Umansky & Dumont (2021) Analysis & Replication

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```r
dat <- import(here("data","dumont_umansky_ECLSK.dta"))
```

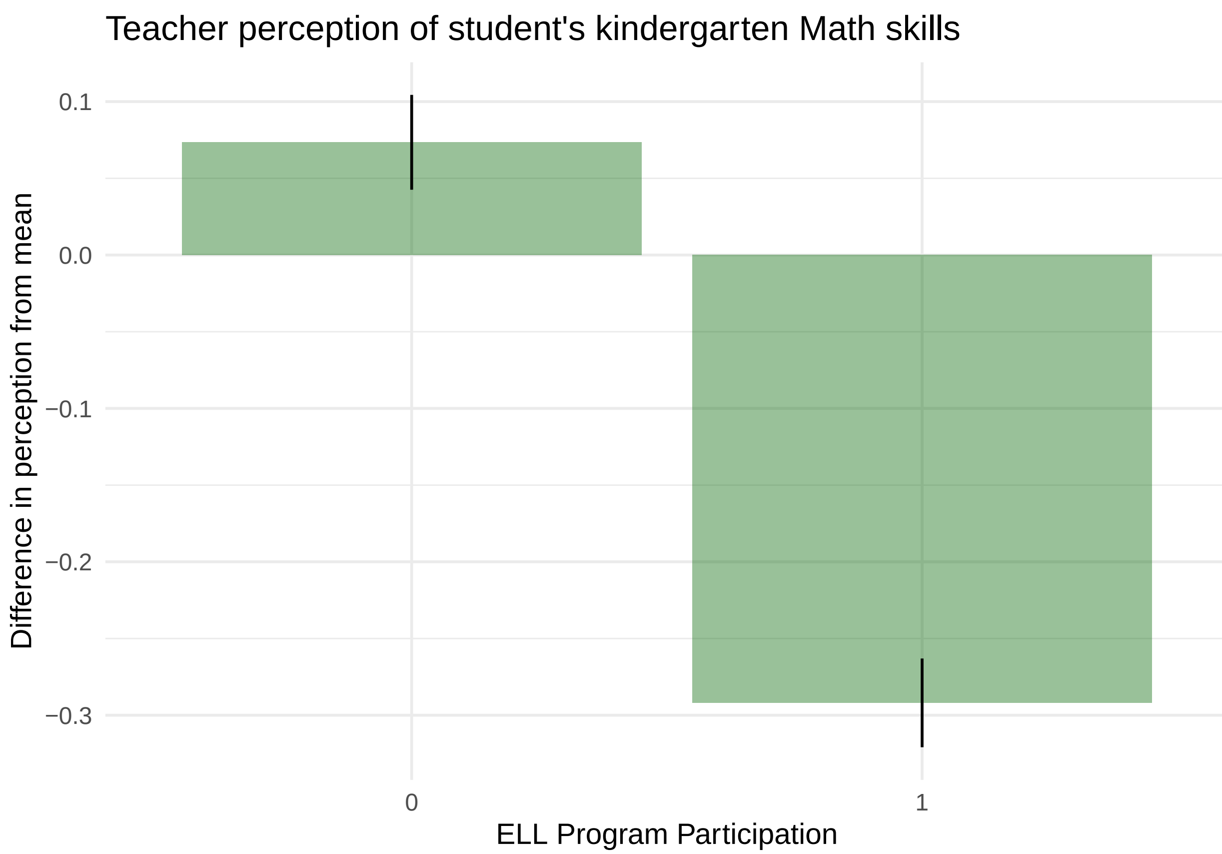
A. Baseline differences (3 points)

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

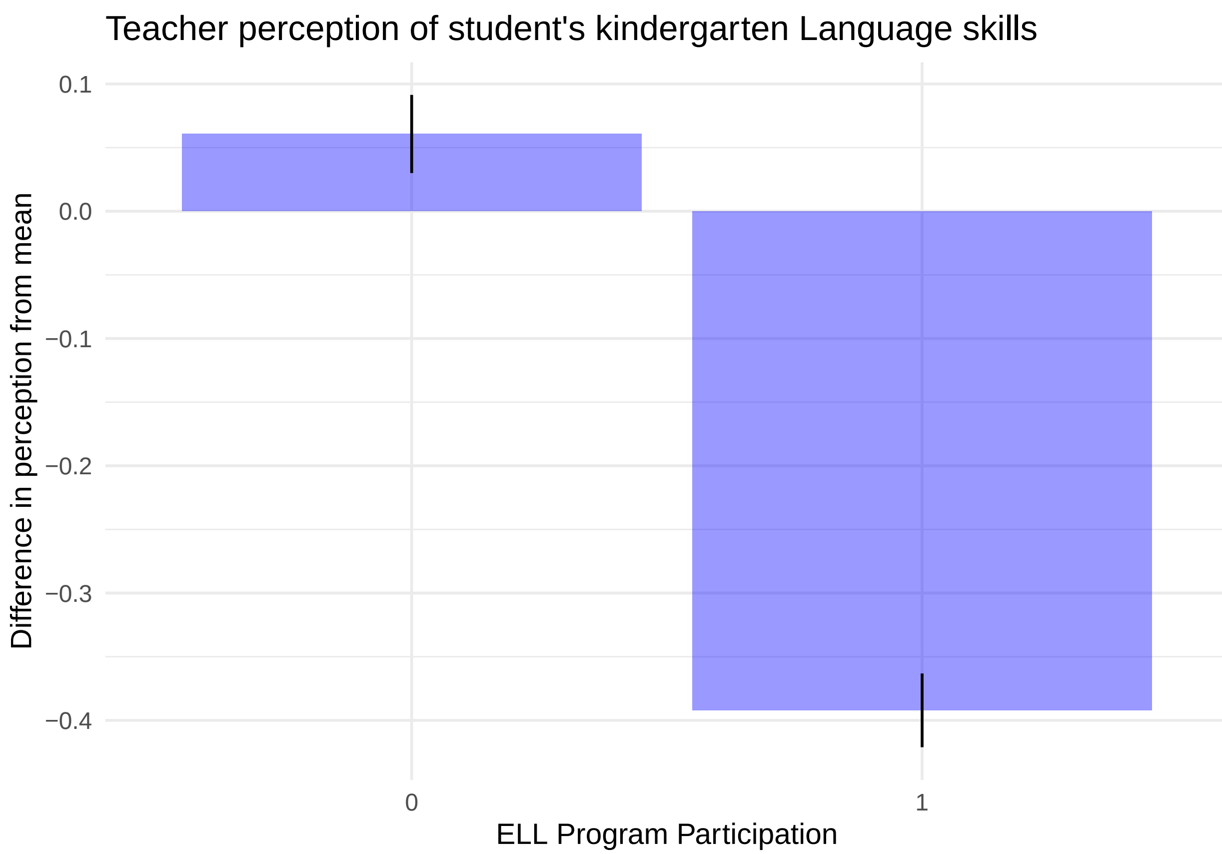
A1 Present graphical and/or numerical evidence on whether teachers perceive students who are classified as ELs as having weaker language and mathematics skills in this data set. Describe the results of your assessment in 3-4 sentences. Should the evidence you have shared here be interpreted as a plausibly causal estimate of the effect of being classified as an EL student on teachers' perceptions of students' ability? In 1-2 sentences, answer why or why not.

