MACS30000_Assignment2_JunhoChoi

October 17, 2018

1 Assignment 2, MACS 30000 (Dr. Evans)

1.0.1 Submitted by Junho Choi

Due Wednesday, Oct. 17 at 11:30 AM

This file contains the coding work that was used in completing this assignment. Please refer to the .pdf file for more detailed answers.

```
In [279]: # Import packages
          import numpy as np
          import pandas as pd
          import statsmodels.api as sm
          import matplotlib.pyplot as plt
          import math
          plt.style.use('seaborn')
```

1.0.2 Problem 1

Problem 1-(b)

```
In [280]: # Reading in the datasets
          header1 = ["labinc", "capinc", "height", "weight"]
          header2 = ["totinc", "weight", "age", "female"]
          besty = pd.read_csv('BestIncome.txt', sep = ",", header = None, names = header1)
          survy = pd.read_csv('SurvIncome.txt', sep = ",", header = None, names = header2)

          # Creating total income in BestIncome
          totinc_impu = besty["labinc"] + besty["capinc"]
          besty["totinc_impu"] = totinc_impu
          print(besty.head())
```

```
         labinc        capinc     height      weight   totinc_impu
0  52655.605507   9279.509829  64.568138  152.920634  61935.115336
1  70586.979225   9451.016902  65.727648  159.534414  80037.996127
2  53738.008339   8078.132315  66.268796  152.502405  61816.140654
3  55128.180903  12692.670403  62.910559  149.218189  67820.851305
4  44482.794867   9812.975746  68.678295  152.726358  54295.770612
```

```
In [281]: # Regression analysis (no. 1, OLS) with SurvIncome
          # dependent variable: age
          # explanatory variable: totinc, weight

          # Setting up the regression variables
          exp_vars = survy[["totinc", "weight"]]
          exp_vars = sm.add_constant(exp_vars, prepend=False)
          dep_var = survy["age"]

          # Running the aforementioned regression
          m1 = sm.OLS(dep_var, exp_vars)
          result = m1.fit()
          print(result.summary())

          # Extracting and saving the regression coefficients
          coeff = result.params
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    age   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.6326
Date:                Wed, 17 Oct 2018   Prob (F-statistic):              0.531
Time:                        00:59:10   Log-Likelihood:                -3199.4
No. Observations:                1000   AIC:                             6405.
Df Residuals:                     997   BIC:                             6419.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
totinc       2.52e-05   2.26e-05      1.114      0.266   -1.92e-05    6.96e-05
weight        -0.0067      0.010     -0.686      0.493      -0.026       0.013
const         44.2097      1.490     29.666      0.000      41.285      47.134
==============================================================================
Omnibus:                        2.460   Durbin-Watson:                   1.921
Prob(Omnibus):                  0.292   Jarque-Bera (JB):                2.322
Skew:                          -0.109   Prob(JB):                        0.313
Kurtosis:                       3.092   Cond. No.                     5.20e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.2e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
In [282]: # Imputing the age in BestIncome
          age_impu = coeff[2] + coeff[0] * besty["totinc_impu"] \
```

```
                + coeff[1] * besty["weight"]
    besty["age_impu"] = age_impu

    # Presenting the "head" of SurvIncome after height imputation
    print(besty.head())
```

```
         labinc        capinc     height      weight   totinc_impu   age_impu
0  52655.605507   9279.509829  64.568138  152.920634  61935.115336  44.742614
1  70586.979225   9451.016902  65.727648  159.534414  80037.996127  45.154387
2  53738.008339   8078.132315  66.268796  152.502405  61816.140654  44.742427
3  55128.180903  12692.670403  62.910559  149.218189  67820.851305  44.915836
4  44482.794867   9812.975746  68.678295  152.726358  54295.770612  44.551391
```

