Analysis

In [7]:

import pandas as pd

import numpy as np
import matplotlib.pyplot as plt

In [4]:

data = pd.read_csv('results.csv')

In [69]:

data.head(20)

Out[69]:

	company	date	average_v olatility	highest_vo latility	lowest_vol atility	
0	AMZN	2023-04- 03	0.225	0.800	0.087	
1	AMZN	2023-04- 04	0.264	0.710	0.090	
2	AMZN	2023-04- 05	0.243	1.160	0.092	
3	AMZN	2023-04- 06	0.234	0.740	0.086	
4	AMZN	2023-04- 10	0.222	0.920	0.095	
5	AMZN	2023-04- 11	0.221	0.860	0.079	
6	AMZN	2023-04- 12	0.277	1.010	0.075	
7	AMZN	2023-04- 13	0.243	0.805	0.080	
8	AMZN	2023-04- 14	0.283	1.220	0.120	
9	BABA	2023-04- 03	0.312	1.520	0.100	
10	BABA	2023-04- 04	0.360	1.598	0.090	
11	BABA	2023-04-	0.296	1.050	0.065	

	company	date	average_v olatility	highest_vo latility	lowest_vol atility	
		05				
12	BABA	2023-04- 06	0.315	1.170	0.080	
13	BABA	2023-04- 10	0.250	1.620	0.053	
14	BABA	2023-04- 11	0.280	2.625	0.050	
15	BABA	2023-04- 12	0.320	1.240	0.095	
16	BABA	2023-04- 13	0.269	1.380	0.070	
17	BABA	2023-04- 14	0.203	0.762	0.040	
18	ВВҮ	2023-04- 03	0.135	0.357	0.050	
19	ВВҮ	2023-04- 04	0.163	0.579	0.050	

In [8]:

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90 entries, 0 to 89

Data columns (total 5 columns):

#	Column	Non-Null Count	Dtype
0	company	90 non-null	object
1	date	90 non-null	object
2	average_volatility	90 non-null	float64
3	highest_volatility	90 non-null	float64
4	lowest volatility	90 non-null	float64

dtypes: float64(3), object(2)

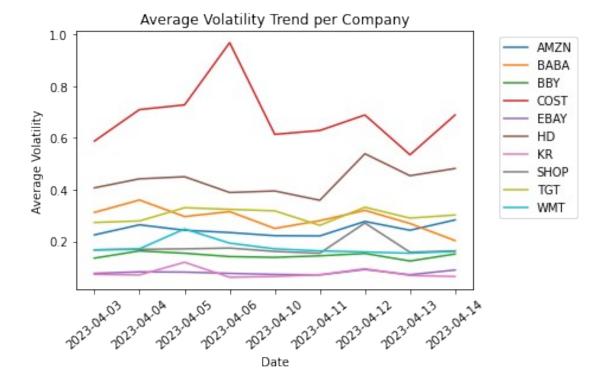
memory usage: 3.6+ KB

1) Graph the average volatility trend per company, Which company is the most volatile?¶

```
In [10]:
```

```
average_volatility = data.groupby('company')
['average_volatility'].mean()
average_volatility
```

```
Out[10]:
company
AMZN
        0.245778
BABA
        0.289444
BBY
        0.144778
COST 0.683444
EBAY
        0.078667
        0.435222
HD
KR
        0.075889
SH0P
        0.176444
TGT
        0.301111
WMT
        0.176333
Name: average volatility, dtype: float64
In [76]:
companies = data['company'].unique()
for company in companies:
    company data = data[data['company'] == company]
    plt.plot(company_data['date'], company_data['average_volatility'],
label=company)
plt.xlabel('Date')
plt.ylabel('Average Volatility')
plt.title('Average Volatility Trend per Company')
plt.xticks(rotation=40)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



As you can see from Average volatility trend per company, company COST is the most volatile company, and the average volatility number is 0.683444.

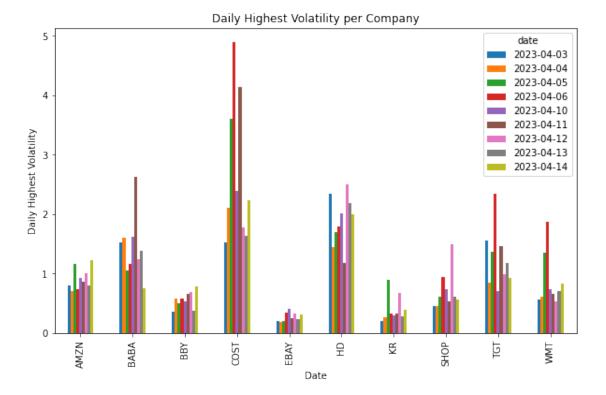
2) Graph the daily highest volatility per company, Do the findings from this graph support your conclusion from the first graph?¶

