FIN3210 Week 3 Assignment Report

Ma Kexuan 120090651

Abstract

This report provides monthly returns stats based on the size and institutional ownership of last quarter, and a panel regression result, as well as a figure containing the online sales and reported sales.

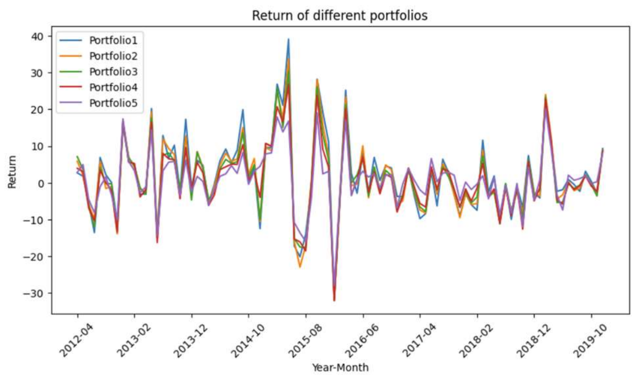
Data Preprocessing

The preprocessing procedures and some interpretations of the code are described in each code blocks in the appendix, please check.

Questions

<u>1) Using the data set of stock returns, sort stocks into quintiles by size every quarter, hold stocks over the quarter, and calculate monthly portfolio returns</u>

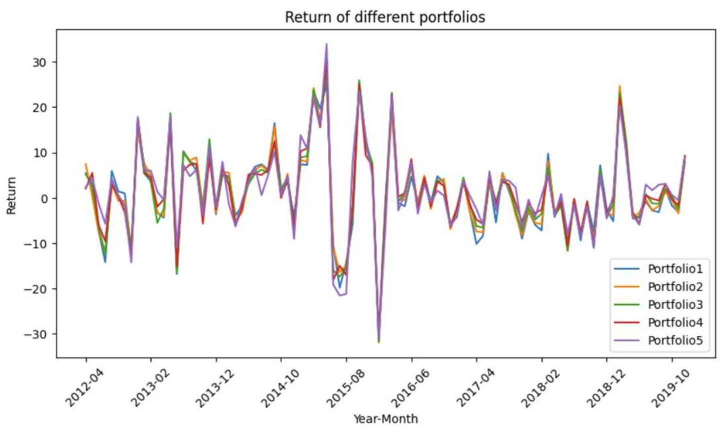
	month	last_size_label	retrf
0	2012-04	1	2.688905
1	2012-04	2	5.861874
2	2012-04	3	7.099519
3	2012-04	4	3.920090
4	2012-04	5	2.800216
5	2012-05	1	1.778694
6	2012-05	2	2.056422
7	2012-05	3	3.618288
8	2012-05	4	3.030542
9	2012-05	5	4.962478



I divide the size of all the firms into 5 groups, and use the size in last quarter to invest, ultimately get the monthly return in the next quarter, the result is shown above. It has shown ambiguous relationship between the size and portfolio return, I think maybe performing a cumulative return result will be more convincing.

<u>2) Using the data set of stock returns, sort stocks into quintiles by institutional ownership every quarter, hold stocks over the quarter, and calculate monthly portfolio returns</u>

	month	last_inst_label	retrf
0	2012-04	1	5.411529
1	2012-04	2	7.414722
2	2012-04	3	5.176190
3	2012-04	4	2.049471
4	2012-04	5	2.287461
5	2012-05	1	2.237273
6	2012-05	2	0.351318
7	2012-05	3	3.046009
8	2012-05	4	5.482549
9	2012-05	5	4.313619



This time, I use the institutional ownership to divide the firms into 5 groups, the conclusion is the same as for Question 1, it's better to do a cumulative return to discover the relationship underneath.

<u>3) Using the data set of stock returns, perform panel regression, and regress stock returns on firm characteristics such as size, book-to-market ratio, return12, roa, leverage, ppe, intang,</u>

<u>number of analysts, institutional ownership, controlling for or not for firm and year-month fixed effects. Cluster standard errors by firm and year-month (double clustering)</u>

Dep. Variable:	retrf	R-squared:	0.0133
Estimator:	PanelOLS	R-squared (Between):	-1228.5
No. Observations:	85397	R-squared (Within):	0.0171
Date:	Thu, Oct 05 2023	R-squared (Overall):	-45.250
Time:	15:22:52	Log-likelihood	-3.2e+05
Cov. Estimator:	Clustered		
		F-statistic:	124.83
Entities:	2035	P-value	0.0000
Avg Obs:	41.964	Distribution:	F(9,83262)
Min Obs:	2.0000		
Max Obs:	92.000	F-statistic (robust):	14.436
		P-value	0.0000
Time periods:	92	Distribution:	F(9,83262)
Avg Obs:	928.23		
Min Obs:	377.00		
Max Obs:	1825.0		

