# Replication Beg. et al. (2022)

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2023-02-27

## Preamble

I will replicate Table 1 - Summary Statistics in page 75 and columns (1), (3) and (5) from Panel A. Table 2 - Achievement Effects in page 76. Unfortunately, I wasn't able to replicate any of the LASSO results in Panel B. Still, I present the code below and compare with the selected controls to offer possible explanations.

```
# Loads main packages
library(tidyverse)
## -- Attaching packages ------ tidyverse 1.3.2 --
## v ggplot2 3.4.1
                   v purrr
                            1.0.1
## v tibble 3.1.8
                   v dplyr
                           1.1.0
## v tidyr
         1.3.0
                   v stringr 1.5.0
## v readr
          2.1.4
                   v forcats 1.0.0
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                 masks stats::lag()
library(estimatr)
```

# Table 1 - Summary statistics

```
# Loads data
elearn_balance_data <- haven::read_dta("data/Elearn/elearn_balance_data.dta")</pre>
# Columns 1 and 2
table1_panelA_columns12 <- elearn_balance_data %>%
  group_by(treatment) %>%
  summarise(
    across(
      c(
        z_score_total_bl,
        age_bl,
        attendance_bl,
        computer_yn_bl,
        m_ed_noschool,
        f_ed_noschool
      list(mean = ~ mean(.x, na.rm=T),
           sd = ~ sd(.x, na.rm=T))
    )
 ) %>%
```

```
pivot_longer(-treatment,
               names_to = "var",
               values_to = "value") %>%
  pivot_wider(names_from = treatment, values_from = value) %>%
  rename(
   variable = var,
   control = `0`,
   treatment = `1`
  )
# Column 3
table1_panelA_column3_models <- elearn_balance_data %>%
  filter(child interviewed bl==1) %>%
  select(
   school_code,
   treatment,
   z_score_total_bl,
   age_bl,
   attendance_bl,
   computer_yn_bl,
   m_ed_noschool,
   f_ed_noschool
  ) %>%
 pivot_longer(c(-school_code, -treatment),
               names to = "variable",
               values_to = "value") %>%
  group_by(variable) %>%
 nest() %>%
  mutate(
   model = purrr::map(data,
                       ~ estimatr::lm_robust(
                         data = .,
                         formula = value ~ treatment,
                         cluster = school_code,
                         se_type = "stata"))
 )
table1_panelA_column3 <- cbind(table1_panelA_column3_models$variable,
                               purrr::map_dfr(
                                 .x =table1_panelA_column3_models$model,
                                 .f = broom::tidy) %>% filter(term=="treatment")
                               ) %>%
  select(`table1_panelA_column3_models$variable`,
         estimate,
         `std.error`,
         `p.value`)
(knitr::kable(table1_panelA_columns12,
              caption = "Table 1 Panel A Columns 1 and 2"))
```

Table 1: Table 1 Panel A Columns 1 and 2

variable	control	treatment
z_score_total_bl_mean	0.0679137	-0.0559342
$z\_score\_total\_bl\_sd$	1.0100126	0.9860643
age_bl_mean	13.8696296	13.8962766
$age\_bl\_sd$	1.2305022	1.2374050
$attendance\_bl\_mean$	1.1674074	1.4946809
$attendance\_bl\_sd$	1.7877273	2.4094738
$computer\_yn\_bl\_mean$	0.4074074	0.4268617
$computer\_yn\_bl\_sd$	0.4917162	0.4949511
$m\_ed\_noschool\_mean$	0.3333333	0.3523936
$m\_ed\_noschool\_sd$	0.4717541	0.4780337
$f_{ed}_{noschool}_{mean}$	0.1970370	0.1728723
$f_{ed}_{noschool\_sd}$	0.3980555	0.3783885

Table 2: Table 1 Panel A Column 3

table1_panelA_column3_models\$variable	estimate	std.error	p.value
z_score_total_bl	-0.1240815	0.1904352	0.5172533
age_bl	0.0266470	0.1018226	0.7944799
attendance_bl	0.3272734	0.1732048	0.0638243
computer_yn_bl	0.0194543	0.0484134	0.6892807
$m_ed_noschool$	0.0190603	0.0576065	0.7419346
f_ed_noschool	-0.0241647	0.0340920	0.4812821

