final-after-run

December 5, 2023

[1]:
```
# import necessary libraries
import numpy   as np
import pandas  as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib as mlb

## filter warning to suppress warning message
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
## importing the dataset
stock_data = pd.read_csv("../input/stock-market-data/Stock_Market_Data.csv")
stock_data['Date'] = pd.to_datetime(stock_data['Date'],dayfirst=True)
stock_data.head()
```

[2]:

	Date	Name	Open	High	Low	Close	Volume
0	2022-01-02	01.Bank	22.83	23.20	22.59	22.93	1842350.41
1	2022-01-03	01.Bank	23.03	23.29	22.74	22.90	1664989.63
2	2022-01-04	01.Bank	22.85	23.13	22.64	22.84	1354510.97
3	2022-01-05	01.Bank	22.91	23.20	22.70	22.98	1564334.81
4	2022-01-06	01.Bank	23.12	23.65	23.00	23.37	2586344.19

1 Part 1: Data Cleaning and Exploration:

1.Calculate basic summary statistics for each column (mean, median, standard deviation, etc.).

[3]:
```
summ_stat = stock_data.describe()
summ_stat
```

[3]:

	Date	Open	High	\
count	49158	49158.000000	49158.000000	
mean	2022-03-31 12:56:37.436836608	157.869018	159.588214	
min	2022-01-02 00:00:00	3.900000	3.900000	
25%	2022-02-13 00:00:00	19.000000	19.300000	
50%	2022-03-30 00:00:00	40.300000	41.000000	

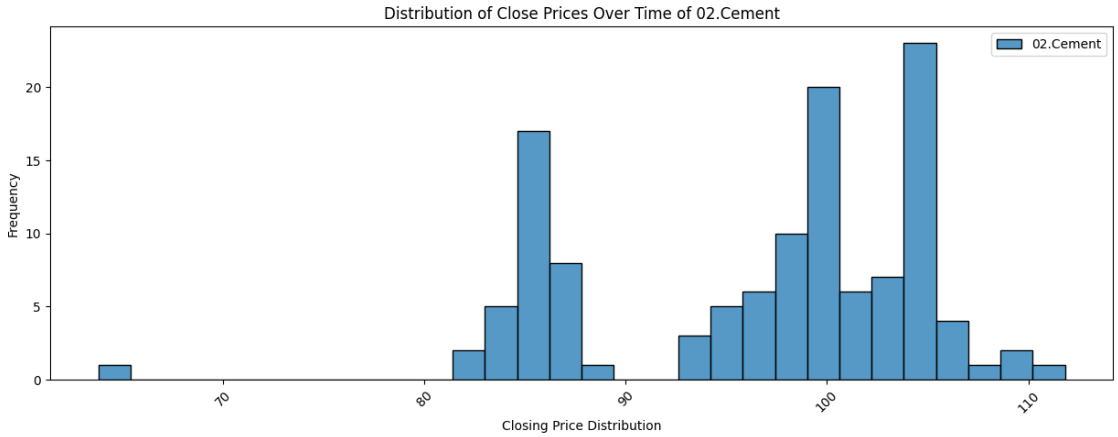
```
75%                  2022-05-19 00:00:00     89.400000     90.500000
max                  2022-06-30 00:00:00   6000.000000   6050.000000
std                                  NaN    520.191624    523.348078
```

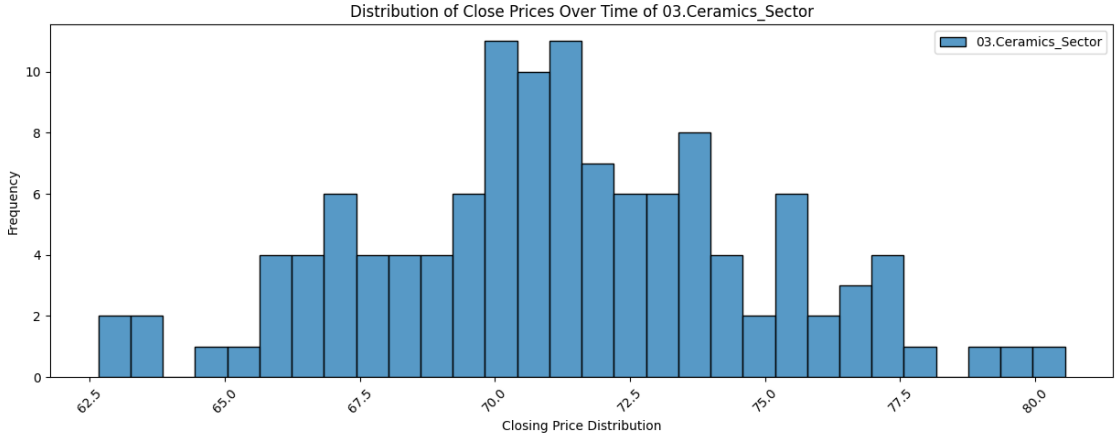
```
                Low         Close        Volume
count  49158.000000  49158.000000  4.915800e+04
mean     155.906364    157.351462  5.619999e+05
min        3.000000      3.800000  1.000000e+00
25%       18.700000     19.000000  5.109475e+04
50%       39.535000     40.100000  1.824160e+05
75%       87.700000     88.700000  5.401398e+05
max     5975.000000   6000.500000  6.593180e+07
std      517.136149    519.711667  1.276909e+06
```

2.Explore the distribution of the 'Close' prices over time.

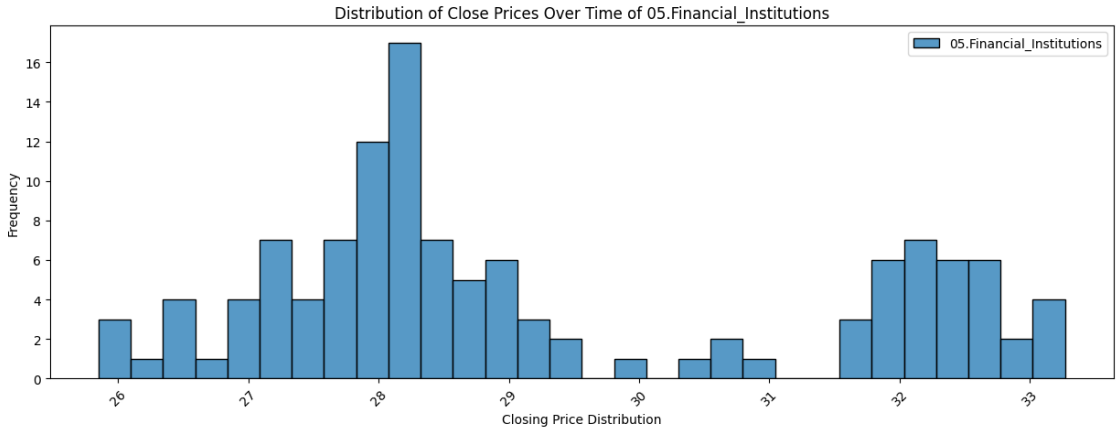
[4]:
```
## randomly select 5 company
unique_names = ['01.Bank', '02.Cement', '03.Ceramics_Sector', '04.Engineering',
       '05.Financial_Institutions']
```

[5]:
```
for name in unique_names:
    company_data = stock_data[stock_data['Name'] == name]
    plt.figure(figsize=(15,5))
    sns.histplot(data=company_data ,x="Close",bins=30,label=name)
    plt.xlabel("Closing Price Distribution")
    plt.ylabel("Frequency")
    plt.title("Distribution of Close Prices Over Time of {}".format(name))
    plt.legend()
    plt.xticks(rotation=45)
    plt.show()
```


Distribution of Close Prices Over Time of 02.Cement
02.Cement
Frequency
Closing Price Distribution

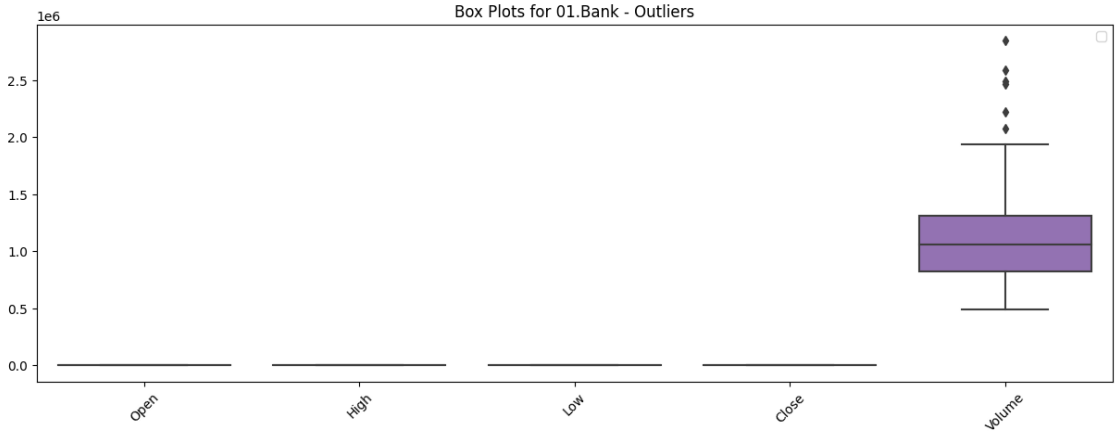

Distribution of Close Prices Over Time of 03.Ceramics_Sector
03.Ceramics_Sector
Frequency
Closing Price Distribution

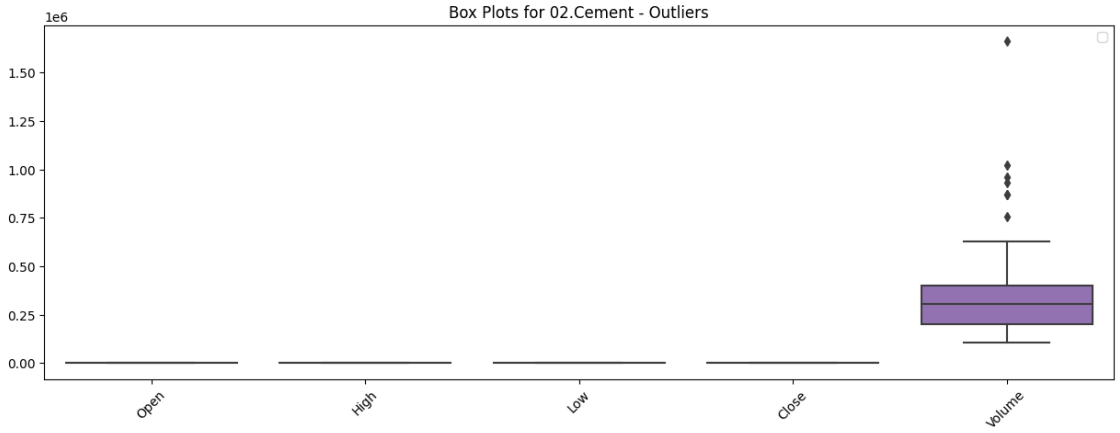

Distribution of Close Prices Over Time of 04.Engineering
04.Engineering
Frequency
Closing Price Distribution

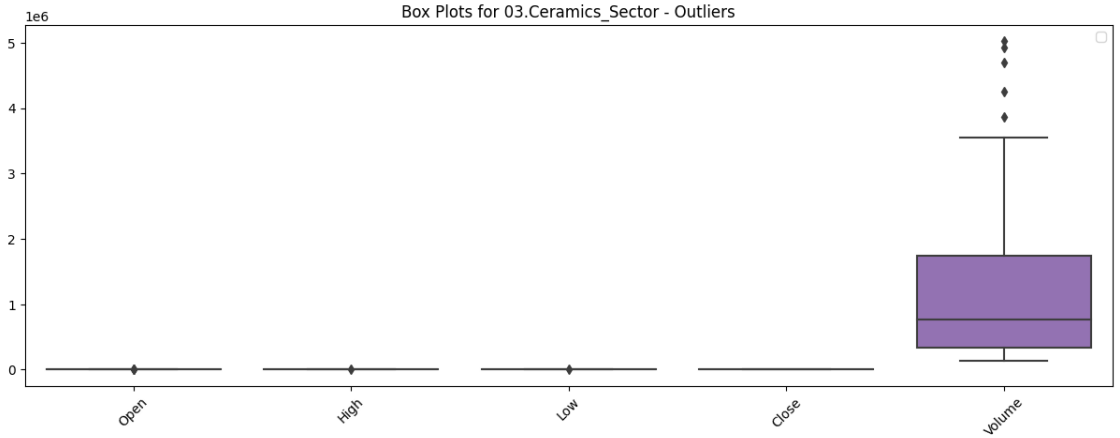


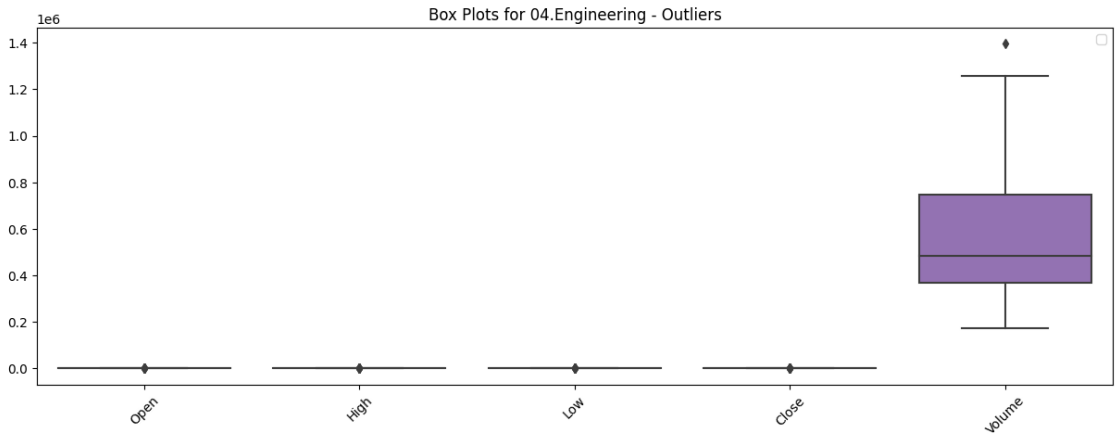
3.Identify and analyze any outliers (if any) in the dataset.

