DARE 1

Anwesha Guha & Merly Klaas

1/11/2022

A. Data Management Tasks (1 point)

For these tasks, no write up is required. The code you submit will be sufficient.

A1. Convert the raw counts of enrollment by race/ethnicity into percentages (i.e., divide the enrollment count for each ethno-racial category by total enrollment). For programming efficiency, can you use a function to do this task?

```
dare1 <- dare1 %>%
  mutate(across(c(10:15), ~ . / !! dare1$enroll * 100))
```

A2. Generate dichotomous policy predictor variables that take the value of 1 in state-year observations in which the policy is in place. Call them eval, class remove and suspension. They should take the value of 0 in years during which these policies were not in place.

```
dare1 <- dare1 %>%
  mutate(eval = case_when(eval_year>=school_year ~ 1,
         TRUE ~ 0)) %>%
  mutate(class_remove = case_when(class_remove_year>=school_year ~ 1,
         TRUE ~ 0)) %>%
  mutate(suspension = case_when(suspension_year>=school_year ~ 1,
         TRUE ~ 0))

#          mutate(eval = ifelse(is.na(eval_year),0,1)) %>%
#          mutate(class_remove = ifelse(is.na(class_remove_year),0,1)) %>%
#          mutate(suspension = ifelse(is.na(suspension_year),0,1)) %>%
#          runtime_classremove = eval_year - class_remove_year,
#          runtime_suspension = eval_year - suspension_year,
#          evalXclass_removeyear = eval * runtime_classremove,
#          evalXsuspyear = eval * runtime_suspension)
```

Also, generate a running time variable (run time) that reflects how far or close the state-year observation is from the implementation of higher stakes teacher evaluation and a variable that permits the effects of the evaluation policy to vary (linearly) over time (evalXyear). How will you deal with states that never implement evaluation? Do that too.

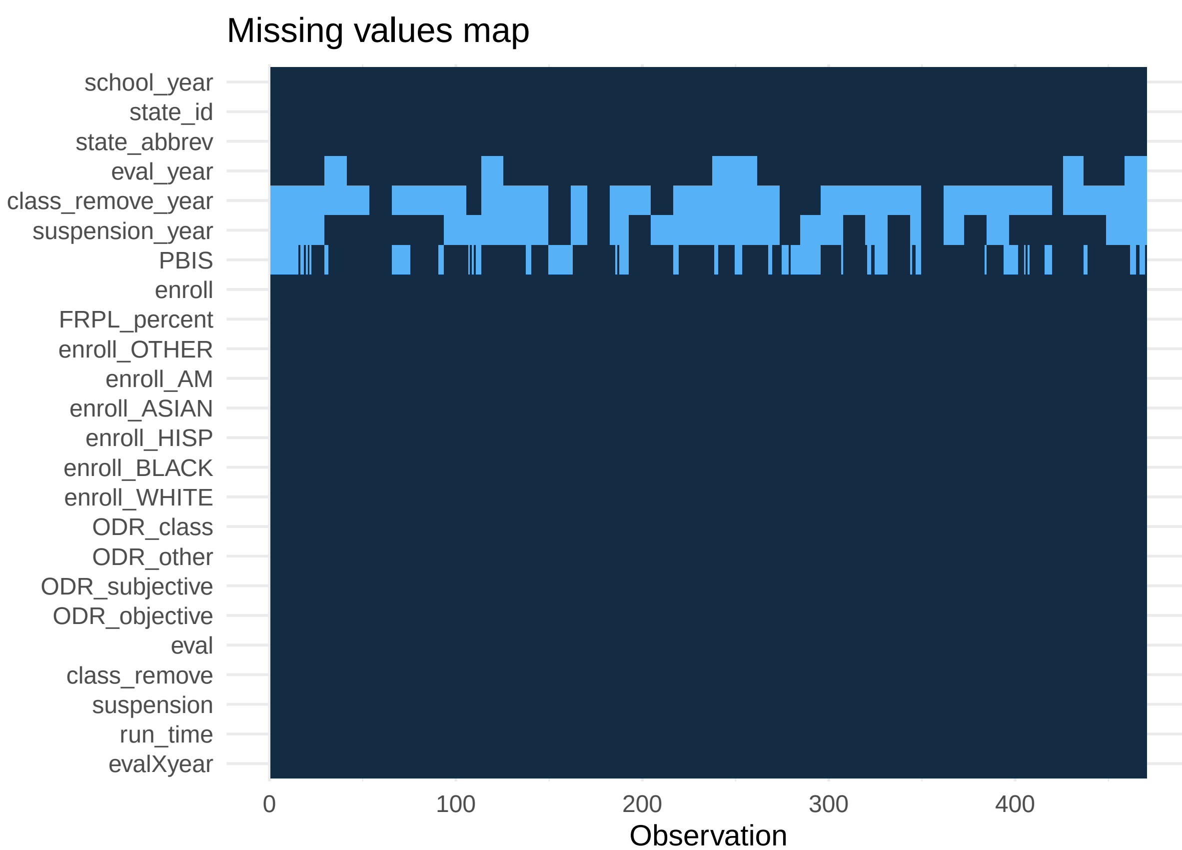
```
dare1 <- dare1 %>%
  mutate(run_time = ifelse(is.na(eval_year), -99, school_year-eval_year)) %>% # -99 for states that nev
  mutate(evalXyear = eval*run_time)
```

B. Understanding the Data and Descriptive Statistics (3 points)

For the following tasks, give your best attempt at completing the analysis and write-up. If you are unable to conduct the programming or analysis, describe what you are attempting to do and what your results would mean.

