ECONhw5

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3/31/2022

```
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 <- read.csv("C:/Users/Nick/Downloads/pntsprd.csv")

#2.1

data$sprdcvr
```

```
##   [1] 1 1 1 0 0 1 0 1 0 1 1 1 1 0 0 0 0 1 0 0 1 0 0 1 1 0 1 1 1 1 1 1 1 0
0 0 1
##  [38] 1 0 1 0 1 0 0 1 0 1 1 0 1 1 0 1 0 1 1 0 1 1 1 1 0 0 1 1 1 1 1 1 1 1
1 1 0
##  [75] 0 1 0 1 1 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 1 1 1 1 1 0 1
0 1 1
## [112] 0 0 0 0 0 0 0 1 0 0 1 1 0 0 0 0 0 1 1 0 1 1 1 1 0 1 1 1 1 0 1 0 1 0
1 0 1
## [149] 1 0 0 0 0 0 0 1 0 1 1 1 1 1 0 1 0 0 0 1 0 0 0 1 1 1 1 0 0 1 0 0 0 0
1 0 1
## [186] 0 0 1 0 1 1 0 0 1 0 1 0 1 1 0 1 0 1 0 0 0 1 1 1 0 0 1 1 1 1 1 0 0 1
0 1 0
## [223] 0 1 0 1 0 1 0 1 0 0 1 0 0 0 0 1 1 1 1 1 0 0 0 0 1 0 1 0 0 1 1 1 1 1
1 0 0
## [260] 1 1 0 0 1 0 0 1 0 1 1 0 0 1 1 1 1 0 1 1 1 0 1 1 0 0 1 0 1 0 1 1 0 1
1 1 0
## [297] 1 1 0 1 0 0 1 1 0 1 1 0 0 0 1 0 0 0 1 0 1 1 1 1 0 1 0 0 1 0 1 0 0 1
0 1 0
## [334] 1 0 1 1 1 0 0 1 1 0 1 1 1 0 0 1 1 1 1 1 0 1 1 0 1 1 0 1 0 1 0 0 1 0
1 1 1
## [371] 1 0 0 1 1 0 0 1 1 1 1 0 0 1 1 1 1 1 1 1 0 1 1 0 1 0 1 0 1 0 1 0 1 0
1 1 1
## [408] 1 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 1 1 1 0 1 1 0 0 1 1 1 0 0 1
0 0 1
```

```
## [445] 0 0 1 1 0 1 0 0 0 1 0 1 1 1 1 1 0 0 0 0 0 1 1 0 0 0 0 1 1 0 1 1 0 0
0 1 0
## [482] 0 0 0 1 1 1 0 0 0 0 1 0 1 0 0 0 1 1 0 1 0 0 1 1 0 1 0 1 0 1 0 1 0 1
1 1 1
## [519] 0 1 0 0 0 1 1 0 1 0 0 1 1 1 1 1 0 1 1 0 1 1 1 0 1 0 0 0 1 0 0 1 1 0
0

t.test(data$sprdcvr,mu = .5, paired = F, conf.level=.9)

##
##  One Sample t-test
##
## data:  data$sprdcvr
## t = 0.7226, df = 552, p-value = 0.4702
## alternative hypothesis: true mean is not equal to 0.5
## 90 percent confidence interval:
##  0.4803236 0.5504178
## sample estimates:
## mean of x
## 0.5153707