In [283]:

```
'''
Regression analysis (no. 2, logistic) with SurvIncome
dependent variable: female
explanatory variable: totinc, weight, age
'''

# Setting up the regression variables
exp_vars2 = survy[["totinc", "weight"]]
exp_vars2 = sm.add_constant(exp_vars2)
dep_var2 = survy["female"]

# Running the aforementioned regression
m2 = sm.Logit(dep_var2, exp_vars2)
result2 = m2.fit()
print(result2.summary2())

# Extracting and saving the regression coefficients
coeff2 = result2.params
```

```
Optimization terminated successfully.
         Current function value: 0.036050
         Iterations 11
                        Results: Logit
===============================================================
Model:              Logit            No. Iterations:   11.0000
Dependent Variable: female           Pseudo R-squared: 0.948
Date:               2018-10-17 00:59 AIC:              78.1009
No. Observations:   1000             BIC:              92.8242
Df Model:           2                Log-Likelihood:   -36.050
Df Residuals:       997              LL-Null:          -693.15
Converged:          1.0000           Scale:            1.0000
---------------------------------------------------------------
            Coef.   Std.Err.     z     P>|z|    [0.025   0.975]
---------------------------------------------------------------
```

```
const      76.7929   10.5690   7.2659  0.0000  56.0781  97.5077
totinc     -0.0002    0.0000  -3.6602  0.0003  -0.0002  -0.0001
weight     -0.4460    0.0618  -7.2185  0.0000  -0.5672  -0.3249
==============================================================
```

In [284]:
```python
# Manually calculating the probability has led to a math range error,
# and therefore I will be relying on scikit-learn.

from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(fit_intercept = True, C = 1e9)
exp_vars2 = survy[["totinc", "weight"]]

# scikit-learn's LogisticRegression has different configurations
# in comparison to statsmodel.api; therefore, the coefficients
# and intercept are different.

result2_2 = lr.fit(exp_vars2, dep_var2)
print(result2_2.intercept_, result2_2.coef_)

# Imputing the variable 'female' in BestIncome
fem_impu = result2_2.predict(besty[["totinc_impu", "weight"]])
besty["female_impu"] = fem_impu

# Presenting the "head" of SurvIncome after height imputation
print(besty.head())
```

```
[0.03294246] [[ 9.22210066e-05 -4.17849763e-02]]
         labinc        capinc     height      weight   totinc_impu   age_impu  \
0  52655.605507   9279.509829  64.568138  152.920634  61935.115336  44.742614
1  70586.979225   9451.016902  65.727648  159.534414  80037.996127  45.154387
2  53738.008339   8078.132315  66.268796  152.502405  61816.140654  44.742427
3  55128.180903  12692.670403  62.910559  149.218189  67820.851305  44.915836
4  44482.794867   9812.975746  68.678295  152.726358  54295.770612  44.551391

   female_impu
0          0.0
1          1.0
2          0.0
3          1.0
4          0.0
```

Problem 1-(c)

In [285]:
```python
# descStat = besty[["totinc_impu", "age_impu", "female_impu"]].describe()
print(descStat)
```

```
descStat2 = survy[["totinc", "age", "female"]].describe()
print(descStat2)
```

```
        totinc_impu      age_impu   female_impu
count  10000.000000  10000.000000  10000.000000
mean   67038.723697     44.890828      0.471700
std     8294.497996      0.219150      0.499223
min    33651.691815     43.976495      0.000000
25%    61452.517672     44.743776      0.000000
50%    67042.751487     44.886944      0.000000
75%    72636.874684     45.038991      1.000000
max    98996.053756     45.703819      1.000000
             totinc          age      female
count   1000.000000  1000.000000  1000.00000
mean   64871.210860    44.839320     0.50000
std     9542.444214     5.939185     0.50025
min    31816.281649    25.741333     0.00000
25%    58349.862384    41.025231     0.00000
50%    65281.271149    44.955981     0.50000
75%    71749.038000    48.817644     1.00000
max    92556.135462    66.534646     1.00000
```

Problem 1-(d)