Merly **B1.** Inspect your data. What sorts of missingness exist within the data file? What sorts of missingness should concern you? Which do not? In this assignment, please restrict your sample to state-years with non-missing outcomes.

```
dare1 %>%
  drop_na(ODR_class, ODR_objective, ODR_other, ODR_objective)%>%
  missing_plot()
```




```
dare1 %>% summary()
```

```
##   school_year      state_id     state_abbrev         eval_year
##  Min.   :2006   Min.   : 2.00   Length:516         Min.   :2011
##  1st Qu.:2009   1st Qu.:18.00   Class :character   1st Qu.:2013
##  Median :2012   Median :29.00   Mode  :character   Median :2014
##  Mean   :2012   Mean   :29.16                      Mean   :2014
##  3rd Qu.:2014   3rd Qu.:41.00                      3rd Qu.:2014
##  Max.   :2017   Max.   :56.00                      Max.   :2016
##                                                    NA's   :72
##  class_remove_year suspension_year      PBIS             enroll
```

```
##  Min.   :2009      Min.   :2007    Min.   :0.0000   Min.   :   216  
##  1st Qu.:2009      1st Qu.:2011    1st Qu.:0.0000   1st Qu.:  2891  
##  Median :2012      Median :2014    Median :1.0000   Median :  9764  
##  Mean   :2012      Mean   :2013    Mean   :0.7214   Mean   : 21897  
##  3rd Qu.:2015      3rd Qu.:2016    3rd Qu.:1.0000   3rd Qu.: 26510  
##  Max.   :2018      Max.   :2018    Max.   :1.0000   Max.   :207879  
##  NA's   :408       NA's   :288     NA's   :175      NA's   :46      
##   FRPL_percent      enroll_OTHER        enroll_AM        enroll_ASIAN   
##  Min.   :0.07763   Min.   : 0.00000   Min.   : 0.0000   Min.   : 0.000  
##  1st Qu.:0.44201   1st Qu.: 0.00000   1st Qu.: 0.3189   1st Qu.: 1.076  
##  Median :0.53159   Median : 0.00000   Median : 0.5504   Median : 1.965  
##  Mean   :0.54094   Mean   : 0.32800   Mean   : 3.1194   Mean   : 3.091  
##  3rd Qu.:0.62681   3rd Qu.: 0.00492   3rd Qu.: 1.2069   3rd Qu.: 3.826  
##  Max.   :1.00000   Max.   :20.81448   Max.   :86.8996   Max.   :17.611  
##  NA's   :46        NA's   :46         NA's   :46        NA's   :46      
##   enroll_HISP      enroll_BLACK     enroll_WHITE       ODR_class     
##  Min.   : 0.000   Min.   : 0.000   Min.   :  9.607   Min.   :0.1612  
##  1st Qu.: 3.760   1st Qu.: 2.860   1st Qu.: 47.575   1st Qu.:0.9673  
##  Median : 8.697   Median : 6.094   Median : 67.423   Median :1.4329  
##  Mean   :13.744   Mean   :11.663   Mean   : 62.068   Mean   :1.6872  
##  3rd Qu.:18.147   3rd Qu.:18.487   3rd Qu.: 78.330   3rd Qu.:1.9747  
##  Max.   :76.691   Max.   :88.201   Max.   :137.468   Max.   :9.8629  
##  NA's   :46       NA's   :46       NA's   :46        NA's   :46      
##    ODR_other      ODR_subjective    ODR_objective          eval       
##  Min.   :0.1533   Min.   :0.09597   Min.   :0.04506   Min.   :0.0000  
##  1st Qu.:0.9565   1st Qu.:0.59837   1st Qu.:0.37276   1st Qu.:0.0000  
##  Median :1.4003   Median :0.89286   Median :0.52533   Median :1.0000  
##  Mean   :1.5334   Mean   :1.09670   Mean   :0.60468   Mean   :0.6124  
##  3rd Qu.:1.8548   3rd Qu.:1.29252   3rd Qu.:0.76524   3rd Qu.:1.0000  
##  Max.   :7.9305   Max.   :6.84706   Max.   :3.06346   Max.   :1.0000  
##  NA's   :46       NA's   :46        NA's   :46                        
##   class_remove     suspension        run_time        evalXyear      
##  Min.   :0.000   Min.   :0.0000   Min.   :-99.00   Min.   :-10.000  
##  1st Qu.:0.000   1st Qu.:0.0000   1st Qu.: -7.00   1st Qu.: -5.000  
##  Median :0.000   Median :0.0000   Median : -3.00   Median : -1.000  
##  Mean   :0.126   Mean   :0.2888   Mean   :-15.57   Mean   : -2.384  
##  3rd Qu.:0.000   3rd Qu.:1.0000   3rd Qu.:  0.00   3rd Qu.:  0.000  
##  Max.   :1.000   Max.   :1.0000   Max.   :  6.00   Max.   :  0.000  
## 
```

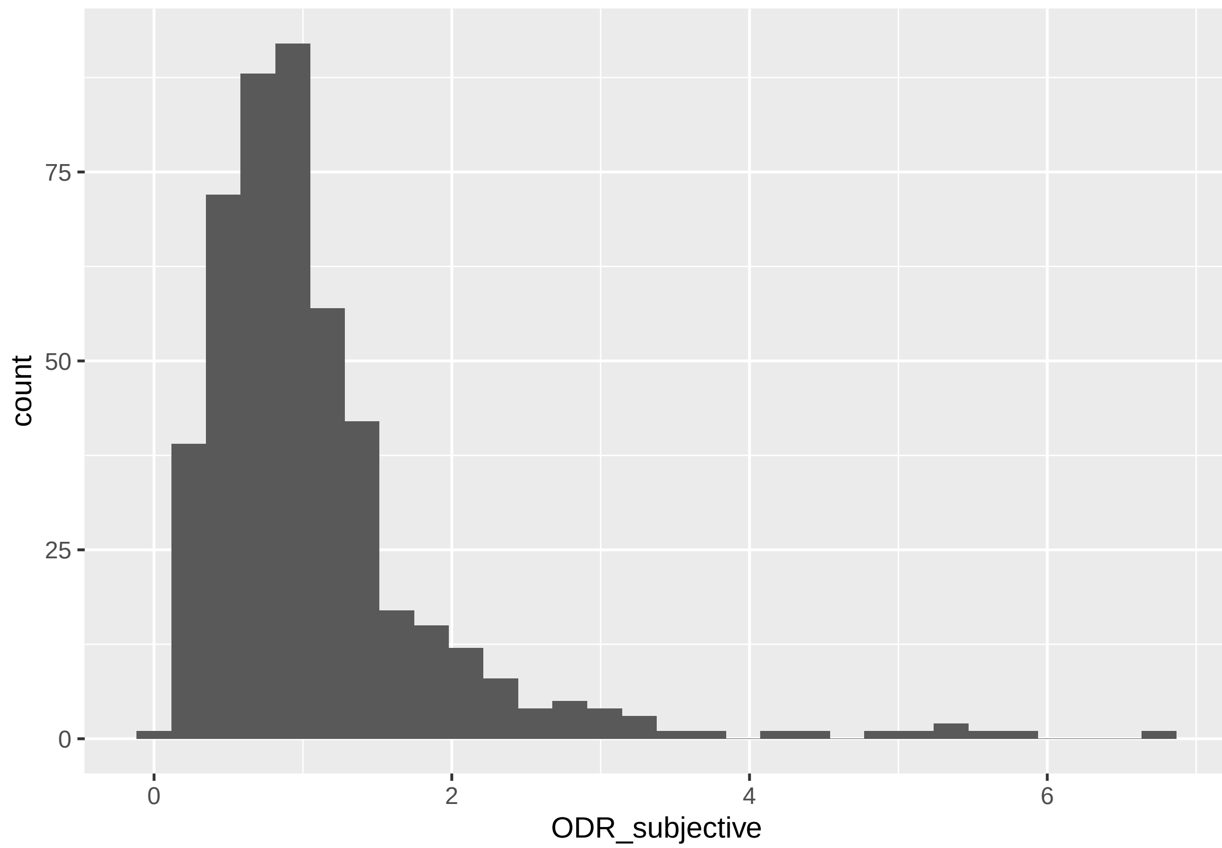
```
dare1_clean <- dare1 %>%
  drop_na(ODR_class, ODR_objective, ODR_other, ODR_objective)
```