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
size	-4.0216	0.4473	-8.9917	0.0000	-4.8983	-3.1450
bm	0.2309	0.8461	0.2729	0.7849	-1.4274	1.8893
return12	-0.0023	0.0030	-0.7629	0.4455	-0.0081	0.0036
roa	4.6914	3.1983	1.4668	0.1424	-1.5772	10.960
lev	-1.3608	0.6284	-2.1655	0.0304	-2.5925	-0.1291
ppe	-0.0489	1.0345	-0.0473	0.9623	-2.0765	1.9788
intang	3.0578	2.5080	1.2192	0.2228	-1.8579	7.9736
numanalyst	0.0113	0.0163	0.6901	0.4901	-0.0207	0.0432
instown	0.0086	0.0160	0.5349	0.5927	-0.0228	0.0399

F-test for Poolability: 28.922
P-value: 0.0000
Distribution: F(2125,83262)

Included effects: Entity, Time

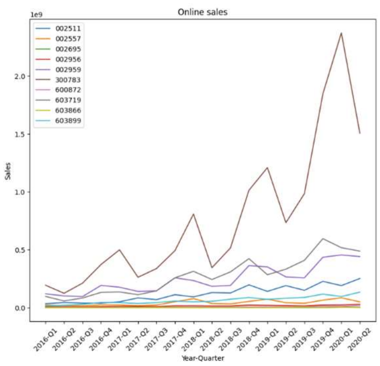
Parameter Estimates

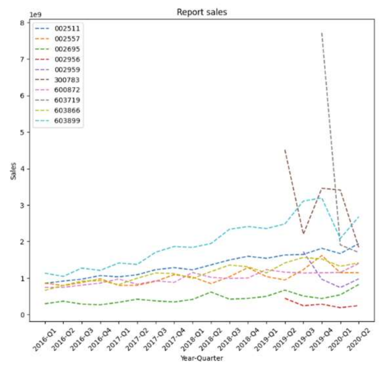
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
size	-0.0107	0.0508	-0.2100	0.8337	-0.1102	0.0888
bm	1.4906	0.8773	1.6991	0.0893	-0.2288	3.2101
return12	0.0036	0.0141	0.2555	0.7983	-0.0241	0.0313
roa	5.3103	7.6867	0.6908	0.4897	-9.7556	20.376
lev	0.5546	1.8904	0.2934	0.7692	-3.1504	4.2597
ppe	0.1788	1.2655	0.1413	0.8877	-2.3016	2.6592
intang	0.3477	1.2780	0.2721	0.7855	-2.1571	2.8526
numanalyst	-0.0084	0.0157	-0.5371	0.5912	-0.0392	0.0224
instown	0.0436	0.0165	2.6450	0.0082	0.0113	0.0759

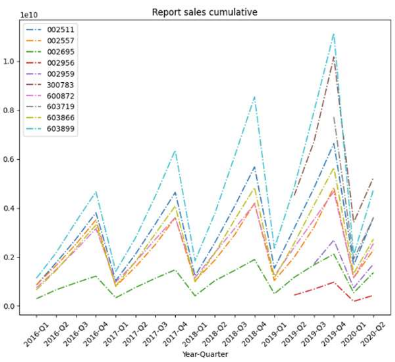
For the controlled fixed effect and time group, we find that size and lev are at 95% significance level. There is a negative correlation between size and return, which may be caused by the reason that large companies are focusing on profiting, and the profit gained has been issued to investors, not using in further industrial developing, resulting in a lower growth, thus fewer people expect them to rise sharply, so lower return. The more leverage the firm has, may indicate that the firm has a larger debt to be paid, more bankrupt risk, so lower future return. For the not controlled group, only instown is at the same level of significance. The positive sign maybe indicate that more institutional investor likes this stock, so others follow, in order to get a higher return.

Finally I compare the two models, the R-square of the controlled one is 0.0133 and that of the uncontrolled one is 0.0062, which illustrates that both models are quite weak to dig out the concrete relationship, but the former one is better than the latter one. Overall, the introduction of fixed effects has illuminated crucial variations in the relationships between predictors and the dependent variable, emphasizing the importance of accounting for unobserved heterogeneity in panel data analyses.

<u>4) Using the data set of Online sales, aggregate monthly online sales over quarters, download reported quarterly total sales from CSMAR, and plot figures including both online sales and reported quarterly sales.</u>







I have processed the data from CSMAR, removing the January data, since it's the same as the whole data of last year, then get the difference between each quarter, because the original data is cumulative. The result of both online sales and the reported sales from CSMAR are shown above. Also, I print out the cumulative one, that is the original data from CSMAR, you can check it as a reference. The 3 more limpid graphs are in the appendix below.

