Project 1

September 11, 2019

1 Importing

In [1]:
```
import pandas as pd
import numpy as np
import statsmodels.api as sm
import statsmodels.formula.api as smf
import matplotlib.pyplot as plt
import matplotlib
```

In [2]:
```
url = 'https://raw.githubusercontent.com/fivethirtyeight/data/master/college-majors/re
data=pd.read_csv(url)
data.head()
#data.shape
```

Out[2]:

	Rank	Major_code	Major	Total	\
0	1	2419	PETROLEUM ENGINEERING	2339.0	
1	2	2416	MINING AND MINERAL ENGINEERING	756.0	
2	3	2415	METALLURGICAL ENGINEERING	856.0	
3	4	2417	NAVAL ARCHITECTURE AND MARINE ENGINEERING	1258.0	
4	5	2405	CHEMICAL ENGINEERING	32260.0	

	Men	Women	Major_category	ShareWomen	Sample_size	Employed	...	\
0	2057.0	282.0	Engineering	0.120564	36	1976	...	
1	679.0	77.0	Engineering	0.101852	7	640	...	
2	725.0	131.0	Engineering	0.153037	3	648	...	
3	1123.0	135.0	Engineering	0.107313	16	758	...	
4	21239.0	11021.0	Engineering	0.341631	289	25694	...	

	Part_time	Full_time_year_round	Unemployed	Unemployment_rate	Median	\
0	270	1207	37	0.018381	110000	
1	170	388	85	0.117241	75000	
2	133	340	16	0.024096	73000	
3	150	692	40	0.050125	70000	
4	5180	16697	1672	0.061098	65000	

	P25th	P75th	College_jobs	Non_college_jobs	Low_wage_jobs
0	95000	125000	1534	364	193

```
1  55000   90000          350               257            50
2  50000  105000          456               176             0
3  43000   80000          529               102             0
4  50000   75000        18314              4440           972

[5 rows x 21 columns]
```

- I want to understand any factors that might affect average earnings(Median).

2 Cleaning & Organizing

```
In [3]: #data.describe()
        data.dtypes
        list(data)
```

```
Out[3]: ['Rank',
         'Major_code',
         'Major',
         'Total',
         'Men',
         'Women',
         'Major_category',
         'ShareWomen',
         'Sample_size',
         'Employed',
         'Full_time',
         'Part_time',
         'Full_time_year_round',
         'Unemployed',
         'Unemployment_rate',
         'Median',
         'P25th',
         'P75th',
         'College_jobs',
         'Non_college_jobs',
         'Low_wage_jobs']
```

```
In [4]: data2 = data.drop([21],axis = 0)
        data2[['Median', 'ShareWomen','Low_wage_jobs']] = data[['Median','ShareWomen','Low_wage
        data2.rename(columns={'Unemployment_rate':'UnemploymentRate','Non_college_jobs':'NonCJ
        #data2['ShareWomen']= data2['ShareWomen']*100
        #data2.dtypes
        data3 = data2.drop(columns = ['Major_code'])
        data3.head()
```