In [286]:
```
# Correlation matrix code and output

wout_tot = ["labinc", "capinc", "height", "weight", "age_impu", "female_impu"]
besty_wout_tot = besty[wout_tot]
print(besty_wout_tot.corr())
```

```
               labinc    capinc    height    weight  age_impu  female_impu
labinc       1.000000  0.005325  0.002790  0.004507  0.924053     0.677675
capinc       0.005325  1.000000  0.021572  0.006299  0.234159     0.176901
height       0.002790  0.021572  1.000000  0.172103 -0.045083    -0.066972
weight       0.004507  0.006299  0.172103  1.000000 -0.300288    -0.382659
age_impu     0.924053  0.234159 -0.045083 -0.300288  1.000000     0.784260
female_impu  0.677675  0.176901 -0.066972 -0.382659  0.784260     1.000000
```

1.0.3 Problem 2

Problem 2-(a)

In [287]:
```
# Dataset read-in: IncomeIntel.txt
head = ["gradyr", "greqnt", "salary"]
iintel = pd.read_csv('IncomeIntel.txt', sep = ",", header = None, names = head)
```

```
# Declaring variables
gradyr = iintel[head[0]]
greqnt = iintel[head[1]]
salary = iintel[head[2]]

# Setting up the regression variables
exp_vars = sm.add_constant(greqnt, prepend=False)

# Running the aforementioned regression
m_q2 = sm.OLS(salary, exp_vars)
result_q2 = m_q2.fit()
print(result_q2.summary())

# Extracting and saving the regression coefficients
coeff_q2 = result_q2.params
```

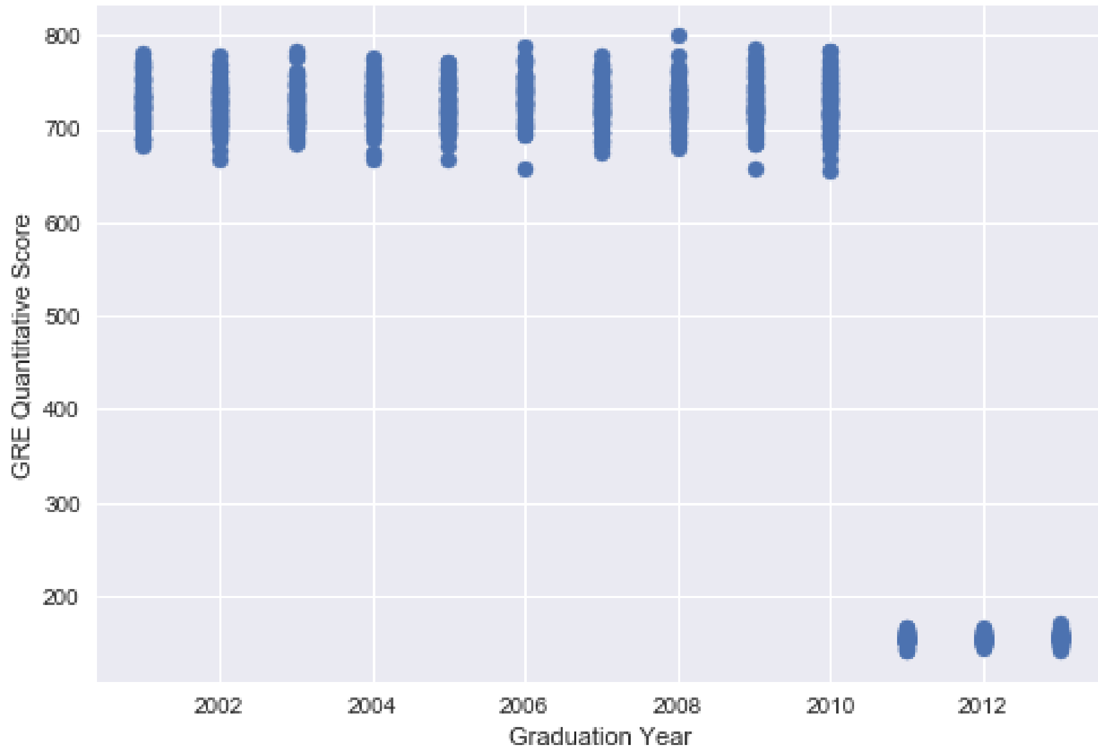
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 salary   R-squared:                       0.263
Model:                            OLS   Adj. R-squared:                  0.262
Method:                 Least Squares   F-statistic:                     356.3
Date:                Wed, 17 Oct 2018   Prob (F-statistic):           3.43e-68
Time:                        01:01:37   Log-Likelihood:                -10673.
No. Observations:                1000   AIC:                         2.135e+04
Df Residuals:                     998   BIC:                         2.136e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
greqnt       -25.7632      1.365    -18.875      0.000     -28.442     -23.085
const       8.954e+04    878.764    101.895      0.000    8.78e+04    9.13e+04
==============================================================================
Omnibus:                        9.118   Durbin-Watson:                   1.424
Prob(Omnibus):                  0.010   Jarque-Bera (JB):                9.100
Skew:                           0.230   Prob(JB):                       0.0106
Kurtosis:                       3.077   Cond. No.                     1.71e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.71e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Problem 2-(b)

