Problem Set 2

Introduction to the assignment

For this assignment, you will be using data from the Progresa program (http://en.wikipedia.org/wiki/Oportunidades), a government social assistance program in Mexico. This program, as well as the details of its impact, are described in the paper "School subsidies for the poor: evaluating the Mexican Progresa poverty program (http://www.sciencedirect.com/science/article/pii/S0304387803001858)", by Paul Shultz (available on bCourses). Please familiarize yourself with the PROGRESA program before beginning this problem set, so you have a rough sense of where the data come from and how they were generated. If you just proceed into the problem set without understanding Progresa or the data, it will be very difficult!

The goal of this problem set is to implement some of the basic econometric techniques that you are learning in class to measure the impact of Progresa on secondary school enrollment rates. The timeline of the program was:

- Baseline survey conducted in 1997
- Intervention begins in 1998, "Wave 1" of surveys conducted in 1998
- "Wave 2" of surveys conducted in 1999
- Evaluation ends in 2000, at which point the control villages were treated.

When you are ready, download the progresa_sample.csv data from bCourses. The data are actual data collected to evaluate the impact of the Progresa program. In this file, each row corresponds to an observation taken for a given child for a given year. There are two years of data (1997 and 1998), and just under 40,000 children who are surveyed in each year. For each child-year observation, the following variables are collected:

Variable name	Description
year	year in which data is collected
sex	male = 1
indig	indigenous = 1
dist_sec	nearest distance to a secondary school
sc	enrolled in school in year of survey
grc	grade enrolled
fam_n	family size
min_dist	min distance to an urban center
dist_cap	min distance to the capital
poor	poor = 1
progresa	treatment =1
hohedu	years of schooling of head of household
hohwag	monthly wages of head of household
welfare_index	welfare index used to classify poor
hohsex	gender of head of household (male=1)
hohage	age of head of household
age	years old

Variable name	Description
folnum	individual id
village	village id
sc97	schooling in 1997
grc97	grade enrolled in 1997

Part 1: Descriptive analysis

1.1 Summary Statistics

Present summary statistics (mean, median and standard deviation) for all of the demographic variables in the dataset (i.e., everything except year, folnum, village). Present these in a single table alphabetized by variable name. Do NOT simply expect the grader to scroll through your output!

Note: For this and subsequent problems, you will need to be careful in how you deal with missing (NULL) values. You should not blindly drop rows and columns where any data field is missing. For instance, in calculating the average `hohwag` , you should average the `hohwag` values from all households that report a value (even if the household does not have a recorded `age` value, for example).

In [2]:

```
#import libraries
import numpy as np
from scipy import stats
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

In [3]:

```
df = pd.read_csv('progresa_sample.csv')
df['poor'] = df['poor'].apply(lambda x: 1 if x == 'pobre' else 0) #recode variable
df['progresa'] = df['progresa'].apply(lambda x: 1 if x == 'basal' else 0) #recode va
df.head()
```

Out[3]:

```
   year  sex  indig  dist_sec   sc  grc  fam_n   min_dist    dist_cap  poor  ...  hohedu  hohwag
0    97  0.0    0.0     4.473  1.0  7.0      7  21.168384  21.168384     1  ...       6     0.0
1    98  0.0    0.0     4.473  1.0  8.0      7  21.168384  21.168384     1  ...       6     0.0
2    97  1.0    0.0     4.473  1.0  6.0      7  21.168384  21.168384     1  ...       6     0.0
3    98  1.0    0.0     4.473  1.0  7.0      7  21.168384  21.168384     1  ...       6     0.0
4    97  0.0    0.0     4.473  1.0  2.0      7  21.168384  21.168384     1  ...       6     0.0

5 rows × 21 columns
```

In [4]:

```
summary = df.describe()
summary = summary.transpose() #transpose the df
summary.drop(['village','year','folnum']).sort_index() #drop village, year, folnum a
```

...

1.2 Differences at baseline?

Are the baseline (1997) demographic characteristics **for the poor** different in treatment and control villages? Present your results in a single table with the following columns and 14 (or so) rows (alphabetized by variable name):

Variable name	Average value (Treatment villages)	Average value (Control villages)	Difference (Treat - Control)	p-value
Male	?	?	?	?

Hint: Use a T-Test to determine whether there is a statistically significant difference in the average values of each of the variables in the dataset. Focus only on the data from 1997 from poor households (i.e., poor=='pobre').

In [41]:

```
#calcualte the average of treatment and control group
df_poor97= df[np.logical_and(df['poor']==1, df['year']==97)]
df_poor_sum= df_poor97.groupby('progresa').mean().transpose()
df_poor_sum.reset_index(inplace=True) # new column: variable name
df_poor_sum['Difference (Treat - Control)'] = df_poor_sum[1] - df_poor_sum[0]

