Estimate Std. Error z value Pr(>|z|)
###
## (Intercept) -0.46919 0.07253 -6.469 9.86e-11 ***
## tobacco.fSmoker 0.40066 0.09277 4.319 1.57e-05 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
###
      Null deviance: 2747.0 on 1999 degrees of freedom
##
## Residual deviance: 2728.2 on 1998 degrees of freedom
## ATC: 2732.2
##
## Number of Fisher Scoring iterations: 4
```

Characteristic	Alive , N = 1,113	Deceased, N = 887
alcohol.f		
Never	382 (34%)	235 (26%)
Moderate	526 (47%)	436 (49%)
Excessive	205 (18%)	216 (24%)

```
summary(glm(status ~ alcohol.f. data = df. family = "binomial"))
##
## Call:
## glm(formula = status ~ alcohol.f, family = "binomial", data = df)
###
## Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
##
## (Intercept) -0.4858 0.0829 -5.860 4.62e-09 ***
## alcohol.fModerate 0.2982 0.1052 2.834 0.00459 **
## alcohol.fExcessive 0.5381 0.1280 4.204 2.62e-05 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
###
      Null deviance: 2747.0 on 1999 degrees of freedom
##
## Residual deviance: 2728.5 on 1997 degrees of freedom
## ATC: 2734.5
###
## Number of Fisher Scoring iterations: 4
```

Characteristic	Alive , N = 1,113	Deceased, N = 887
hiv.f	33 (3.0%)	58 (6.5%)

```
summary(glm(status ~ hiv.f, data = df, family = "binomial"))
##
## Call:
### glm(formula = status ~ hiv.f, family = "binomial", data = df)
##
## Coefficients:
             Estimate Std. Error z value Pr(>|z|)
###
## hiv.fYes 0.82843 0.22288 3.717 0.000202 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
      Null deviance: 2747.0 on 1999 degrees of freedom
##
## Residual deviance: 2732.5 on 1998 degrees of freedom
## ATC: 2736.5
##
## Number of Fisher Scoring iterations: 4
```



EFFECT OF OTHER VARIABLES ON MORTALITY

■ Most variables appear to be prognostic



3

COMPARISON OF TREATED AND UNTREATED

Characteristic	Unexposed, N = 1,537	Exposed, N = 463	p-value
	onexposed, N = 1,537	Exposed, N = 403	p-value
age	60 (7)	60 (7)	0.6
sex.f			0.4
Male	722 (47%)	207 (45%)	
Female	815 (53%)	256 (55%)	
tobacco.f			0.010
Non-smoker	641 (42%)	162 (35%)	
Smoker	896 (58%)	301 (65%)	
alcohol.f			< 0.001
Never	441 (29%)	176 (38%)	
Moderate	746 (49%)	216 (47%)	
Excessive	350 (23%)	71 (15%)	
bili	77 (208)	155 (389)	< 0.001
hiv.f	91 (5.9%)	0 (0%)	< 0.001



QUICK ANALYSIS

■ What do you think?

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- What do you think?
- Several variables are significantly unbalanced between treated and untreated subjects

QUICK ANALYSIS

- What do you think?
- Several variables are significantly unbalanced between treated and untreated subjects
- The hiv variable is extreme in this regard: there are no HIV-positive subjects treated with fecal transplantation
- What would you do?

QUICK ANALYSIS



- What do you think?
- Several variables are significantly unbalanced between treated and untreated subjects
- The hiv variable is extreme in this regard: there are no HIV-positive subjects treated with fecal transplantation
- What would you do?
- Being HIV-positive seems to be a contraindication for transplantation
 → positivity problem → exclusion of HIV-positive patients

```
df \leftarrow df[df$hiv = 0,]
```



STANDARDIZED DIFFERENCES

■ Example for age (quantitative variable)

STANDARDIZED DIFFERENCES

■ Example for age (quantitative variable)