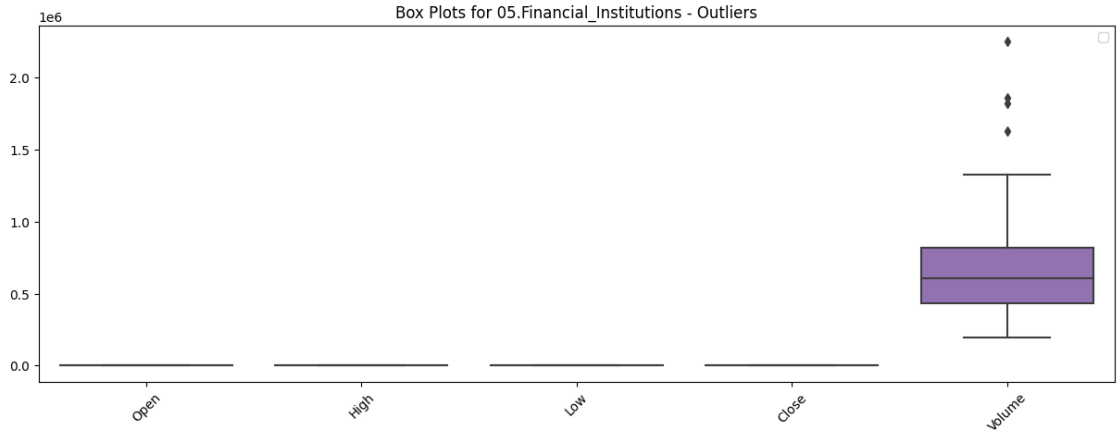
[6]:
```
for name in unique_names:
    company_data = stock_data[stock_data['Name']==name]
    plt.figure(figsize=(15,5))
    sns.boxplot(data=company_data.select_dtypes(include=np.number))
    plt.title(f'Box Plots for {name} - Outliers')
    plt.legend()
    plt.xticks(rotation=45)
    plt.show()
```




Box Plots for 02.Cement - Outliers
1e6
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Open
High
Low
Close
Volume


Box Plots for 03.Ceramics_Sector - Outliers
1e6
5
4
3
2
1
0
Open
High
Low
Close
Volume

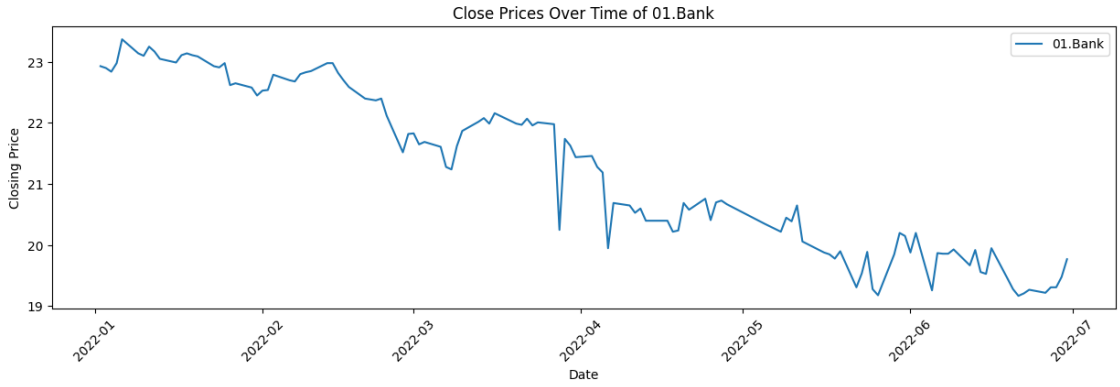

Box Plots for 04.Engineering - Outliers
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Open
High
Low
Close
Volume

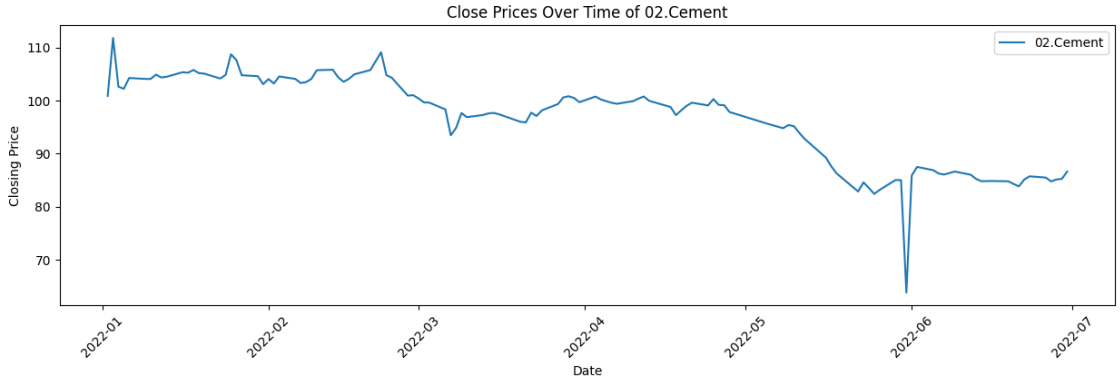


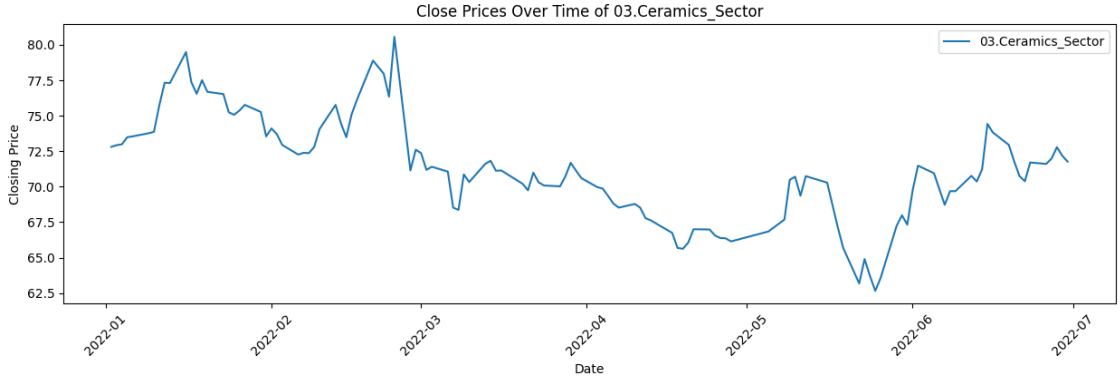
2 Part 2: Time Series Analysis / Rolling Window / Moving Averages :

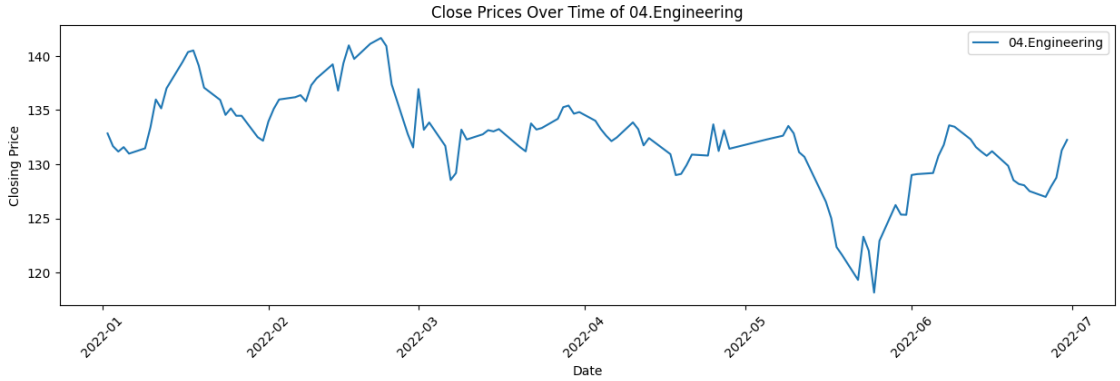
1.Create a line chart to visualize the 'Close' prices over time.

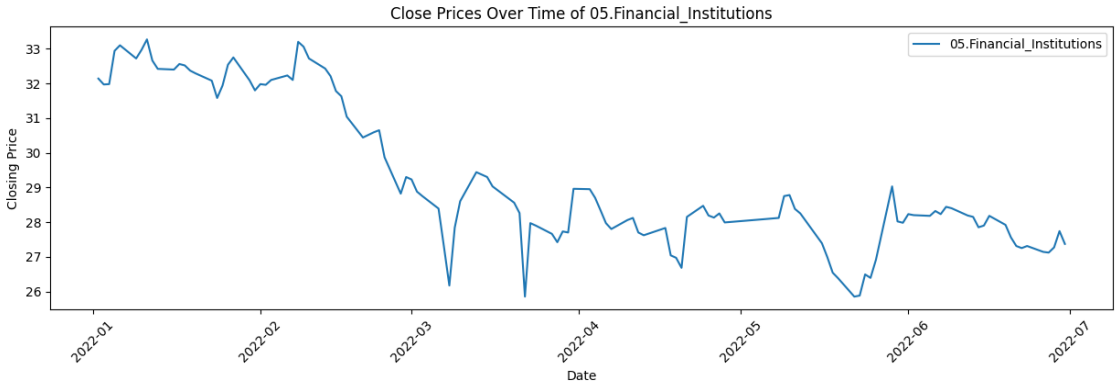
[7]:
```
for name in unique_names:
    company_data = stock_data[stock_data['Name'] == name]
    plt.figure(figsize=(15, 4))
    plt.plot(company_data['Date'],company_data['Close'],label ="{}".
 ↪format(name))
    plt.xlabel('Date')
    plt.ylabel('Closing Price')
    plt.title('Close Prices Over Time of {}'.format(name))
    plt.legend()
    plt.xticks(rotation=45)
    plt.show()
```




Close Prices Over Time of 02.Cement
02.Cement
Closing Price
110
100
90
80
70
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date

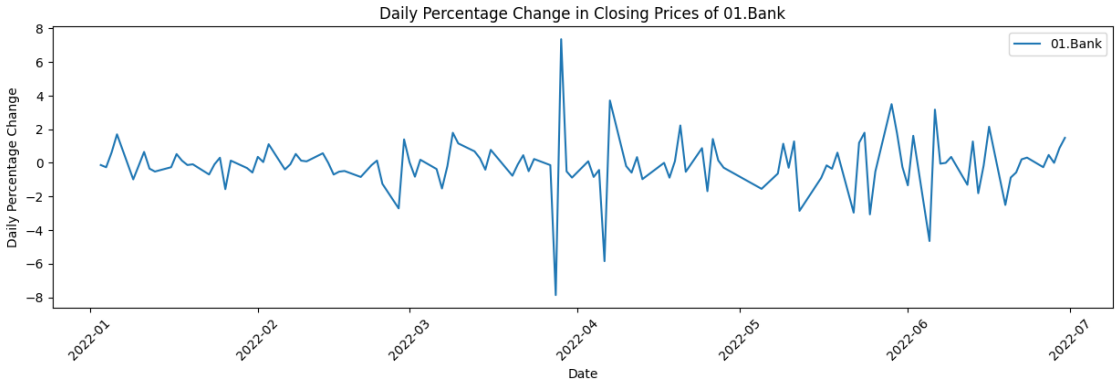

Close Prices Over Time of 03.Ceramics_Sector
03.Ceramics_Sector
Closing Price
80.0
77.5
75.0
72.5
70.0
67.5
65.0
62.5
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date

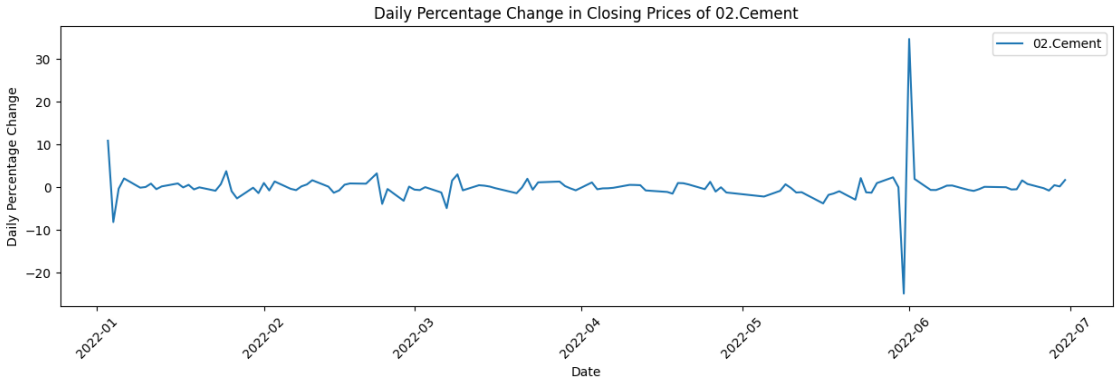

Close Prices Over Time of 04.Engineering
04.Engineering
Closing Price
140
135
130
125
120
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date

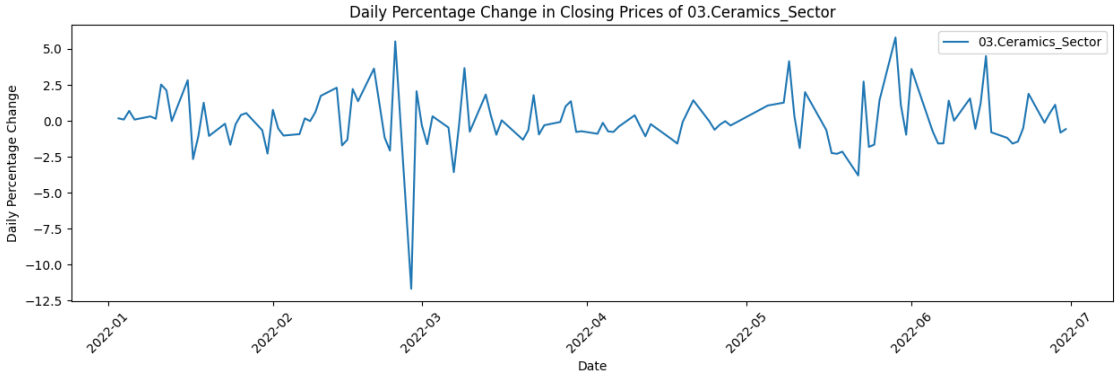


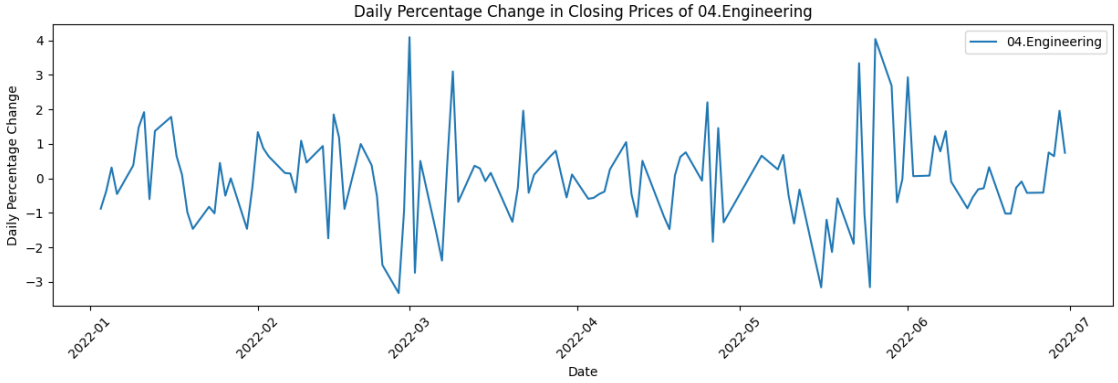
2. Calculate and plot the daily percentage change in closing prices.