# Fail to reject the null hyothesis as the p-value if greater than .05.

#2.2

gamesonneutralcourt = sum(data$neutral)
gamesonneutralcourt

## [1] 35

#2.3

lm.fit <- lm(data$sprdcvr ~ data$favhome + data$neutral + data$fav25 +
data$und25)
summary(lm.fit)

##
## Call:
## lm(formula = data$sprdcvr ~ data$favhome + data$neutral + data$fav25 +
##     data$und25)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.6072 -0.5242  0.3928  0.4758  0.5339
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.48957    0.04476  10.938   <2e-16 ***
## data$favhome  0.03459    0.04972   0.696    0.487
## data$neutral  0.11762    0.09466   1.242    0.215
## data$fav25   -0.02347    0.05019  -0.468    0.640
```

```
## data$und25    0.01787    0.09188   0.195    0.846
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5012 on 548 degrees of freedom
## Multiple R-squared:  0.0034, Adjusted R-squared:  -0.003874
## F-statistic: 0.4674 on 4 and 548 DF,  p-value: 0.7597
```

```
# Load libraries
library("lmtest")
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
library("sandwich")

# Robust t test
hetero.fit <- coeftest(lm.fit, vcov = vcovHC(lm.fit, type = "HC0"))
hetero.fit
```

```
##
## t test of coefficients:
##
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.489567   0.044648 10.9651   <2e-16 ***
## data$favhome  0.034591   0.049597  0.6974   0.4858
## data$neutral  0.117618   0.092701  1.2688   0.2051
## data$fav25   -0.023467   0.050154 -0.4679   0.6400
## data$und25    0.017873   0.089655  0.1994   0.8421
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(hetero.fit)
```

```
##     Estimate          Std. Error         t value           Pr(>|t|)
##  Min.   :-0.02347   Min.   :0.04465   Min.   :-0.4679   Min.   :0.0000
##  1st Qu.: 0.01787   1st Qu.:0.04960   1st Qu.: 0.1993   1st Qu.:0.2051
##  Median : 0.03459   Median :0.05015   Median : 0.6974   Median :0.4858
##  Mean   : 0.12724   Mean   :0.06535   Mean   : 2.5325   Mean   :0.4346
##  3rd Qu.: 0.11762   3rd Qu.:0.08966   3rd Qu.: 1.2688   3rd Qu.:0.6400
##  Max.   : 0.48957   Max.   :0.09270   Max.   :10.9651   Max.   :0.8421
```

```
# Standard errors do not significantly change for any estimators when
assuming heteroskedasticity robust model. heteroskedasticity robust model is
more significant (lower p-values).
```

```
#2.4

# If all of the estimators equal zero (B1 = B2 = B3 = B4 = 0), the OLS fit will just be a horizontal line across the data with a y value at the mean of the regressand (sprdcvr). Since sprdcvr is binary and all estimators equal zero, variance of error will not be dependent on any regressor, suggesting homoskedasticity.

#2.5

# None of the statistics in any of the tests performed on the model above have shown any significance of relationship between the regressors and if the game will cover the spread. This suggests that the market of sports betting is efficient and that one cannot use available data to get advantage in calling sports bets.

#2.6

lm.fit$fitted.values

##         1         2         3         4         5         6         7 
8 
## 0.4660991 0.5241576 0.5241576 0.5241576 0.4895665 0.5837171 0.5241576 
0.5006902 
##         9        10        11        12        13        14        15 
16 
## 0.4895665 0.4895665 0.5241576 0.5241576 0.4660991 0.5241576 0.4895665 
0.5006902 
##        17        18        19        20        21        22        23 
24 
## 0.5241576 0.5241576 0.4895665 0.5241576 0.5241576 0.4895665 0.5241576 
0.5006902 
##        25        26        27        28        29        30        31 
32 
## 0.6071845 0.4895665 0.5241576 0.5241576 0.5006902 0.5241576 0.5006902 
0.5837171 
##        33        34        35        36        37        38        39 
40 
## 0.6071845 0.5241576 0.5241576 0.6071845 0.5241576 0.6071845 0.5241576 
0.6071845 
##        41        42        43        44        45        46        47 
48 
## 0.5241576 0.6071845 0.4895665 0.6071845 0.6071845 0.5241576 0.5837171 
0.5241576 
##        49        50        51        52        53        54        55 
56 
## 0.5006902 0.5241576 0.5241576 0.5006902 0.4660991 0.5241576 0.5241576 
0.5241576 
##        57        58        59        60        61        62        63 
64 
```

```