In [288]:
```
# Scatterplot of GRE quantitative score (y-axis) and graduation year (x-axis)
plt.scatter(x = gradyr, y = greqnt)
```

```
plt.xlabel("Graduation Year")
plt.ylabel("GRE Quantitative Score")
plt.show()
```



In [289]:
```
'''
   It certainly seems that the GRE scores prior to and in the year 2010
   were using a 200-to-800 scale whereas afterwards, they were using
   130-to-170 scale.

   Let us change the scale to the newer version.
'''

# Where does year 2011 begin?
find = 0
for i, yr in enumerate(gradyr):
    if yr == 2011.0:
        find = i
        break

# Min and max of the old score?
print(min(greqnt[0:find]), max(greqnt[0:find]))

# On the conversion table, this maps approximately to
```

```python
# scores between 151 to 166

greqnt_conversion = greqnt.tolist()[:]

def conversion_gre(old_score):

    check1 = old_score >= 200 and old_score <= 800
    check2 = old_score >= 130 and old_score <= 170
    assert check1 or check2, ("The input should either "
                              "be a pre-2011 GRE score "
                              "(200-800), or a post-2011 "
                              "GRE score (130-170).")

    new_score = 0
    if old_score >= 200 and old_score <= 800:
        if old_score == 800:
            new_score = 166
        elif old_score < 800 and old_score >= 790:
            new_score = 164
        elif old_score < 790 and old_score >= 780:
            new_score = 163
        elif old_score < 780 and old_score >= 770:
            new_score = 161
        elif old_score < 770 and old_score >= 760:
            new_score = 160
        elif old_score < 760 and old_score >= 750:
            new_score = 159
        elif old_score < 750 and old_score >= 740:
            new_score = 158
        elif old_score < 740 and old_score >= 730:
            new_score = 157
        elif old_score < 730 and old_score >= 720:
            new_score = 156
        elif old_score < 720 and old_score >= 700:
            new_score = 155
        elif old_score < 700 and old_score >= 690:
            new_score = 154
        elif old_score < 690 and old_score >= 680:
            new_score = 153
        elif old_score < 680 and old_score >= 660:
            new_score = 152
        elif old_score < 660 and old_score >= 640:
            new_score = 151
        # the list can go on, but for convenience's sake
        # I will stop here
        return new_score
    else:
        return old_score
```