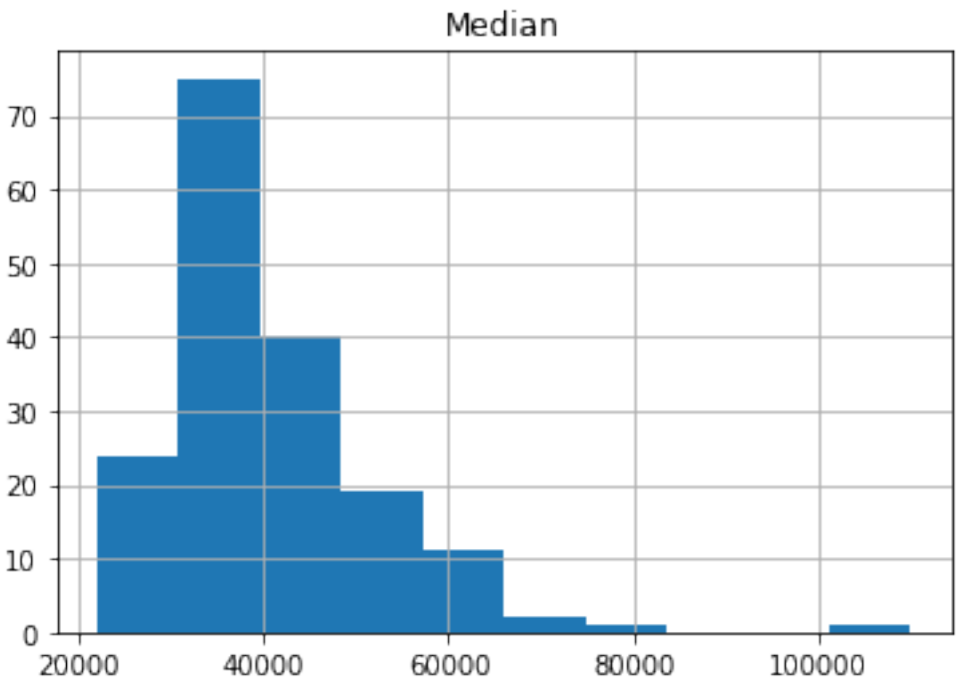
```
Out[4]:    Rank                                    Major    Total      Men    Women  \
        0     1                  PETROLEUM ENGINEERING   2339.0   2057.0    282.0
        1     2          MINING AND MINERAL ENGINEERING    756.0    679.0     77.0
```

```
2     3                  METALLURGICAL ENGINEERING    856.0    725.0    131.0
3     4  NAVAL ARCHITECTURE AND MARINE ENGINEERING   1258.0   1123.0    135.0
4     5                       CHEMICAL ENGINEERING  32260.0  21239.0  11021.0

  Major_category  ShareWomen  Sample_size  Employed  Full_time  Part_time  \
0    Engineering    0.120564           36      1976       1849        270
1    Engineering    0.101852            7       640        556        170
2    Engineering    0.153037            3       648        558        133
3    Engineering    0.107313           16       758       1069        150
4    Engineering    0.341631          289     25694      23170       5180

   Full_time_year_round  Unemployed  UnemploymentRate    Median  P25th  \
0                  1207          37          0.018381  110000.0  95000
1                   388          85          0.117241   75000.0  55000
2                   340          16          0.024096   73000.0  50000
3                   692          40          0.050125   70000.0  43000
4                 16697        1672          0.061098   65000.0  50000

    P75th  College_jobs  NonCJobs  LowWage
0  125000          1534       364    193.0
1   90000           350       257     50.0
2  105000           456       176      0.0
3   80000           529       102      0.0
4   75000         18314      4440    972.0
```

3 Graphing

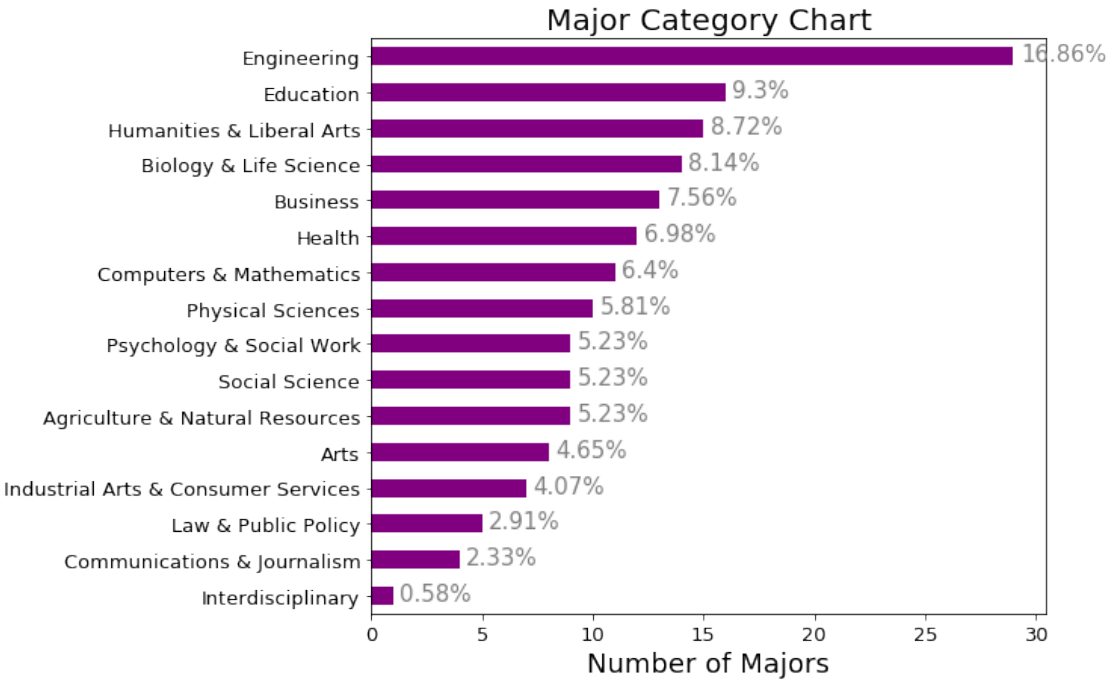
- Generate at least 3 graphs, whatever you like or are curious about, to explore your ideas
- Give brief explanations for why you include the graphs you did and what you've learned.

```
In [5]: data.hist('Median')

Out[5]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1c198d3898>]],
              dtype=object)
```



