THE UNIVERSITY OF CHICAGO
HARRIS SCHOOL OF PUBLIC POLICY
Social Impact, Down to a Science

DIL Research Assistant Report

To: Policymakers of Chicago

From: Pedro Huet **Date:** 09/21/2023

RE: School subsidy randomized control trial analysis and impact evaluation report.

Executive Summary

The literature has argued that subsidies and transfer programs could be effective to increase education and development in communities, so it makes sense to perform experiments to verify the accuracy and magnitude of said variable. An RTC, which employed pairwise randomization treatment assignment, of a proposed subsidy program was conducted in 165 schools across a sample of almost 10,000 elementary-level students located in 2 districts from 2010 to 2012. Two follow-up surveys were conducted after the start of the intervention, one the year after the end of the program, and the second 2 years later. Performing a series of logistic regression models, the data supports the hypothesis that school subsidies reduce the likelihood of school evasion, child pregnancies and marriages during the length of the program, as well as some years afterwards; although the magnitude of the effects are comparatively small when considering other variables. Further, the results of a simple panel difference-in-difference model favors the argument that the subsidy has both short-term and long-term effects on reducing school dropouts. However, the effect of school subsidies wanes when considering that child pregnancies and marriages could also be causes of school dropouts. The conclusion is that school subsidies seem to have a small effect in reducing school evasion, yet the feasibility of this approach isn´t as convincing when considering there could be alternative causes to school dropouts which could be employed at a lower cost.

Background & Research

The bolstering of education as a fundamental component of social development has been a topic of great relevance in the last 3 decades. It has also been supported by the literature and multiple studies (Speil et al., 2018; Öztürk et al., 2022). Given this situation, it follows that there could be some policy alternatives to encourage or aid youths' access to this resource. Among the different paths that have been argued to bolster education among communities, many authors have argued in favor of utilizing subsidies, conditional cash/in-kind transfers (Ullmann et al., 2021;). The argument is that giving children and their families access to additional resources for pursuing their studies adds an additional incentives for the recipients to continue pursuing their education.

This argument is enticing, yet the policy it supports seems to implicate the use of a large amount of resources (Loser et al., 2021), meaning it could have an important toll on public finances. In order to assess if subsidies and cash or in-kind transfers are worth the investment, it would make sense to study the magnitude and reliability of their impact. As a contribution to this task, this report proposes a statistical analysis based on an RTC designed experiment based on a subsidies program targeted towards the education of students.

Study Methodology

The study consist of evaluating an education program that subsidizes the cost of education for students through in-kind transfers. The study consisted of a program that lasted for three years, from 2010 to 2012, and it targeted children enrolled in public schools. Throughout this time period, the subsidies were delivered at the beginning of every school year to the cohort of students enrolled in grade 6 at the start of the program.

To evaluate its effectiveness, an experiment was designed using pairwise randomization to assign schools within two districts to a treatment or control group. The main unit of analysis are the children whose schools did or did not receive the subsidies. All children enrolled in the treatment schools received the subsidy for the three years, conditional that they were still enrolled in school. To conduct the study, baseline data was collected for the schools and cohorts, and two follow-up surveys were conducted: the first one, on the year after the last subsidy was offered to students (year 3), and another two years later (year 5).

With regards to performance metrics for the program, the study considered school evasion, if a student dropped out of his or her educational formation, as the primary outcome of interest. It considered teen pregnancy and teen marriage as secondary variables of interest.

Based on the available data, it would seem reasonable to choose a series of variables that likely have a larger effect on affecting school evasion. The first and most relevant variable for the study is treatment (dichotomous variable), if the student was in a school that gave him or her access to the subsidy, as this result allows us to approach the effectiveness of subsidies and transfer programs. A second variable would be the sex of the student, as its possible that male or female students, due to social and contextual factors, may have a larger tendency to dropout of their education. A third variable is the year of birth of students, since younger students tend to have less motivation of dropping out of school (they are usually less qualified at finding alternative venues of employment than older students). Since this variable is categorized by the year of birth of the students receiving the subsidies (between 1985 and 1992), the variable can be treated as ordinal (continuous, for our purposes). Finally, we also consider the month in which the visit was made to students (nominal variable), since months closer to the start and end of the school year (June, July, August, and December) are likely to be periods in which the students are more prone to end their studying experiencing (students could be more likely to want to finish their semesters due to a process of inertia).

