

Assignment 1_final

April 27, 2022

1 Preparation

```
[1]: import pandas as pd
import statsmodels.api as sm
from statsmodels.stats.diagnostic import het_white
import numpy as np
```

```
[2]: temp = pd.read_stata('Assignment_1(STAR).dta')
```

```
[3]: df = temp[["dist_cod", "county", "district", "enrl_tot", "teachers",
↪ "computer", "testscr", "comp_stu", "expn_stu", "str", "avginc", "el_pct",
↪ "read_scr", "math_scr"]]
```

```
[4]: df.head()
```

```
[4]:
```

	dist_cod	county		district	enrl_tot	teachers	\
0	75119.0	Alameda		Sunol Glen Unified	195.0	10.900000	
1	61499.0	Butte		Manzanita Elementary	240.0	11.150000	
2	61549.0	Butte		Thermalito Union Elementary	1550.0	82.900002	
3	61457.0	Butte		Golden Feather Union Elementary	243.0	14.000000	
4	61523.0	Butte		Palermo Union Elementary	1335.0	71.500000	

	computer	testscr	comp_stu	expn_stu	str	avginc	\
0	67.0	690.799988	0.343590	6384.911133	17.889910	22.690001	
1	101.0	661.200012	0.420833	5099.380859	21.524664	9.824000	
2	169.0	643.599976	0.109032	5501.954590	18.697226	8.978000	
3	85.0	647.700012	0.349794	7101.831055	17.357143	8.978000	
4	171.0	640.849976	0.128090	5235.987793	18.671329	9.080333	

	el_pct	read_scr	math_scr
0	0.000000	691.599976	690.000000
1	4.583333	660.500000	661.900024
2	30.000002	636.299988	650.900024
3	0.000000	651.900024	643.500000
4	13.857677	641.799988	639.900024

2 Q1:

CLRM assumptions A1-A6: 1. Linearity in Parameters 2. Random Sampling 3. Variation in X 4. Zero conditional mean 5. Homoskedasticity 6. Normality

OLS estimators requirements:

- 1) **unbiased:** If our linear regression model follows A1-A4 it should be unbiased.
- 2) **BLUE:** A1-A5 If our linear regression model follows A1-A5 it should be BLUE.
- 3) **BUE:** A1-A6 If our linear regression model follows A1-A6 it should be BUE.

3 Q2:

```
[17]: Y = df["testscr"]
      X = df["str"]
      X = sm.add_constant(X)
      model = sm.OLS(Y, X)
      results = model.fit()
```

```
[6]: results.summary()
```

```
[6]: <class 'statsmodels.iolib.summary.Summary'>
     """
           OLS Regression Results
=====
Dep. Variable:          testscr    R-squared:            0.051
Model:                  OLS       Adj. R-squared:       0.049
Method:                 Least Squares   F-statistic:         22.58
Date:                  Wed, 27 Apr 2022   Prob (F-statistic):   2.78e-06
Time:                  20:41:29          Log-Likelihood:      -1822.2
No. Observations:      420              AIC:                3648.
Df Residuals:          418              BIC:                3657.
Df Model:              1
Covariance Type:       nonrobust
=====
               coef    std err          t      P>|t|      [0.025      0.975]
-----
const         698.9330     9.467     73.825     0.000     680.323     717.543
str           -2.2798     0.480    -4.751     0.000     -3.223     -1.337
=====
Omnibus:                 5.390    Durbin-Watson:           0.129
Prob(Omnibus):            0.068    Jarque-Bera (JB):        3.589
Skew:                    -0.012    Prob(JB):                0.166
Kurtosis:                 2.548    Cond. No.                207.
=====
```

Notes:

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

$$SE(\beta_0) = 9.467$$

$$SE(\beta_1) = 0.48$$

4 Q3: β_1 estimates

4.1 t -statistic = -4.751

```
[7]: results.tvalues
```

```
[7]: const    73.824514
      str      -4.751327
      dtype: float64
```

4.2 p -value = 0.000

```
[8]: results.pvalues
```

```
[8]: const    6.569925e-242
      str      2.783307e-06
      dtype: float64
```

4.3 Inference

$$H_0: \beta_1 = 0$$

Since the p -value is less than 0.05, we reject the null hypothesis.