- Average Median will be around 40000.

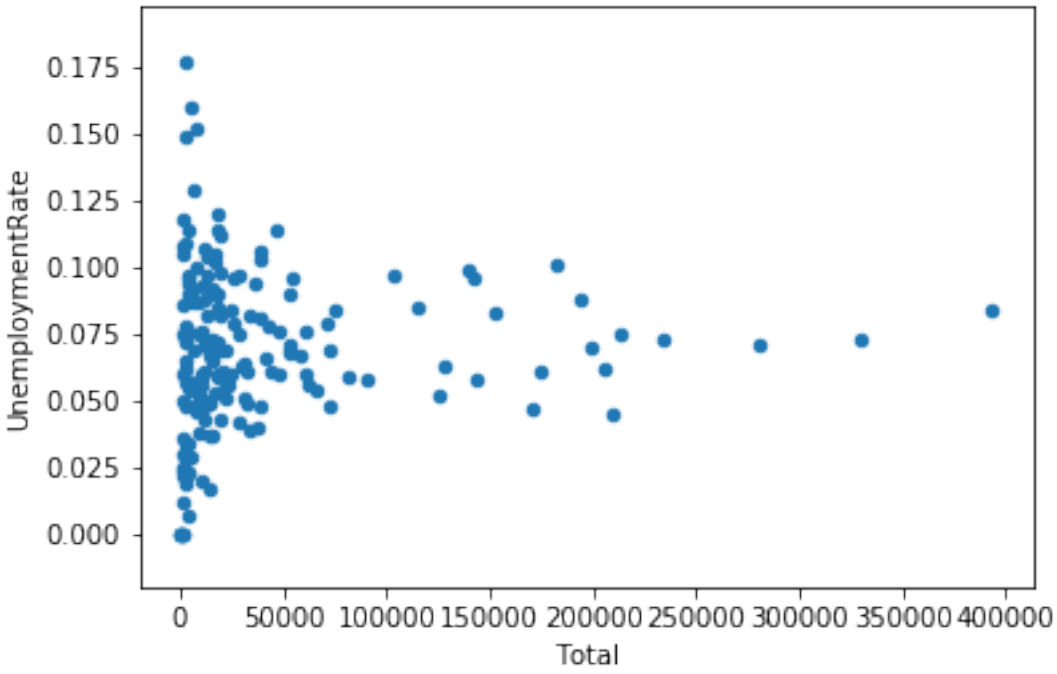
```
In [6]: data4 = data3['Major_category'].value_counts()
        #data4.plot.barh()
        ax = data4.plot(kind='barh', figsize=(8,7), color="purple", fontsize=13)
        ax.set_alpha(0.8)
        ax.set_title("Major Category Chart", fontsize=20)
        ax.set_xlabel("Number of Majors", fontsize=18);
        ax.set_xticks([0, 5, 10, 15, 20, 25, 30])
        # create a list to collect the plt.patches data
        totals = []
        # find the values and append to list
        for i in ax.patches:
            totals.append(i.get_width())
        # set individual bar lables using above list
        total = sum(totals)
        # set individual bar lables using above list
        for i in ax.patches:
        # get_width pulls left or right; get_y pushes up or down
            ax.text(i.get_width()+.3, i.get_y()+.38, \
        str(round((i.get_width()/total)*100,2))+'%', fontsize=15,
        color='grey')
        # invert for largest on top
        ax.invert_yaxis()
```