With regards to the dependent variables, school dropouts (if the student left school), teen pregnancies (if a student or his partner experienced a pregnancy) and marriages (if the student got married) are measured as dichotomous variables (from 0 to 1). These variables will be measured both during the year 3 since the start of the intervention and on year 5 of it occurring.

The study consists of a series of a maximum likelihood logarithmic models estimating the short-term and long-term effects of the intervention, as well as a difference-in-difference panel linear model. The advantage of using a non-linear model is that it is measuring the probabilities of an outcome occurring, in this case, a student dropping out, rather than a continuous quantity (i.e. "the degree in which a student drops out"). Because of this, a non-linear model like a logistic model is more versatile than a regular linear probability model, meaning it'll likely make a more useful estimation. The main model can be summarized by the following equation.

$$\text{School Dropouts} = B_0 + B_1(\text{treatment}) + B_2(\text{sex}) + B_3(\text{year of birth}) + B_4(\text{month of visit}) + u$$

With regards to the linear fixed effects difference-in-difference model, since the panel data only consists of two years, it doesn't make sense to use more sophisticated models (i.e. Difference-in-Difference-in-Differences model or Multiple-Timming-Fixed Effects Models), as there isn't enough data to obtain noticeably different estimations. Perhaps the main problem on the outset of this study is that we cannot verify the Parallel Trends Assumption: it isn't clear that the individuals who were treated on the third year of the program followed the same trend as those who were untreated during this period. Although it would have been preferable to perform this analysis just before the start of the intervention to have more certainty of both groups being comparable, an analysis of this sort can still be insightful to observe if there were differences between the effects of the subsidies at the 3rd year of the intervention and the 5th year. The panel model can be summarized by the following equation.

$$\text{School Dropouts} = B_0 + B_1(\text{treatment}) + B_2(\text{long-term}) + B_3(\text{treatment * long-term}) + u$$

Key Findings

Before starting the analysis, it is important to make sure that the Randomized Control Trial worked in the correct manner. Table 1 shows that a multivariate regression model that includes the variables that could have been affecting the school's assignment does not find much evidence of bias in the assignment. Aside from the number of latrines the schools have, none of the other variables related to the schools (number of teachers and students, average student scores, rural location, etc.) seem to be associated to a significance level of above 10% with being assigned to the treatment group; while none of the variables reaches a confidence level of above 5%. Because of this, it seems that, in general, the baseline characteristics seem balanced.

Table 1

Logistic regression   Number of obs = 155
                                                      LR chi2(11) = 11.61
                                                      Prob > chi2 = 0.3935
Log likelihood = -101.60301   Pseudo R2 = 0.0541

treatment	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
district	-.2465828	.4286512	-0.58	0.565	-1.086724	.5935582
location	-.8957887	.6688227	-1.34	0.180	-2.206657	.4150797
n_teachers	-.0612822	.1076023	-0.57	0.569	-.2721788	.1496143
n_teachers_fem	.0043786	.0850735	0.05	0.959	-.1623624	.1711195
female_head_teacher	.298549	.611635	0.49	0.625	-.9002335	1.497332
n_students_fem	-.0056233	.005323	-1.06	0.291	-.0160562	.0048097
n_students_male	.0016141	.0054949	0.29	0.769	-.0091557	.0123839
n_schools_2km	-.040937	.1052616	-0.39	0.697	-.2472459	.165372
av_teacher_age	.0807291	.0601273	1.34	0.179	-.0371183	.1985764
av_student_score	.0057991	.0070456	0.82	0.410	-.0080101	.0196083
n_latrines	.074235	.038603	1.92	0.054	-.0014256	.1498955
_cons	-2.694787	3.411237	-0.79	0.430	-9.38069	3.991115

With regards to the short-term effects of the subsidies, Tables 2, 3 and 4 show the possible short-term effects of receiving subsidies on children's education. Table 2 shows that treatment into the group after 3 years has a negative and statistically significant effect, at a significance level of above 1%, in the student dropping out. When seeing the magnitude, its size is around 2.2%, meaning that, if all other variables remain equal, a student that is in a school that receives subsidies is 2.2% less likely to drop-out of school. A student's year of birth also show statistically significant negative effects on school evasion, meaning that, for each year a student is younger, all else equal, he or she is almost 6% less likely to dropout. When observing sex, we observe that being a female student, all else equal, seems to be associated with a 8.6% probability of being more prone to dropout of school. Finally, the students who were surveyed in October were less prone to dropout by around 9%, all else equal. The results of these variables are all significant at a level of above 5%. Figure 1 offers a visual summary of the magnitude and significance level of the models' findings.