```
\begin{array}{lll} \text{m0} &<& \text{with}(\text{df}[\text{df}\texttt{strt} = 0, ], \, \text{mean}(\text{age})) \, \# \, \text{moy chez les non exposés} \\ \text{m1} &<& \text{with}(\text{df}[\text{df}\texttt{strt} = 1, ], \, \text{mean}(\text{age})) \, \# \, \text{moy chez les exposés} \\ \text{v0} &<& \text{with}(\text{df}[\text{df}\texttt{strt} = 0, ], \, \text{var}(\text{age})) \, \# \, \text{var chez les non exposés} \\ \text{v1} &<& \text{with}(\text{df}[\text{df}\texttt{strt} = 1, ], \, \text{var}(\text{age})) \, \# \, \text{var chez les exposés} \\ \text{(m1} &-& \text{m0})/\text{sqrt}((\text{v1} + \text{v0})/2) \\ \end{array}
```

```
## [1] -0.04164837
```



■ Example for sex (categorical variable)

■ Example for sex (categorical variable)

```
m0 <- with(df[df$trt = 0, ], mean(sex)) # moy chez les non exposés
m1 <- with(df[df$trt = 1, ], mean(sex)) # moy chez les exposés
v0 <- with(df[df$trt = 0, ], var(sex)) # var chez les non exposés
v1 <- with(df[df$trt = 1, ], var(sex)) # var chez les exposés
(m1 - m0)/sqrt((v1 + v0)/2)</pre>
```

```
## [1] 0.04926628
```

■ Load the cobalt library for an easier calculation:

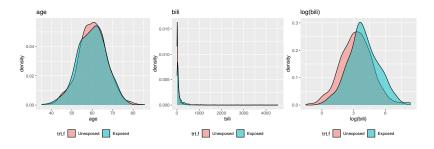
```
library(cobalt)
diffs <- bal.tab(trt ~ age + sex.f + tobacco.f + alcohol.f + bili, data = df,</pre>
                binary = "std")
diffs
## Balance Measures
##
                         Type Diff.Un
                      Contin. -0.0416
## age
## sex.f Female Binary 0.0493
## tobacco.f_Smoker Binary 0.1341
## alcohol.f Never Binary 0.1939
## alcohol.f Moderate Binary -0.0380
## alcohol.f Excessive Binary -0.1848
## bili
                      Contin. 0.2441
##
## Sample sizes
      Control Treated
##
                  463
## All 1446
```



■ Some variables have severe imbalance (bili for example), others have moderate imbalance (alcohol.f)

- Some variables have severe imbalance (bili for example), others have moderate imbalance (alcohol.f)
- In fact, the imbalance between treated and untreated groups can be inspected across the entire distribution

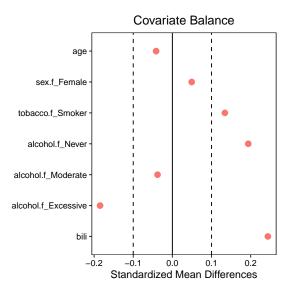
```
# install.packages("ggplot2")
library(ggplot2)
ggplot(dat = df, aes(x = age, fill = trt.f)) + geom_density(alpha = 0.5) +
    ggtitle("age") + theme(legend.position="bottom")
ggplot(data = df, aes(x = bili, fill = trt.f)) + geom_density(alpha = 0.5) +
    ggtitle("bili") + theme(legend.position="bottom")
ggplot(data = df, aes(x = log(bili), fill = trt.f)) + geom_density(alpha = 0.5) +
    ggtitle("log(bili)") + theme(legend.position="bottom")
```



(We observe that bilirubin has a log-normal distribution)

■ It's common practice to display standardized differences on a plot

```
love.plot(diffs, thresholds = c(m = 0.1))
```



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CONCLUSION

- Some variables are imbalanced (bili, and alcohol in particular)
- All variables appear to be prognostic of mortality
- Which variables will you consider?



Standardization



ESTIMATING A PROGNOSTIC MODEL BY TREATMENT GROUP

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ATE ESTIMATION