#calculate p-value
column_list = [x for x in df_poor97.columns if x != 'progresa'] # get a list of all
t_test_results = {} # create an empty dictionary
for column in column_list:    # loop over column_list and execute code explained abo
    groupT = df_poor97[column].where(df_poor97.progresa== 1).dropna()
    groupC = df_poor97[column].where(df_poor97.progresa== 0).dropna()
    t_test_results[column] = stats.ttest_ind(groupT,groupC)[1]   # add the output to

results_df = pd.DataFrame.from_dict(t_test_results,orient='Index')
results_df.columns = ['p-value']
results_df.reset_index(inplace=True) # new column: variable name

#merge two dataframe
df_poor_sum = pd.merge(df_poor_sum, results_df, on = 'index')

#delete uninterested rows
values = ['village', 'poor', 'folnum', 'year']
df_poor_sum = df_poor_sum[df_poor_sum['index'].isin(values) == False]


# rename columns
df_poor_sum.rename({1:'Average value (Treatment villages)',
            0:'Average value (Control villages)',
            'index': 'Variable name'}, axis = 1, inplace = True)

#change column orders
df_poor_sum = df_poor_sum[["Variable name", "Average value (Treatment villages)", "A
df_poor_sum.sort_values(by='Variable name')
```

...

1.3 Interpretation

- A: Are there statistically significant differences between treatment and control villages at baseline?
- B: Why does it matter if there are differences at baseline?
- C: What does this imply about how to measure the impact of the treatment?

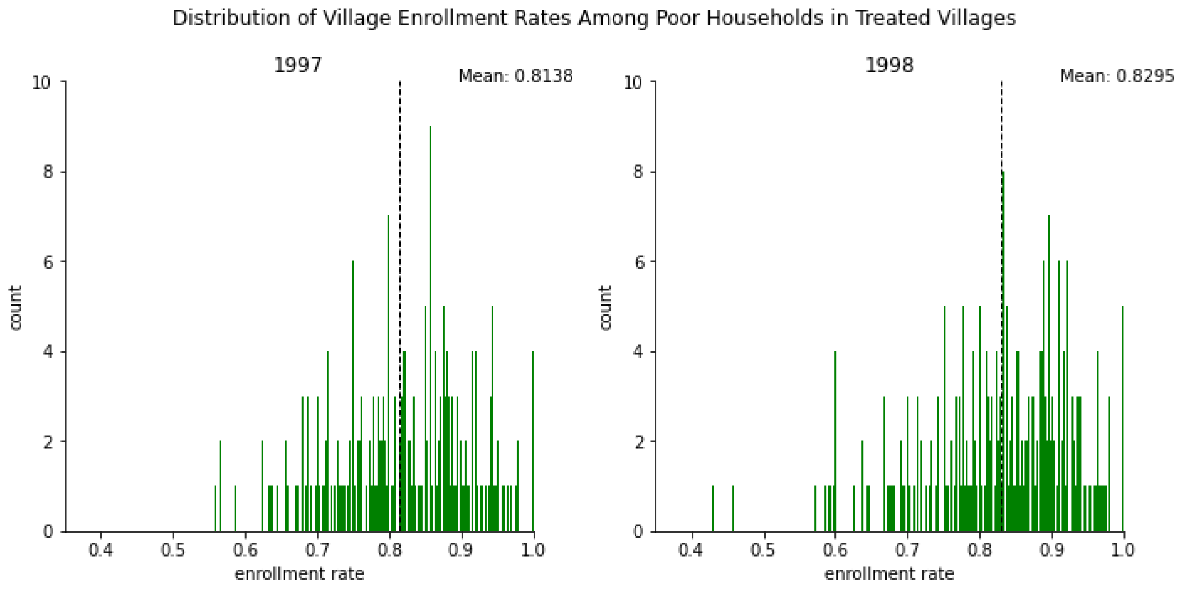
- A: yes, there are statistically significant differences between treatment and control villages at variables such as dist_cap, dist_sec, hohage, hohedu, hohwag, min_dist, sex, welfare_index.
- B: there are differences at baseline, the difference we observed between treatment and control group after treatment might not be the effect of treatment but the already existed difference.
- C: we have to subtract the effect of the basline when measuring the difference after treatment. In other words, it would be better to use the difference-in difference methods.

1.4 Graphical exploration, part 1

Visualize the distribution of village enrollment rates **among poor households in treated villages**, before and after treatment. Specifically, for each village, calculate the average rate of enrollment of poor households in treated villages in 1997, then compute the average rate of enrollment of poor households in treated villages in 1998. Create two separate histograms showing the distribution of these average enrollments rates, one histogram for 1997 and one histogram for 1998. On each histogram, draw a vertical line that intersects the x-axis at the average value (across all households). Does there appear to be a difference? Is this difference statistically significant?

In [32]:

```
df_poor= df[df['poor']==1]

#select rows with data in 1997/1998 and treatment group
df_97_T = df_poor.loc[np.logical_and(df_poor['year']==97, df_poor['progresa']== 1.0)
df_98_T = df_poor.loc[np.logical_and(df_poor['year']==98, df_poor['progresa']== 1.0)

# compute the enrollment rate of each village
rate97_T = df_97_T.groupby('village').mean()['sc'] #1997
rate98_T = df_98_T.groupby('village').mean()['sc'] #1998

#histogram
fig = plt.figure(figsize=[10,5])
fig.suptitle('Distribution of Village Enrollment Rates Among Poor Households in Trea

#97
axs1 = plt.subplot(1, 2, 1)
num_of_bins = len(rate97_T)
plt.hist(rate97_T, color='green', bins = int(num_of_bins))
plt.axvline(rate97_T.mean(), color='k', linestyle='dashed', linewidth=1) #add averag
plt.text(rate97_T.mean()*1.1, 10, 'Mean: {:.4f}'.format(rate97_T.mean())) #add avera
plt.title('1997')
plt.ylim([0, 10])
plt.xlim([0.35, 1])
axs1.set_ylabel('count')
axs1.set_xlabel('enrollment rate')
axs1.spines['right'].set_visible(False)
axs1.spines['top'].set_visible(False)

#98
axs2 = plt.subplot(1, 2, 2)
num_of_bins = len(rate98_T)
plt.hist(rate98_T, color='green', bins = int(num_of_bins))
plt.axvline(rate98_T.mean(), color='k', linestyle='dashed', linewidth=1)
plt.text(rate98_T.mean()*1.1, 10, 'Mean: {:.4f}'.format(rate98_T.mean()))
plt.title('1998')
plt.ylim([0, 10])
plt.xlim([0.35, 1])
axs2.set_ylabel('count')
axs2.set_xlabel('enrollment rate')
axs2.spines['right'].set_visible(False)
axs2.spines['top'].set_visible(False)

#adjust spacing between two subplots
fig.tight_layout()
plt.show()
```



In [36]:

```
# compute t-test of the enrollment rate in 1997 & 1998 at the household level
print(stats.ttest_ind(df_97_T['sc'].dropna(),df_98_T['sc'].dropna()))
```

```
Ttest_indResult(statistic=-6.069273929290983, pvalue=1.2976490728161e-
09)
```

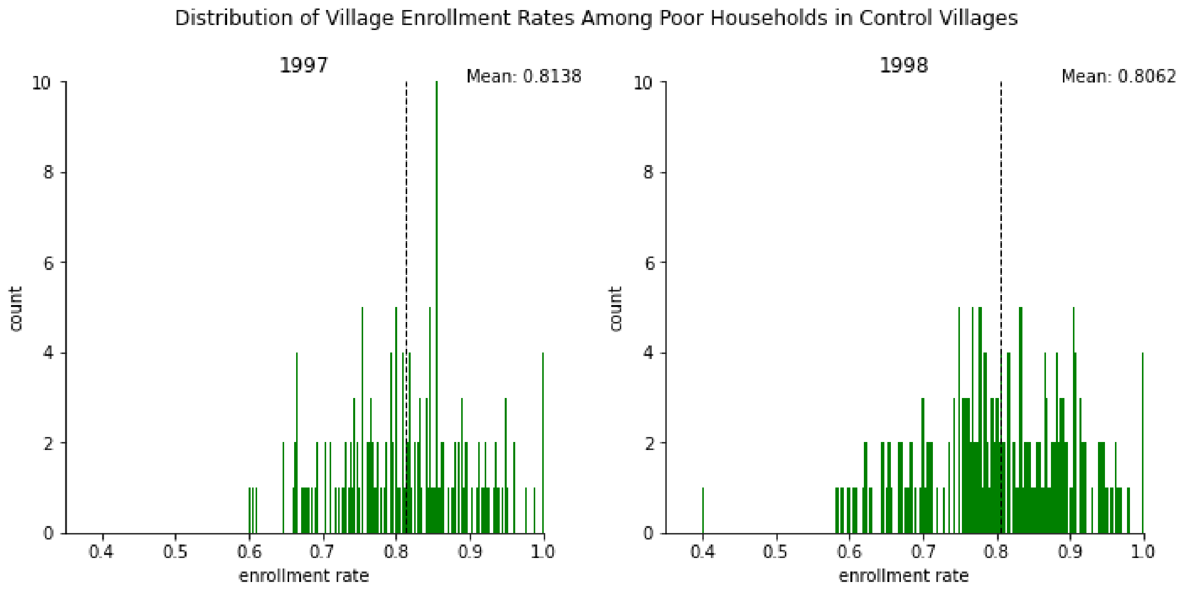
- Does there appear to be a difference? Is this difference statistically significant?
  The data of 1997 seems to be more evenly distributed between 0.6 - 1.0, and the data of 1998 concentrate more between 0.75 - 1.0.The average enrollment rate in 1998 is slightly higher than that of 1997. From the result of paired sample t-test, there is a statistically significant difference between the two distribution (p-value < 0.05).

1.5 Graphical exploration, part 2

Repeat the above exercise for poor households in **control villages**, before and after treatment. Do you observe a difference in enrollment in control villages between 1997 and 1998? How does what you observe here affect how you might approach measuring the impact of PROGRESA?

In [8]:

```
#select rows with data in 1997/1998 and control group
df_97_C = df_poor.loc[np.logical_and(df_poor['year']==97, df_poor['progresa']== 0),[
df_98_C = df_poor.loc[np.logical_and(df_poor['year']==98, df_poor['progresa']== 0),[

# compute the enrollment rate of each village
rate97_C = df_97_C.groupby('village').mean()['sc'] #1997
rate98_C = df_98_C.groupby('village').mean()['sc'] #1998

#histogram
fig = plt.figure(figsize=[10,5])
fig.suptitle('Distribution of Village Enrollment Rates Among Poor Households in Cont

#97
axs1 = plt.subplot(1, 2, 1)
num_of_bins = len(rate97_C)
plt.hist(rate97_C, color='green', bins = int(num_of_bins))
plt.axvline(rate97_C.mean(), color='k', linestyle='dashed', linewidth=1)
plt.text(rate97_C.mean()*1.1, 10, 'Mean: {:.4f}'.format(rate97_C.mean()))
plt.title('1997')
plt.ylim([0, 10])
plt.xlim([0.35, 1])
axs1.set_ylabel('count')
axs1.set_xlabel('enrollment rate')
axs1.spines['right'].set_visible(False)
axs1.spines['top'].set_visible(False)

#98
axs2 = plt.subplot(1, 2, 2)
num_of_bins = len(rate98_C)
plt.hist(rate98_C, color='green', bins = int(num_of_bins))
plt.axvline(rate98_C.mean(), color='k', linestyle='dashed', linewidth=1)
plt.text(rate98_C.mean()*1.1, 10, 'Mean: {:.4f}'.format(rate98_C.mean()))
plt.title('1998')
plt.ylim([0, 10])
plt.xlim([0.35, 1])
axs2.set_ylabel('count')
axs2.set_xlabel('enrollment rate')
axs2.spines['right'].set_visible(False)
axs2.spines['top'].set_visible(False)

#adjust spacing between two subplots
fig.tight_layout()
plt.show()
```



In [37]:

```
# compute t-test of the enrollment rate in 1997 & 1998  at the household level
print(stats.ttest_ind(df_97_C['sc'].dropna(),df_98_C['sc'].dropna()))
```

```
Ttest_indResult(statistic=1.4355850984946787, pvalue=0.151134529701560
8)
```

- Do you observe a difference in enrollment in control villages between 1997 and 1998? How does what you observe here affect how you might approach measuring the impact of PROGRESA?
  Except for the distribution of 1998 being more evenly distributed between 0.6 to 1, it seems that the distributions of the two do not differ a lot. The result of independent sample t-test shows that there is no statistically significant difference between the two distributions (p-value = 0.15). If a difference between the 97 & 98 control groups is observed, we have to subtract the time effect from the treatment effect (the difference between the 1998 and 1997 control group). That is, when measuring the impact of the PROGRESA program on the enrollment rate, in addition to only subtracting the 1998 treatment group with the 1997 treatment group, we also have to subtract (1998 control - 1997 control) with the 1998 treatment group to eliminate the time effect.

Part 2: Measuring Impact

Our goal is to estimate the causal impact of the PROGRESA program on the social and economic outcomes of individuals in Mexico. We will focus on the impact of the program on school enrollment rates among the poor (those with poor=='pobre'), since only the poor were eligible to receive PROGRESA assistance, and since a primary objective of the program was to increase school enrollment.

2.1 Simple differences: T-test

Begin by estimating the impact of Progresa using "simple differences." Restricting yourself to data from 1998 (after treatment), calculate the average enrollment rate among **poor** households in the Treatment villages and the average enrollment rate among **poor** households in the control villages. Use a t-test to determine if this difference is statistically significant. What do you conclude?

In [11]:

```
# average enrollment rate 1998
ER98T = df_98_T.mean()['sc']
ER98C = df_98_C.mean()['sc']
print('1998 average enrollment rate (treatment) = {:.4f}'.format(ER98T)) #average en
print('1998 average enrollment rate (control) = {:.4f}'.format(ER98C)) #average enro

# t-test
a = stats.ttest_ind(df_98_T['sc'].dropna(), df_98_C['sc'].dropna())
print(a)
```

```
1998 average enrollment rate (treatment) = 0.8465
1998 average enrollment rate (control) = 0.8076
Ttest_indResult(statistic=8.358720567418374, pvalue=6.636344447523235e
-17)
```

- `What do you conclude?`
  Since the p-value is smaller than 0.05, we can conclude that there is a significant difference between the treatment group and the control group.

2.2 Simple differences: Regression

Estimate the effects of Progresa on enrollment using a regression model, by regressing the 1998 enrollment rates **of the poor** on treatment assignment. For now, do not include any other variables in your regression. Discuss the following:

- Based on this model, how much did Progresa increase or decrease the likelihood of a child enrolling? Make sure you express you answer in a sentence that your grandmother could understand, using appropriate units.
- How does your regression estimate compare to your t-test estimate from part 2.1?
- Based on this regression model, can we reject the null hypothesis that the treatment effects are zero?
- What is the counterfactual assumption underlying this regression?

In [12]:

```
df98 = df_poor.loc[df_poor['year']==98,:]
smf.ols(formula = 'sc ~ progresa', data=df98).fit().summary() # fitting the model
```

Out[12]:

```
OLS Regression Results

       Dep. Variable:                sc          R-squared:      0.003
               Model:               OLS      Adj. R-squared:      0.003
              Method:     Least Squares          F-statistic:     69.87
                Date:  Sun, 06 Feb 2022  Prob (F-statistic):  6.64e-17
                Time:          22:25:38      Log-Likelihood:    -11926.
    No. Observations:             27450                 AIC:  2.386e+04
        Df Residuals:             27448                 BIC:  2.387e+04
            Df Model:                 1
     Covariance Type:         nonrobust

                coef   std err        t    P>|t|   [0.025   0.975]
   Intercept  0.8076     0.004  220.676    0.000    0.800    0.815
    progresa  0.0388     0.005    8.359    0.000    0.030    0.048

        Omnibus:  7638.939     Durbin-Watson:      1.734
 Prob(Omnibus):     0.000  Jarque-Bera (JB):  15767.534
           Skew:    -1.767          Prob(JB):       0.00
       Kurtosis:     4.140          Cond. No.       3.01


Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

- `Based on this model, how much did Progresa increase or decrease the likelihood of a child enrolling? Make sure you express you answer in a sentence that your grandmother could understand, using appropriate units.`
  The likelihood of a child enrolling increases by 3.88 percent when the treatment increases by 1 units.
- `How does your regression estimate compare to your t-test estimate from part 2.1?`
  The results of the both statistical tests infer that Progresa has an statistically significant impact on the enrollment rate.
- `Based on this regression model, can we reject the null hypothesis that the treatment effects are zero?`
  Yes, since the overall p-value of the model = 6.64e-17, smaller than 0.05, we can reject the null hypothesis.
- `What is the counterfactual assumption underlying this regression?`
  The villages in the treatment groups and the control groups are randomly assigned.

2.3 Multiple Regression

Re-run the above regression, but this time include a set of control variables. Include, for instance, age, distance to a secondary school, gender, education of household head, welfare index, indigenous, etc.

- How do the controls affect the point estimate of treatment effect?
- How do the controls affect the standard error on the treatment effect?
- How do you interpret the differences (or similarities) between your estimates of 2.2 and 2.3?
- Interpet the coefficient associated with the `dist_sec` variable. Is this evidence that the household's distance from a secondary school has a *causal* impact on educational attainment?

In [13]:

```
smf.ols(formula = 'sc ~ progresa + sex + age + indig + dist_sec + hohedu + hohwag',
```

Out[13]:

```
OLS Regression Results

           Dep. Variable:                sc          R-squared:      0.268
                   Model:               OLS     Adj. R-squared:      0.268
                  Method:     Least Squares        F-statistic:      1428.
                    Date:  Sun, 06 Feb 2022  Prob (F-statistic):      0.00
                    Time:          22:25:38     Log-Likelihood:    -7671.8
       No. Observations:             27340                AIC:  1.536e+04
            Df Residuals:             27332                BIC:  1.543e+04
                Df Model:                 7
        Covariance Type:         nonrobust

                 coef    std err        t    P>|t|     [0.025     0.975]
 Intercept     1.5239     0.010  159.309   0.000      1.505      1.543
  progresa     0.0356     0.004    8.908   0.000      0.028      0.043
       sex     0.0310     0.004    7.994   0.000      0.023      0.039
       age    -0.0655     0.001  -95.682   0.000     -0.067     -0.064
     indig     0.0468     0.004   11.224   0.000      0.039      0.055
  dist_sec    -0.0119     0.001  -13.635   0.000     -0.014     -0.010
    hohedu     0.0087     0.001   11.072   0.000      0.007      0.010
    hohwag -6.356e-07    2.8e-06   -0.227   0.821  -6.13e-06   4.85e-06

       Omnibus:  2974.468      Durbin-Watson:     1.717
 Prob(Omnibus):     0.000   Jarque-Bera (JB):  4048.830
          Skew:    -0.935           Prob(JB):      0.00
      Kurtosis:     3.239           Cond. No.  4.51e+03
```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.51e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