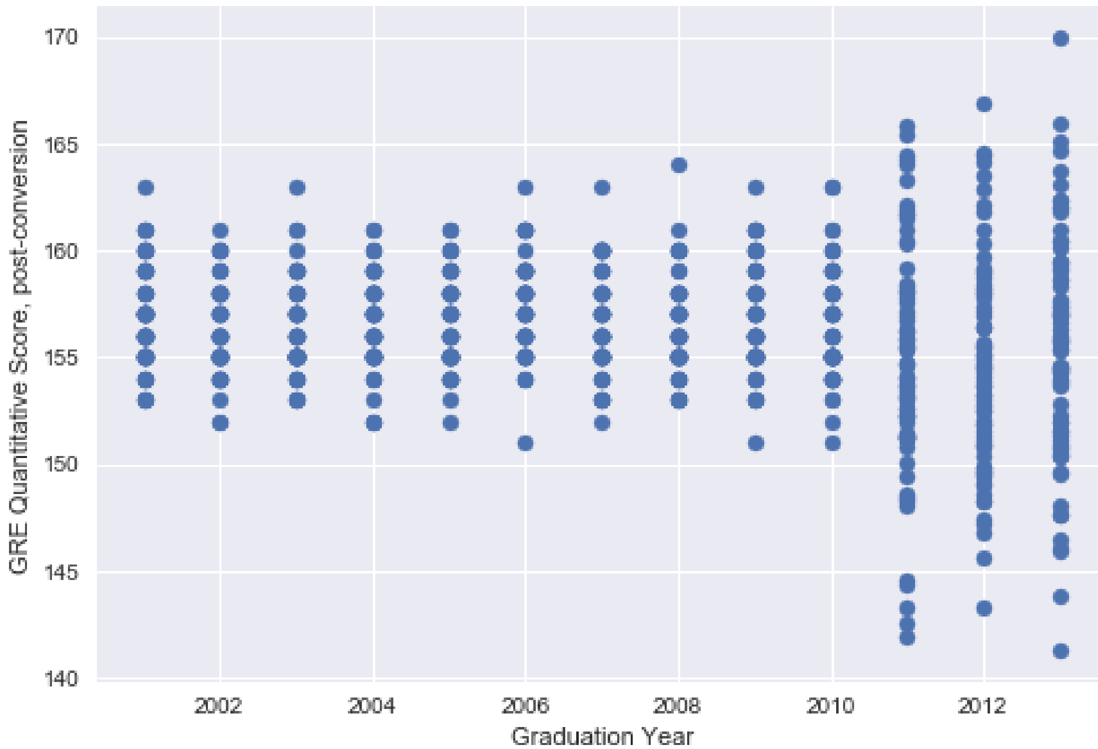
```
    for i in range(0, len(greqnt_conversion)):
        greqnt_conversion[i] = conversion_gre(greqnt_conversion[i])

    iintel["greqnt_conv"] = greqnt_conversion
    print(iintel[["greqnt", "greqnt_conv"]].head())
```

```
655.7025368703108 799.7155331839259
       greqnt  greqnt_conv
0  739.737072        157.0
1  721.811673        156.0
2  736.277908        157.0
3  770.498485        161.0
4  735.002861        157.0
```

