

Florida 2018 Exit Polls Problem Set

Solutions

```
library(tidyverse)

## -- Attaching packages ----- tidyverse 1.3.0 --
## v ggplot2 3.3.2    v purrr   0.3.4
## v tibble  3.0.4    v dplyr   1.0.2
## v tidyr   1.1.2    v stringr 1.4.0
## v readr   1.4.0    v forcats 0.5.0

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()

library(haven)
exit <- read_dta("https://github.com/zilinskyjan/R-stata-tutorials/blob/master/homework/31116399_Florida")
```

R Answers

Part A: Descriptives

1. How many respondents were 65 years old or older? What was their proportion in the sample?

One option:

```
exit %>% count(AGE65)
```

```
## # A tibble: 7 x 2
##   AGE65      n
##   <dbl+lbl> <int>
## 1 1 [18-24]   261
## 2 2 [25-29]   232
## 3 3 [30-39]   431
## 4 4 [40-49]   462
## 5 5 [50-64]   927
## 6 6 [65+]    816
## 7 NA         18
```

```
# Another option:
# exit %>% count(AGE8)
```

Add a column with proportions:

```
exit %>%
  count(AGE65) %>%
  mutate(proportion = n / sum(n))
```

```
## # A tibble: 7 x 3
##   AGE65      n proportion
```

```
##      <dbl+lbl> <int>      <dbl>
## 1  1 [18-24]    261    0.0829
## 2  2 [25-29]    232    0.0737
## 3  3 [30-39]    431    0.137
## 4  4 [40-49]    462    0.147
## 5  5 [50-64]    927    0.295
## 6  6 [65+]      816    0.259
## 7 NA           18    0.00572
```

Another possibility:

```
table(exit$AGE65)
```

```
##
##  1  2  3  4  5  6
## 261 232 431 462 927 816
```

```
table(exit$AGE65) / sum(table(exit$AGE65))
```

```
##
##           1           2           3           4           5           6
## 0.08341323 0.07414509 0.13774369 0.14765101 0.29626079 0.26078619
```

Even better to run:

```
exit %>%
  count(AGE65) %>%
  filter(!is.na(AGE65)) %>%
  mutate(proportion = n / sum(n))
```

```
## # A tibble: 6 x 3
##   AGE65      n proportion
##   <dbl+lbl> <int>      <dbl>
## 1 1 [18-24]    261    0.0834
## 2 2 [25-29]    232    0.0741
## 3 3 [30-39]    431    0.138
## 4 4 [40-49]    462    0.148
## 5 5 [50-64]    927    0.296
## 6 6 [65+]      816    0.261
```

2. What was the proportion of Hispanic respondents who:

- Lived in cities with pop. over 50,000?
- Lived in suburbs?
- Lived in small cities or rural areas?

(Hint: Look at the variation in the variable labeled SIZEPLC3.)

```
exit %>% filter(latino==1) %>%
  group_by(SIZEPLC3) %>%
  summarize(n = n()) %>%
  mutate(proportion = n / sum(n))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 3 x 3
##   SIZEPLC3      n proportion
##   <dbl+lbl> <int>      <dbl>
## 1 1 [Cities over 50,000]    256    0.494
## 2 2 [Suburbs]              257    0.496
```

```
## 3 3 [Small Cities/Rural]      5      0.00965
```

Alternative code:

```
exit %>% filter(latino==1) %>%
  group_by(SIZEPLC3) %>%
  tally() %>%
  mutate(proportion = n / sum(n))
```

```
## # A tibble: 3 x 3
##           SIZEPLC3      n proportion
##           <dbl+lbl> <int>      <dbl>
## 1 1 [Cities over 50,000]    256    0.494
## 2 2 [Suburbs]              257    0.496
## 3 3 [Small Cities/Rural]     5     0.00965
```

3. Prepare a table displaying the proportion of voters who said they were first-time (midterm election) voters, broken down by gender.

```
exit %>% group_by(FTVOTER1) %>% tally()
```

```
## # A tibble: 3 x 2
##   FTVOTER1      n
##   <dbl+lbl> <int>
## 1 1 [Yes]    209
## 2 2 [No]     781
## 3 NA       2157
```

```
exit %>% group_by(FTVOTER1,sex) %>%
  filter(!is.na(FTVOTER1),!is.na(sex)) %>%
  tally() %>%
  mutate(prop = n / sum(n))
```

```
## # A tibble: 4 x 4
## # Groups:   FTVOTER1 [2]
##   FTVOTER1      sex      n prop
##   <dbl+lbl> <dbl+lbl> <int> <dbl>
## 1 1 [Yes] 1 [Male]     78 0.373
## 2 1 [Yes] 2 [Female]   131 0.627
## 3 2 [No] 1 [Male]    349 0.448
## 4 2 [No] 2 [Female]   430 0.552
```

Why is it important to remove the missing observations from the denominator?