- `How do the controls affect the point estimate of treatment effect?`
  The controls decrease the point estimate of treatment effect.
- `How do the controls affect the standard error on the treatment effect?`
  The controls slightly decrease the standard error on the treatment effect.
- `How do you interpret the differences (or similarities) between your estimates of 2.2 and 2.3?`

The increased R-squared indicates that the ability the model can explain the real data increased by adding control variables.

- Interpet the coefficient associated with the dist_sec variable. Is this evidence that the household's distance from a secondary school has a *causal* impact on educational attainment?
  Yes, the p-value is smaller than 0.05, indicating that the household's distance from a secondary school has a causal impact on educational attainment.

2.4 Difference-in-Difference, version 1 (tabular)

Thus far, we have computed the effects of Progresa by estimating the difference in 1998 enrollment rates across villages. An alternative approach would be to compute the treatment effect using a difference-in-differences framework.

Begin by estimating the average treatment effects of the program for poor households using data from 1997 and 1998. Specifically, calculate the difference (between 1997 and 1998) in enrollment rates among poor households in treated villages; then compute the difference (between 1997 and 1998) in enrollment rates among poor households in control villages.

Display your results in a 2x2 table where the rows are Control/Treatment and the columns are 1997/1998.

- What is your difference-in-difference estimate of the impact, and how does it compare to your earlier (simple difference) results?
- What is the counterfactual assumption underlying this estimate?

In [38]:

```
from tabulate import tabulate
Table = [["Progresa\year", 1997,1998],
         ["Control", df_97_C.mean()['sc'], df_98_C.mean()['sc'] ],
         ["Treatment", df_97_T.mean()['sc'], df_98_T.mean()['sc']]]
print(tabulate(Table, headers="firstrow", tablefmt="rst", floatfmt="0.4f"))

did = df_98_T.mean()['sc']- df_98_C.mean()['sc'] - (df_97_T.mean()['sc']-df_97_C.mea
print(did)
```

```
===============  ======  ======
Progresa\year      1997    1998
===============  ======  ======
Control          0.8152  0.8076
Treatment        0.8227  0.8465
===============  ======  ======
0.031331280319323085
```

- What is your difference-in-difference estimate of the impact, and how does it compare to your earlier (simple difference) results?
  The differnce-in-difference estimate of the impact is 0.0313. The estimate is really close to the point estimate of treatment effect in the regression models, which is 0.0075 units different from the earlier result.
- What is the counterfactual assumption underlying this estimate?
  The conterfactual of the post treatment group = pre treatment + (the difference between pre- and post-control). The assumptions are:

  1. “Parallel trends”: Trends in pre-treatment outcomes are the same in treatment and control groups
  2. Composition of treatment and control groups stable across time

3. No spillover effects

2.5 Difference-in-Difference, version 2 (regression)

Now use a regression specification to estimate the average treatment effects of the program in a difference-in-differences, for the poor households. Do this (i) first without including any control variables; and then (ii) do it a second time including at least 5 control variables.

- What is your estimate (i) of the impact of Progresa? Be very specific in interpreting your coefficients and standard errors, and make sure to specify exactly what units you are measuring and estimating.
- Does your estimate of the impact of Progresa from (i) change when you add control variables as in (ii)? How do you explain these changes, or the lack of changes on the `progresa` coefficient between (i) and (ii)?
- How do the estimates from (i) and (ii) compare to the difference-in-difference estimates from 2.4 above? What accounts for these differences, if any exist?
- What is the counterfactual assumption underlying regression (ii)?

In [15]:

```
# (i)
# dif-in-dif formula: Y = B0 + B1*Time + B2*Intervention + B3*(Time*Intervention)
df_poor['progresa*year'] = df_poor['progresa']*df_poor['year']
model = smf.ols(formula='sc ~ year + progresa + progresa*year', data=df_poor).fit()
print(model.summary())
```

...

In [16]:

```
#(ii)
model = smf.ols(formula='sc ~ progresa + year + year*progresa + sex + age + indig +
                data=df_poor).fit()
print(model.summary())
```

```
                            OLS Regression Results
======================================================================
========
Dep. Variable:                     sc   R-squared:
0.279
Model:                            OLS   Adj. R-squared:
0.279
Method:                 Least Squares   F-statistic:
2498.
Date:                Sun, 06 Feb 2022   Prob (F-statistic):
0.00
Time:                        22:25:38   Log-Likelihood:
-16717.
No. Observations:               58165   AIC:
3.345e+04
Df Residuals:                   58155   BIC:
3.354e+04
Df Model:                           9
Covariance Type:            nonrobust
======================================================================
============
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
------------
Intercept        -1.1247      0.424     -2.653      0.008      -1.956
-0.294
progresa         -3.0407      0.538     -5.651      0.000      -4.095
-1.986
year              0.0270      0.004      6.202      0.000       0.018
0.036
year:progresa     0.0314      0.006      5.687      0.000       0.021
0.042
sex               0.0339      0.003     12.674      0.000       0.029
0.039
age              -0.0655      0.000   -144.421      0.000      -0.066
-0.065
indig             0.0497      0.003     17.252      0.000       0.044
0.055
dist_sec         -0.0109      0.001    -17.749      0.000      -0.012
-0.010
hohedu            0.0076      0.001     13.926      0.000       0.006
0.009
hohwag         6.502e-07   1.92e-06      0.338      0.735   -3.12e-06
4.42e-06
======================================================================
========
Omnibus:                     5523.881   Durbin-Watson:
1.484
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
7269.474
Skew:                          -0.864   Prob(JB):
0.00
```

```
Kurtosis:                       3.113   Cond. No.
4.40e+05
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 4.4e+05. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

- What is your estimate (i) of the impact of Progresa? Be very specific in interpreting your coefficients and standard errors, and make sure to specify exactly what units you are measuring and estimating.
  On average the enrollment rate of people in the treatment group are -3.0316 percent lower than those in the control group. The significant interaction effect shows that the enrollment rate of the treament group increase 0.0313 by year. Standard error represents the average distance that the observed values fall from the regression line.
- Does your estimate of the impact of Progresa from (i) change when you add control variables as in (ii)? How do you explain these changes, or the lack of changes on the progresa coefficient between (i) and (ii)?
  The interaction effect of year and progresa increases by 0.001 and the estimate average difference of the enrollment rate between the treatment and control group increases by 0.009. Because these control variables are not experimentally controlled, isolating the control variable's effects from the relationship between the variable of interest (sc and progresa), and thus lead to the change in the results.
- How do the estimates from (i) and (ii) compare to the difference-in-difference estimates from 2.4 above? What accounts for these differences, if any exist?
  The estimate from 2.4 and from (i) are almost the same (both are 0.313). The estimate from (ii) is also nearly the same (0.001 different from the other two).
- What is the counterfactual assumption underlying regression (ii)?

  1. "Parallel trends": Trends in pre-treatment outcomes are the same in treatment and control groups
  2. Composition of treatment and control groups stable across time
  3. No spillover effects

2.6 Spillover effects

Thus far, we have focused on the impact of PROGRESA on the school enrollment of poor households. Repeat your analysis in 2.5, instead focusing on (a) the impact of PROGRESA on the school enrollment of non-poor households, and (b) the impact ofo PROGRESA on *other outcomes* of poor households that might plausibly have been affected by the PROGRESA program.

- Do you observe any impacts of PROGRESA on the school enrollment of the non-poor?
- Regardless of whether you find evidence of spillovers to non-poor, describe one or two reasons why PROGRESA *might* have impacted non-poor households. Give concrete examples based on the context in which PROGRESA was implemented.
- Do you observe any impacts of PROGRESA on other aspects of the welfare of poor households?

In [17]:

```
# (a)
df_nonpoor = df[df['poor']== 0]
df_nonpoor['progresa*year'] = df_nonpoor['progresa']*df_nonpoor['year']
model = smf.ols(formula='sc ~ year + progresa + progresa*year', data=df_nonpoor).fit
print(model.summary())
```

...

In [39]:

```
#(b)
print(smf.ols(formula='fam_n ~ year + progresa + progresa*year', data=df_poor).fit()
print(smf.ols(formula='min_dist ~ year + progresa + progresa*year', data=df_poor).fi
print(smf.ols(formula='age ~ year + progresa + progresa*year', data=df_poor).fit().s
```

