In [1]:
```
# this will help in making the Python code more structured automatically (good coding
#%load_ext nb_black

# Libraries to help with reading and manipulating data
import numpy as np
import pandas as pd

# Libraries to help with data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Removes the limit for the number of displayed columns
pd.set_option("display.max_columns", None)
# Sets the limit for the number of displayed rows
pd.set_option("display.max_rows", 200)

# to scale the data using z-score
from sklearn.preprocessing import StandardScaler

# to compute distances
from scipy.spatial.distance import pdist
from scipy.spatial.distance import cdist

# to perform k-means clustering and compute silhouette scores
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score


# to perform hierarchical clustering, compute cophenetic correlation, and create dendr
from sklearn.cluster import AgglomerativeClustering

import warnings
warnings.filterwarnings('ignore')
!pip install yellowbrick
# to visualize the elbow curve and silhouette scores
from yellowbrick.cluster import KElbowVisualizer, SilhouetteVisualizer
from scipy.cluster.hierarchy import dendrogram, linkage, cophenet
```

```
Requirement already satisfied: yellowbrick in c:\users\conne\anaconda3\lib\site-packa
ges (1.5)
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.2 in c:\users\conne\anaconda3
\lib\site-packages (from yellowbrick) (3.7.1)
Requirement already satisfied: scipy>=1.0.0 in c:\users\conne\anaconda3\lib\site-pack
ages (from yellowbrick) (1.10.1)
Requirement already satisfied: scikit-learn>=1.0.0 in c:\users\conne\anaconda3\lib\si
te-packages (from yellowbrick) (1.3.2)
Requirement already satisfied: numpy>=1.16.0 in c:\users\conne\anaconda3\lib\site-pac
kages (from yellowbrick) (1.24.3)
Requirement already satisfied: cycler>=0.10.0 in c:\users\conne\anaconda3\lib\site-pa
ckages (from yellowbrick) (0.11.0)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\conne\anaconda3\lib\site-
packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.0.5)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\conne\anaconda3\lib\site
-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\conne\anaconda3\lib\site
-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.4.4)
Requirement already satisfied: packaging>=20.0 in c:\users\conne\anaconda3\lib\site-p
ackages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (23.0)
Requirement already satisfied: pillow>=6.2.0 in c:\users\conne\anaconda3\lib\site-pac
kages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\conne\anaconda3\lib\site-
packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\conne\anaconda3\lib\s
ite-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (2.8.2)
Requirement already satisfied: joblib>=1.1.1 in c:\users\conne\anaconda3\lib\site-pac
kages (from scikit-learn>=1.0.0->yellowbrick) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\conne\anaconda3\lib\s
ite-packages (from scikit-learn>=1.0.0->yellowbrick) (2.2.0)
Requirement already satisfied: six>=1.5 in c:\users\conne\anaconda3\lib\site-packages
(from python-dateutil>=2.7->matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.16.0)
```

In [2]:
```
df = pd.read_csv('/Users/conne/Downloads/stock_data.csv')
```

In [3]:
```
df
```

Out[3]:

	Ticker Symbol	Security	GICS Sector	GICS Sub Industry	Current Price	Price Change	Volatility	ROE	Cash Ratio
0	AAL	American Airlines Group	Industrials	Airlines	42.349998	9.999995	1.687151	135	51
1	ABBV	AbbVie	Health Care	Pharmaceuticals	59.240002	8.339433	2.197887	130	77
2	ABT	Abbott Laboratories	Health Care	Health Care Equipment	44.910000	11.301121	1.273646	21	67
3	ADBE	Adobe Systems Inc	Information Technology	Application Software	93.940002	13.977195	1.357679	9	180
4	ADI	Analog Devices, Inc.	Information Technology	Semiconductors	55.320000	-1.827858	1.701169	14	272
...	...	...	...	...	...	...	...	...	...
335	YHOO	Yahoo Inc.	Information Technology	Internet Software & Services	33.259998	14.887727	1.845149	15	459
336	YUM	Yum! Brands Inc	Consumer Discretionary	Restaurants	52.516175	-8.698917	1.478877	142	27
337	ZBH	Zimmer Biomet Holdings	Health Care	Health Care Equipment	102.589996	9.347683	1.404206	1	100
338	ZION	Zions Bancorp	Financials	Regional Banks	27.299999	-1.158588	1.468176	4	99
339	ZTS	Zoetis	Health Care	Pharmaceuticals	47.919998	16.678836	1.610285	32	65

340 rows × 15 columns

In [4]:
```
df.rename(columns = {'GICS Sector':'GICS_Sector'}, inplace = True)
```

In [5]:
```
data = df.copy()
```

In [6]:
```
data.shape
```

Out[6]:
```
(340, 15)
```

The dataset has The dataset has 229 rows and 15 columns

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

Out[7]:

	Ticker Symbol	Security	GICS_Sector	GICS Sub Industry	Current Price	Price Change	Volatility	ROE	Cash Ratio	
0	AAL	American Airlines Group	Industrials	Airlines	42.349998	9.999995	1.687151	135	51	-6
1	ABBV	AbbVie	Health Care	Pharmaceuticals	59.240002	8.339433	2.197887	130	77	5
2	ABT	Abbott Laboratories	Health Care	Health Care Equipment	44.910000	11.301121	1.273646	21	67	9
3	ADBE	Adobe Systems Inc	Information Technology	Application Software	93.940002	13.977195	1.357679	9	180	-2
4	ADI	Analog Devices, Inc.	Information Technology	Semiconductors	55.320000	-1.827858	1.701169	14	272	3

In [8]:

```python
data.tail()
```

Out[8]:

	Ticker Symbol	Security	GICS_Sector	GICS Sub Industry	Current Price	Price Change	Volatility	ROE	Cash Ratio	
335	YHOO	Yahoo Inc.	Information Technology	Internet Software & Services	33.259998	14.887727	1.845149	15	459	-1
336	YUM	Yum! Brands Inc	Consumer Discretionary	Restaurants	52.516175	-8.698917	1.478877	142	27	
337	ZBH	Zimmer Biomet Holdings	Health Care	Health Care Equipment	102.589996	9.347683	1.404206	1	100	
338	ZION	Zions Bancorp	Financials	Regional Banks	27.299999	-1.158588	1.468176	4	99	
339	ZTS	Zoetis	Health Care	Pharmaceuticals	47.919998	16.678836	1.610285	32	65	

In [9]:

```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 340 entries, 0 to 339
Data columns (total 15 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Ticker Symbol                 340 non-null    object 
 1   Security                      340 non-null    object 
 2   GICS_Sector                   340 non-null    object 
 3   GICS Sub Industry             340 non-null    object 
 4   Current Price                 340 non-null    float64
 5   Price Change                  340 non-null    float64
 6   Volatility                    340 non-null    float64
 7   ROE                           340 non-null    int64  
 8   Cash Ratio                    340 non-null    int64  
 9   Net Cash Flow                 340 non-null    int64  
 10  Net Income                    340 non-null    int64  
 11  Earnings Per Share            340 non-null    float64
 12  Estimated Shares Outstanding  340 non-null    float64
 13  P/E Ratio                     340 non-null    float64
 14  P/B Ratio                     340 non-null    float64
dtypes: float64(7), int64(4), object(4)
memory usage: 40.0+ KB
```

All the columns seem to have the approptiate Dtype for the data the are representing

In [10]:
```
data.duplicated().sum()
```

Out[10]:
```
0
```

I seem to have no duplicate data

In [11]:
```
data.isnull().sum()
```

Out[11]:
```
Ticker Symbol                   0
Security                        0
GICS_Sector                     0
GICS Sub Industry               0
Current Price                   0
Price Change                    0
Volatility                      0
ROE                             0
Cash Ratio                      0
Net Cash Flow                   0
Net Income                      0
Earnings Per Share              0
Estimated Shares Outstanding    0
P/E Ratio                       0
P/B Ratio                       0
dtype: int64
```

I have no null data

In [12]:
```
data.describe().T
```

Out[12]:

	count	mean	std	min	25%	50%	
Current Price	340.0	8.086234e+01	9.805509e+01	4.500000e+00	3.855500e+01	5.970500e+01	9.288(
Price Change	340.0	4.078194e+00	1.200634e+01	-4.712969e+01	-9.394838e-01	4.819505e+00	1.069!
Volatility	340.0	1.525976e+00	5.917984e-01	7.331632e-01	1.134878e+00	1.385593e+00	1.695!
ROE	340.0	3.959706e+01	9.654754e+01	1.000000e+00	9.750000e+00	1.500000e+01	2.700(
Cash Ratio	340.0	7.002353e+01	9.042133e+01	0.000000e+00	1.800000e+01	4.700000e+01	9.900(
Net Cash Flow	340.0	5.553762e+07	1.946365e+09	-1.120800e+10	-1.939065e+08	2.098000e+06	1.698
Net Income	340.0	1.494385e+09	3.940150e+09	-2.352800e+10	3.523012e+08	7.073360e+08	1.899(
Earnings Per Share	340.0	2.776662e+00	6.587779e+00	-6.120000e+01	1.557500e+00	2.895000e+00	4.620(
Estimated Shares Outstanding	340.0	5.770283e+08	8.458496e+08	2.767216e+07	1.588482e+08	3.096751e+08	5.731
P/E Ratio	340.0	3.261256e+01	4.434873e+01	2.935451e+00	1.504465e+01	2.081988e+01	3.176
P/B Ratio	340.0	-1.718249e+00	1.396691e+01	-7.611908e+01	-4.352056e+00	-1.067170e+00	3.917(

In [13]:

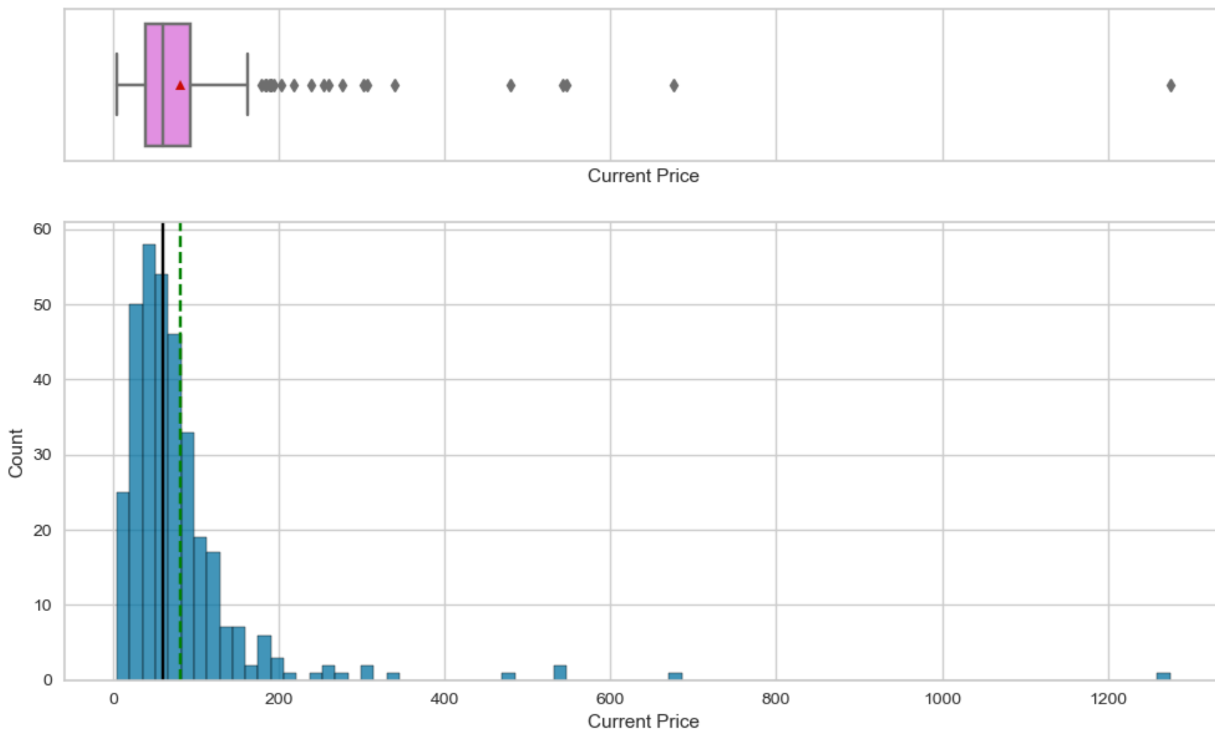
```
# function to plot a boxplot and a histogram along the same scale.


def histogram_boxplot(data, feature, figsize=(12, 7), kde=False, bins=None):
    """
    Boxplot and histogram combined

    data: dataframe
    feature: dataframe column
    figsize: size of figure (default (12,7))
    kde: whether to show the density curve (default False)
    bins: number of bins for histogram (default None)
    """
    f2, (ax_box2, ax_hist2) = plt.subplots(
        nrows=2,  # Number of rows of the subplot grid= 2
        sharex=True,  # x-axis will be shared among all subplots
        gridspec_kw={"height_ratios": (0.25, 0.75)},
        figsize=figsize,
    )  # creating the 2 subplots
    sns.boxplot(
        data=data, x=feature, ax=ax_box2, showmeans=True, color="violet"
    )  # boxplot will be created and a triangle will indicate the mean value of the co
    sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2, bins=bins
    ) if bins else sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2
    )  # For histogram
    ax_hist2.axvline(
        data[feature].mean(), color="green", linestyle="--"
    )  # Add mean to the histogram
```