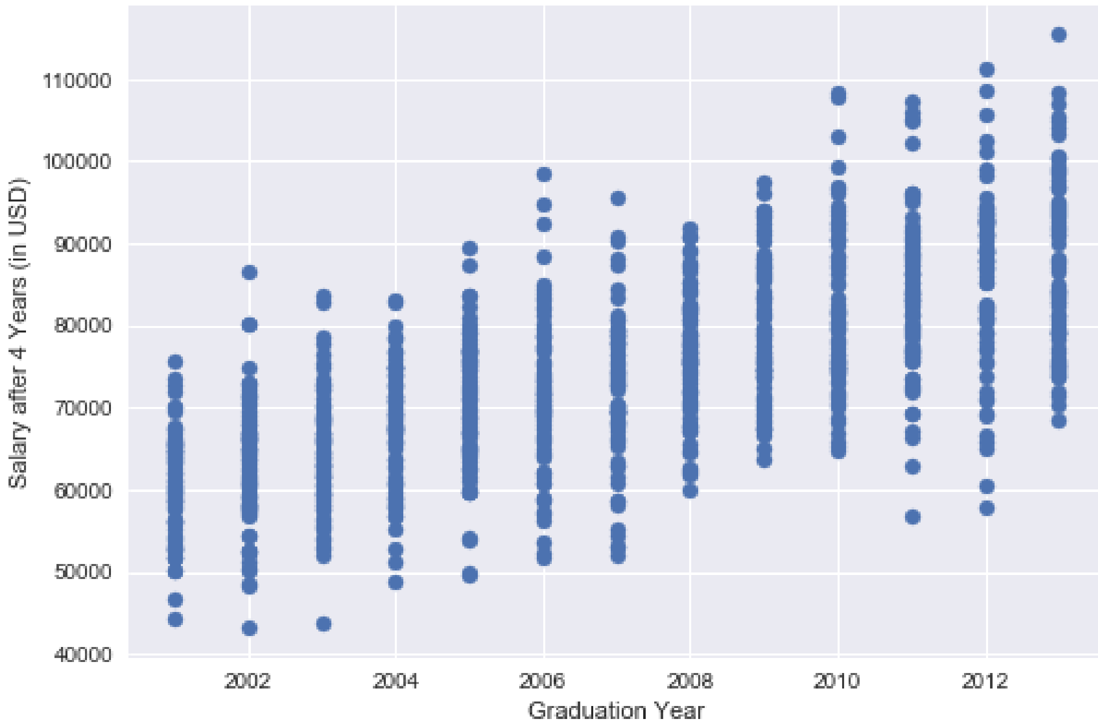
```
In [290]: ## Checking whether the conversion is more or less valid
          ## via describe() and scatterplot
          print(iintel["greqnt_conv"].describe())
          plt.scatter(x = gradyr, y = greqnt_conversion)
          plt.xlabel("Graduation Year")
          plt.ylabel("GRE Quantitative Score, post-conversion")
          plt.show()
```

```
count    1000.000000
mean      156.195657
std         3.169308
min       141.261398
25%       155.000000
50%       156.000000
75%       158.000000
max       170.000000
Name: greqnt_conv, dtype: float64
```



Problem 2-(c)

```
In [291]: # Scatterplot of GRE quantitative score (y-axis) and graduation year (x-axis)
          plt.scatter(x = gradyr, y = salary)
          plt.xlabel("Graduation Year")
          plt.ylabel("Salary after 4 Years (in USD)")
          plt.show()
```



In [292]:
```python
# Finding the average growth rate of income
avg_sal_yr = iintel.groupby(['gradyr'])['salary'].mean()
avg_sal_yr_list = avg_sal_yr.tolist()

avg_sal_g_rate = []
for i, sal in enumerate(avg_sal_yr_list):
    if i == len(avg_sal_yr_list) - 1:
        break
    else:
        next_yr = avg_sal_yr_list[i+1]
        g_rate = (next_yr - sal) / sal
        avg_sal_g_rate.append(g_rate)

def find_mean_list(some_list):
    adder = 0
    for i in some_list:
        adder = adder + i
    arith_mean = adder / len(some_list)

    return arith_mean

# Value of the average growth rate of income
g_overall = find_mean_list(avg_sal_g_rate)
print(g_overall)
```

