Assignment4_Ji_Qi

April 20, 2022

1 *Student Name: Ji Qi , Session B1*

2 Import packages

[42]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

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

3 Basic Info about the Data

[43]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

3.1 temp1.csv

- Download the variables of financial statement for "Data Date" 2021-01 through 2021-12 from WRDS Compustat and store into temp1.csv
- Import temp1.csv file

[44]:
```
temp1 = pd.read_csv('/content/drive/MyDrive/BA_870/HW/4/temp1.csv')
```

- No missing value for temp1.csv

[45]:
```
temp1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1886 entries, 0 to 1885
Data columns (total 16 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   ceq       1886 non-null   float64
 10  csho      1886 non-null   float64
 11  ebit      1886 non-null   float64
 12  ni        1886 non-null   float64
 13  sale      1886 non-null   float64
 14  costat    1886 non-null   object
 15  prcc_c    1886 non-null   float64
dtypes: float64(6), int64(3), object(7)
memory usage: 235.9+ KB
```

- first 5 rows of temp1

[46]:
```
temp1.head()
```

[46]:

	gvkey	datadate	fyear	indfmt	consol	popsrc	datafmt	tic	curcd	ceq	csho	ebit	ni	sale	costat	prcc_c
0	1004	20210531	2020	INDL	C	D	STD	AIR	USD	974.4	35.375	65.50	35.80	1651.400	A	36.22
1	1045	20211231	2021	INDL	C	D	STD	AAL	USD	-7340.0	647.728	-5514.00	-1993.00	29882.000	A	17.96
2	1075	20211231	2021	INDL	C	D	STD	PNW	USD	5906.2	112.927	805.31	618.72	3803.835	A	70.59
3	1078	20211231	2021	INDL	C	D	STD	ABT	USD	35802.0	1764.082	8966.00	7071.00	43075.000	A	140.74
4	1161	20211231	2021	INDL	C	D	STD	AMD	USD	7497.0	1207.000	3678.00	3162.00	16434.000	A	143.90

- For **Common/Ordinary Equity - Total (CEQ)**, **Earnings Before Interest and Taxes (EBIT)**, **Net Income (Loss) (NI)** and **Sales/Turnover (Net) (SALE)**, those financial variables have negative values. Especially, **Earnings Before Interest and Taxes (EBIT)** and **Sales/Turnover (Net) (SALE)** even have value equal to '0'. Thus, when we generate financial ratios like **Price / Sales** or **Price / EBIT**, it would be better to treat those two variables as numerator, which could avoid the infinite values.

[47]:
```
temp1.describe()
```

[47]:
```
                gvkey      datadate        fyear             ceq           csho  \
count     1886.000000  1.886000e+03  1886.000000     1886.000000   1886.000000
mean     62189.838282  2.021110e+07  2020.911983     5024.836357    216.213565
std      67853.146760  2.954896e+02     0.283395    16277.562975    617.870951
min       1004.000000  2.021013e+07  2020.000000   -14999.000000      1.161000
25%      11641.250000  2.021123e+07  2021.000000      416.276000     37.220250
50%      25281.000000  2.021123e+07  2021.000000     1109.486000     73.807500
75%     125591.250000  2.021123e+07  2021.000000     3316.116500    176.940000
max     317264.000000  2.021123e+07  2021.000000   259289.000000  16426.786000

                ebit            ni           sale       prcc_c
count     1886.000000   1886.000000    1886.000000  1886.000000
mean      1309.802269    942.737848    8418.783976   104.209820
std       5154.950167   4208.808452   28707.012557   236.957951
min      -6273.000000  -9501.000000     -69.296000     0.355500
25%         48.110500     16.138750     513.042750    25.022500
50%        211.177000    135.238000    1596.892000    51.940000
75%        807.034250    554.200000    5560.085500   107.657500
max     108949.000000  94680.000000  556933.000000  5908.870000
```