```r
perception_diff <- dat %>%
  group_by(elprgm) %>%
  summarise(n_students = n(),
            mean_math=mean(tmathk),
            se_math = sd(tmathk)/sqrt(n_students),
            mean_lang = mean(tlangk),
            se_lang = sd(tlangk)/sqrt(n_students))
```

```r
ggplot(perception_diff,
       aes(x=as.factor(elprgm), y=mean_math, ymin=mean_math-se_math, ymax=mean_math+se_math)) +
  geom_col(fill = "darkgreen", alpha=0.4) +
  geom_linerange() +
  theme_pander(base_size = 16) +
  labs(x = "ELL Program Participation",
       y = "Difference in perception from mean",
       title = "Teacher perception of student's kindergarten Math skills") +
  theme_minimal()
```




```r
ggplot(perception_diff,
       aes(x=as.factor(elprgm), y=mean_lang, ymin=mean_lang-se_lang, ymax=mean_lang+se_lang)) +
  geom_col(fill = "blue", alpha=0.4) +
  geom_linerange() +
  theme_pander(base_size = 16) +
  labs(x = "ELL Program Participation",
       y = "Difference in perception from mean",
       title = "Teacher perception of student's kindergarten Language skills") +
  theme_minimal()
```




```r
#Naive ols estimation of the effect of EL status on teacher perception of students academic skills
#language skills


ols_lang <- lm(tlangk ~ elprgm,
               data=dat)
summary(ols_lang)
```

```
##
## Call:
## lm(formula = tlangk ~ elprgm, data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.93727 -0.69388  0.08948  0.76093  1.54429
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.06071    0.03198   1.898   0.0578 .
## elprgm      -0.45285    0.04260 -10.631   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9831 on 2164 degrees of freedom
## Multiple R-squared:  0.04964,    Adjusted R-squared:  0.0492
## F-statistic:   113 on 1 and 2164 DF,  p-value: < 2.2e-16
```

```r
#math skills
ols_math <- lm(tmathk ~ elprgm,
               data=dat)
summary(ols_math)
```

```
##
## Call:
## lm(formula = tmathk ~ elprgm, data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1583 -0.6542  0.1479  0.8135  1.4845
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.07350    0.03203   2.295   0.0218 *
## elprgm      -0.36545    0.04266  -8.567   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9845 on 2164 degrees of freedom
## Multiple R-squared:  0.03281,    Adjusted R-squared:  0.03236
## F-statistic:  73.4 on 1 and 2164 DF,  p-value: < 2.2e-16
```

For both language and math skills, teachers perceived multilingual students who participate in the ELL program as having lower ability. However, this should not be interpreted as causal; the causal inference assumptions are not met.

A2 Are there other ways in which students classified as EL learners are different from other students who live in homes where a language other than English is predominantly spoken, but are not classified as ELs? Present a table with quantitative information summarizing this fact and describe how this motivates your analytic strategy in Section B in 3-4 sentences.

```r
table_diff <- tableby(elprgm ~ hisp + ses + chrabsk + kexecfunc1 + female + rural + ebrs + prelas,
                  numeric.stats= c("meansd"), cat.stats=c("N", "countpct"), digits=2, data=dat)