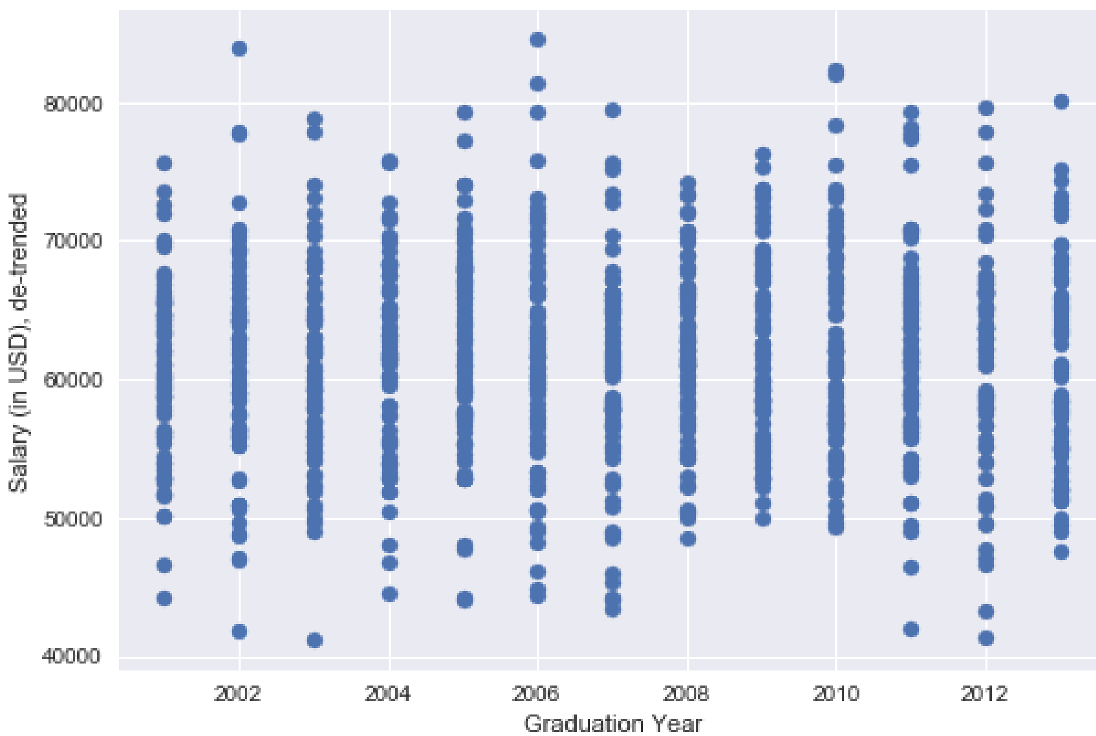
```
0.030835347092883603
```

```
In [293]: # For the de-trending of income
          newsal_list = []
          salcopy = iintel["salary"].tolist()[:]
          for i, sal in enumerate(salcopy):
              newsal = sal
              for t in range(2002, 2014):
                  j = t - 2001
                  if iintel["gradyr"][i] == t:
                      detrend_rate = (1 / (1 + g_overall)) ** j
                      newsal = sal * detrend_rate
              newsal_list.append(newsal)

          iintel["salary_detrend"] = newsal_list
```

```
In [294]: ## Checking whether the de-trending is more or less valid
          ## via scatterplot
          print(iintel["salary_detrend"].describe())
          plt.scatter(x = gradyr, y = newsal_list)
          plt.xlabel("Graduation Year")
          plt.ylabel("Salary (in USD), de-trended")
          plt.show()
```

```
count     1000.000000
mean     61419.808910
std       7135.610865
min      41164.726530
25%      56616.517414
50%      61467.616002
75%      66218.595876
max      84516.856633
Name: salary_detrend, dtype: float64
```



Problem 2-(d)

```
In [295]: # Setting up the regression variables
          dep_var = iintel["salary_detrend"]
          exp_vars = iintel["greqnt_conv"]
          exp_vars = sm.add_constant(exp_vars, prepend=False)

          # Running the regression after making the necessary changes
          m_q2_1 = sm.OLS(dep_var, exp_vars)
          result_q2_1 = m_q2_1.fit()
          print(result_q2_1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:         salary_detrend   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.6590
Date:                Wed, 17 Oct 2018   Prob (F-statistic):              0.417
Time:                        01:02:22   Log-Likelihood:                -10291.
No. Observations:                1000   AIC:                         2.059e+04
Df Residuals:                     998   BIC:                         2.060e+04
Df Model:                           1
Covariance Type:            nonrobust
```

```
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
greqnt_conv   -57.8359     71.246     -0.812      0.417    -197.644      81.972
const        7.045e+04   1.11e+04      6.330      0.000    4.86e+04    9.23e+04
==============================================================================
Omnibus:                        0.777   Durbin-Watson:                   2.026
Prob(Omnibus):                  0.678   Jarque-Bera (JB):                0.684
Skew:                           0.059   Prob(JB):                        0.710
Kurtosis:                       3.052   Cond. No.                     7.71e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.71e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [296]:
```python
# Setting up the regression variables for one with time trend
dep_var = iintel["salary"]

years = iintel["gradyr"].tolist()[:]
time = []
for y in years:
    t = y - 2001
    time.append(t)
iintel["time"] = time

exp_vars = iintel[["time", "greqnt_conv"]]
exp_vars = sm.add_constant(exp_vars, prepend=False)