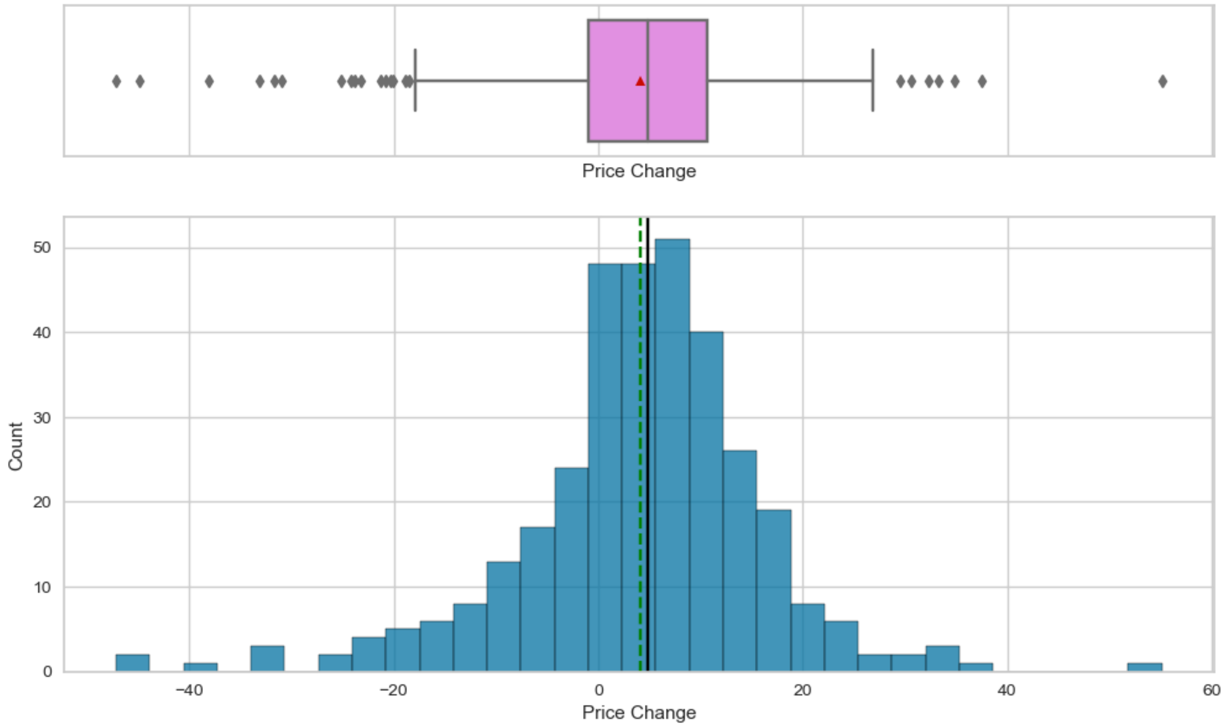
```
    ax_hist2.axvline(
        data[feature].median(), color="black", linestyle="-"
    )  # Add median to the histogram
```

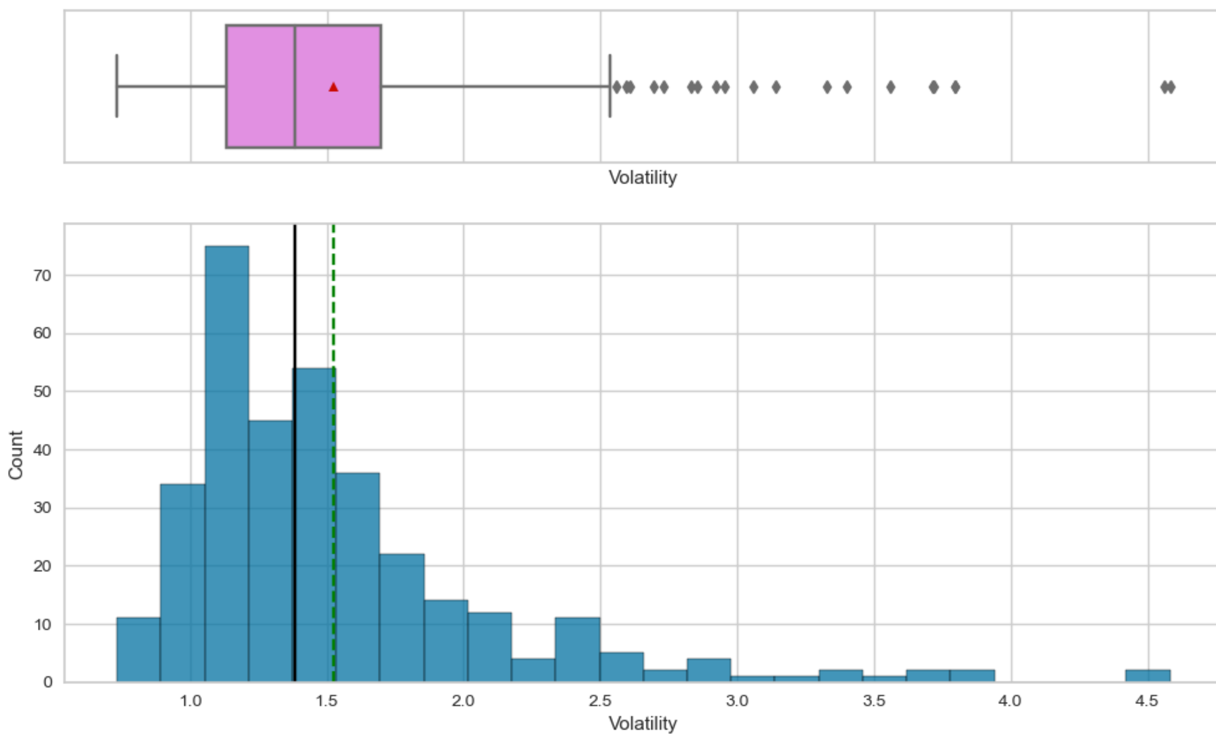
In [14]:
```
# selecting numerical columns
num_col = df.select_dtypes(include=np.number).columns.tolist()

print(num_col)
```

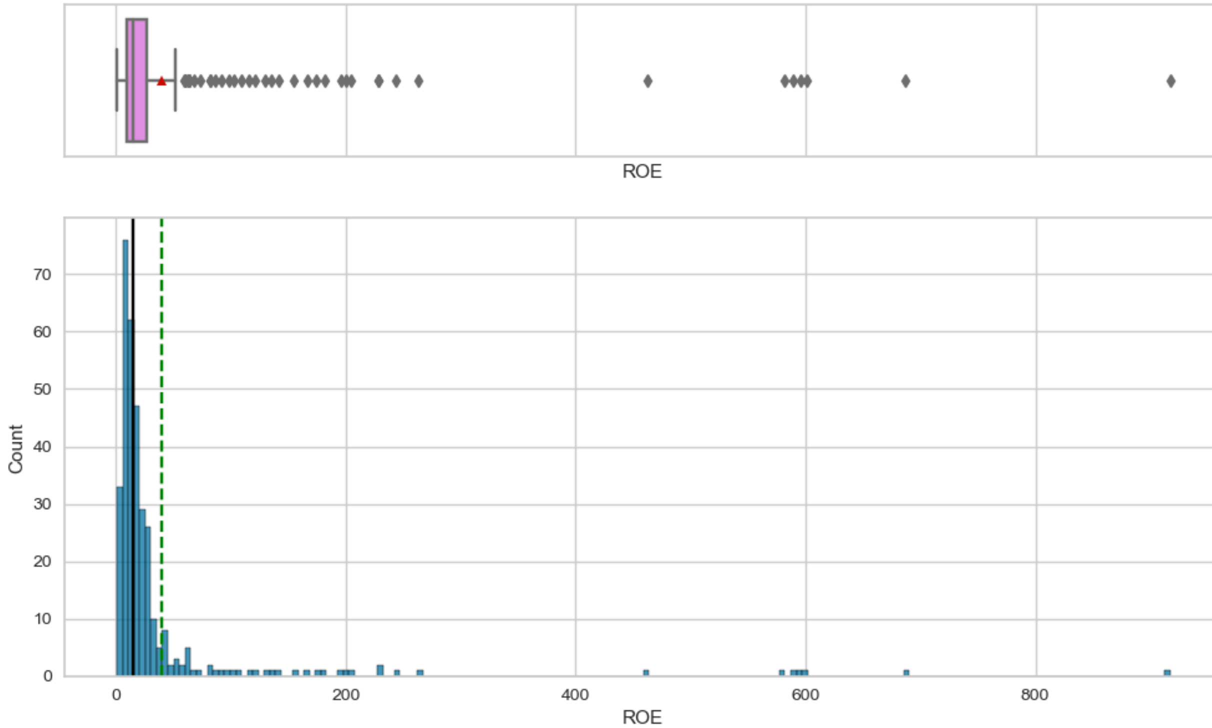
```
['Current Price', 'Price Change', 'Volatility', 'ROE', 'Cash Ratio', 'Net Cash Flow', 'Net Income', 'Earnings Per Share', 'Estimated Shares Outstanding', 'P/E Ratio', 'P/B Ratio']
```

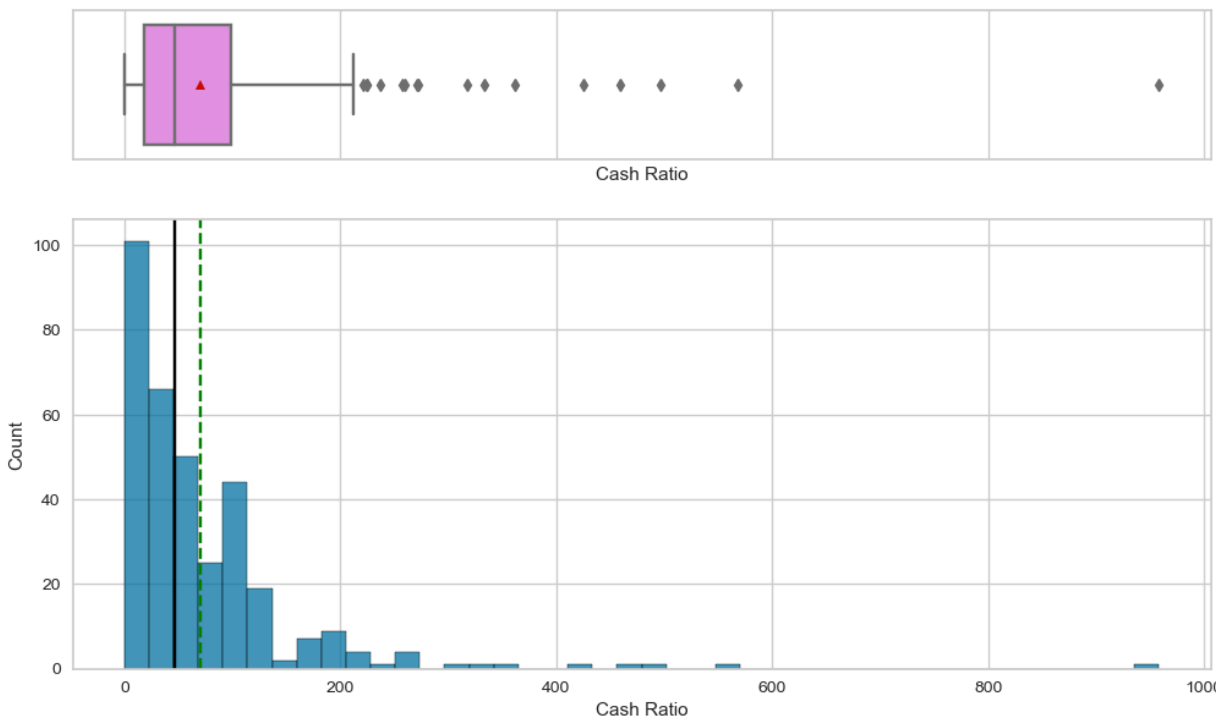
In [15]:
```
for item in num_col:
    histogram_boxplot(df, item)
```