Table 2

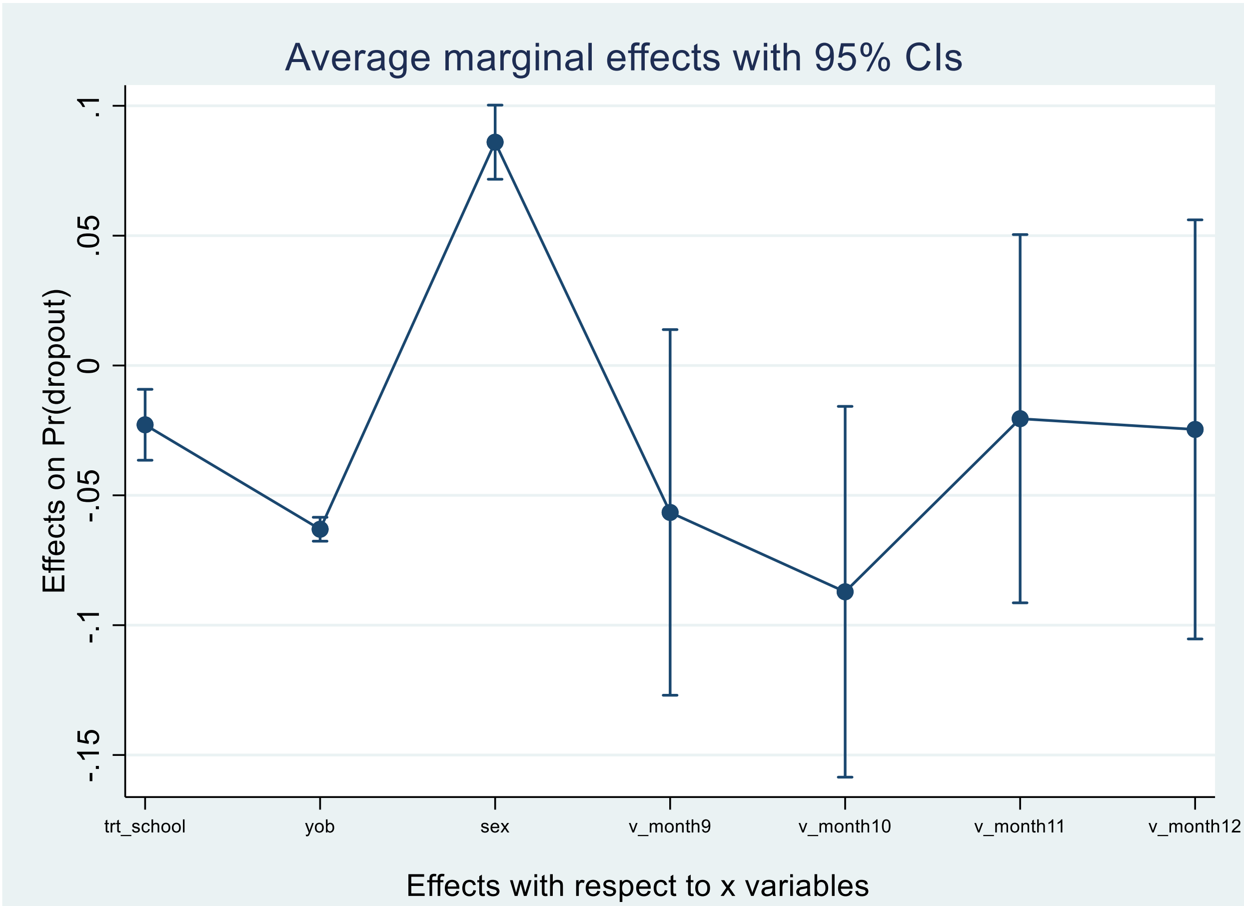
```
Logistic regression                                     Number of obs =  9,004
                                                        LR chi2(7)    = 787.01
                                                        Prob > chi2   = 0.0000
Log likelihood = -3222.5966                             Pseudo R2     = 0.1088

------------------------------------------------------------------------------
     dropout | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  trt_school |  -.2130132   .0649831    -3.28   0.001    -.3403776   -.0856488
         yob |  -.5882476   .0231562   -25.40   0.000     -.633633   -.5428623
         sex |   .8022253   .0684522    11.72   0.000     .6680614    .9363893
             |
 visit_month |
          9  |  -.4789905   .2690345    -1.78   0.075    -1.006288    .0483074
         10  |  -.8116111   .2812518    -2.89   0.004    -1.362854   -.2603678
         11  |  -.1588488   .2698362    -0.59   0.556    -.6877179    .3700204
         12  |  -.1925838   .3149806    -0.61   0.541    -.8099344    .4247669
             |
       _cons |   1168.343   46.05379    25.37   0.000     1078.079    1258.607
------------------------------------------------------------------------------
Average marginal effects                                 Number of obs = 9,004
Model VCE: OIM

Expression: Pr(dropout), predict()
dy/dx wrt:  trt_school yob sex 9.visit_month 10.visit_month 11.visit_month 12.visit_month

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  trt_school |   -.022835   .0069611    -3.28   0.001    -.0364786   -.0091915
         yob |  -.0630602   .0023503   -26.83   0.000    -.0676666   -.0584538
         sex |   .0859986   .0072841    11.81   0.000      .071722    .1002753
             |
 visit_month |
          9  |  -.0565799   .0359211    -1.58   0.115    -.1269839    .0138242
         10  |  -.0871516   .0364265    -2.39   0.017    -.1585462    -.015757
         11  |  -.0204904   .0361792    -0.57   0.571    -.0914004    .0504196
         12  |  -.0246181   .0411715    -0.60   0.550    -.1053128    .0560767
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.
```

