

Siddhant Rai

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PREPARING DATA

1. Education

```
#Create continuous for EDUCD
acs_data = pd.merge(acs_data, crosswalk, left_on='EDUCD', right_on='educd')
acs_data
```

	YEAR	SAMPLE	SERIAL	CBSERIAL	HHWT	CLUSTER	STRATA	GQ	PERNUM	PERWT	NCHILD	NCHLT5	SEX	AGE	MARST	RACE
0	2019	201901	2811	2019000016124	19504.8	20190000026111	80001	1	1	19659.6	1	1	1	29	1	1
1	2019	201901	6016	2019000247422	1702.8	2019000060161	230001	1	1	1702.8	3	1	1	41	1	1
2	2019	201901	6790	2019000301008	8868.8	2019000067901	190001	1	3	20278.8	0	0	1	21	6	1
3	2019	201901	9577	2019000497180	42105.6	2019000095771	10001	1	1	42105.6	0	0	1	20	6	1
4	2019	201901	9731	2019000507929	7430.4	2019000097311	270201	1	1	7275.6	0	0	1	33	6	2
...
9049	2019	201901	1220732	2019000282619	28006.4	2019012207321	230548	1	1	25851.6	2	1	1	47	1	1
9050	2019	201901	1222589	2019000308283	33746.4	2019012225891	680448	1	2	30628.8	0	0	1	43	6	1
9051	2019	201901	1237295	2019000512472	20433.6	2019012372951	670248	1	2	21207.6	2	0	2	59	1	1
9052	2019	201901	1302776	2019001404140	27554.4	2019013027761	461548	1	1	27554.4	0	0	2	49	3	7
9053	2019	201901	1308039	2019000485767	13312.8	2019013080391	5700249	1	1	13312.8	2	0	1	61	1	1

RACED	HISPAN	HISPAND	EDUC	EDUCD	EMPSTAT	EMPSTATD	INCWAGE	VETSTAT	VETSTATD	educd	educdc
100	0	0	8	81	1	10	59000	1	11	81	14.0
100	0	0	8	81	1	10	50000	2	20	81	14.0
100	0	0	8	81	1	10	10000	1	11	81	14.0
100	0	0	8	81	1	10	800	1	11	81	14.0
200	0	0	8	81	1	10	45000	1	11	81	14.0
...
100	1	100	2	22	1	10	25000	1	11	22	5.0
100	1	100	2	22	1	10	21600	1	11	22	5.0
100	1	100	2	22	1	10	18000	1	11	22	5.0
700	4	416	2	22	1	10	17000	1	11	22	5.0
100	1	100	1	14	1	10	38000	1	11	14	1.0

2. Dummy Variables

```
#Get Dummies
acs_data['hsdip'] = np.where(acs_data['EDUCD'] == 63, 1, 0)
acs_data['coldip'] = np.where(acs_data['EDUCD'] == 101, 1, 0)
acs_data['white'] = np.where(acs_data['RACE'] == 1, 1, 0)
acs_data['black'] = np.where(acs_data['RACE'] == 2, 1, 0)
acs_data['hispanic'] = np.where(acs_data['RACE'] != 0, 1, 0)
acs_data['married'] = np.where(acs_data['MARST'] == 1, 1, 0)
acs_data['female'] = np.where(acs_data['SEX'] == 2, 1, 0)
acs_data['vet'] = np.where(acs_data['VETSTAT'] == 2, 1, 0)
acs_data.head()
```

educd	educdc	hsdip	coldip	white	black	hispanic	married	female	vet
81	14.0	0	0	1	0	1	1	0	0
81	14.0	0	0	1	0	1	1	0	1
81	14.0	0	0	1	0	1	0	0	0
81	14.0	0	0	1	0	1	0	0	0
81	14.0	0	0	0	1	1	0	0	0

3. Interaction Terms

```
#Interaction
acs_data['EDUC:educdc'] = acs_data['EDUC'].mul(acs_data['educdc'])
acs_data.head()
```