## 0.4895665 0.5241576 0.5006902 0.6071845 0.6071845 0.4895665 0.5241576
0.5241576
##        65        66        67        68        69        70        71
72
## 0.6015899 0.5241576 0.5241576 0.5241576 0.5241576 0.5241576 0.6071845
0.4895665
##        73        74        75        76        77        78        79
80
## 0.4660991 0.5241576 0.4895665 0.4895665 0.5241576 0.4895665 0.5241576
0.4895665
##        81        82        83        84        85        86        87
88
## 0.4895665 0.5185630 0.4660991 0.5241576 0.5006902 0.5006902 0.5241576
0.5241576
##        89        90        91        92        93        94        95
96
## 0.5006902 0.6071845 0.5241576 0.6071845 0.5241576 0.5241576 0.6071845
0.5241576
##        97        98        99       100       101       102       103
104
## 0.6071845 0.5006902 0.5241576 0.5241576 0.5241576 0.5241576 0.6015899
0.5420304
##       105       106       107       108       109       110       111
112
## 0.4660991 0.5241576 0.5241576 0.5006902 0.5241576 0.5241576 0.5241576
0.4660991
##       113       114       115       116       117       118       119
120
## 0.5241576 0.4660991 0.5241576 0.5241576 0.5837171 0.5241576 0.5185630
0.5241576
##       121       122       123       124       125       126       127
128
## 0.5241576 0.5241576 0.5241576 0.5241576 0.5241576 0.5241576 0.5006902
0.5241576
##       129       130       131       132       133       134       135
136
## 0.4895665 0.5241576 0.5241576 0.4895665 0.5241576 0.5241576 0.5241576
0.5241576
##       137       138       139       140       141       142       143
144
## 0.5241576 0.5241576 0.5241576 0.4895665 0.4895665 0.6071845 0.6071845
0.5241576
##       145       146       147       148       149       150       151
152
## 0.5241576 0.6071845 0.4895665 0.5241576 0.5420304 0.5241576 0.4660991
0.5241576
##       153       154       155       156       157       158       159
160
## 0.5837171 0.5241576 0.5006902 0.5837171 0.5006902 0.4895665 0.4895665
0.5241576
```

```
##       161       162       163       164       165       166       167 
168 
## 0.5006902 0.4660991 0.5420304 0.4660991 0.4660991 0.4660991 0.4895665 
0.5006902 
##       169       170       171       172       173       174       175 
176 
## 0.5241576 0.4895665 0.5241576 0.5241576 0.5006902 0.5241576 0.4660991 
0.4895665 
##       177       178       179       180       181       182       183 
184 
## 0.5241576 0.5241576 0.4895665 0.4895665 0.5241576 0.5241576 0.5241576 
0.4895665 
##       185       186       187       188       189       190       191 
192 
## 0.5241576 0.5241576 0.5241576 0.4895665 0.5241576 0.5241576 0.5241576 
0.5006902 
##       193       194       195       196       197       198       199 
200 
## 0.5241576 0.5241576 0.5241576 0.4895665 0.5006902 0.5241576 0.5241576 
0.5006902 
##       201       202       203       204       205       206       207 
208 
## 0.5241576 0.5006902 0.4895665 0.5241576 0.5241576 0.4895665 0.5241576 
0.5241576 
##       209       210       211       212       213       214       215 
216 
## 0.5241576 0.5185630 0.5006902 0.5241576 0.5241576 0.5241576 0.5241576 
0.4895665 
##       217       218       219       220       221       222       223 
224 
## 0.5241576 0.5241576 0.5241576 0.4895665 0.5241576 0.5241576 0.5241576 
0.5241576 
##       225       226       227       228       229       230       231 
232 
## 0.5241576 0.5241576 0.4839719 0.5241576 0.5006902 0.4895665 0.5006902 
0.5241576 
##       233       234       235       236       237       238       239 
240 
## 0.4895665 0.4895665 0.5006902 0.4895665 0.4895665 0.5006902 0.4660991 
0.5241576 
##       241       242       243       244       245       246       247 
248 
## 0.5006902 0.5006902 0.5241576 0.5241576 0.4895665 0.5241576 0.5241576 
0.5837171 
##       249       250       251       252       253       254       255 
256 
## 0.4895665 0.5241576 0.5241576 0.5006902 0.5420304 0.5241576 0.5006902 
0.5006902 
##       257       258       259       260       261       262       263 
264 
```

```
## 0.6071845 0.5241576 0.5837171 0.6071845 0.4895665 0.4895665 0.5241576
0.4895665
##       265       266       267       268       269       270       271
272
## 0.5241576 0.4895665 0.5241576 0.4895665 0.5241576 0.4895665 0.5241576
0.5241576