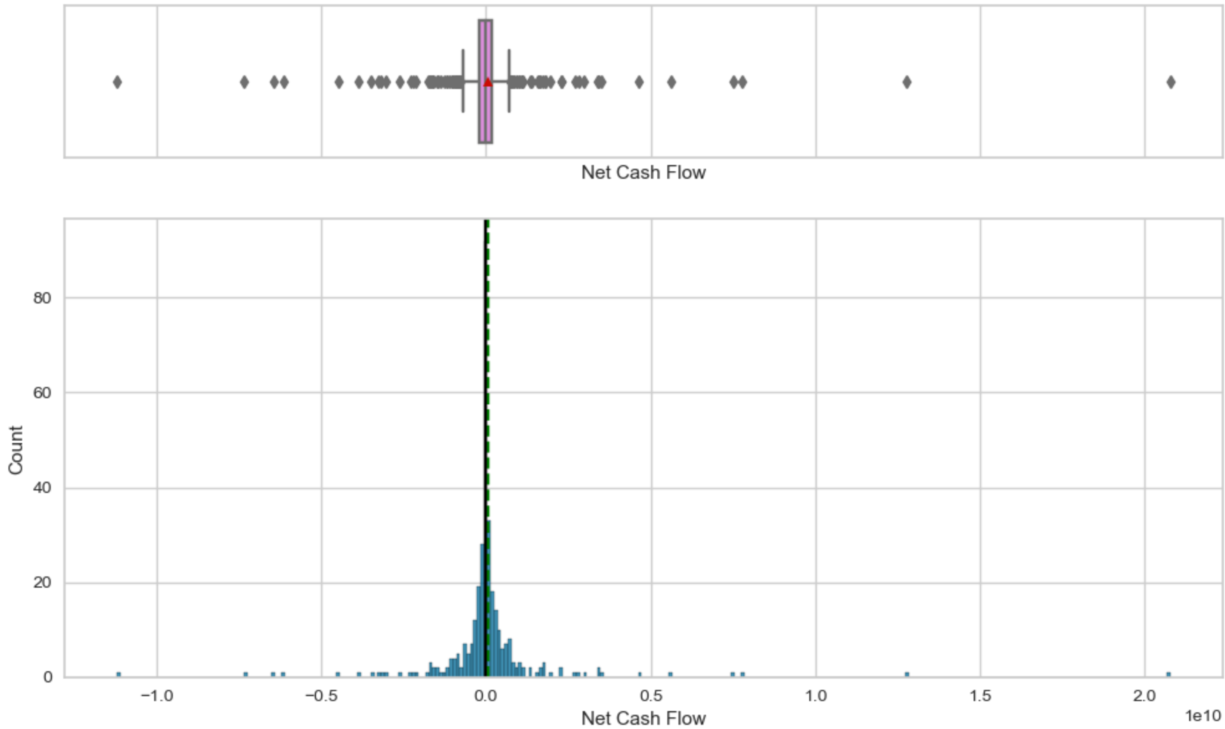


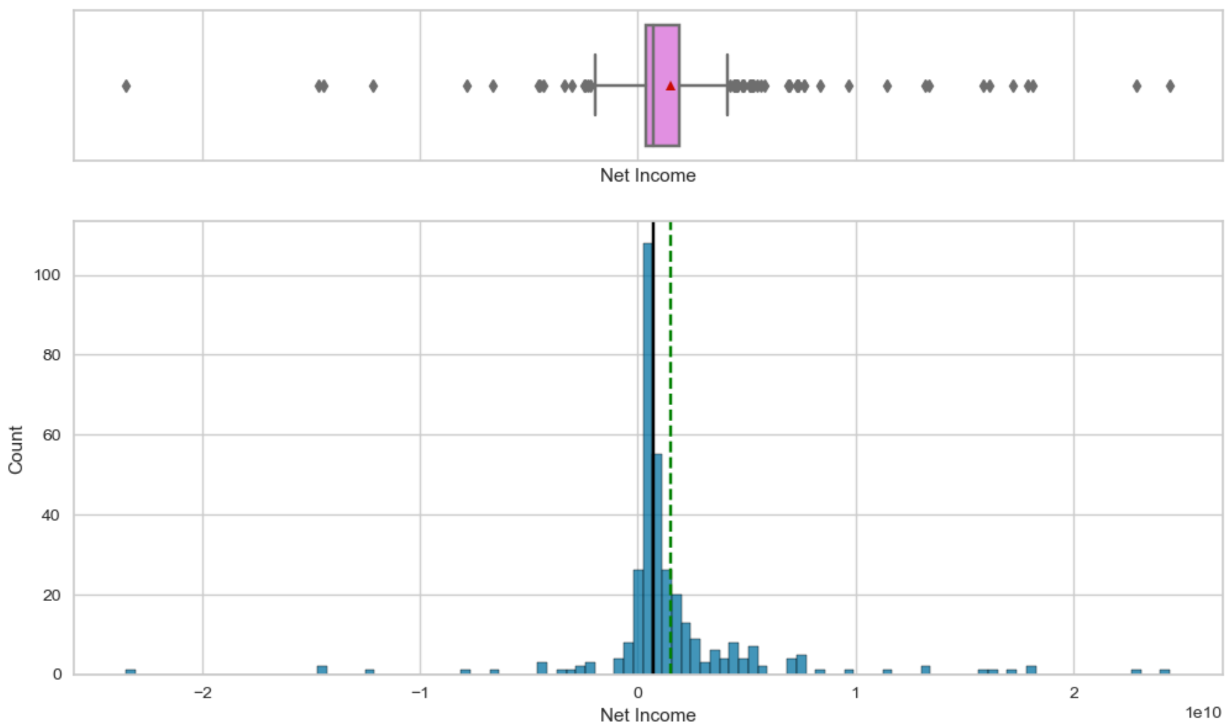

Price Change
Count
50
40
30
20
10
0
−40
−20
0
20
40
60
Price Change

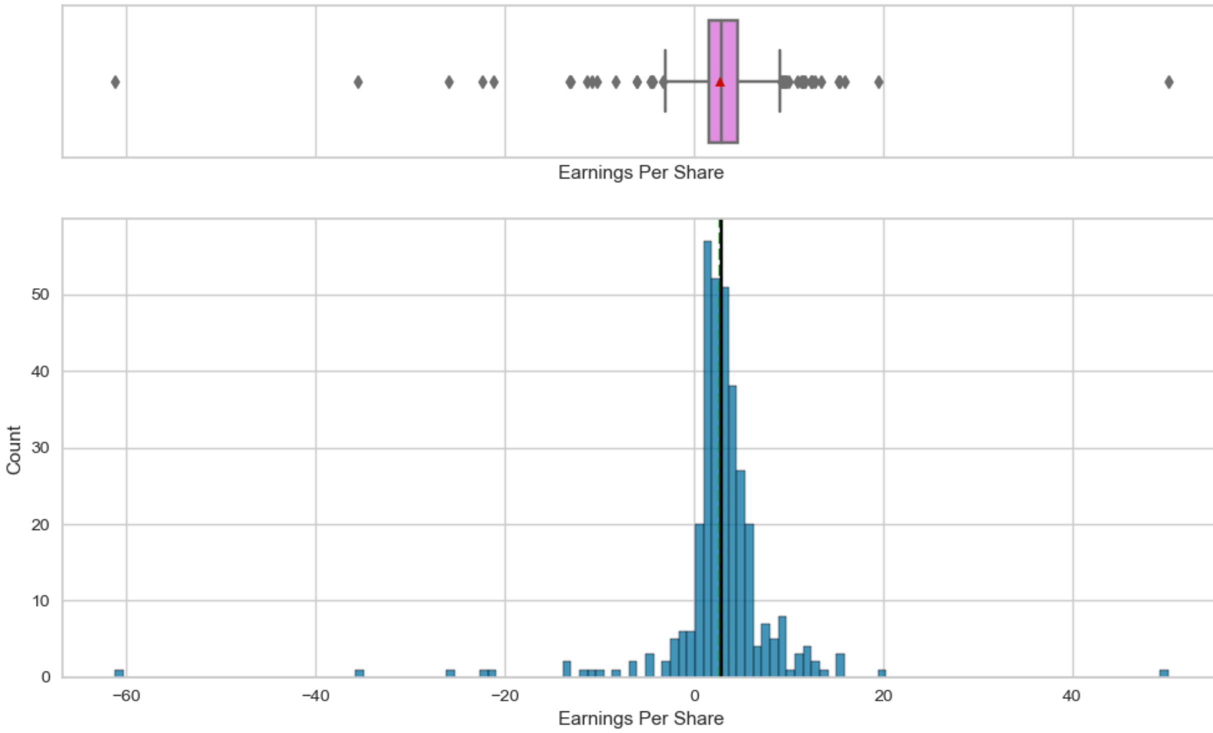

Volatility
Count
70
60
50
40
30
20
10
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
Volatility

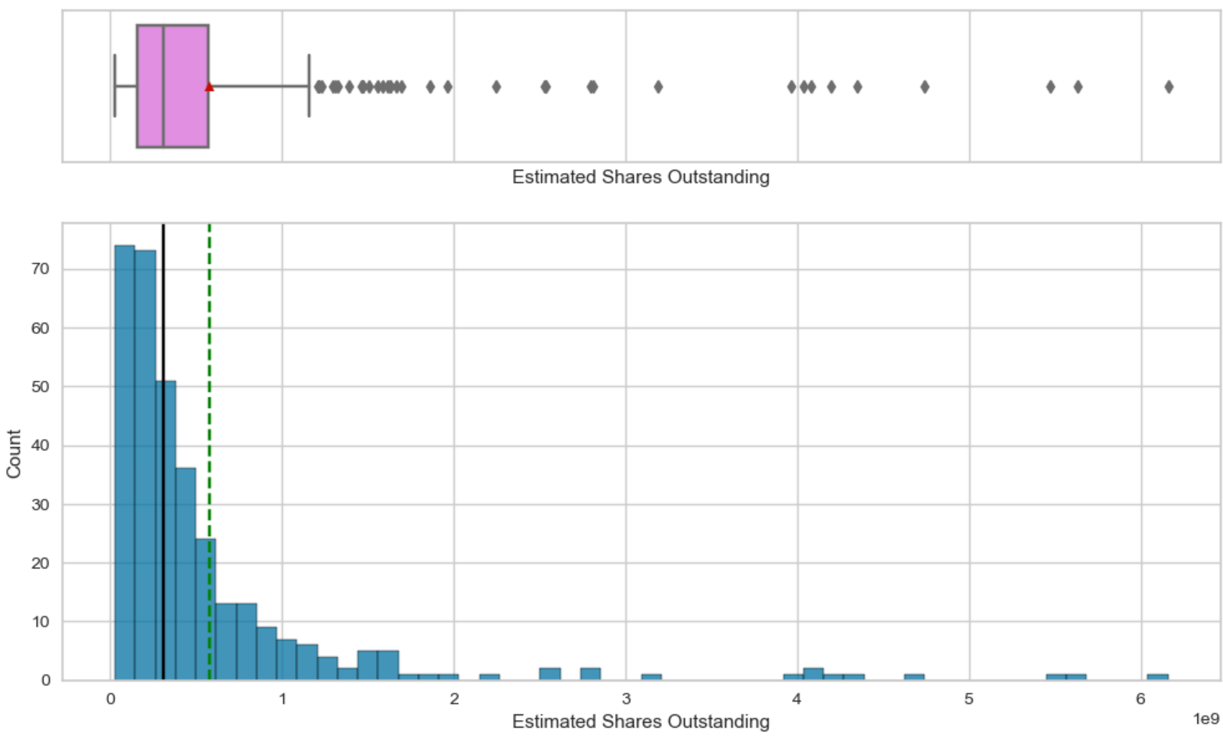

ROE
Count
70
60
50
40
30
20
10
0
0
200
400
600
800
ROE

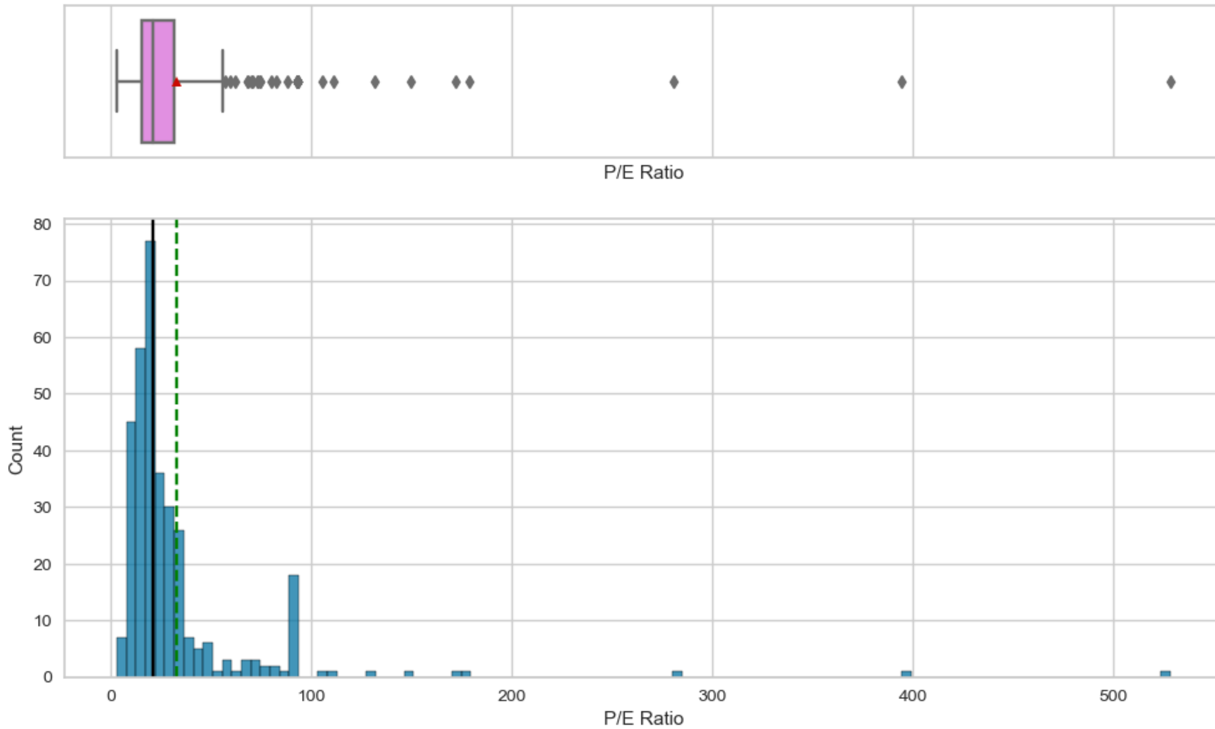

Cash Ratio
Count
100
80
60
40
20
0
0
200
400
600
800
1000
Cash Ratio

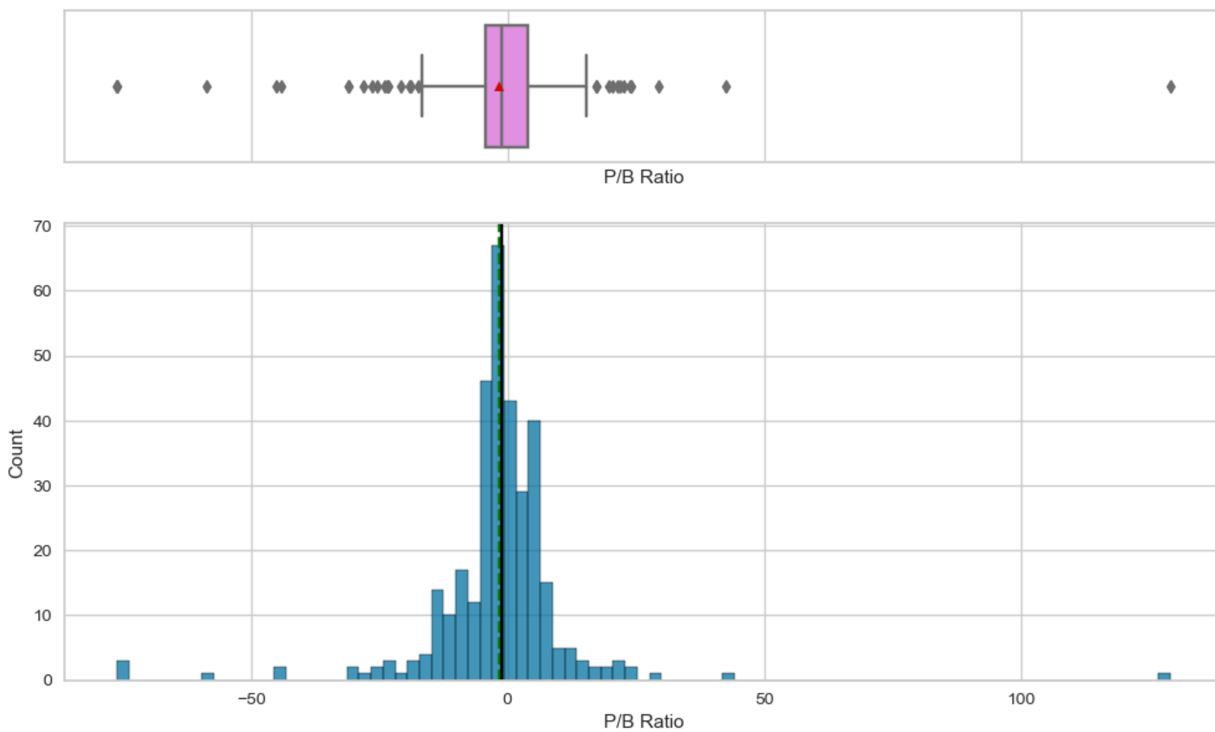

Net Cash Flow
Count
80
60
40
20
0
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
1e10
Net Cash Flow