summary(table_diff)
```

	0 (N=945)	1 (N=1221)	Total (N=2166)	p value
hisp				< 0.001
Mean (SD)	0.50 (0.50)	0.75 (0.44)	0.64 (0.48)	
continuous measure of student's socioeconomic status				< 0.001
Mean (SD)	-0.21 (0.91)	-0.69 (0.68)	-0.48 (0.82)	
student chronically absent in kinder				0.025
Mean (SD)	0.13 (0.33)	0.10 (0.30)	0.11 (0.31)	
student's kinder executive functioning score 1: card sort				< 0.001
Mean (SD)	14.17 (3.26)	12.97 (3.89)	13.49 (3.68)	
student is female				0.396
Mean (SD)	0.51 (0.50)	0.49 (0.50)	0.50 (0.50)	
student attends school in a rural area				< 0.001
Mean (SD)	0.14 (0.34)	0.08 (0.27)	0.11 (0.31)	
student's total EBRS score				< 0.001

	0 (N=945)	1 (N=1221)	Total (N=2166)	p value
Mean (SD)	13.41 (4.57)	10.79 (4.72)	11.94 (4.83)	
student's total PreLAS score				< 0.001
Mean (SD)	17.62 (3.32)	14.55 (4.89)	15.89 (4.54)	

Students participating in the EL program differed significantly on the quantitative characteristics of proportion Hispanic/Latinx, socioeconomic status, proportion rural, and on executive functioning score. Because of these significant differences, we will match based on these covariates. We will also match based on the executive functioning assessment, as suggested by Umansky & Dumont. There is no significant difference between those who are chronically absent and by gender.

B. Replication and Extension (7 points)

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

B1. Develop a formal model (an equation) that describes the probability that a student who lives in a home where a language other than English is predominantly spoken will be identified as an EL. Start with a basic model that defines EL-classification as a function of PreLAS score, EBRS score, SES, Rurality, Gender and Ethnicity (Hispanic/Latinx or not). From this starting probability, present a visual describing the region of common support for EL- and non-EL-classified students. Describe the substantive implications to your analytic strategy of this figure in 2-3 sentences.

For our analysis, we will use the following model:

$$elprgm = PreLAS + EBRS + kmath + kreading + SES + rural + female + hisp$$

where $elprgm$ is student participation in the EL program, $PreLAS$ and $EBRS$ are student's total scores from those two tests, $kmath$ is kindergarten math test score, $kread$ is kindergarten reading test score, $rural$ is student attending school in a rural area, $female$ is student identifying as female, and $hisp$ is student identifying as Hispanic/Latinx.

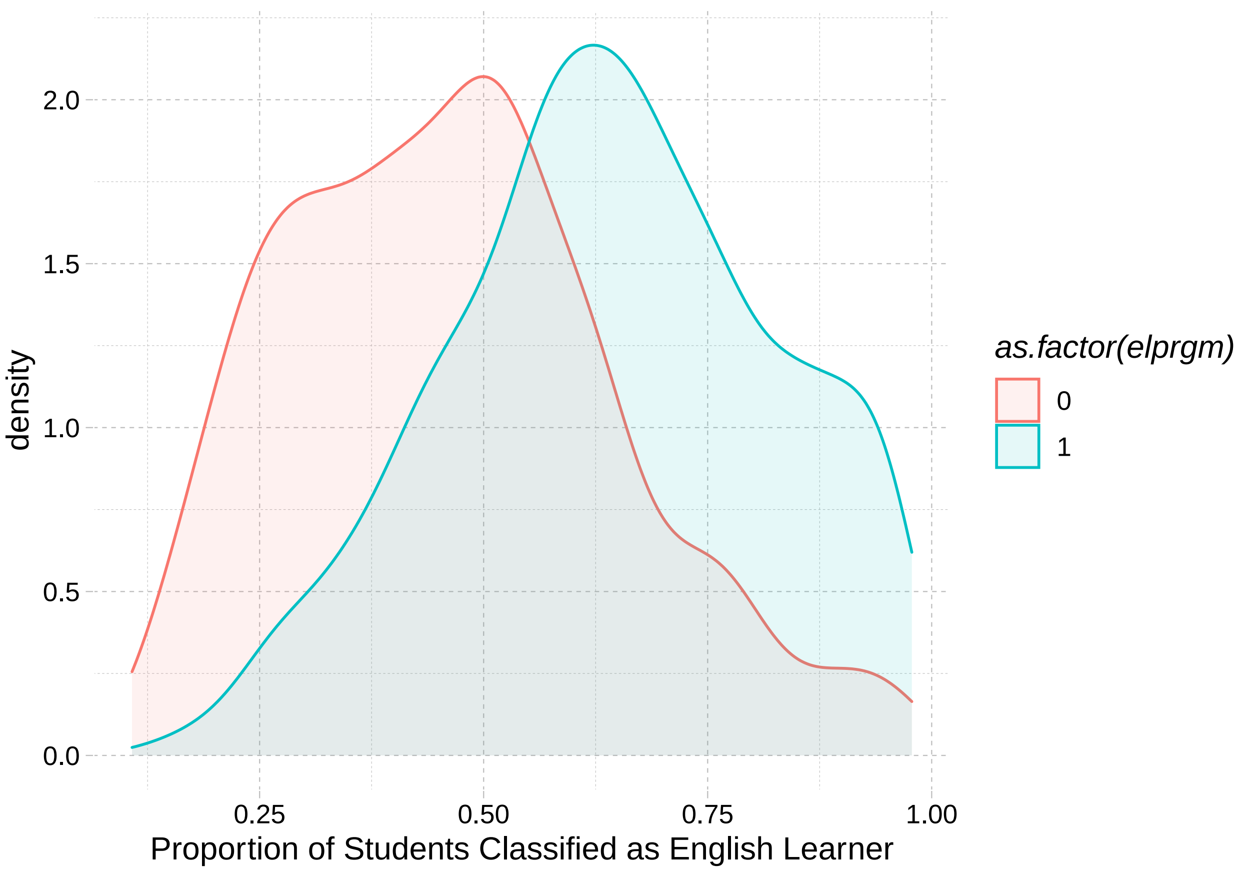
```
# 1. Fit logistic selection model estimating probability of participating in program, given covariates
pscores <- feglm(elprgm ~ prelas + ebrs + ses + kexecfunc1 + rural + female + hisp, family=c("logit"), 
summary(pscores)
```