EDUC:educdc

112.0

112.0

112.0

112.0

112.0

4. Created Variables

```
#Age Squared
acs_data['AGE^2'] = np.power(acs_data['AGE'],2)
acs_data.head()
```

AGE^2

841

1681

441

400

1089

```
#Log of Wage
acs_data = acs_data[acs_data['INCWAGE'] != 0] #Only one row had a 0 so needed to remove it
acs_data['LNINCWAGE'] = np.log(acs_data['INCWAGE'])
acs_data.head()
```

LNINCWAGE

10.985293

10.819778

9.210340

6.684612

10.714418

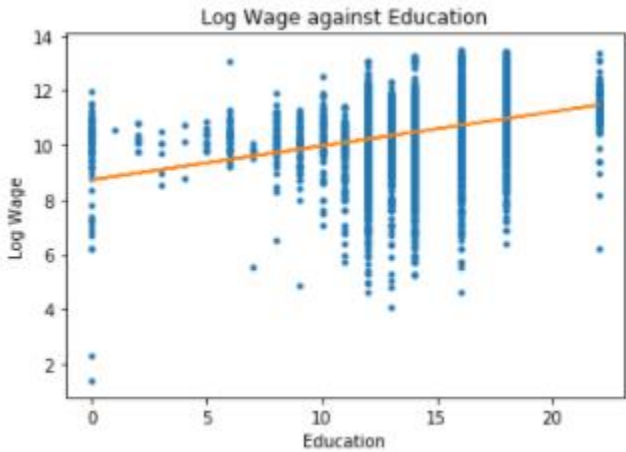
DATA ANALYSIS

1.

	YEAR	INCWAGE	LNINCWAGE	educdc	female	AGE	AGE^2	white	black	hispanic	married
count	8606.0	8606.000000	8606.000000	8606.000000	8606.000000	8606.000000	8606.000000	8606.000000	8606.000000	8606.0	8606.000000
mean	2019.0	58420.063212	10.496826	14.187427	0.486521	41.849059	1931.513479	0.773298	0.090286	1.0	0.525912
std	0.0	68115.268196	1.097734	2.857626	0.499847	13.423513	1126.920775	0.418723	0.286607	0.0	0.499357
min	2019.0	4.000000	1.386294	0.000000	0.000000	18.000000	324.000000	0.000000	0.000000	1.0	0.000000
25%	2019.0	22725.000000	10.031219	12.000000	0.000000	30.000000	900.000000	1.000000	0.000000	1.0	0.000000
50%	2019.0	41300.000000	10.628615	14.000000	0.000000	42.000000	1764.000000	1.000000	0.000000	1.0	1.000000
75%	2019.0	70750.000000	11.166889	16.000000	1.000000	54.000000	2916.000000	1.000000	0.000000	1.0	1.000000
max	2019.0	717000.000000	13.482831	22.000000	1.000000	65.000000	4225.000000	1.000000	1.000000	1.0	1.000000

NCHILD	vet	hsdip	coldip	EDUC:educdc
8606.000000	8606.000000	8606.000000	8606.000000	8606.000000
0.784801	0.049733	0.210783	0.236812	117.493028
1.100708	0.217405	0.407888	0.425150	51.649895
0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	72.000000
0.000000	0.000000	0.000000	0.000000	98.000000
1.000000	0.000000	0.000000	0.000000	160.000000
9.000000	1.000000	1.000000	1.000000	242.000000

2.