After excluding row with missing outcomes, there are only 470 observations left. Missing valuesfound in these following variable: Var eval_year = 71, class_remove_year = 374, suspension_year = 259, PBIS = 129, based on the missingness pattern reflected in the plot above we see that missing data values do not relate to any other data in the dataset and there is no pattern to the actual values of the missing data themselves. Therefore we can conclude that this is Missing Completely at Random (MCAR). We should be concerned if there is specific pattern of the missingness.

AG **B2.** Graphically display the distribution of the outcome data. What do you notice about the distribution of outcomes? Are there any actions, transformations or sensitivity tests you would like to conduct based on this evidence?

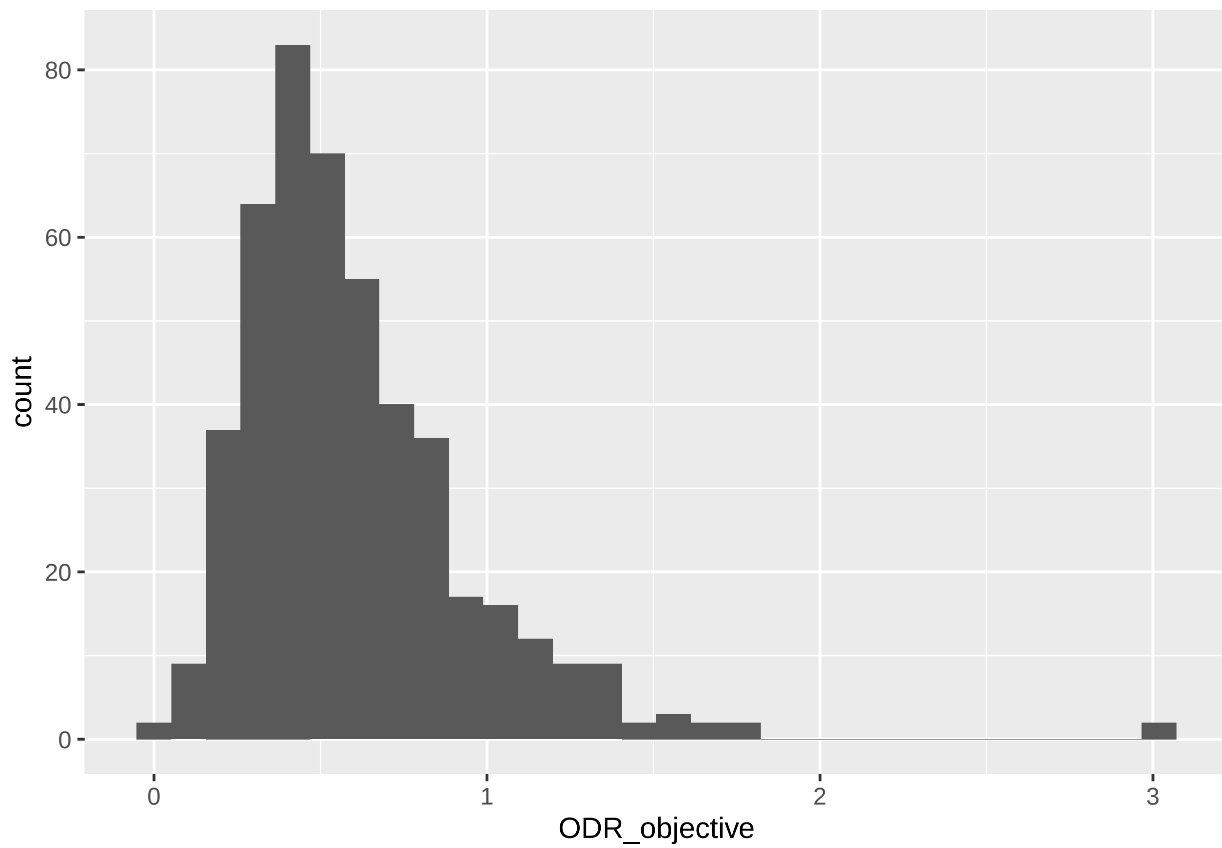
```r
outcome_data <- dare1_clean %>%
  select(ODR_class, ODR_other, ODR_subjective, ODR_objective)
# maybe pivot_longer --> values to "ODR"

outcome_data %>%
  ggplot(aes(ODR_subjective)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



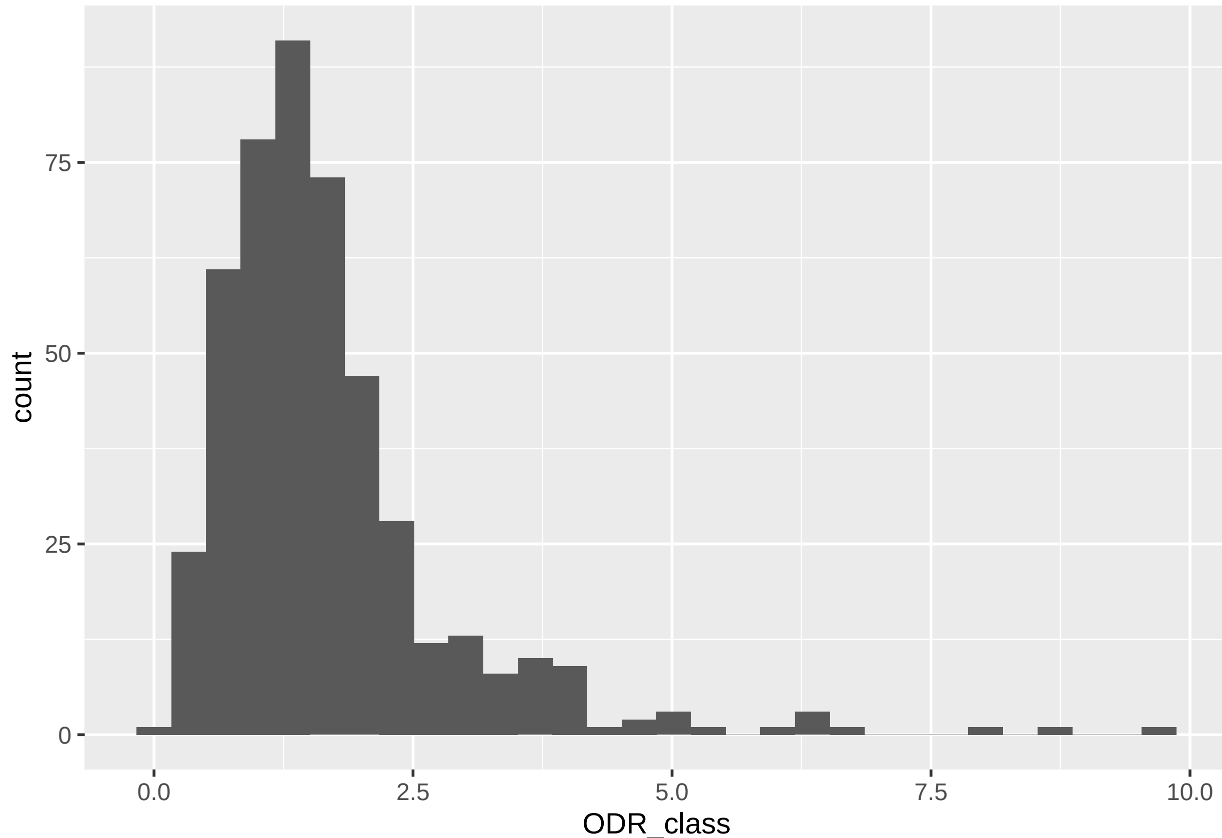