##       273       274       275       276       277       278       279
280
## 0.5241576 0.5241576 0.5241576 0.5241576 0.5006902 0.5241576 0.5006902
0.6015899
##       281       282       283       284       285       286       287
288
## 0.5837171 0.5006902 0.4895665 0.4660991 0.4895665 0.5241576 0.5241576
0.5241576
##       289       290       291       292       293       294       295
296
## 0.4839719 0.5241576 0.5241576 0.5006902 0.5420304 0.4895665 0.5241576
0.5241576
##       297       298       299       300       301       302       303
304
## 0.5185630 0.5006902 0.4895665 0.5006902 0.4895665 0.4660991 0.5241576
0.5006902
##       305       306       307       308       309       310       311
312
## 0.4660991 0.4660991 0.5241576 0.5006902 0.5241576 0.5241576 0.5241576
0.5241576
##       313       314       315       316       317       318       319
320
## 0.5185630 0.5006902 0.5420304 0.5241576 0.5006902 0.5006902 0.5241576
0.5006902
##       321       322       323       324       325       326       327
328
## 0.4895665 0.5185630 0.5185630 0.5006902 0.5185630 0.4895665 0.5241576
0.5241576
##       329       330       331       332       333       334       335
336
## 0.4660991 0.4895665 0.5006902 0.5241576 0.5241576 0.4660991 0.5241576
0.5006902
##       337       338       339       340       341       342       343
344
## 0.4660991 0.5241576 0.4895665 0.5241576 0.4895665 0.5420304 0.4839719
0.4895665
##       345       346       347       348       349       350       351
352
## 0.5241576 0.5420304 0.5006902 0.5006902 0.5006902 0.4895665 0.4895665
0.5241576
##       353       354       355       356       357       358       359
360
## 0.5241576 0.5420304 0.4660991 0.5241576 0.5241576 0.5006902 0.5006902
0.5006902
```

```
##       361       362       363       364       365       366       367 
368 
## 0.5241576 0.5241576 0.4895665 0.4660991 0.4839719 0.5241576 0.5420304 
0.5241576 
##       369       370       371       372       373       374       375 
376 
## 0.5241576 0.4660991 0.5006902 0.4895665 0.5241576 0.4895665 0.4660991 
0.5241576 
##       377       378       379       380       381       382       383 
384 
## 0.5241576 0.5241576 0.5241576 0.4660991 0.4895665 0.5241576 0.5241576 
0.5241576 
##       385       386       387       388       389       390       391 
392 
## 0.5241576 0.5241576 0.5006902 0.5241576 0.5241576 0.5241576 0.4895665 
0.4895665 
##       393       394       395       396       397       398       399 
400 
## 0.5241576 0.5185630 0.5241576 0.5185630 0.5006902 0.5006902 0.5241576 
0.4895665 
##       401       402       403       404       405       406       407 
408 
## 0.5006902 0.5241576 0.5241576 0.4895665 0.5241576 0.5241576 0.5241576 
0.5185630 
##       409       410       411       412       413       414       415 
416 
## 0.5241576 0.5241576 0.5241576 0.5241576 0.4895665 0.4895665 0.5241576 
0.5006902 
##       417       418       419       420       421       422       423 
424 
## 0.5006902 0.5241576 0.5241576 0.5241576 0.4895665 0.5241576 0.4895665 
0.5241576 
##       425       426       427       428       429       430       431 
432 
## 0.4660991 0.4895665 0.5006902 0.5241576 0.5241576 0.5241576 0.4895665 
0.4660991 
##       433       434       435       436       437       438       439 
440 
## 0.5241576 0.5241576 0.5241576 0.5006902 0.5006902 0.5241576 0.5241576 
0.5241576 
##       441       442       443       444       445       446       447 
448 
## 0.5241576 0.5241576 0.5241576 0.5241576 0.5006902 0.5241576 0.4895665 
0.5241576 
##       449       450       451       452       453       454       455 
456 
## 0.5241576 0.5241576 0.4895665 0.5420304 0.5241576 0.5241576 0.4895665 
0.5185630 
##       457       458       459       460       461       462       463 
464 
```

```
## 0.4660991 0.5241576 0.5241576 0.5241576 0.5241576 0.5241576 0.4895665
0.5241576
##       465       466       467       468       469       470       471
472
## 0.5006902 0.4660991 0.4660991 0.4660991 0.5241576 0.5241576 0.4660991
0.4895665
##       473       474       475       476       477       478       479
480
## 0.5185630 0.6071845 0.4895665 0.5241576 0.4895665 0.5241576 0.4895665
0.5241576
