

# Homework2

April 6, 2024

## 1 Homework 2 by Wei Minn

### 1.1 Question 1 Findings

Vanilla OLS coefficients, OLS coefficients with White SE, OLS coefficients Clustered by Firm and Year, and Fama-Macbeth coefficients produce roughly the same Standard Errors ( $\simeq 0.028$  for the constant and  $\simeq 0.28$  for the independent variable) and T-statistics ( $\simeq 1.05$  for the constant and  $\simeq 36.2$  for the independent variable).

On the other hand, OLS coefficients Clustered by Firm and OLS coefficients Clustered by Year produce roughly the same Standard Errors ( $\simeq 0.023$  for the constant and  $\simeq 0.033$  for the independent variable) and T-statistics ( $\simeq 1.27$  for the constant and  $\simeq 30.99$  for the independent variable).

The code for processing the data and producing the coefficients and standard errors are shown in the below sections.

#### 1.1.1 Import Libraries

```
[ ]: import numpy as np
import pandas as pd
import re
import statsmodels.api as sm
```

#### 1.1.2 Import Data

```
[ ]: data = []
with open("test_data.txt", "r") as file:
    for line in file:
        # Process each line here
        _line = line.strip()
        __line = re.sub(r"\s+", ' ', line)
        splitted = __line.split(' ')
        data.append(splitted[1:-1])

df = pd.DataFrame(np.array(data, dtype=float))
df
```

```
[ ]:      0      1      2      3
0      1.0      1.0 -1.113973  2.251535
```

```

1      1.0    2.0 -0.080854  1.242346
2      1.0    3.0 -0.237607 -1.426376
3      1.0    4.0 -0.152486 -1.109394
4      1.0    5.0 -0.001426  0.914686
...    ...    ...    ...    ...
4995   500.0    6.0 -0.077057  3.720502
4996   500.0    7.0  0.218847  0.559121
4997   500.0    8.0 -0.155530 -3.766785
4998   500.0    9.0 -0.040172  0.903354
4999   500.0   10.0 -0.001172 -0.529761

```

[5000 rows x 4 columns]

Save Data

```
[ ]: df.to_csv('./hw2.csv')
```

### 1.1.3 OLS Coefficients and Standard Errors

```
[ ]: X = df[2].to_numpy()
X = sm.add_constant(X)
y = df[3].to_numpy()
model = sm.OLS(y, X)
results = model.fit()
print(results.summary())
```

#### OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.208
Model:                OLS      Adj. R-squared:       0.208
Method:              Least Squares      F-statistic:       1311.
Date:                Fri, 05 Apr 2024      Prob (F-statistic):   4.25e-255
Time:                22:55:34      Log-Likelihood:      -10573.
No. Observations:      5000      AIC:                2.115e+04
Df Residuals:          4998      BIC:                2.116e+04
Df Model:              1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0297	0.028	1.047	0.295	-0.026	0.085
x1	1.0348	0.029	36.204	0.000	0.979	1.091

```

=====
Omnibus:              4.912      Durbin-Watson:       1.096
Prob(Omnibus):        0.086      Jarque-Bera (JB):     4.862
Skew:                 0.070      Prob(JB):             0.0880
Kurtosis:             3.063      Cond. No.             1.01
=====

```

Notes:

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

#### 1.1.4 OLS Coefficients and White Standard Errors

```
[ ]: X = df[2].to_numpy()
      X = sm.add_constant(X)
      y = df[3].to_numpy()
      model = sm.OLS(y, X)
      results = model.fit(cov_type='HCO')
      print(results.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  y      R-squared:                0.208
Model:                            OLS    Adj. R-squared:          0.208
Method:                 Least Squares  F-statistic:              1329.
Date:                Fri, 05 Apr 2024  Prob (F-statistic):       3.48e-258
Time:                  22:56:06      Log-Likelihood:          -10573.
No. Observations:          5000      AIC:                    2.115e+04
Df Residuals:              4998      BIC:                    2.116e+04
Df Model:                    1
Covariance Type:            HCO
=====

```

	coef	std err	z	P> z	[0.025	0.975]
const	0.0297	0.028	1.047	0.295	-0.026	0.085
x1	1.0348	0.028	36.451	0.000	0.979	1.090

```
=====
Omnibus:                  4.912    Durbin-Watson:           1.096
Prob(Omnibus):             0.086    Jarque-Bera (JB):         4.862
Skew:                      0.070    Prob(JB):                 0.0880
Kurtosis:                  3.063    Cond. No.:                 1.01
=====
```

Notes:

[1] Standard Errors are heteroscedasticity robust (HCO)