```
## status predicted if trt = 1
v1ate <- predict(mod1. newdata = df. type = "response")</pre>
## status predicted if trt = 0
y0ate <- predict(mod0, newdata = df, type = "response")</pre>
mean(y1ate) - mean(y0ate) ## Risk difference ATE
## [1] -0.08804777
log(mean(y1ate) / mean(y0ate)) ## log(RR) ATE
## [1] -0.2191475
log((mean(y1ate)/(1-mean(y1ate)))) / (mean(y0ate)/(1-mean(y0ate)))) ## log(OR) ATE
## [1] -0.3669941
```

ATT ESTIMATION

```
## status predicted if trt = 1
v1att <- predict(mod1. newdata = subset(df. trt = 1). type = "response")
## status predicted if trt = 0
y0att <- predict(mod0, newdata = subset(df, trt == 1), type = "response")</pre>
mean(y1att) - mean(y0att) ## Risk difference ATT
## [1] -0.05420141
log(mean(y1att) / mean(y0att)) ## log(RR) ATT
## [1] -0.1210609
log((mean(y1att)/(1-mean(y1att))) / (mean(y0att)/(1-mean(y0att)))) ## log(OR) ATT
## [1] -0.2193785
```



library(marginaleffects)

WITH THE marginaleffects PACKAGE

###

```
## Term Contrast Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 % ## trt mean(1) - mean(0) -0.0542 0.0245 -2.21 0.0271 5.2 -0.102 -0.00615 ## ## Columns: term, contrast, estimate, std.error, statistic, p.value, s.value, conf.lo ## Type: response
```

Columns: term, contrast, estimate, std.error, statistic, p.value, s.value, conf.lo

###

Type: response



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PROPENSITY SCORE WEIGHTING



ESTIMATION OF THE PROPENSITY MODEL

- The exposure is binary, so we can estimate the propensity score using logistic regression
- Since all variables appear to be prognostic, we include all variables in the model

```
mod.trt <- glm(trt ~ age + sex.f + tobacco.f + alcohol.f + logbili,</pre>
              data = df, family = "binomial")
summary(mod.trt)
##
## Call:
### glm(formula = trt ~ age + sex.f + tobacco.f + alcohol.f + logbili,
      family = "binomial", data = df)
##
###
## Coefficients:
##
                   Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.820024 0.505249 -3.602 0.000315 ***
                 -0.006039 0.007876 -0.767 0.443261
## age
## sex.fFemale 0.094588 0.110417 0.857 0.391642
## tobacco.fSmoker 0.248305 0.113930 2.179 0.029297 *
## alcohol.fModerate -0.314444 0.121818 -2.581 0.009844 **
## alcohol.fExcessive -0.685826   0.162349   -4.224   2.4e-05 ***
## logbili 0.312401 0.037919 8.239 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
###
## (Dispersion parameter for binomial family taken to be 1)
###
##
      Null deviance: 2115.1 on 1908 degrees of freedom
## Residual deviance: 2016.6 on 1902 degrees of freedom
## ATC: 2030.6
```

Causal estimation - TP



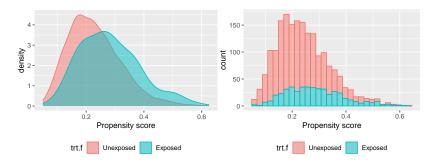
ESTIMATION OF THE PROPENSITY SCORE

```
df$score <- predict(mod.trt, type = "response")</pre>
```



COMPARISON OF THE PROPENSITY SCORE DISTRIBUTION BETWEEN TREATED AND UNTREATED