Figure. 1



Tables 3 and 4 offer similar results. They show that, as with school evasion, it would also seem that the subsidies program has negative and statistically significant effects (of a significance level of above 95%) towards experiencing teen pregnancy and marriages, yet it also seems relatively small (around 2% reduction).

Table 3

Logistic regression

Number of obs	= 4,328
LR chi2(6)	= 465.06
Prob > chi2	= 0.0000
Pseudo R2	= 0.1489

Log likelihood = -1328.7058

pregnt	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
trt_school	-.2561749	.1026331	-2.50	0.013	-.4573321	-.0550178
yob	-.7762106	.040134	-19.34	0.000	-.8548718	-.6975493
sex	0	(omitted)				
visit_month						
9	.2279757	.530794	0.43	0.668	-.8123613	1.268313
10	-.3226972	.5488073	-0.59	0.557	-1.39834	.7529454
11	.5934452	.5323371	1.11	0.265	-.4499164	1.636807
12	.1519605	.614408	0.25	0.805	-1.052257	1.356178
_cons	1541.963	79.8308	19.32	0.000	1385.498	1698.429

Average marginal effects   Number of obs = 4,328
Model VCE: OIM

Expression: Pr(pregnt), predict()
dy/dx wrt: trt_school yob sex 9.visit_month 10.visit_month 11.visit_month 12.visit_month

	dy/dx	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
trt_school	-.0228837	.0091636	-2.50	0.013	-.040844	-.0049233
yob	-.0693375	.0034071	-20.35	0.000	-.0760153	-.0626597
sex	0	(omitted)				
visit_month						
9	.0184215	.0398947	0.46	0.644	-.0597706	.0966136
10	-.0216869	.0404933	-0.54	0.592	-.1010523	.0576784
11	.0539865	.0403937	1.34	0.181	-.0251837	.1331566
12	.0119742	.0473682	0.25	0.800	-.0808657	.104814

Note: dy/dx for factor levels is the discrete change from the base level.