Net Income
Count
100
80
60
40
20
0
−2
−1
0
1
2
1e10
Net Income


Earnings Per Share
Count
50
40
30
20
10
0
−60
−40
−20
0
20
40
Earnings Per Share


Estimated Shares Outstanding
Count
70
60
50
40
30
20
10
0
0
1
2
3
4
5
6
1e9
Estimated Shares Outstanding

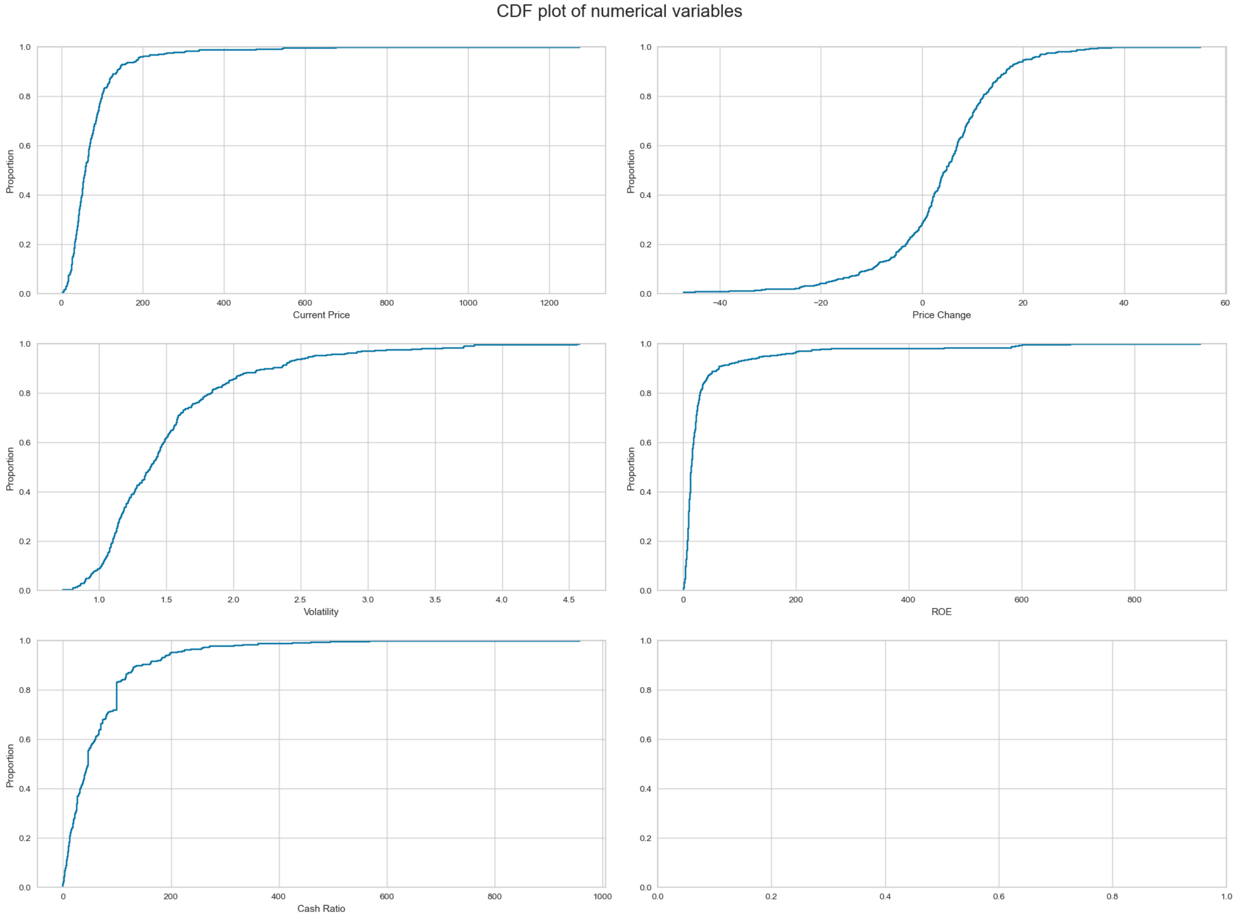




current price and price change seem to be good tools for anylizing stocks

In [16]:
```
fig, axes = plt.subplots(3, 2, figsize=(20, 15))
fig.suptitle("CDF plot of numerical variables", fontsize=20)
counter = 0
for ii in range(3):
    sns.ecdfplot(ax=axes[ii][0], x=df[num_col[counter]])
    counter = counter + 1
    if counter != 5:
        sns.ecdfplot(ax=axes[ii][1], x=df[num_col[counter]])
        counter = counter + 1
    else:
```

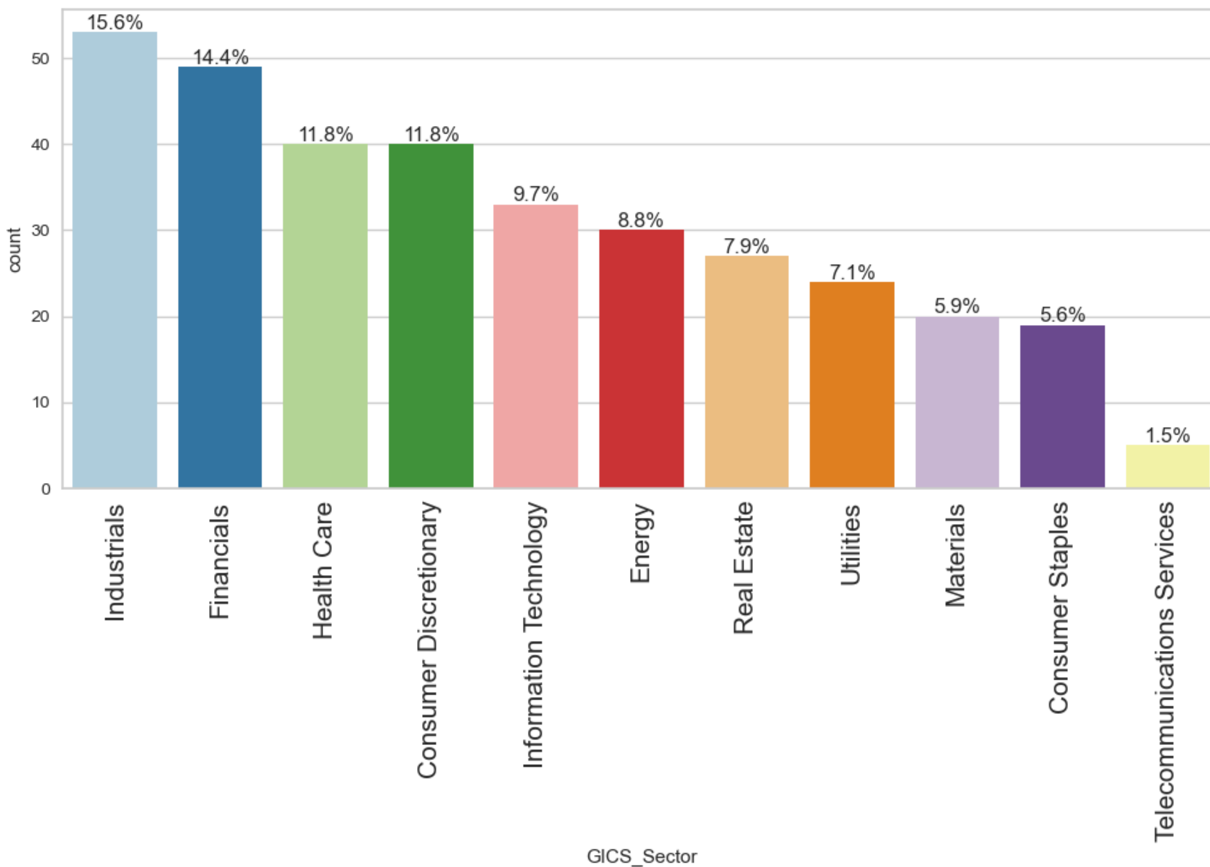
```
        pass

fig.tight_layout(pad=2.0)
```



In [17]:
```
# function to create labeled barplots


def labeled_barplot(data, feature, perc=False, n=None):
    """
    Barplot with percentage at the top

    data: dataframe
    feature: dataframe column
    perc: whether to display percentages instead of count (default is False)
    n: displays the top n category levels (default is None, i.e., display all levels)
    """

    total = len(data[feature])  # length of the column
    count = data[feature].nunique()
    if n is None:
        plt.figure(figsize=(count + 1, 5))
    else:
        plt.figure(figsize=(n + 1, 5))

    plt.xticks(rotation=90, fontsize=15)
    ax = sns.countplot(
        data=data,
        x=feature,
        palette="Paired",
        order=data[feature].value_counts().index[:n],
    )
```

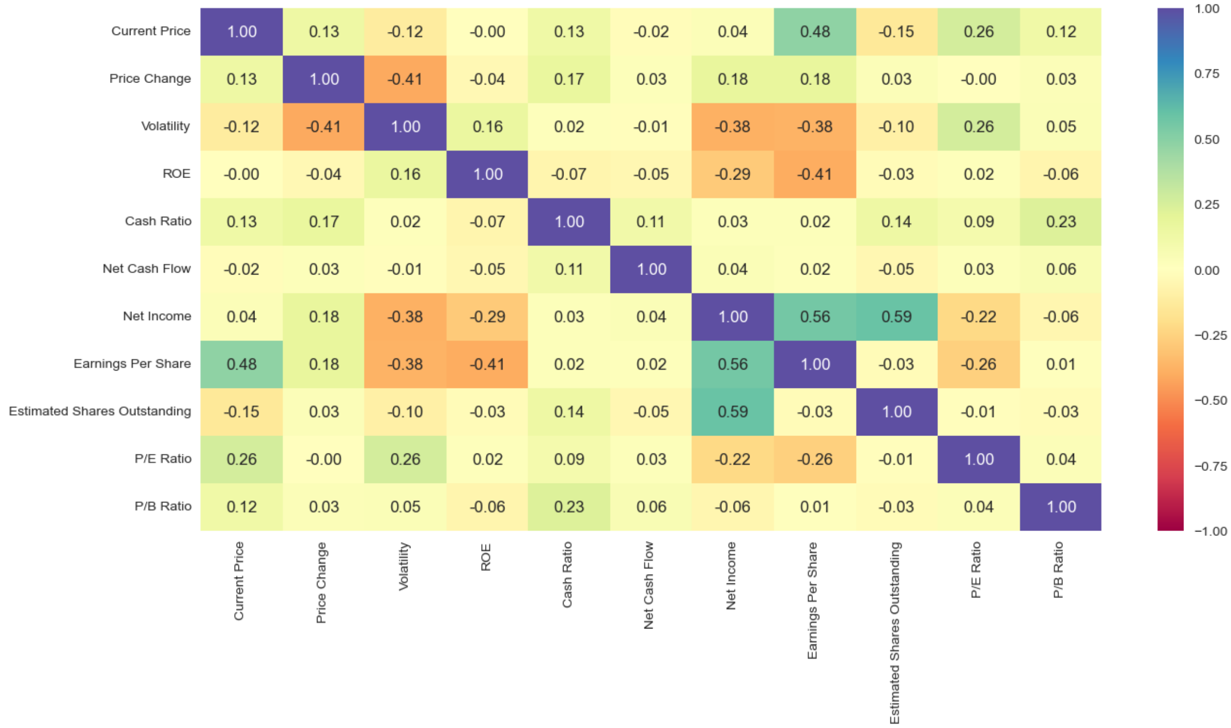
```
    for p in ax.patches:
        if perc == True:
            label = "{:.1f}%".format(
                100 * p.get_height() / total
            )  # percentage of each class of the category
        else:
            label = p.get_height()  # count of each level of the category

        x = p.get_x() + p.get_width() / 2  # width of the plot
        y = p.get_height()  # height of the plot

        ax.annotate(
            label,
            (x, y),
            ha="center",
            va="center",
            size=12,
            xytext=(0, 5),
            textcoords="offset points",
        )  # annotate the percentage

    plt.show()  # show the plot
```

In [18]:
```
labeled_barplot(df, "GICS_Sector", perc=True)
```

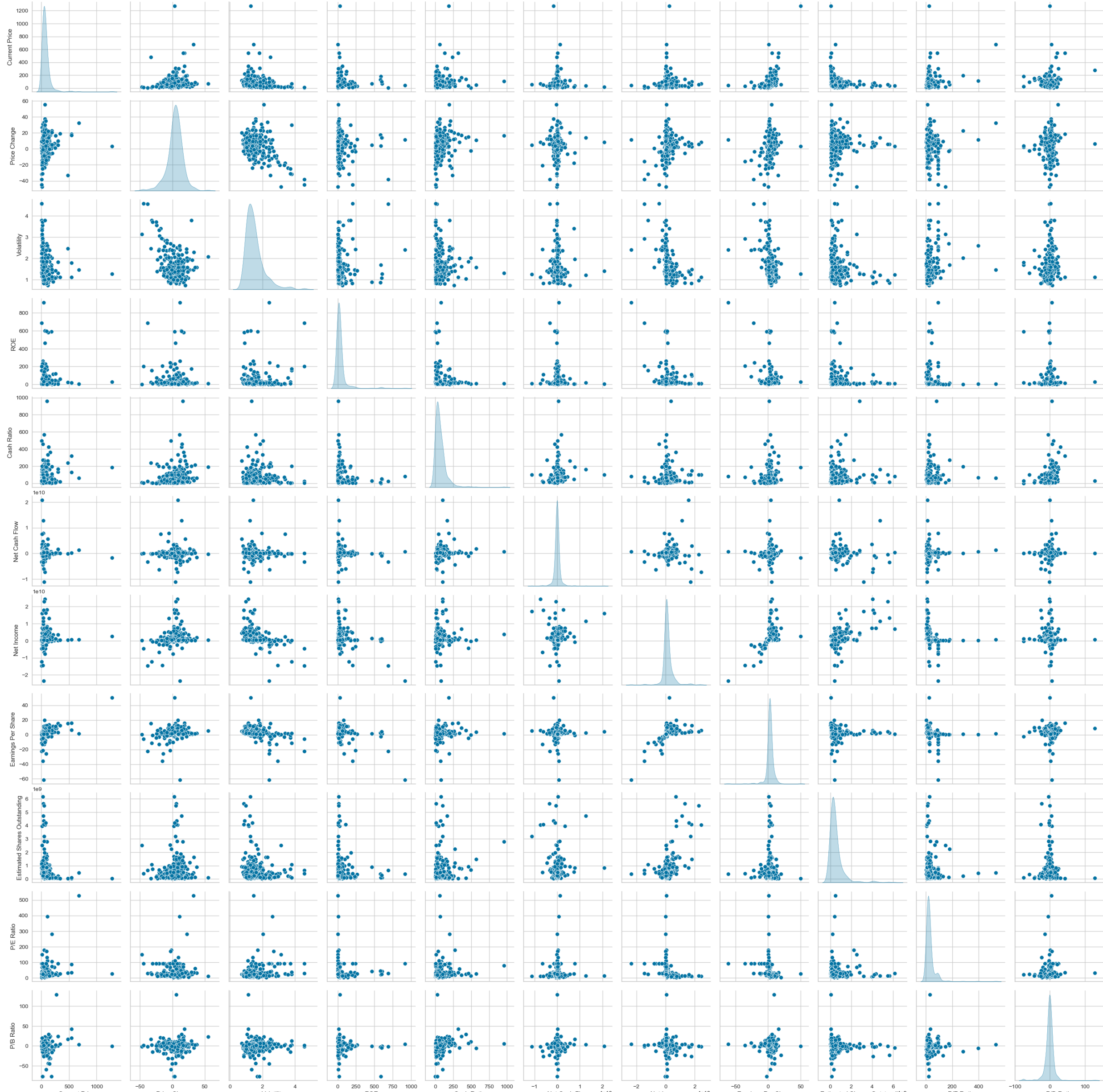


industial financial and helth care are the top 3 largest sectors

In [19]:
```
plt.figure(figsize=(15, 7))
sns.heatmap(df[num_col].corr(), annot=True, vmin=-1, vmax=1, fmt=".2f", cmap="Spectral
plt.show()
```



