Biotech_Portfolio

September 29, 2021

1 Biotech Portfolio Risk and Returns

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import math

import warnings
warnings.filterwarnings("ignore")

# fix_yahoo_finance is used to fetch data
import fix_yahoo_finance as yf
yf.pdr_override()
```

[2]:
```
# input
# Biotech Stock
symbols =␣
 ↪['AXSM','BBIO','KOD','ABBV','CELG','EXEL','LGND','VRTX','INCY','NVS','LLY','MGNX','CALA','A
start = '2016-01-01'
end = '2019-01-01'
```

[3]:
```
df = yf.download(symbols,start,end)['Adj Close']
```

```
[*******************100%**********************]  15 of 15 downloaded
```

[4]:
```
#df = pd.DataFrame()
#for s in symbols:
#    df[s] = yf.download(s,start,end)['Adj Close']
```

[5]:
```
from datetime import datetime
from dateutil import relativedelta

d1 = datetime.strptime(start, "%Y-%m-%d")
d2 = datetime.strptime(end, "%Y-%m-%d")
delta = relativedelta.relativedelta(d2,d1)
print('How many years of investing?')
```

```python
print('%s years' % delta.years)
```

```
How many years of investing?
3 years
```

[6]:
```python
number_of_years = delta.years
```

[7]:
```python
days = (df.index[-1] - df.index[0]).days
days
```

[7]: 1092

[8]:
```python
df.head()
```

[8]:
```
                 ABBV  AGEN   AXSM  CALA        CELG  EXEL        INCY  KOD  \
2016-01-04  48.749779  4.46  12.19  7.44  117.620003  5.49  103.320000  NaN
2016-01-05  48.546680  4.43  14.98  7.79  117.959999  5.27  103.800003  NaN
2016-01-06  48.555145  4.25  14.47  7.04  116.709999  5.29  102.260002  NaN
2016-01-07  48.411289  3.89  12.45  6.41  111.889999  4.93   95.760002  NaN
2016-01-08  47.091213  3.78  11.86  5.98  108.980003  4.89   94.779999  NaN

                  LGND        LLY       MGNX  MRUS        NVS        VRTX
2016-01-04  102.470001  74.540886  29.410000   NaN  66.679474  122.889999
2016-01-05  100.650002  75.656258  28.520000   NaN  67.037170  123.449997
2016-01-06  102.019997  75.179520  27.620001   NaN  66.119591  122.230003
2016-01-07   98.620003  73.227615  26.070000   NaN  65.272011  114.959999
2016-01-08   97.919998  73.083710  24.820000   NaN  63.421318  110.709999
```

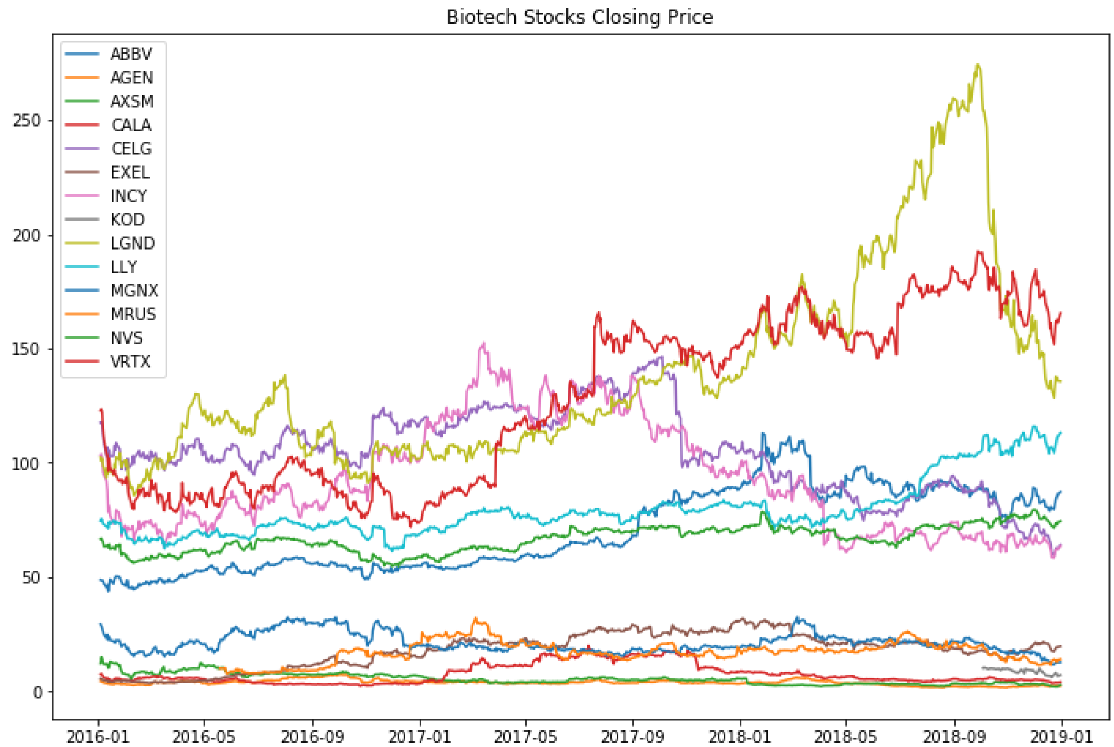
[9]:
```python
df.tail()
```

[9]:
```
                 ABBV  AGEN  AXSM  CALA       CELG       EXEL       INCY  \
2018-12-24  79.658409  2.22  2.15  3.72  59.209999  17.469999  58.500000
2018-12-26  84.277382  2.50  2.05  3.88  62.500000  18.950001  62.020000
2018-12-27  85.100853  2.39  2.00  3.78  62.810001  19.260000  62.340000
2018-12-28  86.246124  2.39  2.18  3.85  62.430000  19.440001  62.279999
2018-12-31  87.258888  2.38  2.82  4.01  64.089996  19.670000  63.590000