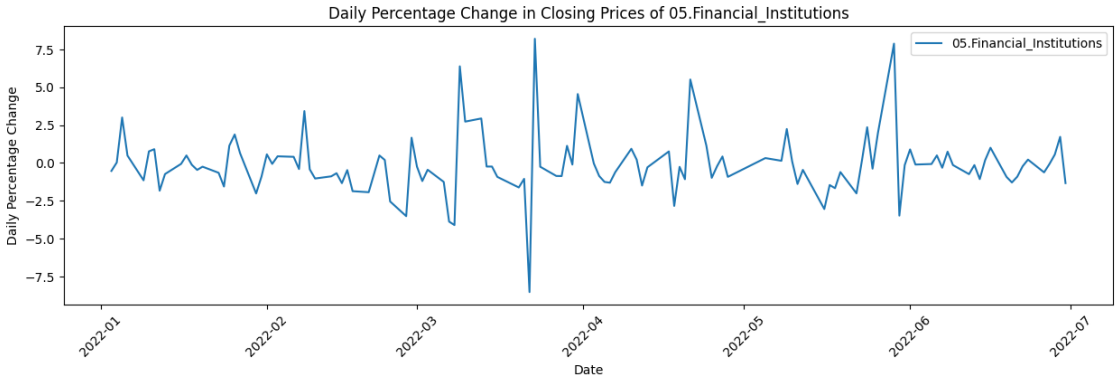
[8]:
```
for name in unique_names:
    plt.figure(figsize=(15, 4))
    company_data = stock_data[stock_data['Name'] == name]
    company_data['Daily_PCT_Change'] = company_data['Close'].pct_change() * 100
    plt.plot(company_data['Date'], company_data['Daily_PCT_Change'], label=name)
    plt.xlabel('Date')
    plt.ylabel('Daily Percentage Change')
    plt.title('Daily Percentage Change in Closing Prices of {}'.format(name))
    plt.legend()
    plt.xticks(rotation=45)
    plt.show()
```




Daily Percentage Change in Closing Prices of 02.Cement
02.Cement
Daily Percentage Change
30
20
10
0
−10
−20
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date

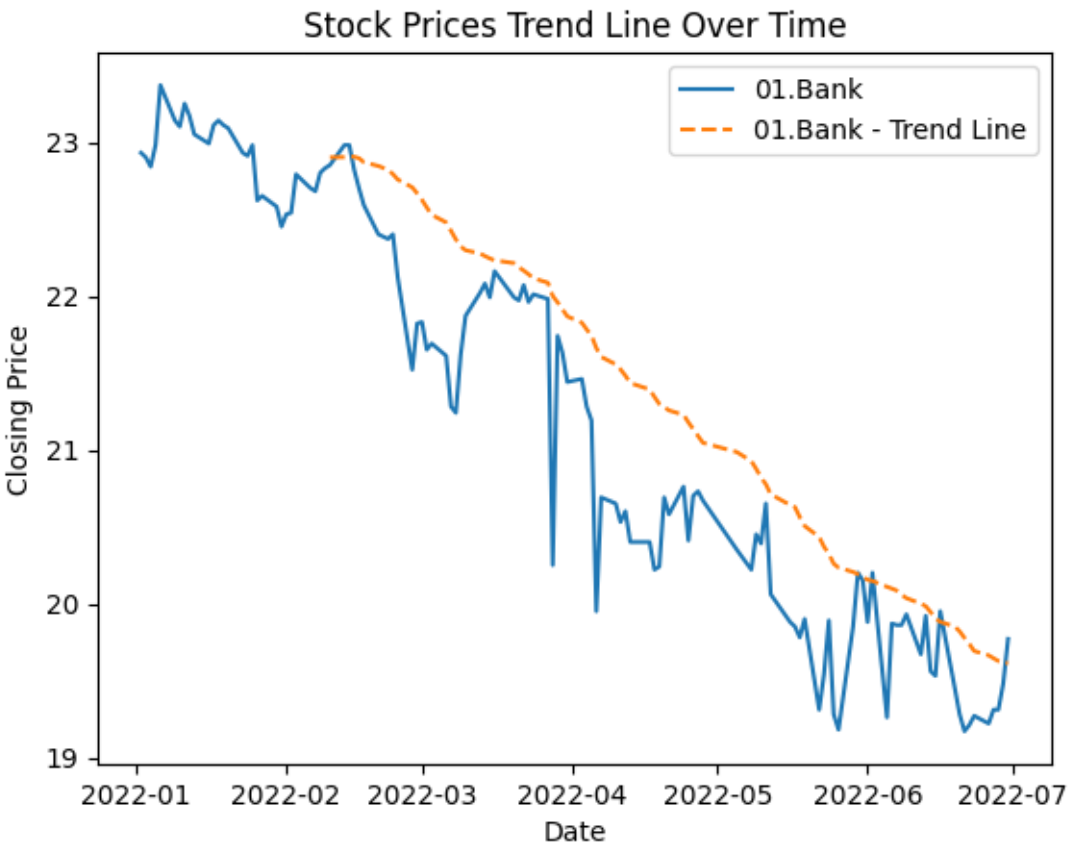

Daily Percentage Change in Closing Prices of 03.Ceramics_Sector
03.Ceramics_Sector
Daily Percentage Change
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0
−12.5
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date

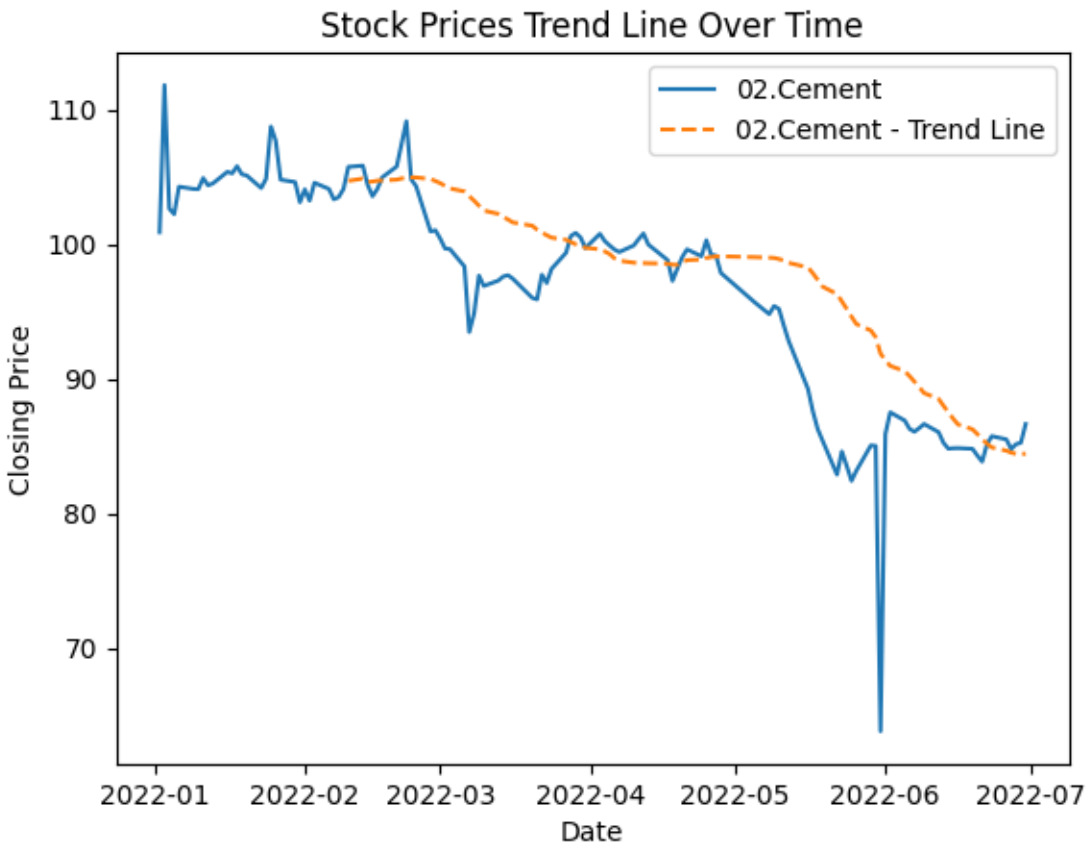

Daily Percentage Change in Closing Prices of 04.Engineering
04.Engineering
Daily Percentage Change
4
3
2
1
0
−1
−2
−3
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date

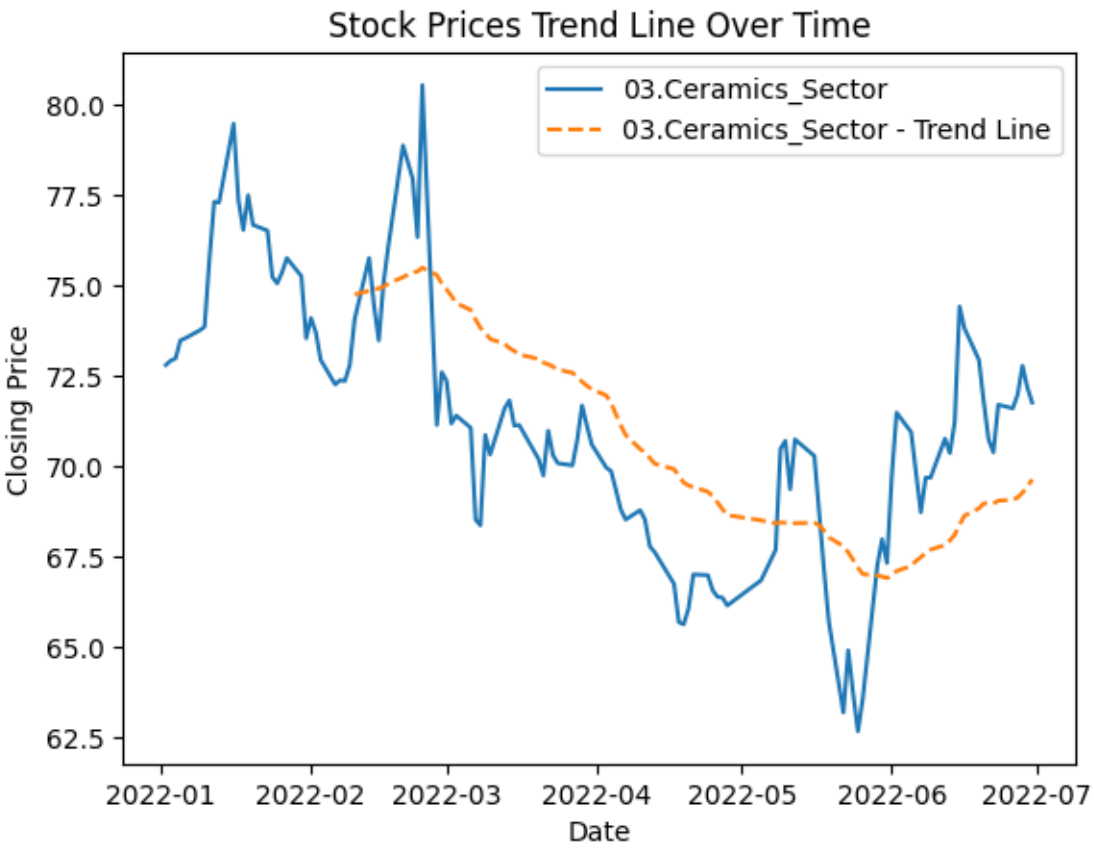


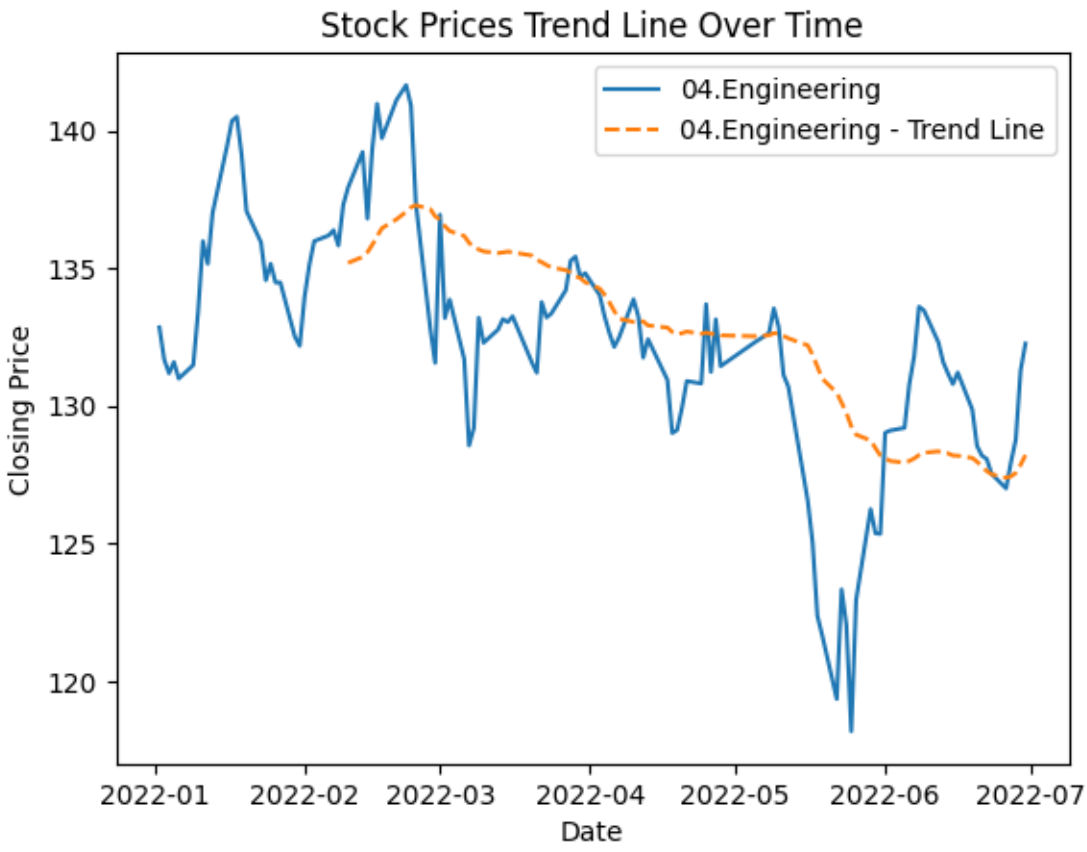
3.Investigate the presence of any trends or seasonality in the stock prices.

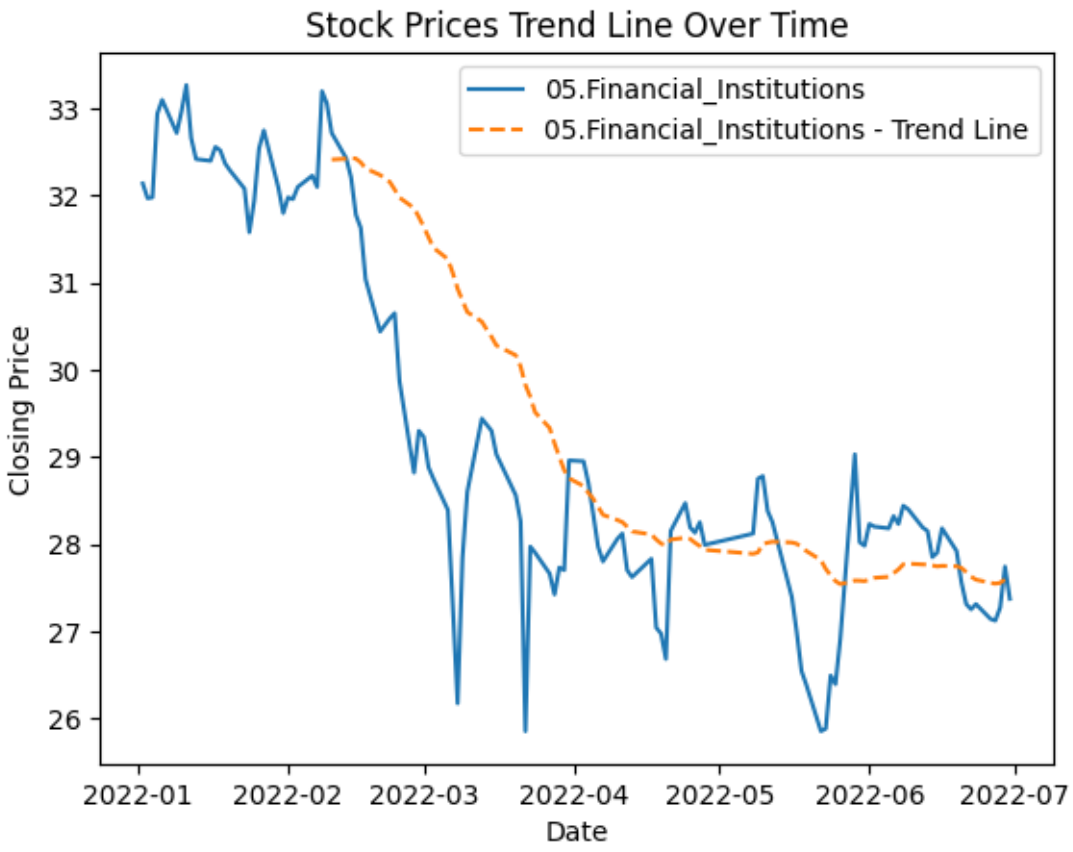
[9]:
```
for name in unique_names:
    company_data = stock_data[stock_data['Name'] == name]
    plt.plot(company_data['Date'],company_data['Close'], label=name)
    # Plotting a rolling average (e.g., 30 days) for trend visualization
    rolling_avg = company_data['Close'].rolling(window=30).mean()
    plt.plot(company_data['Date'],rolling_avg, label=f'{name} - Trend Line',␣
 ↪linestyle='--')
    plt.title('Stock Prices Trend Line Over Time')
    plt.xlabel('Date')
    plt.ylabel('Closing Price')
    plt.legend()
    plt.show()
```