## Table 2 - Achievement Scores

```
# Loads data
elearn_reg_data <- haven::read_dta("data/Elearn/elearn_reg_data.dta") %>%
  rename_with(.cols = starts_with("_"), ~ stringr::str_replace(.x, "_", "v_"))
```

**Remark:** there is no available dataset to replicate the results of column (2).

```
# ---- Panel A Col 1-4 ----
# Clasrooms
project_classrooms <- elearn_reg_data %>%
    filter(tooktest_el==1) %>%
    estimatr::lm_robust(
    formula = z_irt_total_el ~
        treatment +
        v_z_irt_math_bl +
        v_z_irt_sci_bl +
        strataFE1 +
        strataFE2 +
        strataFE3 +
        strataFE4 +
        strataFE5,
```

```
clusters = school_code,
  se_type = "stata"
) %>%
  broom::tidy() %>%
  select(1,2,4)
project_clasrooms_group_mean <- elearn_reg_data %>%
  filter(treatment==0 & tooktest_el==1) %>%
  summarise(mean = mean(z_irt_total_el, na.rm=T))
# Column 2
pec_classrooms <- elearn_reg_data %>%
  filter(tooktest_el==1 & took_std==1) %>%
  estimatr::lm_robust(
    formula = z_scoreindex_el ~
      treatment +
      v_z_{irt_math_bl} +
      v_z_irt_sci_bl +
      v_meanmath_pec_2016 +
      v_meansci_pec_2016 +
      v_meaneng_pec_2016 +
      v_meaneng_pec_2016_mi +
      strataFE1 +
      strataFE2 +
      strataFE3 +
      strataFE4 +
      strataFE5,
    clusters = school_code,
    se_type = "stata"
  )%>%
  broom::tidy() %>%
  select(1,2,4)
pec_clasrooms_group_mean <- elearn_reg_data %>%
  filter(treatment==0 & tooktest_el==1 & took_std==1) %>%
  summarise(mean = mean(z_scoreindex_el, na.rm=T))
(knitr::kable(project_classrooms,
              caption = "Table 2 Panel A Column 1"))
```

Table 3: Table 2 Panel A Column 1

estimate	statistic
0.9856713	4.393863
0.2556772	1.896638
0.2703520	5.889213
0.1609753	4.140037
-0.5963266	-1.784091
-0.8529614	-3.071121
-0.6507201	-2.557387
-0.4738788	-1.939964
-0.6764262	-2.526221
	0.9856713 0.2556772 0.2703520 0.1609753 -0.5963266 -0.8529614 -0.6507201 -0.4738788

Table 4: Project Average control group change or mean

 $\frac{\text{mean}}{0.4917922}$ 

Table 5: Table 2 Panel A Column 3

term	estimate	statistic
(Intercept)	0.1054971	0.5061549
treatment	0.2690645	2.2653021
$v_z_{irt_math_bl}$	0.2153490	6.4781188
$v_z_{irt\_sci\_bl}$	0.1196785	3.2452808
$v_meanmath_pec_2016$	0.1056084	1.2676751
$v_meansci_pec_2016$	0.0139204	0.1387179
$v_meaneng_pec_2016$	-0.0618132	-0.7482025
$v\_meaneng\_pec\_2016\_mi$	0.0267513	0.3291950
strataFE1	-0.5893693	-2.2509843
strataFE2	-0.5045070	-2.0457491
strataFE3	-0.0612791	-0.2127759
strataFE4	0.3168674	1.4224077
strataFE5	-0.4533764	-1.6182046