In [20]:
```
sns.pairplot(data=df[num_col], diag_kind="kde")
plt.show()
```



In [21]:
```
# variables used for clustering
num_col
```

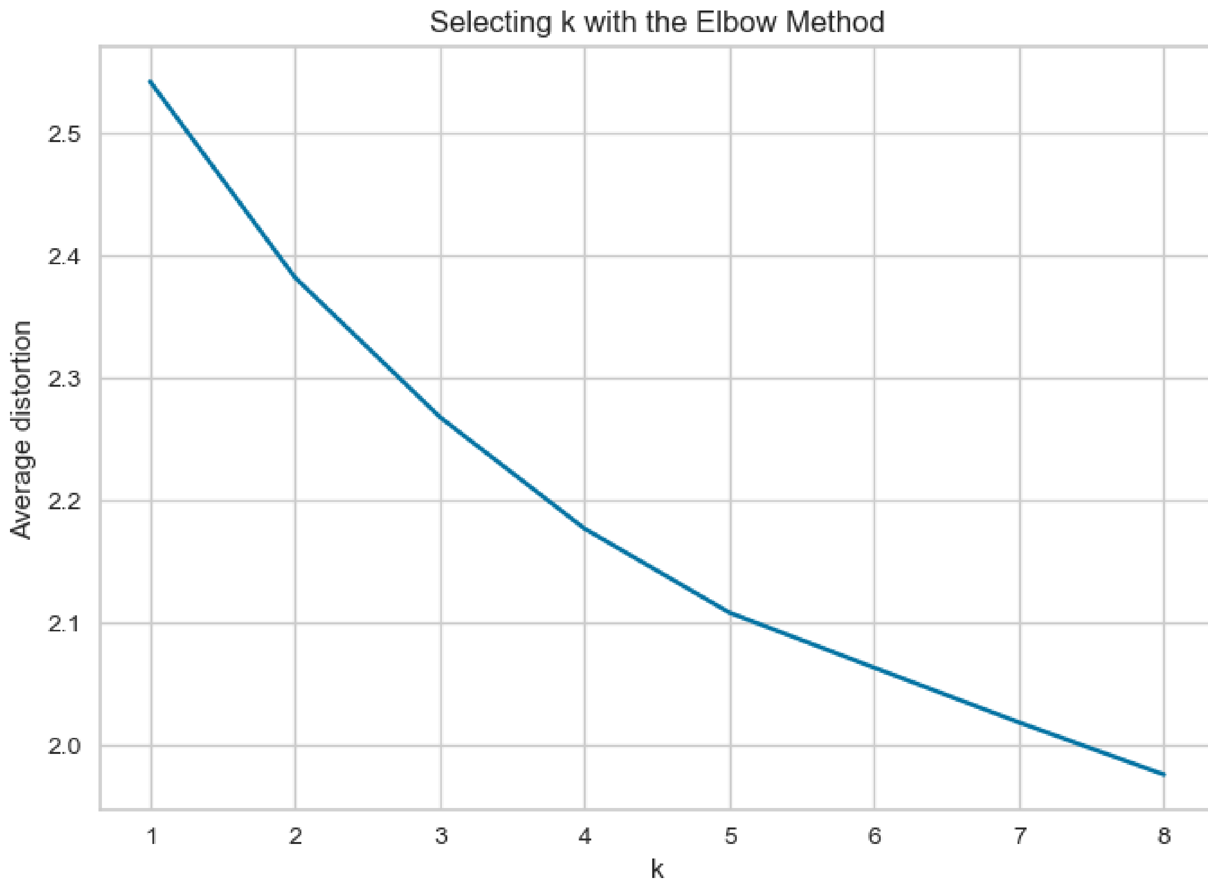
Out[21]:
```
['Current Price',
 'Price Change',
 'Volatility',
 'ROE',
 'Cash Ratio',
 'Net Cash Flow',
 'Net Income',
 'Earnings Per Share',
 'Estimated Shares Outstanding',
 'P/E Ratio',
 'P/B Ratio']
```

In [22]:
```
# scaling the dataset before clustering
scaler = StandardScaler()
subset = df[num_col].copy()
subset_scaled = scaler.fit_transform(subset)
```

In [23]:
```
# creating a dataframe of the scaled columns
subset_scaled_df = pd.DataFrame(subset_scaled, columns=subset.columns)
```

In [24]:
```
clusters = range(1, 9)
meanDistortions = []

for k in clusters:
    model = KMeans(n_clusters=k)
    model.fit(subset_scaled_df)
    prediction = model.predict(subset_scaled_df)
    distortion = (
        sum(
            np.min(cdist(subset_scaled_df, model.cluster_centers_, "euclidean"), axis=
        )
        / subset_scaled_df.shape[0]
    )

    meanDistortions.append(distortion)

    print("Number of Clusters:", k, "\tAverage Distortion:", distortion)

plt.plot(clusters, meanDistortions, "bx-")
plt.xlabel("k")
plt.ylabel("Average distortion")
plt.title("Selecting k with the Elbow Method")
plt.show()
```

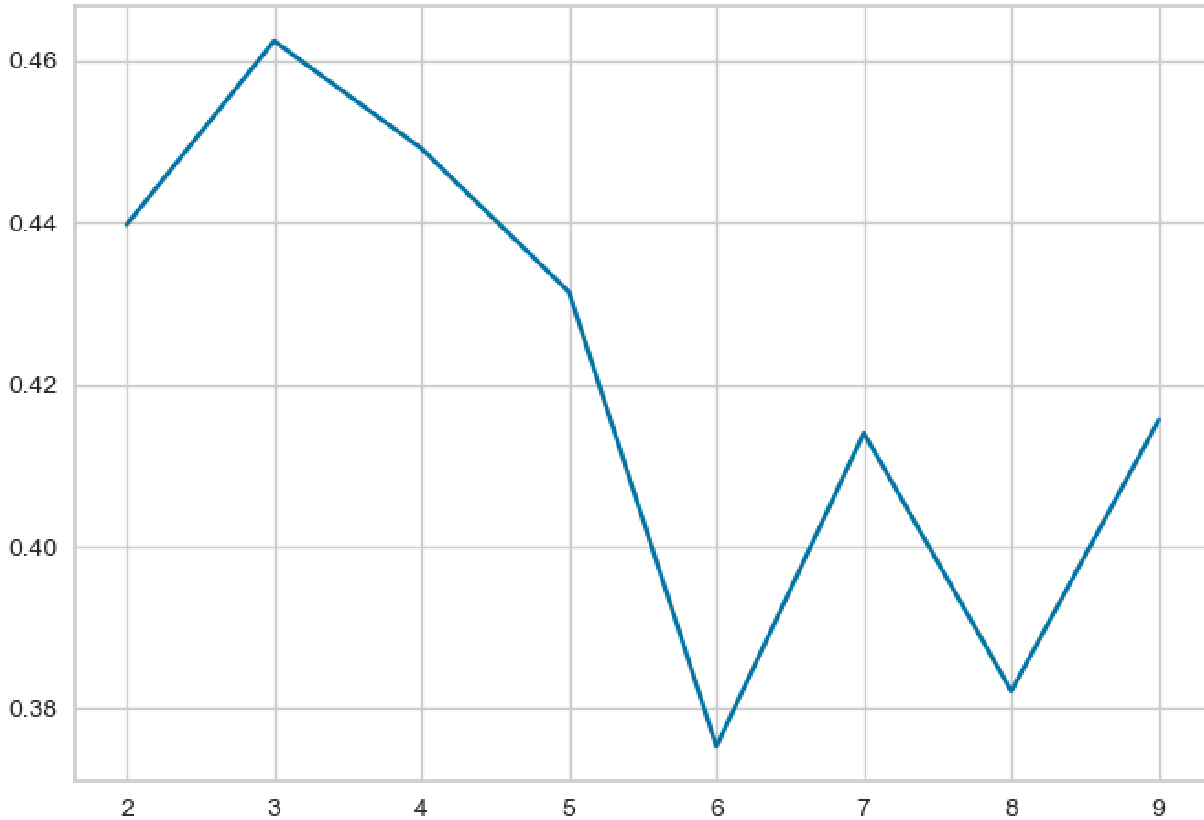
```
Number of Clusters: 1   Average Distortion: 2.5425069919221697
Number of Clusters: 2   Average Distortion: 2.382318498894466
Number of Clusters: 3   Average Distortion: 2.2683105560042285
Number of Clusters: 4   Average Distortion: 2.177016653596875
Number of Clusters: 5   Average Distortion: 2.108395860807457
Number of Clusters: 6   Average Distortion: 2.0633627257816647
Number of Clusters: 7   Average Distortion: 2.0186475535112742
Number of Clusters: 8   Average Distortion: 1.9760595422320009
```



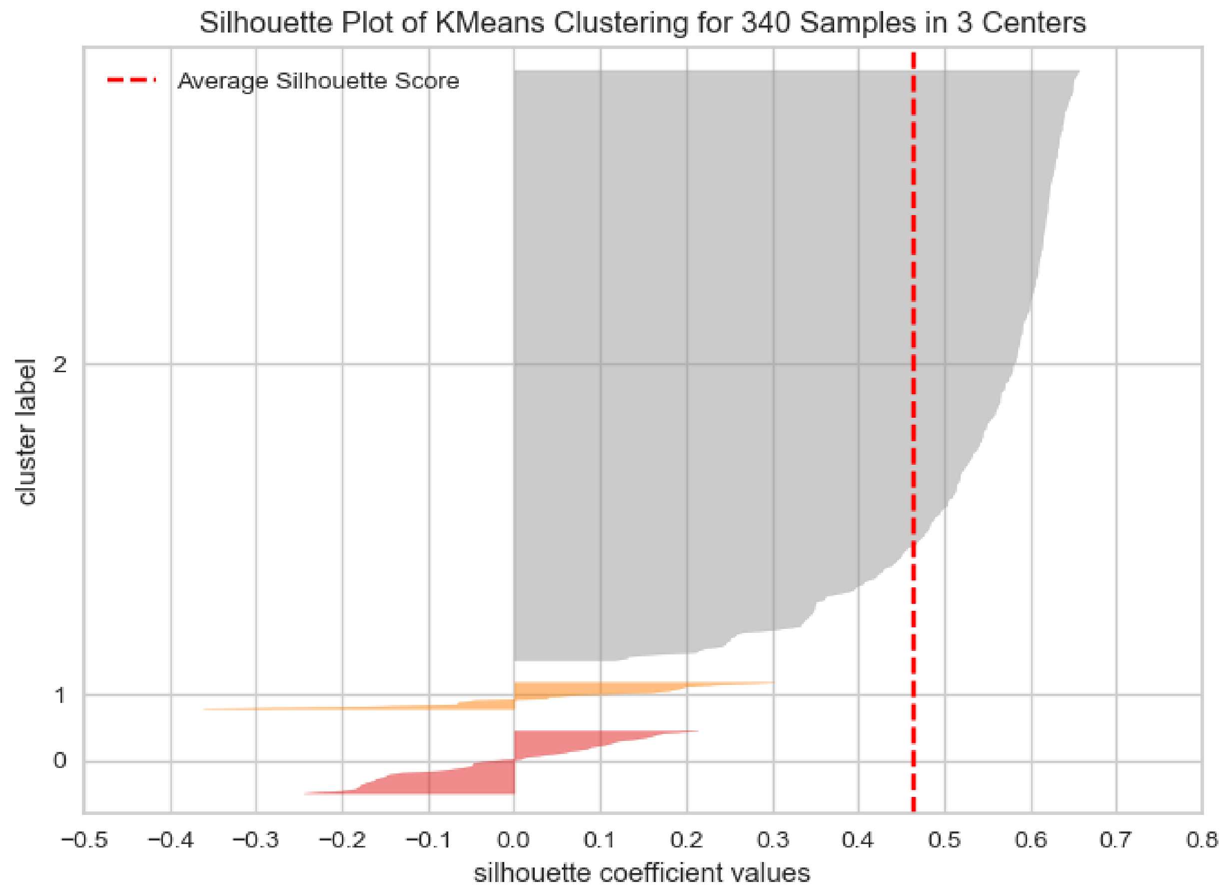
use cluster 8 because it has the lowest Average Distortion: 1.9760595422320009

In [25]:
```
sil_score = []
cluster_list = list(range(2, 10))
for n_clusters in cluster_list:
    clusterer = KMeans(n_clusters=n_clusters)
    preds = clusterer.fit_predict((subset_scaled_df))
    # centers = clusterer.cluster_centers_
    score = silhouette_score(subset_scaled_df, preds)
    sil_score.append(score)
    print("For n_clusters = {}, the silhouette score is {})".format(n_clusters, score)

plt.plot(cluster_list, sil_score)
plt.show()
```

```
For n_clusters = 2, the silhouette score is 0.43969639509980457)
For n_clusters = 3, the silhouette score is 0.4623841900167334)
For n_clusters = 4, the silhouette score is 0.4490996460354298)
For n_clusters = 5, the silhouette score is 0.4314106887964818)
For n_clusters = 6, the silhouette score is 0.3753563786475513)
For n_clusters = 7, the silhouette score is 0.4140059404422559)
For n_clusters = 8, the silhouette score is 0.3821962375959941)
For n_clusters = 9, the silhouette score is 0.41563727678873896)
```