Table 4

```
Logistic regression                                     Number of obs =  8,791
                                                        LR chi2(7)     = 774.77
                                                        Prob > chi2    = 0.0000
Log likelihood = -1414.583                              Pseudo R2      = 0.2150

------------------------------------------------------------------------------
     married | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  trt_school |  -.3384766   .1045114    -3.24   0.001    -.5433152    -.133638
         yob |  -.7737201   .0377909   -20.47   0.000    -.8477889   -.6996513
         sex |   2.625267   .1480263    17.74   0.000     2.335141    2.915394
             |
 visit_month |
          9  |   .0700375   .5211146     0.13   0.893    -.9513283    1.091403
         10  |  -.700827    .5449954    -1.29   0.198    -1.768998    .3673443
         11  |   .3370815   .5230385     0.64   0.519    -.6880551    1.362218
         12  |   .2403885   .5833123     0.41   0.680    -.9028827     1.38366
             |
       _cons |   1534.292    75.1138    20.43   0.000     1387.072    1681.513
------------------------------------------------------------------------------

. margins, dydx(*)

Average marginal effects                                 Number of obs = 8,791
Model VCE: OIM

Expression: Pr(married), predict()
dy/dx wrt:  trt_school yob sex 9.visit_month 10.visit_month 11.visit_month 12.visit_month

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  trt_school |  -.0144753   .0044809    -3.23   0.001    -.0232577   -.0056928
         yob |  -.0330889   .0017358   -19.06   0.000     -.036491   -.0296868
         sex |   .1122722   .0068607    16.36   0.000     .0988254     .125719
             |
 visit_month |
          9  |   .0029293    .021273     0.14   0.890     -.038765    .0446236
         10  |  -.0222196   .0214501    -1.04   0.300    -.0642611    .0198218
         11  |   .0155237   .0215015     0.72   0.470    -.0266184    .0576658
         12  |   .0106921   .0248125     0.43   0.667    -.0379395    .0593236
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.
```

With regards to long-term effects, Tables 5, 6 and 7 show that the results remained similar: if a student recieves subsidies, his or her dropout rate decreased by around 5%, which is slightly higher than what was found in the short term? at a level of statistical significante of above 5%. Perhaps the most important difference in the long-term can be seen in Table 7: the negative effect of subsidies on teen marriage seems to decrease noticeably after 5 years of the program's start, which is reflected in the fact that the significance level of this variable decrease to below 5% , but comfortably above 10%, and the magnitude of the effect decreased to around 1%.

Table 5

```
Logistic regression                                     Number of obs =  8,990
                                                        LR chi2(5)    = 858.02
                                                        Prob > chi2   = 0.0000
Log likelihood = -4538.2994                             Pseudo R2     = 0.0864

------------------------------------------------------------------------------
     dropout | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  trt_school |  -.3251957   .0526112    -6.18   0.000    -.4283118   -.2220795
         yob |  -.4891332   .0190829   -25.63   0.000    -.5265351   -.4517313
         sex |   .7239195   .0546015    13.26   0.000     .6169025    .8309366
             |
 visit_month |
          5  |   .2983619   .0757346     3.94   0.000     .1499247    .4467991
          7  |   .1621009   .0686074     2.36   0.018     .0276329    .2965689
             |
       _cons |   971.4962   37.95153    25.60   0.000     897.1126     1045.88
------------------------------------------------------------------------------
Average marginal effects                                 Number of obs = 8,990
Model VCE: OIM

Expression: Pr(dropout), predict()
dy/dx wrt:  trt_school yob sex 5.visit_month 7.visit_month

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  trt_school |  -.0537056   .0086365    -6.22   0.000    -.0706327   -.0367784
         yob |  -.0807796    .002787   -28.98   0.000    -.0862421   -.0753171
         sex |   .1195542    .008775    13.62   0.000     .1023554    .1367529
             |
 visit_month |
          5  |   .0490473   .0123383     3.98   0.000     .0248647    .0732299
          7  |   .0258428   .0107618     2.40   0.016     .0047501    .0469355
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.
```

Table 6

```
Logistic regression                                     Number of obs =  3,974
                                                        LR chi2(4)    = 555.27
                                                        Prob > chi2   = 0.0000
Log likelihood = -2058.9237                             Pseudo R2     = 0.1188

------------------------------------------------------------------------------
      pregnt | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  trt_school |  -.2683974   .0775899    -3.46   0.001    -.4204708    -.116324
         yob |   -.687464   .0327906   -20.97   0.000    -.7517324   -.6231956
         sex |          0  (omitted)
             |
 visit_month |
          5  |   .0621545   .1149647     0.54   0.589    -.1631722    .2874813
          7  |   .3013065   .1019705     2.95   0.003     .1014479    .5011651
             |
       _cons |   1366.754   65.23754    20.95   0.000      1238.89    1494.617
------------------------------------------------------------------------------
Average marginal effects                                 Number of obs = 3,974
Model VCE: OIM

Expression: Pr(pregnt), predict()
dy/dx wrt:  trt_school yob sex 5.visit_month 7.visit_month

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  trt_school |  -.0459515   .0132241    -3.47   0.001    -.0718702   -.0200328
         yob |  -.1176987   .0045147   -26.07   0.000    -.1265474   -.1088499
         sex |          0  (omitted)
             |
 visit_month |
          5  |   .0100682   .0185936     0.54   0.588    -.0263746     .046511
          7  |   .0511042   .0168327     3.04   0.002     .0181128    .0840956
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.
```