[48]:
```
# For Earnings Before Interest and Taxes (EBIT) = 0
temp1[temp1.ebit.isin([0])]
```

[48]:
```
     gvkey  datadate  fyear indfmt consol popsrc datafmt  tic curcd     ceq  \
943  25283  20210131   2020   INDL      C      D     STD  KSS   USD  5196.0

      csho  ebit     ni     sale costat  prcc_c
943  158.0   0.0 -163.0  15955.0      A   40.69
```

[49]:
```
# For Sales/Turnover (Net) (SALE) = 0
temp1[temp1.sale.isin([0])]
```

[49]:
```
       gvkey  datadate  fyear indfmt consol popsrc datafmt   tic curcd  \
515    12711  20210930   2021   INDL      C      D     STD   CVM   USD
673    18159  20211231   2021   INDL      C      D     STD  AGIO   USD
737    19600  20211231   2021   INDL      C      D     STD  CBAY   USD
755    20018  20211231   2021   INDL      C      D     STD  ALDX   USD
772    20600  20211130   2021   INDL      C      D     STD    NG   USD
793    21032  20211231   2021   INDL      C      D     STD  VKTX   USD
978    26081  20211231   2021   INDL      C      D     STD  KURA   USD
988    26349  20211231   2021   INDL      C      D     STD  AXSM   USD
1025   27716  20211231   2021   INDL      C      D     STD  MDGL   USD
1109   29251  20210430   2020   INDL      C      D     STD  KALV   USD
1252   63650  20211231   2021   INDL      C      D     STD  SPPI   USD
1628  165798  20210731   2021   INDL      C      D     STD   UEC   USD
1634  166447  20210930   2021   INDL      C      D     STD  AVXL   USD
1766  183593  20211231   2021   INDL      C      D     STD  OMER   USD
```

```
1788  184465  20211231   2021   INDL      C      D     STD  AMPE   USD
1817  185659  20211231   2021   INDL      C      D     STD  ATOS   USD
1864  190856  20211231   2021   INDL      C      D     STD  TNXP   USD

           ceq     csho     ebit        ni  sale costat   prcc_c
515     56.534   43.207  -36.194   -36.361   0.0      A   7.1000
673   1291.975   54.334 -378.418  1604.715   0.0      A  32.8700
737    132.937   84.678  -87.582   -89.998   0.0      A   3.3800
755    205.736   58.081  -56.219   -57.776   0.0      A   4.0000
772     78.282  332.416  -20.210   -40.536   0.0      A   6.8600
793    201.884   78.248  -55.682   -54.990   0.0      A   4.6000
978    506.609   66.572 -131.258  -130.466   0.0      A  14.0000
988     15.630   37.817 -124.707  -130.403   0.0      A  37.7800
1025   196.107   17.103 -242.482  -241.846   0.0      A  84.7400
1109   257.193   24.423  -57.923   -46.244   0.0      A  18.9900
1252    47.553  164.502 -139.930  -158.628   0.0      A   1.2700
1628   151.455  236.797  -17.512   -14.814   0.0      A   3.3500
1634   150.818   75.918  -42.001   -37.909   0.0      A  17.3400
1766    23.780   62.629 -173.617   194.235   0.0      A   6.4300
1788    27.284  227.325  -20.571   -17.075   0.0      A   0.5700
1817   138.136  126.624  -19.521   -20.606   0.0      A   1.6000
1864   218.717  496.246  -92.312   -92.287   0.0      A   0.3577
```

3.2 ProjectTickers.csv

- Import ProjectTickers.csv file
- 3 columns: **Ticker** (the stock's ticker symbol), **Name** (the name of each company), and **RetTYD** (the year-to-date stock return of each company from January 1, 2022 to April 14, 2022).

[50]:
```
ticker = pd.read_csv('/content/drive/MyDrive/BA_870/HW/4/ProjectTickers.csv')
ticker.head()
```

[50]:
```
  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
```

- No missing value for ProjectTickers.csv file

[51]:
```
ticker.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
```

- first 5 rows of ticker

[52]:
```
ticker.head()
```

[52]:
```
  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
```

4 Data Merging (temp1.csv & ProjectTickers.csv)

[53]:
```
df = pd.merge(temp1, ticker, how = 'outer', left_on= 'tic', right_on= 'Ticker',␣
 ↪indicator= True)
df._merge.value_counts()
```

[53]:
```
both          1886
left_only        0
right_only       0
Name: _merge, dtype: int64
```

- No missing value for this merged dataset

[54]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1886 entries, 0 to 1885
Data columns (total 20 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   ceq       1886 non-null   float64
 10  csho      1886 non-null   float64
 11  ebit      1886 non-null   float64
 12  ni        1886 non-null   float64
 13  sale      1886 non-null   float64
 14  costat    1886 non-null   object
 15  prcc_c    1886 non-null   float64
 16  Ticker    1886 non-null   object
 17  Name      1886 non-null   object
 18  RetYTD    1886 non-null   float64
 19  _merge    1886 non-null   category
dtypes: category(1), float64(7), int64(3), object(9)
memory usage: 296.7+ KB
```

- first 5 rows of this merged dataset

[55]:
```
df.head()
```

[55]:

	gvkey	datadate	fyear	indfmt	consol	popsrc	datafmt	tic	curcd	ceq	csho	ebit	ni	sale	costat	prcc_c	Ticker	Name	RetYTD	_merge
0	1004	20210531	2020	INDL	C	D	STD	AIR	USD	974.4	35.375	65.50	35.80	1651.400	A	36.22	AIR	AAR Corp	0.2944	both
1	1045	20211231	2021	INDL	C	D	STD	AAL	USD	-7340.0	647.728	-5514.00	-1993.00	29882.000	A	17.96	AAL	American Airlines Gp	0.0579	both
2	1075	20211231	2021	INDL	C	D	STD	PNW	USD	5906.2	112.927	805.31	618.72	3803.835	A	70.59	PNW	Pinnacle West Capital Corp	0.0985	both
3	1078	20211231	2021	INDL	C	D	STD	ABT	USD	35802.0	1764.082	8966.00	7071.00	43075.000	A	140.74	ABT	Abbott Laboratories	-0.1638	both
4	1161	20211231	2021	INDL	C	D	STD	AMD	USD	7497.0	1207.000	3678.00	3162.00	16434.000	A	143.90	AMD	Adv Micro Devices	-0.3533	both

5 Feature Engineering (Creates 4 Market Ratios)

- Price/Book = (PRCC_C * CSHO) / CEQ
- P/E = (PRCC_C * CSHO) / NI
- P/EBIT = (PRCC_C * CSHO) / EBIT
- P/SALES = (PRCC_C * CSHO) / SALE

- Invert each of the ratios to make them "better behaved".
- Book/Price = 1/[Price/Book]
- E/P = 1/[P/E]
- EBIT/P = 1/[P/EBIT]
- SALE/P = 1/[P/SALES]

[56]:
```
df['Book/Price'] = df['ceq'] / (df['prcc_c'] * df['csho'])
df['E/P'] = df['ni'] / (df['prcc_c'] * df['csho'])
df['EBIT/P'] = df['ebit'] / (df['prcc_c'] * df['csho'])
df['SALE/P'] = df['sale'] / (df['prcc_c'] * df['csho'])
```

6 Check for missing values, outliers and data error

- Create a new dataframe by selecting the 4 finance ratios as the independent variables and RetYTD as a dependent variable.

[57]:
```
df = df[['Ticker','Book/Price', 'E/P', 'EBIT/P','SALE/P', 'RetYTD']]
```

- No missing value for each created financial ratios

[58]:
```
df[['Book/Price', 'E/P', 'EBIT/P','SALE/P']].isnull().sum()
```

[58]:
```
Book/Price    0
E/P           0
EBIT/P        0
SALE/P        0
dtype: int64
```

[59]:
```
df_model = df[['Book/Price', 'E/P', 'EBIT/P','SALE/P']]
```

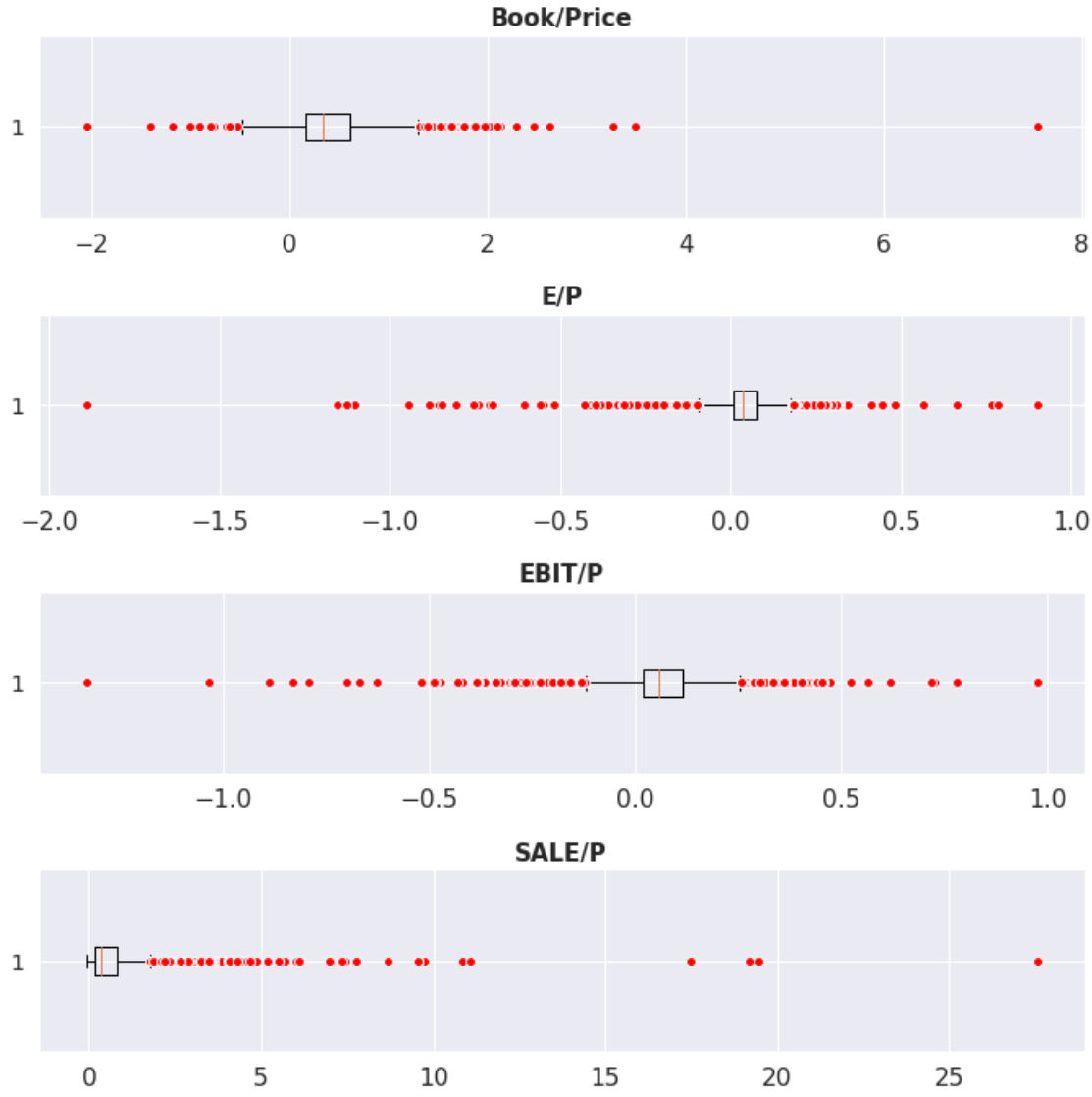
- below are the boxplots for all those finance ratios.

[60]:
```
#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()
```



- below are the histograms for all those finance ratios.

[61]:
```
#Creating histogram of each column with its own scale
fig, axs = plt.subplots(2,2, figsize=(10,7))

for i, ax in enumerate(axs.flat):
    ax.hist(df_model.iloc[:,i], bins = 30)
    ax.set_title(df_model.columns[i], fontsize=15, fontweight='bold')
    ax.tick_params(axis='y', labelsize=14)

plt.tight_layout()
```

6.1 Summary

- According to the multiple box plots above, every column has several outliers above 75 percentile and below 25 percentile. However, **sale / price** only has outliers which are above 75 percentile. In other words, the distribution of **sale / price** is right-skewed and the distributions of the rest 3 ratios are close to normal, which is proved by the above 4 histograms.
- Since, we only have 1886 data points, dropping some outliers may decrease the model predictive power
- I will use Winsorization method to deal with outliers before establishing the linear regression models

7 Handle the outliers (Winsorization)

- WINSORIZE within the range of 1% and 98% quantiles

[62]:
```
from scipy.stats.mstats import winsorize
# WINSORIZE within the range of 1% and 98% quantiles
df_win = winsorize(df_model, (0.01, 0.02))
df_win = pd.DataFrame(df_win, columns = df_model.columns )
```

```
df_win.describe()
```

[62]:

	Book/Price	E/P	EBIT/P	SALE/P
count	1886.000000	1886.000000	1886.000000	1886.000000
mean	0.421641	0.033190	0.063735	0.607557
std	0.368372	0.100633	0.113970	0.609798
min	-0.310090	-0.310090	-0.310090	-0.087004
25%	0.161112	0.008113	0.019641	0.176223
50%	0.337004	0.036704	0.056821	0.350729
75%	0.613868	0.076322	0.113822	0.814565
max	2.113777	0.898517	0.974888	2.113777

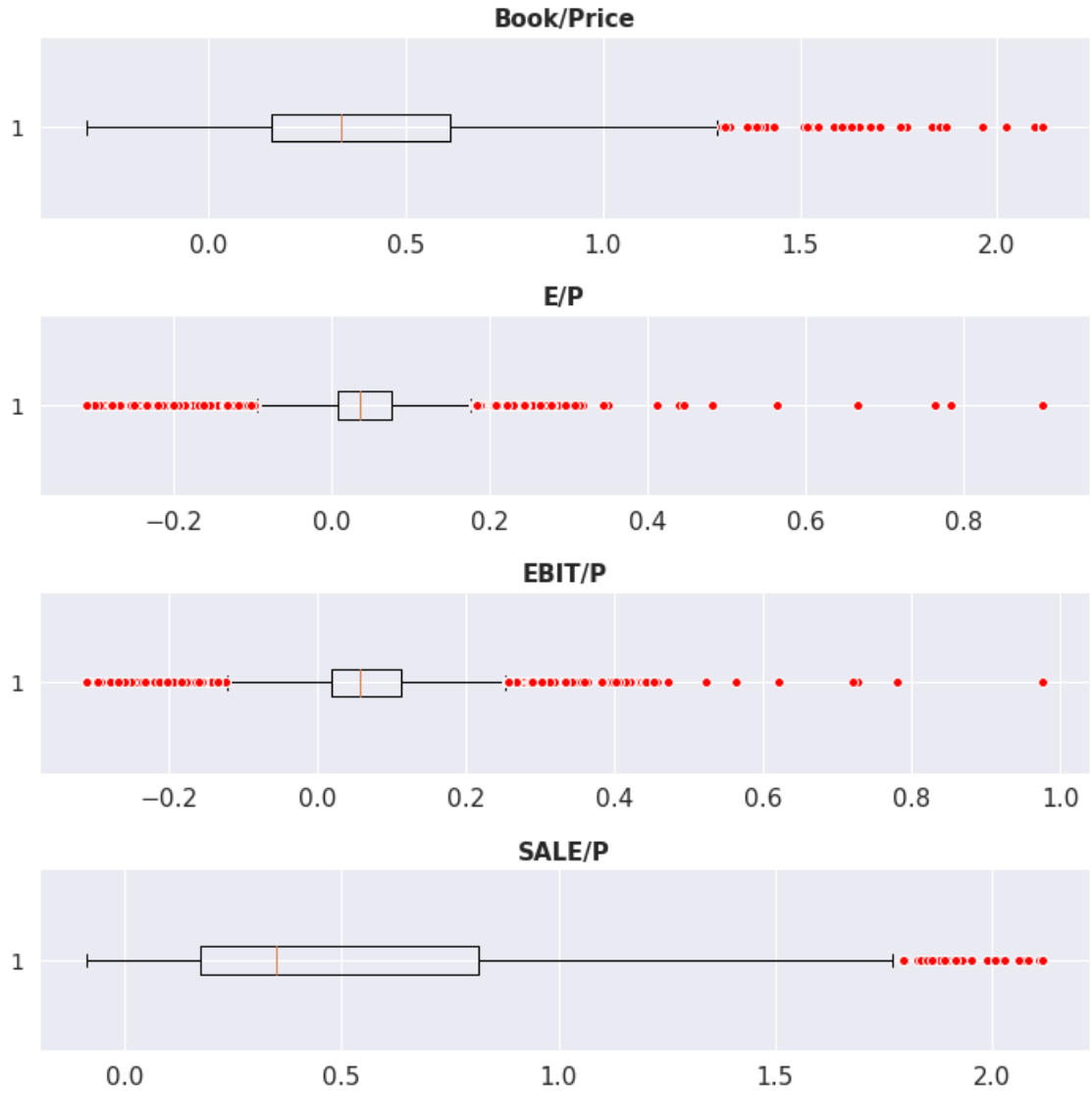
- Check the outliers after winsorization

[63]:
```
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()
```



- Check the outliers after winsorization

[64]:
```
fig, axs = plt.subplots(2,2, figsize=(10,7))

for i, ax in enumerate(axs.flat):
    ax.hist(df_win.iloc[:,i], bins = 30)
    ax.set_title(df_win.columns[i], fontsize=15, fontweight='bold')
    ax.tick_params(axis='y', labelsize=14)

plt.tight_layout()
```

7.1 Summary

- After Winsorization, **sale / price** is less right-skewed and the distributions of the rest 3 ratios are more close to normal, which is proved by the above 4 histograms and 4 boxplots.

7.2 Well-prepared dataset

[65]:
```
df_final = pd.concat([df['Ticker'], df_win, df['RetYTD']], axis = 1)
df_final.head()
```

[65]:

	Ticker	Book/Price	E/P	EBIT/P	SALE/P	RetYTD
0	AIR	0.760488	0.027941	0.051121	1.288865	0.2944
1	AAL	-0.310090	-0.171320	-0.310090	2.113777	0.0579
2	PNW	0.740913	0.077616	0.101023	0.477178	0.0985
3	ABT	0.144202	0.028480	0.036113	0.173496	-0.1638
4	AMD	0.043164	0.018205	0.021176	0.094618	-0.3533

7.3 Export assign4.csv file

[66]:
```
df_final.to_csv('assign4.csv', index = False)
```

8 Correlations between Book/Price, E/P, EBIT/P, SALES/P, and RetYTD

[67]:
```
corr = df_final.iloc[:,1:].corr()
corr
```

[67]:

	Book/Price	E/P	EBIT/P	SALE/P	RetYTD
Book/Price	1.000000	0.231359	0.259630	0.289212	0.242576
E/P	0.231359	1.000000	0.701646	0.141892	0.062988
EBIT/P	0.259630	0.701646	1.000000	0.320887	0.130663
SALE/P	0.289212	0.141892	0.320887	1.000000	0.172801
RetYTD	0.242576	0.062988	0.130663	0.172801	1.000000

[68]:
```
plt.figure(figsize = (10, 7))
sns.set(font_scale=1.4)
sns.heatmap(corr,annot=True,cmap="YlGnBu",annot_kws={"fontsize":20})
```

[68]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f249b87db50>
```

8.1 Summary

- **Book / Price** is the **most positive correlated** to **RetYTD** and **E / P** is the **least positive correlated** to **RetYTD**. The corresponding pearson's correlation coefficients are **0.24** and **0.063**, respectively.
- The pearson's correlation coefficients of **EBIT/P & RetYTD (0.13)** and **SALES/P & RetYTD (0.17)** are all more than 0, which demonstrates that there are positive correlation between EBIT/P & RetYTD or SALES/P & RetYTD. **However, the correlation of two pairs are not significant.**

9 Estimate 4 linear regression models (using StatsModel API) as follows:

- RetYTD = a + b1*Book/P + e
- RetYTD = a + b2*E/P + e
- RetYTD = a + b3*EBIT/P + e
- RetYTD = a + b4*SALES/P + e

[94]:
```
# Create a empty output dataframe
output = pd.DataFrame(columns = ['Independent-Financial-Ratio', 'Coefficients',␣
↪'t-value', 'p-value', '[0.025', '0.975]', 'R-squared', 'Adj. R-squared'])
output
```

[94]:
```
Empty DataFrame
Columns: [Independent-Financial-Ratio, Coefficients, t-value, p-value, [0.025,
0.975], R-squared, Adj. R-squared]
Index: []
```

[95]:
```
# Define a Linear Regression function
def lrmodel(datax,datay, i):
    y = datay
    X = datax[i]
    # Use statsmodels
    X = sm.add_constant(X) # adding a constant
    model = sm.OLS(y, X).fit()
    #print(model.pvalues[1])
    ci_low = model.conf_int(alpha=0.05, cols=None).iloc[1,:][0]
    ci_high = model.conf_int(alpha=0.05, cols=None).iloc[1,:][1]
    #return regression output
    return (i, model.params[1], model.tvalues[1],model.pvalues[1],ci_low,␣
↪ci_high, model.rsquared, model.rsquared_adj)

for i in df_final[['Book/Price',        'E/P' ,        'EBIT/P', 'SALE/P']].
↪columns:
    output.loc[len(output.index)] = lrmodel(df_final[['Book/Price',        'E/
↪P' ,        'EBIT/P', 'SALE/P']], df_final['RetYTD'] ,i)
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:117:
FutureWarning: In a future version of pandas all arguments of concat except for
the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

[96]:
```
output
```

[96]:

	Independent-Financial-Ratio	Coefficients	t-value	p-value	[0.025	0.975]	R-squared	Adj. R-squared
0	Book/Price	0.160545	10.853201	1.162647e-26	0.131534	0.189557	0.058843	0.058344
1	E/P	0.152599	2.739441	6.212389e-03	0.043350	0.261848	0.003967	0.003439
2	EBIT/P	0.279509	5.720477	1.232900e-08	0.183681	0.375337	0.017073	0.016551
3	SALE/P	0.069087	7.614997	4.145130e-14	0.051294	0.086880	0.029860	0.029345

9.1 Explain and interpret the R2 and AdjR2 for the 4 regressions

- Based on the R2 and AdjR2, I realized that R2 and AdjR2 are almost the same. To compare the model predictive power, I will use AdjR2.
- we found that the model using **Book / Price** with (**highest R2 = 0.058843 and highest AdjR2 = 0.058344**) indicates a better fit and 5.83% of year-to-date stock return could be explained by **Book / Price** ratio. However, highest AdjR2 = 0.058344 still indicates that **it predicts year-to-date stock return poorly**.
- In addition, the model using **E / P** with (**lowest R2 = 0.003967 and lowest AdjR2 = 0.003439**) shows that 0.34% of year-to-date stock return could be explained by **E / P** ratio and **the model has the least predictive power**.
- Lastly, the model with **EBIT/P** or **SALE/P** has **medium level predictive power** among all 4 models.
- the model using **EBIT/P** with (**R2 = 0.017073 and AdjR2 = 0.016551**) shows that 1.66% of year-to-date stock return could be explained by **EBIT/P** ratio
- the model using **SALE/P** with (**R2 = 0.029860 and AdjR2 = 0.029345**) shows that 2.93% of year-to-date stock return could be explained by **SALE/P** ratio
- In genearl, **All 4 models predict year-to-date stock return poorly based on the Adj R2**.

9.2 Explain and interpret and compare the values of b1 to b4

- For all 4 Models, **The coefficients of Book/Price, E/P, EBIT/P, SALE/P** are **all statistically significant at 5%** based on their correponding p-values (< 0.05).
- **On average, for each increase in *Book/Price* (Double Book Value and Keep the Price same), the RetYTD will increase 0.160545**. In other words, lower Price / Book ratio will increase RetYTD (the stock may be undervalued). **95% of coefficients of Book/Price** are within [0.131534, 0.189557].
- **On average, for each increase in *E/P* (Double Earning Per Share and Keep the Price same), the RetYTD will increase 0.152599**. In other words, lower P/E ratio will increase RetYTD (the stock may be undervalued). **95% of coefficients of E/P** are within [0.043350, 0.261848].
- **On average, for each increase in *EBIT/P* (Double EBIT and Keep the Price same), the RetYTD will increase 0.279509**. In other words, lower P/EBIT ratio will increase RetYTD (The investment are more attractive). **95% of coefficients of EBIT/P** are within [0.183681, 0.375337].
- **On average, for each increase in *SALE/P* (Double Sales and Keep the Price same), the RetYTD will increase 0.069087**. In other words, lower P/Sales ratio will increase RetYTD (The investment are more attractive). **95% of coefficients of SALE/P** are within [0.051294, 0.086880].

- In summary, if we assume the same unit increase in each of 4 ratios, EBIT/P will cause the most increase in RetYTD by 0.279509, and SALE/P will lead to the least increase in RetYTD by 0.069087. Book/Price and E/P will result in the similar increase in RetYTD by 0.160545 and 0.152599, respectively.

9.3 Explain and interpret and compare the t-stats of b1 to b4

- **All 4 *t-values*** are **10.853201, 2.739441, 5.720477 and 7.614997**, respectively and all more than 1.96.
- Thus, it indicates that **coefficients for those 4 variables are significant different from 0 at 5% level**.

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

[99]:
```
!jupyter nbconvert --to pdf '/content/drive/MyDrive/BA_870/HW/4/
↪Assignment4_Ji_Qi.ipynb'
```

```
[NbConvertApp] Converting notebook
/content/drive/MyDrive/BA_870/HW/4/Assignment4_Ji_Qi.ipynb to pdf
[NbConvertApp] Support files will be in Assignment4_Ji_Qi_files/
[NbConvertApp] Making directory ./Assignment4_Ji_Qi_files
[NbConvertApp] Making directory ./Assignment4_Ji_Qi_files
[NbConvertApp] Making directory ./Assignment4_Ji_Qi_files
[NbConvertApp] Making directory ./Assignment4_Ji_Qi_files
[NbConvertApp] Making directory ./Assignment4_Ji_Qi_files
[NbConvertApp] Writing 100300 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 236728 bytes to
/content/drive/MyDrive/BA_870/HW/4/Assignment4_Ji_Qi.pdf
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