- Bar graph is suitable when dealing with categorical data. Number of majors in the categories are within 20 except engineering.

```
In [7]: data3.plot.scatter('Total','UnemploymentRate')
```

```
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1c19ca4470>
```



- No clear relationship between class size and unemployment rate

4 Analyzing

- Identify at least 3 trends or patterns you think are interesting by manipulating the table.

```
In [8]: datae = data3.loc[data3['Major_category'] == 'Engineering']
        datae.describe()
```

Out[8]:

	Rank	Total	Men	Women	ShareWomen
count	29.000000	29.000000	29.000000	29.000000	29.000000
mean	22.620690	18537.344828	14079.551724	4457.793103	0.238889
std	18.640229	25231.657274	20413.370507	5788.262905	0.101771
min	1.000000	720.000000	488.000000	77.000000	0.077453
25%	10.000000	2906.000000	2200.000000	506.000000	0.153037
50%	17.000000	4790.000000	4419.000000	1385.000000	0.227118
75%	31.000000	18968.000000	12953.000000	6548.000000	0.322222
max	67.000000	91227.000000	80320.000000	20957.000000	0.451465

	Sample_size	Employed	Full_time	Part_time
count	29.000000	29.000000	29.000000	29.000000
mean	169.862069	14495.586207	13167.827586	2935.724138
std	240.169245	19947.570356	18221.877254	3919.031357
min	3.000000	604.000000	524.000000	126.000000
25%	26.000000	2449.000000	2038.000000	343.000000
50%	71.000000	4428.000000	4175.000000	1040.000000
75%	183.000000	15604.000000	14879.000000	2724.000000
max	1029.000000	76442.000000	71298.000000	13101.000000

	Full_time_year_round	Unemployed	UnemploymentRate	Median
count	29.000000	29.000000	29.000000	29.000000
mean	9963.862069	1028.172414	0.063334	57382.758621
std	13932.153015	1416.339953	0.034998	13626.079747
min	340.000000	16.000000	0.006334	40000.000000
25%	1449.000000	78.000000	0.042876	50000.000000
50%	3413.000000	400.000000	0.059824	57000.000000
75%	11326.000000	1019.000000	0.075038	60000.000000
max	54639.000000	4650.000000	0.177226	110000.000000

	P25th	P75th	College_jobs	NonCJobs	LowWage
count	29.000000	29.000000	29.000000	29.000000	29.000000
mean	41555.172414	70448.275862	9302.310345	3530.448276	864.793103
std	12553.132398	16938.093599	13820.546496	4473.251866	1198.416824
min	25000.000000	50000.000000	350.000000	50.000000	0.000000
25%	35000.000000	60000.000000	1394.000000	649.000000	142.000000

```
50%    40000.000000   67000.000000   2446.000000   2121.000000   372.000000
75%    45000.000000   75000.000000   8306.000000   3896.000000   789.000000
max    95000.000000  125000.000000  52844.000000  16384.000000  4221.000000
```

```
In [9]: data3.describe()
```

```
Out[9]:              Rank          Total            Men          Women  ShareWomen  \
count  172.000000     172.000000     172.000000     172.000000  172.000000
mean    87.377907   39370.081395   16723.406977   22646.674419    0.522223
std     49.983181   63483.491009   28122.433474   41057.330740    0.231205
min      1.000000     124.000000     119.000000       0.000000    0.000000
25%     44.750000    4549.750000    2177.500000    1778.250000    0.336026
50%     87.500000   15104.000000    5434.000000    8386.500000    0.534024
75%    130.250000   38909.750000   14631.000000   22553.750000    0.703299
max    173.000000  393735.000000  173809.000000  307087.000000    0.968954

       Sample_size      Employed      Full_time      Part_time  \
count   172.000000     172.00000     172.000000     172.000000
mean    357.941860   31355.80814   26165.767442    8877.232558
std     619.680419   50777.42865   42957.122320   14679.038729
min       2.000000       0.00000     111.000000       0.000000
25%      42.000000    3734.75000    3181.000000    1013.750000
50%     131.000000   12031.50000   10073.500000    3332.500000
75%     339.000000   31701.25000   25447.250000    9981.000000
max    4212.000000  307933.00000  251540.000000  115172.000000

       Full_time_year_round    Unemployed  UnemploymentRate         Median  \
count            172.000000    172.000000        172.000000     172.000000
mean           19798.843023   2428.412791          0.068024   40076.744186
std            33229.227514   4121.730452          0.030340   11461.388773
min              111.000000      0.000000          0.000000   22000.000000
25%             2474.750000    299.500000          0.050261   33000.000000
50%             7436.500000    905.000000          0.067544   36000.000000
75%            17674.750000   2397.000000          0.087247   45000.000000
max           199897.000000  28169.000000          0.177226  110000.000000

                P25th          P75th   College_jobs       NonCJobs       LowWage
count      172.000000     172.000000     172.000000     172.000000    172.000000
mean     29486.918605   51386.627907   12387.401163   13354.325581   3878.633721
std       9190.769927   14882.278650   21344.967522   23841.326605   6960.467621
min      18500.000000   22000.000000       0.000000       0.000000      0.000000
25%      24000.000000   41750.000000    1744.750000    1594.000000    336.750000
50%      27000.000000   47000.000000    4467.500000    4603.500000   1238.500000
75%      33250.000000   58500.000000   14595.750000   11791.750000   3496.000000
max      95000.000000  125000.000000  151643.000000  148395.000000  48207.000000
```