#### 1.1.5 OLS Coefficients and Standard Errors Clustered by Year

```
[ ]: ye_X = sm.add_constant(df[2])
      year_dummies = pd.get_dummies(df, columns=[1], drop_first=True) # Avoid
      ↪ collinearity
      ye_X = pd.concat([ye_X, year_dummies], axis=1)
      ye_X = ye_X.replace({True: 1, False: 0})
      ye_X
```

```
/tmp/ipykernel_72982/1769855915.py:4: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
ye_X = ye_X.replace({True: 1, False: 0})
```

```
[ ]:      const      2      0      2      3  1_2.0  1_3.0  1_4.0  1_5.0  \
0      1.0 -1.113973      1.0 -1.113973  2.251535      0      0      0      0
1      1.0 -0.080854      1.0 -0.080854  1.242346      1      0      0      0
2      1.0 -0.237607      1.0 -0.237607 -1.426376      0      1      0      0
3      1.0 -0.152486      1.0 -0.152486 -1.109394      0      0      1      0
4      1.0 -0.001426      1.0 -0.001426  0.914686      0      0      0      1
...
4995      1.0 -0.077057  500.0 -0.077057  3.720502      0      0      0      0
4996      1.0  0.218847  500.0  0.218847  0.559121      0      0      0      0
4997      1.0 -0.155530  500.0 -0.155530 -3.766785      0      0      0      0
4998      1.0 -0.040172  500.0 -0.040172  0.903354      0      0      0      0
4999      1.0 -0.001172  500.0 -0.001172 -0.529761      0      0      0      0

      1_6.0  1_7.0  1_8.0  1_9.0  1_10.0
0      0      0      0      0      0
1      0      0      0      0      0
2      0      0      0      0      0
3      0      0      0      0      0
4      0      0      0      0      0
...
4995      1      0      0      0      0
4996      0      1      0      0      0
4997      0      0      1      0      0
4998      0      0      0      1      0
4999      0      0      0      0      1
```

[5000 rows x 14 columns]

```
[ ]: year_clusters = df[1]
ye_model = sm.OLS(df[3], ye_X)
ye_results = model.fit(cov_type='cluster', cov_kwds={'groups': year_clusters})

print("Parameters: [Constant IndependentVariable]")
print("Coefficients:", ye_results.params)
print("Standard Error:", ye_results.bse)
print("T-statistic:", ye_results.tvalues)
print("R-Squared:", ye_results.rsquared)
```

```
Parameters: [Constant IndependentVariable]
Coefficients: [0.02967972 1.03483344]
Standard Error: [0.02338672 0.03338891]
T-statistic: [ 1.26908428 30.99332495]
```

R-Squared: 0.20776573087275374

### 1.1.6 OLS Coefficients and Standard Errors Clustered by Firm

```
[ ]: fe_X = sm.add_constant(df[2])
firm_dummies = pd.get_dummies(df, columns=[0], drop_first=True) # Avoid
↳ collinearity
fe_X = pd.concat([fe_X, firm_dummies], axis=1)
fe_X = fe_X.replace({True: 1, False: 0})
fe_X
```

/tmp/ipykernel\_72982/3006770163.py:4: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer\_objects(copy=False)`. To opt-in to the future behavior, set `pd.set\_option('future.no\_silent\_downcasting', True)`

```
fe_X = fe_X.replace({True: 1, False: 0})
```

```
[ ]:      const      2      1      2      3  0_2.0  0_3.0  0_4.0  0_5.0  \
0      1.0 -1.113973  1.0 -1.113973  2.251535      0      0      0      0
1      1.0 -0.080854  2.0 -0.080854  1.242346      0      0      0      0
2      1.0 -0.237607  3.0 -0.237607 -1.426376      0      0      0      0
3      1.0 -0.152486  4.0 -0.152486 -1.109394      0      0      0      0
4      1.0 -0.001426  5.0 -0.001426  0.914686      0      0      0      0
...
4995    1.0 -0.077057  6.0 -0.077057  3.720502      0      0      0      0
4996    1.0  0.218847  7.0  0.218847  0.559121      0      0      0      0
4997    1.0 -0.155530  8.0 -0.155530 -3.766785      0      0      0      0
4998    1.0 -0.040172  9.0 -0.040172  0.903354      0      0      0      0
4999    1.0 -0.001172 10.0 -0.001172 -0.529761      0      0      0      0

      0_6.0  ...  0_491.0  0_492.0  0_493.0  0_494.0  0_495.0  0_496.0  \
0          0  ...      0          0          0          0          0          0
1          0  ...      0          0          0          0          0          0
2          0  ...      0          0          0          0          0          0
3          0  ...      0          0          0          0          0          0
4          0  ...      0          0          0          0          0          0
...
4995      0  ...      0          0          0          0          0          0
4996      0  ...      0          0          0          0          0          0
4997      0  ...      0          0          0          0          0          0
4998      0  ...      0          0          0          0          0          0
4999      0  ...      0          0          0          0          0          0

      0_497.0  0_498.0  0_499.0  0_500.0
0              0          0          0          0
1              0          0          0          0
2              0          0          0          0
3              0          0          0          0
```

```

4          0          0          0          0
...      ...      ...      ...      ...
4995          0          0          0          1
4996          0          0          0          1
4997          0          0          0          1
4998          0          0          0          1
4999          0          0          0          1

