DIL-Data Task

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Load Data

```
df_outcome <- read.csv("student_follow_ups.csv")
df_stu_base<-read.csv("student_baseline.csv")
df_sch_base<-read.csv("schools.csv")
df_visit<-read.csv("school_visits_log.csv")</pre>
```

Detect Missing Values

```
missing_percentages <- df_outcome %>%
   summarise_all(~ mean(is.na(.)) * 100)
missing_percentages <- as.data.frame(t(missing_percentages))
colnames(missing_percentages) <- "Missing_Percentage"
print(missing_percentages)</pre>
```

```
##
              Missing Percentage
## school id
                     0.00000000
## student_id
                     0.00000000
## year
                    0.00000000
## died
                     0.02063771
## married
                     0.02063771
## children
                     49.57176762
## pregnant
                     49.57176762
## dropout
                      0.37147869
```

It seems like outcome of pregnancy and whether have children have great amount of missing values, thus these two outcome variable may be carefully considered when processed regression.

Concatenate Datasets

```
merged_df <- merge(df_outcome, df_stu_base, by = "student_id", all.x = TRUE)
merged_df <- merge(merged_df,df_sch_base,by="school_id",all.x=TRUE)
df_visit<- df_visit %>% select(-year)
merged_df <- merge(merged_df,df_visit,by="school_id",all.x=TRUE)</pre>
```

Balance Table

```
### school level covariates
df sch base 1 \leftarrow-df sch base[,-c(1:3)] %>%
  mutate(Urban = ifelse(location == 1, 1, 0))%>%
  select(-location)
table <-df_sch_base_1 %>%
  group_by(treatment)%>%
  summarize_all(list(~mean(.))) %>%
  mutate_all(list(~round(., 3))) %>%
  t() %>%
  as.data.frame()
colnames(table) <- c("mean_control", "mean_treat")</pre>
p_values <- data.frame(variable = rownames(table), p_value = NA)</pre>
# Calculate p-values using t-tests
for (var in rownames(table)[-1]) { # Exclude the treatment row itself
  control_values <- df_sch_base_1 %>% filter(treatment == 0) %>% pull(var)
  treat_values <- df_sch_base_1 %>% filter(treatment == 1) %>% pull(var)
  # Perform t-test
  t_test_result <- t.test(control_values, treat_values)</pre>
  # Store p-value
 p_values$p_value[p_values$variable == var] <- t_test_result$p.value
# Merge the means and p-values
final_table_A <- cbind(table, p_values[,-1])</pre>
final_table_A<-final_table_A[-1,]</pre>
# Display the final table
knitr::kable(final table A)
```

	$mean_control$	$mean_treat$	$p_values[, -1]$
n_teachers	14.537	14.181	0.5788467
$n_teachers_fem$	7.146	7.205	0.9259432
$female_head_teacher$	0.085	0.096	0.8069064
$n_students_fem$	254.963	231.675	0.1283670
$n_students_male$	253.573	232.952	0.1713085
$n_schools_2km$	1.951	2.012	0.8315288
av_teacher_age	37.922	38.287	0.8808257
$av_student_score$	245.024	242.422	0.7849296
$n_{latrines}$	5.585	11.627	0.0314354
Urban	0.098	0.157	0.2571961

The balance table shows the means of covariates for the control and treatment groups. P-values indicate if the difference in means between groups is statistically significant. In this table, only n_latrines shows a significant difference (p = 0.0314354), suggesting a potential imbalance in the number of latrines between the groups. The balance table indicates that the randomization was generally successful, with the exception of n_latrines. This imbalance should be addressed in the analysis phase to ensure it does not confound the treatment effects.

```
## indivial level covariates
table_ind <- merged_df %>%
filter(year==3) %>%
```

```
select(c(sex,yob,treatment)) %>%
  mutate(sex = ifelse(sex == 1, 1, 0))\%\%
  group_by(treatment)%>%
  summarize_all(list(~mean(.))) %>%
  mutate_all(list(~round(., 3))) %>%
  t() %>%
  as.data.frame()
colnames(table_ind) <- c("mean_control", "mean_treat")</pre>
# Function to calculate p-values
calc_p_value <- function(var) {</pre>
  control_values <- merged_df %>% filter(year == 3 & treatment == 0) %>% pull(!!sym(var))
  treat_values <- merged_df %% filter(year == 3 & treatment == 1) %% pull(!!sym(var))
  t.test(control_values, treat_values)$p.value
}
# Calculate p-values for the relevant columns
variables <- c("sex", "yob")</pre>
p_values <- map_dbl(variables, calc_p_value)</pre>
\# Create a dataframe for p-values
p_value_df <- data.frame(variable = rownames(table_ind)[-1], p_value = p_values)</pre>
rownames(p_value_df) <- p_value_df$variable</pre>
p_value_df$variable <- NULL</pre>
# Merge the p-values with the table of means
final_table_B <- cbind(table_ind, p_value = c(NA, p_values))</pre>
final_table_B<-final_table_B[-1, ]</pre>
# Display the final table
knitr::kable(final_table_B)
```