             KOD        LGND         LLY   MGNX    MRUS        NVS        VRTX
2018-12-24  7.34  128.360001  104.393227  11.75  13.965  71.598831  151.910004
2018-12-26  8.22  137.860001  108.637405  12.50  13.400  73.577797  161.839996
2018-12-27  7.25  136.889999  110.397659  12.59  12.800  72.970222  162.369995
2018-12-28  6.62  135.839996  111.678741  12.61  13.730  74.003105  161.419998
2018-12-31  7.10  135.699997  113.165184  12.70  14.000  74.480492  165.710007
```

[10]:
```python
plt.figure(figsize=(12,8))
plt.plot(df)
plt.title('Biotech Stocks Closing Price')
```

```
plt.legend(labels=df.columns)
```

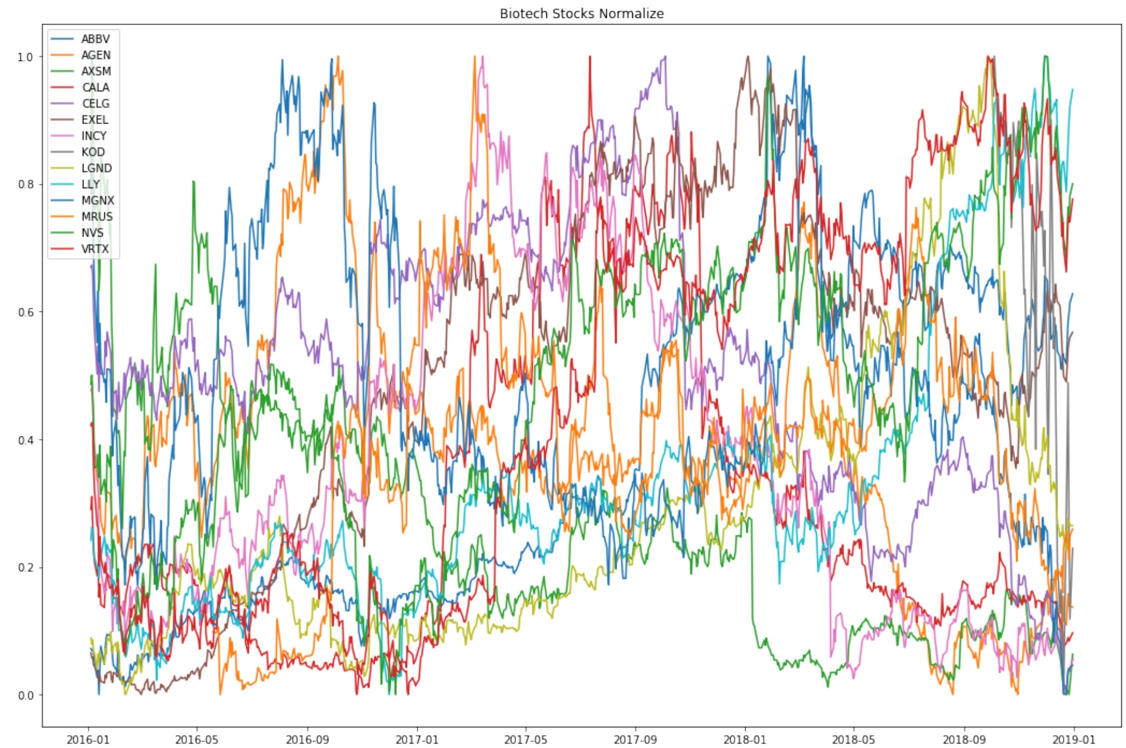
[10]: <matplotlib.legend.Legend at 0x1e1bca11b38>



[11]:
```