Stock Prices Trend Line Over Time
01.Bank
01.Bank - Trend Line
Closing Price
23
22
21
20
19
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date


Stock Prices Trend Line Over Time
02.Cement
02.Cement - Trend Line
Closing Price
110
100
90
80
70
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date


Stock Prices Trend Line Over Time
03.Ceramics_Sector
03.Ceramics_Sector - Trend Line
Closing Price
80.0
77.5
75.0
72.5
70.0
67.5
65.0
62.5
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date


Stock Prices Trend Line Over Time
04.Engineering
04.Engineering - Trend Line
Closing Price
140
135
130
125
120
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date



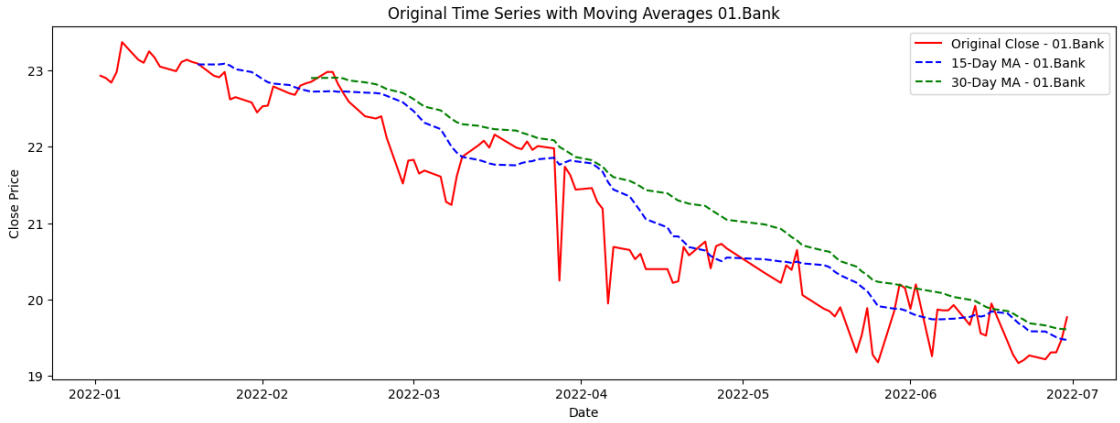
2.0.1 Stock Price Trend Analysis Report

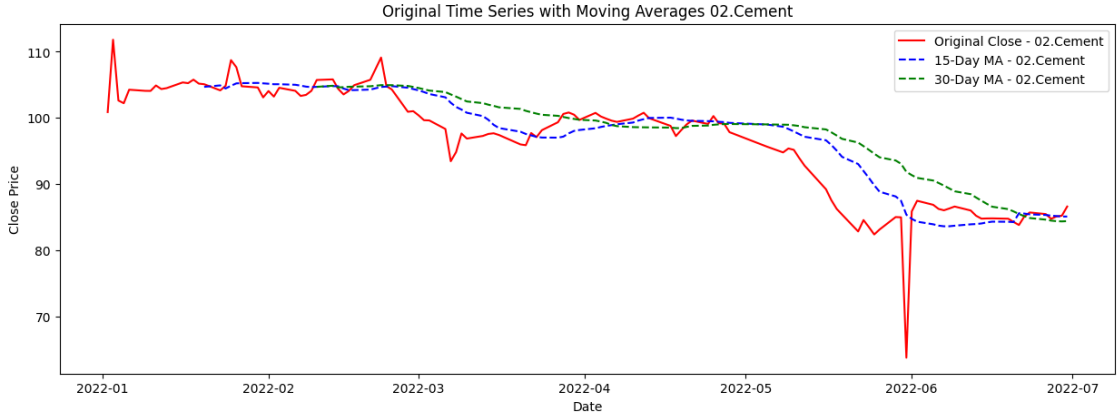
The analysis of historical stock prices for companies reveals a noticeable **downward trend**. This trend is depicted through the plotted closing prices and 30-day rolling averages. The decline suggests a potential shift in market sentiment or underlying economic factors affecting these sectors.

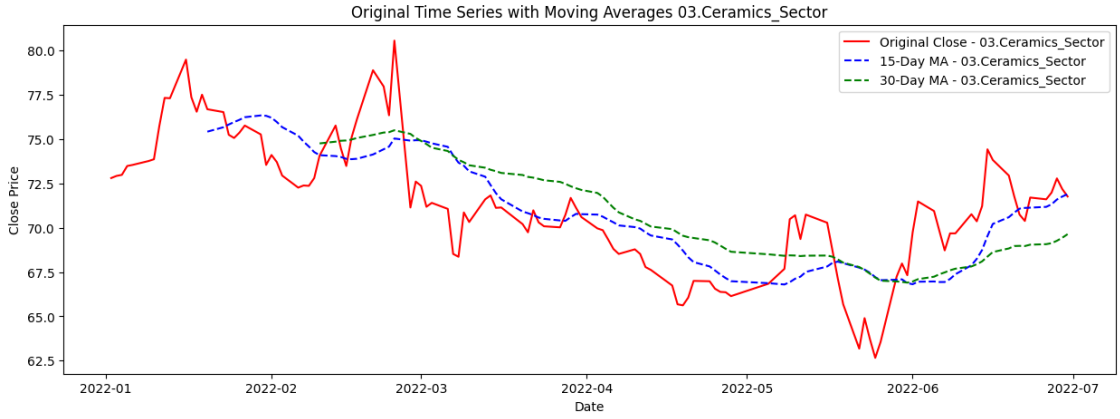
4.Apply moving averages to smooth the time series data in 15/30 day intervals against the original graph.

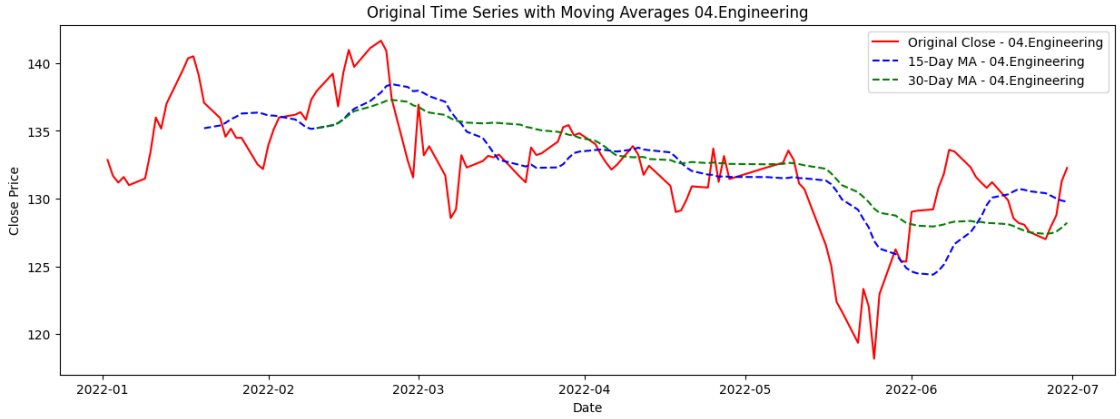
[10]:
```
for name in unique_names:
    plt.figure(figsize=(15, 5))
    company_data = stock_data[stock_data['Name'] == name]
    company_data['15_Day_MA'] = company_data['Close'].rolling(window=15).mean()
    company_data['30_Day_MA'] = company_data['Close'].rolling(window=30).mean()

    # Plotting for the current company
    plt.plot(company_data['Date'], company_data['Close'], label=f'Original␣
↪Close - {name}',color="red")
    plt.plot(company_data['Date'], company_data['15_Day_MA'], label=f'15-Day MA␣
↪- {name}', linestyle='--',color="blue")
```

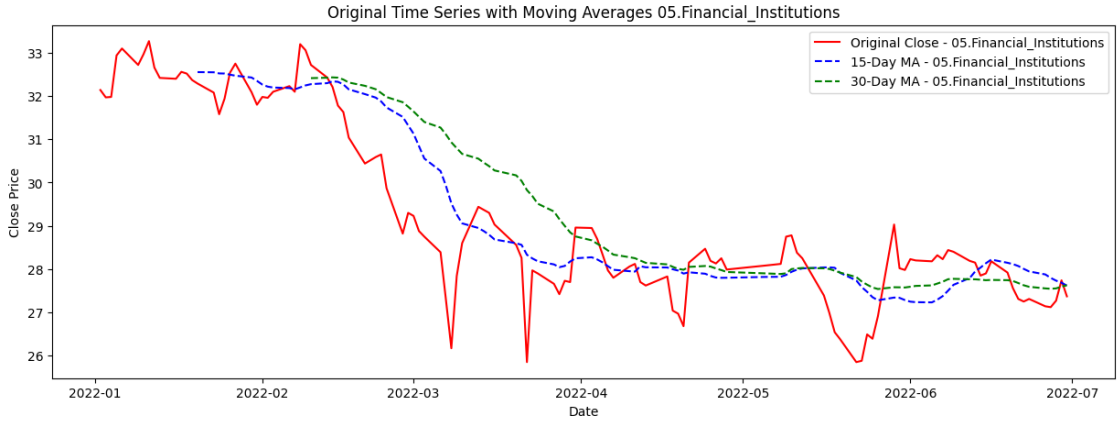
```
    plt.plot(company_data['Date'], company_data['30_Day_MA'], label=f'30-Day MA␣
↪- {name}', linestyle='--',color="green")
    plt.xlabel('Date')
    plt.ylabel('Close Price')
    plt.title('Original Time Series with Moving Averages {}'.format(name))
    plt.legend()
    plt.show()
```











5. Calculate the average closing price for each stock.

[11]:
```
df = pd.DataFrame(stock_data.groupby('Name')['Close'].mean()).reset_index()
df.columns=['Name','AvgClosingPrice']
df.head()
```

[11]:

	Name	AvgClosingPrice
0	01.Bank	21.260902
1	02.Cement	96.600820
2	03.Ceramics_Sector	71.225164
3	04.Engineering	132.352459
4	05.Financial_Institutions	29.253525

6. Identify the top 5 and bottom 5 stocks based on average closing price.

[12]:
```
df_sorted = df.sort_values(by='AvgClosingPrice',ascending=False)
```

[13]:
```
top5 = df_sorted.head(5)
top5
```

[13]:

	Name	AvgClosingPrice
56	APSCLBOND	5413.238636
320	RECKITTBEN	5342.024793
298	PREBPBOND	4918.357143
178	IBBL2PBOND	4851.330357
283	PBLPBOND	4836.195652

[14]:
```
bottom5 = df_sorted.tail(5)
bottom5
```

[14]:

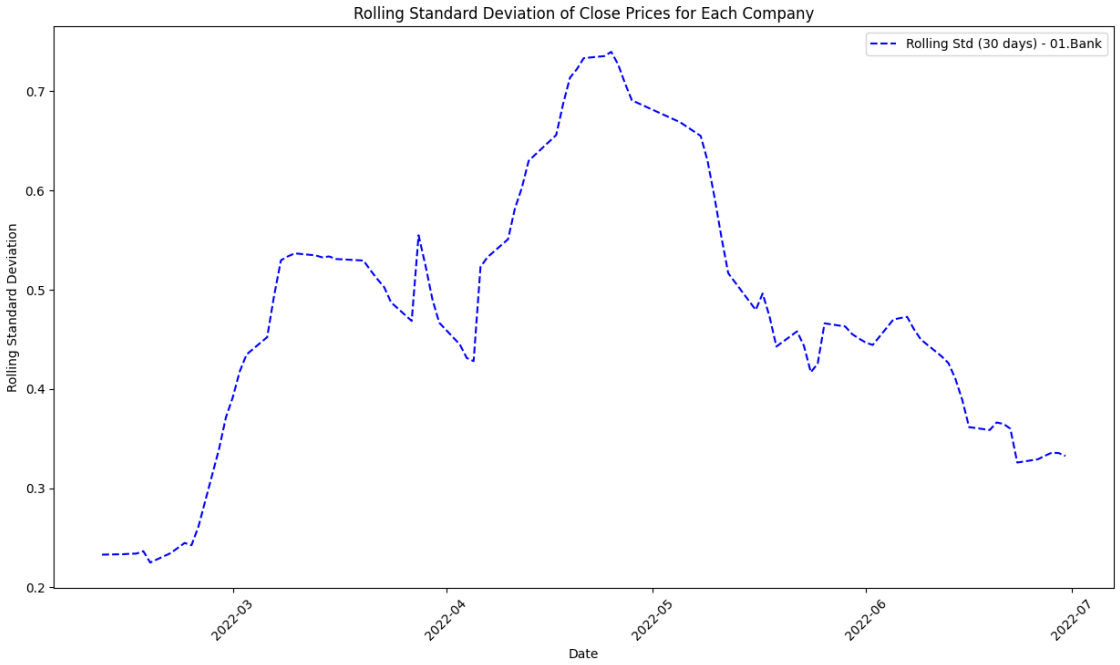
	Name	AvgClosingPrice
291	PHPMF1	5.417213
293	POPULAR1MF	5.368033
149	FBFIF	5.289344
187	ICBIBANK	4.725620
144	FAMILYTEX	4.698361

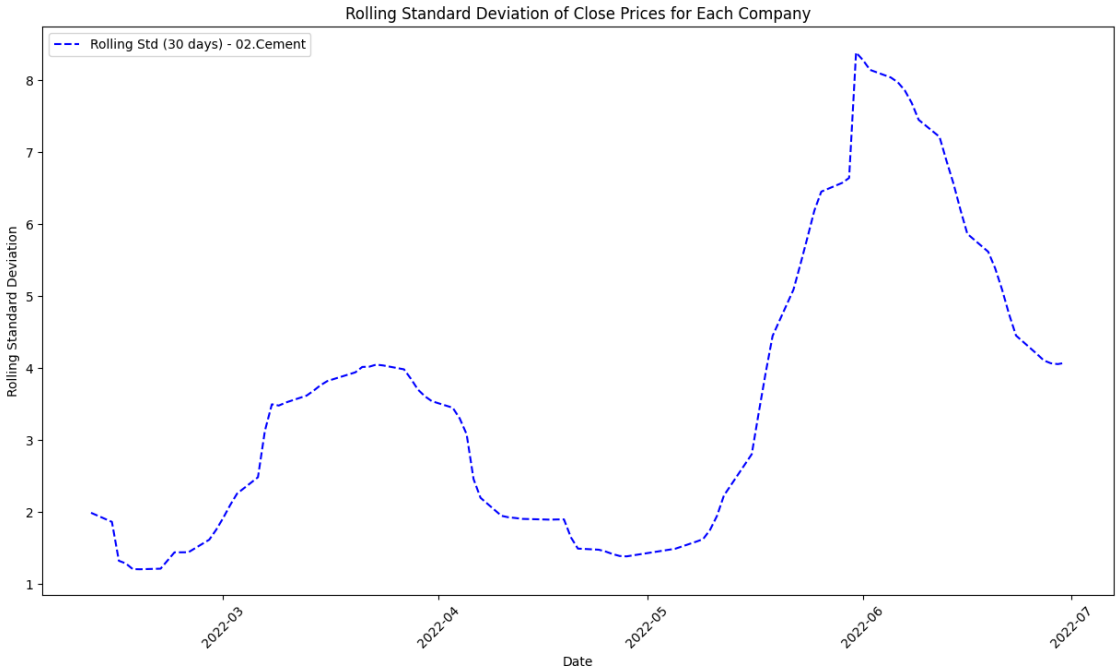
3 Part 3: Volatility Analysis:

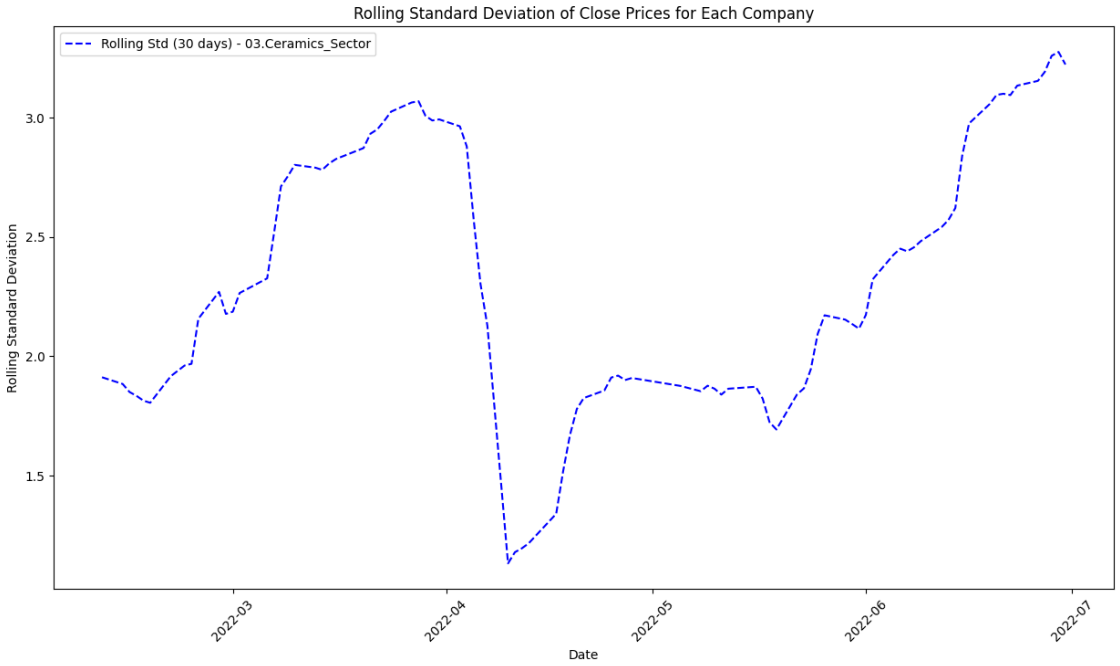
1.Calculate and plot the rolling standard deviation of the 'Close' prices.

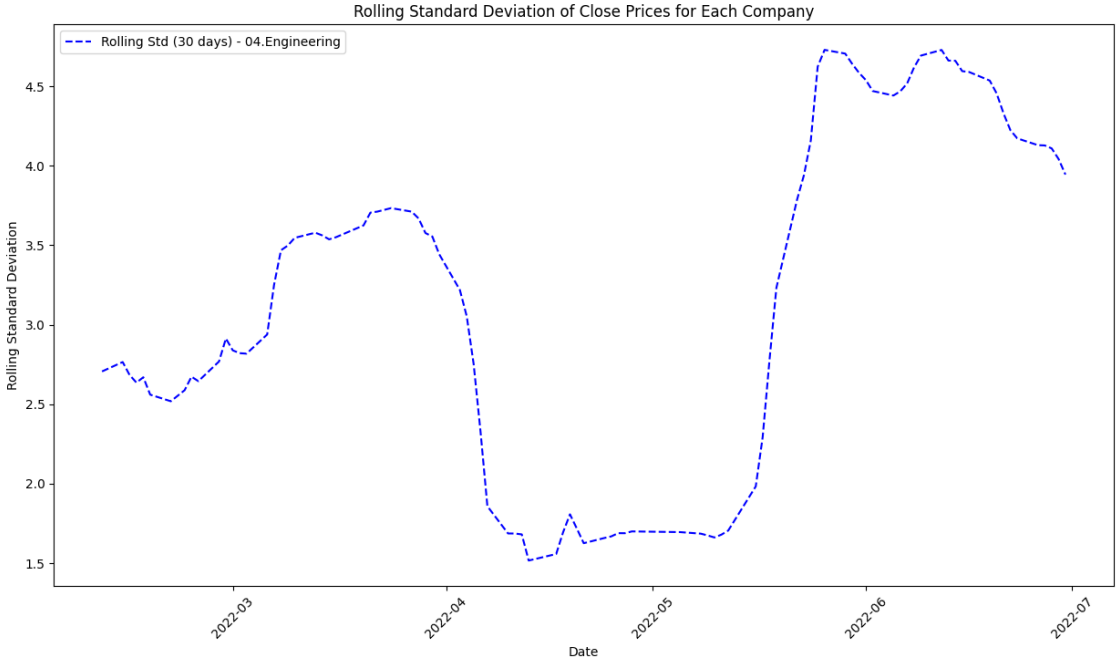
[15]:
```
for name in unique_names:
    company_data = stock_data[stock_data['Name'] == name]
    plt.figure(figsize=(15, 8))
    rolling_std = company_data['Close'].rolling(window=30).std()
    plt.plot(company_data['Date'],rolling_std, label=f'Rolling Std (30 days) -␣
 ↪{name}',linestyle='--',color="blue")
    plt.xlabel('Date')
    plt.ylabel('Rolling Standard Deviation')
```

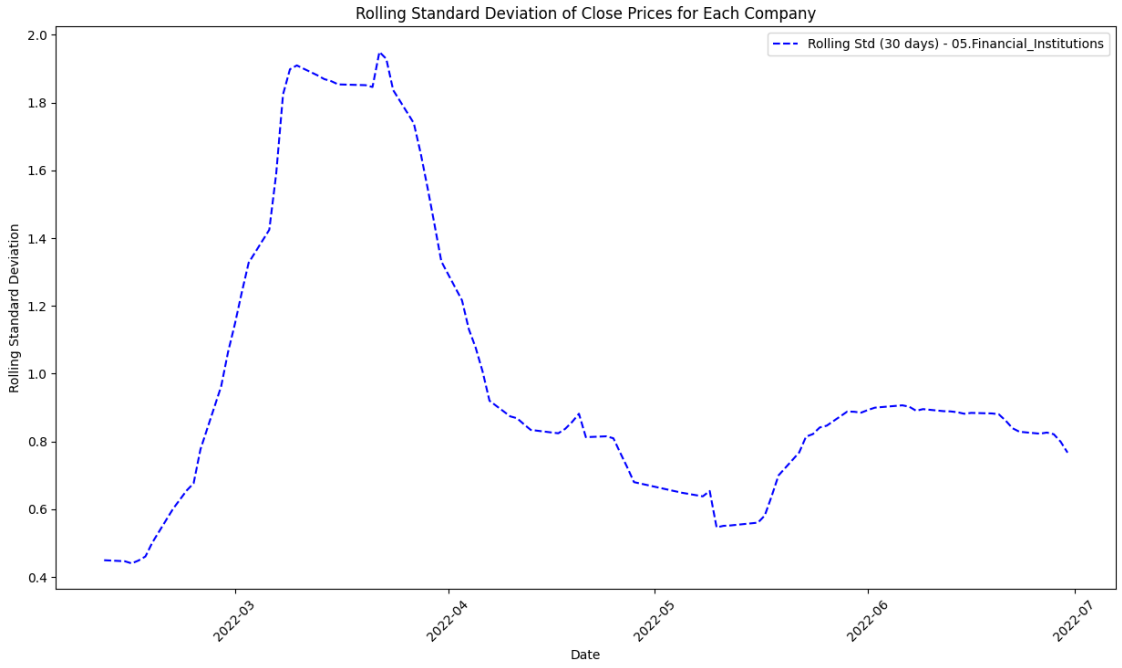
```
    plt.title('Rolling Standard Deviation of Close Prices for Each Company')
    plt.legend()
    plt.xticks(rotation=45)
    plt.show()
```






Rolling Standard Deviation of Close Prices for Each Company
Rolling Std (30 days) - 03.Ceramics_Sector
Rolling Standard Deviation
3.0
2.5
2.0
1.5
2022-03
2022-04
2022-05
2022-06
2022-07
Date


Rolling Standard Deviation of Close Prices for Each Company
Rolling Std (30 days) - 04.Engineering
Rolling Standard Deviation
4.5
4.0
3.5
3.0
2.5
2.0
1.5
2022-03
2022-04
2022-05
2022-06
2022-07
Date



2.Create a new column for daily price change (Close - Open)

[16]:
```
stock_data['daily_price_change'] = stock_data['Close'] - stock_data['Open']
stock_data.head()
```

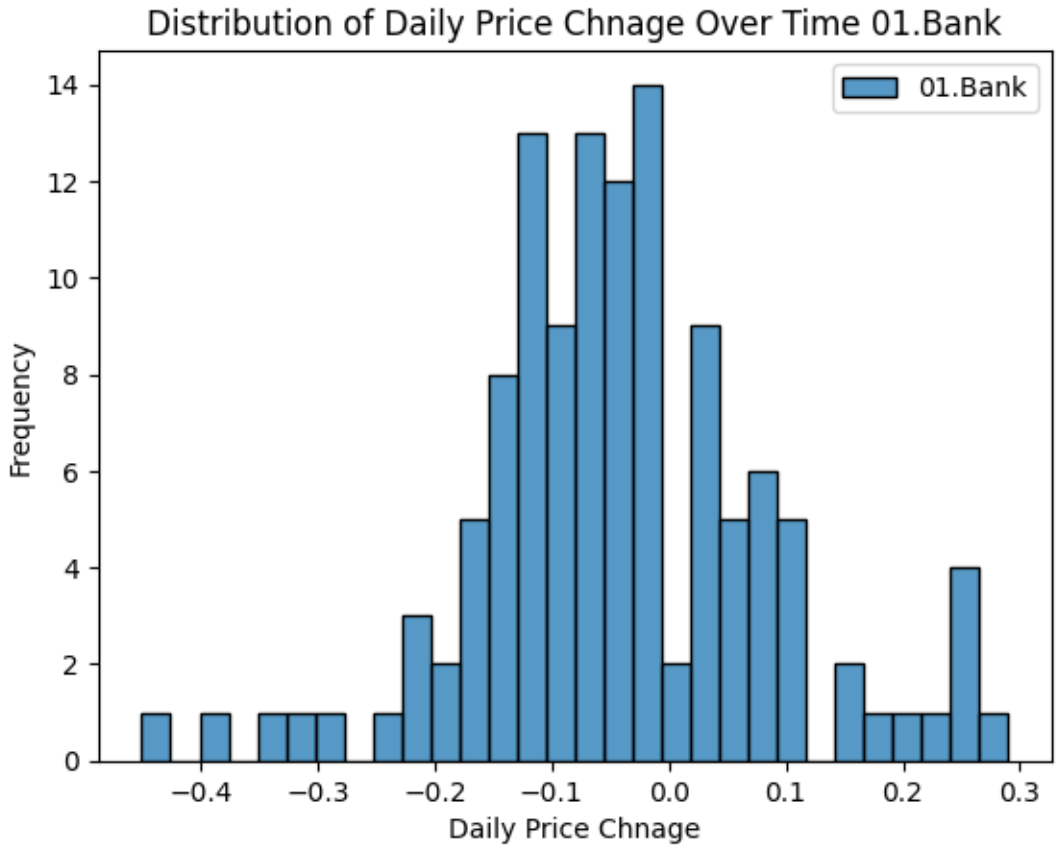
[16]:

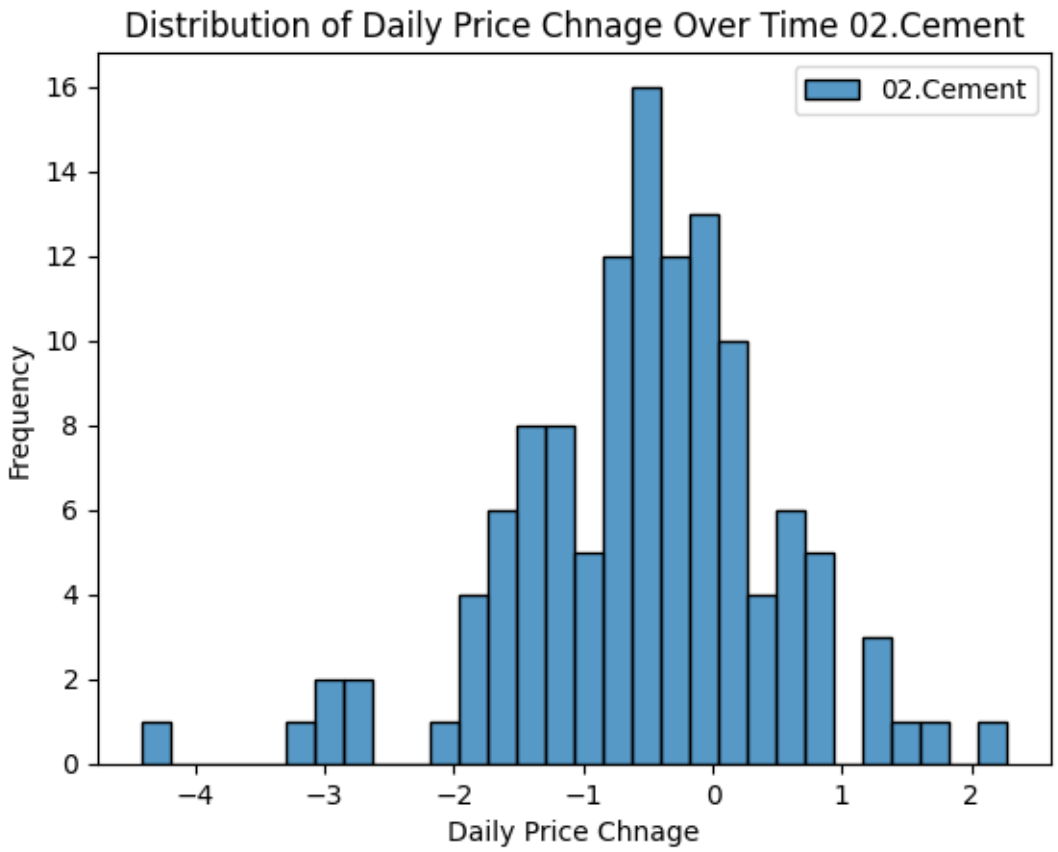
	Date	Name	Open	High	Low	Close	Volume	daily_price_change
0	2022-01-02	01.Bank	22.83	23.20	22.59	22.93	1842350.41	0.10
1	2022-01-03	01.Bank	23.03	23.29	22.74	22.90	1664989.63	-0.13
2	2022-01-04	01.Bank	22.85	23.13	22.64	22.84	1354510.97	-0.01
3	2022-01-05	01.Bank	22.91	23.20	22.70	22.98	1564334.81	0.07
4	2022-01-06	01.Bank	23.12	23.65	23.00	23.37	2586344.19	0.25

