Yilun Wang(yilun830@bu.edu) - final project

convert notebook to html then print as PDF

In [ ]:

```
!jupyter nbconvert --to html /content/Assignment_05_Yilun_Wang.ipynb
```

main content

In [264]:

```
%matplotlib inline
```

In [329]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import seaborn as sns
```

In [266]:

```
# project tickers
pt = pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-assignme
nts/main/ProjectTickers.csv')
```

In [267]:

```
pt.head()
```

Out[267]:

	Ticker	Name	RetYTD
0	A	Agilent Technologies	-0.2080
1	AA	Alcoa Corp	0.4731
2	AAL	American Airlines Gp	0.0579
3	AAN	Aarons Holdings Company	-0.1327
4	AAON	Aaon Inc	-0.3456

In [267]:

```
```

(2) Determine Risk Exposures

In [268]:

```
# upload stock return
data_return = pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765
-assignments/main/efevj68i6ylkiw7c.csv')
```

In [269]:

```
# upload ff factors of year 2017-2021
ff_factors = pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-
assignments/main/FF-Factors-2017-2021.csv')
```

In [270]:

```
pt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1886 entries, 0 to 1885
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   Ticker   1886 non-null   object 
 1   Name     1886 non-null   object 
 2   RetYTD   1886 non-null   float64
dtypes: float64(1), object(2)
memory usage: 44.3+ KB
```

In [271]:

```
data_return.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 114715 entries, 0 to 114714
Data columns (total 4 columns):
 #   Column   Non-Null Count   Dtype 
---  ------   --------------   ----- 
 0   PERMNO   114715 non-null  int64 
 1   date     114715 non-null  int64 
 2   TICKER   114653 non-null  object
 3   RET      114700 non-null  object
dtypes: int64(2), object(2)
memory usage: 3.5+ MB
```

In [272]:

```
# change RET type to float, outliers would be transfer to "NaN"
data_return['RET'] = pd.to_numeric(data_return['RET'],errors='coerce')
```

In [273]:

```
# check again type
data_return.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 114715 entries, 0 to 114714
Data columns (total 4 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   PERMNO  114715 non-null  int64  
 1   date    114715 non-null  int64  
 2   TICKER  114653 non-null  object 
 3   RET     114629 non-null  float64
dtypes: float64(1), int64(2), object(1)
memory usage: 3.5+ MB
```

In [274]:

```
# check null values
data_return.isna().sum()
```

Out[274]:

```
PERMNO     0
date       0
TICKER    62
RET       86
dtype: int64
```

In [275]:

```
# fill NA with 0
data_return['RET'].fillna(0, inplace=True)
```

In [276]:

```
# check NA again
data_return.isna().sum()
```

Out[276]:

```
PERMNO     0
date       0
TICKER    62
RET        0
dtype: int64
```

In [277]:

```
data_return.head()
```

Out[277]:

	PERMNO	date	TICKER	RET
0	10026	20170131	JJSF	-0.043918
1	10026	20170228	JJSF	0.048836
2	10026	20170331	JJSF	0.016293
3	10026	20170428	JJSF	-0.007229
4	10026	20170531	JJSF	-0.033289

In [278]:

```
ff_factors.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60 entries, 0 to 59
Data columns (total 5 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   dateff   60 non-null     int64
 1   mktrf    60 non-null     float64
 2   smb      60 non-null     float64
 3   hml      60 non-null     float64
 4   rf       60 non-null     float64
dtypes: float64(4), int64(1)
memory usage: 2.5 KB
```

In [279]:

```
ff_factors.head()
```

Out[279]:

	dateff	mktrf	smb	hml	rf
0	20170131	0.0194	-0.0113	-0.0274	0.0004
1	20170228	0.0357	-0.0204	-0.0167	0.0004
2	20170331	0.0017	0.0113	-0.0333	0.0003
3	20170428	0.0109	0.0072	-0.0213	0.0005
4	20170531	0.0106	-0.0252	-0.0375	0.0006

Rename date column to "date" to match WRDS data "date" column for each stock

In [280]:

```
# Rename date column to "date" to match WRDS data "date" column for each stock
ff_factors.rename(columns={'dateff':'date'}, inplace=True)
ff_factors.head()
```

Out[280]:

	date	mktrf	smb	hml	rf
0	20170131	0.0194	-0.0113	-0.0274	0.0004
1	20170228	0.0357	-0.0204	-0.0167	0.0004
2	20170331	0.0017	0.0113	-0.0333	0.0003
3	20170428	0.0109	0.0072	-0.0213	0.0005
4	20170531	0.0106	-0.0252	-0.0375	0.0006

Create loops for each stock to get new dataframe for each stock's monthly data

create a vacant dataframe for final outputs

In [281]:

```
# create a vacant dataframe for final outputs
final_outputs = pd.DataFrame(columns=['TICKER', 'mktrf','smb','hml'])
final_outputs.head()
```

Out[281]:

TICKER	mktrf	smb	hml

create loop

In [282]:

```
for x in pt['Ticker']:
  # create new df for x stock
  x_data = data_return[data_return["TICKER"] == x]

  # merge x_data & ff_factors for each x
  x_ff = pd.merge(x_data, ff_factors, on='date', how='outer')

  # Run OLS regression for each x (60 months) using FF 3-factor model
  y = x_ff["RET"] - x_ff["rf"]
  X = x_ff[['mktrf' , 'smb' , 'hml']]

  # Use statsmodels
  X = sm.add_constant(X) # adding a constant
  model = sm.OLS(y, X).fit()

  # create a new df for our necessary parameters
  # model.params has 4 numbers: alpha/mktrf/smb/hml
  # tickers = X'name, and we also have other two r-squareds.
  # As a result, we get a new df with 7 parameters as following:
  new=pd.DataFrame({'mktrf': [model.params[1]],
                    'smb': [model.params[2]],
                    'hml': [model.params[3]],
                    'TICKER': [x]
                    })

  # Store the above items (TICKER, R-squared, Adj. R-squared, const, mktrf, smb,
hml) to a row in the final_outputs dataframe.
  final_outputs=final_outputs.append(new,ignore_index=True)
  # finish!
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:1
17: FutureWarning: In a future version of pandas all arguments of co
ncat except for the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

In [283]:

```
# check our final results
final_outputs.head(20)
```

Out[283]:

	TICKER	mktrf	smb	hml
0	A	1.014152	-0.253674	-0.143608
1	AA	1.984149	0.527862	1.924844
2	AAL	1.315550	0.612825	1.248123
3	AAN	1.640807	0.141355	0.841349
4	AAON	0.516779	0.422130	-0.117068
5	AAP	1.112646	0.123161	0.469651
6	AAPL	1.314647	-0.344850	-0.714986
7	AAT	1.007945	0.384752	0.685424
8	AAWW	0.971779	0.591275	0.283819
9	ABBV	0.774071	0.083434	0.204134
10	ABC	0.520776	-0.279820	-0.040484
11	ABCB	0.893665	1.158212	1.270126
12	ABG	1.277690	0.165531	1.103423
13	ABM	1.238217	-0.426307	0.524660
14	ABMD	1.302492	0.935928	-1.006187
15	ABR	1.625833	0.853485	0.547468
16	ABT	0.764430	-0.304822	-0.266568
17	ABTX	0.717397	0.892790	0.768598
18	ABUS	2.344090	2.002693	0.223151
19	ACAD	0.540352	0.984864	-0.459562

In [284]:

```
final_outputs.isna().sum()
```

Out[284]:

```
TICKER    0
mktrf     0
smb       0
hml       0
dtype: int64
```

Write the contents of the dataframe to a CSV file with the name "FF-Exposures.csv"

In [285]:

```
final_outputs.to_csv("FF-Exposures.csv")
```

(3) Calculate Financial Ratios

In [286]:

```
# import financials
fin = pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-assignm
ents/main/Project-2021-Financials.csv')
```

In [287]:

```
fin.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1886 entries, 0 to 1885
Data columns (total 21 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   gvkey     1886 non-null   int64  
 1   datadate  1886 non-null   int64  
 2   fyear     1886 non-null   int64  
 3   indfmt    1886 non-null   object 
 4   consol    1886 non-null   object 
 5   popsrc    1886 non-null   object 
 6   datafmt   1886 non-null   object 
 7   tic       1886 non-null   object 
 8   curcd     1886 non-null   object 
 9   at        1886 non-null   float64
 10  ceq       1886 non-null   float64
 11  csho      1886 non-null   float64
 12  dt        1649 non-null   float64
 13  ebit      1886 non-null   float64
 14  lt        1881 non-null   float64
 15  ni        1886 non-null   float64
 16  oancf     1885 non-null   float64
 17  sale      1886 non-null   float64
 18  seq       1886 non-null   float64
 19  costat    1886 non-null   object 
 20  prcc_c    1886 non-null   float64
dtypes: float64(11), int64(3), object(7)
memory usage: 309.5+ KB
```

In [288]:

```
# rename column
fin.rename(columns={'tic':'Ticker'}, inplace=True)
fin.head()
```

Out[288]:

	gvkey	datadate	fyear	indfmt	consol	popsrc	datafmt	Ticker	curcd	at	...	
0	1004	20210531	2020	INDL	C	D	STD	AIR	USD	1539.700	...	
1	1045	20211231	2021	INDL	C	D	STD	AAL	USD	66467.000	...	6
2	1075	20211231	2021	INDL	C	D	STD	PNW	USD	22003.222	...	1
3	1078	20211231	2021	INDL	C	D	STD	ABT	USD	75196.000	...	17
4	1161	20211231	2021	INDL	C	D	STD	AMD	USD	12419.000	...	12

5 rows × 21 columns

In [289]:

```
# merge two datasets
df = pd.merge(fin, pt, how='outer', on='Ticker')
```

In [290]:

```
df.head()
```

Out[290]:

	gvkey	datadate	fyear	indfmt	consol	popsrc	datafmt	Ticker	curcd	at	...	
0	1004	20210531	2020	INDL	C	D	STD	AIR	USD	1539.700	...	
1	1045	20211231	2021	INDL	C	D	STD	AAL	USD	66467.000	...	-5
2	1075	20211231	2021	INDL	C	D	STD	PNW	USD	22003.222	...	[illegible]
3	1078	20211231	2021	INDL	C	D	STD	ABT	USD	75196.000	...	8
4	1161	20211231	2021	INDL	C	D	STD	AMD	USD	12419.000	...	3

5 rows × 23 columns

Create ratios

In [291]:

```
# create 4 market ratios and take the inverse
df['book/price'] = df['ceq'] / (df['prcc_c'] * df['csho'])
df['e/price'] = df['ni'] / (df['prcc_c'] * df['csho'])
df['sale/price'] = df['sale'] / (df['prcc_c'] * df['csho'])
df['ebit/price'] = df['ebit'] / (df['prcc_c'] * df['csho'])

# create 6 other ratios
df['price/cashflow'] = (df['prcc_c'] * df['csho']) / df['oancf']
df['totaldebt/totalassets'] = df['dt'] / df['at']
df['totaldebt/equity'] = df['lt'] / df['seq']
df['roa'] = df['ebit'] / df['at']
df['totaldebt/totalliabilies'] = df['lt'] / df['at']
df['totaldebt/capital'] = df['dt'] / (df['dt'] + df['ceq'])
```

In [292]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1886 entries, 0 to 1885
Data columns (total 33 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   gvkey                       1886 non-null   int64
 1   datadate                    1886 non-null   int64
 2   fyear                       1886 non-null   int64
 3   indfmt                      1886 non-null   object
 4   consol                      1886 non-null   object
 5   popsrc                      1886 non-null   object
 6   datafmt                     1886 non-null   object
 7   Ticker                      1886 non-null   object
 8   curcd                       1886 non-null   object
 9   at                          1886 non-null   float64
 10  ceq                         1886 non-null   float64
 11  csho                        1886 non-null   float64
 12  dt                          1649 non-null   float64
 13  ebit                        1886 non-null   float64
 14  lt                          1881 non-null   float64
 15  ni                          1886 non-null   float64
 16  oancf                       1885 non-null   float64
 17  sale                        1886 non-null   float64
 18  seq                         1886 non-null   float64
 19  costat                      1886 non-null   object
 20  prcc_c                      1886 non-null   float64
 21  Name                        1886 non-null   object
 22  RetYTD                      1886 non-null   float64
 23  book/price                  1886 non-null   float64
 24  e/price                     1886 non-null   float64
 25  sale/price                  1886 non-null   float64
 26  ebit/price                  1886 non-null   float64
 27  price/cashflow              1885 non-null   float64
 28  totaldebt/totalassets       1649 non-null   float64
 29  totaldebt/equity            1881 non-null   float64
 30  roa                         1886 non-null   float64
 31  totaldebt/totalliabilies    1881 non-null   float64
 32  totaldebt/capital           1649 non-null   float64
dtypes: float64(22), int64(3), object(8)
memory usage: 501.0+ KB
```

In [293]:

```
# check null value
df.isna().sum()
```

Out[293]:

```
gvkey                           0
datadate                        0
fyear                           0
indfmt                          0
consol                          0
popsrc                          0
datafmt                         0
Ticker                          0
curcd                           0
at                              0
ceq                             0
csho                            0
dt                            237
ebit                            0
lt                              5
ni                              0
oancf                           1
sale                            0
seq                             0
costat                          0
prcc_c                          0
Name                            0
RetYTD                          0
book/price                      0
e/price                         0
sale/price                      0
ebit/price                      0
price/cashflow                  1
totaldebt/totalassets         237
totaldebt/equity                5
roa                             0
totaldebt/totalliabilies        5
totaldebt/capital             237
dtype: int64
```

Winsorize

In [294]:

```
#import winsorize
from scipy.stats.mstats import winsorize
```

winsorize for price/cashflow:

In [295]:

```
# winsorize
df['price/cashflow'] = winsorize(df['price/cashflow'], (0.01,0.01))
df['price/cashflow'].describe()
```

Out[295]:

```
count     1886.000000
mean        18.696278
std         49.327257
min       -142.704032
25%          5.901279
50%         12.229813
75%         23.454398
max        340.564298
Name: price/cashflow, dtype: float64
```

winsorize for totaldebt/totalassets:

In [296]:

```
# because we lose 237 values, which is a lot. So we fill the NA with average val
ue
df['totaldebt/totalassets'].fillna(df['totaldebt/totalassets'].mean(), inplace=T
rue)
df['totaldebt/totalassets'].describe()
```

Out[296]:

```
count     1886.000000
mean         0.330024
std          0.237333
min          0.000000
25%          0.176501
50%          0.330024
75%          0.430186
max          3.165332
Name: totaldebt/totalassets, dtype: float64
```

winsorize for totaldebt/equity:

In [297]:

```
# winsorize
df['totaldebt/equity'] = winsorize(df['totaldebt/equity'], (0.01,0.01))
df['totaldebt/equity'].describe()
```

Out[297]:

```
count    1886.000000
mean        2.755861
std         5.741946
min       -24.094786
25%         0.759778
50%         1.538695
75%         3.468388
max        31.522617
Name: totaldebt/equity, dtype: float64
```

winsorize for totaldebt/totalliabilies:

In [298]:

```
# winsorize
df['totaldebt/totalliabilies'] = winsorize(df['totaldebt/totalliabilies'], (0.01
,0.01))
df['totaldebt/totalliabilies'].describe()
```

Out[298]:

```
count    1886.000000
mean        0.631315
std         0.256761
min         0.086737
25%         0.460233
50%         0.633081
75%         0.802777
max         1.552428
Name: totaldebt/totalliabilies, dtype: float64
```

winsorize for totaldebt/capital:

In [299]:

```
# winsorize
df['totaldebt/capital'].fillna(df['totaldebt/capital'].mean(), inplace=True)
df['totaldebt/capital'].describe()
```

Out[299]:

```
count    1886.000000
mean        0.470835
std         0.392527
min        -3.714286
25%         0.276201
50%         0.470835
75%         0.588980
max         6.584568
Name: totaldebt/capital, dtype: float64
```

double check:

In [300]:

```
df.isna().sum()
```

Out[300]:

```
gvkey                         0
datadate                      0
fyear                         0
indfmt                        0
consol                        0
popsrc                        0
datafmt                       0
Ticker                        0
curcd                         0
at                            0
ceq                           0
csho                          0
dt                          237
ebit                          0
lt                            5
ni                            0
oancf                         1
sale                          0
seq                           0
costat                        0
prcc_c                        0
Name                          0
RetYTD                        0
book/price                    0
e/price                       0
sale/price                    0
ebit/price                    0
price/cashflow                0
totaldebt/totalassets         0
totaldebt/equity              0
roa                           0
totaldebt/totalliabilies      0
totaldebt/capital             0
dtype: int64
```

Save variables to new csv

In [301]:

```
# save 10 ratios and ticker symbol to new dataframe
  new=pd.DataFrame({'Ticker': df['Ticker'],
                    'book/price': df['book/price'],
                    'e/price': df['e/price'],
                    'sale/price': df['sale/price'],
                    'ebit/price': df['ebit/price'],
                    'price/cashflow': df['price/cashflow'],
                    'totaldebt/totalassets': df['totaldebt/totalassets'],
                    'totaldebt/equity': df['totaldebt/equity'],
                    'roa': df['roa'],
                    'totaldebt/totalliabilies': df['totaldebt/totalliabilies'],
                    'totaldebt/capital': df['totaldebt/capital'],
                    })
  new.head(5)
```

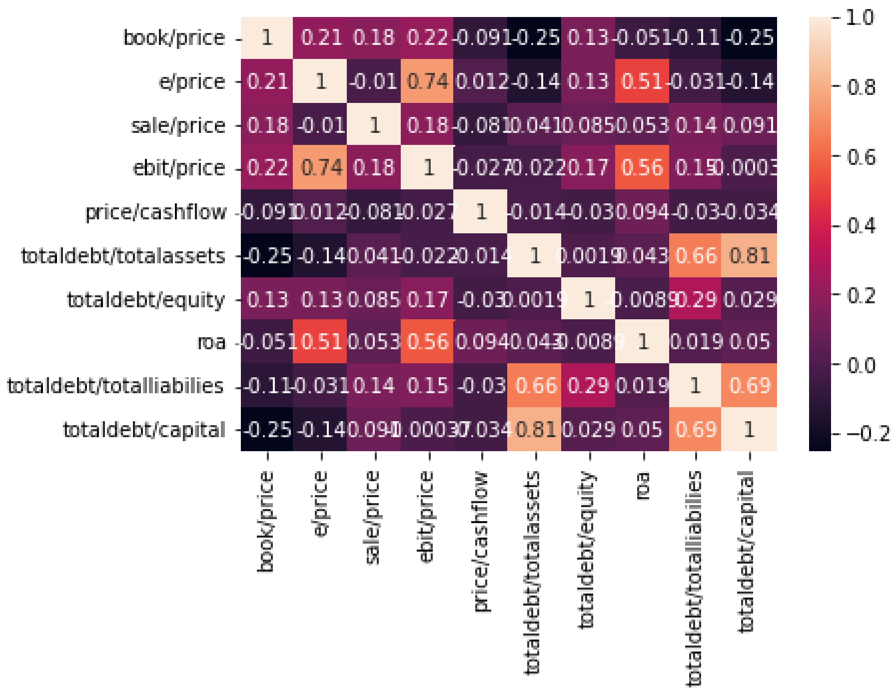
Out[301]:

	Ticker	book/price	e/price	sale/price	ebit/price	price/cashflow	totaldebt/totalassets	t
0	AIR	0.760488	0.027941	1.288865	0.051121	12.179491	0.133208	
1	AAL	-0.630953	-0.171320	2.568684	-0.473988	16.524425	0.694736	
2	PNW	0.740913	0.077616	0.477178	0.101023	9.269055	0.330024	
3	ABT	0.144202	0.028480	0.173496	0.036113	23.571338	0.256011	
4	AMD	0.043164	0.018205	0.094618	0.021176	49.328969	0.058942	

plot the heatmap

In [330]:

```
sns.heatmap(new.corr(), annot=True)
plt.show()
```



In [302]:

```
# dataframe to csv
new.to_csv("Fin-Ratios.csv")
```

(4) Industry Indicators

In [303]:

```
# import temGICS.csv
temp = pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-sessio
n02/main/tempGICSS.csv')
```

In [304]:

```
# import project tickers.csv
data1 = pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-sessi
on02/main/ProjectTickers.csv')
```

In [305]:

```
temp.isna().sum()
```

Out[305]:

```
gvkey       0
datadate    0
fyear       0
indfmt      0
consol      0
popsrc      0
datafmt     0
tic         0
curcd       0
costat      0
ggroup      0
dtype: int64
```

In [306]:

```
data1.isna().sum()
```

Out[306]:

```
Ticker    0
Name      0
RetYTD    0
dtype: int64
```

In [307]:

```
# rename column
temp.rename(columns={'tic':'Ticker'}, inplace=True)
temp.head()
```

Out[307]:

	gvkey	datadate	fyear	indfmt	consol	popsrc	datafmt	Ticker	curcd	costat	ggroup
0	1004	20210531	2020	INDL	C	D	STD	AIR	USD	A	2010
1	1045	20211231	2021	INDL	C	D	STD	AAL	USD	A	2030
2	1075	20211231	2021	INDL	C	D	STD	PNW	USD	A	5510
3	1078	20211231	2021	INDL	C	D	STD	ABT	USD	A	3510
4	1161	20211231	2021	INDL	C	D	STD	AMD	USD	A	4530

In [308]:

```
# merge two datasets
df2 = pd.merge(temp, data1, how='outer', on='Ticker')
```

In [309]:

```
df2.head()
```

Out[309]:

	gvkey	datadate	fyear	indfmt	consol	popsrc	datafmt	Ticker	curcd	costat	ggroup
0	1004	20210531	2020	INDL	C	D	STD	AIR	USD	A	2010
1	1045	20211231	2021	INDL	C	D	STD	AAL	USD	A	2030
2	1075	20211231	2021	INDL	C	D	STD	PNW	USD	A	5510
3	1078	20211231	2021	INDL	C	D	STD	ABT	USD	A	3510
4	1161	20211231	2021	INDL	C	D	STD	AMD	USD	A	4530

In [310]:

```
# get dummy
df2 = pd.get_dummies(df2, columns=['ggroup'])
df2.head()
```

Out[310]:

	gvkey	datadate	fyear	indfmt	consol	popsrc	datafmt	Ticker	curcd	costat	...	ggrou
0	1004	20210531	2020	INDL	C	D	STD	AIR	USD	A	...	
1	1045	20211231	2021	INDL	C	D	STD	AAL	USD	A	...	
2	1075	20211231	2021	INDL	C	D	STD	PNW	USD	A	...	
3	1078	20211231	2021	INDL	C	D	STD	ABT	USD	A	...	
4	1161	20211231	2021	INDL	C	D	STD	AMD	USD	A	...	

5 rows × 36 columns

In [311]:

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1886 entries, 0 to 1885
Data columns (total 36 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   gvkey        1886 non-null   int64  
 1   datadate     1886 non-null   int64  
 2   fyear        1886 non-null   int64  
 3   indfmt       1886 non-null   object 
 4   consol       1886 non-null   object 
 5   popsrc       1886 non-null   object 
 6   datafmt      1886 non-null   object 
 7   Ticker       1886 non-null   object 
 8   curcd        1886 non-null   object 
 9   costat       1886 non-null   object 
 10  Name         1886 non-null   object 
 11  RetYTD       1886 non-null   float64
 12  ggroup_1010  1886 non-null   uint8  
 13  ggroup_1510  1886 non-null   uint8  
 14  ggroup_2010  1886 non-null   uint8  
 15  ggroup_2020  1886 non-null   uint8  
 16  ggroup_2030  1886 non-null   uint8  
 17  ggroup_2510  1886 non-null   uint8  
 18  ggroup_2520  1886 non-null   uint8  
 19  ggroup_2530  1886 non-null   uint8  
 20  ggroup_2550  1886 non-null   uint8  
 21  ggroup_3010  1886 non-null   uint8  
 22  ggroup_3020  1886 non-null   uint8  
 23  ggroup_3030  1886 non-null   uint8  
 24  ggroup_3510  1886 non-null   uint8  
 25  ggroup_3520  1886 non-null   uint8  
 26  ggroup_4010  1886 non-null   uint8  
 27  ggroup_4020  1886 non-null   uint8  
 28  ggroup_4030  1886 non-null   uint8  
 29  ggroup_4510  1886 non-null   uint8  
 30  ggroup_4520  1886 non-null   uint8  
 31  ggroup_4530  1886 non-null   uint8  
 32  ggroup_5010  1886 non-null   uint8  
 33  ggroup_5020  1886 non-null   uint8  
 34  ggroup_5510  1886 non-null   uint8  
 35  ggroup_6010  1886 non-null   uint8  
dtypes: float64(1), int64(3), object(8), uint8(24)
memory usage: 235.8+ KB
```

In [312]:

```
# delete useless columns
del df2['gvkey']
del df2['datadate']
del df2['fyear']
del df2['indfmt']
del df2['consol']
del df2['popsrc']
del df2['datafmt']
del df2['curcd']
del df2['costat']
del df2['Name ']
del df2['RetYTD']
```

In [313]:

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1886 entries, 0 to 1885
Data columns (total 25 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Ticker       1886 non-null   object
 1   ggroup_1010  1886 non-null   uint8 
 2   ggroup_1510  1886 non-null   uint8 
 3   ggroup_2010  1886 non-null   uint8 
 4   ggroup_2020  1886 non-null   uint8 
 5   ggroup_2030  1886 non-null   uint8 
 6   ggroup_2510  1886 non-null   uint8 
 7   ggroup_2520  1886 non-null   uint8 
 8   ggroup_2530  1886 non-null   uint8 
 9   ggroup_2550  1886 non-null   uint8 
 10  ggroup_3010  1886 non-null   uint8 
 11  ggroup_3020  1886 non-null   uint8 
 12  ggroup_3030  1886 non-null   uint8 
 13  ggroup_3510  1886 non-null   uint8 
 14  ggroup_3520  1886 non-null   uint8 
 15  ggroup_4010  1886 non-null   uint8 
 16  ggroup_4020  1886 non-null   uint8 
 17  ggroup_4030  1886 non-null   uint8 
 18  ggroup_4510  1886 non-null   uint8 
 19  ggroup_4520  1886 non-null   uint8 
 20  ggroup_4530  1886 non-null   uint8 
 21  ggroup_5010  1886 non-null   uint8 
 22  ggroup_5020  1886 non-null   uint8 
 23  ggroup_5510  1886 non-null   uint8 
 24  ggroup_6010  1886 non-null   uint8 
dtypes: object(1), uint8(24)
memory usage: 73.7+ KB
```

Save variables to new csv

In [314]:

```
# dataframe to csv
df2.to_csv("Industry.csv")
```

(5) Run OLS explanatory for 4 categories

a. Risk Regressions:

In [315]:

```
# import FF exposures csv
ff1=pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-assignmen
ts/main/FF-Exposures.csv')
```

In [316]:

```
# rename column
ff1.rename(columns={'TICKER':'Ticker'}, inplace=True)
```

In [317]:

```
# merge FF exposures and tickers retYTD
dfa = pd.merge(ff1, pt, how='outer', on='Ticker')
```

In [318]:

```
dfa.head()
```

Out[318]:

	Unnamed: 0	Ticker	mktrf	smb	hml	Name	RetYTD
0	0	A	1.014152	-0.253674	-0.143608	Agilent Technologies	-0.2080
1	1	AA	1.984149	0.527862	1.924844	Alcoa Corp	0.4731
2	2	AAL	1.315550	0.612825	1.248123	American Airlines Gp	0.0579
3	3	AAN	1.640807	0.141355	0.841349	Aarons Holdings Company	-0.1327
4	4	AAON	0.516779	0.422130	-0.117068	Aaon Inc	-0.3456

In [319]:

```
# Run OLS regression
y = dfa["RetYTD"]
X = dfa[['mktrf' , 'smb' , 'hml']]
# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()
model.summary()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:1
17: FutureWarning: In a future version of pandas all arguments of co
ncat except for the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

Out[319]:

OLS Regression Results

Dep. Variable:	RetYTD	**R-squared:**	0.095
Model:	OLS	**Adj. R-squared:**	0.093
Method:	Least Squares	**F-statistic:**	65.51
Date:	Thu, 28 Apr 2022	**Prob (F-statistic):**	2.76e-40
Time:	01:50:54	**Log-Likelihood:**	79.945
No. Observations:	1886	**AIC:**	-151.9
Df Residuals:	1882	**BIC:**	-129.7
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0981	0.011	-8.783	0.000	-0.120	-0.076
mktrf	0.0082	0.009	0.957	0.339	-0.009	0.025
smb	-0.0120	0.004	-2.736	0.006	-0.021	-0.003
hml	0.1068	0.008	13.814	0.000	0.092	0.122

Omnibus:	642.171	**Durbin-Watson:**	2.005
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3599.566
Skew:	1.492	**Prob(JB):**	0.00
Kurtosis:	9.074	**Cond. No.**	4.56

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

Through the regression, we can find the R-squared is 0.095 and Adj.R-squared is 0.093, which is not good. The explanatory level is low. Also, mktrf and hml's coefficient are positive(0.0082 and 0.1068), which means the size and market exposure have posive effect on stock return. Finally, the negative coefficient(-0.0120) of smb means that size exposure has negative effect on stock return.

b. Financial Characteristics:

In [320]:

```
# import fin ratios csv
ff2=pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-assignmen
ts/main/Fin-Ratios.csv')

# merge FF exposures and tickers retYTD
dfb = pd.merge(ff2, pt, how='outer', on='Ticker')

# Run OLS regression
y = dfb["RetYTD"]
X = dfb[['book/price' , 'e/price' , 'sale/price','ebit/price','price/cashflow',
          'totaldebt/totalassets','totaldebt/equity','roa','totaldebt/totalliabil
ies','totaldebt/capital']]

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()
model.summary()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:1
17: FutureWarning: In a future version of pandas all arguments of co
ncat except for the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

Out[320]:

OLS Regression Results

Dep. Variable:	RetYTD	**R-squared:**	0.085
Model:	OLS	**Adj. R-squared:**	0.080
Method:	Least Squares	**F-statistic:**	17.46
Date:	Thu, 28 Apr 2022	**Prob (F-statistic):**	9.87e-31
Time:	01:50:54	**Log-Likelihood:**	70.268
No. Observations:	1886	**AIC:**	-118.5
Df Residuals:	1875	**BIC:**	-57.57
Df Model:	10		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-0.1639	0.017	-9.731	0.000	-0.197	-0.131
book/price	0.1370	0.014	9.704	0.000	0.109	0.165
e/price	-0.1240	0.063	-1.965	0.050	-0.248	-0.000
sale/price	0.0130	0.004	3.251	0.001	0.005	0.021
ebit/price	0.1436	0.071	2.020	0.043	0.004	0.283
price/cashflow	-0.0001	0.000	-1.105	0.269	-0.000	9.49e-05
totaldebt/totalassets	0.0759	0.041	1.855	0.064	-0.004	0.156
totaldebt/equity	-0.0020	0.001	-1.976	0.048	-0.004	-1.49e-05
roa	0.1464	0.044	3.322	0.001	0.060	0.233
totaldebt/totalliabilies	-0.0155	0.033	-0.463	0.644	-0.081	0.050
totaldebt/capital	0.0277	0.026	1.078	0.281	-0.023	0.078

Omnibus:	649.740	**Durbin-Watson:**	1.948
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	4325.518
Skew:	1.454	**Prob(JB):**	0.00
Kurtosis:	9.826	**Cond. No.**	849.

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

Through the regression, we can find the R-squared is 0.085 and Adj.R-squared is 0.080, which is not good. The explanatory level is low. Also, (book/price, sale/price, ebit/price, totaldebt/ totalassets, roa, totaldebt/capital)'s coefficient are positive, which means they have posive effect on stock return. Finally, the negative coefficient of (e/price, price/cashflow, totaldebt/equity, totaldebt/totalliabilities) means that they have negative effect on stock return.

c. Industry Dummies:

In [321]:

```
# import fin ratios csv
ff3=pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-assignmen
ts/main/Industry.csv')

# merge FF exposures and tickers retYTD
dfc = pd.merge(ff3, pt, how='outer', on='Ticker')
```

In [322]:

```
dfc.head()
```

Out[322]:

	Unnamed: 0	Ticker	ggroup_1010	ggroup_1510	ggroup_2010	ggroup_2020	ggroup_2030	gg
0	0	AIR	0	0	1	0	0	
1	1	AAL	0	0	0	0	1	
2	2	PNW	0	0	0	0	0	
3	3	ABT	0	0	0	0	0	
4	4	AMD	0	0	0	0	0	

5 rows × 28 columns

In [323]:

```
# Run OLS regression
y = dfc["RetYTD"]
X = dfc.iloc[:,2:-2]

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()
model.summary()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:1
17: FutureWarning: In a future version of pandas all arguments of co
ncat except for the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

Out[323]:

OLS Regression Results

Dep. Variable:	RetYTD	**R-squared:**	0.326
Model:	OLS	**Adj. R-squared:**	0.317
Method:	Least Squares	**F-statistic:**	39.07
Date:	Thu, 28 Apr 2022	**Prob (F-statistic):**	6.29e-141
Time:	01:50:54	**Log-Likelihood:**	357.63
No. Observations:	1886	**AIC:**	-667.3
Df Residuals:	1862	**BIC:**	-534.2
Df Model:	23		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0525	0.006	-9.154	0.000	-0.064	-0.041
ggroup_1010	0.5675	0.023	24.634	0.000	0.522	0.613
ggroup_1510	0.1103	0.021	5.346	0.000	0.070	0.151
ggroup_2010	-0.0381	0.015	-2.473	0.013	-0.068	-0.008
ggroup_2020	0.0173	0.025	0.692	0.489	-0.032	0.066
ggroup_2030	-0.0150	0.031	-0.476	0.634	-0.077	0.047
ggroup_2510	-0.1555	0.039	-3.980	0.000	-0.232	-0.079
ggroup_2520	-0.1561	0.025	-6.242	0.000	-0.205	-0.107
ggroup_2530	-0.0101	0.025	-0.407	0.684	-0.059	0.039
ggroup_2550	-0.0987	0.022	-4.569	0.000	-0.141	-0.056
ggroup_3010	0.1308	0.047	2.770	0.006	0.038	0.223
ggroup_3020	0.0913	0.030	3.074	0.002	0.033	0.149
ggroup_3030	-0.1013	0.047	-2.145	0.032	-0.194	-0.009
ggroup_3510	-0.0140	0.018	-0.755	0.450	-0.050	0.022
ggroup_3520	-0.1115	0.016	-6.887	0.000	-0.143	-0.080
ggroup_4010	-0.0354	0.016	-2.275	0.023	-0.066	-0.005
ggroup_4020	-0.0700	0.021	-3.344	0.001	-0.111	-0.029
ggroup_4030	0.0563	0.025	2.215	0.027	0.006	0.106
ggroup_4510	-0.0562	0.019	-3.005	0.003	-0.093	-0.020
ggroup_4520	-0.1196	0.022	-5.412	0.000	-0.163	-0.076
ggroup_4530	-0.2003	0.027	-7.509	0.000	-0.253	-0.148
ggroup_5010	0.0643	0.054	1.193	0.233	-0.041	0.170
ggroup_5020	-0.0184	0.030	-0.606	0.545	-0.078	0.041
ggroup_5510	0.0932	0.026	3.584	0.000	0.042	0.144
ggroup_6010	0.0167	0.018	0.934	0.350	-0.018	0.052

Omnibus:	403.265	**Durbin-Watson:**	2.008
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2314.656
Skew:	0.877	**Prob(JB):**	0.00
Kurtosis:	8.136	**Cond. No.**	2.02e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 4.91e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Through the regression, we can find the R-squared is 0.326 and Adj.R-squared is 0.317, which is below 0.5 and not good. The explanatory level is low. Also, (ggroup_1010,1510,2020,3010,3020,4030,5010,5510,6010)'s coefficient are positive, which means they have posive effect on stock return. Finally, the negative coefficient of the rest ggroups mean that they have negative effect on stock return.

d. Combined Regressions:

In [324]:

```
# combine datasets and tickers
f1 = pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-assignments/main/FF-Exposures.csv')
f1.rename(columns={'TICKER':'Ticker'}, inplace=True)
f2 =pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-assignments/main/Fin-Ratios.csv')
f3 =pd.read_csv('https://raw.githubusercontent.com/ChasteloveCNN/ba765-assignments/main/Industry.csv')

dff1 = pd.merge(f1, f2, how='outer', on='Ticker')
dff2 = pd.merge(dff1, f3, how='outer', on='Ticker')
dfff = pd.merge(dff2, pt, how='outer', on='Ticker')
```

In [325]:

```
dfff.head()
```

Out[325]:

	Unnamed: 0_x	Ticker	mktrf	smb	hml	Unnamed: 0_y	book/price	e/price	sale/p
0	0	A	1.014152	-0.253674	-0.143608	1420	0.111695	0.025079	0.13
1	1	AA	1.984149	0.527862	1.924844	1020	0.425940	0.039111	1.10
2	2	AAL	1.315550	0.612825	1.248123	1	-0.630953	-0.171320	2.56
3	3	AAN	1.640807	0.141355	0.841349	1182	0.940491	0.143967	2.41
4	4	AAON	0.516779	0.422130	-0.117068	803	0.111730	0.014083	0.12

5 rows × 43 columns

In [326]:

```
dfff.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1886 entries, 0 to 1885
Data columns (total 43 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Unnamed: 0_x                   1886 non-null   int64  
 1   Ticker                         1886 non-null   object 
 2   mktrf                          1886 non-null   float64
 3   smb                            1886 non-null   float64
 4   hml                            1886 non-null   float64
 5   Unnamed: 0_y                   1886 non-null   int64  
 6   book/price                     1886 non-null   float64
 7   e/price                        1886 non-null   float64
 8   sale/price                     1886 non-null   float64
 9   ebit/price                     1886 non-null   float64
 10  price/cashflow                 1886 non-null   float64
 11  totaldebt/totalassets          1886 non-null   float64
 12  totaldebt/equity               1886 non-null   float64
 13  roa                            1886 non-null   float64
 14  totaldebt/totalliabilies       1886 non-null   float64
 15  totaldebt/capital              1886 non-null   float64
 16  Unnamed: 0                     1886 non-null   int64  
 17  ggroup_1010                    1886 non-null   int64  
 18  ggroup_1510                    1886 non-null   int64  
 19  ggroup_2010                    1886 non-null   int64  
 20  ggroup_2020                    1886 non-null   int64  
 21  ggroup_2030                    1886 non-null   int64  
 22  ggroup_2510                    1886 non-null   int64  
 23  ggroup_2520                    1886 non-null   int64  
 24  ggroup_2530                    1886 non-null   int64  
 25  ggroup_2550                    1886 non-null   int64  
 26  ggroup_3010                    1886 non-null   int64  
 27  ggroup_3020                    1886 non-null   int64  
 28  ggroup_3030                    1886 non-null   int64  
 29  ggroup_3510                    1886 non-null   int64  
 30  ggroup_3520                    1886 non-null   int64  
 31  ggroup_4010                    1886 non-null   int64  
 32  ggroup_4020                    1886 non-null   int64  
 33  ggroup_4030                    1886 non-null   int64  
 34  ggroup_4510                    1886 non-null   int64  
 35  ggroup_4520                    1886 non-null   int64  
 36  ggroup_4530                    1886 non-null   int64  
 37  ggroup_5010                    1886 non-null   int64  
 38  ggroup_5020                    1886 non-null   int64  
 39  ggroup_5510                    1886 non-null   int64  
 40  ggroup_6010                    1886 non-null   int64  
 41  Name                           1886 non-null   object 
 42  RetYTD                         1886 non-null   float64
dtypes: float64(14), int64(27), object(2)
memory usage: 648.3+ KB
```

In [327]:

```
# Run OLS regression
y = dfff["RetYTD"]
X = dfff[['mktrf','smb','hml','book/price','e/price','sale/price','ebit/price',
'price/cashflow','totaldebt/totalassets','totaldebt/equity',
          'roa','totaldebt/totalliabilies','totaldebt/capital','ggroup_1010','gg
roup_1510',
          'ggroup_2010','ggroup_2020','ggroup_2030','ggroup_2510','ggroup_2520',
'ggroup_2530','ggroup_2550',
          'ggroup_3010','ggroup_3020','ggroup_3030','ggroup_3510','ggroup_3520',
          'ggroup_4010','ggroup_4020','ggroup_4030','ggroup_4510','ggroup_4520',
'ggroup_4530','ggroup_5010',
          'ggroup_5020','ggroup_5510','ggroup_6010']]
# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()
model.summary()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:1
17: FutureWarning: In a future version of pandas all arguments of co
ncat except for the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

Out[327]:

OLS Regression Results

Dep. Variable:	RetYTD	**R-squared:**	0.382
Model:	OLS	**Adj. R-squared:**	0.370
Method:	Least Squares	**F-statistic:**	31.71
Date:	Thu, 28 Apr 2022	**Prob (F-statistic):**	5.93e-165
Time:	01:50:54	**Log-Likelihood:**	439.74
No. Observations:	1886	**AIC:**	-805.5
Df Residuals:	1849	**BIC:**	-600.4
Df Model:	36		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.1091	0.019	-5.612	0.000	-0.147	-0.071
mktrf	-0.0161	0.008	-1.974	0.049	-0.032	-0.000
smb	-0.0174	0.004	-4.135	0.000	-0.026	-0.009
hml	0.0681	0.009	7.945	0.000	0.051	0.085
book/price	0.0684	0.014	4.956	0.000	0.041	0.095
e/price	-0.0326	0.053	-0.610	0.542	-0.137	0.072
sale/price	0.0026	0.004	0.679	0.497	-0.005	0.010
ebit/price	0.0841	0.062	1.353	0.176	-0.038	0.206
price/cashflow	-4.624e-05	9.36e-05	-0.494	0.621	-0.000	0.000
totaldebt/totalassets	-0.0429	0.039	-1.106	0.269	-0.119	0.033
totaldebt/equity	-0.0001	0.001	-0.123	0.902	-0.002	0.002
roa	0.0753	0.042	1.808	0.071	-0.006	0.157
totaldebt/totalliabilies	0.0193	0.035	0.555	0.579	-0.049	0.088
totaldebt/capital	0.0522	0.022	2.422	0.016	0.010	0.095
ggroup_1010	0.5254	0.025	21.305	0.000	0.477	0.574
ggroup_1510	0.0894	0.020	4.466	0.000	0.050	0.129
ggroup_2010	-0.0372	0.015	-2.474	0.013	-0.067	-0.008
ggroup_2020	0.0144	0.024	0.599	0.549	-0.033	0.062
ggroup_2030	-0.0403	0.031	-1.321	0.187	-0.100	0.020
ggroup_2510	-0.1685	0.038	-4.403	0.000	-0.243	-0.093
ggroup_2520	-0.1633	0.024	-6.707	0.000	-0.211	-0.116
ggroup_2530	-0.0064	0.025	-0.252	0.801	-0.056	0.043
ggroup_2550	-0.0993	0.022	-4.550	0.000	-0.142	-0.057
ggroup_3010	0.1097	0.048	2.279	0.023	0.015	0.204
ggroup_3020	0.0805	0.029	2.787	0.005	0.024	0.137

ggroup_3030	-0.1006	0.046	-2.201	0.028	-0.190	-0.011
ggroup_3510	0.0391	0.018	2.124	0.034	0.003	0.075
ggroup_3520	0.0012	0.019	0.062	0.951	-0.036	0.039
ggroup_4010	-0.1080	0.020	-5.345	0.000	-0.148	-0.068
ggroup_4020	-0.1056	0.021	-4.947	0.000	-0.148	-0.064
ggroup_4030	-0.0136	0.029	-0.475	0.635	-0.070	0.043
ggroup_4510	0.0059	0.019	0.309	0.757	-0.032	0.043
ggroup_4520	-0.0979	0.022	-4.541	0.000	-0.140	-0.056
ggroup_4530	-0.1510	0.026	-5.710	0.000	-0.203	-0.099
ggroup_5010	0.0317	0.052	0.605	0.545	-0.071	0.134
ggroup_5020	0.0036	0.029	0.122	0.903	-0.054	0.061
ggroup_5510	0.0719	0.026	2.754	0.006	0.021	0.123
ggroup_6010	0.0100	0.019	0.535	0.593	-0.027	0.047

Omnibus:	451.293	**Durbin-Watson:**	2.024
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2689.708
Skew:	0.986	**Prob(JB):**	0.00
Kurtosis:	8.508	**Cond. No.**	2.34e+17

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 9.61e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

We can find the R-squared is 0.382 and Adj.R-squared is 0.370, which are not good and below 0.5. So the explanatory power is low.