Table 7

```
Logistic regression                                     Number of obs =   8,063
                                                        LR chi2(5)    = 1306.63
                                                        Prob > chi2   =  0.0000
Log likelihood = -2536.9362                             Pseudo R2     =  0.2048

------------------------------------------------------------------------------
     married | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  trt_school |  -.1371421   .0728537    -1.88   0.060    -.2799328    .0056486
         yob |   -.713078   .0280966   -25.38   0.000    -.7681465   -.6580096
         sex |   2.423646     .09585    25.29   0.000     2.235783    2.611508
             |
 visit_month |
          5  |  -.0470325   .1081712    -0.43   0.664    -.2590442    .1649792
          7  |   .1886655   .0966351     1.95   0.051    -.0007359    .3780669
             |
       _cons |   1414.974     55.852    25.33   0.000     1305.506    1524.442
------------------------------------------------------------------------------
Average marginal effects                                  Number of obs = 8,063
Model VCE: OIM

Expression: Pr(married), predict()
dy/dx wrt:  trt_school yob sex 5.visit_month 7.visit_month

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  trt_school |  -.0130801   .0069457    -1.88   0.060    -.0266934    .0005333
         yob |  -.0680105   .0024052   -28.28   0.000    -.0727246   -.0632965
         sex |   .2311577   .0084983    27.20   0.000     .2145014     .247814
             |
 visit_month |
          5  |  -.0042307   .0097508    -0.43   0.664     -.023342    .0148806
          7  |   .0180713   .0090502     2.00   0.046     .0003332    .0358093
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.
```

Differnece in Differnece approach.

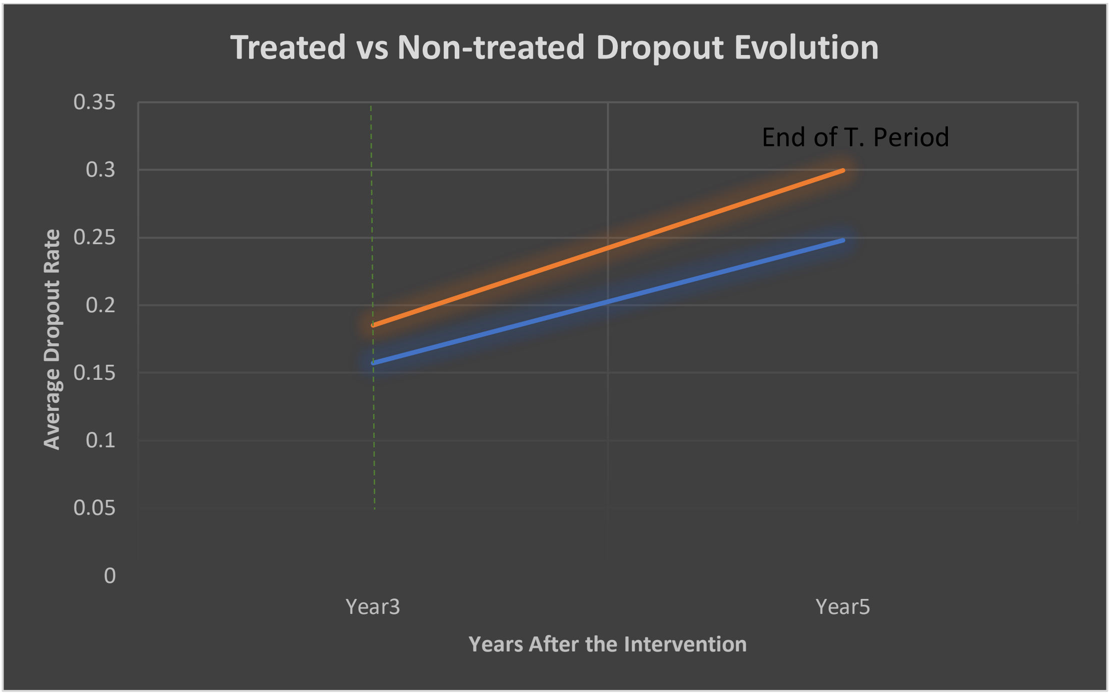
Having seen the previous models, it would appear the effect of the subsidies on school dropout exists both in the short term and the long-term, being slightly higher in the long term. However, it would make sense to ty to get the differentiated effect of each period. For that, a panel model is employed (see Figure 2). The results can be visualized in Table 8. According to these, it would appear that the subsidies intervencytion has a negative effect in school evasion in the short-term as well as the long-term, it being statistically significant at a level of above 5%. What this seems to imply is that the total effect of subsidies on school evasion, when comparado to somewone who didn't receive these is around 2.5% in the short term and around 2.7% less likelihood of dropping out of school.