```r
outcome_data %>%
  ggplot(aes(ODR_objective)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



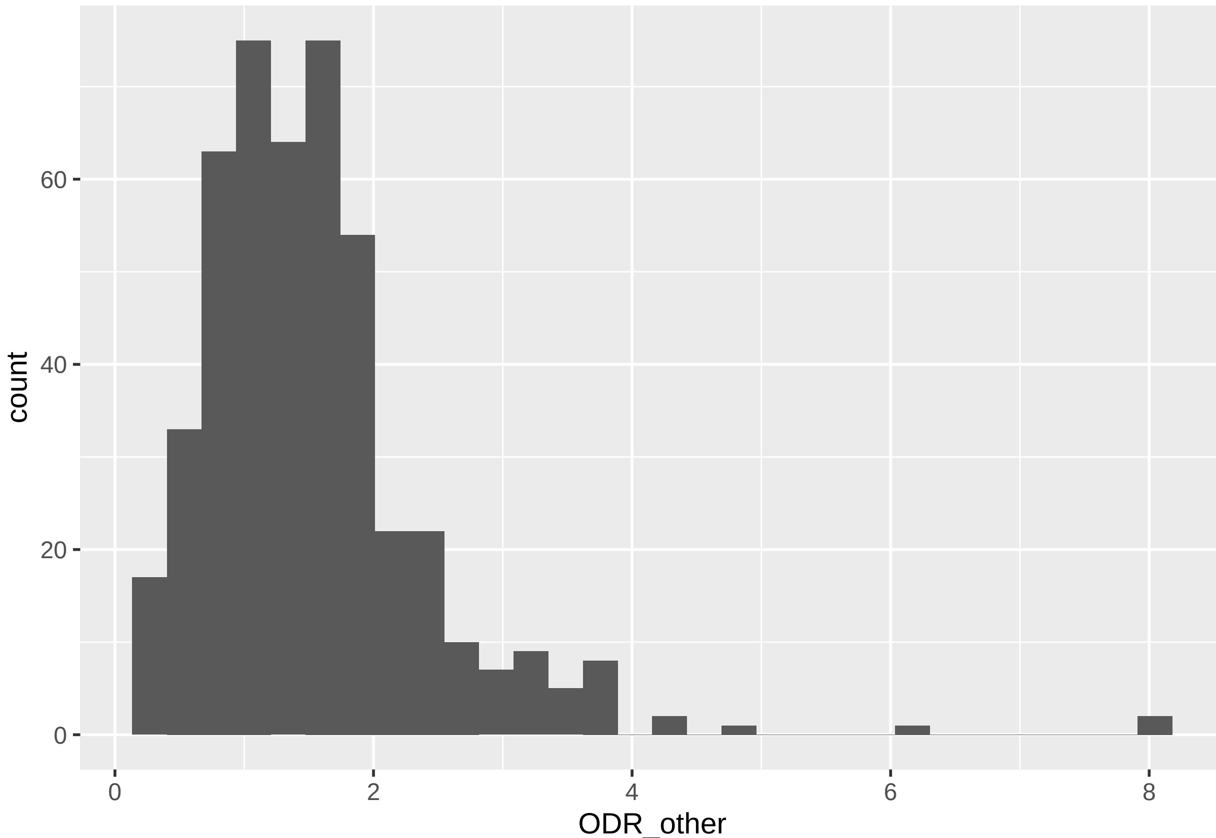

```
outcome_data %>%
  ggplot(aes(ODR_class)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
outcome_data %>%
  ggplot(aes(ODR_other)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Each ODR outcome data is right-skewed.

Merly **B3.** What is the analytic sample from which you will draw your inferences? To what population are you drawing these inferences? For this analytic sample, reproduce Column 1 of Table 1 from Liebowitz, Porter & Bragg (2022) to create a summary of descriptive statistics for the following data elements. All of these statistics (except for state-year and year enrollment) should be weighted by the state-year population:

- Mean state-year enrollment
- Mean year enrollment
- % low-income (FRPL)
- % Am. Indian/Alask. Native
- % Asian/PI
- % Black
- % Hispanic
- % White
- % state-year observations in which PBIS was successfully implemented
- Classroom ODR rate
- Other location ODR rate
- Subjective-Classroom ODR rate
- Objective-Classroom ODR rate