3.

```

=====
                        OLS Regression Results
=====
Dep. Variable:          LNINCWAGE      R-squared:                0.309
Model:                  OLS           Adj. R-squared:           0.308
Method:                 Least Squares   F-statistic:              426.4
Date:                   Sat, 30 Jan 2021 Prob (F-statistic):       0.00
Time:                   19:24:58       Log-Likelihood:          -11425.
No. Observations:      8606           AIC:                    2.287e+04
Df Residuals:          8596           BIC:                    2.294e+04
Df Model:               9
Covariance Type:       nonrobust
=====
                        coef      std err      t      P>|t|      [0.025      0.975]
-----
educdc      0.1112      0.004      31.564      0.000      0.104      0.118
female     -0.4338      0.020     -21.577      0.000     -0.473     -0.394
AGE         0.1567      0.006      27.646      0.000      0.146      0.168
AGE^2      -0.0016      6.7e-05     -24.270      0.000     -0.002     -0.001
white      -0.0297      0.029      -1.024      0.306     -0.087      0.027
black      -0.1875      0.043      -4.410      0.000     -0.271     -0.104
hispanic    5.6555      0.114     49.594      0.000      5.432      5.879
married     0.1955      0.023      8.450      0.000      0.150      0.241
NCHILD     -0.0063      0.010      -0.616      0.538     -0.026      0.014
vet         -0.0396      0.046      -0.856      0.392     -0.130      0.051
=====
Omnibus:            2437.163   Durbin-Watson:           1.867
Prob(Omnibus):      0.000   Jarque-Bera (JB):       10300.166
Skew:               -1.335   Prob(JB):               0.00
Kurtosis:           7.647   Cond. No.:              2.60e+04
=====

```

- The fraction of variation is the R^2 which from our results is 0.309 which indicates that around 30.9% of the log wage as the dependent variable can be explained by the predictor
- The F-statistics: 426.4 and Prob(F-statistic): 0 indicates that we reject the null hypothesis that $\ln(\text{wage})$ is not affected by any of the predictors
- An additional year of education increased the log wage by $(e^{(0.112)}-1)*100 = 11.85129 \sim 11.985\%$ and is statistically significant because we have a p-value of 0 which is less than 0.05.
- According to the model, the $\ln(\text{wage})$ will achieve the highest wage at Age 50.

```

d = {'AGE': [50]}
df = pd.DataFrame(data=d)
predictions = result.get_prediction(df)
predictions.summary_frame(alpha=0.05)

```