FIN3210 Week 3 Assignment

Ma Kexuan 120090651

October 5, 2023

[1]:
```python
import pandas as pd
import numpy as np
from linearmodels import PanelOLS
import matplotlib.pyplot as plt
from matplotlib.pyplot import MultipleLocator
```

[2]:
```python
df = pd.read_excel('FIN3210 Week 3 Stock returns.xlsx', sheet_name='data')
```

[3]:
```python
data = df.drop(['stknme','conme'], axis=1).copy()
data['month'] = pd.to_datetime(data['month'], format='%Y-%m').dt.to_period('M')␣
↪# Transfer to datetime type with month based
data['year_quarter'] = data['month'].dt.strftime('%Y-Q%q') # Transfer to format␣
↪year-quarter
data.head()
```

[3]:
```
   stkcd    month    retrf   mktrf     smb     hml     umd      size  \
0      9  2013-07   9.0756  1.8833  5.1896 -0.1922  6.1829  23.10871
1      9  2013-08  -5.1363  4.5833  5.9407  0.0976 -5.5041  23.10871
2      9  2013-09   3.5840  3.3833  0.5848  2.8554  8.8693  23.10871
3      9  2014-01  -1.0932 -3.6167  5.6921  1.1126  8.9357  23.28204
4      9  2014-02  19.0704  0.9833  3.8899  0.6902 -1.8764  23.28204

         bm  return12       roa       lev       ppe    intang  numanalyst  \
0  0.438860  13.37412  0.007949  0.430605  0.086185  0.031575           0
1  0.438860  13.37412  0.007949  0.430605  0.086185  0.031575           0
2  0.438860  13.37412  0.007949  0.430605  0.086185  0.031575           0
3  0.394303  46.59159  0.025973  0.432246  0.098660  0.029798           0
4  0.394303  46.59159  0.025973  0.432246  0.098660  0.029798           0

   instown           mv year_quarter
0   6.4646  11874173952      2013-Q3
1   6.4646  11874173952      2013-Q3
2   6.4646  11874173952      2013-Q3
3   5.6741  11731143680      2014-Q1
4   5.6741  11731143680      2014-Q1
```

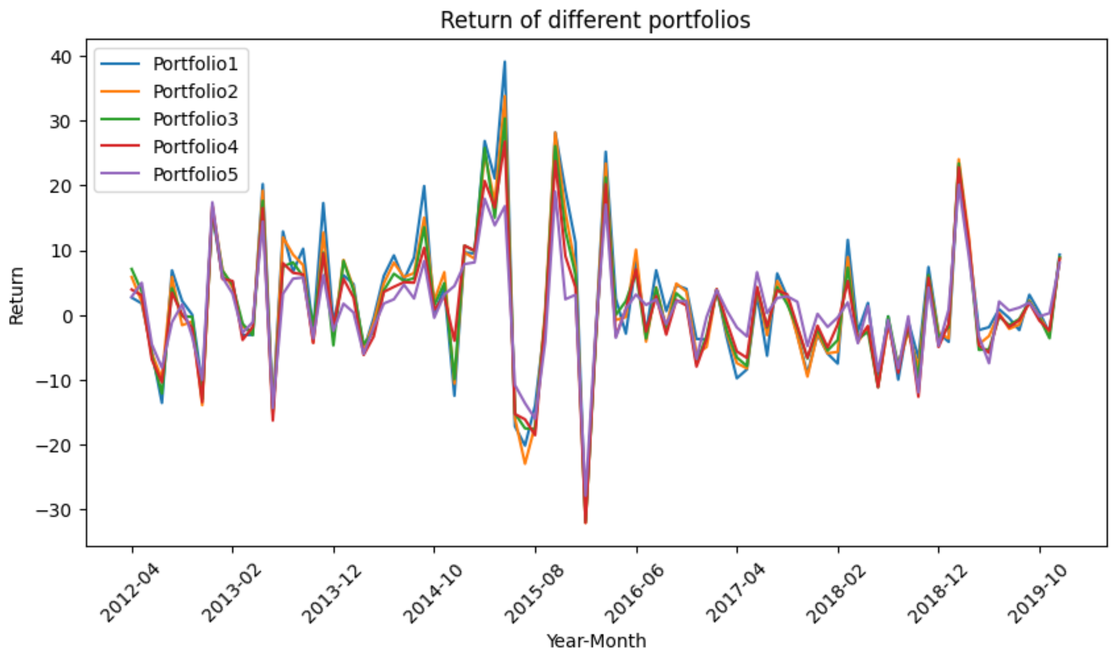
0.1 1) Using the data set of stock returns, sort stocks into quintiles by size every quarter, hold stocks over the quarter, and calculate monthly portfolio returns