- Most student correctly say that 78 of male voters were first-time voters.
- But we cannot divide 78 by the total number of male respondents (1398).
- Rather, we must divide 78 by 427 (i.e. the number of male respondents for who we know their FT-voting status).

```
exit %>% count(sex)
```

```
## # A tibble: 3 x 2
##       sex      n
##   <dbl+lbl> <int>
## 1 1 [Male]   1398
## 2 2 [Female] 1741
## 3 NA         8
```

```
exit %>% filter(!is.na(FTVOTER1)) %>% count(sex)
```

```
## # A tibble: 3 x 2
##       sex      n
##   <dbl+lbl> <int>
## 1 1 [Male]    427
## 2 2 [Female]  561
## 3 NA         2
```

4. What was the proportion of Democrats who said in 2018 that Donald Trump should not be impeached and removed from office?

```
exit %>% count(party, IMPEACH1)
```

```
## # A tibble: 16 x 3
##       party IMPEACH1      n
##   <dbl+lbl> <dbl+lbl> <int>
## 1 1 [Democrat]      1 [Yes]   256
## 2 1 [Democrat]      2 [No]    56
## 3 1 [Democrat]      9 [Omit]   22
## 4 1 [Democrat]     NA       712
## 5 2 [Republican]     1 [Yes]    20
## 6 2 [Republican]     2 [No]   300
## 7 2 [Republican]     9 [Omit]    2
## 8 2 [Republican]     NA      705
## 9 3 [Independent/Something else] 1 [Yes]   114
## 10 3 [Independent/Something else] 2 [No]   169
## 11 3 [Independent/Something else] 9 [Omit]   31
## 12 3 [Independent/Something else] NA      637
## 13 NA              1 [Yes]    6
## 14 NA              2 [No]    5
## 15 NA              9 [Omit]    1
## 16 NA             NA      111
```

Let's limit our attention to Democrats:

```
exit %>% count(party, IMPEACH1) %>% filter(party==1)
```

```
## # A tibble: 4 x 3
##       party IMPEACH1      n
##   <dbl+lbl> <dbl+lbl> <int>
## 1 1 [Democrat] 1 [Yes]   256
## 2 1 [Democrat] 2 [No]    56
## 3 1 [Democrat] 9 [Omit]   22
## 4 1 [Democrat] NA      712
```

Part B

1. Is there an association between 2016 vote choice and the type of area where a voter lives?

```
exit %>% count(SIZEPLC3, VOTE2016)
```

```
## # A tibble: 17 x 3
##       SIZEPLC3 VOTE2016      n
##   <dbl+lbl> <dbl+lbl> <int>
## 1 1 [Cities over 50,000] 1 [Hillary Clinton] 170
## 2 1 [Cities over 50,000] 2 [Donald Trump]   115
```

```
## 3 1 [Cities over 50,000] 3 [Other] 20
## 4 1 [Cities over 50,000] 4 [Didn't vote] 32
## 5 1 [Cities over 50,000] 9 [Omit] 3
## 6 1 [Cities over 50,000] NA 794
## 7 2 [Suburbs] 1 [Hillary Clinton] 222
## 8 2 [Suburbs] 2 [Donald Trump] 271
## 9 2 [Suburbs] 3 [Other] 34
## 10 2 [Suburbs] 4 [Didn't vote] 40
## 11 2 [Suburbs] 9 [Omit] 12
## 12 2 [Suburbs] NA 1266
## 13 3 [Small Cities/Rural] 1 [Hillary Clinton] 19
## 14 3 [Small Cities/Rural] 2 [Donald Trump] 30
## 15 3 [Small Cities/Rural] 3 [Other] 4
## 16 3 [Small Cities/Rural] 4 [Didn't vote] 4
## 17 3 [Small Cities/Rural] NA 111
```

Run a regression:

```
exit$votedForCliton2016 <- ifelse(exit$VOTE2016==1,1,0)

model_vote <- lm(votedForCliton2016 ~ factor(SIZEPLC3), data= exit)
```

2. What percentage of voters said that when choosing their candidate for the US Senate, “Donald Trump was not a factor”?

```
exit %>% count(fortrump)
```

```
## # A tibble: 5 x 2
##               fortrump     n
##               <dbl+lbl> <int>
## 1 1 [To express support for Donald Trump] 189
## 2 2 [To express opposition to Donald Trump] 249
## 3 3 [Donald Trump was not a factor] 334
## 4 9 [Omit] 28
## 5 NA 2347
```

3. What percentage voters said that, in their vote for the US Senate, Bill Nelson’s vote against Brett Kavanaugh’s confirmation “not a factor at all?”

```
exit %>% count(KAVFL18)
```

```
## # A tibble: 6 x 2
##               KAVFL18     n
##               <dbl+lbl> <int>
## 1 1 [The most important factor] 64
## 2 2 [An important factor] 226
## 3 3 [A minor factor] 120
## 4 4 [Not a factor at all] 265
## 5 9 [Omit] 72
## 6 NA 2400
```

Part C:

```
exit$motivated <- ifelse(exit$RUSSIA18==2,1,0)

exit <- exit %>% mutate(politcally_motivated = ifelse(RUSSIA18==2,1,0))
```