Table 8

```
Linear regression                               Number of obs     =     19,310
                                                F(3, 19306)       =     114.39
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0177
                                                Root MSE          =     .41242

--------------------------------------------------------------------------------
                |               Robust
        dropout | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
----------------+---------------------------------------------------------------
   1.trt_school |  -.0278977   .0076554    -3.64   0.000    -.0429031   -.0128924
         1.post |   .1144972   .0085763    13.35   0.000     .0976869    .1313074
                |
trt_school#post |
           1 1  |   -.023748   .0118629    -2.00   0.045    -.0470003   -.0004958
                |
          _cons |   .1850947   .0055426    33.40   0.000     .1742308    .1959586
--------------------------------------------------------------------------------
```

Figure 2



Relationship between school marriage, children and dropouts?

Although it makes sense to asume that dropping out of school and teen marriage and pregnancy shouldn't be included into the regression due to possible bias with dropping out (both could be a product of a third variable, like irresponsability), it is possible to think that teen marriage and teen pregnancy could be relevant variables to explaining the process of dropping out of school. When estimating a regression with these two variables in Tables 9 and 10, we see that the impact of being treated decrease substantially while the explantory effect of these variables increase, especially at the short-term. This could mean that more attention should be put into the causality of these variables, and not Just assuming they are both perforando metrics.

Table 9

```
logit dropout married children trt_school if post == 0

Logistic regression                                    Number of obs =   4,679
                                                       LR chi2(3)    = 2315.06
                                                       Prob > chi2   =  0.0000
Log likelihood = -987.52283                            Pseudo R2     =  0.5396

------------------------------------------------------------------------------
```

```
     dropout | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
     married |   4.327641   .1994044    21.70   0.000     3.936815    4.718466
    children |    4.23428   .2252383    18.80   0.000     3.792821    4.675739
  trt_school |  -.1336577   .1269921    -1.05   0.293    -.3825577    .1152423
       _cons |  -2.825353   .0928272   -30.44   0.000    -3.007291   -2.643415
------------------------------------------------------------------------------
```

Table 10

```
Logistic regression                                     Number of obs =   4,231
                                                        LR chi2(3)     = 2336.73
                                                        Prob > chi2    =  0.0000
Log likelihood = -1273.7816                             Pseudo R2      =  0.4784

------------------------------------------------------------------------------
     dropout | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
     married |   2.109351   .1208567    17.45   0.000     1.872476    2.346226
    children |   2.685343   .1188434    22.60   0.000     2.452414    2.918271
  trt_school |  -.2074639   .1057219    -1.96   0.050    -.4146751   -.0002528
       _cons |  -2.577347   .0866784   -29.73   0.000    -2.747233    -2.40746
------------------------------------------------------------------------------

. margins, dydx(*)

Average marginal effects                                  Number of obs = 4,231
Model VCE: OIM

Expression: Pr(dropout), predict()
dy/dx wrt:  married children trt_school

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
     married |   .1788809   .0096967    18.45   0.000     .1598757     .197886
    children |   .2277271   .0086478    26.33   0.000     .2107777    .2446765
  trt_school |  -.0175937   .0089682    -1.96   0.050     -.035171   -.0000164
------------------------------------------------------------------------------
```

Conclusions and Recommendations

I would hace liked to repeat the main findings of the text in this sección.