- Mean value for median earnings of engineering majors was higher compare to the whole data.

```
In [10]: data3['SharePercentile'] = pd.qcut(data3['ShareWomen'],100,labels=False,
                                            duplicates = 'drop')
         #data3['UnempRatePercentile'] = pd.qcut(data3['UnemploymentRate'],100,labels=False,du
         data3.head()
         data3.sort_values('SharePercentile',ascending=False).head()
         data3.sort_values('SharePercentile',ascending=True).head()
```

Out[10]:

	Rank	Major	Total	Men	Women	Major_category	ShareWomen	Sample_size	Employed	Full_time	...	Full_time_year_round	Unemployed	UnemploymentRate	Median	P25th	P75th	College_jobs	NonCJobs	LowWage	SharePercentile
73	74	MILITARY TECHNOLOGIES	124.0	124.0	0.0	Industrial Arts & Consumer Services	0.000000	4	0	111	...	111	0	0.000000	40000.0	40000	40000	0	0	0.0	0
66	67	MECHANICAL ENGINEERING RELATED TECHNOLOGIES	4790.0	4419.0	371.0	Engineering	0.077453	71	4186	4175	...	3607	250	0.056357	40000.0	27000	52000	1861	2121	406.0	0
1	2	MINING AND MINERAL ENGINEERING	756.0	679.0	77.0	Engineering	0.101852	7	640	556	...	388	85	0.117241	75000.0	55000	90000	350	257	50.0	1
26	27	CONSTRUCTION SERVICES	18498.0	16820.0	1678.0	Industrial Arts & Consumer Services	0.090713	295	16318	15690	...	12313	1042	0.060023	50000.0	36000	60000	3275	5351	703.0	1
3	4	NAVAL ARCHITECTURE AND MARINE ENGINEERING	1258.0	1123.0	135.0	Engineering	0.107313	16	758	1069	...	692	40	0.050125	70000.0	43000	80000	529	102	0.0	2

[5 rows x 21 columns]