[4]:
```python
# Divide into 5 groups
data['size_label'] = data.groupby('year_quarter')['size'].transform(lambda x:␣
↪pd.qcut(x, 5, labels=[1,2,3,4,5]))
# Use the size of last month to predict next month
data['last_size_label'] = data.groupby(['stkcd','year_quarter'])['size_label'].
↪shift(1)
# fill in NAN value
data.loc[data['last_size_label'].isnull(),'last_size_label'] = data.
↪loc[data['last_size_label'].isnull(),'size_label']
# Equal weighted result of portfolio return
port_res = data.groupby(['month','last_size_label'])['retrf'].mean().
↪reset_index()
port_res.head(10)
```

[4]:

	month	last_size_label	retrf
0	2012-04	1	2.688905
1	2012-04	2	5.861874
2	2012-04	3	7.099519
3	2012-04	4	3.920090
4	2012-04	5	2.800216
5	2012-05	1	1.778694
6	2012-05	2	2.056422
7	2012-05	3	3.618288
8	2012-05	4	3.030542
9	2012-05	5	4.962478

[5]:
```python
port_res['month'] = port_res['month'].astype(str)
plt.figure(figsize = (10,5))
for i in [1,2,3,4,5]:
    plt.plot(port_res.loc[port_res['last_size_label']==i, 'month'],
             port_res.loc[port_res['last_size_label']==i, 'retrf'],
             label = 'Portfolio{}'.format(i))
plt.xlabel('Year-Month')
plt.ylabel('Return')
plt.title('Return of different portfolios')
plt.xticks(rotation = 45)
x_major_locator=MultipleLocator(10)
ax = plt.gca()
ax.xaxis.set_major_locator(x_major_locator)
plt.legend()
plt.show()
```



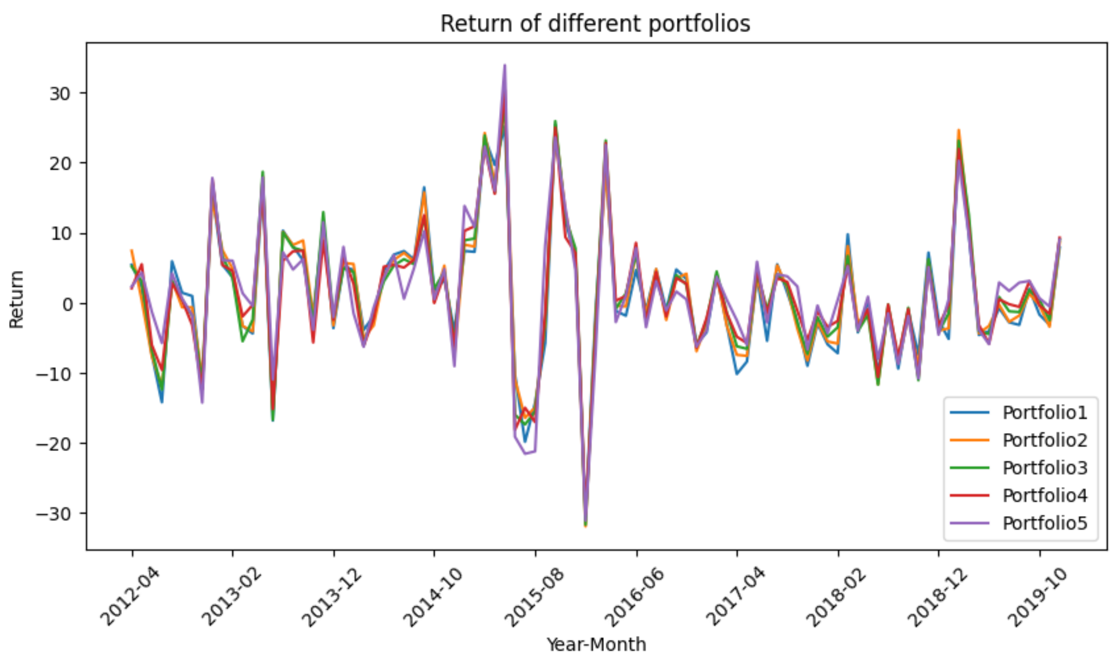
0.2 2) Using the data set of stock returns, sort stocks into quintiles by institutional ownership every quarter, hold stocks over the quarter, and calculate monthly portfolio returns