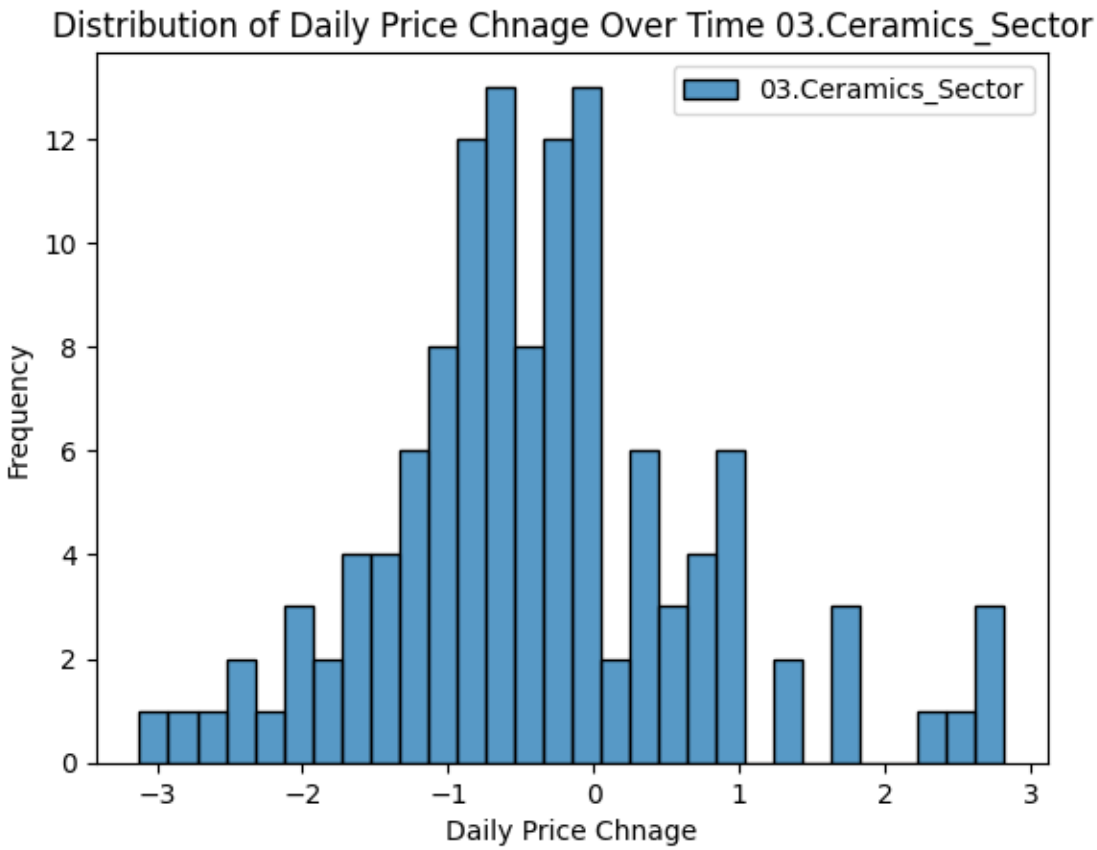
3.Analyze the distribution of daily price changes.

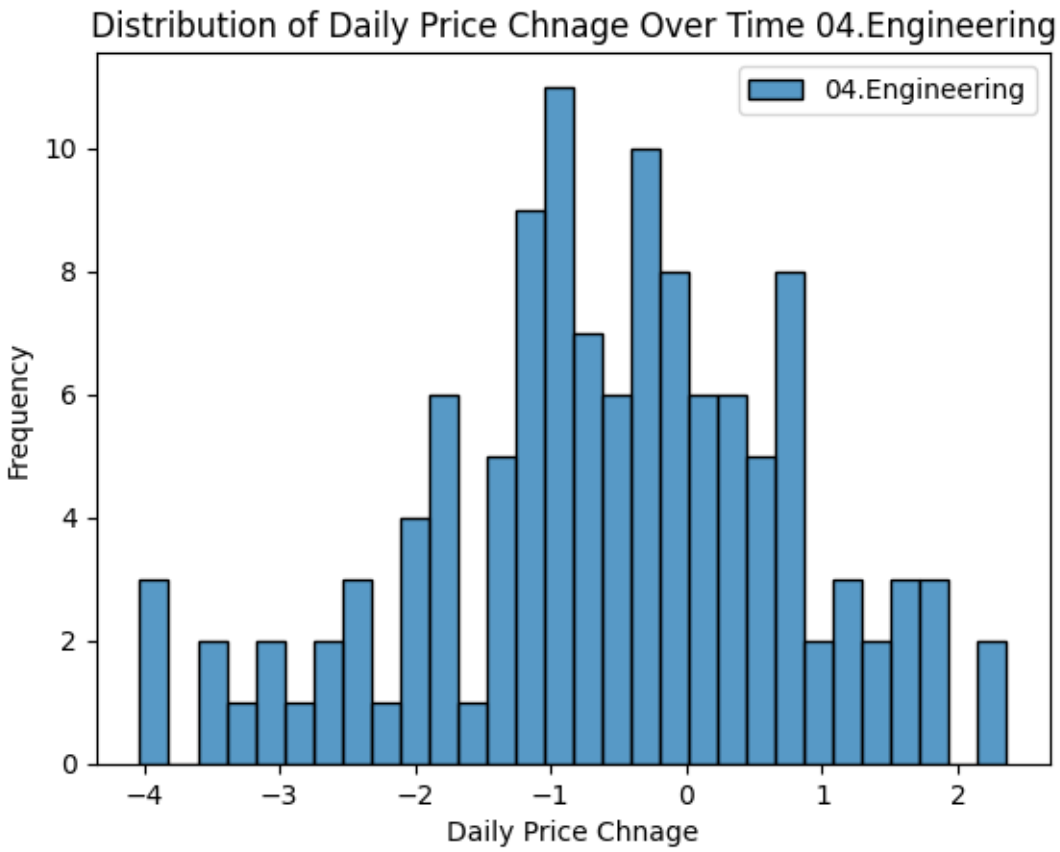
[17]:
```
for name in unique_names:
    company_data = stock_data[stock_data['Name'] == name]
    sns.histplot(data=company_data, x='daily_price_change', bins=30, label=name)
    plt.xlabel('Daily Price Chnage')
    plt.ylabel('Frequency')
```

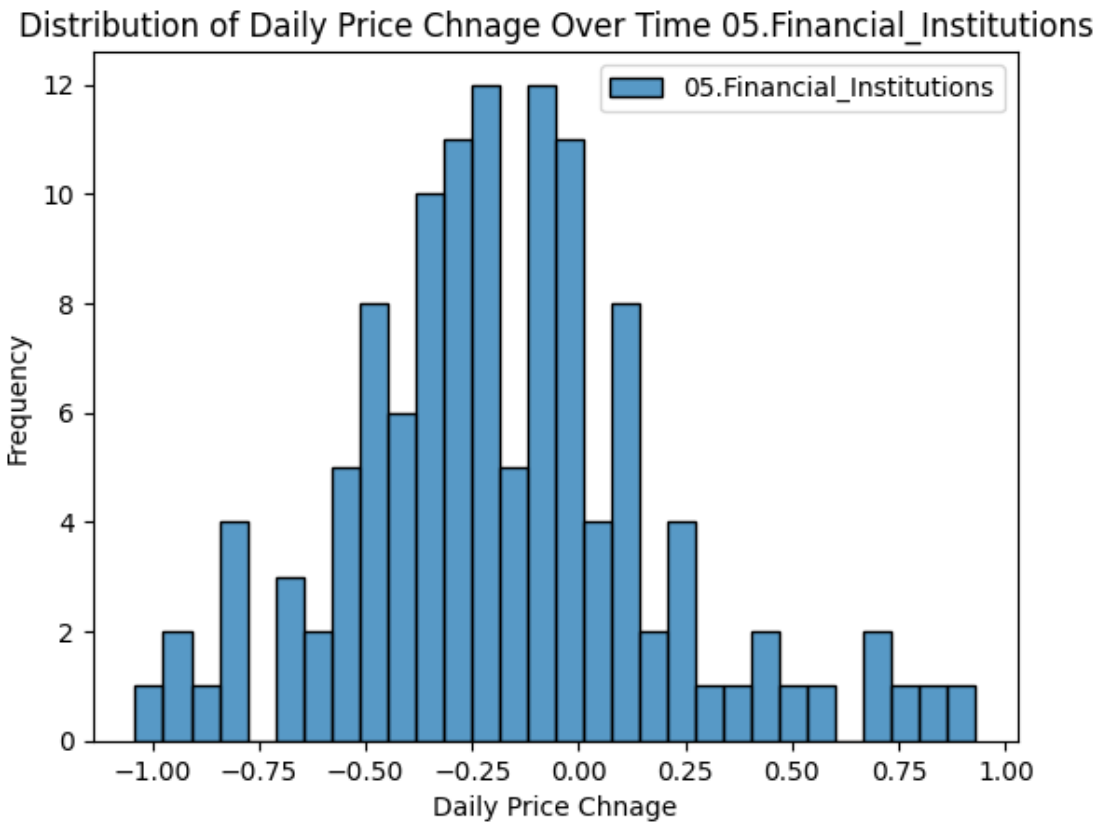
```
    plt.title('Distribution of Daily Price Chnage Over Time {}'.format(name))
    plt.legend()
    plt.show()
```




Distribution of Daily Price Chnage Over Time 02.Cement
02.Cement
Frequency
Daily Price Chnage
0
2
4
6
8
10
12
14
16
−4
−3
−2
−1
0
1
2


Distribution of Daily Price Chnage Over Time 03.Ceramics_Sector
03.Ceramics_Sector
Frequency
Daily Price Chnage
0
2
4
6
8
10
12
−3
−2
−1
0
1
2
3


Distribution of Daily Price Chnage Over Time 04.Engineering
04.Engineering
Frequency
Daily Price Chnage
0
2
4
6
8
10
−4
−3
−2
−1
0
1
2



4.Identify days with the largest price increases and decreases.

[18]:
```
sorted_data = stock_data.sort_values("daily_price_change",ascending=False)
```

[19]:
```
largest_price_increase = sorted_data.head(1)
largest_price_increase
```

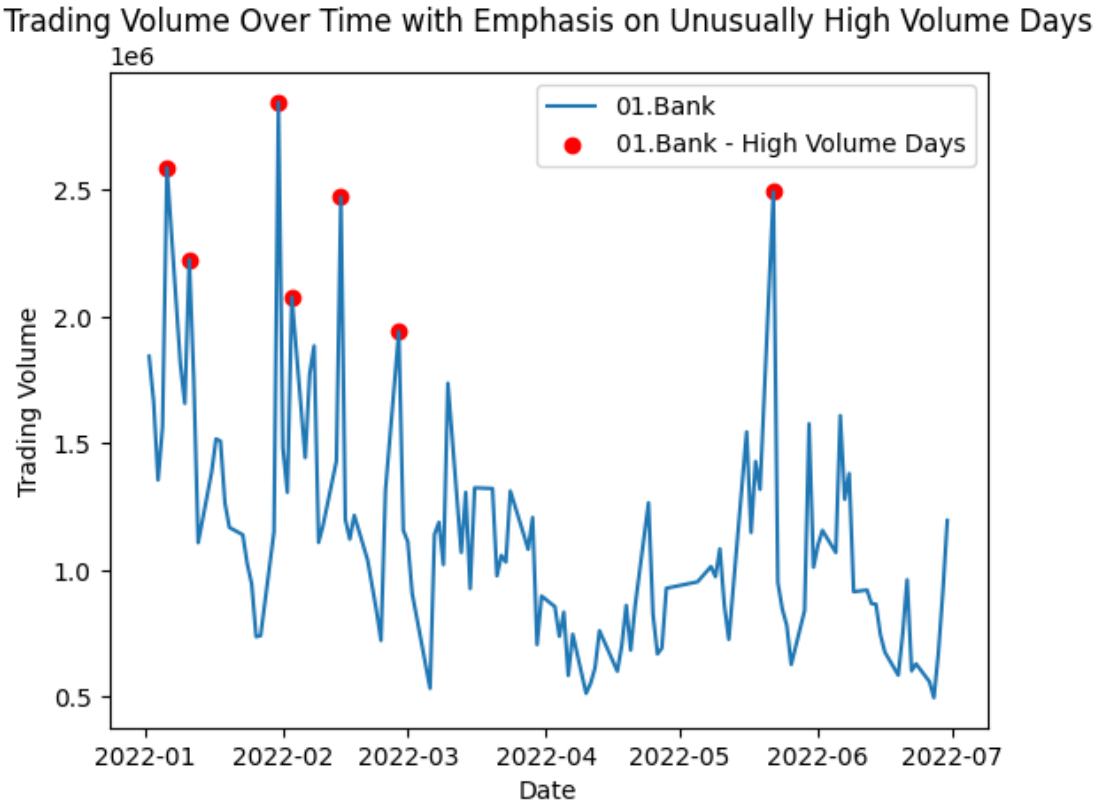
[19]:
```
            Date        Name    Open    High     Low   Close  Volume  \
48081 2022-06-29  SJIBLPBOND  4710.0  4899.0  4710.0  4897.0   101.0

       daily_price_change
48081               187.0
```

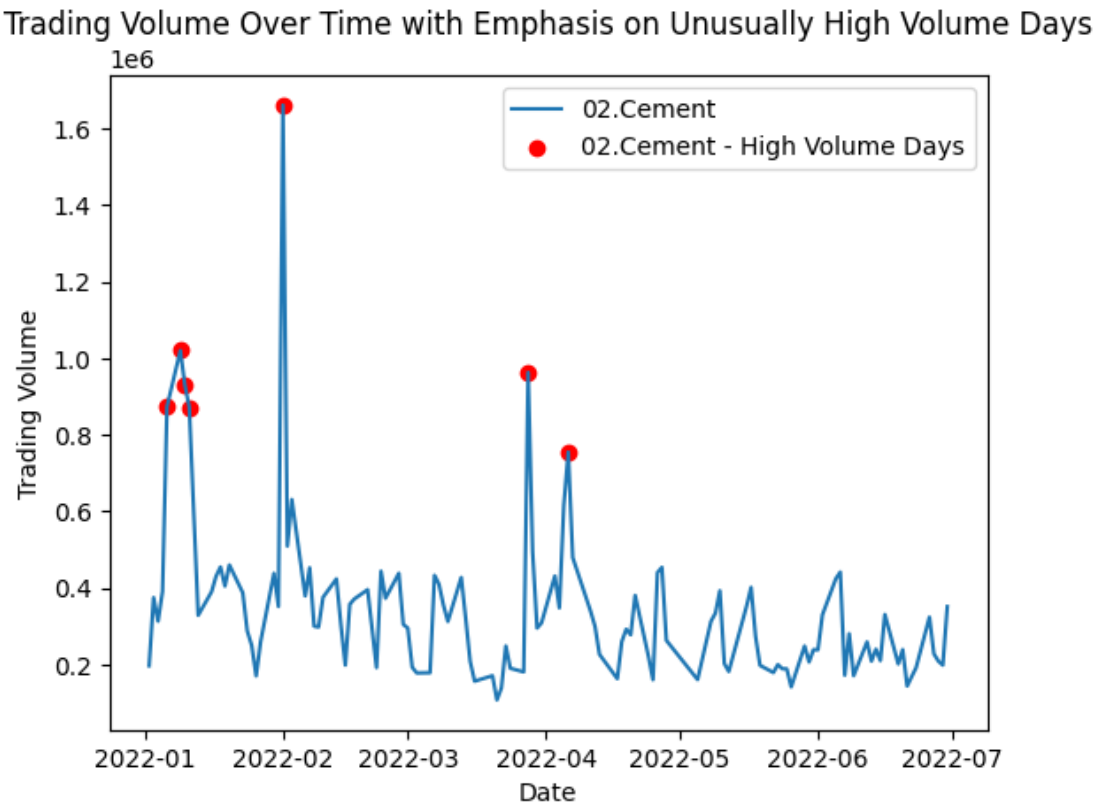
[20]:
```
largest_price_decrease = sorted_data.tail(1)
largest_price_decrease
```