```
## GLM estimation, family = binomial(link = "logit"), Dep. Var.: elprgm
## Observations: 2,166
## Standard-errors: IID
##              Estimate Std. Error   t value   Pr(>|t|)
## (Intercept)  3.046762   0.320047  9.519736  < 2.2e-16 ***
## prelas      -0.147814   0.016233 -9.105686  < 2.2e-16 ***
## ebrs        -0.024275   0.012284 -1.976174 4.8135e-02 *
## ses         -0.379779   0.071417 -5.317766 1.0505e-07 ***
## kexecfunc1  -0.027185   0.014318 -1.898632 5.7613e-02 .
## rural       -0.614306   0.156862 -3.916217 8.9949e-05 ***
## female      -0.054920   0.095492 -0.575125 5.6521e-01
## hisp         0.337650   0.114721  2.943230 3.2481e-03 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Log-Likelihood: -1,284.4   Adj. Pseudo R2: 0.129599
##            BIC:  2,630.3     Squared Cor.: 0.182884
```

```r
# 2. Estimate fitted probability of selection into treatment for each individual
pscore_df <- data.frame(p_score = predict(pscores, type = "response"),
                        elprgm = dat$elprgm)
head(pscore_df)
```

```
##     p_score elprgm
## 1 0.7484722      1
## 2 0.3117790      0
## 3 0.4185726      0
## 4 0.6425941      0
## 5 0.7599968      1
## 6 0.4264998      1
```

```r
# 3. Examine common support
ggplot(pscore_df, aes(p_score,fill = as.factor(elprgm), color = as.factor(elprgm))) +
  geom_density(alpha=0.1) +
  theme_pander(base_size = 12) +
  xlab("Proportion of Students Classified as English Learner")
```



Before matching, the figure above shows the region of common support. However, the two samples (participating in the EL program or not) are different on other characteristics as explained earlier, so we will try to increase the region of common support by matching below.

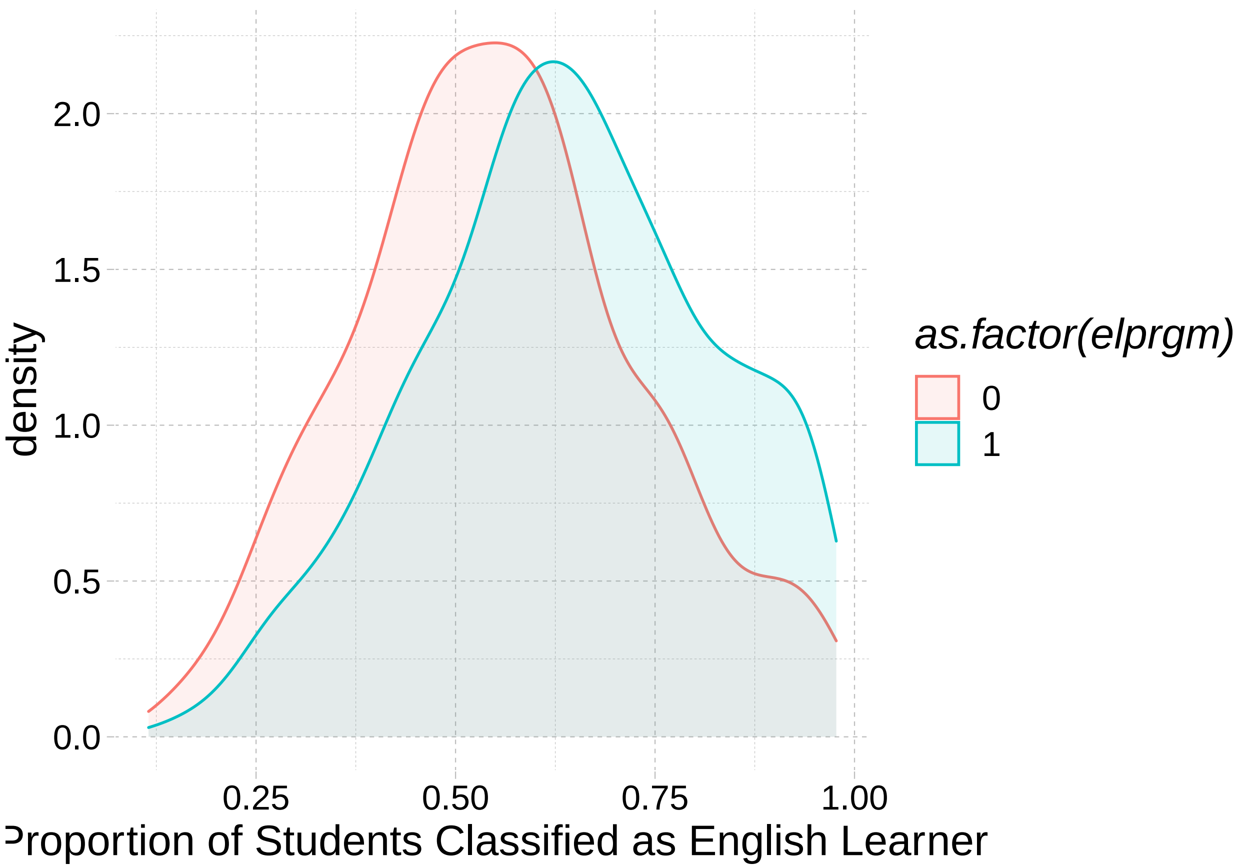
```r
# 1. Generate matches
matched <- matchit(elprgm ~ prelas + ebrs + kexecfunc1 + ses + rural + female + hisp, method="nearest",
                   discard="both", data=dat)