Note: Republicans are `party==2`:

```
mod <- lm(motivated ~ factor(party) + factor(AGE8),
          data = exit %>% filter(!is.na(RUSSIA18)))

summary(mod)

##
## Call:
## lm(formula = motivated ~ factor(party) + factor(AGE8), data = exit %>%
##   filter(!is.na(RUSSIA18)))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.8587 -0.3345  0.1773  0.4264  0.7663
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.33454    0.05549   6.029 2.37e-09 ***
## factor(party)2  0.50565    0.03583  14.113 < 2e-16 ***
## factor(party)3  0.22062    0.03676   6.002 2.79e-09 ***
## factor(AGE8)2  -0.03962    0.07376  -0.537   0.591
## factor(AGE8)3  -0.10083    0.06600  -1.528   0.127
## factor(AGE8)4  -0.08811    0.07835  -1.125   0.261
## factor(AGE8)5   0.01846    0.07391   0.250   0.803
## factor(AGE8)6  -0.05155    0.06050  -0.852   0.394
## factor(AGE8)7  -0.01745    0.06984  -0.250   0.803
## factor(AGE8)8  -0.03441    0.05969  -0.576   0.564
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4514 on 935 degrees of freedom
## (23 observations deleted due to missingness)
## Multiple R-squared:  0.1879, Adjusted R-squared:  0.1801
## F-statistic: 24.04 on 9 and 935 DF, p-value: < 2.2e-16
```

What are the key things to notice here?

- Higher values of `party` do not mean that a respondent is “more Republican”.
- The values are not ordered in a meaningful way (1 = Democrat; 2 = Republican; 3 = “Independent”).
- Even if the values were ordered in an ideological manner, it still doesn’t mean that treating the variable as continuous is necessarily a defensible choice.
- The values are unordered, so you *must* include a series of indicator/dummy variables, if you wish to control for partisanship.
- One way to achieve that is to add `factor(party)` to your regression formula.

Of course, you can create binary variables:

```
exit$democrat <- ifelse(exit$party==1, 1, 0)
exit$republican <- ifelse(exit$party==2, 1, 0)
```

And then you can estimate the same model, but exchanging the baseline category from “Democrat” (table above) to “Independent”. So now the coefficient on “Republican” will be smaller, because the estimated magnitude is *relative to Independents*:

```
(lm(motivated ~ factor(AGE8) +
    democrat + republican,
    data = exit %>% filter(!is.na(RUSSIA18))) %>%
```

```
summary() )
```

```
##
## Call:
## lm(formula = motivated ~ factor(AGE8) + democrat + republican,
##     data = exit %>% filter(!is.na(RUSSIA18)))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.8587 -0.3345  0.1773  0.4264  0.7663
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.55515    0.05573   9.961 < 2e-16 ***
## factor(AGE8)2  -0.03962    0.07376  -0.537  0.591
## factor(AGE8)3  -0.10083    0.06600  -1.528  0.127
## factor(AGE8)4  -0.08811    0.07835  -1.125  0.261
## factor(AGE8)5   0.01846    0.07391   0.250  0.803
## factor(AGE8)6  -0.05155    0.06050  -0.852  0.394
## factor(AGE8)7  -0.01745    0.06984  -0.250  0.803
## factor(AGE8)8  -0.03441    0.05969  -0.576  0.564
## democrat       -0.22062    0.03676  -6.002 2.79e-09 ***
## republican      0.28503    0.03629   7.855 1.09e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4514 on 935 degrees of freedom
## (23 observations deleted due to missingness)
## Multiple R-squared:  0.1879, Adjusted R-squared:  0.1801
## F-statistic: 24.04 on 9 and 935 DF,  p-value: < 2.2e-16
```

STATA Answers

```
tab AGE8 or tab AGE65
gen hispanic = (latino==1) if !mi(latino)
tabstat hispanic, by(SIZEPLC3)
tab FTVOTER1 sex
tab party IMPEACH1, row nof
```

Part B:

```
B1: tab SIZEPLC3 VOTE2016 [aw=weight], row nof
B2: tab fortrump
B3: tab KAVFL18
```

Part C:

```
gen motivated = (RUSSIA18==2) if !mi(RUSSIA18)
reg motivated i.AGE8 ib3.party
```

It is important to note that:

- Higher values of party do not mean that a respondent is “more Republican”.
- The values are of the variable not ordered in a meaningful way (1 = Democrat; 2 = Republican; 3 = "Independent). And even if the values were ordered ideologically, it still doesn't mean that treating the variable as continuous is necessarily a defensible choice.
- Given that the values are unordered, then you *must* include a series of indicator/dummy variables.
- One way to achieve that is to use the “i.” operator.

The “i.” operator is a quick way to deal with categorical variables but, of course, you can create binary variables for each category (minus 1, as you will not be including the baseline category in the model)

You can run:

```
gen democrat = (party==1) if !missing(party)
gen republican = (party==2) if !missing(party)
reg motivated i.AGE8 democrat republican
```