```
                            OLS Regression Results
======================================================================
========
Dep. Variable:                  fam_n   R-squared:
0.000
Model:                            OLS   Adj. R-squared:
-0.000
Method:                 Least Squares   F-statistic:
0.4205
Date:                Mon, 07 Feb 2022   Prob (F-statistic):
0.738
Time:                        00:03:45   Log-Likelihood:            -1.
4833e+05
No. Observations:               65392   AIC:
2.967e+05
Df Residuals:                   65388   BIC:
2.967e+05
Df Model:                           3
Covariance Type:            nonrobust
======================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
Intercept         7.3025      2.887      2.530      0.011       1.644
12.961
year          -5.196e-13      0.030  -1.75e-11      1.000      -0.058
0.058
progresa         -0.0211      3.671     -0.006      0.995      -7.216
7.174
progresa:year -5.013e-13      0.038  -1.33e-11      1.000      -0.074
0.074
======================================================================
========
Omnibus:                     6951.980   Durbin-Watson:
0.346
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1
2696.028
Skew:                           0.721   Prob(JB):
0.00
Kurtosis:                       4.606   Cond. No.
5.70e+04
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 5.7e+04. This might indicate that t
here are
strong multicollinearity or other numerical problems.
                            OLS Regression Results
```

```
==============================================================================
========
Dep. Variable:               min_dist   R-squared:
0.002
Model:                            OLS   Adj. R-squared:
0.002
Method:                 Least Squares   F-statistic:
44.90
Date:                Mon, 07 Feb 2022   Prob (F-statistic):
5.63e-29
Time:                        00:03:45   Log-Likelihood:            -3.
3705e+05
No. Observations:               65392   AIC:
6.741e+05
Df Residuals:                   65388   BIC:
6.741e+05
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----------
Intercept       103.2379     51.733      1.996      0.046       1.842
204.634
year           6.604e-11      0.531   1.24e-10      1.000      -1.040
1.040
progresa          3.9151     65.781      0.060      0.953    -125.016
132.846
progresa:year -1.466e-10      0.675  -2.17e-10      1.000      -1.322
1.322
==============================================================================
========
Omnibus:                    11985.978   Durbin-Watson:
0.034
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
4196.004
Skew:                          -0.413   Prob(JB):
0.00
Kurtosis:                       2.073   Cond. No.
5.70e+04
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 5.7e+04. This might indicate that t
here are
strong multicollinearity or other numerical problems.
                            OLS Regression Results
==============================================================================
========
Dep. Variable:                    age   R-squared:
0.025
Model:                            OLS   Adj. R-squared:
0.025
Method:                 Least Squares   F-statistic:
566.4
Date:                Mon, 07 Feb 2022   Prob (F-statistic):
```

```
0.00
Time:                        00:03:45   Log-Likelihood:             -1.
6683e+05
No. Observations:               65392   AIC:
3.337e+05
Df Residuals:                   65388   BIC:
3.337e+05
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----------
Intercept       -86.2580      3.831    -22.518      0.000     -93.766
-78.750
year              1.0000      0.039     25.453      0.000       0.923
1.077
progresa         -0.0250      4.871     -0.005      0.996      -9.572
9.522
progresa:year  1.883e-12      0.050   3.77e-11      1.000      -0.098
0.098
==============================================================================
========
Omnibus:                    48447.637   Durbin-Watson:
0.904
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
3875.955
Skew:                           0.088   Prob(JB):
0.00
Kurtosis:                       1.820   Cond. No.
5.70e+04
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 5.7e+04. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

- Do you observe any impacts of PROGRESA on the school enrollment of the non-poor?

  On average there is no statistically significant impacts of PROGRESA on the school enrollment of the non-poor. (p-value = 0.738)
- Regardless of whether you find evidence of spillovers to non-poor, describe one or two reasons why PROGRESA *might* have impacted non-poor households. Give concrete examples based on the context in which PROGRESA was implemented.

  Perhaps the randomization failed so that the treatment and control villages were different to begin with. Another explanation could be the possible spillover effects from poor to non-poor in treated village. The poor household get money and hence become unpoor.
- Do you observe any impacts of PROGRESA on other aspects of the welfare of poor households?

  From the results of the outcomes of the poor households I tried (family size, age, min distance to an urban center), I do not observed any impacts of PROGRESA on other aspects of the welfare of poor households.

2.7 Summary

- Based on all the analysis you have undertaken to date, do you believe that Progresa had a causal impact on the enrollment rates of poor households in Mexico?
- Using several different empirical frameworks, we have explored the impact of the PROGRESA program on enrollment rates of poor households in Mexico. In general, it appears that PROGRESA did have positive impact on the school enrollment rates, though the exact estimate depends on the method used to measure impact. After controlling for other observable characteristics, the most reliable difference-in-difference estimator estimates that PROGRESA raised enrollment rates by roughly 3.13 percentage points. A separate estimator, that includes externalities on non-poor households, produces a more conservative, and statistically insignificant, estimate.

Discuss your results here