Table 6: Combined project and PEC Average control group change or mean

 $\frac{\overline{\text{mean}}}{0}$ 

### LASSO

Here I show my attempts to replicate the results in Panel B, which includes additional controls selected by the post-double LASSO. In the Online Appendix, the authors mention that set of potential controls have 298 variables. For eLearn Classrooms, LASSO selected: teacher employment rank, time spent on non-classroom duties and extra classes, mothers occupations, and parents rela- tionship status. Below, I show the Stata code made available by the authors that is responsible for estimating the coefficient in Panel B Column (1):

```
foreach outcome of varlist z_irt_total_el {
  pdslasso `outcome' treatment (`prepped' $strata ) if `conditions_proj',
  partial($strata $partialled_proj) cluster(school_code)
  outreg2 using PanelB, replace dta label keep(treatment*)
}
```

z\_irt\_total\_el is outcome of interest. The second line regresses this outcome against the treatment variable using the pdslasso command. According to the pdslasso documentation, (`prepped' \$strata ) the set of potential controls. They are already standardized. if `conditions\_proj simply tells Stata to select only students that took the test, that is, tooktest\_el==1. partial(\$strata \$partialled\_proj) indicates which variables are always to be included in the model: all strata dummys and the student's scores in math and science, \_z\_irt\_math\_bl and \_z\_irt\_sci\_bl, respectively. Finally, they cluster at the school\_code.

I attempted to replicate the result using two packages: glmnet and hdm.

#### Using glmnet

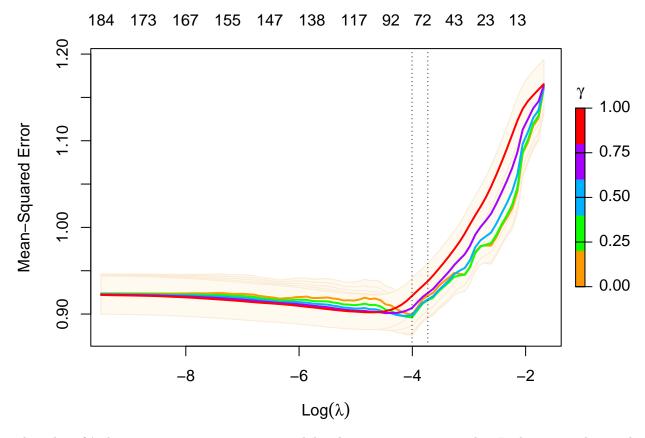
First I filter the dataframe to include only the students who took the test:

```
elearn_reg_data_tooktest <- elearn_reg_data %>%
  filter(tooktest_el==1)
```

Then I create the matrix including all potential controls. I remove strataFE6to avoid perfect collinearity, like I did before. I also select the variables in a specific order that allows me to easily handle the penalty.factor argument in the next chunk of code. Notice that elearn\_reg\_data\_lasso\_matrix has 305 variables, of which 7 are always to be included in the model and the remaining 298 is the number of items in the set of potential controls. So the set of potential controls is not the reason why the replication fails.

Then I perform the cross-validation using glmnet::cv.glmnet. x is the set of potential controls, y is the outcome of interest, alpha = 1 represents a LASSO regularization, relax=Tallows me to select gamma parameters in the regularization, and the penalty.factor indicates which variables are to be always included in the model.

```
plot(cv_model)
```



The value of  $\lambda$  that gives minimum mean cross-validated error is 0.0086541. Then I select optimal controls using glmnet::glmnet for this value of  $\lambda$ :

```
best_model <- glmnet::glmnet(
    x = elearn_reg_data_lasso_matrix,
    y = elearn_reg_data_tooktest %>% pull(z_irt_total_el),
    lambda = cv_model$lambda.min,
    alpha = 1,
    penalty.factor = c(rep(0, 7), rep(1, 298)),
    relax = T
)

selected_coef <- as.data.frame(as.matrix(best_model$beta)) %>%
    filter(s0 != 0)
```

This method selects a total of 101 coefficients, which is a much larger set than the one found by the authors. I am not sure why this is happening. glmnet::cv.glmnet should have given us a much larger  $\lambda$  that minimizes the MSE so that we would have a number of controls similar to the one found by the authors. I ran best\_model for every  $\lambda$  in the sequence and none of them resulted in the exact same set of controls found by the authors.