# Normalize the data
normalize = (df - df.min())/ (df.max() - df.min())
```

[12]:
```
plt.figure(figsize=(18,12))
plt.plot(normalize)
plt.title('Biotech Stocks Normalize')
plt.legend(labels=normalize.columns)
```

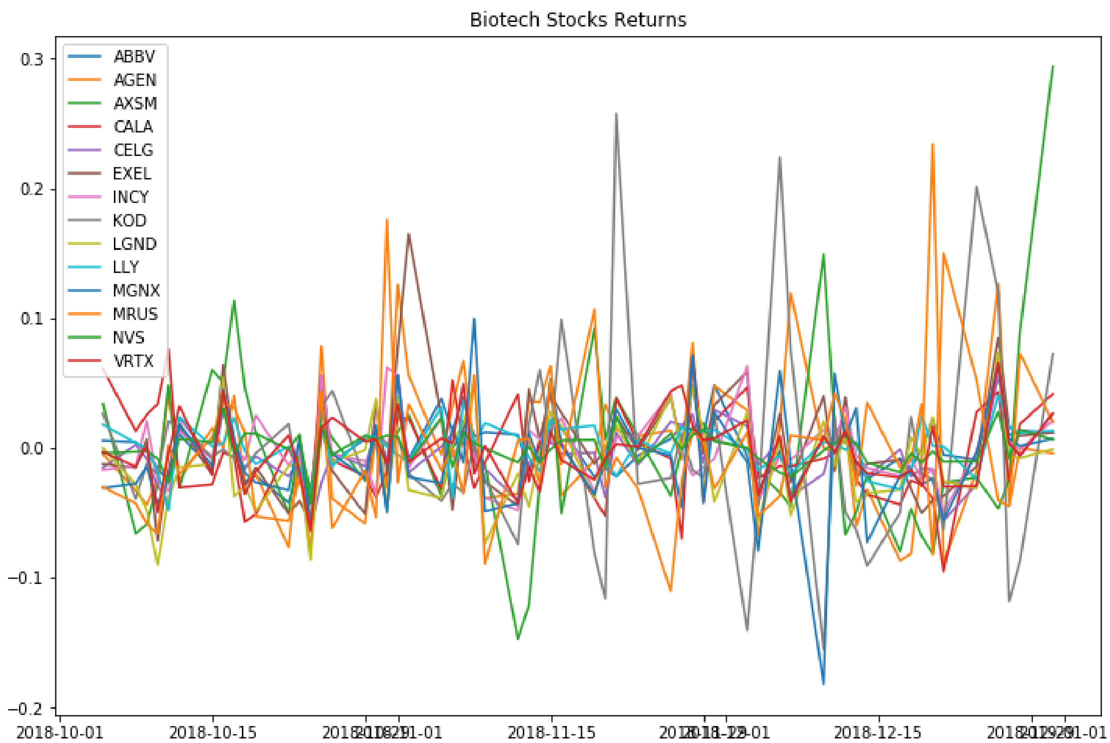
[12]: <matplotlib.legend.Legend at 0x1e1bfc81f28>



[13]:
```
stock_rets = df.pct_change().dropna()
```

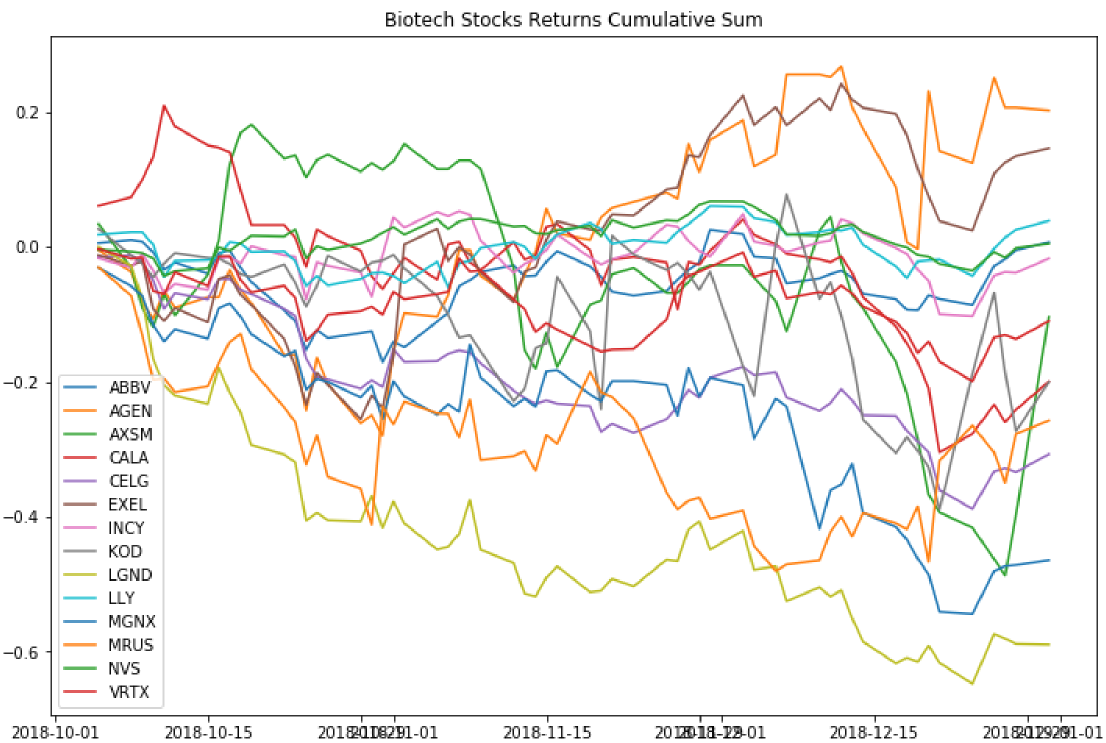