```
In [24]:
grouped_data = data.groupby(['company', 'date'])
['highest_volatility'].max().unstack()
grouped data
Out[24]:
       2023
              2023
                     2023
                             2023
                                    2023
                                           2023
                                                  2023
                                                          2023
                                                                 2023
       -04-
              -04-
                     -04-
                             -04-
                                    -04-
                                           -04-
                                                  -04-
                                                          -04-
                                                                 -04-
       03
              04
                     05
                                    10
                                                   12
                                                                 14
date
                             06
                                           11
                                                          13
comp
any
                             0.74
AMZ
       0.80
              0.71
                      1.16
                                    0.92
                                           0.86
                                                   1.01
                                                          0.80
                                                                 1.22
N
       0
              0
                     0
                             0
                                    0
                                           0
                                                  0
                                                          5
                                                                 0
BAB
       1.52
              1.59
                      1.05
                             1.17
                                    1.62
                                           2.62
                                                   1.24
                                                          1.38
                                                                 0.76
Α
       0
              8
                     0
                             0
                                    0
                                           5
                                                  0
                                                          0
                                                                 2
BBY
       0.35
              0.57
                     0.51
                             0.58
                                    0.53
                                           0.66
                                                  0.69
                                                          0.37
                                                                 0.79
              9
                                                  5
       7
                     0
                             0
                                    0
                                           0
                                                          2
                                                                 0
```

date	2023	2023	2023	2023	2023	2023	2023	2023	2023
	-04-	-04-	-04-	-04-	-04-	-04-	-04-	-04-	-04-
	03	04	05	06	10	11	12	13	14
comp any									
COST	1.53 0	2.11 1	3.60 0	4.89 0	2.39 0	4.14 0	1.78 0	1.64 0	2.23
EBAY	0.21	0.19	0.21	0.34	0.41	0.25	0.33	0.24	0.31
	0	0	0	0	0	0	0	0	0
HD	2.34	1.45	1.69	1.79	2.01	1.18	2.50	2.18	1.99
	5	0	5	5	0	0	0	5	2
KR	0.21	0.26	0.89	0.33	0.30	0.33	0.67	0.29	0.40
	0	0	0	0	0	0	0	0	0
SHO	0.45	0.46	0.60	0.94	0.74	0.53	1.50	0.62	0.57
P	0	0	9	0	0	0	0	0	2
TGT	1.56	0.85	1.37	2.34	0.70	1.47	0.99	1.18	0.92
	0	0	0	0	5	0	5	0	0
WMT	0.57	0.61	1.35	1.87	0.73	0.66	0.53	0.71	0.82
	0	0	0	5	3	0	0	0	9

In [39]:

```
fig, ax = plt.subplots(figsize=(10, 6))
grouped_data.plot(kind='bar', ax=ax)
plt.xlabel('Date')
plt.ylabel('Daily Highest Volatility')
plt.title('Daily Highest Volatility per Company')
plt.show()
```



Company COST exhibited the highest daily volatility, reaching approximately 5 on April 6, 2023. The second-highest daily volatility was observed on April 11, 2023, with a value of around 4. TGT had a daily highest volatility of approximately 2.5, while WMT recorded a daily highest volatility of approximately 2. Both TGT and WMT experienced their highest volatilizes on the same day as COST.

Therefore, these findings in the second chart are consistent with the conclusion reached in the first chart, which identifies COST companies as the most volatile companies based on the highest average volatility.