	$mean_control$	$mean_treat$	p_value
sex	0.502	0.491	0.1350085
yob	2563.124	2520.784	0.1463867

The balance table indicates that the randomization was generally successful across individual level confounders.

Regression

We will choose cross-section linear regression model to study the impact of the trearment. The unit of analysis is individual students. The regression specification is:

$$Outcome_{it} = \beta_0 + \beta_1 Treatment_i + \beta_2 Baseline Covariates_i + \gamma_d + \epsilon_{it}$$
(1)

Where:

Outcome_{it}: The outcome of interest (school evasion, teen pregnancy, marriage) for student i at time t (3 or 5 years).

Treatment_i: Treatment indicator for student i (1 if treated, 0 if control).

selineCovariates_i: Baseline covariates controls for student i (The control variables include school level controls and student level controls. Specifically, they are sex, age as individual characteristics, number of teachers, number of female teachers, number of female students, number of school within 2km, average teacher age, average student score, number of latrines as school level characteristics. To avoid muticonlinearity between total number of teachers, number of female teachers and number of male teachers, exculde number of male teachers in control selection).

 γ_d : District fixed effects.(urban, district, stratum and month fixed effect variables)

 ϵ_{it} : Error term.

```
merged_df_3_example<- merged_df %>%
  filter(year == 3)
m <- merged_df_3_example %>%
  group_by(died) %>%
  summarize_all(list(~mean(.))) %>%
  mutate_all(list(~round(., 3))) %>%
  t()
colnames(m) <-c("Unknown", "Alive", "Died", "NA")
knitr::kable(m)</pre>
```

	Unknown	Alive	Died	NA
died	-99.000	0.000	1.000	NA
school_id	72.689	80.705	58.963	81.000
student_id	13538984.975	15896858.715	5956328.852	8160055.000
year	3.000	3.000	3.000	3.000
married	-59.823	-0.140	-99.000	NA
children	NA	NA	NA	NA
pregnant	NA	NA	NA	NA
dropout	0.592	0.146	NA	NA
sex	1.589	1.499	1.296	1.500
yob	5213.415	2371.286	4659.444	5995.000
district	1.488	1.592	1.444	1.500
stratum	50.043	43.888	50.519	55.500
treatment	0.499	0.491	0.444	0.500
location	1.800	1.844	1.778	2.000
n_teachers	16.440	15.521	14.926	12.500
$n_teachers_fem$	8.996	7.962	8.667	7.000
female_head_teacher	0.066	0.068	0.037	0.500
$n_students_fem$	293.395	279.388	253.963	246.500
$n_students_male$	296.610	279.556	254.593	263.500
$n_schools_2km$	1.606	1.806	1.296	2.500
av_teacher_age	38.436	38.515	34.819	36.874
av_student_score	251.862	252.520	223.963	217.000
n_latrines	11.242	10.863	5.741	13.000
day	20.169	19.819	20.741	21.500
month	7.589	7.728	7.574	7.500

We can see that all died student have no/unknown data of outcome variables including marriage and drop out, thus removing the died student will not cause much loss in outcome data, we can safely remove them.

```
merged_df_3<- merged_df %>%
  filter(year == 3 ,died == 0) %>%
  mutate(age = 2010-yob) %>% ## create col of age instead of yob, which is more interpretable
  filter(age > 0) %>%
```

```
mutate(urban = ifelse(location == 1, 1, 0))%>%
mutate(sex = ifelse(location == 1, 1, 0))%>%
mutate(stratum = as.factor(stratum)) %>%
mutate(district = as.factor(district)) %>%
mutate(district = as.factor(month)) %>%
select(-c(school_id,student_id,year,yob,location))
```