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	10.923088	0.08992	10.788029	11.060148	8.99937	12.846808

Intercept	8.5613	0.088	96.999	0.000	8.388	8.734
C(AGE)[T.19]	0.1403	0.118	1.192	0.233	-0.090	0.371
C(AGE)[T.20]	0.5995	0.119	5.020	0.000	0.365	0.834
C(AGE)[T.21]	0.8163	0.120	6.803	0.000	0.581	1.052
C(AGE)[T.22]	0.8900	0.113	7.889	0.000	0.669	1.111
C(AGE)[T.23]	1.2769	0.117	10.936	0.000	1.048	1.506
C(AGE)[T.24]	1.5024	0.116	12.901	0.000	1.274	1.731
C(AGE)[T.25]	1.5190	0.115	13.157	0.000	1.293	1.745
C(AGE)[T.26]	1.7094	0.115	14.859	0.000	1.484	1.935
C(AGE)[T.27]	1.8766	0.118	15.876	0.000	1.645	2.108
C(AGE)[T.28]	1.8940	0.114	16.649	0.000	1.671	2.117
C(AGE)[T.29]	1.7146	0.113	15.213	0.000	1.494	1.936
C(AGE)[T.30]	2.0496	0.111	18.489	0.000	1.832	2.267
C(AGE)[T.31]	1.9967	0.114	17.552	0.000	1.774	2.220
C(AGE)[T.32]	2.0790	0.115	18.134	0.000	1.854	2.304
C(AGE)[T.33]	1.9255	0.116	16.658	0.000	1.699	2.152
C(AGE)[T.34]	2.1251	0.112	18.928	0.000	1.905	2.345
C(AGE)[T.35]	1.9479	0.115	16.892	0.000	1.722	2.174
C(AGE)[T.36]	2.0875	0.112	18.593	0.000	1.867	2.308
C(AGE)[T.37]	2.2044	0.117	18.855	0.000	1.975	2.434
C(AGE)[T.38]	2.1583	0.114	18.868	0.000	1.934	2.382
C(AGE)[T.39]	2.3228	0.112	20.689	0.000	2.103	2.543
C(AGE)[T.40]	2.1019	0.115	18.313	0.000	1.877	2.327
C(AGE)[T.41]	2.1998	0.114	19.295	0.000	1.976	2.423
C(AGE)[T.42]	2.1307	0.114	18.770	0.000	1.908	2.353
C(AGE)[T.43]	2.1793	0.115	18.988	0.000	1.954	2.404
C(AGE)[T.44]	2.0735	0.115	17.960	0.000	1.847	2.300
C(AGE)[T.45]	2.2876	0.115	19.931	0.000	2.063	2.513
C(AGE)[T.46]	2.2064	0.115	19.134	0.000	1.980	2.432
C(AGE)[T.47]	2.1709	0.115	18.870	0.000	1.945	2.396
C(AGE)[T.48]	2.2629	0.115	19.738	0.000	2.038	2.488
C(AGE)[T.49]	2.3234	0.115	20.196	0.000	2.098	2.549
C(AGE)[T.50]	2.3618	0.113	20.975	0.000	2.141	2.583
C(AGE)[T.51]	2.2763	0.112	20.389	0.000	2.057	2.495
C(AGE)[T.52]	2.2442	0.112	19.989	0.000	2.024	2.464
C(AGE)[T.53]	2.1435	0.112	19.217	0.000	1.925	2.362
C(AGE)[T.54]	2.2303	0.111	20.085	0.000	2.013	2.448
C(AGE)[T.55]	2.1614	0.114	19.040	0.000	1.939	2.384
C(AGE)[T.56]	2.1321	0.108	19.776	0.000	1.921	2.343
C(AGE)[T.57]	2.3128	0.114	20.373	0.000	2.090	2.535
C(AGE)[T.58]	2.1994	0.111	19.736	0.000	1.981	2.418
C(AGE)[T.59]	2.1471	0.114	18.792	0.000	1.923	2.371
C(AGE)[T.60]	2.1243	0.116	18.355	0.000	1.897	2.351
C(AGE)[T.61]	2.0855	0.113	18.448	0.000	1.864	2.307
C(AGE)[T.62]	2.1106	0.116	18.192	0.000	1.883	2.338
C(AGE)[T.63]	1.9634	0.120	16.336	0.000	1.728	2.199
C(AGE)[T.64]	1.9695	0.120	16.439	0.000	1.735	2.204
C(AGE)[T.65]	2.0175	0.126	16.063	0.000	1.771	2.264