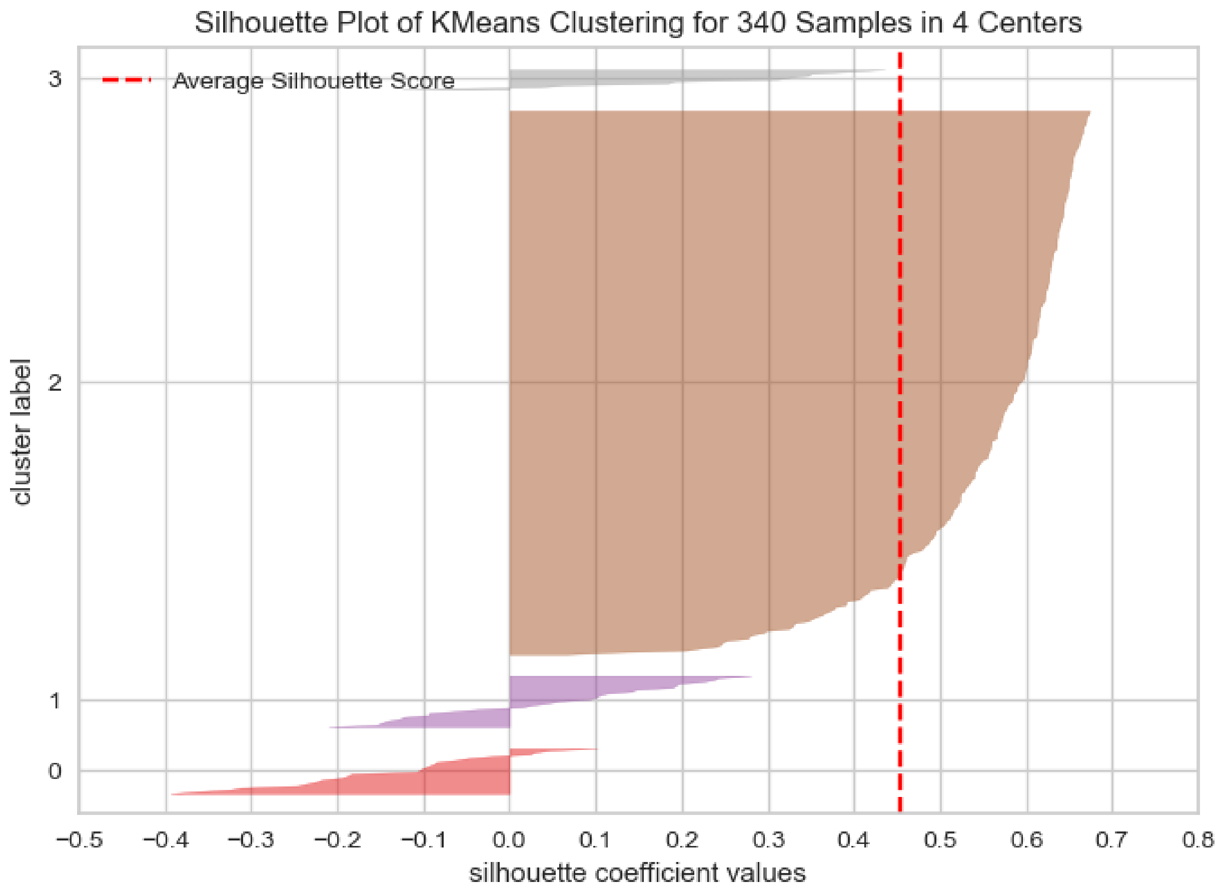


In [26]:
```
# finding optimal no. of clusters with silhouette coefficients
visualizer = SilhouetteVisualizer(KMeans(3, random_state=1))
visualizer.fit(subset_scaled_df)
visualizer.show()
```



Out[26]: <Axes: title={'center': 'Silhouette Plot of KMeans Clustering for 340 Samples in 3 Centers'}, xlabel='silhouette coefficient values', ylabel='cluster label'>

In [27]:
```
# finding optimal no. of clusters with silhouette coefficients
visualizer = SilhouetteVisualizer(KMeans(4, random_state=1))
visualizer.fit(subset_scaled_df)
visualizer.show()
```



Out[27]:
```
<Axes: title={'center': 'Silhouette Plot of KMeans Clustering for 340 Samples in 4 Ce
nters'}, xlabel='silhouette coefficient values', ylabel='cluster label'>
```

In [28]:
```python
# let's take 4 as number of clusters
kmeans = KMeans(n_clusters=4, random_state=0)
kmeans.fit(subset_scaled_df)
```

Out[28]:
```
▾ KMeans
KMeans(n_clusters=4, random_state=0)
```

In [29]:
```python
# adding kmeans cluster labels to the original and scaled dataframes

df["K_means_segments"] = kmeans.labels_
subset_scaled_df["K_means_segments"] = kmeans.labels_
```

In [30]:
```python
cluster_profile = df.groupby("K_means_segments").mean()
```

In [31]:
```python
cluster_profile["count_in_each_segments"] = (
    df.groupby("K_means_segments")["GICS_Sector"].count().values
)
```

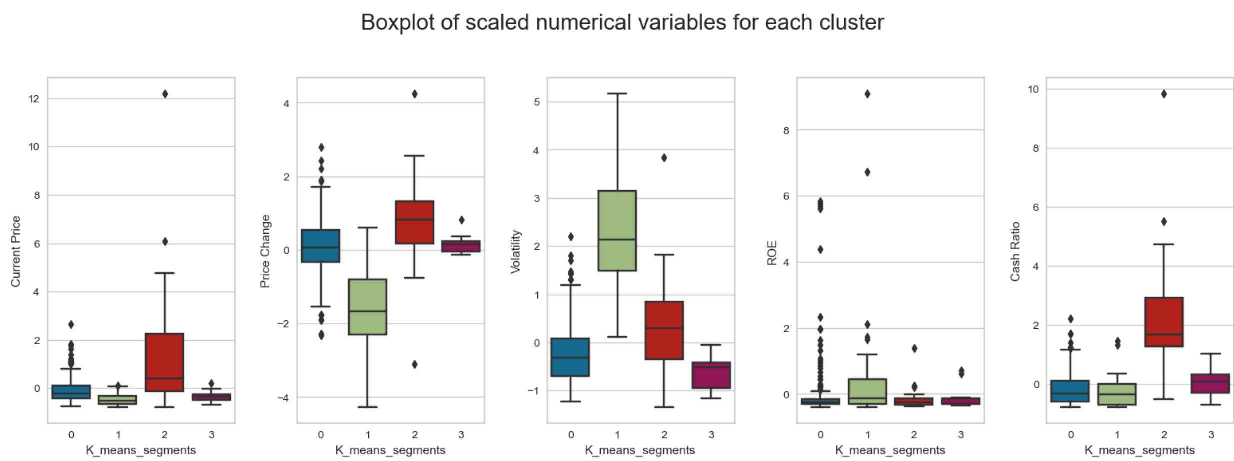
In [32]:
```python
# let's display cluster profiles
cluster_profile.style.highlight_max(color="lightgreen", axis=0)
```

Out[32]:

K_means_segments	Current Price	Price Change	Volatility	ROE	Cash Ratio	Net Cash Flow	
0	72.470050	5.059104	1.388717	34.710145	52.938406	-18021028.985507	147
1	35.165385	-16.390175	2.922214	110.961538	49.461538	-192318884.615385	-404
2	238.072932	13.508882	1.777479	25.600000	276.280000	752195440.000000	94
3	48.103077	6.053507	1.163964	27.538462	77.230769	773230769.230769	1411

In [33]:

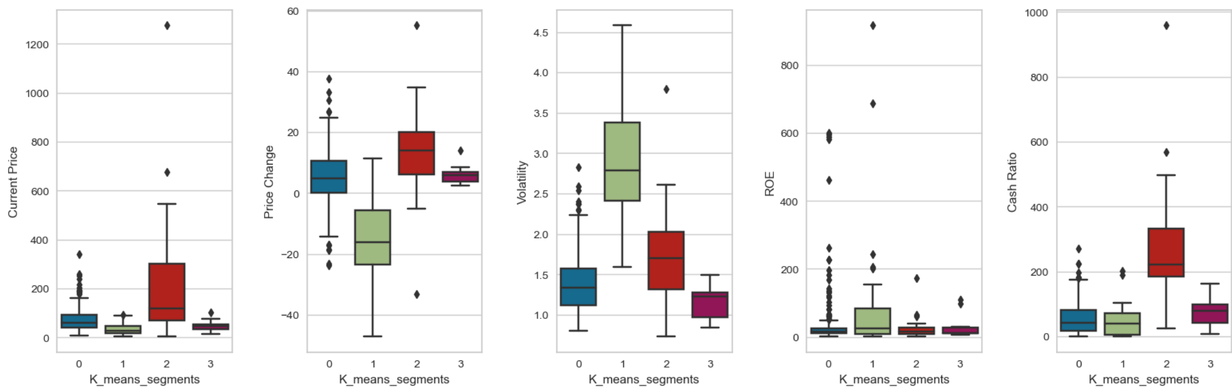
```
fig, axes = plt.subplots(1, 5, figsize=(16, 6))
fig.suptitle("Boxplot of scaled numerical variables for each cluster", fontsize=20)
counter = 0
for ii in range(5):
    sns.boxplot(
        ax=axes[ii],
        y=subset_scaled_df[num_col[counter]],
        x=subset_scaled_df["K_means_segments"],
    )
    counter = counter + 1

fig.tight_layout(pad=2.0)
```



In [34]:

```
fig, axes = plt.subplots(1, 5, figsize=(16, 6))
fig.suptitle("Boxplot of original numerical variables for each cluster", fontsize=20)
counter = 0
for ii in range(5):
    sns.boxplot(ax=axes[ii], y=df[num_col[counter]], x=df["K_means_segments"])
    counter = counter + 1

fig.tight_layout(pad=2.0)
```

Boxplot of original numerical variables for each cluster



In [35]:
```
pd.crosstab(df.K_means_segments, data.GICS_Sector).style.highlight_max(
    color="lightgreen", axis=0
)
```

Out[35]:

GICS_Sector / K_means_segments	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Ma
0	33	17	6	45	28	52	24	
1	0	0	22	0	0	1	2	
2	6	1	1	0	9	0	6	
3	1	1	1	4	3	0	1	

In [36]:
```
# list of distance metrics
distance_metrics = ["euclidean", "chebyshev", "mahalanobis", "cityblock"]

# list of linkage methods
linkage_methods = ["single", "complete", "average", "weighted"]

high_cophenet_corr = 0
high_dm_lm = [0, 0]

for dm in distance_metrics:
    for lm in linkage_methods:
        Z = linkage(subset_scaled_df, metric=dm, method=lm)
        c, coph_dists = cophenet(Z, pdist(subset_scaled_df))
        print(
            "Cophenetic correlation for {} distance and {} linkage is {}.".format(
                dm.capitalize(), lm, c
            )
        )
        if high_cophenet_corr < c:
            high_cophenet_corr = c
            high_dm_lm[0] = dm
            high_dm_lm[1] = lm
```

```
Cophenetic correlation for Euclidean distance and single linkage is 0.931569803255580
4.
Cophenetic correlation for Euclidean distance and complete linkage is 0.8317589892879
516.
Cophenetic correlation for Euclidean distance and average linkage is 0.94115048450057
5.
Cophenetic correlation for Euclidean distance and weighted linkage is 0.9183038140391
157.
Cophenetic correlation for Chebyshev distance and single linkage is 0.917891236702472
6.
Cophenetic correlation for Chebyshev distance and complete linkage is 0.8027612142835
183.
Cophenetic correlation for Chebyshev distance and average linkage is 0.93304522241139
8.
Cophenetic correlation for Chebyshev distance and weighted linkage is 0.9122203090096
584.
Cophenetic correlation for Mahalanobis distance and single linkage is 0.9290783147335
682.
Cophenetic correlation for Mahalanobis distance and complete linkage is 0.81514356690
20113.
Cophenetic correlation for Mahalanobis distance and average linkage is 0.935497512052
5167.
Cophenetic correlation for Mahalanobis distance and weighted linkage is 0.89613072337
29855.
Cophenetic correlation for Cityblock distance and single linkage is 0.924549434179978
4.
Cophenetic correlation for Cityblock distance and complete linkage is 0.6450900595810
168.
Cophenetic correlation for Cityblock distance and average linkage is 0.90804950415938
57.
Cophenetic correlation for Cityblock distance and weighted linkage is 0.6456689300165
109.
```

In [37]:

```python
# printing the combination of distance metric and linkage method with the highest coph
print(
    "Highest cophenetic correlation is {}, which is obtained with {} distance and {} l
        high_cophenet_corr, high_dm_lm[0].capitalize(), high_dm_lm[1]
    )
)
```

```
Highest cophenetic correlation is 0.941150484500575, which is obtained with Euclidean
distance and average linkage.
```

The cophenetic correlation is highest for average and centroid linkage methods. We will move ahead with average linkage.