##       481       482       483       484       485       486       487
488
## 0.5241576 0.5241576 0.5241576 0.5241576 0.4895665 0.5241576 0.5241576
0.5241576
##       489       490       491       492       493       494       495
496
## 0.5241576 0.5241576 0.5006902 0.5241576 0.5241576 0.5241576 0.4895665
0.4895665
##       497       498       499       500       501       502       503
504
## 0.5241576 0.5241576 0.4895665 0.4660991 0.4895665 0.4895665 0.4660991
0.5241576
##       505       506       507       508       509       510       511
512
## 0.4895665 0.5241576 0.4895665 0.5241576 0.5185630 0.4895665 0.5241576
0.5241576
##       513       514       515       516       517       518       519
520
## 0.5241576 0.5241576 0.4895665 0.5241576 0.4895665 0.5241576 0.5006902
0.5241576
##       521       522       523       524       525       526       527
528
## 0.5241576 0.5241576 0.5185630 0.5241576 0.5006902 0.6071845 0.5241576
0.5241576
##       529       530       531       532       533       534       535
536
## 0.5837171 0.4660991 0.5241576 0.4660991 0.5241576 0.5241576 0.5241576
0.4895665
##       537       538       539       540       541       542       543
544
## 0.5241576 0.5006902 0.4895665 0.4895665 0.4660991 0.5185630 0.5241576
0.5241576
##       545       546       547       548       549       550       551
552
## 0.5241576 0.5241576 0.5006902 0.5241576 0.4660991 0.5241576 0.5241576
0.4660991
##       553
## 0.4660991
```

```r
#2.7

library(foreign)

logit <- glm(data$sprdcvr ~ data$favhome + data$neutral + data$fav25 +
data$und25, family=binomial(link="logit"))
logit

##
## Call:  glm(formula = data$sprdcvr ~ data$favhome + data$neutral +
data$fav25 +
##     data$und25, family = binomial(link = "logit"))
##
## Coefficients:
##  (Intercept)  data$favhome  data$neutral    data$fav25    data$und25
##     -0.04169       0.13845       0.47618      -0.09424       0.07177
##
## Degrees of Freedom: 552 Total (i.e. Null);  548 Residual
## Null Deviance:       766.1
## Residual Deviance: 764.2     AIC: 774.2

summary(logit)

##
## Call:
## glm(formula = data$sprdcvr ~ data$favhome + data$neutral + data$fav25 +
##     data$und25, family = binomial(link = "logit"))
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3666  -1.2188   0.9993   1.1366   1.2356
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.04169    0.17873  -0.233    0.816
## data$favhome  0.13845    0.19855   0.697    0.486
## data$neutral  0.47618    0.38413   1.240    0.215
## data$fav25   -0.09424    0.20070  -0.470    0.639
## data$und25    0.07177    0.36783   0.195    0.845
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 766.10  on 552  degrees of freedom
## Residual deviance: 764.21  on 548  degrees of freedom
## AIC: 774.21
##
## Number of Fisher Scoring iterations: 3

probit <- glm(data$sprdcvr ~ data$favhome + data$neutral + data$fav25 +
data$und25, family=binomial(link="probit"))
probit
```

```
##
## Call:  glm(formula = data$sprdcvr ~ data$favhome + data$neutral + 
data$fav25 + 
##     data$und25, family = binomial(link = "probit"))
##
## Coefficients:
##  (Intercept)  data$favhome  data$neutral    data$fav25    data$und25  
##     -0.02606       0.08665       0.29798      -0.05916       0.04591  
##
## Degrees of Freedom: 552 Total (i.e. Null);  548 Residual
## Null Deviance:       766.1 
## Residual Deviance: 764.2     AIC: 774.2
```

```r
summary(probit)
```

```
##
## Call:
## glm(formula = data$sprdcvr ~ data$favhome + data$neutral + data$fav25 + 
##     data$und25, family = binomial(link = "probit"))
##
## Deviance Residuals: 
##    Min      1Q  Median      3Q     Max  
## -1.367  -1.219   0.999   1.137   1.236  
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.02606    0.11197  -0.233    0.816
## data$favhome  0.08665    0.12439   0.697    0.486
## data$neutral  0.29798    0.23901   1.247    0.213
## data$fav25   -0.05916    0.12566  -0.471    0.638
## data$und25    0.04591    0.23020   0.199    0.842
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 766.10  on 552  degrees of freedom
## Residual deviance: 764.21  on 548  degrees of freedom
## AIC: 774.21
##
## Number of Fisher Scoring iterations: 3
```

```r
# Probit and logit models still return similar results without statisticsal 
significance.
```