```
#Mean State-Year Enrollment
state_year_enrl <- dare1_clean %>%
  group_by(state_id) %>%
  summarise(mean_state = mean(enroll))
state_year_enrl
```

```
## # A tibble: 43 x 2
##    state_id mean_state
##       <int>      <dbl>
##  1        2       230.
##  2        4      2983.
##  3        5      3859.
##  4        6    111710.
##  5        8     26989.
##  6        9     26782.
##  7       12      2165.
##  8       13     21169.
##  9       16      2768
## 10       17    109560.
## # ... with 33 more rows
```

```
#Mean Year Enrollment
year_enrl <-
dare1_clean %>%
   group_by(school_year) %>%
  summarise(mean_year = mean(enroll))
year_enrl
```

```
## # A tibble: 12 x 2
##    school_year mean_year
##          <int>     <dbl>
##  1        2006    10504.
##  2        2007    13881.
##  3        2008    16379.
##  4        2009    20562.
##  5        2010    22764.
##  6        2011    24405.
##  7        2012    25130.
##  8        2013    24339.
##  9        2014    26065.
## 10        2015    26949.
## 11        2016    23948.
## 12        2017    22309
```

```
#Summary statistics for demograpic infomation and outcome variables.

dare1_clean %>%
  select(
         `% low-income (FRPL)` = FRPL_percent,
         `% Am. Indian/Alask. Native` = enroll_AM,
         `% Asian/PI` = enroll_ASIAN,
         `% Black` = enroll_BLACK,
         `% Hispanic ` = enroll_HISP,
         `% White` = enroll_WHITE,
         `% Schools by Year Implementing PBIS` = PBIS,
        `Classroom ODR Rate` = ODR_class,
        `Other location ODR Rate` = ODR_other,
        `Subjective-Classroom ODR rate` = ODR_subjective,
        `Objective-Classroom ODR rate` = ODR_objective) %>% drop_na() %>%
```

```
tbl_summary(statistic = list(all_continuous() ~ "{mean} ({sd})")) %>%
  modify_footnote(
    all_stat_cols() ~ "Mean (SD)1"
  ) %>%
  modify_caption("**Table 1. Summary Statistics**")
```

```
## Table printed with ‘knitr::kable()‘, not {gt}. Learn why at
## http://www.danieldsjoberg.com/gtsummary/articles/rmarkdown.html
## To suppress this message, include ‘message = FALSE‘ in code chunk header.
```

Table 1: **Table 1. Summary Statistics**

Characteristic	**N = 341**
% low-income (FRPL)	0.52 (0.13)
% Am. Indian/Alask. Native	1.44 (3.70)
% Asian/PI	3.4 (3.2)
% Black	11 (11)
% Hispanic	13 (12)
% White	65 (18)
% Schools by Year Implementing PBIS	246 (72%)
Classroom ODR Rate	1.65 (0.91)
Other location ODR Rate	1.55 (0.74)
Subjective-Classroom ODR rate	1.06 (0.63)
Objective-Classroom ODR rate	0.61 (0.30)

Describe the characteristics of your sample as you would report these statistics in an academic paper. How are the characteristics of the sample you will be using for this replication exercise different from the sample in Liebowitz, Porter & Bragg (2022)? How, if at all, do you anticipate this will affect your results?

B4. Optional Extension Plot the average classroom (ODR class) and classroom-subjective ODRs (ODR subjective) by how close the stateyear observation is to the implementation of the teacher evaluation policy for the states that implemented evaluation reform. (Note: this is similar to Figure 2 in the original paper). What do you notice about the raw outcome data plotted against the secular trend? Are there any actions, transformations or sensitivity tests you would like to conduct based on this evidence? Why do we stress plotting these raw averages only for states that implemented evaluation reform? How would including these states alter the interpretation of this figure?

C. Replication and Extension (6 points)

For the following tasks, give your best attempt at completing the analysis and write-up. If you are unable to conduct the programming or analysis, describe what you are attempting to do and what your results would mean.

AG **C1.** Estimate the effects of the introduction of higher-stakes teacher evaluation reforms on Office Disciplinary Referrals. In one of your models, assume that the effects are constant and in another relax this assumption to allow the effects to differ (linearly) over time. Present these difference-in-differences estimates in a table and the associated writeup as you would report these results in an academic paper. Do you notice any important differences in these results and those reported in the original paper? If so, how would you consider addressing them (it is not necessary at this point for you to actually conduct the analysis, just describe approaches you might take)?

For classroom ODRs: Assume effects are constant

```r
library(fixest)
mod_class_constant <- feols(ODR_class ~ eval |
              state_id + school_year, #default clustering on state id
              data = dare1,
              weights = dare1$enroll)
```

```
## NOTE: 46 observations removed because of NA values (LHS: 46, Weights: 46).
```

```r
summary(mod_class_constant)
```

```
## OLS estimation, Dep. Var.: ODR_class
## Observations: 470
## Fixed-effects: state_id: 43,  school_year: 12
## Standard-errors: Clustered (state_id)
##      Estimate Std. Error  t value Pr(>|t|)
## eval 0.035771   0.060818 0.588161  0.55957
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 41.9     Adj. R2: 0.801764
##               Within R2: 0.001163
```

Allow effects to differ over time

```r
mod_class_time <- feols(ODR_class ~ evalXyear |
              state_id + school_year,
              data = dare1,
              vcov = ~school_year^state_id,
              weights = dare1$enroll)
```

```
## NOTE: 46 observations removed because of NA values (LHS: 46, Weights: 46).
```

```r
summary(mod_class_time)
```

```
## OLS estimation, Dep. Var.: ODR_class
## Observations: 470
## Fixed-effects: state_id: 43,  school_year: 12
## Standard-errors: Clustered (school_year^state_id)
##            Estimate Std. Error  t value Pr(>|t|)
## evalXyear -0.032718   0.014562 -2.24677 0.025119 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 41.7     Adj. R2: 0.804111
##               Within R2: 0.012988
```

For subjective ODRs:

Assume effects are constant