- Health and Education majors have the highest ShareWomen percentile, while Engineering and Military tech major have the lowest. Highest percentile has value around 0.97 and the lowest percentiles have value around 0-0.08

```
In [11]: data3.sort_values('Total',ascending=False).head()
```

```
Out[11]:      Rank                                Major     Total       Men  \
         145   146                           PSYCHOLOGY  393735.0   86648.0
         76     77  BUSINESS MANAGEMENT AND ADMINISTRATION  329927.0  173809.0
         123   124                             BIOLOGY  280709.0  111762.0
         57     58                      GENERAL BUSINESS  234590.0  132238.0
         93     94                        COMMUNICATIONS  213996.0   70619.0

                Women               Major_category  ShareWomen  Sample_size  Employed  \
         145  307087.0     Psychology & Social Work    0.779933         2584    307933
         76   156118.0                     Business    0.473190         4212    276234
         123  168947.0       Biology & Life Science    0.601858         1370    182295
         57   102352.0                     Business    0.436302         2380    190183
         93   143377.0  Communications & Journalism    0.669999         2394    179633

              Full_time  ...  Full_time_year_round  Unemployed  UnemploymentRate  \
         145     233205  ...                174438       28169          0.083811
         76      251540  ...                199897       21502          0.072218
         123     144512  ...                100336       13874          0.070725
         57      171385  ...                138299       14946          0.072861
         93      147335  ...                116251       14602          0.075177

               Median  P25th  P75th  College_jobs  NonCJobs  LowWage  SharePercentile
         145  31500.0  24000  41000        125148    141860  48207.0               87
         76   38000.0  29000  50000         36720    148395  32395.0               41
         123  33400.0  24000  45000         88232     81109  28339.0               59
         57   40000.0  30000  55000         29334    100831  27320.0               36
         93   35000.0  27000  45000         40763     97964  27440.0               68

         [5 rows x 21 columns]
```

- Psychology and Business major have the largest class size.

5 Hypothesis formation

5.1 Write out your regression model as an equation, with "ladder" as the DV.

Median = aShareWomen + bCollegeJobs + c

5.2 What are your IVs, and why? What do you expect to find?

IV = ShareWomen and Non College Jobs. I saw a tweet that says gender ratio affect the earnings of an industry. I expect negative 'a'. Also, people say college degree payoffs. Thus, I expect positive 'b'

5.3 Formally write your null and alternative hypotheses.

- H1 = There is positive relationship between College Jobs and Meidan; negative relationship between sharewomen and median.
- H0 = There is no relationship between Median, share women, and non college jobs.

6 Regression

```
In [12]: X = data3[['ShareWomen','College_jobs']]
         Y = data3['Median']
         X = sm.add_constant(X)

         model = sm.OLS(Y, X).fit()
         predictions = model.predict(X)

         print_model = model.summary()
         print(print_model)
```

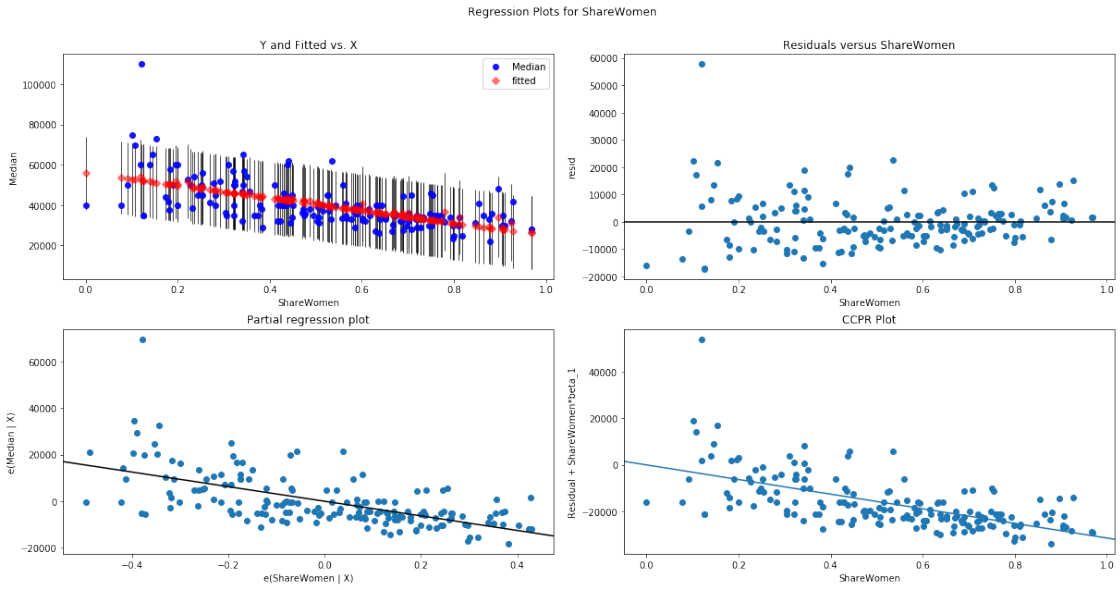
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Median   R-squared:                       0.388
Model:                            OLS   Adj. R-squared:                  0.381
Method:                 Least Squares   F-statistic:                     53.68
Date:                Wed, 05 Jun 2019   Prob (F-statistic):           8.97e-19
Time:                        21:19:03   Log-Likelihood:                -1808.9
No. Observations:                 172   AIC:                             3624.
Df Residuals:                     169   BIC:                             3633.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       5.597e+04   1705.051     32.827      0.000    5.26e+04    5.93e+04
ShareWomen -3.142e+04   3040.717    -10.331      0.000   -3.74e+04   -2.54e+04
College_jobs     0.0413      0.033      1.253      0.212      -0.024       0.106
==============================================================================
Omnibus:                       94.383   Durbin-Watson:                   0.727
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              699.740
Skew:                           1.891   Prob(JB):                    1.13e-152
Kurtosis:                      12.129   Cond. No.                     1.22e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.22e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
/anaconda3/lib/python3.7/site-packages/numpy/core/fromnumeric.py:2389: FutureWarning: Method .p
  return ptp(axis=axis, out=out, **kwargs)
```