```
ggplot(data = df, aes(x = score, color = trt.f, fill = trt.f)) +
  geom_density(alpha = 0.5) +
  xlab("Propensity score") +
  theme(legend.position="bottom")
ggplot(data = df, aes(x = score, color = trt.f, fill = trt.f)) +
  geom_histogram(alpha = 0.5) +
  xlab("Propensity score") +
  theme(legend.position="bottom")
```





COMPARISON OF THE PROPENSITY SCORE DISTRIBUTION BETWEEN TREATED AND UNTREATED

■ What do you think?



COMPARISON OF THE PROPENSITY SCORE DISTRIBUTION BETWEEN TREATED AND UNTREATED

- What do you think?
- The distributions of propensity scores for treated and untreated subjects are not perfectly overlapping
- However, their overlap appears adequate, which is reassuring regarding the positivity assumption

- We will create two types of weights: an "ATE" weight and an "ATT" weight
- "ATE" weight

```
df\$wate \leftarrow ifelse(df\$trt = 1, 1/df\$score, 1/(1 - df\$score))
```

- We will create two types of weights: an "ATE" weight and an "ATT" weight
- "ATE" weight

```
df$wate <- ifelse(df$trt = 1, 1/df$score, 1/(1 - df$score))</pre>
```

■ "ATT" weight: no weighting for the treated, untreated weighted by score/(1-score)

- We will create two types of weights: an "ATE" weight and an "ATT" weight
- "ATE" weight

```
df$wate <- ifelse(df$trt = 1, 1/df$score, 1/(1 - df$score))</pre>
```

■ "ATT" weight: no weighting for the treated, untreated weighted by score/(1-score)

```
df$watt <- ifelse(df$trt = 1, 1, df$score/(1 - df$score))</pre>
```

- We will create two types of weights: an "ATE" weight and an "ATT" weight
- "ATE" weight

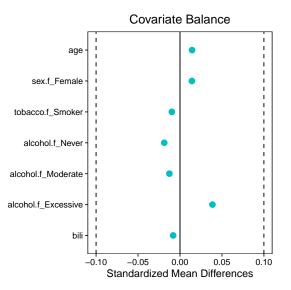
```
df\$wate \leftarrow ifelse(df\$trt = 1, 1/df\$score, 1/(1 - df\$score))
```

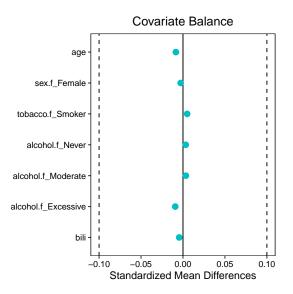
■ "ATT" weight: no weighting for the treated, untreated weighted by score/(1-score)

```
df$watt <- ifelse(df$trt = 1, 1, df$score/(1 - df$score))</pre>
```

Examine the balance after applying the different weights (you should use the std.diff function with the option weights = "wate" or "wate")

BALANCE INSPECTION





TREATMENT EFFECT

ATE

```
m1 <- with(subset(df, trt = 1), weighted.mean(status, wate))</pre>
m0 <- with(subset(df, trt = 0), weighted.mean(status, wate))</pre>
m1 - m0 ## Risk difference ATE
## [1] -0.08294736
log(m1/m0) ## log RR ATE
## [1] -0.203498
log(((m1)/(1-m1))/((m0)/(1-m0))) ## log RR ATE
## [1] -0.3440832
```

ATT

```
m1 <- with(subset(df, trt = 1), weighted.mean(status, watt))</pre>
m0 <- with(subset(df, trt = 0), weighted.mean(status, watt))</pre>
m1 - m0 ## Risk difference ATE
## [1] -0.06696335
log(m1/m0) ## log RR ATE
## [1] -0.1475533
log(((m1)/(1-m1))/((m0)/(1-m0))) ## log RR ATE
## [1] -0.2704971
```

WITH THE survey PACKAGE