```r
mod_subj_constant <- feols(ODR_subjective ~ eval |
              state_id + school_year,
              data = dare1,
              weights = dare1$enroll)
```

```
## NOTE: 46 observations removed because of NA values (LHS: 46, Weights: 46).
```

```r
summary(mod_subj_constant)
```

```
## OLS estimation, Dep. Var.: ODR_subjective
## Observations: 470
## Fixed-effects: state_id: 43,  school_year: 12
## Standard-errors: Clustered (state_id)
##      Estimate Std. Error  t value Pr(>|t|)
## eval  0.03298   0.043522 0.757784  0.45281
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 29.3     Adj. R2: 0.791287
##              Within R2: 0.002023
```

Allow effects to differ over time

```r
mod_subj_time <- feols(ODR_subjective ~ evalXyear |
              state_id + school_year,
              data = dare1,
              vcov = ~school_year^state_id,
              weights = dare1$enroll)
```

```
## NOTE: 46 observations removed because of NA values (LHS: 46, Weights: 46).
```

```r
summary(mod_subj_time)
```

```
## OLS estimation, Dep. Var.: ODR_subjective
## Observations: 470
## Fixed-effects: state_id: 43,  school_year: 12
## Standard-errors: Clustered (school_year^state_id)
##            Estimate Std. Error t value  Pr(>|t|)
## evalXyear -0.027721   0.009401 -2.9488 0.0033494 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 29.1     Adj. R2: 0.794853
##              Within R2: 0.019074
```

Difference can stem from other controls not being accounted for.

Merly **C2.** Liebowitz et al. (2022) conduct a broad set of robustness checks. For this DARE assignment, you will conduct two (2). First test whether the main results you present in Question C1 are robust to the introduction of potentially simultaneous discipline policy reforms. Present the table and associated write-up as you would report these results in an academic paper. Then select an additional robustness check (either from the paper or not) and present evidence on whether your findings are sensitive to this test.

The first set of robustness check is test the effect of evaluation policy implementation on rates on suspension from the Civil Right Data Collection (B11 - B13 of Figure 4)

For ODR Class

```r
#Robustness check with CRDC (B11)
rc_b11 <- feols(ODR_class ~ suspension |
              state_id + school_year, #default clustering on state id
              data = dare1_clean,
              weights = dare1_clean$enroll)
summary(rc_b11)
```

```
## OLS estimation, Dep. Var.: ODR_class
## Observations: 470
## Fixed-effects: state_id: 43,  school_year: 12
## Standard-errors: Clustered (state_id)
##             Estimate Std. Error   t value Pr(>|t|)
## suspension -0.069408   0.083888 -0.827386  0.41269
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 41.9     Adj. R2: 0.802307
##               Within R2: 0.0039
```

```r
#Robustness check with CRDC and Controls (B12)
rc_b12 <- feols(ODR_class ~ suspension + FRPL_percent + enroll_OTHER + enroll_AM + enroll_AM + enroll_HI
                        state_id + school_year,
                      data = dare1_clean,
                      weights = dare1_clean$enroll)
summary(rc_b12)
```

```
## OLS estimation, Dep. Var.: ODR_class
## Observations: 470
## Fixed-effects: state_id: 43,  school_year: 12
## Standard-errors: Clustered (state_id)
##               Estimate Std. Error   t value  Pr(>|t|)
## suspension   -0.053887   0.084717 -0.636092 0.5281680
## FRPL_percent -0.027840   0.395350 -0.070418 0.9441949
## enroll_OTHER -0.005647   0.021916 -0.257644 0.7979399
## enroll_AM     0.016950   0.024893  0.680926 0.4996557
## enroll_HISP  -0.000645   0.007778 -0.082870 0.9343485
## enroll_ASIAN -0.057915   0.023983 -2.414858 0.0201743 *
## enroll_BLACK  0.030102   0.010863  2.770956 0.0082916 **
## enroll_WHITE  0.005572   0.004948  1.125922 0.2665912
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 40.6     Adj. R2: 0.8105
##               Within R2: 0.061285
```

```r
#Robustness check with CRDC, controls, and Time (B13)

rc_b13 <- feols(ODR_class ~ suspension + FRPL_percent + enroll_OTHER + enroll_AM + enroll_AM + enroll_HI
                        state_id + school_year,
                      data = dare1_clean,
                      weights = dare1_clean$enroll)
summary(rc_b13)
```

```
## OLS estimation, Dep. Var.: ODR_class
```

```
## Observations: 470
## Fixed-effects: state_id: 43,  school_year: 12
## Standard-errors: Clustered (state_id)
##               Estimate Std. Error   t value  Pr(>|t|)
## suspension   -0.049651   0.087273 -0.568921 0.5724397
## FRPL_percent  0.017980   0.388742  0.046251 0.9633297
## enroll_OTHER -0.008510   0.021061 -0.404061 0.6882184
## enroll_AM     0.012607   0.028456  0.443042 0.6600089
## enroll_HISP  -0.003277   0.010160 -0.322551 0.7486359
## enroll_ASIAN -0.054135   0.026296 -2.058643 0.0457663 *
## enroll_BLACK  0.029763   0.010876  2.736620 0.0090596 **
## enroll_WHITE  0.005682   0.004939  1.150313 0.2565225
## run_time     -0.015746   0.030840 -0.510578 0.6123197
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 40.6     Adj. R2: 0.810682
##              Within R2: 0.064489
```

For ODRs Subjective

```
#Robustness check with CRDC (B11)
rc_b11s <- feols(ODR_subjective ~ suspension |
              state_id + school_year, #default clustering on state id
              data = dare1_clean,
              weights = dare1_clean$enroll)
summary(rc_b11s)
```

```
## OLS estimation, Dep. Var.: ODR_subjective
## Observations: 470
## Fixed-effects: state_id: 43,  school_year: 12
## Standard-errors: Clustered (state_id)
##             Estimate Std. Error   t value Pr(>|t|)
## suspension -0.007453   0.058637 -0.127102  0.89947
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 29.3     Adj. R2: 0.790883
##              Within R2: 9.199e-5
```

```
#Robustness check with CRDC and Controls (B12)
rc_b12s <- feols(ODR_subjective ~ suspension + FRPL_percent + enroll_OTHER + enroll_AM + enroll_AM + en
                        state_id + school_year,
                      data = dare1_clean,
                      weights = dare1_clean$enroll)
summary(rc_b12s)
```