# Create dataframe from matched data
df_match <- match.data(matched)

# Dimensions of dataframe
dim(df_match) #compared to 2166 x 16
```

```
## [1] 1689   18
```

```r
## 2. Examine common support (post-match)
ggplot(df_match, aes(distance,fill = as.factor(elprgm), color = as.factor(elprgm))) +
        geom_density(alpha=0.1) +
        theme_pander(base_size = 16) +
        xlab("Proportion of Students Classified as English Learner")
```




```r
## 3. Examine quality of matches, descriptively
summary(matched) # see slide 29 to interpret quality of matches
```

```
##
## Call:
## matchit(formula = elprgm ~ prelas + ebrs + kexecfunc1 + ses +
```

```
##     rural + female + hisp, data = dat, method = "nearest", discard = "both",
##     replace = T)
##
## Summary of Balance for All Data:
##            Means Treated Means Control Std. Mean Diff. Var. Ratio eCDF Mean
## distance          0.6401        0.4650          0.9628     0.9571    0.2521
## prelas           14.5479       17.6201         -0.6277     2.1724    0.1463
## ebrs             10.7944       13.4127         -0.5541     1.0710    0.1247
## kexecfunc1       12.9689       14.1704         -0.3086     1.4280    0.0667
## ses              -0.6864       -0.2113         -0.6945     0.5679    0.1306
## rural             0.0811        0.1376         -0.2069          .    0.0565
## female            0.4906        0.5090         -0.0368          .    0.0184
## hisp              0.7461        0.5005          0.5642          .    0.2456
##            eCDF Max
## distance     0.4057
## prelas       0.3523
## ebrs         0.2395
## kexecfunc1   0.1194
## ses          0.2612
## rural        0.0565
## female       0.0184
## hisp         0.2456
##
##
## Summary of Balance for Matched Data:
##            Means Treated Means Control Std. Mean Diff. Var. Ratio eCDF Mean
## distance          0.6401        0.6401         -0.0000     0.9969    0.0011
## prelas           14.5479       14.7740         -0.0462     0.9619    0.0188
## ebrs             10.7944       11.0524         -0.0546     0.9639    0.0131
## kexecfunc1       12.9689       12.6749          0.0755     0.9678    0.0178
## ses              -0.6864       -0.7216          0.0514     1.0803    0.0116
## rural             0.0811        0.0590          0.0810          .    0.0221
## female            0.4906        0.4742          0.0328          .    0.0164
## hisp              0.7461        0.7576         -0.0263          .    0.0115
##            eCDF Max Std. Pair Dist.
## distance     0.0131          0.0040
## prelas       0.0541          0.3414
## ebrs         0.0401          0.8939
## kexecfunc1   0.0598          0.9085
## ses          0.0328          0.7772
## rural        0.0221          0.4171
## female       0.0164          0.9961
## hisp         0.0115          0.5758
##
## Percent Balance Improvement:
##            Std. Mean Diff. Var. Ratio eCDF Mean eCDF Max
## distance             100.0       92.9      99.6     96.8
## prelas                92.6       95.0      87.2     84.7
## ebrs                  90.1       46.5      89.5     83.2
## kexecfunc1            75.5       90.8      73.3     49.9
## ses                   92.6       86.4      91.1     87.5
## rural                 60.9          .      60.9     60.9
## female                11.0          .      11.0     11.0
## hisp                  95.3          .      95.3     95.3
```

```
##
## Sample Sizes:
##               Control Treated
## All            945.      1221
## Matched (ESS)  255.68    1221
## Matched        468.      1221
## Unmatched      473.         0
## Discarded        4.         0
```

In the summary of balance, we see that the standard mean difference decreases for the the matched data.

```r
## 4. Once happy with matches, estimate treatment effect in matched sample

#Estimate of EL status on Teacher perception of students' language skills using nearest neighbor matchi
psmatch_lang <- lm(tlangk ~ elprgm + prelas + ebrs + kexecfunc1+ ses+ rural + female + hisp,
              data=df_match,
              weights=weights)

#Estimate of EL status on Teacher perception of students' math skills using nearest neighbor matching

psmatch_math <- lm(tmathk ~ elprgm + prelas + ebrs + kexecfunc1 + ses + rural + female + hisp,
              data=df_match,
              weights=weights)


summary(psmatch_lang)
```

```
##
## Call:
## lm(formula = tlangk ~ elprgm + prelas + ebrs + kexecfunc1 + ses +
##     rural + female + hisp, data = df_match, weights = weights)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1387 -0.5438  0.0588  0.5985  3.1642
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.144357   0.113218 -18.940  < 2e-16 ***
## elprgm      -0.065489   0.047400  -1.382  0.16727
## prelas      -0.001142   0.005118  -0.223  0.82338
## ebrs         0.105994   0.005390  19.664  < 2e-16 ***
## kexecfunc1   0.030730   0.005707   5.385 8.29e-08 ***
## ses          0.036266   0.036312   0.999  0.31807
## rural       -0.069051   0.080697  -0.856  0.39230
## female       0.138029   0.042521   3.246  0.00119 **
## hisp         0.340997   0.056489   6.036 1.93e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8695 on 1680 degrees of freedom
## Multiple R-squared:  0.2803, Adjusted R-squared:  0.2768
## F-statistic: 81.77 on 8 and 1680 DF,  p-value: < 2.2e-16
```

```r
summary(psmatch_math)
```

```
##
## Call:
## lm(formula = tmathk ~ elprgm + prelas + ebrs + kexecfunc1 + ses +
##     rural + female + hisp, data = df_match, weights = weights)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.6069 -0.5671  0.0797  0.6850  3.1753
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.568497   0.122358 -12.819  < 2e-16 ***
## elprgm      -0.035946   0.051226  -0.702 0.482949
## prelas      -0.005660   0.005531  -1.023 0.306324
## ebrs         0.082367   0.005825  14.139  < 2e-16 ***
## kexecfunc1   0.023865   0.006168   3.869 0.000113 ***
## ses          0.047197   0.039243   1.203 0.229267
## rural       -0.043448   0.087212  -0.498 0.618418
## female       0.092594   0.045954   2.015 0.044069 *
## hisp         0.250247   0.061049   4.099 4.35e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9397 on 1680 degrees of freedom
## Multiple R-squared:  0.1612, Adjusted R-squared:  0.1572
## F-statistic: 40.37 on 8 and 1680 DF,  p-value: < 2.2e-16
```

```r
# Estimate confidence intervals
confint(psmatch_lang)
```

```
##                   2.5 %       97.5 %
## (Intercept) -2.36642140 -1.922293300
## elprgm      -0.15845805  0.027479243
## prelas      -0.01118048  0.008895551
## ebrs         0.09542163  0.116566254
## kexecfunc1   0.01953630  0.041923874
## ses         -0.03495529  0.107486487
## rural       -0.22732915  0.089227228
## female       0.05462894  0.221428522
## hisp         0.23020050  0.451794172
```

```r
confint(psmatch_math)
```

```
##                    2.5 %       97.5 %
## (Intercept) -1.808487390 -1.328507429
## elprgm      -0.136419960  0.064526966
## prelas      -0.016508049  0.005188601
## ebrs         0.070941692  0.093793201
## kexecfunc1   0.011767369  0.035962163
## ses         -0.029773186  0.124167088
```

```
## rural       -0.214502692  0.127607431
## female       0.002461917  0.182726254
## hisp         0.130506432  0.369988069
```

In a matched sample of students who had nearly identical language proficiency scores, executive functioning score, rurality, Gender and Ethnicity (Hispanic/Latinx or not) and were equally likely to be labelled as EL on these observable conditions, the effect of being classified as EL to **decrease** teacher perception of student's language skills scores by 0.065 scale score points [95% CI: -0.16, 0.03] and not significantly to **decrease** teacher perception of student's math skills scores by 0.035 scale score points [95% CI: -0.13, 0.06]. However, both of these effects are **not statistically significant**. To the extent that students' classification as English Learner is based entirely on these characteristics, we can interpret this a credibly causal estimate of the effect of EL status on teacher perception of students' academic skills among Multilingual Students, purged of observable variable bias.

B2. Construct a Coarsened Exact Matching (CEM) algorithm similar to Umansky and Dumont (see Class 8 Lecture) that relies on the following matching variables: (1) prelas, (2) ebrs, (3) ses, (4) rural, (5) female and (6) hisp. Variables 1-3 are continuous. You should decide whether you will follow Umansky and Dumont's choices for cutpoints or select other reasonable cutpoint values. Variables 4-6 are dichomotous and you should insist on exact matches for these categories. Write 1-2 paragraphs describing the identification strategy (remember this is different from your estimation strategy), its accompanying assumptions, your matching procedures and the resulting number of excluded sample members.

```r
#Coarsened Exact Matching
#Step 1. Define coarsened bins of covariates within which to match
# Create coarsened forPreLAS variable
prelas_quints <- quantcut(dat$prelas, 5)
table(prelas_quints)
```

```
## prelas_quints
##  [0,13] (13,16] (16,18] (18,20)      20
##     455     440     552     251     468
```

```r
#Create coarsened for EBRS
ebrs_quints <- quantcut(dat$ebrs, 5)
table(ebrs_quints)
```

```
## ebrs_quints
##   [0,7]  (7,11] (11,14] (14,17] (17,20]
##     471     465     435     526     269
```

```r
#Create coarsened for SES
ses_quints <- quantcut(dat$ses, 5)
table(ses_quints)
```

```
## ses_quints
## [-2.33,-1.12] (-1.12,-0.84] (-0.84,-0.52]  (-0.52,0.14]   (0.14,2.44]
##           438           429           435           431           433
```

```r
cem <- matchit(elprgm ~ prelas_quints + ebrs_quints + ses_quints + rural + female + hisp,
               method="cem",
               data=dat)
```

```r
# Create dataframe from matched data
df_cem <- match.data(cem)
# Dimensions of dataframe
dim(df_cem)
```

```
## [1] 1646   18
```

```r
table(df_cem$elprgm)
```

```
## 
##   0   1 
## 710 936
```

```r
summary(cem)
```

```
## 
## Call:
## matchit(formula = elprgm ~ prelas_quints + ebrs_quints + ses_quints + 
##     rural + female + hisp, data = dat, method = "cem")
## 
## Summary of Balance for All Data:
##                          Means Treated Means Control Std. Mean Diff. Var. Ratio
## prelas_quints[0,13]             0.3071        0.0847          0.4823          .
## prelas_quints(13,16]            0.2555        0.1354          0.2753          .
## prelas_quints(16,18]            0.2383        0.2762         -0.0889          .
## prelas_quints(18,20)            0.0876        0.1524         -0.2290          .
## prelas_quints20                 0.1114        0.3513         -0.7627          .
## ebrs_quints[0,7]                0.2752        0.1429          0.2963          .
## ebrs_quints(7,11]               0.2596        0.1566          0.2350          .
## ebrs_quints(11,14]              0.2007        0.2011         -0.0010          .
## ebrs_quints(14,17]              0.1974        0.3016         -0.2618          .
## ebrs_quints(17,20]              0.0672        0.1979         -0.5223          .
## ses_quints[-2.33,-1.12]         0.2514        0.1386          0.2600          .
## ses_quints(-1.12,-0.84]         0.2432        0.1397          0.2414          .
## ses_quints(-0.84,-0.52]         0.2170        0.1799          0.0901          .
## ses_quints(-0.52,0.14]          0.1777        0.2265         -0.1275          .
## ses_quints(0.14,2.44]           0.1106        0.3153         -0.6530          .
## rural                           0.0811        0.1376         -0.2069          .
## female                          0.4906        0.5090         -0.0368          .
## hisp                            0.7461        0.5005          0.5642          .
##                          eCDF Mean eCDF Max
## prelas_quints[0,13]         0.2225   0.2225
## prelas_quints(13,16]        0.1201   0.1201
## prelas_quints(16,18]        0.0379   0.0379
## prelas_quints(18,20)        0.0647   0.0647
## prelas_quints20             0.2399   0.2399
## ebrs_quints[0,7]            0.1323   0.1323
## ebrs_quints(7,11]           0.1030   0.1030
## ebrs_quints(11,14]          0.0004   0.0004
## ebrs_quints(14,17]          0.1042   0.1042
## ebrs_quints(17,20]          0.1307   0.1307
## ses_quints[-2.33,-1.12]     0.1128   0.1128
```

```
## ses_quints(-1.12,-0.84]    0.1036   0.1036
## ses_quints(-0.84,-0.52]    0.0371   0.0371
## ses_quints(-0.52,0.14]     0.0487   0.0487
## ses_quints(0.14,2.44]      0.2048   0.2048
## rural                      0.0565   0.0565
## female                     0.0184   0.0184
## hisp                       0.2456   0.2456
##
##
## Summary of Balance for Matched Data:
##                         Means Treated Means Control Std. Mean Diff. Var. Ratio
## prelas_quints[0,13]            0.2949        0.2949              -0          .
## prelas_quints(13,16]           0.2340        0.2340              -0          .
## prelas_quints(16,18]           0.2682        0.2682              -0          .
## prelas_quints(18,20)           0.0801        0.0801              -0          .
## prelas_quints20                0.1229        0.1229              -0          .
## ebrs_quints[0,7]               0.2810        0.2810              -0          .
## ebrs_quints(7,11]              0.2714        0.2714              -0          .
## ebrs_quints(11,14]             0.1795        0.1795              -0          .
## ebrs_quints(14,17]             0.2126        0.2126              -0          .
## ebrs_quints(17,20]             0.0556        0.0556              -0          .
## ses_quints[-2.33,-1.12]        0.2596        0.2596              -0          .
## ses_quints(-1.12,-0.84]        0.2468        0.2468              -0          .
## ses_quints(-0.84,-0.52]        0.2190        0.2190              -0          .
## ses_quints(-0.52,0.14]         0.1571        0.1571              -0          .
## ses_quints(0.14,2.44]          0.1175        0.1175              -0          .
## rural                          0.0214        0.0214              -0          .
## female                         0.4861        0.4861               0          .
## hisp                           0.7906        0.7906               0          .
##                         eCDF Mean eCDF Max Std. Pair Dist.
## prelas_quints[0,13]             0        0               0
## prelas_quints(13,16]            0        0               0
## prelas_quints(16,18]            0        0               0
## prelas_quints(18,20)            0        0               0
## prelas_quints20                 0        0               0
## ebrs_quints[0,7]                0        0               0
## ebrs_quints(7,11]               0        0               0
## ebrs_quints(11,14]              0        0               0
## ebrs_quints(14,17]              0        0               0
## ebrs_quints(17,20]              0        0               0
## ses_quints[-2.33,-1.12]         0        0               0
## ses_quints(-1.12,-0.84]         0        0               0
## ses_quints(-0.84,-0.52]         0        0               0
## ses_quints(-0.52,0.14]          0        0               0
## ses_quints(0.14,2.44]           0        0               0
## rural                           0        0               0
## female                          0        0               0
## hisp                            0        0               0
##
## Percent Balance Improvement:
##                         Std. Mean Diff. Var. Ratio eCDF Mean eCDF Max
## prelas_quints[0,13]                 100          .       100      100
## prelas_quints(13,16]                100          .       100      100
## prelas_quints(16,18]                100          .       100      100
```

```
## prelas_quints(18,20)                100          .         100       100
## prelas_quints20                     100          .         100       100
## ebrs_quints[0,7]                    100          .         100       100
## ebrs_quints(7,11]                   100          .         100       100
## ebrs_quints(11,14]                  100          .         100       100
## ebrs_quints(14,17]                  100          .         100       100
## ebrs_quints(17,20]                  100          .         100       100
## ses_quints[-2.33,-1.12]             100          .         100       100
## ses_quints(-1.12,-0.84]             100          .         100       100
## ses_quints(-0.84,-0.52]             100          .         100       100
## ses_quints(-0.52,0.14]              100          .         100       100
## ses_quints(0.14,2.44]               100          .         100       100
## rural                               100          .         100       100
## female                              100          .         100       100
## hisp                                100          .         100       100
##
## Sample Sizes:
##               Control Treated
## All             945.     1221
## Matched (ESS)   265.9     936
## Matched         710.      936
## Unmatched       235.      285
## Discarded         0.        0
```

In this analysis, we decided to utilize Coarsened exact matching (CEM) strategy to reduce observed variable bias by removing from the sample and subsequent estimation any individuals in EL group who cannot be matched with individuals in the non EL group. Further, for each observed variable, we chose number of bins based on prior knowledge about our data and match our sample within each bin. Following Umansky and Dumont's strategy, we binned PreLAS, EBRS and SES into quintiles, executive function score into halves, and forced exact match for rurality, gender and ethnicity (Hispanic or Not). Matching by quintiles has been shown to eliminate more than 90% of bias (Umansky & Dumont, 2021). We dropped 43 more sample of nearest-neighbor matched sample, and in total we dropped 520 sample from pre-matched sample.

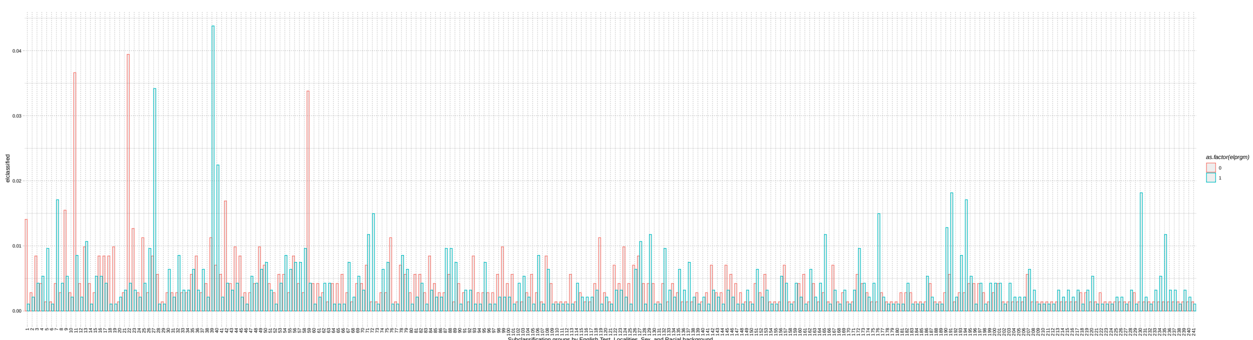
B3. Assess the quality of your matches by looking at the region of common support in your newly matched sample. Assess the quality of your matches by comparing baseline variable values in the treated and non-treated conditions. Provide a summary assessment of the quality of your matches, the extent to which you have accomplished balance, and the impact your matching has had on your sample as it relates to both variance and generalizability. Do you think you should try different matching criteria to achieve a better result? Why or why not (it is not necessary at this point to actually conduct multiple re-matching procedures, just assess whether they would be valuable)?

```r
# Plot common support
df_cem2 <- df_cem %>% group_by(elprgm, subclass) %>%
              summarise(count= n())
```

```
## 'summarise()' has grouped output by 'elprgm'. You can override using the
## '.groups' argument.
```

```r
df_cem2 <- df_cem2 %>%  mutate(elclassified = count / sum(count))

# Examine quality of matches for each variable grouping
p <- ggplot(df_cem2, aes(subclass,elclassified, color = as.factor(elprgm))) +
          geom_col(alpha=0.1, position = position_dodge()) +
          theme_pander(base_size = 10) +
          xlab("Subclassification groups by English Test, Localities, Sex, and Racial background")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
p
```




```r
ggsave("p.pdf", width = 30, height = 8, units= "in")
```

Table 2: Comparison of OLS, PSM and CEM estimates of Effect of EL Status on Teacher Perceptions of Students'academic Skills, Among Multilingual Students

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS Language	OLS Math	PSM Language	PSM Math	CEM Language	CEM Math
EL status	-0.453^{***}	-0.365^{***}	-0.065	-0.036	-0.057	-0.015
	(0.043)	(0.043)	(0.047)	(0.051)	(0.042)	(0.046)
Num.Obs.	2166	2166	1689	1689	1646	1646

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B4. Using your newly matched sample, estimate the average treatment effect of EL classification on teachers' perceptions of students' math and language ability in your newly matched sample. If you decide to do B5, present these results and associated discussion along with the rest of your results in B5. If you do not, answer the rest of the prompt with just the CEM results. Present your CEM results and compare them to your results in A1 in a table and an accompanying write-up as you would report these in an academic paper in 1-2 paragraphs.

Table footnotes Model 3-6 match on English proficiency & Executive functioning score, SES, Rurality, Gender, and Ethnicity. Model 5-6 use narrower bins. The english proficiency variables were matched by sample distribution quantile while the executive functioning measure was matched by sample distribution halves. All CEM and PSM estimates are double-robust.

We further implement *Coarsened Exact Matching* to compare student with EL status and non EL status within more restricted similarity of characteristics (region of common support) to avoid estimation bias. Although the effect of EL status on teacher perception of students kindergarten academic skill is still not significant, the downwardly biased perceptions of their students' abilities as a direct result of EL label were overstated in the propensity score matching (nearest-neighbor) sample. Using CEM, we found a 0.056 scale point decreased on teacher perception id EL students' language score and a 0.014 scale point decreased on teacher perception of EL students' math score.

B5. (OPTIONAL) Conduct a robustness check by estimating the causal effect of EL classification on teacher perceptions of student skills by using a propensity score matching approach (or another approach from the matching family if you choose). Share information on the quality of these matches and any additional assumptions associated with this approach. Present these results alongside your results in B4 in an accompanying table(s) and write-up as you would report these in an academic paper in 2-3 paragraphs.

B6. Write a discussion paragraph in which you present the substantive conclusions (and limitations) of your results about the effects of EL classification on teacher perception of student skills in Kindergarten.