##(merged_df_3)

We can see that there is no

Regression Results -- 3 year Dependent variable: ## ______ ## married pregnant children (1) 0.158* (0.077) 0.275 (0.166) 0.241 (0.124) ## treatment ## sex 0.118 (0.185) 1.140** (0.388) 0.736* (0.290) -0.079** (0.025) -0.112 (0.059) -0.017 (0.044) ## age -0.195** (0.064) -0.105* (0.047) 0.054 (0.054) 0.032 (0.040) -0.617 (0.409) 0.329 (0.305) 0.003 (0.002) 0.078 (0.075) 0.0004 (0.008) 0.001 (0.001) 0.090 (0.056) 0.005 (0.006) -0.004 (0.002) 0.003 (0.002) -0.009** (0.004) ## n_latrines 0.026*** (0.008) -0.005 (0.006) ## urban ## district5 0.054 (0.193) 0.145 (0.410) 0.015 (0.306) ## district7 0.125 (0.215) -0.579 (0.451) -0.229 (0.337) ## district9 0.035 (0.152) 0.092 (0.322) 0.015 (0.240) -0.031 (0.205) -0.365 (0.323) ## district10 -0.495 (0.433) 0.210 (0.231) -0.469 (0.486) -0.116 (0.363) ## district11 -0.107 (0.397) ## district12 -2.381** (0.876) -0.873 (0.654) ## month ## Constant 1.009 (0.840) 6.169*** (1.832) -0.483 (1.367) ## stratum Yes Yes Yes

```
## Observations
                       17,342
                                            8,532
                                                               8,532
## R2
                        0.016
                                            0.030
                                                               0.019
## Adjusted R2
                         0.010
                                            0.019
                                                               0.008
## F Statistic
                 2.827*** (df = 98; 17243) 2.666*** (df = 98; 8433) 1.684*** (df = 98; 8433)
## Note:
                                                    *p<0.05; **p<0.01; ***p<0.001
model.3.dropout <- lm(dropout ~ treatment+ sex + age + n_teachers + n_teachers_fem+ female_head_teacher +
stargazer(model.3.dropout, type = "text",
         omit = "stratum", omit.labels = "stratum",
         star.cutoffs = c(0.05, 0.01, 0.001),
         #dep.var.labels = c("Outcome"),
         keep.stat = c("n", "rsq", "adj.rsq", "f"),
         single.row = TRUE,
         title = "Regression Results -- 3 year")
##
## Regression Results -- 3 year
##
                     Dependent variable:
##
                 -----
                         dropout
## -----
## treatment
                     -0.016** (0.005)
## sex
                      -0.021 (0.013)
0.069*** (0.002)
## age
## urban
## district5
                      -0.002 (0.013)
## district7
                      0.024 (0.015)
                      -0.002 (0.010)
## district9
## district10
                       0.006 (0.014)
## district11
                      0.034* (0.016)
## district12
                       0.013 (0.027)
## month
                      -1.320*** (0.058)
## Constant
## -----
## stratum
                           Yes
## Observations
                         17,342
## R2
                          0.110
```

For three year sample, as we can see from the table above, the coefficient before treatment is not significant (at 5% level) for outcome variable: marriage, children and pregnant, implying that the intervention did not change these

0.105

*p<0.05; **p<0.01; ***p<0.001

F Statistic 21.755*** (df = 98; 17243)

Adjusted R2

Note:

concerns evidently. However, we can see a significant negative impact of treatment on drop-out rate, meaning that offer transfers can decrease students' dropout.

```
## effect after 5 years
merged_df_5<- merged_df %>%
  filter(year == 5 ,died == 0) %>%
  mutate(age = 2010-yob) %>% ## create col of age instead of yob, which is more interpretable
  filter(age > 0) %>%
  mutate(urban = ifelse(location == 1, 1, 0))%>%
  mutate(sex = ifelse(location == 1, 1, 0))%>%
  mutate(stratum = as.factor(stratum)) %>%
  mutate(district = as.factor(district)) %>%
  mutate(district = as.factor(month)) %>%
  select(-c(school_id,student_id,year,yob,location))
```