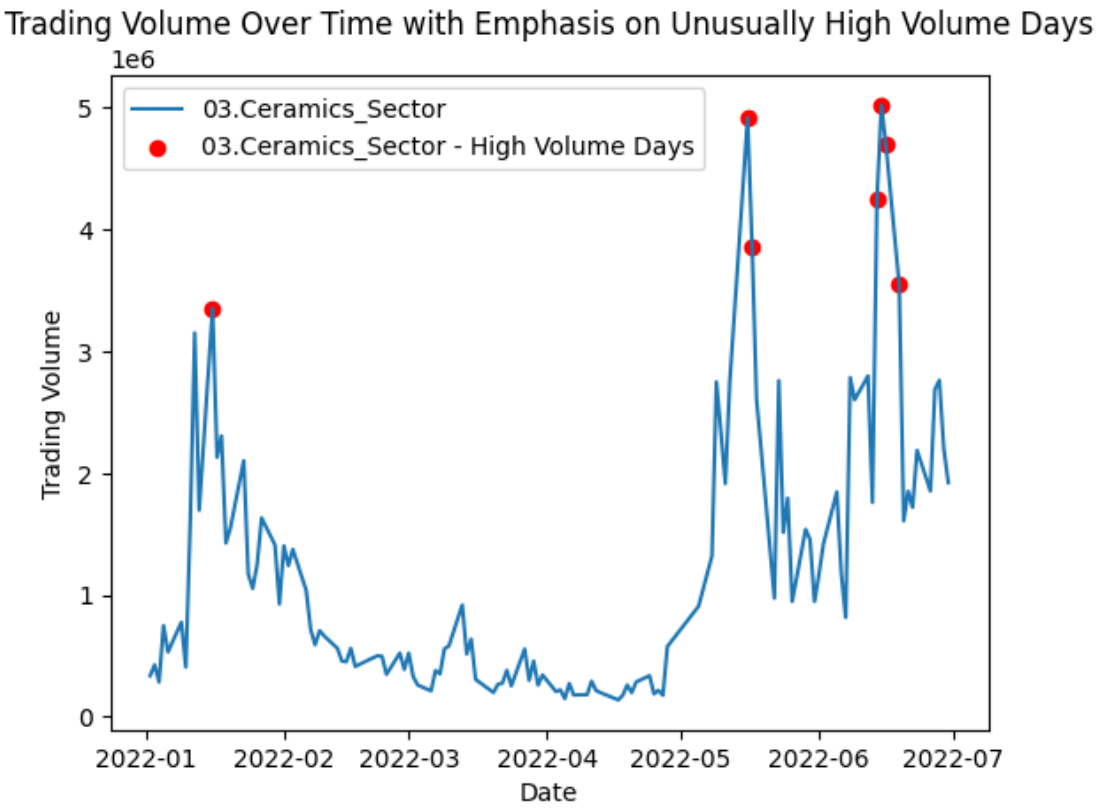
[20]:
```
            Date        Name    Open    High     Low   Close  Volume  \
23365 2022-03-07  RECKITTBEN  5753.0  5753.0  5550.0  5563.8  1876.0

       daily_price_change
23365              -189.2
```

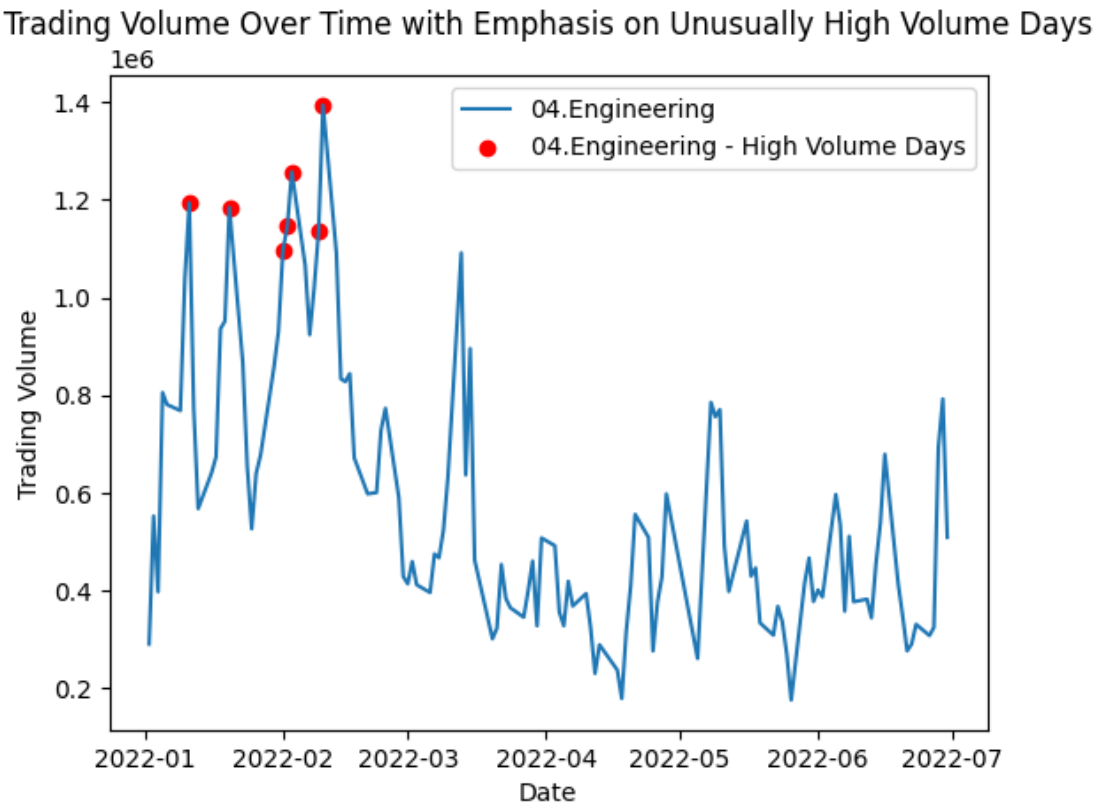
5.Identify stocks with unusually high trading volume on certain days.

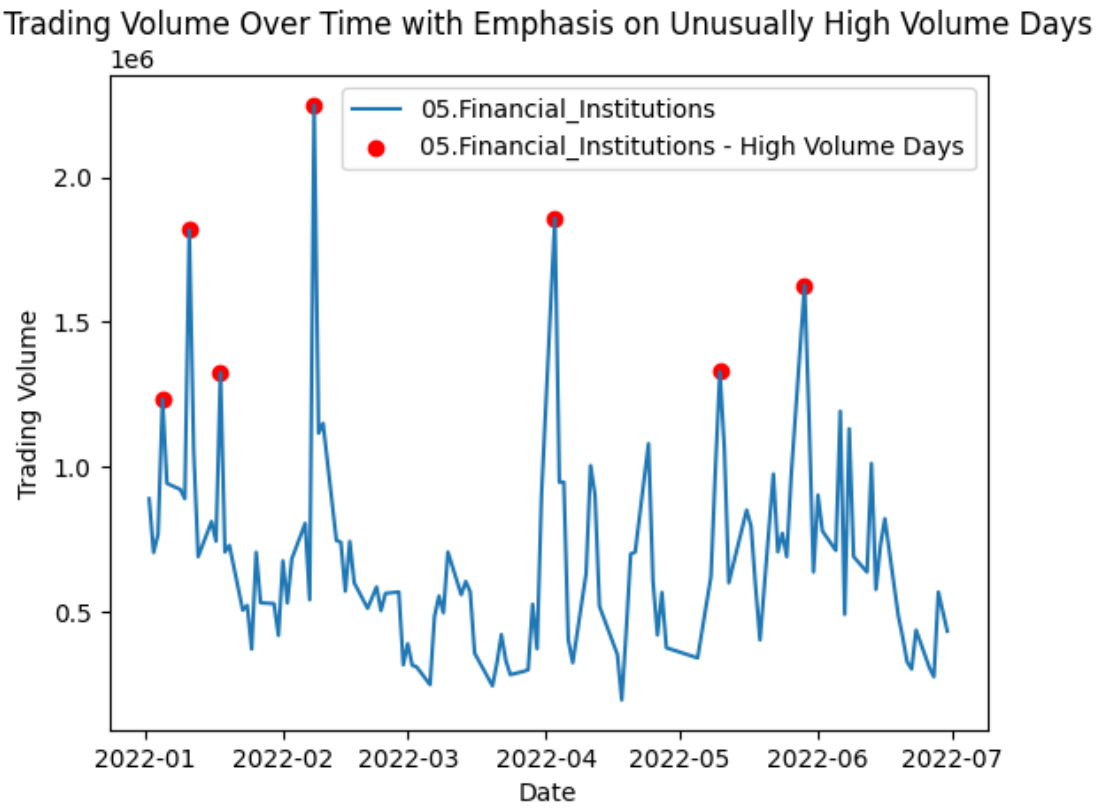
[21]:
```
for name in unique_names:
    company_data = stock_data[stock_data['Name'] == name]
    plt.plot(company_data['Date'],company_data['Volume'],label=name)
    threshold = company_data['Volume'].quantile(0.95)
    high_volume_data = company_data[company_data['Volume'] > threshold]
    plt.
↪scatter(high_volume_data['Date'],high_volume_data['Volume'],color="red",marker='o',label="{
↪- High Volume Days".format(name))
    plt.title('Trading Volume Over Time with Emphasis on Unusually High Volume␣
↪Days')
    plt.xlabel('Date')
    plt.ylabel('Trading Volume')
    plt.legend()
    plt.show()
```




Trading Volume Over Time with Emphasis on Unusually High Volume Days
1e6
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Trading Volume
02.Cement
02.Cement - High Volume Days
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date


Trading Volume Over Time with Emphasis on Unusually High Volume Days
1e6
03.Ceramics_Sector
03.Ceramics_Sector - High Volume Days
Trading Volume
Date
0
1
2
3
4
5
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07


Trading Volume Over Time with Emphasis on Unusually High Volume Days
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Trading Volume
04.Engineering
04.Engineering - High Volume Days
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date



3.0.1 Trading Volume Analysis Report

The line chart illustrates the trading volume over time . Notably, days with unusually high trading volume, represented by red dots, stand out. These instances may indicate significant market activity or events impacting the trading behavior of these stocks.

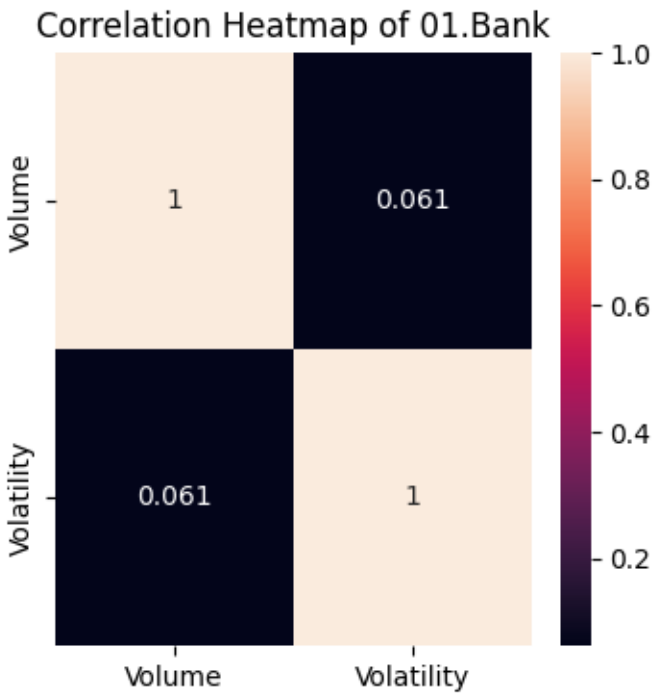
4 Part 4: Correlation and Heatmaps:

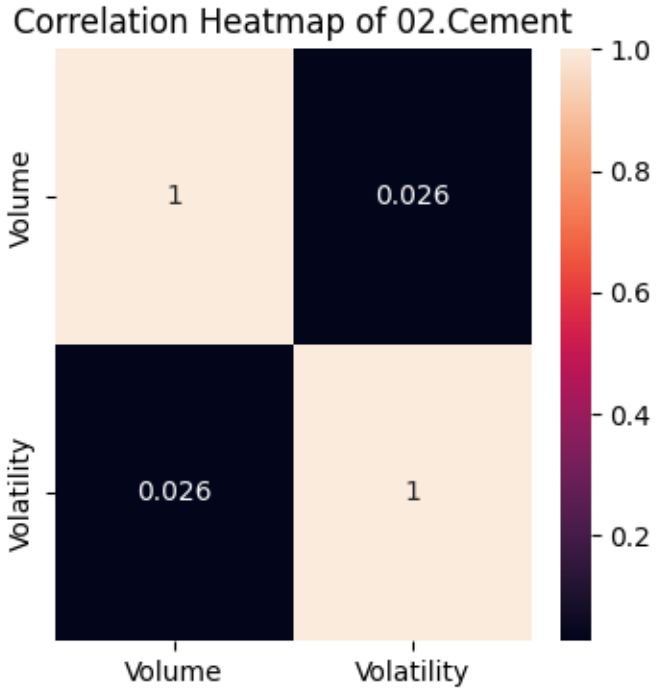
1.Explore the relationship between trading volume and volatility.