- e) The model predicts that men will have a slightly higher wage than females and according to our results the coefficient for females is -0.4338. We might investigate this pattern to see when males start to have a higher wage gap than females at a certain age, married status, or birth to a child

```
d = {'SEX': [1]}
df = pd.DataFrame(data=d)
predictions = result.get_prediction(df)
predictions.summary_frame(alpha=0.05)
```

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	10.89204	0.016234	10.861118	10.924762	8.577313	12.808567

```
d = {'SEX': [2]}
df = pd.DataFrame(data=d)
predictions = result.get_prediction(df)
predictions.summary_frame(alpha=0.05)
```

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	10.289845	0.016077	10.257153	10.322536	8.174204	12.405485

- f) Interpreting the coefficients White: -0.0297, Black:-0.1875, Hispanic: 5.655 indicates that Hispanics have the highest percentage increase in wages controlling for all variables, whites had a small decrease, but is NOT statistically significant, and blacks have the highest decrease in wages in 2019.

g) Null Hypothesis: $H_0: B_{\text{race}} = 0$

Alternative Hypothesis: $H_A: B_{\text{race}} \neq 0$

```

=====
                        OLS Regression Results
=====
Dep. Variable:          LNINCWAGE      R-squared:            0.001
Model:                  OLS            Adj. R-squared:       0.001
Method:                 Least Squares   F-statistic:          12.56
Date:                   Sun, 31 Jan 2021 Prob (F-statistic):    0.000397
Time:                   17:10:32        Log-Likelihood:       -13007.
No. Observations:       8606           AIC:                  2.602e+04
Df Residuals:           8604           BIC:                  2.603e+04
Df Model:                1
Covariance Type:        nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept              10.5374      0.016      639.840      0.000      10.505      10.570
RACE                   -0.0225      0.006      -3.543      0.000      -0.035      -0.010
=====
Omnibus:                1902.558      Durbin-Watson:        1.627
Prob(Omnibus):           0.000      Jarque-Bera (JB):      6042.310
Skew:                   -1.122      Prob(JB):              0.00
Kurtosis:                6.437      Cond. No.              3.89
=====

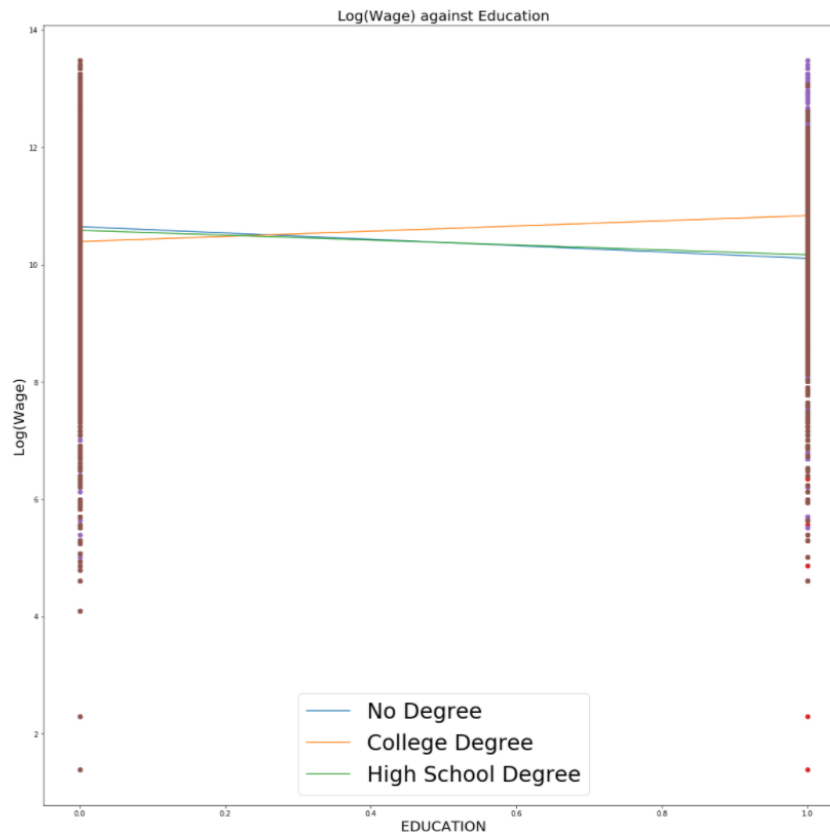
```

Warnings:

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

Running an OLS of LNWAGE on RACE. We reject the null hypothesis that race has nothing to do with wages because it is not statistically significant, but the variation is very small of R^2 at 0.001.

4. All three of the scatter plots in the graph below tend to overall each other. Also, College is shown to increase, while High School Diploma and No degree show a decrease.



- a) The wages which predict from our model which we get is a mean of \$1269.65

		High School	College
Intercept	4.034		
female	-0.4459	1	1
age	0.0168	22	22
age^2	0.004	484	484
white	-0.0294	0	0
black	-0.1537	0	0
hispanic	4.0434	0	0
married	0.2366	0	0
NCHILD	0.0803	0	0
vet	-0.0246	0	0
educdc	0.111	12	16
hsdip	-0.0396	1	1
coldip	0.1747	0	0
educdc:hsdip	-0.0033	12	16
educdc:coldip	0.0109	0	0
		7.1465	7.5773
		1269.654379	1953.348

- b) Yes, the individuals do receive a higher wage, and according to our model for the female student who got a college education, of about \$1953.35 which is a \$683 dollar increase with a collage degree
- c) From my point of view, it is crucial to expand college education to increase wages for male and female workers. However, allowing subsidies will increase the cost of attending college which can cause the students to fall into debt knowing college administrators can raise the prices because banks are providing easy money loans without any application.
7. To improve this model, I would probably include more interaction between education and variables such as Age, Married, and NCHILD to see where the increase or drop off is in wages. The reason why is when women give birth to a child wages tends to slip as they focus on more part-time jobs.