5 Q4:

HC0: White's (1980) heteroskedasticity robust standard errors

```
[9]: results_hetero = model.fit(cov_type='HC0')
```

```
[10]: results_hetero.summary()
```

```
[10]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                                OLS Regression Results
=====
Dep. Variable:                  testscr    R-squared:                0.051
Model:                            OLS      Adj. R-squared:            0.049
Method:                 Least Squares    F-statistic:                 19.35
Date:                   Wed, 27 Apr 2022    Prob (F-statistic):          1.38e-05
```

```

Time:                20:41:30    Log-Likelihood:        -1822.2
No. Observations:    420        AIC:                3648.
Df Residuals:        418        BIC:                3657.
Df Model:            1
Covariance Type:      HCO

```

```

=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
const         698.9330      10.340      67.597      0.000      678.668      719.198
str           -2.2798       0.518     -4.399      0.000      -3.296      -1.264
=====

```

```

Omnibus:                5.390    Durbin-Watson:           0.129
Prob(Omnibus):           0.068    Jarque-Bera (JB):        3.589
Skew:                   -0.012    Prob(JB):               0.166
Kurtosis:               2.548    Cond. No.               207.
=====

```

Notes:

```

[1] Standard Errors are heteroscedasticity robust (HCO)
"""

```

$$SE(\beta_0) = 10.340$$

$$SE(\beta_1) = 0.518$$

Answer for question 3. won't change.

6 Q5:

R-square = 0.051

A low R-squared value indicates that the independent variable is not explaining much in the variation of your dependent variable regardless of the variable significance, this is letting you know that the identified independent variable, even though significant, is not accounting for much of the mean of your dependent variable. We may want to add more non-correlated independent variables to the model variables that some how relate to the dependent variable.

7 Q6:

```
[11]: df["str"].describe()
```

```

[11]: count    420.000000
      mean      19.640427
      std       1.891812
      min      14.000000
      25%      18.582360
      50%      19.723208
      75%      20.871815

```

```
max          25.799999
Name: str, dtype: float64
```

If we have an additional education district with a student teacher ratio of merely 5, the average test score will go up.

8 Q7:

```
[18]: X_new = df[["str","avginc","expn_stu"]]
      X_new = sm.add_constant(X_new)
      model = sm.OLS(Y, X_new)
      results_new = model.fit()
```

```
[13]: results_new.summary()
```

```
[13]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                        OLS Regression Results
=====
Dep. Variable:          testscr      R-squared:                0.519
Model:                  OLS         Adj. R-squared:            0.516
Method:                 Least Squares   F-statistic:           149.9
Date:                  Wed, 27 Apr 2022   Prob (F-statistic):    7.65e-66
Time:                  20:41:30         Log-Likelihood:        -1679.4
No. Observations:      420             AIC:                  3367.
Df Residuals:          416             BIC:                  3383.
Df Model:               3
Covariance Type:       nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
const          669.7451      13.974      47.928      0.000      642.277      697.213
str             -1.3258       0.437      -3.035      0.003       -2.184       -0.467
avginc          1.8944       0.095     20.039      0.000        1.709        2.080
expn_stu       -0.0035       0.001      -2.616      0.009       -0.006       -0.001
=====
Omnibus:                 2.414    Durbin-Watson:              0.693
Prob(Omnibus):           0.299    Jarque-Bera (JB):         2.489
Skew:                   -0.165    Prob(JB):                 0.288
Kurtosis:                2.819    Cond. No.                 1.16e+05
=====
```

Notes:

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

[2] The condition number is large, 1.16e+05. This might indicate that there are

strong multicollinearity or other numerical problems.
"""

- The coef of **str** increases from -2.2798 to -1.3258.
- R-square increases from 0.051 to 0.519.
- Adding more valuable x variables makes the prediction better(considering Adj. R-squared also improves lots).

9 Q8:

Tests under heteroskedasticity assumptions that $\text{avginc} = \text{expn_stu} = 0$

```
[14]: B = np.array([[0,0,1,0],[0,0,0,1]])  
  
print(results_new.f_test(B))
```

```
<F test: F=array([[202.60802797]]), p=3.6666287886540695e-62, df_denom=416,  
df_num=2>
```

Tests under heteroskedasticity assumptions that each coefficient is jointly statistically significantly different from zero.

```
[15]: A = np.identity(len(results_new.params))  
A = A[1:,:]   
  
print(results_new.f_test(A))
```

```
<F test: F=array([[149.85594469]]), p=7.651663583855308e-66, df_denom=416,  
df_num=3>
```

As a result, we can reject the null hypothesis that $\text{avginc}=0$ and $\text{expn_stu}=0$ since the p value is less than given significance level.