[14]:
```
plt.figure(figsize=(12,8))
plt.plot(stock_rets)
plt.title('Biotech Stocks Returns')
plt.legend(labels=stock_rets.columns)
```

[14]: <matplotlib.legend.Legend at 0x1e1bfa924a8>



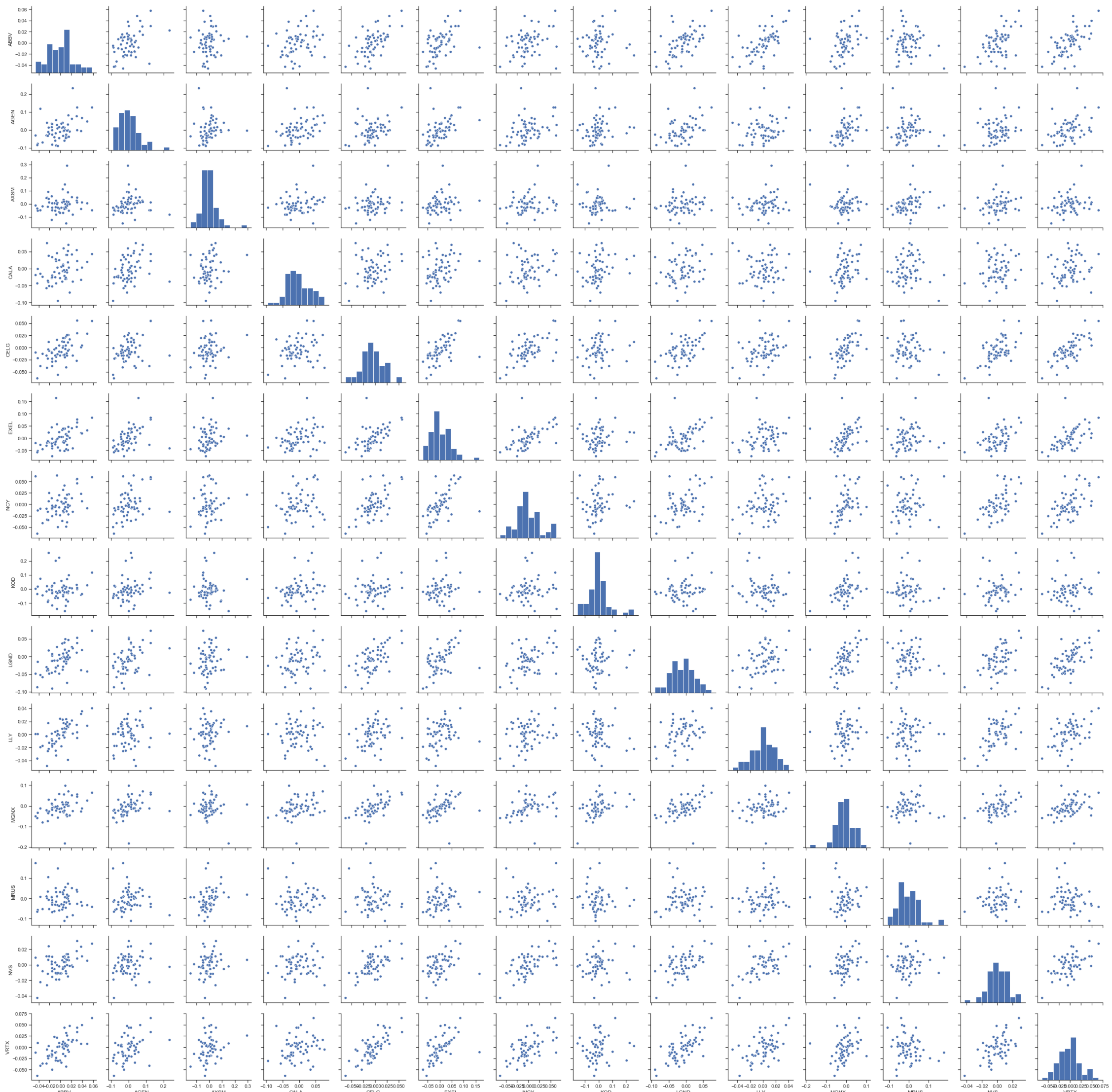
[15]:
```
plt.figure(figsize=(12,8))
plt.plot(stock_rets.cumsum())
plt.title('Biotech Stocks Returns Cumulative Sum')