```
## OLS estimation, Dep. Var.: ODR_subjective
## Observations: 470
## Fixed-effects: state_id: 43,  school_year: 12
## Standard-errors: Clustered (state_id)
##               Estimate Std. Error   t value  Pr(>|t|)
## suspension    0.014078   0.063985  0.220019 0.8269224
## FRPL_percent -0.007931   0.254774 -0.031131 0.9753124
```

```
## enroll_OTHER -0.018570   0.017833 -1.041306 0.3036909
## enroll_AM     0.027864   0.013830  2.014800 0.0503569 .
## enroll_HISP   0.003294   0.005387  0.611401 0.5442294
## enroll_ASIAN -0.039956   0.017313 -2.307812 0.0260057 *
## enroll_BLACK  0.023673   0.008287  2.856477 0.0066334 **
## enroll_WHITE  0.005224   0.003964  1.317919 0.1946740
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 28.2     Adj. R2: 0.803454
##              Within R2: 0.076053
```

```r
#Robustness check with CRDC, controls, and Time (B13)

rc_b13s <- feols(ODR_subjective ~ suspension + FRPL_percent + enroll_OTHER + enroll_AM + enroll_AM + en
                        state_id + school_year,
                      data = dare1_clean,
                      weights = dare1_clean$enroll)
summary(rc_b13s)
```

```
## OLS estimation, Dep. Var.: ODR_subjective
## Observations: 470
## Fixed-effects: state_id: 43,  school_year: 12
## Standard-errors: Clustered (state_id)
##               Estimate Std. Error   t value  Pr(>|t|)
## suspension    0.018022   0.064916  0.277617 0.7826681
## FRPL_percent  0.034728   0.245331  0.141557 0.8881069
## enroll_OTHER -0.021236   0.017199 -1.234702 0.2238048
## enroll_AM     0.023820   0.015699  1.517306 0.1366811
## enroll_HISP   0.000843   0.006986  0.120623 0.9045651
## enroll_ASIAN -0.036436   0.018615 -1.957318 0.0569776 .
## enroll_BLACK  0.023356   0.008332  2.803175 0.0076263 **
## enroll_WHITE  0.005326   0.003931  1.354890 0.1826960
## run_time     -0.014660   0.021005 -0.697938 0.4890622
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 28.1     Adj. R2: 0.804183
##              Within R2: 0.081735
```

Another Robustness check mentioned in the paper is to use ODRs from locations other than the classroom and ODRs for behavioral infraction that involved objective reasons to send students to the office (B1 - B6)

```r
#Other (B1)
rc_b1 <- feols(ODR_other ~ eval|
              state_id + school_year, #default clustering on state id
              data = dare1_clean,
              weights = dare1_clean$enroll)
summary(rc_b1)
```

OLS estimation, Dep. Var.: ODR_other Observations: 470 Fixed-effects: state_id: 43, school_year: 12 Standard-errors: Clustered (state_id) Estimate Std. Error t value Pr(>|t|) eval -0.04855 0.037355 -1.29969 0.2008 — Signif. codes: 0 '' ***0.001*** '' *0.01* '' 0.05 '.' 0.1 ' ' 1 RMSE: 26.8 Adj. R2: 0.896358 Within R2: 0.005222

```r
#Other and controls (B2)
rc_b2 <- feols(ODR_other ~ eval + FRPL_percent + enroll_OTHER + enroll_AM + enroll_AM + enroll_HISP + en
                        state_id + school_year,
                      data = dare1_clean,
                      weights = dare1_clean$enroll)
summary(rc_b2)
```

OLS estimation, Dep. Var.: ODR_other Observations: 470 Fixed-effects: state_id: 43, school_year: 12 Standard-errors: Clustered (state_id) Estimate Std. Error t value Pr(>|t|)
eval -0.038656 0.046233 -0.836121 0.407819
FRPL_percent 0.061635 0.297257 0.207347 0.836741
enroll_OTHER -0.017391 0.021072 -0.825316 0.413856
enroll_AM 0.002127 0.012003 0.177202 0.860202
enroll_HISP 0.003719 0.005812 0.639876 0.525728
enroll_ASIAN -0.008396 0.021224 -0.395569 0.694425
enroll_BLACK 0.016501 0.006219 2.653176 0.011208 *
enroll_WHITE 0.004592 0.003668 1.251791 0.217573
— Signif. codes: 0 '*' ***0.001*** *'' 0.01* '' 0.05 '.' 0.1 ' ' 1 RMSE: 26.4 Adj. R2: 0.89794 Within R2: 0.036929

```r
#Other, controls, and time (B3)
rc_b3 <- rc_b2 <- feols(ODR_other ~ eval + FRPL_percent + enroll_OTHER + enroll_AM + enroll_AM + enroll_
                        state_id + school_year,
                      data = dare1_clean,
                      weights = dare1_clean$enroll)
summary(rc_b3)
```

OLS estimation, Dep. Var.: ODR_other Observations: 470 Fixed-effects: state_id: 43, school_year: 12 Standard-errors: Clustered (state_id) Estimate Std. Error t value Pr(>|t|)
eval -0.046307 0.052382 -0.884024 0.381716
FRPL_percent 0.071396 0.303894 0.234936 0.815400
enroll_OTHER -0.018051 0.021328 -0.846318 0.402172
enroll_AM 0.001342 0.012364 0.108553 0.914074
enroll_HISP 0.003213 0.006392 0.502673 0.617820
enroll_ASIAN -0.007552 0.022370 -0.337595 0.737350
enroll_BLACK 0.016308 0.006515 2.503110 0.016286 *
enroll_WHITE 0.004693 0.003711 1.264728 0.212942
run_time -0.003883 0.016017 -0.242402 0.809649
— Signif. codes: 0 '*' ***0.001*** *'' 0.01* '' 0.05 '.' 0.1 ' ' 1 RMSE: 26.4 Adj. R2: 0.897727 Within R2: 0.037286

```r
#Objective (B4)
rc_b4 <- feols(ODR_objective ~ eval|
              state_id + school_year, #default clustering on state id
              data = dare1_clean,
              weights = dare1_clean$enroll)
summary(rc_b4)
```

OLS estimation, Dep. Var.: ODR_objective Observations: 470 Fixed-effects: state_id: 43, school_year: 12 Standard-errors: Clustered (state_id) Estimate Std. Error t value Pr(>|t|) eval -0.010117 0.016461 -0.614613 0.54213 — Signif. codes: 0 '*' ***0.001*** *'' 0.01* '' 0.05 '.' 0.1 ' ' 1 RMSE: 10.7 Adj. R2: 0.888442 Within R2: 0.00143