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Appendix

THE UNIVERSITY OF CHICAGO
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Table A1

c) Possible Interaction Effects of the Subsidy (Mentioned, but placed in Appendix)

```
Iteration 0:   log likelihood = -3616.1031
Iteration 1:   log likelihood = -3256.3472
Iteration 2:   log likelihood = -3222.3153
Iteration 3:   log likelihood = -3222.2188
Iteration 4:   log likelihood = -3222.2188

Logistic regression                                     Number of obs =  9,004
                                                        LR chi2(8)    = 787.77
                                                        Prob > chi2   = 0.0000
Log likelihood = -3222.2188                             Pseudo R2     = 0.1089

------------------------------------------------------------------------------
       dropout | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
---------------+--------------------------------------------------------------
         1.sex |   .8553479   .0919104     9.31   0.000     .6752069    1.035489
  1.trt_school |  -.1497789   .0974509    -1.54   0.124    -.3407792    .0412214
               |
sex#trt_school |
          1 1  |  -.1130723   .1300684    -0.87   0.385    -.3680017    .1418571
               |
           yob |   -.588758   .0231685   -25.41   0.000    -.6341675   -.5433485
               |
   visit_month |
            9  |  -.4786788    .269078    -1.78   0.075    -1.006062    .0487045
           10  |  -.8135247   .2813077    -2.89   0.004    -1.364878   -.2621717
           11  |  -.1599604   .2698813    -0.59   0.553    -.6889181    .3689972
           12  |  -.1935362   .3150058    -0.61   0.539    -.8109362    .4238637
               |
         _cons |   1169.329   46.07736    25.38   0.000     1079.019    1259.639
------------------------------------------------------------------------------

.
```

Table A2

```
. logit dropout yob##trt_school sex i.visit_month if post == 0
```

THE UNIVERSITY OF CHICAGO
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Social Impact, Down to a Science

```
Iteration 0:   log likelihood = -3616.1031
Iteration 1:   log likelihood = -3287.2836
Iteration 2:   log likelihood = -3225.7565
Iteration 3:   log likelihood = -3214.0638
Iteration 4:   log likelihood = -3213.9853
Iteration 5:   log likelihood = -3213.9852

Logistic regression                                     Number of obs =  9,004
                                                        LR chi2(20)   = 804.24
                                                        Prob > chi2   = 0.0000
Log likelihood = -3213.9852                             Pseudo R2     = 0.1112

------------------------------------------------------------------------------
     dropout | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
         yob |
       1986  |  -.6087783   .3355975    -1.81   0.070    -1.266537    .0489807
       1987  |  -1.342022   .2951157    -4.55   0.000    -1.920438   -.7636056
       1988  |  -1.846885   .2800821    -6.59   0.000    -2.395836   -1.297934
       1989  |  -2.488037   .2780185    -8.95   0.000    -3.032943   -1.943131
       1990  |  -3.067124   .2808695   -10.92   0.000    -3.617619    -2.51663
       1991  |  -3.708385   .3010533   -12.32   0.000    -4.298439   -3.118332
       1992  |  -3.654042    .362087   -10.09   0.000    -4.363719   -2.944364
             |
1.trt_school |  -.3982257   .4187955    -0.95   0.342     -1.21905    .4225984
             |
yob#trt_school |
     1986 1  |   .0298708   .5236579     0.06   0.955    -.9964797    1.056221
     1987 1  |   .1919541   .4610569     0.42   0.677    -.7117008    1.095609
     1988 1  |   .2949508   .4407094     0.67   0.503    -.5688237    1.158725
     1989 1  |   .2607892    .436644     0.60   0.550    -.5950174    1.116596
     1990 1  |    .028782    .442476     0.07   0.948     -.838455     .896019
     1991 1  |     .10818   .4708202     0.23   0.818    -.8146107    1.030971
     1992 1  |   .3134019   .5543103     0.57   0.572    -.7730263     1.39983
             |
         sex |   .8105168   .0688728    11.77   0.000     .6755287     .945505
             |
 visit_month |
          9  |  -.4962747   .2703959    -1.84   0.066    -1.026241    .0336915
         10  |  -.8174601   .2824944    -2.89   0.004    -1.371139   -.2637813
         11  |  -.1663211    .271211    -0.61   0.540    -.6978849    .3652427
         12  |  -.2035364   .3163445    -0.64   0.520    -.8235603    .4164875
             |
       _cons |    .784527   .3731042     2.10   0.035     .0532563    1.515798
------------------------------------------------------------------------------
```

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