```

[5000 rows x 504 columns]

```

[ ]: fe_clusters = df[1]
fe_model = sm.OLS(df[3], fe_X)
fe_results = model.fit(cov_type='cluster', cov_kws={'groups': fe_clusters})

print("Parameters: [Constant IndependentVariable]")
print("Coefficients:", fe_results.params)
print("Standard Error:", fe_results.bse)
print("T-statistic:", fe_results.tvalues)
print("R-Squared:", fe_results.rsquared)

```

```

Parameters: [Constant IndependentVariable]
Coefficients: [0.02967972 1.03483344]
Standard Error: [0.02338672 0.03338891]
T-statistic: [ 1.26908428 30.99332495]
R-Squared: 0.20776573087275374

```

### 1.1.7 OLS Coefficients and Standard Errors Clustered by Firm-Year

```

[ ]: fy_clusters = pd.DataFrame({'cluster': df[[0, 1]].apply(tuple, 1)})
fy_X = df[2].to_numpy()
fy_X = sm.add_constant(fy_X)
fy_y = df[3].to_numpy()
fy_model = sm.OLS(fy_y, fy_X, clusters=fy_clusters.cluster)
fy_results = fy_model.fit()
print(fy_results.summary())

```

#### OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.208
Model:                OLS      Adj. R-squared:      0.208
Method:             Least Squares      F-statistic:      1311.
Date:                Fri, 05 Apr 2024      Prob (F-statistic):      4.25e-255
Time:                23:00:14      Log-Likelihood:      -10573.
No. Observations:      5000      AIC:                2.115e+04
Df Residuals:          4998      BIC:                2.116e+04
Df Model:              1
Covariance Type:      nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
-----	-----	-----	-----	-----	-----	-----
const	0.0297	0.028	1.047	0.295	-0.026	0.085
x1	1.0348	0.029	36.204	0.000	0.979	1.091
=====	=====	=====	=====	=====	=====	=====
Omnibus:		4.912	Durbin-Watson:			1.096
Prob(Omnibus):		0.086	Jarque-Bera (JB):			4.862
Skew:		0.070	Prob(JB):			0.0880
Kurtosis:		3.063	Cond. No.			1.01
=====	=====	=====	=====	=====	=====	=====

Notes:

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

```
/home/weiminn/Documents/FDA/venv/lib/python3.11/site-
packages/statsmodels/base/model.py:130: ValueWarning: unknown kwargs
['clusters']
  warnings.warn(msg, ValueWarning)
```

### 1.1.8 Fama-Macbeth Coefficients and Standard Errors

```
[ ]: unique_t = df[1].unique()
time_groups = {}
fb_regresults = []

for t in unique_t:
    time_groups[t] = df.loc[df[1]==t]

    fb_X = df[2].to_numpy()
    fb_X = sm.add_constant(fb_X)
    fb_y = df[3].to_numpy()
    fb_model = sm.OLS(fb_y, fb_X)
    fb_results = fb_model.fit()
    fb_regresults.append(fb_results)

[ ]: coeffs = np.array([fb.params for fb in fb_regresults])
tstats = np.array([fb.tvalues for fb in fb_regresults])
stderr = np.array([fb.bse for fb in fb_regresults])

avg_coeffs = np.mean(coeffs, axis=0)
avg_tstats = np.mean(tstats, axis=0)
avg_stderr = np.mean(stderr, axis=0)

[ ]: print("Parameters: [Constant IndependentVariable]")
print("Average Coefficients:", avg_coeffs)
print("Average T-Statistic:", avg_tstats)
print("Average Standard Error:", avg_stderr)
```

```
print("R-Squared:", fb_results.rsquared)
```

```
Parameters: [Constant IndependentVariable]  
Average Coefficients: [0.02967972 1.03483344]  
Average T-Statistic: [ 1.04655977 36.20414301]  
Average Standard Error: [0.02835932 0.02858329]  
R-Squared: 0.20776573087275374
```