```r
#Objective and controls (B5)
rc_b5 <- feols(ODR_objective ~ eval + FRPL_percent + enroll_OTHER + enroll_AM + enroll_AM + enroll_HISP
                        state_id + school_year,
                      data = dare1_clean,
                      weights = dare1_clean$enroll)
summary(rc_b5)
```

OLS estimation, Dep. Var.: ODR_objective Observations: 470 Fixed-effects: state_id: 43, school_year: 12 Standard-errors: Clustered (state_id) Estimate Std. Error t value Pr(>|t|)
eval -0.004918 0.018187 -0.270435 0.788150
FRPL_percent 0.036497 0.119482 0.305459 0.761526
enroll_OTHER -0.001820 0.006672 -0.272762 0.786373
enroll_AM -0.002449 0.006751 -0.362800 0.718574
enroll_HISP 0.000679 0.002207 0.307692 0.759837
enroll_ASIAN -0.001799 0.007370 -0.244080 0.808357
enroll_BLACK 0.005165 0.001944 2.656704 0.011108 *
enroll_WHITE 0.001255 0.001312 0.956997 0.344045
— Signif. codes: 0 '*' ***0.001*** '' *0.01* '' 0.05 '.' 0.1 ' ' 1 RMSE: 10.6 Adj. R2: 0.888813 Within R2: 0.02154

```r
#Objective, controls, and time (B6)
rc_b6 <- feols(ODR_objective ~ eval + FRPL_percent + enroll_OTHER + enroll_AM + enroll_AM + enroll_HISP
                        state_id + school_year,
                      data = dare1_clean,
                      weights = dare1_clean$enroll)
summary(rc_b6)
```

OLS estimation, Dep. Var.: ODR_objective Observations: 470 Fixed-effects: state_id: 43, school_year: 12 Standard-errors: Clustered (state_id) Estimate Std. Error t value Pr(>|t|)
eval -0.003323 0.018866 -0.176145 0.861027
FRPL_percent 0.034462 0.123933 0.278070 0.782323
enroll_OTHER -0.001682 0.006557 -0.256581 0.798755
enroll_AM -0.002286 0.006769 -0.337687 0.737281
enroll_HISP 0.000784 0.002453 0.319777 0.750723
enroll_ASIAN -0.001975 0.007935 -0.248855 0.804686
enroll_BLACK 0.005205 0.002015 2.583252 0.013359 *
enroll_WHITE 0.001234 0.001304 0.946253 0.349432
run_time 0.000809 0.005512 0.146841 0.883960
— Signif. codes: 0 '*' ***0.001*** '' *0.01* '' 0.05 '.' 0.1 ' ' 1 RMSE: 10.6 Adj. R2: 0.888551 Within R2: 0.021638

```r
compare_performance(rc_b11, rc_b12,rc_b13, rc_b11s, rc_b12s, rc_b13s, rc_b1, rc_b2, rc_b3, rc_b4, rc_b5
  print_md()
```

```
## Warning: When comparing models, please note that probably not all models were fit from
##   same data.
```

Table 2: Comparison of Model Performance Indices

Name	Model	R2	R2 (adj.)	RMSE	Sigma	AIC weights	BIC weights	Performance-Score
rc_b4	fixest	0.90	0.89	0.19	11.38	0.997	1.000	96.81%
rc_b5	fixest	0.90	0.89	0.19	11.36	0.002	< 0.001	63.94%

Name	Model	R2	R2 (adj.)	RMSE	Sigma	AIC weights	BIC weights	Performance-Score
rc_b6	fixest	0.90	0.89	0.19	11.38	< 0.001	< 0.001	63.86%
rc_b2	fixest	0.91	0.90	0.48	28.34	< 0.001	< 0.001	49.66%
rc_b3	fixest	0.91	0.90	0.48	28.34	< 0.001	< 0.001	49.66%
rc_b1	fixest	0.91	0.90	0.48	28.53	< 0.001	< 0.001	48.69%
rc_b13s	fixest	0.83	0.80	0.54	30.21	< 0.001	< 0.001	18.18%
rc_b12s	fixest	0.83	0.80	0.54	30.26	< 0.001	< 0.001	17.82%
rc_b11s	fixest	0.81	0.79	0.54	31.21	< 0.001	< 0.001	12.87%
rc_b13	fixest	0.84	0.81	0.75	43.61	< 0.001	< 0.001	7.21%
rc_b12	fixest	0.84	0.81	0.75	43.63	< 0.001	< 0.001	7.06%
rc_b11	fixest	0.83	0.80	0.75	44.56	< 0.001	< 0.001	3.53%

```
stargazer(rc_b11, rc_b12,rc_b13, rc_b11s, rc_b12s, rc_b13s, type='latex', out="Tables/robustness_result
          omit= c("FRPL_percent", "enroll_AM_prop", "enroll_WHITE_prop", "enroll_BLACK_prop", "enroll_H
```

% Error: Unrecognized object type. % Error: Unrecognized object type. % Error: Unrecognized object type. % Error: Unrecognized object type. % Error: Unrecognized object type. % Error: Unrecognized object type.

C3. Write a discussion paragraph in which you present the substantive conclusions of your results about the effects of the introduction of higher-stakes teacher evaluation on ODRs.

C4. Optional Extension Use an event-study approach to this difference-in-differences research design to estimate the effects of the introduction of higher-stakes teacher evaluation reforms on Office Disciplinary Referrals (ODRs). Present these findings in an event-study graph. Present the figure and associated write-up as you would report these results in an academic paper. Do you notice any important differences in these results and those reported in the original paper? If so, how would you consider addressing them (At this point, it is not necessary for you to actually conduct the analysis. Just describe approaches you might take.)?

C5. Optional Extension Use one (or more) approaches to present the extent to which the successful implementation of Positive Behavioral Intervention and Supports (PBIS) framework moderating the effects of the introduction of higher-stakes teacher evaluation policies. Present these difference-in-differences estimates and associated write-up as you would report these results in an academic paper. Do you notice any important differences in these results and those reported in the original paper? If so, how would you consider addressing them?