[6]:
```
data['inst_label'] = data.groupby('year_quarter')['instown'].transform(lambda x:
    pd.qcut(x, 5, labels=[1,2,3,4,5]))
data['last_inst_label'] = data.groupby(['stkcd','year_quarter'])['inst_label'].
    shift(1)
data.loc[data['last_inst_label'].isnull(),'last_inst_label'] = data.
    loc[data['last_inst_label'].isnull(),'inst_label']
port_res = data.groupby(['month','last_inst_label'])['retrf'].mean().
    reset_index()
port_res.head(10)
```

[6]:

	month	last_inst_label	retrf
0	2012-04	1	5.411529
1	2012-04	2	7.414722
2	2012-04	3	5.176190
3	2012-04	4	2.049471
4	2012-04	5	2.287461
5	2012-05	1	2.237273
6	2012-05	2	0.351318
7	2012-05	3	3.046009
8	2012-05	4	5.482549
9	2012-05	5	4.313619

[7]:
```
port_res['month'] = port_res['month'].astype(str)
plt.figure(figsize = (10,5))
for i in [1,2,3,4,5]:
    plt.plot(port_res.loc[port_res['last_inst_label']==i, 'month'],
            port_res.loc[port_res['last_inst_label']==i, 'retrf'],
            label = 'Portfolio{}'.format(i))
plt.xlabel('Year-Month')
plt.ylabel('Return')
plt.title('Return of different portfolios')
plt.xticks(rotation = 45)
x_major_locator=MultipleLocator(10)
ax = plt.gca()
ax.xaxis.set_major_locator(x_major_locator)
plt.legend()
plt.show()
```



0.3 3) Using the data set of stock returns, perform panel regression, and regress stock returns on firm characteristics such as size, book-to-market ratio, return12, roa, leverage, ppe, intang, number of analysts, institutional ownership, controlling for or not for firm and year-month fixed effects. Cluster standard errors by firm and year-month (double clustering)

[8]:
```
panel_data = data[['stkcd','month','retrf','size','bm','return12',
                   'roa','lev','ppe','intang','numanalyst','instown']].copy()
panel_data[['size','bm','return12','roa','lev','ppe','intang','numanalyst','instown']]␣
↪= panel_data.groupby('stkcd')[['size',
            'bm','return12','roa','lev','ppe','intang','numanalyst','instown']].
↪shift(1)
panel_data.dropna(inplace = True)
panel_data
```

[8]:
```
         stkcd    month    retrf      size        bm   return12       roa  \
1            9  2013-08  -5.1363  23.10871  0.438860  13.374120  0.007949
2            9  2013-09   3.5840  23.10871  0.438860  13.374120  0.007949
3            9  2014-01  -1.0932  23.10871  0.438860  13.374120  0.007949
4            9  2014-02  19.0704  23.28204  0.394303  46.591590  0.025973
5            9  2014-03  -5.9711  23.28204  0.394303  46.591590  0.025973
…          …        …        …         …         …          …         …
87427   900956  2019-08  -5.3373  19.54512  5.124264  -4.492293  0.005443
87428   900956  2019-09  11.0761  19.54512  5.124264  -4.492293  0.005443
87429   900956  2019-10  12.3759  19.54512  5.124264  -4.492293  0.005443
87430   900956  2019-11   0.5954  19.41050  5.950344 -14.776860  0.010888
87431   900956  2019-12   7.2701  19.41050  5.950344 -14.776860  0.010888

             lev       ppe    intang  numanalyst  instown
1       0.430605  0.086185  0.031575         0.0   6.4646
2       0.430605  0.086185  0.031575         0.0   6.4646
3       0.430605  0.086185  0.031575         0.0   6.4646
4       0.432246  0.098660  0.029798         0.0   5.6741
5       0.432246  0.098660  0.029798         0.0   5.6741
…            …         …         …           …        …
87427   0.598459  0.267594  0.025879         0.0   0.0000
87428   0.598459  0.267594  0.025879         0.0   0.0000
87429   0.598459  0.267594  0.025879         0.0   0.0000
87430   0.425125  0.269671  0.025286         0.0   0.0000
87431   0.425125  0.269671  0.025286         0.0   0.0000

[85397 rows x 12 columns]
```

[9]:
```
panel_data['month'] = pd.to_numeric(panel_data['month'].dt.strftime('%Y%m'))
panel_data.set_index(['stkcd','month'], inplace=True) # Control for firm and␣
↪year-month fixed effects
model = PanelOLS(panel_data['retrf'], panel_data[['size','bm','return12','roa',
```

```python
        'lev','ppe','intang','numanalyst','instown']], entity_effects=True,␣
  ↪time_effects=True)
res = model.fit(cov_type='clustered', cluster_entity=True, cluster_time=True) #␣
  ↪Cluster standard errors
res.summary
```