```
In [13]: results = smf.ols('Median ~ ShareWomen', data=data3).fit()
         results.summary()
```

Out[13]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Median   R-squared:                       0.383
Model:                            OLS   Adj. R-squared:                  0.379
Method:                 Least Squares   F-statistic:                     105.4
Date:                Wed, 05 Jun 2019   Prob (F-statistic):           1.51e-19
Time:                        21:19:03   Log-Likelihood:                -1809.7
No. Observations:                 172   AIC:                             3623.
Df Residuals:                     170   BIC:                             3630.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   5.609e+04   1705.115     32.897      0.000    5.27e+04    5.95e+04
ShareWomen -3.067e+04   2987.010    -10.268      0.000   -3.66e+04   -2.48e+04
==============================================================================
Omnibus:                       92.256   Durbin-Watson:                   0.732
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              659.444
Skew:                           1.851   Prob(JB):                     6.36e-144
Kurtosis:                      11.850   Cond. No.                         5.57
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
"""
```

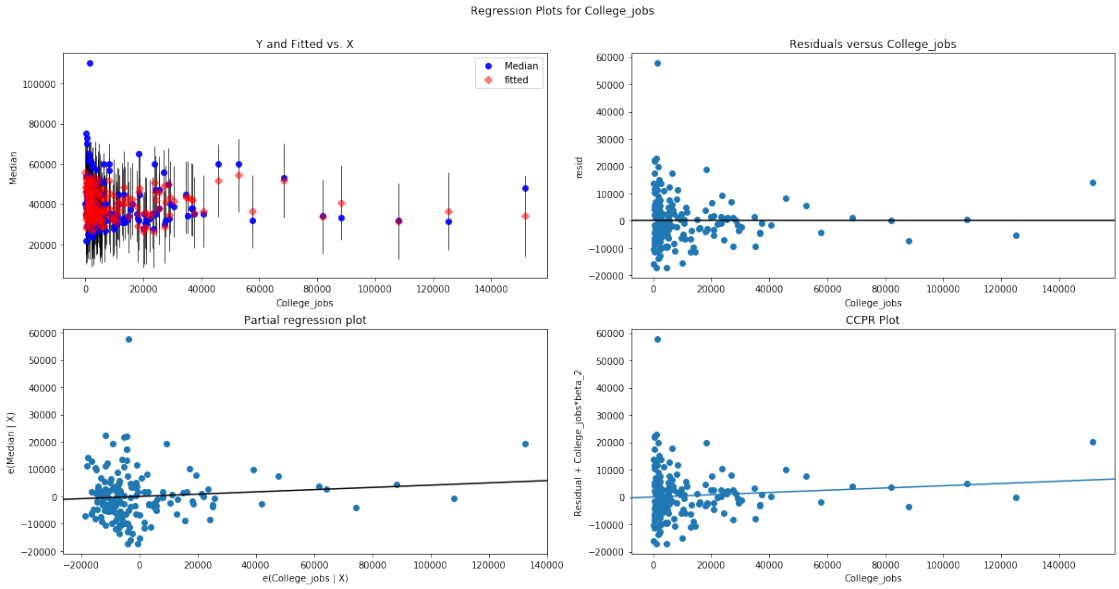
In [14]:
```
fig = plt.figure(figsize=(17,9))
fig = sm.graphics.plot_regress_exog(model, 'ShareWomen', fig=fig)
```