: :	Dependent variable:				
	married (1)	pregnant (2)	children (3)		
treatment	-0.133 (0.138)	-0.371 (0.303)	0.266 (0.274)		
sex	0.270 (0.342)	0.720 (0.724)	0.337 (0.654)	-	
t age	-0.172*** (0.044)	-0.232* (0.107)	-0.194* (0.097)	(
n_teachers	0.100 (0.053)	0.125 (0.116)	0.105 (0.105)		
n_teachers_fem	-0.084 (0.046)	-0.072 (0.100)	-0.003 (0.090)		
female_head_teacher	-0.054 (0.342)	-0.383 (0.731)	0.693 (0.661)	(
n_students_fem	-0.004* (0.002)	-0.009** (0.004)	-0.007* (0.003)	0	
n_schools_2km	0.118 (0.065)	-0.002 (0.146)	0.215 (0.132)	(
av_teacher_age	0.005 (0.007)	0.0002 (0.016)	0.007 (0.015)	-	
av_student_score	0.002 (0.002)	-0.007 (0.004)	0.001 (0.004)	-0	
n_latrines urban	0.001 (0.006)	-0.004 (0.014)	-0.010 (0.012)	-	
district5	0.295 (0.348)	0.418 (0.746)	0.195 (0.674)		
district7	-0.194 (0.391)	-0.438 (0.829)	0.084 (0.750)		

0.290 (0.589)

-0.251 (0.821)

-0.344 (0.892)

0.054 (0.533)

-0.055(0.743)

0.428 (0.807)

0

0

0.198 (0.276)

-0.243 (0.387)

-0.147 (0.420)

district9
district10

district11

```
## district12
                   -0.551 (0.719)
                                     -2.860 (1.632)
                                                       -1.516 (1.476)
                                                                          0
## month
## Constant
            2.706 (1.494) 6.698* (3.266) 1.584 (2.953)
## stratum
                        Yes
                                         Yes
                                                           Yes
## -----
                                         7,708
## Observations
                      15,734
                                                           7,708
                       0.018
                                         0.025
                                                           0.024
                       0.012
## Adjusted R2
                                         0.013
                                                           0.011
## F Statistic 2.896*** (df = 98; 15635) 2.008*** (df = 98; 7609) 1.874*** (df = 98; 7609) 24.280*
## Note:
                                                                    *p<0.05; *
model.5.dropout <- lm(dropout ~ treatment+ sex + age + n_teachers + n_teachers_fem+ female_head_teacher + n_teachers_fem+ female_head_teacher</pre>
stargazer(model.5.dropout, type = "text",
        omit = "stratum", omit.labels = "stratum",
        star.cutoffs = c(0.05, 0.01, 0.001),
        \#dep.var.labels = c("Outcome"),
        keep.stat = c("n", "rsq", "adj.rsq", "f"),
        single.row = TRUE,
        title = "Regression Results -- 3 year")
##
## Regression Results -- 3 year
Dependent variable:
##
##
                -----
##
                       dropout
## -----
## treatment
                   -0.020** (0.007)
                  -0.046** (0.017)
0.087*** (0.002)
## sex
## age
0.009** (0.003)
-0.0004 (0.0003)
## n_schools_2km
## urban
## district5
                     0.020 (0.017)
## district7
                    0.030 (0.019)
## district9
                    0.011 (0.013)
## district10
                    0.019 (0.019)
## district11
                     0.032 (0.020)
## district12
                     0.068 (0.035)
## month
             -1.727*** (0.072)
## Constant
## -----
## Observations
                        15,734
```

0.132

F Statistic 24.280*** (df = 98; 15635)