[9]:
```
<class 'linearmodels.compat.statsmodels.Summary'>
"""
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:                  retrf   R-squared:                        0.0133
Estimator:                   PanelOLS   R-squared (Between):             -1228.5
No. Observations:               85397   R-squared (Within):               0.0171
Date:                Thu, Oct 05 2023   R-squared (Overall):             -45.250
Time:                        15:22:52   Log-likelihood                  -3.2e+05
Cov. Estimator:             Clustered
                                        F-statistic:                      124.83
Entities:                        2035   P-value                           0.0000
Avg Obs:                       41.964   Distribution:                 F(9,83262)
Min Obs:                       2.0000
Max Obs:                       92.000   F-statistic (robust):             14.436
                                        P-value                           0.0000
Time periods:                      92   Distribution:                 F(9,83262)
Avg Obs:                       928.23
Min Obs:                       377.00
Max Obs:                       1825.0

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
size          -4.0216     0.4473    -8.9917     0.0000     -4.8983     -3.1450
bm             0.2309     0.8461     0.2729     0.7849     -1.4274      1.8893
return12      -0.0023     0.0030    -0.7629     0.4455     -0.0081      0.0036
roa            4.6914     3.1983     1.4668     0.1424     -1.5772      10.960
lev           -1.3608     0.6284    -2.1655     0.0304     -2.5925     -0.1291
ppe           -0.0489     1.0345    -0.0473     0.9623     -2.0765      1.9788
intang         3.0578     2.5080     1.2192     0.2228     -1.8579      7.9736
numanalyst     0.0113     0.0163     0.6901     0.4901     -0.0207      0.0432
instown        0.0086     0.0160     0.5349     0.5927     -0.0228      0.0399
==============================================================================

F-test for Poolability: 28.922
P-value: 0.0000
Distribution: F(2125,83262)

Included effects: Entity, Time
```

```
"""
```

[10]:
```
model = PanelOLS(panel_data['retrf'], panel_data[['size','bm','return12',
        'roa','lev','ppe','intang','numanalyst','instown']],
        entity_effects=False, time_effects=False) # Not control for these two␣
 ↪effects
# Cluster standard errors
res = model.fit(cov_type='clustered', cluster_entity=True, cluster_time=True)
res.summary
```

[10]:
```
<class 'linearmodels.compat.statsmodels.Summary'>
"""
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:                  retrf   R-squared:                        0.0062
Estimator:                   PanelOLS   R-squared (Between):              0.0578
No. Observations:               85397   R-squared (Within):               0.0027
Date:                Thu, Oct 05 2023   R-squared (Overall):              0.0062
Time:                        15:22:53   Log-likelihood                -3.438e+05
Cov. Estimator:             Clustered
                                        F-statistic:                      59.151
Entities:                        2035   P-value                           0.0000
Avg Obs:                       41.964   Distribution:                F(9,85388)
Min Obs:                       2.0000
Max Obs:                       92.000   F-statistic (robust):             2.1815
                                        P-value                           0.0203
Time periods:                      92   Distribution:                F(9,85388)
Avg Obs:                       928.23
Min Obs:                       377.00
Max Obs:                       1825.0

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
size          -0.0107     0.0508    -0.2100     0.8337     -0.1102      0.0888
bm             1.4906     0.8773     1.6991     0.0893     -0.2288      3.2101
return12       0.0036     0.0141     0.2555     0.7983     -0.0241      0.0313
roa            5.3103     7.6867     0.6908     0.4897     -9.7556      20.376
lev            0.5546     1.8904     0.2934     0.7692     -3.1504      4.2597
ppe            0.1788     1.2655     0.1413     0.8877     -2.3016      2.6592
intang         0.3477     1.2780     0.2721     0.7855     -2.1571      2.8526
numanalyst    -0.0084     0.0157    -0.5371     0.5912     -0.0392      0.0224
instown        0.0436     0.0165     2.6450     0.0082      0.0113      0.0759
==============================================================================
```

"""

0.4 4) Using the data set of Online sales, aggregate monthly online sales over quarters, download reported quarterly total sales from CSMAR, and plot figures including both online sales and reported quarterly sales.