In [38]:

```python
# list of linkage methods
linkage_methods = ["single", "complete", "average", "centroid", "ward", "weighted"]

high_cophenet_corr = 0
high_dm_lm = [0, 0]

for lm in linkage_methods:
    Z = linkage(subset_scaled_df, metric="euclidean", method=lm)
    c, coph_dists = cophenet(Z, pdist(subset_scaled_df))
    print("Cophenetic correlation for {} linkage is {}.".format(lm, c))
    if high_cophenet_corr < c:
        high_cophenet_corr = c
```

```
        high_dm_lm[0] = "euclidean"
        high_dm_lm[1] = lm
```

```
Cophenetic correlation for single linkage is 0.9315698032555804.
Cophenetic correlation for complete linkage is 0.8317589892879516.
Cophenetic correlation for average linkage is 0.941150484500575.
Cophenetic correlation for centroid linkage is 0.9396689710822762.
Cophenetic correlation for ward linkage is 0.7524063147770085.
Cophenetic correlation for weighted linkage is 0.9183038140391157.
```

In [39]:

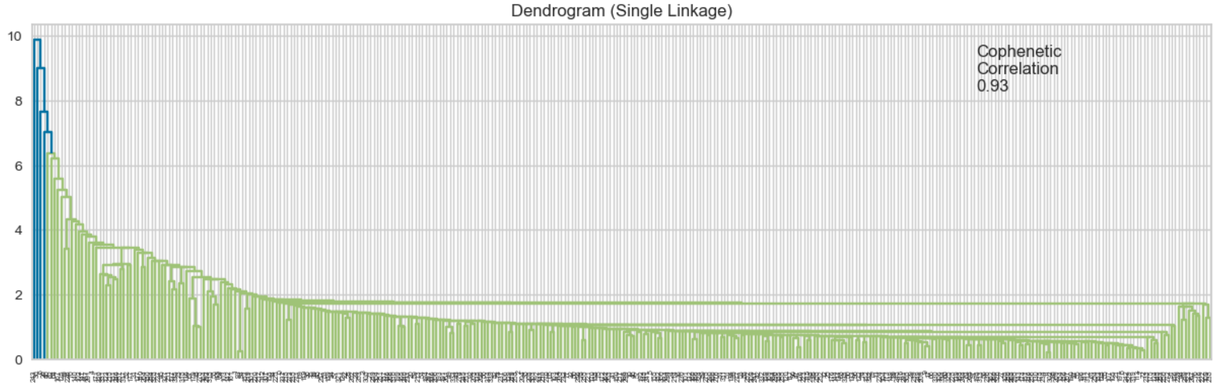
```
# printing the combination of distance metric and linkage method with the highest coph
print(
    "Highest cophenetic correlation is {}, which is obtained with {} linkage.".format(
        high_cophenet_corr, high_dm_lm[1]
    )
)
```

```
Highest cophenetic correlation is 0.941150484500575, which is obtained with average l
inkage.
```

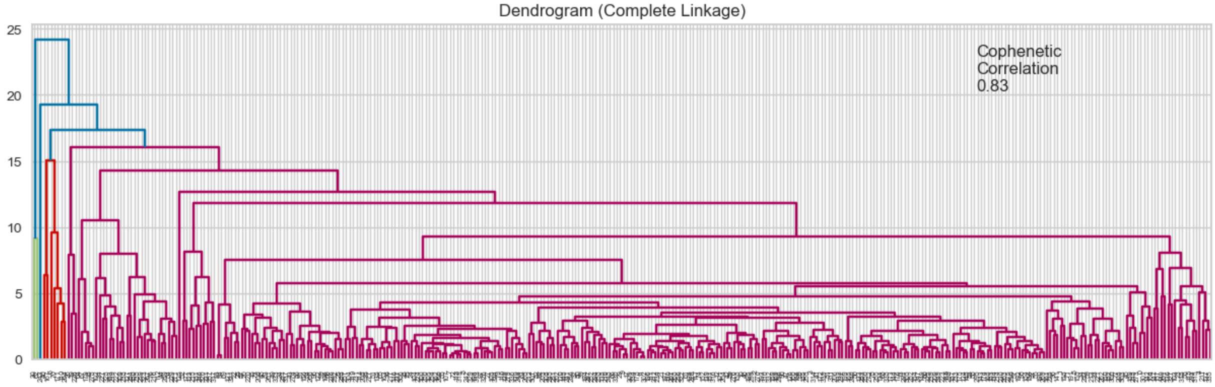
In [40]:

```
# list of linkage methods
linkage_methods = ["single", "complete", "average", "centroid", "ward", "weighted"]
# lists to save results of cophenetic correlation calculation
compare_cols = ["Linkage", "Cophenetic Coefficient"]
compare = []

# to create a subplot image
fig, axs = plt.subplots(len(linkage_methods), 1, figsize=(15, 30))

# We will enumerate through the list of linkage methods above
# For each linkage method, we will plot the dendrogram and calculate the cophenetic cc
for i, method in enumerate(linkage_methods):
    Z = linkage(subset_scaled_df, metric="euclidean", method=method)

    dendrogram(Z, ax=axs[i])
    axs[i].set_title(f"Dendrogram ({method.capitalize()} Linkage)")

    coph_corr, coph_dist = cophenet(Z, pdist(subset_scaled_df))
    axs[i].annotate(
        f"Cophenetic\nCorrelation\n{coph_corr:0.2f}",
        (0.80, 0.80),
        xycoords="axes fraction",
    )

    compare.append([method, coph_corr])
```

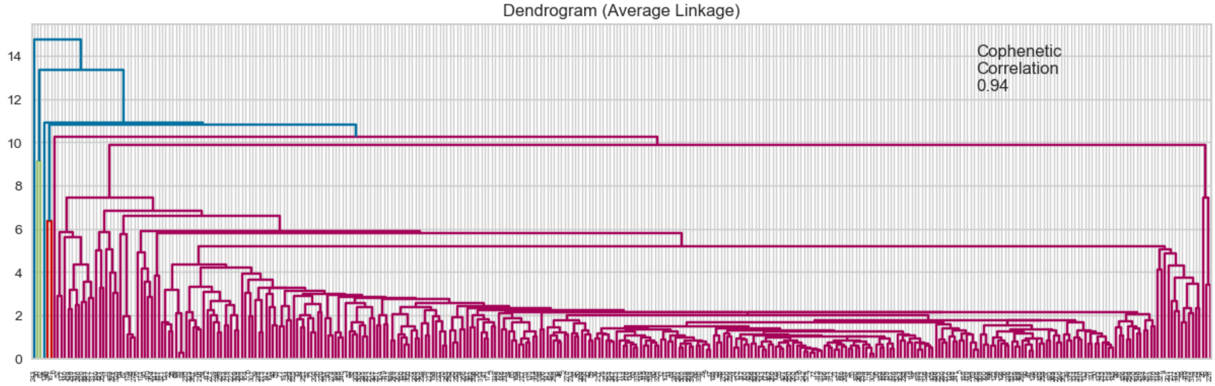
Dendrogram (Single Linkage)



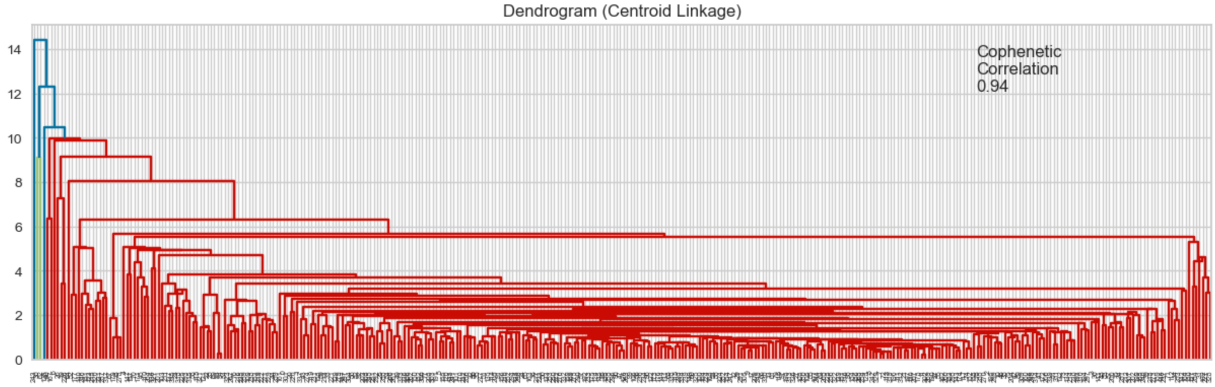
Dendrogram (Complete Linkage)



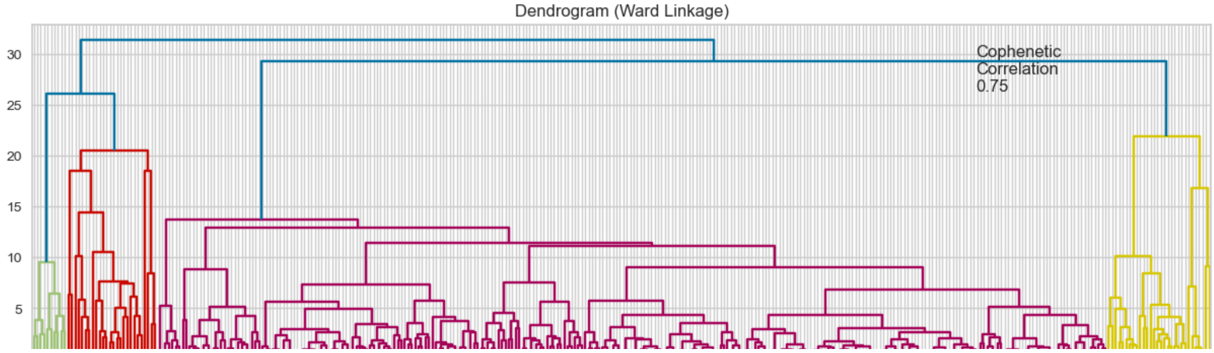
Dendrogram (Average Linkage)

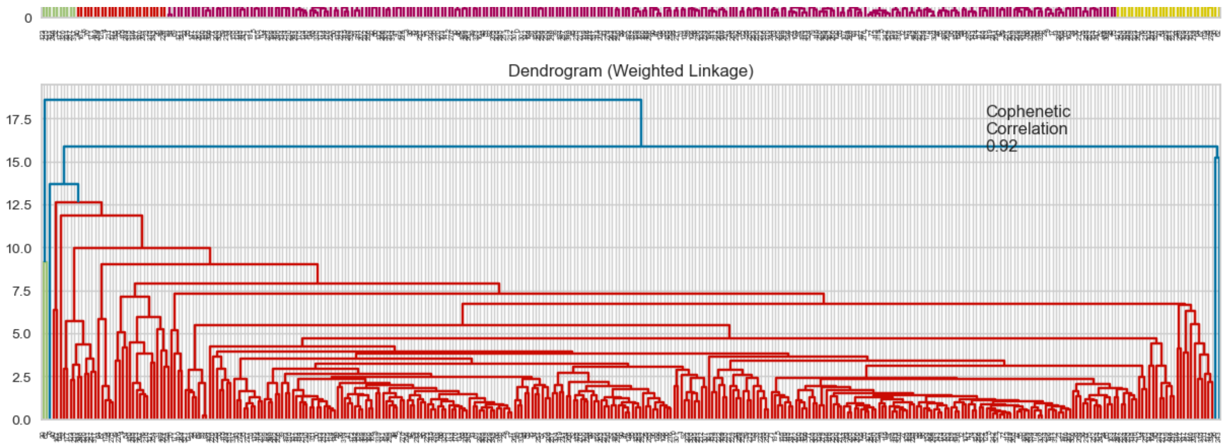


Dendrogram (Centroid Linkage)



Dendrogram (Ward Linkage)





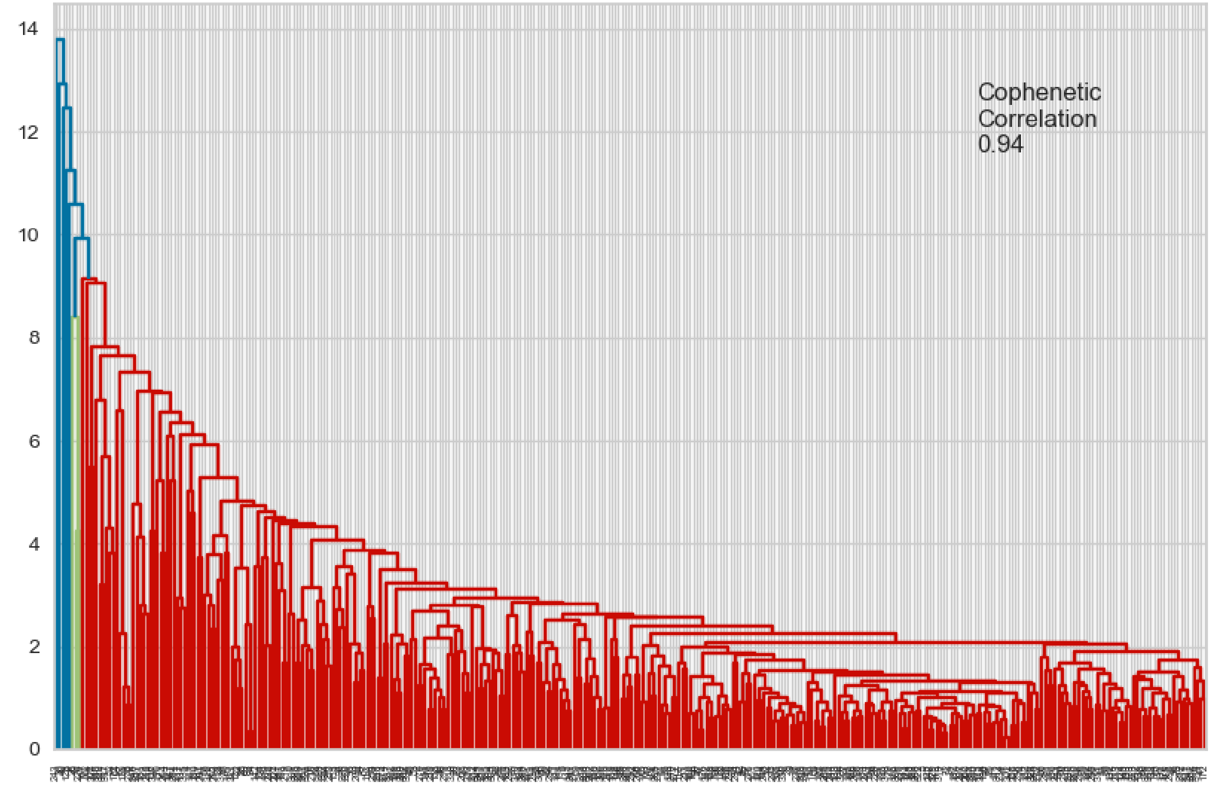
In [41]:
```python
# let's create a dataframe to compare cophenetic correlations for each linkage method
df_cc = pd.DataFrame(compare, columns=compare_cols)
df_cc
```

Out[41]:

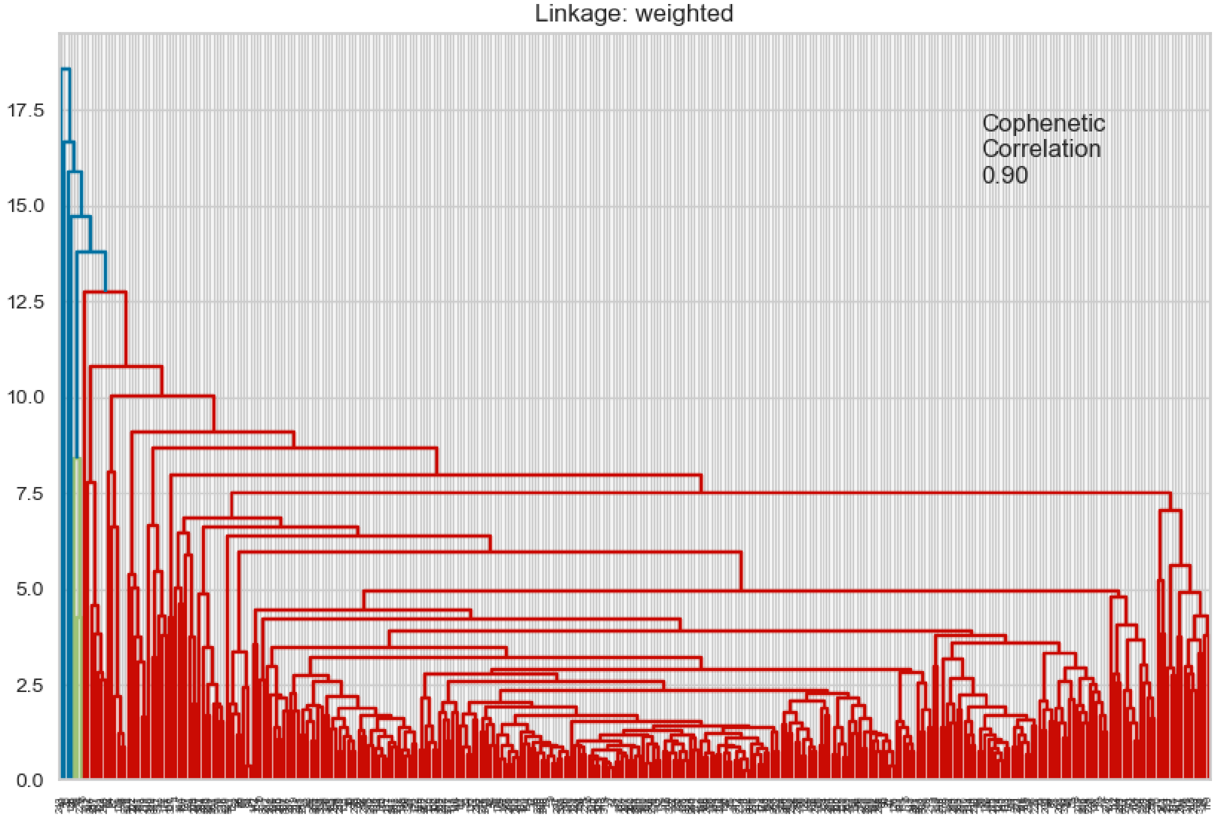
	Linkage	Cophenetic Coefficient
0	single	0.931570
1	complete	0.831759
2	average	0.941150
3	centroid	0.939669
4	ward	0.752406
5	weighted	0.918304

In [42]:
```python
# list of distance metrics
distance_metrics = ["mahalanobis", "cityblock"]

# list of linkage methods
linkage_methods = ["average", "weighted"]

# to create a subplot image
fig, axs = plt.subplots(
    len(distance_metrics) + len(distance_metrics), 1, figsize=(10, 30)
)

i = 0
for dm in distance_metrics:
    for lm in linkage_methods:
        Z = linkage(subset_scaled_df, metric=dm, method=lm)

        dendrogram(Z, ax=axs[i])
        axs[i].set_title("Distance metric: {}\nLinkage: {}".format(dm.capitalize(), lm

        coph_corr, coph_dist = cophenet(Z, pdist(subset_scaled_df))
        axs[i].annotate(
            f"Cophenetic\nCorrelation\n{coph_corr:0.2f}",
            (0.80, 0.80),
            xycoords="axes fraction",
        )
        i += 1
```

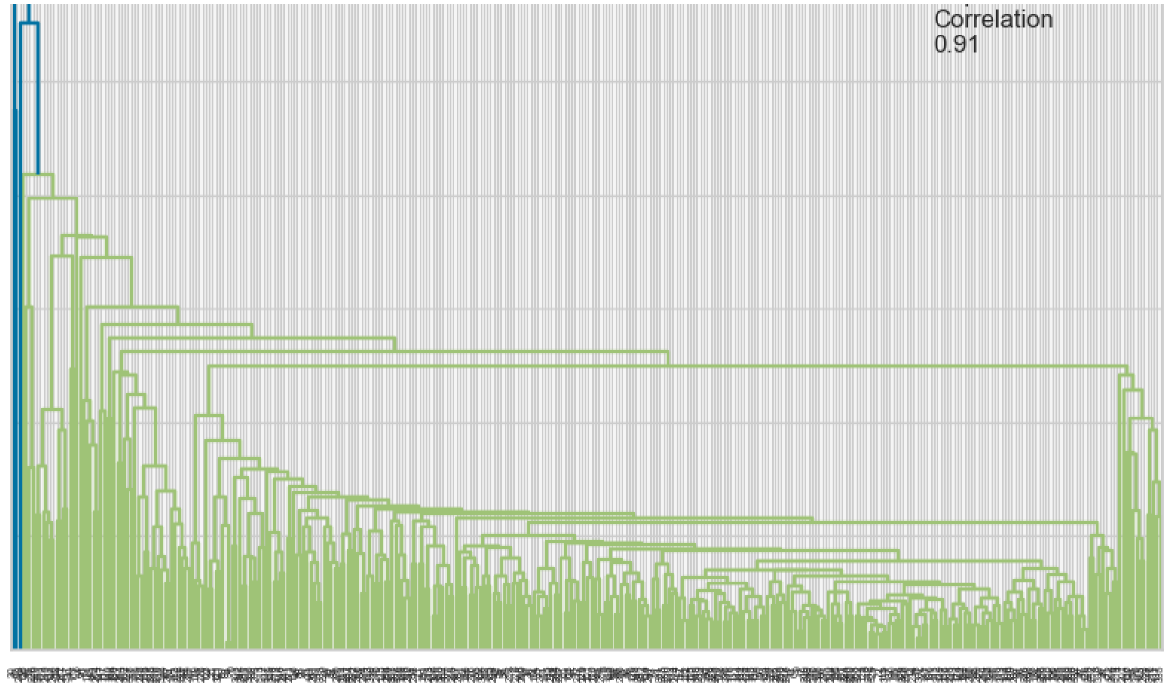
Distance metric: Mahalanobis
Linkage: average

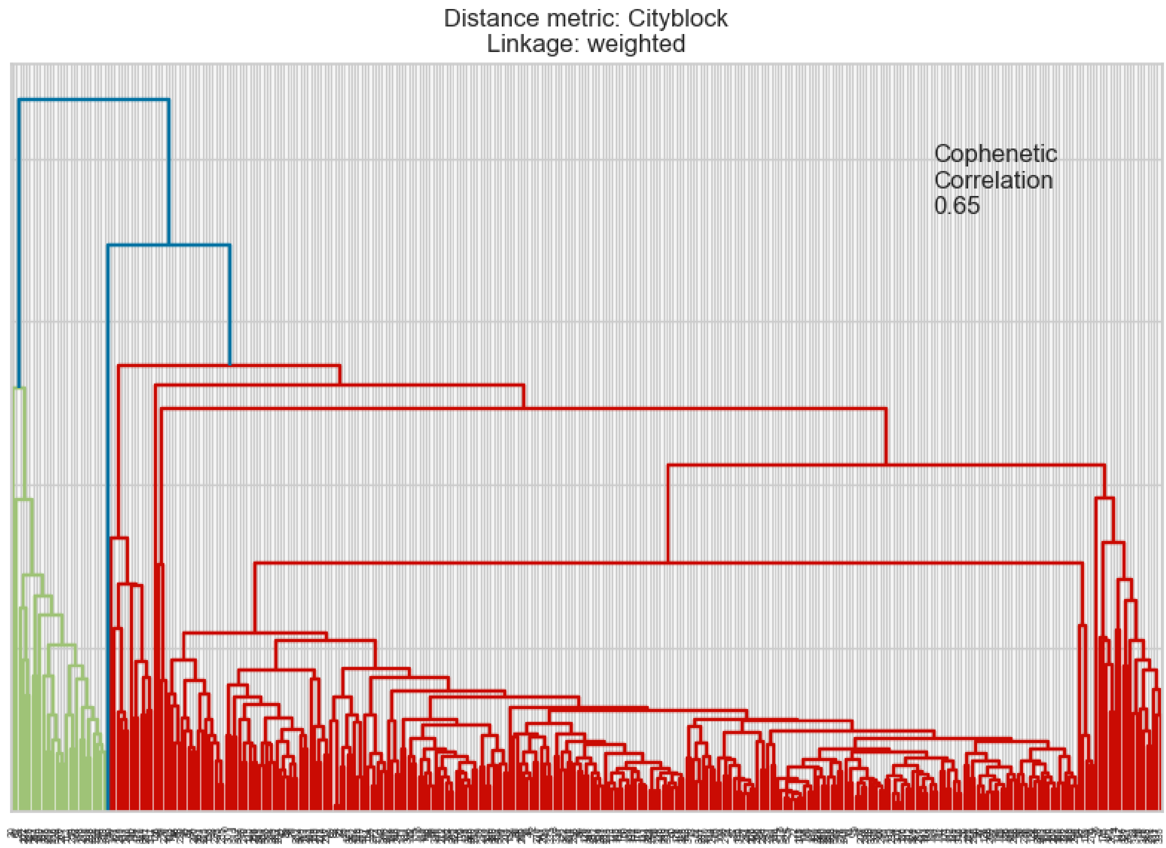


Distance metric: Mahalanobis
Linkage: weighted



Distance metric: Cityblock
Linkage: average





In [43]:

```
HCmodel = AgglomerativeClustering(n_clusters=3, affinity="euclidean", linkage="ward")
HCmodel.fit(subset_scaled_df)
```

Out[43]:

```
AgglomerativeClustering
AgglomerativeClustering(affinity='euclidean', n_clusters=3)
```

In [44]:
```
# adding hierarchical cluster labels to the original and scaled dataframes

subset_scaled_df["HC_Clusters"] = HCmodel.labels_
df["HC_Clusters"] = HCmodel.labels_
```

In [45]:
```
cluster_profile = df.groupby("HC_Clusters").mean()
```

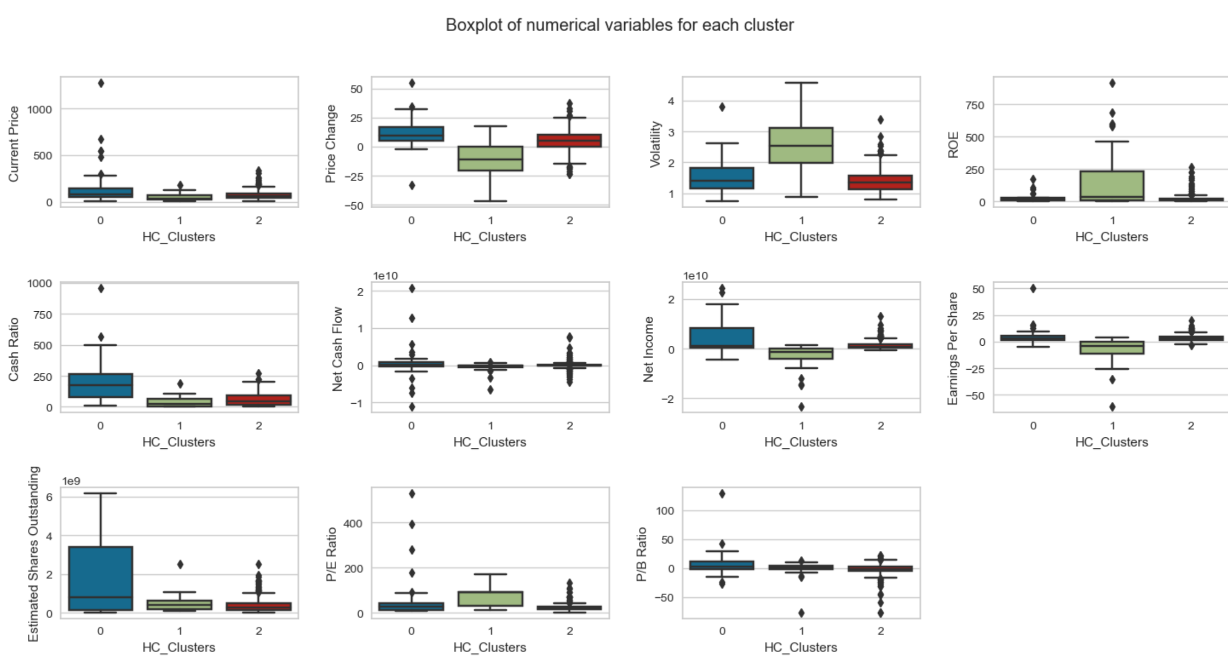
In [46]:
```
cluster_profile["count_in_each_segments"] = (
    df.groupby("HC_Clusters")["GICS_Sector"].count().values
)
```

In [47]:
```
# let's display cluster profiles
cluster_profile.style.highlight_max(color="lightgreen", axis=0)
```

Out[47]:

HC_Clusters	Current Price	Price Change	Volatility	ROE	Cash Ratio	Net Cash Flow	Net
0	173.243702	11.572262	1.549346	26.555556	210.805556	581166277.777778	5671331472
1	47.081001	-11.442082	2.602381	190.333333	39.300000	-481429800.000000	-346660903
2	72.423335	4.792872	1.405051	24.806569	54.890511	45268974.452555	148876314

In [48]:
```
plt.figure(figsize=(15, 10))
plt.suptitle("Boxplot of numerical variables for each cluster")

for i, variable in enumerate(num_col):
    plt.subplot(4, 4, i + 1)
    sns.boxplot(data=df, x="HC_Clusters", y=variable)

plt.tight_layout(pad=2.0)
```



Business recommendations for hierarchical clustering use cluster 0 Cluster 0 stocks are good places to provide stock advice based on cluster profiling done above. for K-mean clustering use cluster 2 Cluster 2 stocks are good places to provide stock advice based on cluster profiling done above. It also has the best data in the reliveant columns.