0.127

R2

Adjusted R2

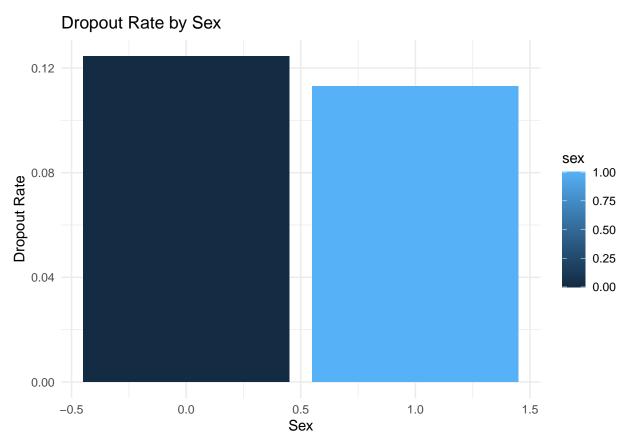
For five year sample, as we can see from the table above, the coefficient before treatment is not significant (at 5% level) for outcome variable: marriage, children and pregnant, implying that the intervention did not change these concerns evidently. However, we can still see a significant impact of treatment on drop-out rate. Moreover, the impact is greater than 3 year situation, meaning that the effects of treatment amplified overtime.

Further Analysis

I want to seperately analyze the impact of treatment on male and female students.

```
##
## Regression Results -- 3 year
## -----
##
                       Dependent variable:
##
                   -----
                             dropout
## -----
## treatment
                         -0.005(0.008)
## sex
## age
                       0.089*** (0.002)
                        0.0001 (0.003)
## n_teachers
## n_teachers_fem
## n_teachers_fem
## female_head_teacher
## n_students_fem
                        -0.002 (0.002)
                      0.044* (0.019)
                       0.001*** (0.0001)
## n_students_fem
## n_schools_2km
                        0.013*** (0.003)
                        -0.0004 (0.0005)
## av_teacher_age
                     -0.0004 (0.0005)
-0.001*** (0.0001)
## av_student_score
                        -0.001* (0.0003)
## n_latrines
## urban
## district5
                          0.021 (0.020)
## district7
                          0.022 (0.022)
                          0.014 (0.016)
## district9
## district10
                          0.003 (0.020)
## district11
                          0.029 (0.023)
## district12
                          0.018 (0.038)
## month
                        -1.763*** (0.077)
## Constant
## stratum
                               Yes
## -----
## Observations
                             13,480
## R2
                              0.132
## Adjusted R2
                              0.126
```

```
## F Statistic
                                                21.706*** (df = 94; 13385)
   ## Note:
                                                 *p<0.05; **p<0.01; ***p<0.001
   merged_df_5_m<- merged_df_5 %>% filter(sex == 1)
   model.5.dropout <- lm(dropout ~ treatment+ sex + age + n_teachers + n_teachers_fem+ female_head_teacher +
   stargazer(model.5.dropout, type = "text",
                            omit = "stratum", omit.labels = "stratum",
                            star.cutoffs = c(0.05, 0.01, 0.001),
                            #dep.var.labels = c("Outcome"),
                            keep.stat = c("n", "rsq", "adj.rsq", "f"),
                            single.row = TRUE,
                           title = "Regression Results -- 3 year")
   ##
   ## Regression Results -- 3 year
   ##
                                                          Dependent variable:
   ##
                                                 -----
   ##
                                                                    dropout
##
## treatment
## sex
## age
## n_teachers
## n_teachers_fem
# n_teachers_fem
#female_head_teacher
## n_students_fem
## n_schools_2km
## av_teacher_age
   ## district5
                                                             -0.000 (0.040)
   ## district7
                                                             -0.000 (0.041)
   ## district9
                                                            -0.000 (0.024)
   ## district10
                                                             -0.000 (0.063)
   ## district11
                                                               -0.000 (0.051)
   ## month
   ## Constant
                                                             8.408** (2.897)
   ## -----
   ## stratum
                                                                          Yes
   ## -----
   ## Observations
                                                                          2,254
   ## R2
                                                                          0.163
   ## Adjusted R2 0.154
## F Statistic 16.733*** (df = 26; 2227)
   *p<0.05; **p<0.01; ***p<0.001
   ## Note:
   library(ggplot2)
   dropout_rate_by_sex <- merged_df_3 %>%
       group_by(sex) %>%
       summarize(dropout_rate = mean(dropout, na.rm = TRUE))
   # Create the plot
```



(should turn sex into categorical variable but run out of time..)

As we can see from the analysis above, the impact of treatment mostly come from change in dropout rate of male students, not female. and from the graph above, we can see that for male student have lower drop out rate.

Further, I want to conduct the same analysis on variable including married, pregnant and children, to see if there is also hetergenous treatment effects.