[11]:
```
sales = pd.read_excel('FIN3210 Week 3 Online sales.xlsx', sheet_name='  ')
# Change the columns into rows in the dataframe
sales = sales.melt(id_vars=[' '], var_name='Brand', value_name='online_sales')
sales.rename({' ':'month'}, axis=1, inplace=True)
sales
```

[11]:
```
          month          Brand  online_sales
0    2016-01-01     603899.SH    3888967.80
1    2016-02-01     603899.SH    3983190.45
2    2016-03-01     603899.SH    6395686.99
3    2016-04-01     603899.SH    4968614.43
4    2016-05-01     603899.SH    6566980.86
..          …              …             …
545  2020-03-01     002956.SZ    8621983.82
546  2020-04-01     002956.SZ    8476046.53
547  2020-05-01     002956.SZ    8540964.70
548  2020-06-01     002956.SZ   11706599.62
549  2020-07-01     002956.SZ    6767988.81

[550 rows x 3 columns]
```

[12]:
```
sales['month'] = pd.to_datetime(sales['month'], format='%Y-%m').dt.
 ↪to_period('M')
sales['year_quarter'] = sales['month'].dt.strftime('%Y-Q%q')
sales['stkcd'] = sales['Brand'].str.extract('(\d+)').astype('int') # Extract␣
 ↪stock id
sales
```

[12]:
```
        month          Brand  online_sales year_quarter   stkcd
0     2016-01     603899.SH    3888967.80      2016-Q1  603899
1     2016-02     603899.SH    3983190.45      2016-Q1  603899
2     2016-03     603899.SH    6395686.99      2016-Q1  603899
3     2016-04     603899.SH    4968614.43      2016-Q2  603899
4     2016-05     603899.SH    6566980.86      2016-Q2  603899
..        …              …             …           …       …
545   2020-03     002956.SZ    8621983.82      2020-Q1    2956
546   2020-04     002956.SZ    8476046.53      2020-Q2    2956
547   2020-05     002956.SZ    8540964.70      2020-Q2    2956
548   2020-06     002956.SZ   11706599.62      2020-Q2    2956
549   2020-07     002956.SZ    6767988.81      2020-Q3    2956
```

```
[550 rows x 5 columns]
```

[13]:
```
sales = sales.groupby(['stkcd','year_quarter'])['online_sales'].sum().
 ↪reset_index() # Aggregate to get the sum of sales in each quarter
sales
```

[13]:
```
      stkcd year_quarter  online_sales
0      2511      2016-Q1  3.384803e+07
1      2511      2016-Q2  4.424781e+07
2      2511      2016-Q3  3.921140e+07
3      2511      2016-Q4  3.867866e+07
4      2511      2017-Q1  5.079266e+07
..      ...          ...           ...
185  603899      2019-Q3  8.817731e+07
186  603899      2019-Q4  1.169147e+08
187  603899      2020-Q1  9.600548e+07
188  603899      2020-Q2  1.338863e+08
189  603899      2020-Q3  4.121578e+07

[190 rows x 3 columns]
```