```
# install.packages("survey")
library(survey)
## Risk difference ATE
summarv(svvglm(status ~ trt.f. family = binomial(link = "identity").
             svvdesign(data = df. ids = ~ 1, weight = ~ wate)))
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
##
## Call:
## svvglm(formula = status ~ trt.f. design = svvdesign(data = df.
      ids = ~1. weight = ~wate), family = binomial(link = "identity"))
##
##
## Survey design:
## svvdesign(data = df. ids = ~1. weight = ~wate)
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
###
## (Intercept) 0.45049 0.01326 33.98 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
ш
```

```
## log RR ATE
summary(svyglm(status ~ trt.f, family = binomial(link = "log"),
               svydesign(data = df, ids = ~ 1, weight = ~ wate)))
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
###
## Call:
## svyglm(formula = status ~ trt.f, design = svydesign(data = df,
       ids = ~1, weight = ~wate), family = binomial(link = "log"))
##
###
## Survey design:
## svydesign(data = df, ids = ~1, weight = ~wate)
###
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) -0.79743 0.02942 -27.101 < 2e-16 ***
## trt.fExposed -0.20350 0.07151 -2.846 0.00448 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
###
## (Dispersion parameter for binomial family taken to be 1.000524)
##
## Number of Fisher Scoring iterations: 6
```

```
## log OR ATE
summary(svyglm(status ~ trt.f, family = binomial(link = "logit"),
              svydesign(data = df, ids = ~ 1, weight = ~ wate)))
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
###
## Call:
## svyglm(formula = status ~ trt.f, design = svydesign(data = df,
      ids = ~1, weight = ~wate), family = binomial(link = "logit"))
##
###
## Survey design:
## svydesign(data = df, ids = ~1, weight = ~wate)
###
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) -0.19870 0.05355 -3.711 0.000212 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
###
## (Dispersion parameter for binomial family taken to be 1.000524)
##
## Number of Fisher Scoring iterations: 4
```

```
## Risk difference ATT
summary(svyglm(status ~ trt.f, family = binomial(link = "identity"),
              svydesign(data = df, ids = ~ 1, weight = ~ watt)))
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
###
## Call:
## svyglm(formula = status ~ trt.f, design = svydesign(data = df,
       ids = ~1, weight = ~watt), family = binomial(link = "identity"))
##
###
## Survey design:
## svydesign(data = df, ids = ~1, weight = ~watt)
###
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 0.48813 0.01523 32.060 <2e-16 ***
## trt.fExposed -0.06696 0.02754 -2.431 0.0151 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1.000524)
##
## Number of Fisher Scoring iterations: 3
```

```
## log RR ATT
summary(svyglm(status ~ trt.f, family = binomial(link = "log"),
              svydesign(data = df, ids = ~ 1, weight = ~ watt)))
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
###
## Call:
## svyglm(formula = status ~ trt.f, design = svydesign(data = df,
      ids = ~1, weight = ~watt), family = binomial(link = "log"))
##
###
## Survey design:
## svydesign(data = df, ids = ~1, weight = ~watt)
###
## Coefficients:
           Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) -0.71717 0.03119 -22.99 <2e-16 ***
## trt.fExposed -0.14755 0.06279 -2.35 0.0189 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
###
## (Dispersion parameter for binomial family taken to be 1.000524)
##
## Number of Fisher Scoring iterations: 6
```

```
## log OR ATE
summary(svyglm(status ~ trt.f, family = binomial(link = "logit"),
              svydesign(data = df, ids = ~ 1, weight = ~ watt)))
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
###
## Call:
## svyglm(formula = status ~ trt.f, design = svydesign(data = df,
      ids = ~1, weight = ~watt), family = binomial(link = "logit"))
##
###
## Survey design:
## svydesign(data = df, ids = ~1, weight = ~watt)
###
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) -0.04749 0.06094 -0.779 0.436
## trt.fExposed -0.27050 0.11215 -2.412 0.016 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
###
## (Dispersion parameter for binomial family taken to be 1.000524)
##
## Number of Fisher Scoring iterations: 4
```

THANKS FOR WATCHING!