In [15]:
```
results = smf.ols('Median ~ College_jobs', data=data3).fit()
results.summary()
```

Out[15]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Median   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                 -0.004
Method:                 Least Squares   F-statistic:                    0.3773
Date:                Wed, 05 Jun 2019   Prob (F-statistic):              0.540
Time:                        21:19:04   Log-Likelihood:                -1851.0
No. Observations:                 172   AIC:                             3706.
Df Residuals:                     170   BIC:                             3712.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   4.039e+04   1013.019     39.871      0.000    3.84e+04    4.24e+04
College_jobs    -0.0253      0.041     -0.614      0.540      -0.106       0.056
==============================================================================
Omnibus:                       94.209   Durbin-Watson:                   0.061
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              513.545
Skew:                           2.030   Prob(JB):                    3.06e-112
Kurtosis:                      10.428   Cond. No.                     2.85e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
[2] The condition number is large, 2.85e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

In [16]:
```
fig = plt.figure(figsize=(17,9))
fig = sm.graphics.plot_regress_exog(model, 'College_jobs', fig=fig)
```



7 Interpretation & diagnostics

7.1 What do the results mean? Interpret the coefficient, p-values, and confidence intervals for each coefficient (you don't have to do the intercept), and the R2 and Adj. R2 (if relevant), and prof(F) for the whole model.

- coefficient for ShareWomen=-3.142e+04, meaning when ShareWomen increases by 1unit, Median decreases by $31420.
- coeff for college jobs = 0.04, meaning when college jobs increses by 1 unit, Median increases by 0.04.
- p-value for ShareWomen=0, rejecting the null hypothesis at a 95% confidence threshold. However, the p value for college jobs is 0.212. Thus, we cannot reject the null hypothesis.
- If we repeat the analysis with other samples, 95% of the time [-3.74e+04 ~ -2.54e+04] will capture the true value for shareWomen coefficient. Similarly, [-0.024 ~ 0.106] for college jobs coefficient.
- R2 = 0.388, adj R2 = 0.381. As a whole, this model captures 38.8% of the variance of the median. When adding college jobs, R2 value decreased to 0.383; adding variable did not increase the explanatory power of the model. R^2 and adj R^2 value for ShareWomen and college jobs are different. The possible reason is that the datasets are discrete.

7.2 Which hypotheses do you reject and fail to reject, and why?

Prob F is a probability the null hypothesis in the model cannot be rejected. In this case, 8.97e- 19. Since it is small, we can say that the independent variables affect Median.

7.3 Does this model satisfy the major assumptions of OLS regression? Evaluate your model according to each one.

- The sample size is more than 20 or 30. Compare to the sample size, there is little outliers. However, if we remove it, the coefficient for ShareWomen might decrease slightly.
- Scatter plot for median and ShareWomen is linear. For college jobs, it is hard to say that the plot is linear.
- Since adding variable has little change to the coefficients, there is little multicollinearity. Prob F for median & college jobs was relatively large, thus we can drop the college jobs in the equation.
- Heteroscedasticity occurs for college jobs (fan shape). ShareWomen is homoscedastic.
- No autocorrelation since the data is not dealing with time series.

8 Conclusions

8.1 What biases might be present in the sample itself that could be affecting this outcome?

- Response bias: The data is self-reported through American Community survey.
- Selection bias: Access to the survey is not clear.
- Information bias: random error might occur when putting data.
- Invisibility bias: List of majors and major categories are from Carnevale et al, "What's It Worth?: The Economic Value of College Majors." Thus, some majors may be missing.

8.2 Overall, are you confident in your findings? Why or why not? What might improve this analysis? (This can be about anythign from the original data, bias, and/or results and diagnostics.)

I am not confident with the result since the original data aggregates and rounds individual data. However, assuming the data is reliable, I am confident that there is a weak negative relationship between women ratio and earnings. At the same time, I am not confident with the result from testing college jobs and median. Having more college degree jobs does not increase earnings significantly, and R2 value was low. I can improve the analysis by adding more majors and increasing the sample size. For further study, analyzing with different independent variables or data from a different organization can be done.