[14]:
```
report_sales = pd.read_csv('FS_Comins.csv')
report_sales['Accper'] = pd.to_datetime(report_sales['Accper'],␣
 ↪format='%Y-%m-%d').dt.to_period('M')
report_sales['Accper'] = report_sales['Accper'].dt.strftime('%Y-Q%q')
report_sales = report_sales.loc[report_sales['Typrep']=='A',:] # Count for all␣
 ↪of the relevant companies
report_sales.drop(['B001101000','Typrep'], axis=1, inplace=True)
report_sales.reset_index(drop=True, inplace=True)
report_sales.rename({'B001100000':'report_sales_cum'}, axis=1, inplace=True)
report_sales['year'] = pd.to_datetime(report_sales['Accper']).dt.year
# Remove the first line, because it's the data of last year
report_sales = report_sales.groupby(['Stkcd','year']).apply(lambda x: x.iloc[1:
 ↪])
report_sales.reset_index(drop=True, inplace=True)
report_sales['report_sales_sft'] = report_sales.
 ↪groupby(['Stkcd','year'])['report_sales_cum'].shift(1)
# Calculate the quartly sales since the original data is cumulative
report_sales['report_sales'] = report_sales['report_sales_cum'] -␣
 ↪report_sales['report_sales_sft']
# Fill in the NAN values of the first line using the original sales
report_sales.loc[report_sales['report_sales'].isnull(),
    'report_sales'] = report_sales.loc[report_sales['report_sales'].isnull(),␣
 ↪'report_sales_cum']
report_sales.drop(['report_sales_sft'], axis = 1, inplace = True)
report_sales.reset_index(drop=True, inplace=True)
report_sales
```

```
[14]:       Stkcd ShortName   Accper  report_sales_cum  year  report_sales
      0      2511           2016-Q1      8.540908e+08  2016  8.540908e+08
      1      2511           2016-Q2      1.771553e+09  2016  9.174619e+08
      2      2511           2016-Q3      2.740959e+09  2016  9.694064e+08
      3      2511           2016-Q4      3.809349e+09  2016  1.068390e+09
      4      2511           2017-Q1      1.032247e+09  2017  1.032247e+09
      ..      …        …        …               …     …           …
      120  603899           2019-Q2      4.838623e+09  2019  2.483009e+09
      121  603899           2019-Q3      7.947344e+09  2019  3.108721e+09
      122  603899           2019-Q4      1.114110e+10  2019  3.193757e+09
      123  603899           2020-Q1      2.083587e+09  2020  2.083587e+09
      124  603899           2020-Q2      4.761424e+09  2020  2.677836e+09

      [125 rows x 6 columns]
```

```
[15]: online_report = pd.merge(sales, report_sales, how='left',␣
       ↪left_on=['stkcd','year_quarter'], right_on=['Stkcd','Accper'])
      online_report = online_report.loc[online_report['year_quarter']!='2020-Q3']
      online_report
```

```
[15]:       stkcd year_quarter  online_sales     Stkcd ShortName   Accper  \
      0      2511      2016-Q1  3.384803e+07    2511.0            2016-Q1
      1      2511      2016-Q2  4.424781e+07    2511.0            2016-Q2
      2      2511      2016-Q3  3.921140e+07    2511.0            2016-Q3
      3      2511      2016-Q4  3.867866e+07    2511.0            2016-Q4
      4      2511      2017-Q1  5.079266e+07    2511.0            2017-Q1
      ..      …          …            …        …         …       …
      184  603899      2019-Q2  8.132643e+07  603899.0            2019-Q2
      185  603899      2019-Q3  8.817731e+07  603899.0            2019-Q3
      186  603899      2019-Q4  1.169147e+08  603899.0            2019-Q4
      187  603899      2020-Q1  9.600548e+07  603899.0            2020-Q1
      188  603899      2020-Q2  1.338863e+08  603899.0            2020-Q2

           report_sales_cum    year  report_sales
      0        8.540908e+08  2016.0  8.540908e+08
      1        1.771553e+09  2016.0  9.174619e+08
      2        2.740959e+09  2016.0  9.694064e+08
      3        3.809349e+09  2016.0  1.068390e+09
      4        1.032247e+09  2017.0  1.032247e+09
      ..                …       …           …
      184      4.838623e+09  2019.0  2.483009e+09
      185      7.947344e+09  2019.0  3.108721e+09
      186      1.114110e+10  2019.0  3.193757e+09
      187      2.083587e+09  2020.0  2.083587e+09
      188      4.761424e+09  2020.0  2.677836e+09

      [180 rows x 9 columns]
```

[16]:
```
stkcd_list = online_report['stkcd'].unique().astype('str').tolist()
for i in range(len(stkcd_list)):
    if len(stkcd_list[i])==4:
        stkcd_list[i] = '00'+stkcd_list[i]
stkcd_list
```

[16]:
```
['002511',
 '002557',
 '002695',
 '002956',
 '002959',
 '300783',
 '600872',
 '603719',
 '603866',
 '603899']
```

[17]:
```
plt.figure(figsize=(20,16))
plt.subplot(2,2,1)
for stkcd in stkcd_list:
    int_stk = int(stkcd)
    plt.plot(online_report.loc[online_report['stkcd']==int_stk, 'year_quarter'],
             online_report.loc[online_report['stkcd']==int_stk,␣
 ↪'online_sales'], label = '{}'.format(stkcd))
plt.title('Online sales')
plt.xticks(rotation=45)
plt.xlabel('Year-Quarter')
plt.ylabel('Sales')
plt.legend()

plt.subplot(2,2,2)
for stkcd in stkcd_list:
    int_stk = int(stkcd)
    plt.plot(online_report.loc[online_report['stkcd']==int_stk, 'year_quarter'],
             online_report.loc[online_report['stkcd']==int_stk, 'report_sales'],
             label = '{}'.format(stkcd), linestyle = 'dashed')
plt.title('Report sales')
plt.xticks(rotation=45)
plt.xlabel('Year-Quarter')
plt.ylabel('Sales')
plt.legend()

plt.subplot(2,2,3)
for stkcd in stkcd_list:
    int_stk = int(stkcd)
    plt.plot(online_report.loc[online_report['stkcd']==int_stk, 'year_quarter'],
```

```
             online_report.loc[online_report['stkcd']==int_stk, 'report_sales_cum'],
             label = '{}'.format(stkcd), linestyle = 'dashdot')
plt.title('Report sales cumulative')
plt.xticks(rotation=45)
plt.xlabel('Year-Quarter')
plt.ylabel('Sales')
plt.legend()
plt.show()
```