# Running the regression after making the necessary changes
m_q2_2 = sm.OLS(dep_var, exp_vars)
result_q2_2 = m_q2_2.fit()
print(result_q2_2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 salary   R-squared:                       0.490
Model:                            OLS   Adj. R-squared:                  0.489
Method:                 Least Squares   F-statistic:                     478.8
Date:                Wed, 17 Oct 2018   Prob (F-statistic):          1.78e-146
Time:                        01:02:25   Log-Likelihood:                -10489.
No. Observations:                1000   AIC:                         2.098e+04
Df Residuals:                     997   BIC:                         2.100e+04
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
```

```
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
time        2265.4860     74.503     30.408      0.000    2119.286    2411.686
greqnt_conv  -86.9987     87.932     -0.989      0.323    -259.552      85.555
const       7.418e+04   1.38e+04      5.370      0.000    4.71e+04    1.01e+05
==============================================================================
Omnibus:                        2.453   Durbin-Watson:                   2.056
Prob(Omnibus):                  0.293   Jarque-Bera (JB):                2.373
Skew:                           0.076   Prob(JB):                        0.305
Kurtosis:                       3.184   Cond. No.                     7.85e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.85e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [297]:
```
## Splitting the dataset (pre-2011 vs. post-2011)
## and running similar regressions

## Where to split?
for i, yr in enumerate(gradyr):
    if yr == 2011.0:
        split = i
        break

## Pre-2011
dep_var = iintel["salary_detrend"][0:split]
exp_vars = iintel["greqnt_conv"][0:split]
exp_vars = sm.add_constant(exp_vars, prepend=False)

m_q2_sp = sm.OLS(dep_var, exp_vars)
result_q2_sp = m_q2_sp.fit()
print(result_q2_sp.summary())

## In-and-Post-2011
dep_var = iintel["salary_detrend"][split:]
exp_vars = iintel["greqnt_conv"][split:]
exp_vars = sm.add_constant(exp_vars, prepend=False)

m_q2_sp2 = sm.OLS(dep_var, exp_vars)
result_q2_sp2 = m_q2_sp2.fit()
print()
print(result_q2_sp2.summary())
```

```
                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:         salary_detrend   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.3201
Date:                Wed, 17 Oct 2018   Prob (F-statistic):              0.572
Time:                        01:02:29   Log-Likelihood:                -7916.7
No. Observations:                 770   AIC:                         1.584e+04
Df Residuals:                     768   BIC:                         1.585e+04
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
greqnt_conv   -69.1882    122.297     -0.566      0.572    -309.264     170.887
const        7.229e+04   1.92e+04      3.775      0.000    3.47e+04     1.1e+05
==============================================================================
Omnibus:                        1.218   Durbin-Watson:                   1.968
Prob(Omnibus):                  0.544   Jarque-Bera (JB):                1.074
Skew:                           0.079   Prob(JB):                        0.585
Kurtosis:                       3.092   Cond. No.                     1.18e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.18e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

                            OLS Regression Results
==============================================================================
Dep. Variable:         salary_detrend   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                 -0.002
Method:                 Least Squares   F-statistic:                    0.4616
Date:                Wed, 17 Oct 2018   Prob (F-statistic):              0.498
Time:                        01:02:29   Log-Likelihood:                -2373.9
No. Observations:                 230   AIC:                             4752.
Df Residuals:                     228   BIC:                             4759.
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
greqnt_conv   -63.7588     93.848     -0.679      0.498    -248.678     121.161
const        7.118e+04   1.45e+04      4.894      0.000    4.25e+04    9.98e+04
==============================================================================
Omnibus:                        0.003   Durbin-Watson:                   2.194
Prob(Omnibus):                  0.998   Jarque-Bera (JB):                0.066
Skew:                           0.004   Prob(JB):                        0.968
Kurtosis:                       2.918   Cond. No.                     4.63e+03
==============================================================================
```

```
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.63e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```