Kim, Capotosto, Hartry & Fitzgerald (2011) Analysis and Replication

Anwesha Guha, Merly Klaas, Thuy Nguyen

2/8/2022

A. Baseline randomization checks

A1. Create a table comparing the baseline characteristics (family income, gender, test score) for students assigned to the treatment and control conditions. Assess and describe whether the randomization process generated identical treatment and control conditions. Describe the results of your assessment in 1-2 sentences. If it did not (or if it had not), would this invalidate the causal claims of the study? Why or why not?

```
##
##
## |                            |    0 (N=157)     |    1 (N=155)     |  Total (N=312)   | p value|
## |:---------------------------|:----------------:|:----------------:|:----------------:|-------:|
## |**frpl**                    |                  |                  |                  |   0.493|
## |   Mean (SD) |  0.707 (0.457)   |  0.671 (0.471)   |  0.689 (0.464)   |        |
## |   Range     |  0.000 - 1.000   |  0.000 - 1.000   |  0.000 - 1.000   |        |
## |**female**                  |                  |                  |                  |   0.503|
## |   Mean (SD) |  0.561 (0.498)   |  0.523 (0.501)   |  0.542 (0.499)   |        |
## |   Range     |  0.000 - 1.000   |  0.000 - 1.000   |  0.000 - 1.000   |        |
## |**dorf**                    |                  |                  |                  |   0.783|
## |   Mean (SD) | 86.245 (25.936)  | 87.121 (30.117)  | 86.680 (28.049)  |        |
## |   Range     | 18.791 - 153.762 | 15.315 - 165.104 | 15.315 - 165.104 |        |
```

Table 1: Descriptive statistics by assigned treatment

	0 (N=157)	1 (N=155)	Total (N=312)	p value
Free/Reduced Price Lunch				0.493
Mean (SD)	0.71 (0.46)	0.67 (0.47)	0.69 (0.46)	
Prop. Female				0.503
Mean (SD)	0.56 (0.50)	0.52 (0.50)	0.54 (0.50)	
Baseline DIBELS				0.783
Mean (SD)	86.24 (25.94)	87.12 (30.12)	86.68 (28.05)	

The randomization process created identical treatment and control conditions for the baseline characteristics of free or reduced price lunch (FRPL), gender (% female), and test score (DIBELS). If these characteristics were significantly different from one group to another, the equal in expectation assumption would be violated.

While data is not large, can still use an omnibus F test for balance as a different check:

```
##
```

```
## Call:
## lm(formula = treat ~ frpl + female + dorf, data = dare3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5511 -0.5025 -0.4587  0.4965  0.5422
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.5338301  0.1143816   4.667 4.56e-06 ***
## frpl        -0.0407333  0.0619871  -0.657    0.512
## female      -0.0372214  0.0573499  -0.649    0.517
## dorf         0.0001292  0.0010291   0.126    0.900
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5025 on 308 degrees of freedom
## Multiple R-squared:  0.002993,   Adjusted R-squared:  -0.006718
## F-statistic: 0.3082 on 3 and 308 DF,  p-value: 0.8195
```

B. Replication and Extension

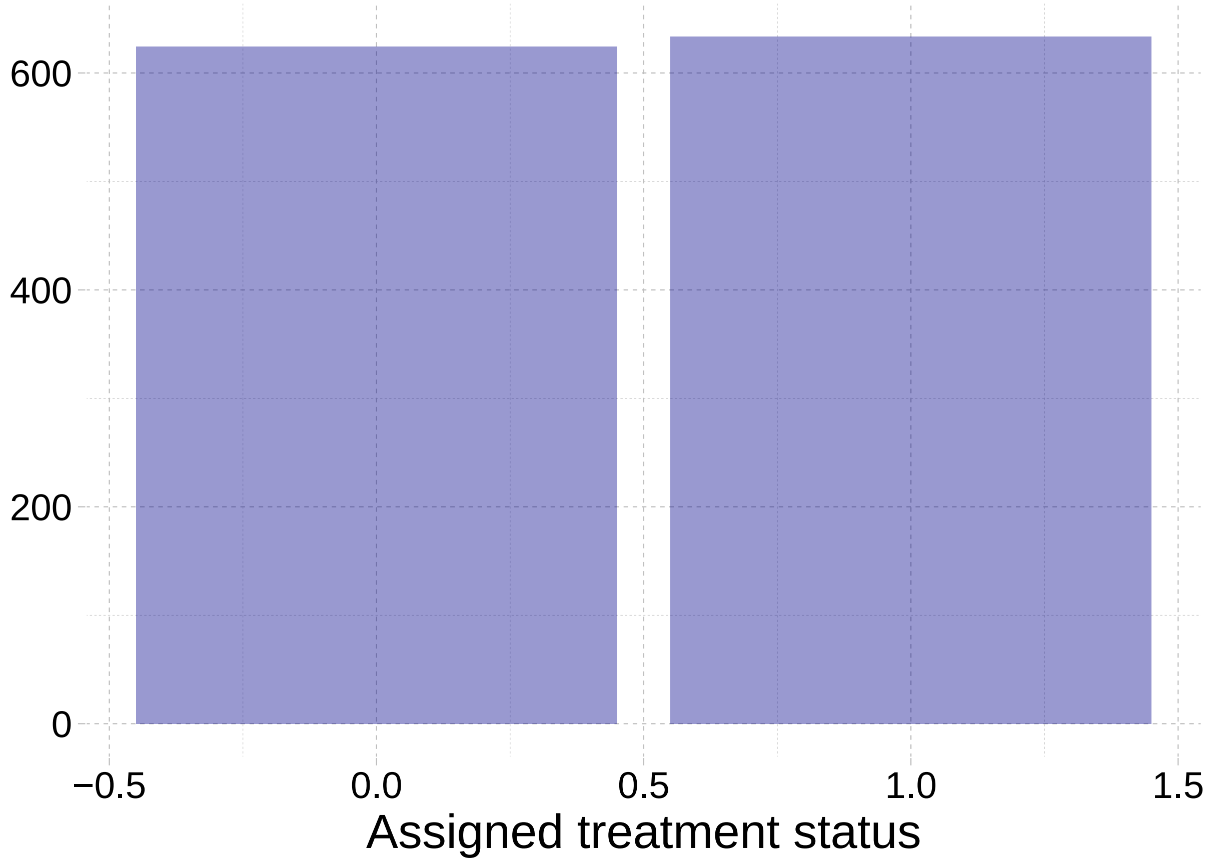
B1. Estimate the bivariate relationship between students' final reading comprehension outcomes and their attendance rate (proportion of days attended) in a seven-month READ180 program. Present these results in a table with an accompanying discussion of what these results show and whether they should be understood as the causal effect of READ180 on reading comprehension outcomes in 1 paragraph.

Table 2: Naïve OLS estimates of attending READ 180 program on Reading outcome

	(1)	(2)
READ180 attendance	11.111*	9.662***
	(4.326)	(2.261)
Pre-test Score		0.984***
		(0.035)
Female		1.183
		(1.945)
Eligibity for Free Lunch		−4.307*
		(2.106)
Observations	312	312
R^2	0.021	0.736
Note:	*p<0.05; **p<0.01; ***p<0.001	

It is likely to have endogenous differences in the expected outcomes between children who attended after-school program at a high rate and those attended at a lower rate. The OLS estimate of the predictor read180_attend is likely to be correlated with the residuals in the outcome test score sat10_compreh.

B2. Compare the average post-test reading comprehension scores of students who were assigned to participate in the READ180 intervention with those who were not. Present a figure comparing these mean differences. Is the difference in these scores meaningful and does the difference reflect anything other than sampling idiosyncrasy?



It appears that there is no meaningful differences in the average post-test reading comprehension scores of students who were assigned to participate in the READE180 intervention with those who were not. The height of the treated group column is slightly higher than the control group column, but the difference is minor and could be due to sampling idiosyncrasy.

B3. Estimate Intent-to-Treat estimates of being assigned to participate in an after-school READ180 intervention. Present these results in a table and an accompanying write-up as you would report these in an academic paper in 1 paragraph. What differences are there in the results you estimated in response to this question and those for question B2?

```
# Estimate the models
itt1 <- lm(sat10_compreh ~ treat, data=dare3)
itt2 <- lm(sat10_compreh ~ treat + frpl + female + dorf, data=dare3)
itt3 <- lm(sat10_compreh ~ treat + frpl + female + dorf +
             as.factor(school), data=dare3)
```

```
# Create a decent-looking table

# Create a row indicating FEs
row <- tribble(~term,          ~'1',  ~'2', ~'3',
              'School Fixed Effects', 'No', 'No', 'Yes')
attr(row, 'position') <- c(7)

# Produce the table; can export to markdown, tex, etc. by changing the type
```

Table 3: Intent-to-Treat Estimates of READ180 on Test of Comprehension

	Model 1	Model 2	Model 3
Assigned to READ180	9.014*	8.037***	8.003***
	(3.703)	(1.935)	(1.935)
Eligible for free lunch		−4.553*	−4.243*
		(2.106)	(2.122)
Female		1.328	1.232
		(1.949)	(1.953)
School Fixed Effects	No	No	Yes
Pretest Score		0.985***	0.985***
		(0.035)	(0.035)
Num.Obs.	312	312	312

Table 4: Instrumental variable estimates of attending READ 180 Intervention on Test Scores due to random assignment to after-school READ180 intervention

	(1)	(2)	(3)	(4)
READ180 attendance	11.472*	10.236***	10.208***	10.208***
	(4.708)	(2.460)	(2.464)	(0.788)
Pretest Score		0.984***	0.985***	0.985***
		(0.035)	(0.035)	(0.049)
Eligible for free lunch		−4.273*	−3.992	−3.992
		(2.107)	(2.121)	(4.061)
Female		1.192	1.114	1.114
		(1.945)	(1.949)	(1.480)
School FE	No	No	Yes	Yes
Num.Obs.	312	312	312	312

* p < 0.05, ** p < 0.01, *** p < 0.001 The table displays coefficients from Equation X and standard errors in parentheses. Model 4 uses cluster-robust standard errors at school level.

```
modelsummary(list(itt1, itt2, itt3),
             title = "Intent-to-Treat Estimates of READ180 on Test of Comprehension",
             stars=c('*' = 0.05, '**' = 0.01, '***' = 0.001),
             coef_omit = "(Intercept)|as.factor",
             coef_rename = c("fit_read180_attend" = "READ180 attendance", "dorf" = "Pretest Score", "
             estimate = "{estimate}{stars}",
             gof_omit= "Adj|Pseudo|Log|Within|AIC|BIC|FE|Std|R2|F",
             add_rows = row,
             threeparttable= T,
          #    notes = c("Notes: The table displays coefficients from Equation X and standard errors i
             type='html')
```

B4. Identify the effects of full participation in a seven month after-school READ180 reading intervention. In other words: what are the effects of 100 percent attendance in a seven-month reading program, compared to not attending at all? Describe the model you estimate, its accompanying assumptions and defend the extent to which these assumptions are met in your analysis. Present these results in a table and an accompanying write-up as you would report these in an academic paper in 2-3 paragraphs.

Table 5: Comparison of OLS, ITT and IV estimates of Full Attendance of READ180 intervention on Post-test scores due to random offer to participate in READ180

	(1)	(2)	(3)	(4)	(5)
	OLS	ITT	TOT	TOT	TOT
READ180 attendance	9.662***		11.472*	10.236***	10.208***
	(2.261)		(4.708)	(2.460)	(0.788)
Random Offer to READ180		8.037***			
		(1.935)			
School FE	No	No	No	No	Yes
Student Chars.	Yes	Yes	No	Yes	Yes
Clust. SEs	No	No	No	No	Yes
Num.Obs.	312	312	312	312	312

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ The table displays coefficients from Equation X and standard errors in parentheses.

Table 4 presents the treatment-on-the-treated (TOT) estimate of attending READ 180 enterprise on students' reading achievement. We used the two-stage least squares (2SLS) approach to obtain an Instrumental Variable estimate using the exogenous assignment of offer to participate (*intent to treat*) in READ 180 intervention program as our instrument. In the first-stage, we estimate the predicted values of potentially endogenous predictor. After comparing our F statistics of 1,654 and the cutoff of 10, we are confident that this instrument is strong. Then, in the second stage, we use the newly predicted values to estimate the effect of attending READ 180 on reading achievement.

In model 1, when we did not control for any covariate, we found a gain of 11 points for students who participated in READ 180 program, while after including students background characteristics such as eligibility for free lunch status, sex, and pre-test scores, we found a 1.2 point lower increase on the reading score. A similar estimation of a 10.2 points increase was also found in model 3 and 4 when we accounted for school fixed effects and clustering standard errors at the level of randomization (within school).

B5. Write a discussion paragraph in which you present the substantive conclusions (and limitations) of your results about the effects of the after-school READ180 intervention you have documented.

Table 5 displays Comparison of OLS, ITT and IV estimates of Full Attendance of READ180 intervention on Post-test scores due to random offer to participate in READ180. The estimates of the endogenous relationship between attending READ 180 Enterprise Intervention program to improve the reading achievement of Low-Performing Elementary School Students (Model 1) imply that reading achievement for students who attended Read 180 program is 9 points higher than those who did not. In Model 2, we present results of being randomly assigned to attend READ 180 instead of the traditional after-school program. We found that the offer of attending READ 180 program increased reading test scores about 8 points. Finally, Models 3-5 present a taxonomy of TOT estimates in which we use the randomized assignment to READ 180 program as an instrument to estimate impact on attending READ 180 on students reading achievement. We found consistent effects of attending READ 180 Intervention on the increased reading achievement score for about 10 scaled score points. These models are robust to the inclusion of baseline student characteristics, school fixed effects, and the clustering of standard errors at the level of randomization (within school).