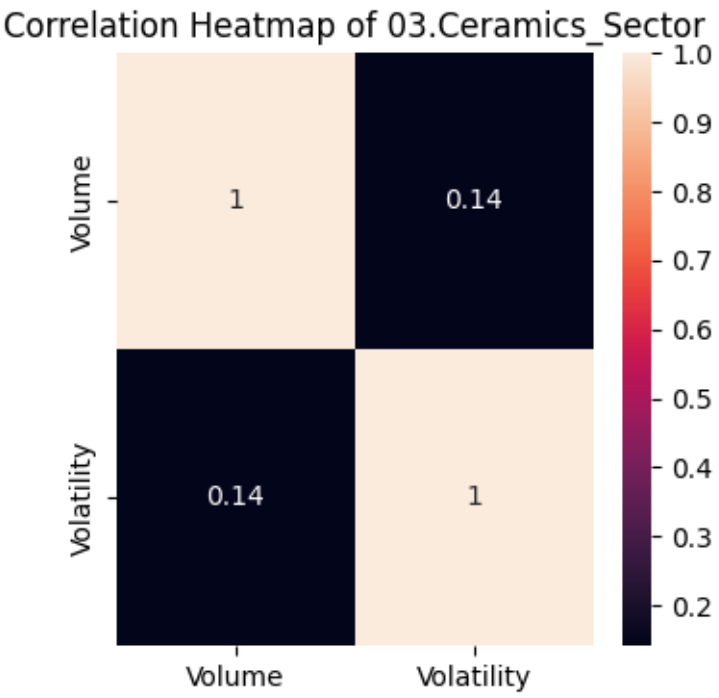
[22]:
```
## find the volatility/ daily pct change
stock_data['Volatility'] = stock_data.groupby("Name")['Close'].pct_change()
```

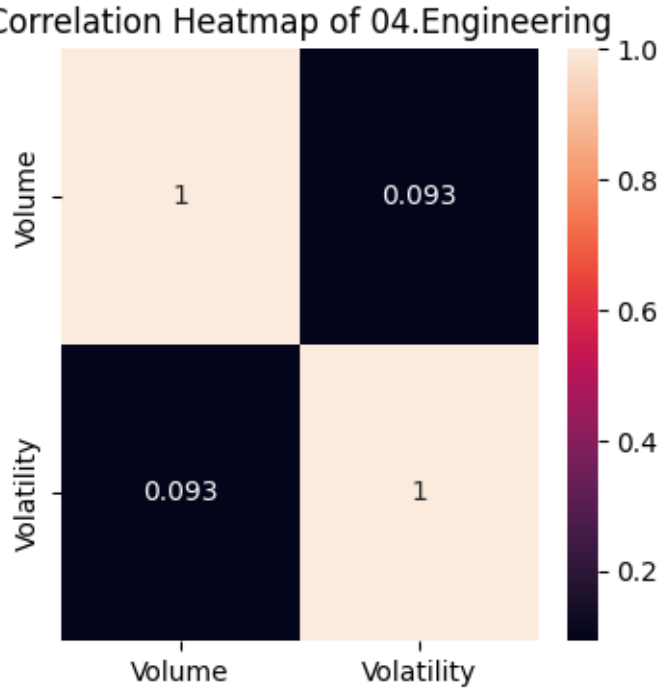
[23]:
```
correlation_matrix = stock_data.groupby("Name")[['Volume','Volatility']].corr()
```

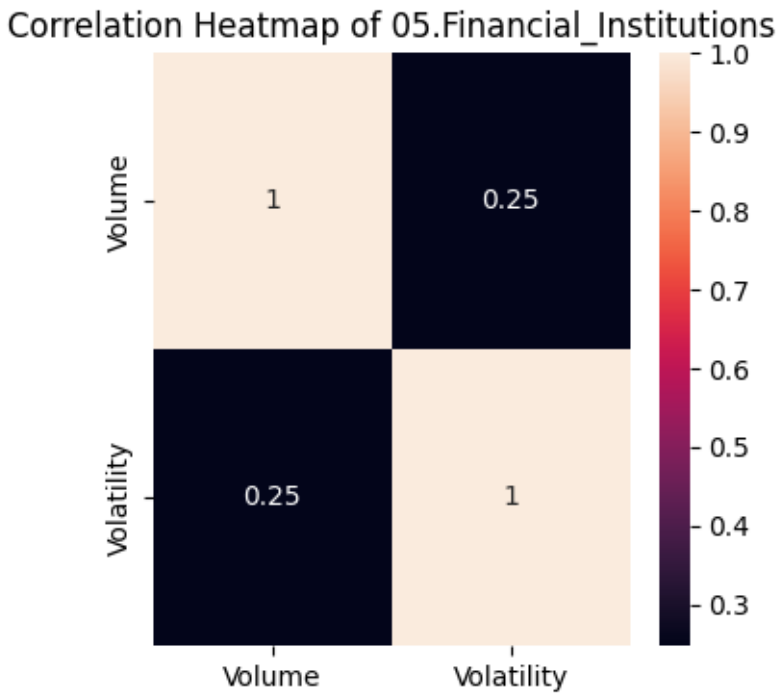
[24]:
```
## showing the random 5 company correlation matrix
for name in unique_names:
    plt.figure(figsize=(4,4))
    sns.heatmap(correlation_matrix.loc[name],annot=True)
    plt.title("Correlation Heatmap of {}".format(name))
    plt.show()
```


Correlation Heatmap of 01.Bank
Volume
Volatility
1
0.061
0.061
1
Volume
Volatility
1.0
0.8
0.6
0.4
0.2


Correlation Heatmap of 02.Cement
Volume
Volatility
1
0.026
0.026
1
Volume
Volatility
1.0
0.8
0.6
0.4
0.2


Correlation Heatmap of 03.Ceramics_Sector
Volume
Volatility
1
0.14
0.14
1
Volume
Volatility
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2


Correlation Heatmap of 04.Engineering
Volume
Volatility
1
0.093
0.093
1
Volume
Volatility
1.0
0.8
0.6
0.4
0.2



2.Calculate the correlation matrix between the 'Open' & 'High', 'Low' &'Close' prices.

[25]:
```
price_columns = ['Open', 'High', 'Low', 'Close']

# Group by 'Name' and calculate the correlation matrix for each group
correlation_matrices = stock_data.groupby('Name')[price_columns].corr()
```

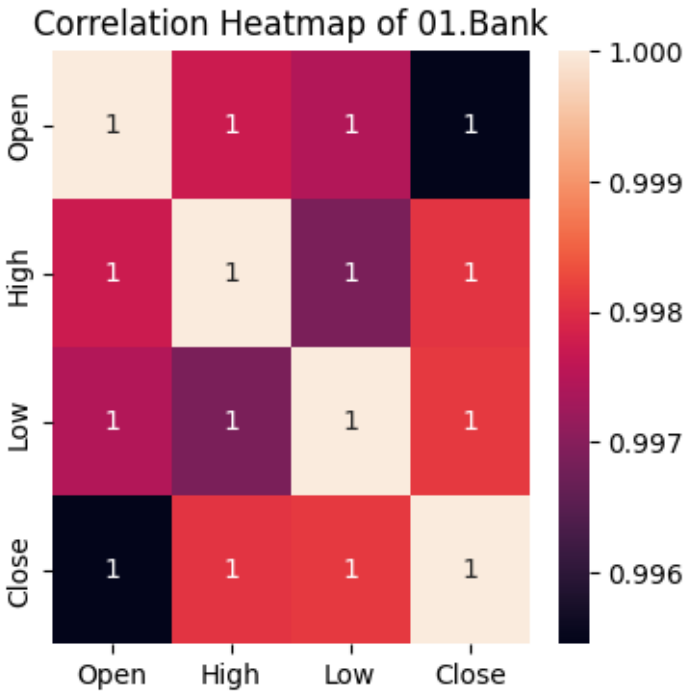
[26]:
```
## showing random 5 company correlation matrix
for name in unique_names:
    print("Company Name : {}".format(name))
    print("-"*50)
    print(correlation_matrices.loc[name])
    print("-"*50)
```

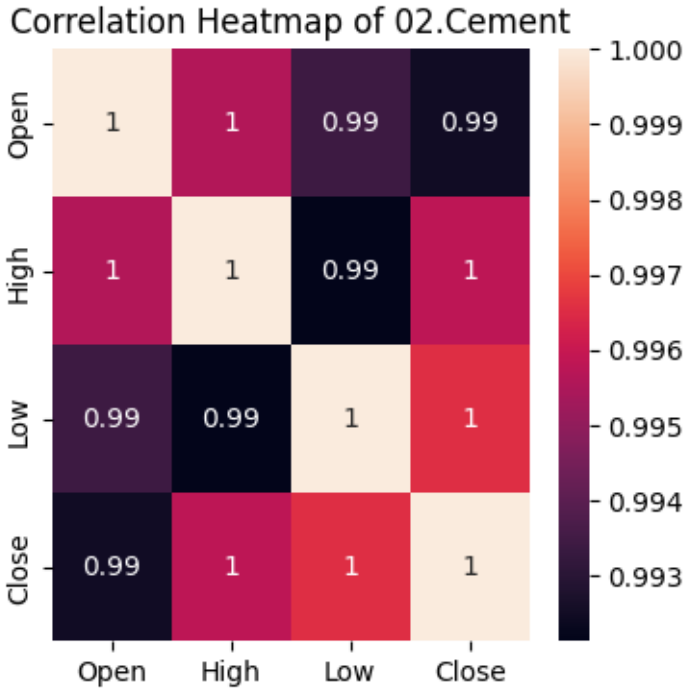
```
Company Name : 01.Bank
--------------------------------------------------
           Open      High       Low     Close
Open   1.000000  0.997736  0.997456  0.995453
High   0.997736  1.000000  0.996873  0.998074
Low    0.997456  0.996873  1.000000  0.998132
Close  0.995453  0.998074  0.998132  1.000000
--------------------------------------------------
Company Name : 02.Cement
--------------------------------------------------
           Open      High       Low     Close
```

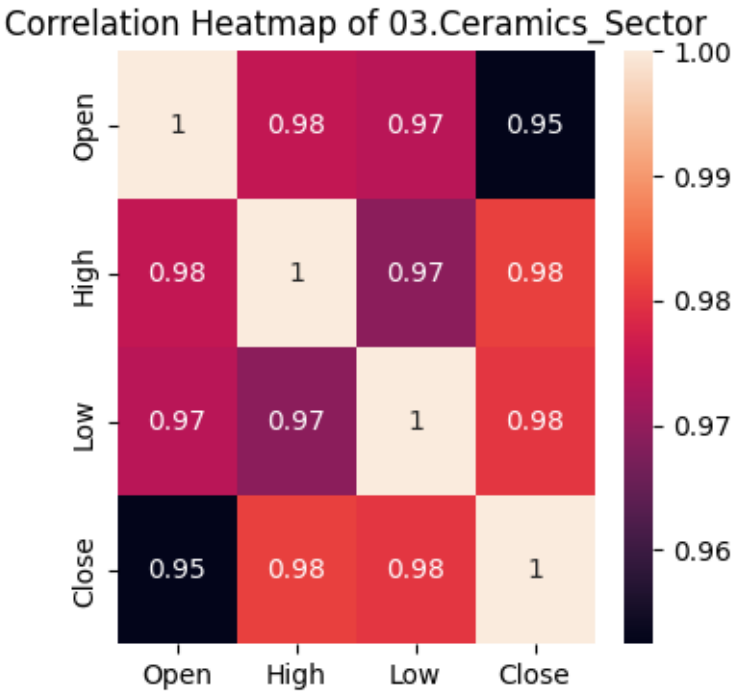
```
Open   1.000000  0.995589  0.993419  0.992501
High   0.995589  1.000000  0.992134  0.995799
Low    0.993419  0.992134  1.000000  0.996541
Close  0.992501  0.995799  0.996541  1.000000
--------------------------------------------------
Company Name : 03.Ceramics_Sector
--------------------------------------------------
           Open      High       Low     Close
Open   1.000000  0.975167  0.974133  0.952451
High   0.975167  1.000000  0.969056  0.981141
Low    0.974133  0.969056  1.000000  0.980080
Close  0.952451  0.981141  0.980080  1.000000
--------------------------------------------------
Company Name : 04.Engineering
--------------------------------------------------
           Open      High       Low     Close
Open   1.000000  0.978843  0.970790  0.951664
High   0.978843  1.000000  0.966365  0.978897
Low    0.970790  0.966365  1.000000  0.981220
Close  0.951664  0.978897  0.981220  1.000000
--------------------------------------------------
Company Name : 05.Financial_Institutions
--------------------------------------------------
           Open      High       Low     Close
Open   1.000000  0.992630  0.993292  0.985467
High   0.992630  1.000000  0.992698  0.995416
Low    0.993292  0.992698  1.000000  0.994682
Close  0.985467  0.995416  0.994682  1.000000
--------------------------------------------------
```

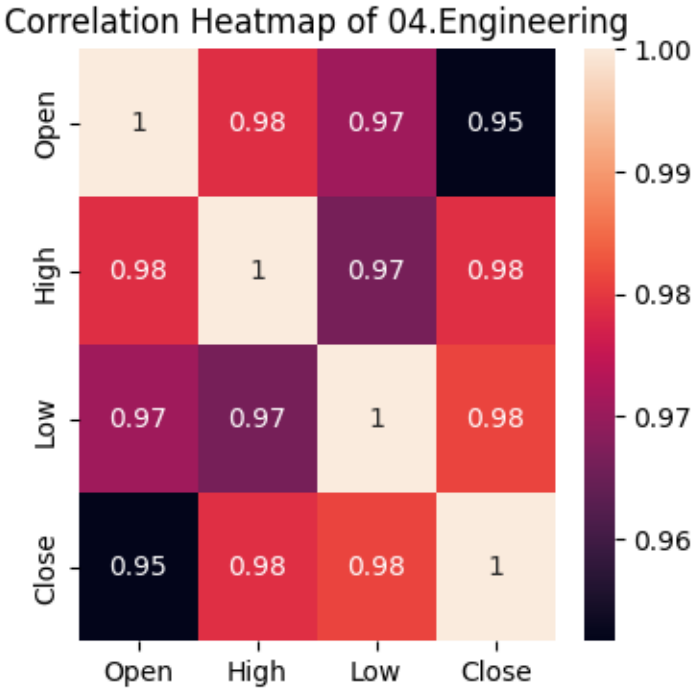
3.Create a heatmap to visualize the correlations using the seaborn package.

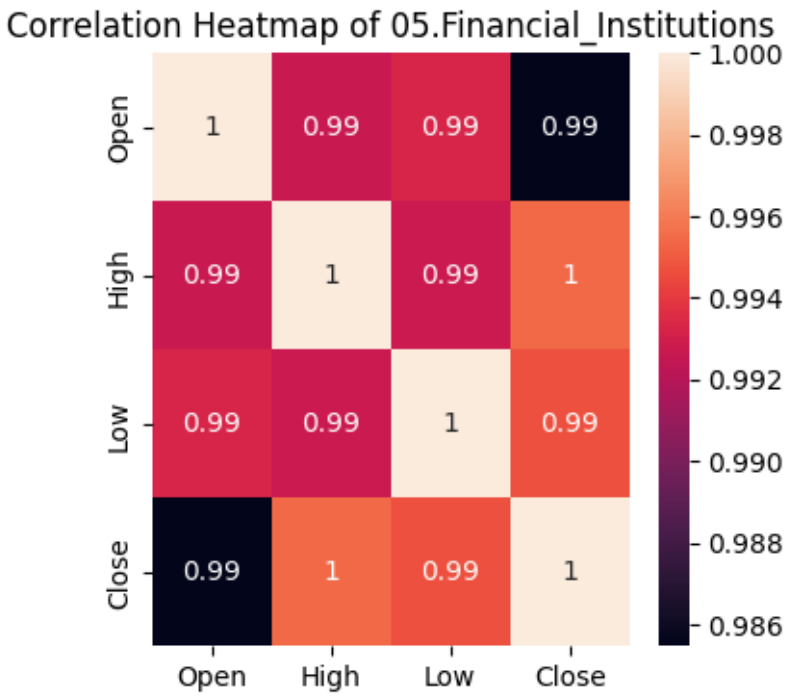
[27]:
```
for name in unique_names:
    plt.figure(figsize=(4,4))
    sns.heatmap(correlation_matrices.loc[name],annot=True)
    plt.title("Correlation Heatmap of {}".format(name))
    plt.show()
```


Correlation Heatmap of 01.Bank
Open
High
Low
Close
1
1
1
1
1
1
1
1
1
1
1
1
1
1
1
1
Open
High
Low
Close
1.000
0.999
0.998
0.997
0.996


Correlation Heatmap of 02.Cement
Open
High
Low
Close
1
1
0.99
0.99
1
1
0.99
1
0.99
0.99
1
1
0.99
1
1
1
Open
High
Low
Close
1.000
0.999
0.998
0.997
0.996
0.995
0.994
0.993


Correlation Heatmap of 03.Ceramics_Sector
Open
High
Low
Close
1
0.98
0.97
0.95
0.98
1
0.97
0.98
0.97
0.97
1
0.98
0.95
0.98
0.98
1
Open
High
Low
Close
1.00
0.99
0.98
0.97
0.96


Correlation Heatmap of 04.Engineering
Open
High
Low
Close
1
0.98
0.97
0.95
0.98
1
0.97
0.98
0.97
0.97
1
0.98
0.95
0.98
0.98
1
Open
High
Low
Close
1.00
0.99
0.98
0.97
0.96


Correlation Heatmap of 05.Financial_Institutions
Open
High
Low
Close
1
0.99
0.99
0.99
0.99
1
0.99
1
0.99
0.99
1
0.99
0.99
1
0.99
1
Open
High
Low
Close
1.000
0.998
0.996
0.994
0.992
0.990
0.988
0.986

[ ]: