Assignment2_Ji_Qi

April 7, 2022

1 ***Student Name: Ji Qi , Session B1***

1.0.1 Import packages

[3]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

import statsmodels.api as sm
from statsmodels.sandbox.regression.predstd import wls_prediction_std
```

2 Model preparation

2.1 Basic Info about the Data

- 2 missing values in current assets
- 1 missing values in current liability
- Don't fill nan with '0'
- `CA = alpha + beta 1 * TA + beta 2 * sales` to predict current assets
- More interested in finance ratio, convert to the current ratio like CA/CL, and impute the missing values with the mean of CA/CL

[4]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[5]:
```
data = pd.read_csv('/content/drive/MyDrive/BA_870/HW/2/assignment2.csv')
```

[6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 354 entries, 0 to 353
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
```

```
---  ------              --------------  -----
 0   TICKER              354 non-null    object
 1   CURRENT ASSETS      352 non-null    float64
 2   TOTAL ASSETS        354 non-null    float64
 3   EBIT                354 non-null    float64
 4   CURRENT LIABIL      353 non-null    float64
 5   TOTAL LIABILITIES   354 non-null    float64
 6   RETAINED EARNINGS   354 non-null    float64
 7   TOTAL SALES         354 non-null    float64
 8   CREDIT_RATING       354 non-null    int64
dtypes: float64(7), int64(1), object(1)
memory usage: 25.0+ KB
```

[7]:
```
data.head()
```

[7]:
```
  TICKER  CURRENT ASSETS  TOTAL ASSETS      EBIT  CURRENT LIABIL  \
0   ARXX         328.354       638.022    47.473         119.215
1    ABT       11281.883     36178.172  4860.219       11951.195
2    AMD        3963.000     13147.000   401.000        2852.000
3    APD        2612.600     11180.700  1013.500        2323.400
4    HON       12304.000     30941.000  3544.000       10135.000

   TOTAL LIABILITIES  RETAINED EARNINGS  TOTAL SALES  CREDIT_RATING
0            150.352             95.273      551.846              7
1          22123.986           9958.494    22476.322             19
2           7072.000            464.000     5649.000              7
3           6078.700           5521.800     8850.400             16
4          21221.000          11256.000    31367.000             16
```

[8]:
```
data.describe()
```

[8]:
```
       CURRENT ASSETS   TOTAL ASSETS          EBIT  CURRENT LIABIL  \
count      352.000000     354.000000    354.000000      353.000000
mean      4573.438503   13252.169178   1646.369554     3219.204343
std       9732.694678   31574.580520   4853.767859     7791.253422
min         22.094000     112.675000  -8167.000000       18.740000
25%        593.983750    1599.039500    123.920000      283.542000
50%       1429.000000    3525.339000    356.000000      749.289000
75%       4019.000000   10444.750000   1009.450250     2560.000000
max      91885.000000  278554.000000  56939.000000    76748.000000

       TOTAL LIABILITIES  RETAINED EARNINGS   TOTAL SALES  CREDIT_RATING
count         354.000000         354.000000    354.000000     354.000000
mean         7597.233605        4432.749562  12661.515785      12.129944
std         20785.050912       15233.620782  34093.899680       3.594938
min            48.123000       -7863.000000      4.159000       1.000000
25%           912.250000          74.619500   1496.367000       9.000000
```

50%	1987.700000	760.108000	3648.101000	12.000000
75%	6153.828750	2408.700000	9588.753500	15.000000
max	280860.000000	192445.000000	335086.000000	22.000000

2.2 Data Merging (Credit Rating + WRDS Compustat)

[11]:
```
data1 = pd.read_csv('/content/drive/MyDrive/BA_870/HW/2/wrds_assignment2.csv')
data1.head()
```

[11]:

	gvkey	datadate	fyear	indfmt	consol	popsrc	datafmt	tic	curcd	ceq \
0	1056	20060630	2006	INDL	C	D	STD	ARXX	USD	487.670
1	1078	20061231	2006	INDL	C	D	STD	ABT	USD	14054.186
2	1161	20061231	2006	INDL	C	D	STD	AMD	USD	5785.000
3	1209	20060930	2006	INDL	C	D	STD	APD	USD	4924.000
4	1300	20061231	2006	INDL	C	D	STD	HON	USD	9720.000

	csho	ni	costat	prcc_c
0	75.270	26.959	I	11.72
1	1537.243	1716.755	A	48.71
2	547.000	-166.000	A	20.35
3	217.251	723.400	A	70.28
4	800.592	2083.000	A	45.24

[12]:
```
print(data.TICKER.nunique())
print(data1.tic.nunique())
```

354
344

[13]:
```
df = pd.merge(data, data1, how = 'left', left_on= 'TICKER', right_on= 'tic',␣
↪indicator= True)
df._merge.value_counts()
```

[13]:
```
both          344
left_only      10
right_only      0
Name: _merge, dtype: int64
```

[14]:
```
df[df._merge == 'left_only']
```

[14]:

	TICKER	CURRENT ASSETS	TOTAL ASSETS	EBIT	CURRENT LIABIL \
75	DNA	5704.000	14842.000	3219.000	2157.000
94	IMO	5309.000	16141.000	3845.000	5348.000
115	LZ	1836.300	4390.900	384.700	634.400
194	RDS.A	91885.000	235276.000	37678.000	76748.000
209	SU	2302.000	18781.000	3395.000	2158.000

```
212     PCZ        2826.000      22646.000   4366.000         3348.000
231     ETH         423.756        812.241    146.913          145.718
244     PRM         323.104       1254.329    109.688          295.267
303      AG          22.094        112.675     -6.557           18.740
305     LLL        3929.800      13286.700   1279.100         2376.400

     TOTAL LIABILITIES  RETAINED EARNINGS  TOTAL SALES  CREDIT_RATING  gvkey  \
75            5364.000           -634.000     9284.000             19    NaN
94            8735.000           5729.000    23231.000             22    NaN
115           2656.500            973.000     4040.800             12    NaN
194         120331.000         108497.000   318845.000             19    NaN
209           9829.000           8058.000    14842.000             15    NaN
212          12205.000           8606.000    18911.000             13    NaN
231            394.799            530.431     1066.390             15    NaN
244           1777.559          -2817.028      849.309              7    NaN
303             56.687              5.857        4.159             11    NaN
305           7896.500           1929.400    12476.900             12    NaN

     …  popsrc  datafmt  tic curcd ceq csho  ni costat  prcc_c     _merge
75   …     NaN      NaN  NaN   NaN NaN  NaN NaN    NaN     NaN  left_only
94   …     NaN      NaN  NaN   NaN NaN  NaN NaN    NaN     NaN  left_only
115  …     NaN      NaN  NaN   NaN NaN  NaN NaN    NaN     NaN  left_only
194  …     NaN      NaN  NaN   NaN NaN  NaN NaN    NaN     NaN  left_only
209  …     NaN      NaN  NaN   NaN NaN  NaN NaN    NaN     NaN  left_only
212  …     NaN      NaN  NaN   NaN NaN  NaN NaN    NaN     NaN  left_only
231  …     NaN      NaN  NaN   NaN NaN  NaN NaN    NaN     NaN  left_only
244  …     NaN      NaN  NaN   NaN NaN  NaN NaN    NaN     NaN  left_only
303  …     NaN      NaN  NaN   NaN NaN  NaN NaN    NaN     NaN  left_only
305  …     NaN      NaN  NaN   NaN NaN  NaN NaN    NaN     NaN  left_only

[10 rows x 24 columns]
```

- The WRDS (price and shares) data will have about 344 observations (compared to 354 for Assignment2.csv)
- Decide to drop 10 rows of missing observation in the WRDS dataset
- Except for the Current Assets and Current Liabillity Columns, prcc_c also has 11 missing data

[15]:
```python
df = df[df._merge == 'both']
df.reset_index(inplace = True)
df = df.drop(columns='index')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 344 entries, 0 to 343
Data columns (total 24 columns):
 #   Column             Non-Null Count  Dtype
```

```
---  ------            --------------  -----
 0   TICKER            344 non-null    object
 1   CURRENT ASSETS    342 non-null    float64
 2   TOTAL ASSETS      344 non-null    float64
 3   EBIT              344 non-null    float64
 4   CURRENT LIABIL    343 non-null    float64
 5   TOTAL LIABILITIES 344 non-null    float64
 6   RETAINED EARNINGS 344 non-null    float64
 7   TOTAL SALES       344 non-null    float64
 8   CREDIT_RATING     344 non-null    int64
 9   gvkey             344 non-null    float64
 10  datadate          344 non-null    float64
 11  fyear             344 non-null    float64
 12  indfmt            344 non-null    object
 13  consol            344 non-null    object
 14  popsrc            344 non-null    object
 15  datafmt           344 non-null    object
 16  tic               344 non-null    object
 17  curcd             344 non-null    object
 18  ceq               344 non-null    float64
 19  csho              344 non-null    float64
 20  ni                344 non-null    float64
 21  costat            344 non-null    object
 22  prcc_c            333 non-null    float64
 23  _merge            344 non-null    category
dtypes: category(1), float64(14), int64(1), object(8)
memory usage: 62.4+ KB
```

2.3 Fill the NaN values using the Predictive Model

[16]:
```
# 13 Rows with at least one missing value
df[df.isna().any(axis=1)]
```

[16]:

	TICKER	CURRENT ASSETS	TOTAL ASSETS	EBIT	CURRENT LIABIL	\
73	F	NaN	278554.000	-8167.000	NaN	
165	TXT	NaN	17550.000	1413.000	6317.000	
174	DOW2	3485.000	8190.000	873.000	943.000	
208	TRS	311.600	1286.060	104.950	205.270	
223	3525B	167.304	1423.501	138.668	89.243	
238	8135A	500.100	944.000	-16.200	377.100	
274	LYO1	1010.000	2414.000	32.000	509.000	
291	3368B	307.509	663.355	60.010	92.094	
312	9971B	139.699	1427.783	113.268	124.042	
321	0252B	114.009	242.665	42.163	54.542	
322	0282B	62.374	156.741	16.484	34.354	
339	0507B	355.845	807.330	62.362	157.103	

342	MX	244.064	770.053	-119.488	121.449

	TOTAL LIABILITIES	RETAINED EARNINGS	TOTAL SALES	CREDIT_RATING	\
73	280860.000	-7863.000	160123.000	7	
165	14901.000	5567.000	11490.000	15	
174	3767.000	4299.000	7528.000	12	
208	1053.280	-166.500	1020.530	8	
223	1030.661	83.030	424.134	8	
238	2161.600	-2092.600	1331.400	5	
274	2226.000	-943.000	1948.000	8	
291	952.286	-256.426	742.683	3	
312	1160.824	61.518	835.876	9	
321	164.390	21.643	428.616	7	
322	242.602	-92.386	271.603	6	
339	531.909	72.130	927.797	8	
342	937.220	-339.713	744.352	13	

	gvkey	…	popsrc	datafmt	tic	curcd	ceq	csho	\
73	4839.0	…	D	STD	F	USD	-3465.000	1892.538	
165	10519.0	…	D	STD	TXT	USD	2639.000	125.596	
174	10857.0	…	D	STD	DOW2	USD	4420.000	0.001	
208	15252.0	…	D	STD	TRS	USD	232.780	20.760	
223	22839.0	…	D	STD	3525B	USD	392.840	0.001	
238	28004.0	…	D	STD	8135A	USD	-1272.200	0.005	
274	63637.0	…	D	STD	LYO1	USD	143.000	0.001	
291	66440.0	…	D	STD	3368B	USD	-288.931	0.001	
312	138143.0	…	D	STD	9971B	USD	59.520	2.298	
321	148250.0	…	D	STD	0252B	USD	78.275	0.827	
322	148310.0	…	D	STD	0282B	USD	-85.861	11.931	
339	165360.0	…	D	STD	0507B	USD	275.421	0.011	
342	233491.0	…	D	STD	MX	USD	-284.541	52.721	

	ni	costat	prcc_c	_merge
73	-12613.000	A	7.51	both
165	601.000	A	93.77	both
174	1046.000	A	NaN	both
208	-128.910	A	NaN	both
223	54.386	I	NaN	both
238	-244.500	A	NaN	both
274	159.000	I	NaN	both
291	-84.311	I	NaN	both
312	1.077	I	NaN	both
321	16.254	I	NaN	both
322	-28.766	I	NaN	both
339	14.686	I	NaN	both
342	-229.310	A	NaN	both

```
[13 rows x 24 columns]
```

2.3.1 Data Imputation for `Current Assets` (Linear Regression)

[21]:
```python
# DataFrame without any missing value
df_nan_c = df[~df.isna().any(axis=1)]
df_nan_c
```

[21]:
```
    TICKER  CURRENT ASSETS  TOTAL ASSETS      EBIT  CURRENT LIABIL  \
0     ARXX         328.354       638.022    47.473         119.215
1      ABT       11281.883     36178.172  4860.219       11951.195
2      AMD        3963.000     13147.000   401.000        2852.000
3      APD        2612.600     11180.700  1013.500        2323.400
4      HON       12304.000     30941.000  3544.000       10135.000
..     …              …            …         …             …
337   DEIX         321.326       678.707    56.688         160.388
338   ARII         196.874       338.926    43.189          70.788
340   WCRX         295.805      3162.545   112.114         170.985
341    ABB       17177.000     25142.000  2437.000       12376.000
343    SYT        5546.000     11852.000  1155.000        2968.000

     TOTAL LIABILITIES  RETAINED EARNINGS  TOTAL SALES  CREDIT_RATING  \
0              150.352             95.273      551.846              7
1            22123.986           9958.494    22476.322             19
2             7072.000            464.000     5649.000              7
3             6078.700           5521.800     8850.400             16
4            21221.000          11256.000    31367.000             16
..                 …                …            …              …
337            554.316              9.579      437.778              8
338             88.746             14.200      646.052              9
340           1834.313           -708.821      754.457              8
341          18653.000           1628.000    24412.000             15
343           6158.000           2474.000     8046.000             16

        gvkey  …  popsrc  datafmt   tic curcd        ceq      csho  \
0      1056.0  …       D      STD  ARXX   USD    487.670    75.270
1      1078.0  …       D      STD   ABT   USD  14054.186  1537.243
2      1161.0  …       D      STD   AMD   USD   5785.000   547.000
3      1209.0  …       D      STD   APD   USD   4924.000   217.251
4      1300.0  …       D      STD   HON   USD   9720.000   800.592
..        …  …      …       …    …    …        …        …
337  164758.0  …       D      STD  DEIX   USD    124.391    25.164
338  165358.0  …       D      STD  ARII   USD    250.180    21.208
340  175163.0  …       D      STD  WCRX   USD   1328.232   250.558
341  210418.0  …       D      STD   ABB   USD   6038.000  2178.973
343  241216.0  …       D      STD   SYT   USD   5666.000   487.146
```

```
            ni costat  prcc_c  _merge
0       26.959       I   11.72    both
1     1716.755       A   48.71    both
2     -166.000       A   20.35    both
3      723.400       A   70.28    both
4     2083.000       A   45.24    both
..         …      …       …      …
337     21.009       I   11.45    both
338     35.204       I   34.04    both
340   -153.510       I   13.82    both
341   1390.000       A   17.98    both
343    634.000       I   37.14    both

[331 rows x 24 columns]
```

[22]:

```
df_nan_c = df_nan_c[['CURRENT ASSETS', 'TOTAL ASSETS', 'EBIT',
       'TOTAL LIABILITIES', 'RETAINED EARNINGS', 'TOTAL SALES',
       'CREDIT_RATING', 'ceq', 'csho', 'ni',
       'prcc_c']]
```

[23]:

```
df_nan_c['constant'] = 1 # intercept
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

[24]:

```
Xc = df_nan_c.drop(columns='CURRENT ASSETS')
yc = df_nan_c['CURRENT ASSETS']
```

[25]:

```
modelc = sm.OLS(yc, Xc)
resultsc = modelc.fit()
print(resultsc.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:         CURRENT ASSETS   R-squared:                       0.941
Model:                            OLS   Adj. R-squared:                  0.939
Method:                 Least Squares   F-statistic:                     511.5
Date:                Thu, 07 Apr 2022   Prob (F-statistic):          3.54e-190
Time:                        20:25:08   Log-Likelihood:                -3005.5
No. Observations:                 331   AIC:                             6033.
```

```
Df Residuals:                     320   BIC:                             6075.
Df Model:                          10
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
TOTAL ASSETS          1.5580      0.237      6.579      0.000       1.092
2.024
EBIT                 -1.1465      0.138     -8.325      0.000      -1.417
-0.876
TOTAL LIABILITIES    -1.3049      0.245     -5.316      0.000      -1.788
-0.822
RETAINED EARNINGS     0.0049      0.027      0.180      0.857      -0.048
0.058
TOTAL SALES           0.1585      0.016     10.198      0.000       0.128
0.189
CREDIT_RATING        94.4967     48.543      1.947      0.052      -1.007
190.001
ceq                  -1.6198      0.239     -6.776      0.000      -2.090
-1.149
csho                  3.4754      0.261     13.321      0.000       2.962
3.989
ni                    0.9646      0.153      6.295      0.000       0.663
1.266
prcc_c               10.3477      6.486      1.595      0.112      -2.414
23.109
constant          -1246.8726    491.673     -2.536      0.012   -2214.192
-279.554
==============================================================================
Omnibus:                      111.785   Durbin-Watson:                   2.047
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5298.160
Skew:                           0.525   Prob(JB):                         0.00
Kurtosis:                      22.572   Cond. No.                     2.04e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.04e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[26]:

```
CA = df.iloc[[73, 165],:][[ 'TOTAL ASSETS', 'EBIT',
       'TOTAL LIABILITIES', 'RETAINED EARNINGS', 'TOTAL SALES',
       'CREDIT_RATING', 'ceq', 'csho', 'ni',
```

```
       'prcc_c']]
CA['constant'] = 1
resultsc.predict(CA)
```

[26]:
```
73     101720.780786
165      6009.966305
dtype: float64
```

[27]:
```
df.iloc[[73, 165], 1] = resultsc.predict(CA)
```

2.3.2 Data Imputation for CURRENT LIABIL (Linear Regression)

[28]:
```
df_nan_c = df[~df.isna().any(axis=1)]
```

[29]:
```
df_nan_cl = df_nan_c[['CURRENT ASSETS', 'CURRENT LIABIL','TOTAL ASSETS', 'EBIT',
       'TOTAL LIABILITIES', 'RETAINED EARNINGS', 'TOTAL SALES',
       'CREDIT_RATING', 'ceq', 'csho', 'ni',
       'prcc_c']]
```

[30]:
```
df_nan_cl['constant'] = 1 # intercept
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

[31]:
```
Xcl = df_nan_cl.drop(columns='CURRENT LIABIL')
ycl = df_nan_cl['CURRENT LIABIL']
```

[32]:
```
modelcl = sm.OLS(ycl, Xcl)
resultscl = modelcl.fit()
print(resultscl.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:         CURRENT LIABIL   R-squared:                       0.978
Model:                            OLS   Adj. R-squared:                  0.977
Method:                 Least Squares   F-statistic:                     1280.
Date:                Thu, 07 Apr 2022   Prob (F-statistic):         4.94e-257
Time:                        20:25:18   Log-Likelihood:                -2774.0
No. Observations:                 332   AIC:                             5572.
Df Residuals:                     320   BIC:                             5618.
```

```
Df Model:                          11
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
CURRENT ASSETS        0.4167      0.027     15.361      0.000       0.363
0.470
TOTAL ASSETS         -0.8612      0.122     -7.038      0.000      -1.102
-0.620
EBIT                 -0.4861      0.074     -6.595      0.000      -0.631
-0.341
TOTAL LIABILITIES     1.1864      0.124      9.558      0.000       0.942
1.431
RETAINED EARNINGS     0.0761      0.013      5.807      0.000       0.050
0.102
TOTAL SALES           0.0515      0.009      5.934      0.000       0.034
0.069
CREDIT_RATING        -3.8181     23.687     -0.161      0.872     -50.421
42.785
ceq                   0.7181      0.124      5.792      0.000       0.474
0.962
csho                  0.0550      0.158      0.348      0.728      -0.256
0.365
ni                    0.0814      0.079      1.033      0.302      -0.074
0.236
prcc_c                4.6745      3.141      1.488      0.138      -1.505
10.854
constant           -447.8666    240.891     -1.859      0.064    -921.797
26.064
==============================================================================
Omnibus:                       69.138   Durbin-Watson:                   2.093
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              882.961
Skew:                          -0.380   Prob(JB):                    1.85e-192
Kurtosis:                      10.953   Cond. No.                     2.10e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.1e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[33]:
```
CL = df.iloc[[73],:][[ 'CURRENT ASSETS','TOTAL ASSETS', 'EBIT',
       'TOTAL LIABILITIES', 'RETAINED EARNINGS', 'TOTAL SALES',
```

```
       'CREDIT_RATING', 'ceq', 'csho', 'ni',
       'prcc_c']]
CL['constant'] = 1
resultscl.predict(CL)
```

[33]:
```
73    143474.242256
dtype: float64
```

[34]:
```
df.iloc[[73], 4] = resultscl.predict(CL)
```

2.3.3 Data Imputation for prcc_c (Random Forest)

- The reason I chose random forest method to predict Price Close - Annual - Calendar (PRCC_C) is that the linear regression mdoel doesn't show a accurate prediction with R squared around 0.36. However, random forest could capture more non-linearity among those features and the prediction outcomes are much better than linear regression with R squared around 0.94.

[35]:
```
df_nan_c = df[~df.isna().any(axis=1)]
```

[36]:
```
df_nan_pr = df_nan_c[['CURRENT ASSETS', 'CURRENT LIABIL','TOTAL ASSETS', 'EBIT',
       'TOTAL LIABILITIES', 'RETAINED EARNINGS', 'TOTAL SALES',
       'CREDIT_RATING', 'ceq', 'csho', 'ni',
       'prcc_c']]
```

[37]:
```
# Fitting Random Forest Regression to the dataset
# import the regressor
from sklearn.ensemble import RandomForestRegressor

 # create regressor object
regressor = RandomForestRegressor(n_estimators = 100, random_state = 0)

Xpr = df_nan_pr.drop(columns='prcc_c')
ypr = df_nan_pr['prcc_c']

# fit the regressor with x and y data
regressor.fit(Xpr, ypr)
```

[37]:
```
RandomForestRegressor(random_state=0)
```

[38]:
```
prcc = df.iloc[df[df.isnull().any(axis =1)].index,:][[ 'CURRENT␣
 ↪ASSETS','CURRENT LIABIL','TOTAL ASSETS', 'EBIT',
       'TOTAL LIABILITIES', 'RETAINED EARNINGS', 'TOTAL SALES',
       'CREDIT_RATING', 'ceq', 'csho', 'ni']]
```

[39]:
```
regressor.predict(prcc)
```

[39]:
```
array([104.1745,  24.3753,  42.6806,  15.0962,  67.5671,  17.8229,
        40.8957,  20.6442,  10.7412,  30.1091,  25.3892])
```

[40]:
```
print('R squared for the Random Forest method is around {:.4f}.'.
 ↪format(regressor.score(Xpr, ypr)))
```

```
R squared for the Random Forest method is around 0.9376.
```

[41]:
```
df.loc[df[df.isnull().any(axis =1)].index,['prcc_c']] = regressor.predict(prcc)
```

[42]:
```
df.isnull().sum()
```

[42]:
```
TICKER               0
CURRENT ASSETS       0
TOTAL ASSETS         0
EBIT                 0
CURRENT LIABIL       0
TOTAL LIABILITIES    0
RETAINED EARNINGS    0
TOTAL SALES          0
CREDIT_RATING        0
gvkey                0
datadate             0
fyear                0
indfmt               0
consol               0
popsrc               0
datafmt              0
tic                  0
curcd                0
ceq                  0
csho                 0
ni                   0
costat               0
prcc_c               0
_merge               0
dtype: int64
```

2.4 Adding ratios columns (9 new ratio variables)

- Return on Assets = EBIT / TOTAL ASSETS
- Current Ratio = CURRENT ASSETS / CURRENT LIABIL
- NET PROFIT MARGIN = EBIT / TOTAL SALES
- Market Values = prcc_c * csho
- Market Value over TOTAL SALES = market_value / TOTAL SALES
- Market Value over Book Equity = market_value / ceq
- P/E ratio = market_value / ni

- Debt ratio = Total liabilities / EBIT
- RETAINED EARNINGS / TOTAL ASSETS = RE/TA

[43]:
```
df['ROA'] = df['EBIT'] / df['TOTAL ASSETS']
df['Current Ratio'] = df['CURRENT ASSETS'] / df['CURRENT LIABIL']
df['NET PROFIT MARGIN'] = df['EBIT'] / df['TOTAL SALES']

df['mv'] = df['prcc_c'] * df['csho']
df['mv/sales'] = df['mv'] / df['TOTAL SALES']
df['mv/beq'] = df['mv'] / df['ceq']
df['p/e'] = df['mv'] / df['ni']
df['debt_ratio'] = df['TOTAL LIABILITIES'] / df['EBIT']
df['RE/TA'] = df['RETAINED EARNINGS'] / df['TOTAL ASSETS']
```

[44]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 344 entries, 0 to 343
Data columns (total 33 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   TICKER             344 non-null    object
 1   CURRENT ASSETS     344 non-null    float64
 2   TOTAL ASSETS       344 non-null    float64
 3   EBIT               344 non-null    float64
 4   CURRENT LIABIL     344 non-null    float64
 5   TOTAL LIABILITIES  344 non-null    float64
 6   RETAINED EARNINGS  344 non-null    float64
 7   TOTAL SALES        344 non-null    float64
 8   CREDIT_RATING      344 non-null    int64
 9   gvkey              344 non-null    float64
 10  datadate           344 non-null    float64
 11  fyear              344 non-null    float64
 12  indfmt             344 non-null    object
 13  consol             344 non-null    object
 14  popsrc             344 non-null    object
 15  datafmt            344 non-null    object
 16  tic                344 non-null    object
 17  curcd              344 non-null    object
 18  ceq                344 non-null    float64
 19  csho               344 non-null    float64
 20  ni                 344 non-null    float64
 21  costat             344 non-null    object
 22  prcc_c             344 non-null    float64
 23  _merge             344 non-null    category
 24  ROA                344 non-null    float64
 25  Current Ratio      344 non-null    float64
 26  NET PROFIT MARGIN  344 non-null    float64
```

```
 27  mv                  344 non-null    float64
 28  mv/sales            344 non-null    float64
 29  mv/beq              344 non-null    float64
 30  p/e                 344 non-null    float64
 31  debt_ratio          344 non-null    float64
 32  RE/TA               344 non-null    float64
dtypes: category(1), float64(23), int64(1), object(8)
memory usage: 86.6+ KB
```

2.5 Check and Handle Outliers

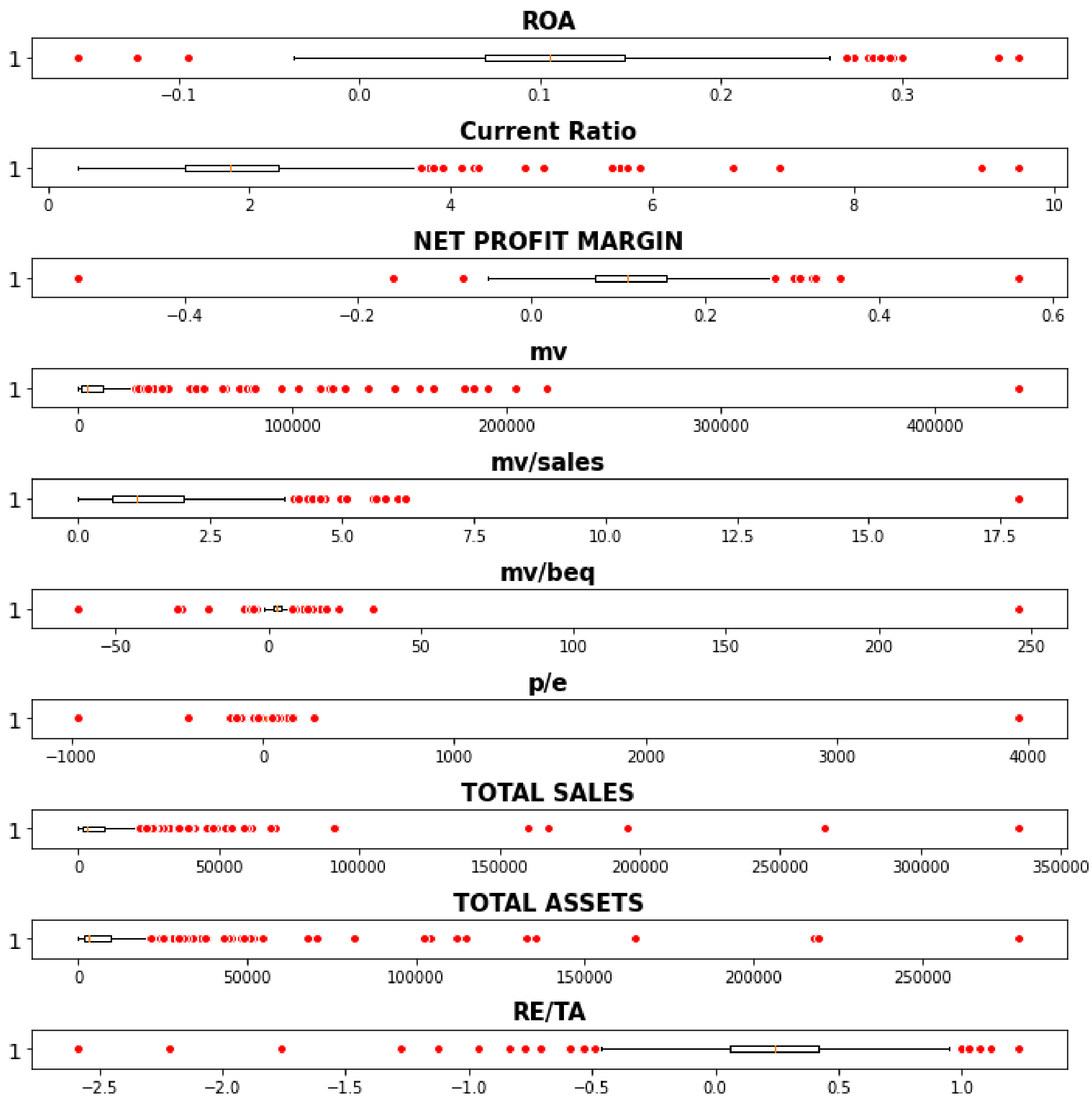
- For the credit rating predictive model, I will select mostly finance ratios as the independent variables.
- Most research found out that total assets and total sales are good indicator of a firm's size and credit scores. So, I will also include both two.
- Thus, below are the boxplots for all those finance ratios.

[46]:
```
df_model = df[['ROA', 'Current Ratio', 'NET PROFIT MARGIN', 'mv', 'mv/sales',␣
↪'mv/beq', 'p/e', 'TOTAL SALES','TOTAL ASSETS','RE/TA']]
```

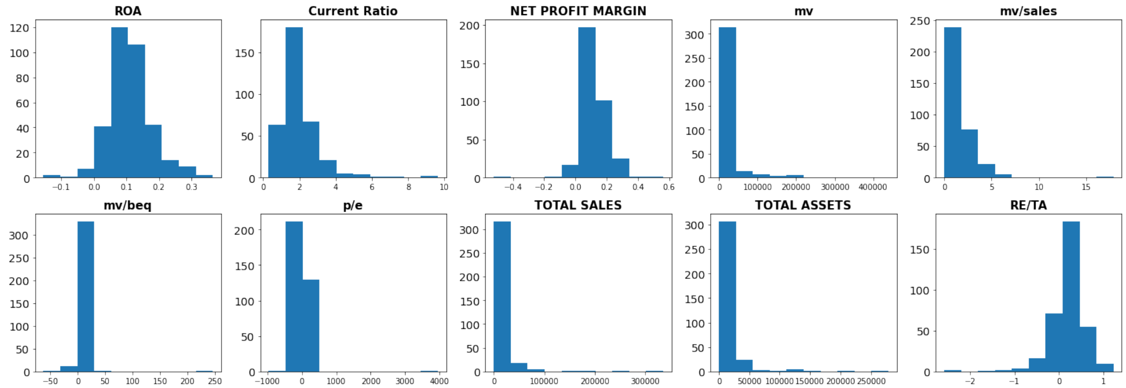
[47]:
```
df_model.columns
```

[47]:
```
Index(['ROA', 'Current Ratio', 'NET PROFIT MARGIN', 'mv', 'mv/sales', 'mv/beq',
       'p/e', 'TOTAL SALES', 'TOTAL ASSETS', 'RE/TA'],
      dtype='object')
```

[48]:
```
#Creating boxplot of each column with its own scale
red_circle = dict(markerfacecolor='red', marker='o', markeredgecolor='white')
mean_shape = dict(markerfacecolor='green', marker='D', markeredgecolor='green')

fig, axs = plt.subplots(len(df_model.columns),1, figsize=(10,10))

for i, ax in enumerate(axs.flat):
    ax.boxplot(df_model.iloc[:,i], flierprops=red_circle, meanprops=mean_shape,␣
↪vert = False)
    ax.set_title(df_model.columns[i], fontsize=15, fontweight='bold')
    ax.tick_params(axis='y', labelsize=14)

plt.tight_layout()
```



[49]:
```python
#Creating histogram of each column with its own scale
fig, axs = plt.subplots(2,5, figsize=(20,7))

for i, ax in enumerate(axs.flat):
    ax.hist(df_model.iloc[:,i])
    ax.set_title(df_model.columns[i], fontsize=15, fontweight='bold')
    ax.tick_params(axis='y', labelsize=14)

plt.tight_layout()
```



[50]:
```
df_model.describe()
```

[50]:

	ROA	Current Ratio	NET PROFIT MARGIN	mv
count	344.000000	344.000000	344.000000	344.000000
mean	0.110642	2.017150	0.116752	17059.179978
std	0.067413	1.106279	0.082952	40655.784292
min	-0.155169	0.304163	-0.521880	0.017823
25%	0.069420	1.363975	0.071748	1494.008200
50%	0.104978	1.805532	0.109695	3783.874905
75%	0.146757	2.291817	0.154258	11230.357020
max	0.364702	9.643438	0.560904	439013.270000

	mv/sales	mv/beq	p/e	TOTAL SALES	TOTAL ASSETS
count	344.000000	344.000000	344.000000	344.000000	344.000000
mean	1.547113	3.589750	24.025285	11856.471017	12685.247221
std	1.496501	14.269730	222.542586	30337.188742	29664.799449
min	0.000014	-62.216453	-964.287735	84.209000	156.741000
25%	0.646135	1.757390	9.872734	1497.479000	1604.782500
50%	1.113466	2.803554	17.075702	3425.340500	3347.255000
75%	1.991899	4.217032	22.231953	9333.922000	9573.700000
max	17.853070	246.084854	3953.541714	335086.000000	278554.000000

	RE/TA
count	344.000000
mean	0.203097
std	0.400364
min	-2.583596
25%	0.058042
50%	0.239480
75%	0.419417
max	1.232304

- According to the multiple box plots above, every column has outliers and most of them have only several anomalies and it is not a big issue.

- However, ”market value”, ’total assets’, ’total sales’ and ”market value / book equity” have more outliers compared to others
- Since, we only have 344 data points, dropping some outliers may decrease the model predictive power
- I will use Winsorization and Log transformation methods to deal with outliers and compare the predictive power later

2.5.1 Winsorization Method

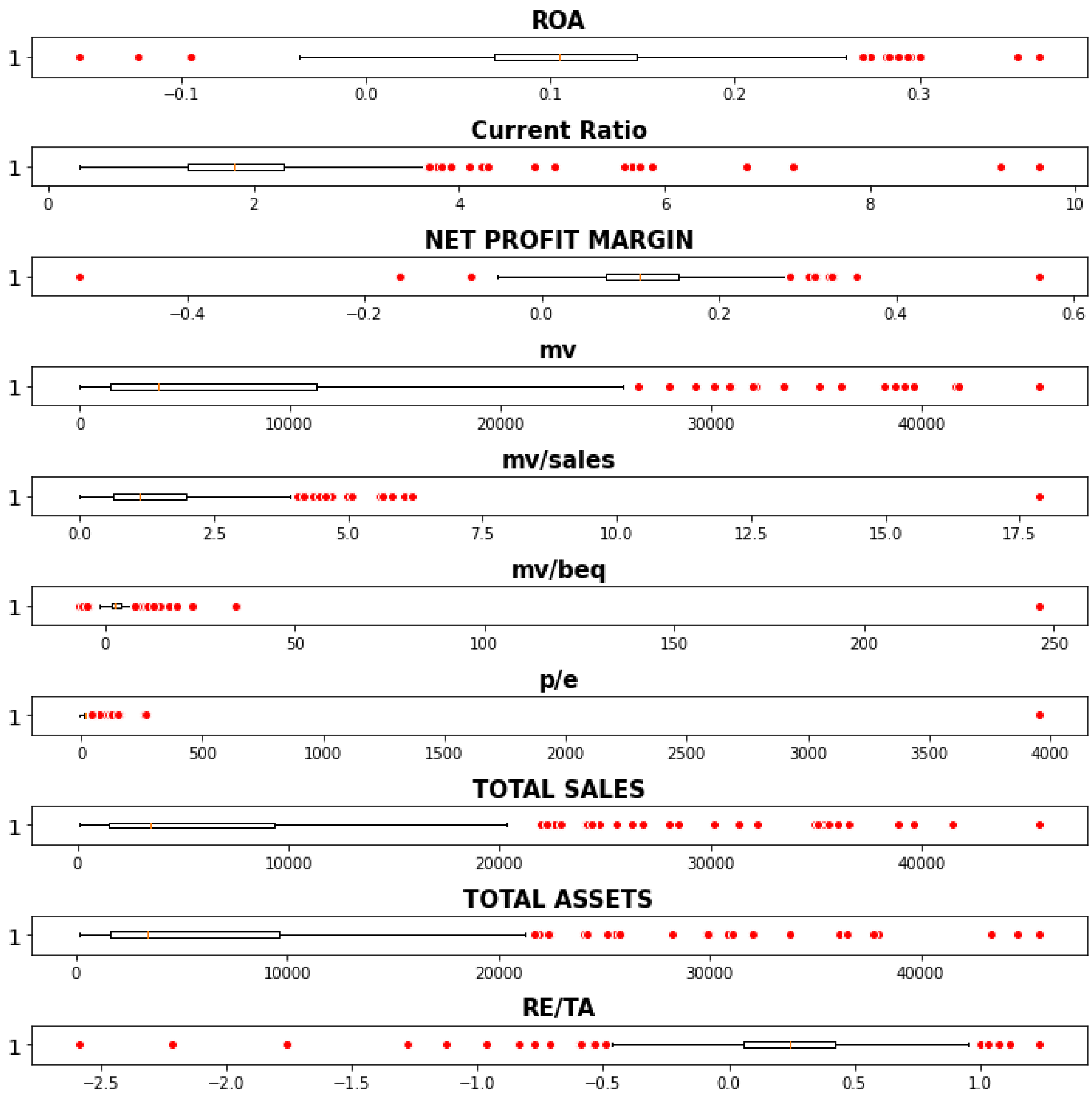
[51]:
```
from scipy.stats.mstats import winsorize
df_win = df_model
col_name_win = df_win.columns
```

[52]:
```
# WINSORIZE within the range of 1% and 98% quantiles
df_win = winsorize(df_win, (0.01, 0.02))
df_win = pd.DataFrame(df_win, columns = col_name_win )
df_win.describe()
```

[52]:
```
              ROA  Current Ratio  NET PROFIT MARGIN            mv    mv/sales  \
count  344.000000     344.000000         344.000000    344.000000  344.000000
mean     0.110642       2.017150           0.116752  10302.423549    1.547113
std      0.067413       1.106279           0.082952  13807.179415    1.496501
min     -0.155169       0.304163          -0.521880      0.017823    0.000014
25%      0.069420       1.363975           0.071748   1494.008200    0.646135
50%      0.104978       1.805532           0.109695   3783.874905    1.113466
75%      0.146757       2.291817           0.154258  11230.357020    1.991899
max      0.364702       9.643438           0.560904  45581.000000   17.853070

           mv/beq          p/e   TOTAL SALES  TOTAL ASSETS       RE/TA
count  344.000000   344.000000    344.000000    344.000000  344.000000
mean     3.922330    30.750842   8634.719782   9061.664820    0.203097
std     13.573103   213.830646  11880.332085  12414.870027    0.400364
min     -6.711166    -6.711166     84.209000    156.741000   -2.583596
25%      1.757390     9.872734   1497.479000   1604.782500    0.058042
50%      2.803554    17.075702   3425.340500   3347.255000    0.239480
75%      4.217032    22.231953   9333.922000   9573.700000    0.419417
max    246.084854  3953.541714  45581.000000  45581.000000    1.232304
```

[53]:
```
#Check the outlier after winsorization
red_circle = dict(markerfacecolor='red', marker='o', markeredgecolor='white')
mean_shape = dict(markerfacecolor='green', marker='D', markeredgecolor='green')

fig, axs = plt.subplots(len(df_win.columns),1, figsize=(10,10))

for i, ax in enumerate(axs.flat):
```

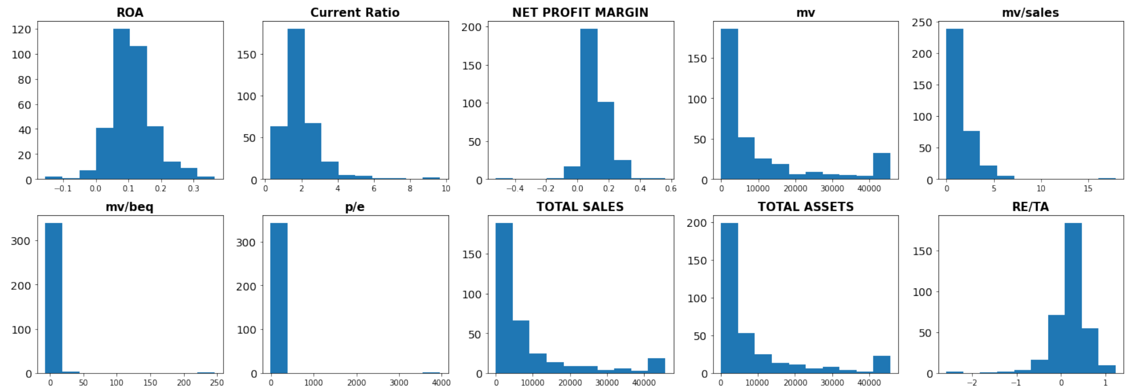
```
    ax.boxplot(df_win.iloc[:,i], flierprops=red_circle, meanprops=mean_shape,␣
↪vert = False)
    ax.set_title(df_win.columns[i], fontsize=15, fontweight='bold')
    ax.tick_params(axis='y', labelsize=14)

plt.tight_layout()
```



[54]:

```
#Check the outliers after Winsorization Method
fig, axs = plt.subplots(2,5, figsize=(20,7))

for i, ax in enumerate(axs.flat):
    ax.hist(df_win.iloc[:,i])
    ax.set_title(df_win.columns[i], fontsize=15, fontweight='bold')
```

```
    ax.tick_params(axis='y', labelsize=14)

plt.tight_layout()
```



2.5.2 Log Tranformation Method + Winsorization Method

[65]:
```
df_logwin =pd.DataFrame()
df_logwin
```

[65]:
```
Empty DataFrame
Columns: []
Index: []
```

[66]:
```
df_model.columns
```

[66]:
```
Index(['ROA', 'Current Ratio', 'NET PROFIT MARGIN', 'mv', 'mv/sales', 'mv/beq',
       'p/e', 'TOTAL SALES', 'TOTAL ASSETS', 'RE/TA'],
      dtype='object')
```

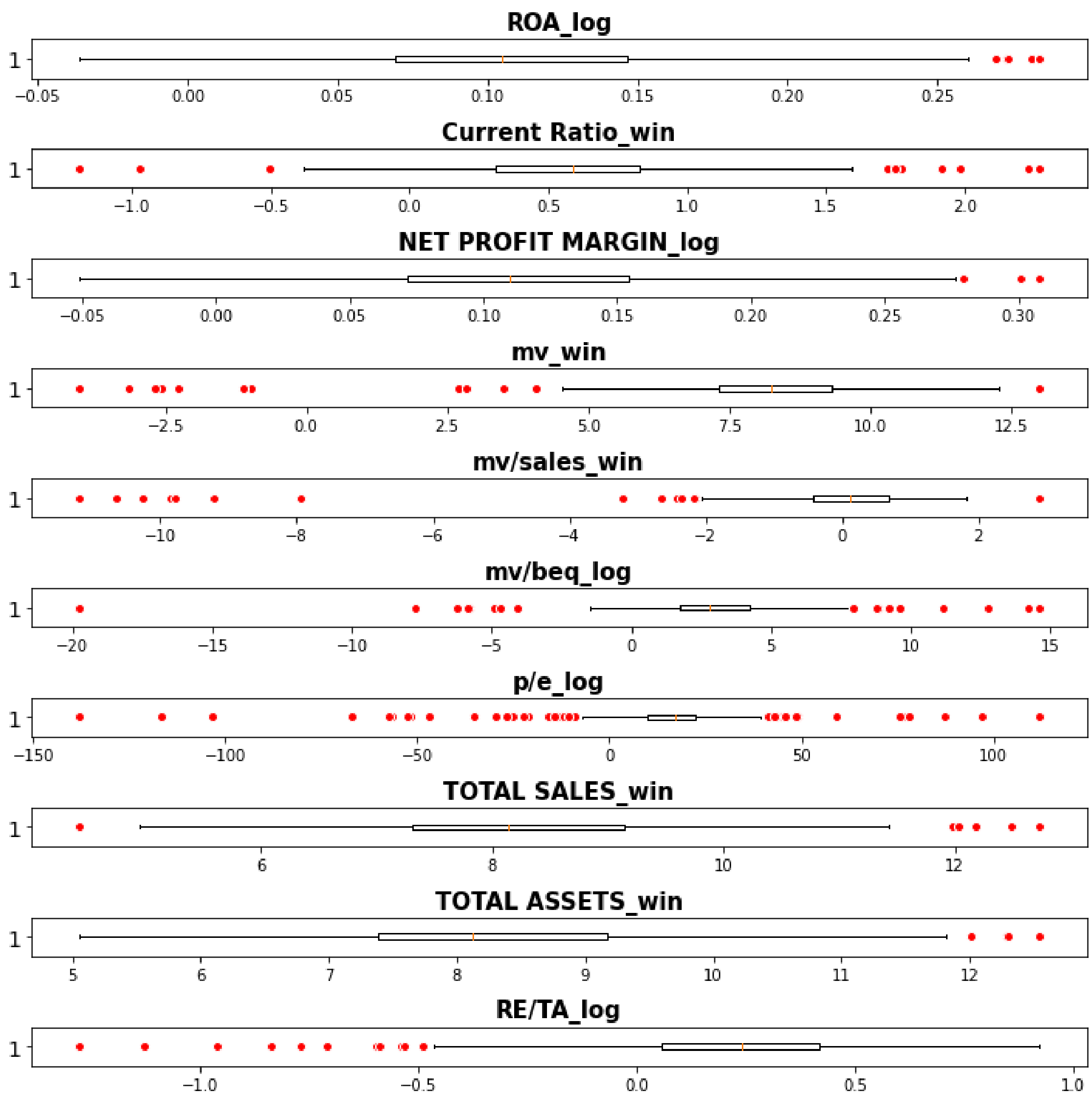
[67]:
```
win_col = []
log_col = []
for i in df_model.columns:
  if df_model[i].min() > 0:
    df_logwin[i+'_win'] = np.log(df_model[i])
    win_col.append(i)
  else:
    df_logwin[i+'_log'] = winsorize(df_model[i], (0.01, 0.02))
    log_col.append(i)

print(win_col,'\n', log_col)
```

```
['Current Ratio', 'mv', 'mv/sales', 'TOTAL SALES', 'TOTAL ASSETS']
 ['ROA', 'NET PROFIT MARGIN', 'mv/beq', 'p/e', 'RE/TA']
```

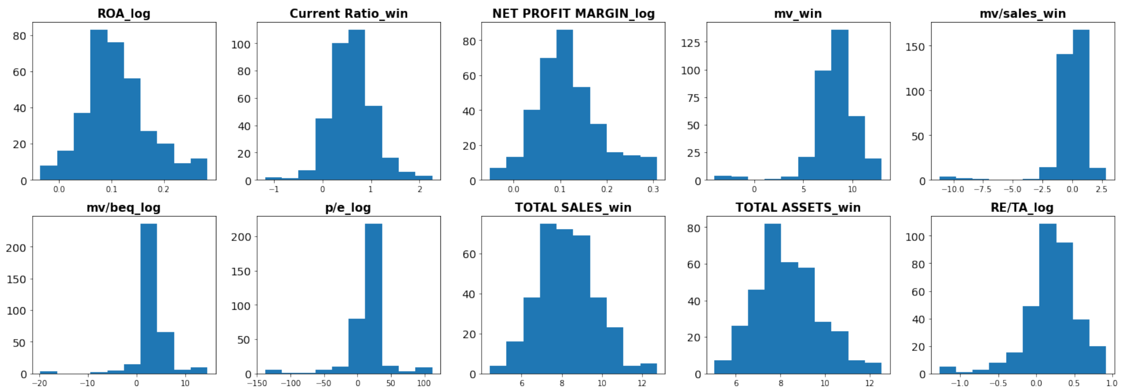
[74]:
```
df_logwin
```

[74]:
```
      ROA_log  Current Ratio_win  NET PROFIT MARGIN_log     mv_win  \
0    0.074407           1.013164               0.086026   6.782378
1    0.134341          -0.057633               0.216237  11.223630
2    0.030501           0.328981               0.070986   9.317530
3    0.090647           0.117314               0.114515   9.633541
4    0.114541           0.193930               0.112985  10.497333
..        …                 …                     …         …
339  0.077245           0.817594               0.067215  -1.105033
340  0.035451           0.548125               0.148602   8.149807
341  0.096929           0.327812               0.099828  10.575869
342 -0.036043           0.697936              -0.051005   7.199338
343  0.097452           0.625189               0.143550   9.803258

     mv/sales_win  mv/beq_log    p/e_log  TOTAL SALES_win  TOTAL ASSETS_win  \
0        0.469109    1.808937  32.722445         6.313269          6.458373
1        1.203413    5.327886  43.616653        10.020218         10.496211
2        0.678296    1.924192 -67.056928         8.639234          9.483949
3        0.545323    3.100812  21.106442         9.088218          9.321944
4        0.143821    3.726212  17.387797        10.353512         10.339837
..            …           …          …              …                 …
339     -7.937846    0.001203   0.022552         6.832813          6.693733
340      1.523809    2.607008 -22.556912         6.625998          8.059132
341      0.473039    6.488562  28.185564        10.102830         10.132295
342      0.586824   -4.704222  -5.837268         6.612514          6.646459
343      0.810328    3.193188  28.537228         8.992930          9.380252

     RE/TA_log
0     0.149326
1     0.275262
2     0.035293
3     0.493869
4     0.363789
..         …
339   0.089344
340  -0.224130
341   0.064752
342  -0.441155
343   0.208741

[344 rows x 10 columns]
```

[75]:
```python
#Check the outlier after Log Transformation
red_circle = dict(markerfacecolor='red', marker='o', markeredgecolor='white')
mean_shape = dict(markerfacecolor='green', marker='D', markeredgecolor='green')

fig, axs = plt.subplots(len(df_logwin.columns),1, figsize=(10,10))

for i, ax in enumerate(axs.flat):
    ax.boxplot(df_logwin.iloc[:,i], flierprops=red_circle,␣
↪meanprops=mean_shape, vert = False)
    ax.set_title(df_logwin.columns[i], fontsize=15, fontweight='bold')
    ax.tick_params(axis='y', labelsize=14)

plt.tight_layout()
```



[76]:
```
#Check the outlier after Log Transformation
fig, axs = plt.subplots(2,5, figsize=(20,7))

for i, ax in enumerate(axs.flat):
    ax.hist(df_logwin.iloc[:,i])
    ax.set_title(df_logwin.columns[i], fontsize=15, fontweight='bold')
    ax.tick_params(axis='y', labelsize=14)

plt.tight_layout()
```



2.5.3 Summary

From the eyeball test, Combining Log transformation and Winsorization together did a better job on dealing with the outliers, since both the boxplots and histograms plotted after both methods show a normal distribution for each financial feature. But, we will still need to use the model result, such as adjusted R2 to compare which method is better on handling the outliers.

3 Linear Regression Model

3.1 Model (Winsorization)

[77]:
```
df_model_win = pd.concat([df_win, df['CREDIT_RATING']], axis = 1)
```

[78]:
```
df_model_win['constant'] = 1 # intercept
```

[79]:
```
X = df_model_win.drop(columns = 'CREDIT_RATING')
y = df_model_win['CREDIT_RATING']
```

[80]:
```
model = sm.OLS(y, X)
results = model.fit()
```

```python
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          CREDIT_RATING   R-squared:                       0.666
Model:                            OLS   Adj. R-squared:                  0.656
Method:                 Least Squares   F-statistic:                     66.48
Date:                Thu, 07 Apr 2022   Prob (F-statistic):           2.98e-73
Time:                        20:36:08   Log-Likelihood:                -734.72
No. Observations:                 344   AIC:                             1491.
Df Residuals:                     333   BIC:                             1534.
Df Model:                          10
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
ROA                   1.8320      2.703      0.678      0.498      -3.486
7.150
Current Ratio        -0.5201      0.119     -4.377      0.000      -0.754
-0.286
NET PROFIT MARGIN     2.8540      2.163      1.319      0.188      -1.401
7.109
mv                    0.0001   2.55e-05      4.941      0.000    7.57e-05
0.000
mv/sales              0.3608      0.101      3.578      0.000       0.162
0.559
mv/beq               -0.0028      0.008     -0.335      0.738      -0.019
0.014
p/e                   0.0020      0.001      3.414      0.001       0.001
0.003
TOTAL SALES        7.753e-05   3.23e-05      2.400      0.017     1.4e-05
0.000
TOTAL ASSETS      -7.582e-05   3.85e-05     -1.969      0.050      -0.000
-6.28e-08
RE/TA                 3.3083      0.366      9.040      0.000       2.588
4.028
constant             10.0145      0.353     28.343      0.000       9.319
10.710
==============================================================================
Omnibus:                        1.207   Durbin-Watson:                   1.930
Prob(Omnibus):                  0.547   Jarque-Bera (JB):                1.203
Skew:                           0.049   Prob(JB):                        0.548
Kurtosis:                       2.727   Cond. No.                     7.45e+05
==============================================================================
```

```
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 7.45e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

3.2 Model (Log Transformation + Winsorization)

[81]:
```python
df_model_logwin = pd.concat([df_logwin, df['CREDIT_RATING']], axis = 1)
```

[82]:
```python
df_model_logwin['constant'] = 1 # intercept
```

[83]:
```python
X2 = df_model_logwin.drop(columns = 'CREDIT_RATING')
y2 = df_model_logwin['CREDIT_RATING']
```

[84]:
```python
model2 = sm.OLS(y2, X2)
results2 = model2.fit()
print(results2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          CREDIT_RATING   R-squared:                       0.718
Model:                            OLS   Adj. R-squared:                  0.710
Method:                 Least Squares   F-statistic:                     94.53
Date:                Thu, 07 Apr 2022   Prob (F-statistic):           2.53e-86
Time:                        20:36:15   Log-Likelihood:                -705.71
No. Observations:                 344   AIC:                             1431.
Df Residuals:                     334   BIC:                             1470.
Df Model:                           9
Covariance Type:            nonrobust
================================================================================
=========
                            coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---------
ROA_log                   3.0977      4.132      0.750      0.454      -5.029
11.225
Current Ratio_win        -0.3038      0.260     -1.169      0.243      -0.815
0.207
NET PROFIT MARGIN_log     6.2329      3.701      1.684      0.093      -1.047
13.513
mv_win                    0.3303      0.158      2.092      0.037       0.020
0.641
mv/sales_win              0.0239      0.143      0.167      0.868      -0.258
0.306
```

```
mv/beq_log                 0.0479      0.029      1.649      0.100      -0.009
0.105
p/e_log                    0.0104      0.004      2.897      0.004       0.003
0.018
TOTAL SALES_win            0.3063      0.293      1.046      0.296      -0.270
0.882
TOTAL ASSETS_win           0.6942      0.448      1.551      0.122      -0.186
1.575
RE/TA_log                  2.8181      0.362      7.782      0.000       2.106
3.530
constant                  -0.7325      0.810     -0.905      0.366      -2.325
0.860
==============================================================================
Omnibus:                        3.263   Durbin-Watson:                   2.049
Prob(Omnibus):                  0.196   Jarque-Bera (JB):                3.446
Skew:                          -0.098   Prob(JB):                        0.179
Kurtosis:                       3.450   Cond. No.                     2.50e+16
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 6.22e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

4 Conclusion

- Both Linear Regression Models selected the same 10 independent varibales, but only differenece is that one applied winsorization only to deal with outliers and the other chose the log transformation and winsorization together to handle anomalies. Based on the R2 and AdjR2, we found that the model using log transformation and winsorization with (R2 = 0.718 > 0.666 and AdjR2 = 0.710 > 0.656)indicates a better fit and 71.8% of credit rating could be explained by those 10 independent varibales.
- For the second Model, The coefficients of *market value*, *LOG_market price over book equity value*, *LOG_retained earning over total assets* are statistically significant at 5%. In addition, *t-values* for all three independent variables are 2.092, 2.897, 7.782, respectively and all more than 1.96, which also proves that coefficients for those 3 variables are significant different from 0 at 5% level.
- **On average, for each dollar increase in *market value*, the credit rating will increase 0.3303 (On average, for 1% dollar increase in *market value*, the credit rating will increase [0.3303 / 100 = 0.003]**
- **On average, for each 10% increase in *market price over book value*, the credit rating will increase [0.0104 * log(1.10) = 0.099%]**
- **On average, for each 1% increase in *retained earning over total assets*, the credit**

rating will increase [2.8181 / 100 = 0.028]

- In sum, **the ratio of *retained earning over total assets* will have more impact on the credit rating prediction**, since the main reason is RE / TA could be a good indicator of companies' profitbaility in the future. For instance, low RE/TA suggests that companies are financing capital expenditure via borrowings rather than retained earnings.

5 Appendix

```
-  Y =  0 +  1*log(X)

- ( 0 +  1*log(1.01)) - ( 0 +  1*log1)

-  1*log(1.01) -  1*log1

-  1*(log(1.01) - log1)

-  1*log(1.01 / 1) =  1*log(1.01)

The result is multiplying the slope coefficient by log(1.01), which is approximately equal to 0
```

[ ]:
```
!sudo apt-get install texlive-xetex texlive-fonts-recommended␣
↪texlive-plain-generic
```

[97]:
```
!jupyter nbconvert --to pdf '/content/drive/MyDrive/BA_870/HW/2/
↪Assignment2_Ji_Qi.ipynb'
```

```
[NbConvertApp] Converting notebook
/content/drive/MyDrive/BA_870/HW/2/Assignment2_Ji_Qi.ipynb to pdf
[NbConvertApp] Support files will be in Assignment2_Ji_Qi_files/
[NbConvertApp] Making directory ./Assignment2_Ji_Qi_files
[NbConvertApp] Making directory ./Assignment2_Ji_Qi_files
[NbConvertApp] Making directory ./Assignment2_Ji_Qi_files
[NbConvertApp] Making directory ./Assignment2_Ji_Qi_files
[NbConvertApp] Making directory ./Assignment2_Ji_Qi_files
[NbConvertApp] Making directory ./Assignment2_Ji_Qi_files
[NbConvertApp] Writing 114323 bytes to ./notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', './notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', './notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 296822 bytes to
/content/drive/MyDrive/BA_870/HW/2/Assignment2_Ji_Qi.pdf
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[ ]:
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```