#### Using hdm

(Chernozhukov, Hansen, and Spindler 2016) published the hdm package on CRAN which performs post-double selection LASSO. It is much more similar to the usage of pdslassoin Stata, in comparison to glmnet. It also comes with a very neat documentation by the authors themselves that can be read here. Following their instructions, I use the hdm::rlassoEffect function. xis the set of potential controls, y is the outcome

of interest, and d is the main regressor that is treated as causal. I use I3 = c(rep(T, 8), rep(F, 298)) so the strata dummies and the two main controls are always included in the model, like I did when using glmnet. I explictly asks for the double selection method using method = "double selection".

```
lasso_x <- elearn_reg_data_tooktest %>%
  select(v_z_irt_math_bl,
         v_z_irt_sci_bl,
         starts_with("strata"),
         starts with("v "),
         -strataFE6) %>%
  as.matrix()
lasso_y <- elearn_reg_data_tooktest %>% pull(z_irt_total_el) %>% as.matrix()
lasso_d <- elearn_reg_data_tooktest %>% pull(treatment) %>% as.matrix()
lasso <- hdm::rlassoEffect(</pre>
  x = lasso_x,
 y = lasso_y,
 d = lasso_d,
 I3 = c(rep(T, 7), rep(F, 298)),
  method = "double selection"
)
```

However:

```
summary(lasso)
```

```
## [1] "Estimates and significance testing of the effect of target variables"
## Estimate. Std. Error t value Pr(>|t|)
## d1 6.037e-02 2.283e+11 0 1
(lasso$no.selected)
```

#### ## [1] 0

My guess is that I was including all levels of some dummy variable, resulting in perfect collinearity that explain the standard error. However, the set of potential controls that I am using is exactly the same used by the authors. Besides, since I have no access to the survey, I cannot say which columns represent different levels of the same dummy variable based solely on their names.

Another possibility is that the 298 potential controls are receiving some treatment before the authors run the pdslasso command. Some kind of treatment is surely being conducted, since I can see the command in the master.do file. If this treatment somehow makes the hdm::rlassoEffect behaves erratically, this could explain the results. Unfortunately, I have no access to the variables before this treatment, neither I can know for certainty what exactly this treatment is doing.

Finally, I can at least be sure that the problem is in the set of potential controls, since hdm::rlassoEffect gives a reasonable result if I exclude them:

```
lasso_y <- elearn_reg_data_tooktest %>% pull(z_irt_total_el) %>% as.matrix()
lasso_d <- elearn_reg_data_tooktest %>% pull(treatment) %>% as.matrix()
lasso <- hdm::rlassoEffect(</pre>
 x = lasso x,
 y = lasso_y,
 d = lasso d,
 # I3 = c(rep(T, 7), rep(F, 298)),
 method = "double selection"
)
summary(lasso)
## [1] "Estimates and significance testing of the effect of target variables"
      Estimate. Std. Error t value Pr(>|t|)
## d1
       0.24551
                  0.04194
                            5.854 4.81e-09 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
And selecting only the students' scores and their square values:
lasso_x <- elearn_reg_data_tooktest %>%
  select(v_z_irt_math_bl,
        v_z_irt_sci_bl,
         starts_with("strata"),
         starts_with("v_z_"),
         -strataFE6) %>%
  as.matrix()
lasso_y <- elearn_reg_data_tooktest %>% pull(z_irt_total_el) %>% as.matrix()
lasso_d <- elearn_reg_data_tooktest %>% pull(treatment) %>% as.matrix()
lasso <- hdm::rlassoEffect(</pre>
 x = lasso_x,
 y = lasso_y,
 d = lasso_d,
 I3 = c(rep(T, 5), rep(F, 6)),
 method = "double selection"
)
summary(lasso)
## [1] "Estimates and significance testing of the effect of target variables"
     Estimate. Std. Error t value Pr(>|t|)
##
       0.24307
                   0.04156 5.849 4.96e-09 ***
## d1
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
(lasso$no.selected)
```

#### ## [1] O

Again a reasonable result. Thus I am convinced that the problem resides with the dummy variables. However, in this last specification, hdm::rlassoEffect again selects no controls.

Chernozhukov, Victor, Chris Hansen, and Martin Spindler. 2016. "High-Dimensional Metrics in r." arXiv. https://doi.org/10.48550/ARXIV.1603.01700.