plt.legend(labels=stock_rets.columns)
```

[15]: <matplotlib.legend.Legend at 0x1e1bfb0dda0>

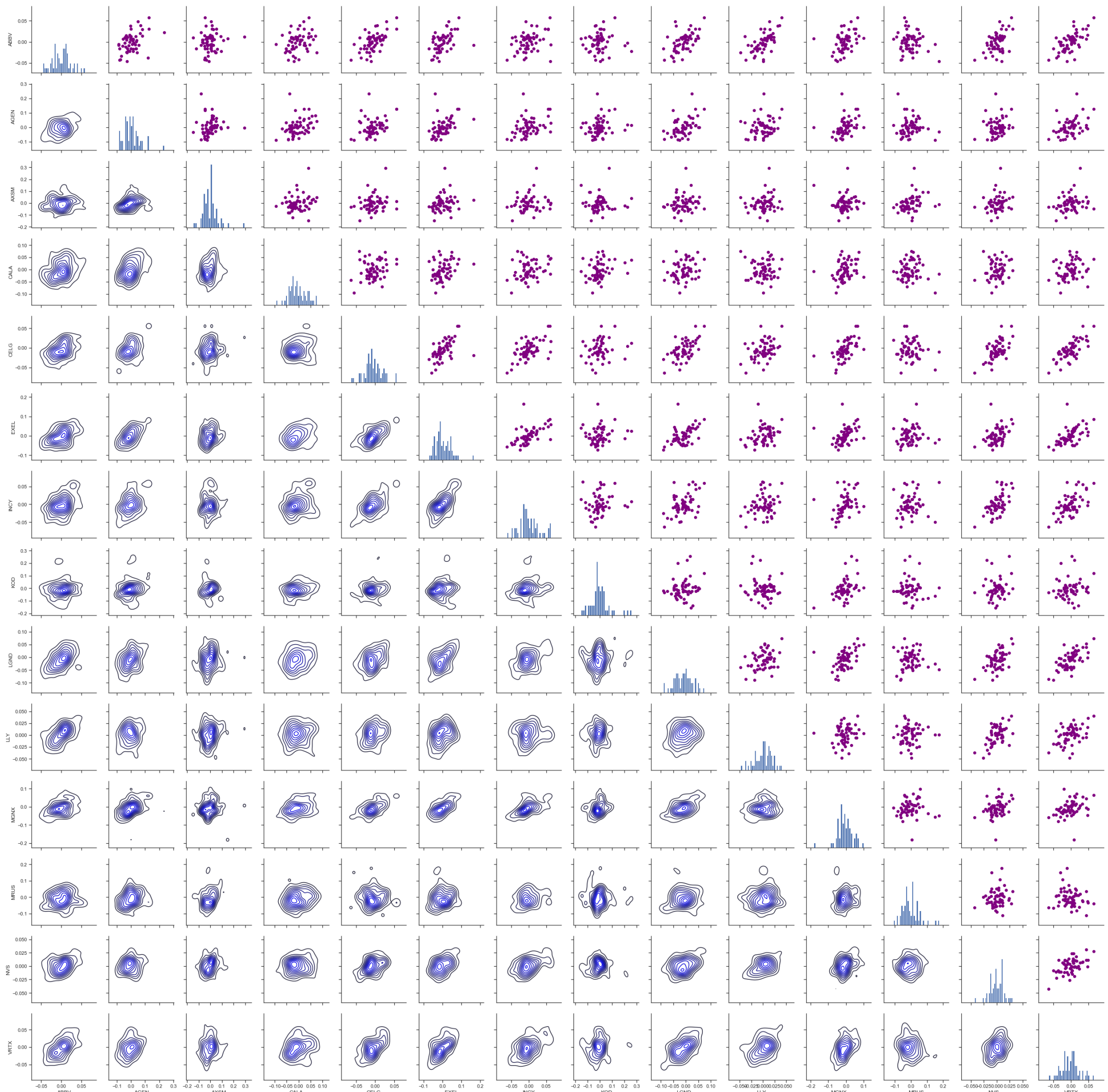


[16]:

```
sns.set(style='ticks')
ax = sns.pairplot(stock_rets, diag_kind='hist')

nplot = len(stock_rets.columns)
for i in range(nplot) :
    for j in range(nplot) :
        ax.axes[i, j].locator_params(axis='x', nbins=6, tight=True)
```

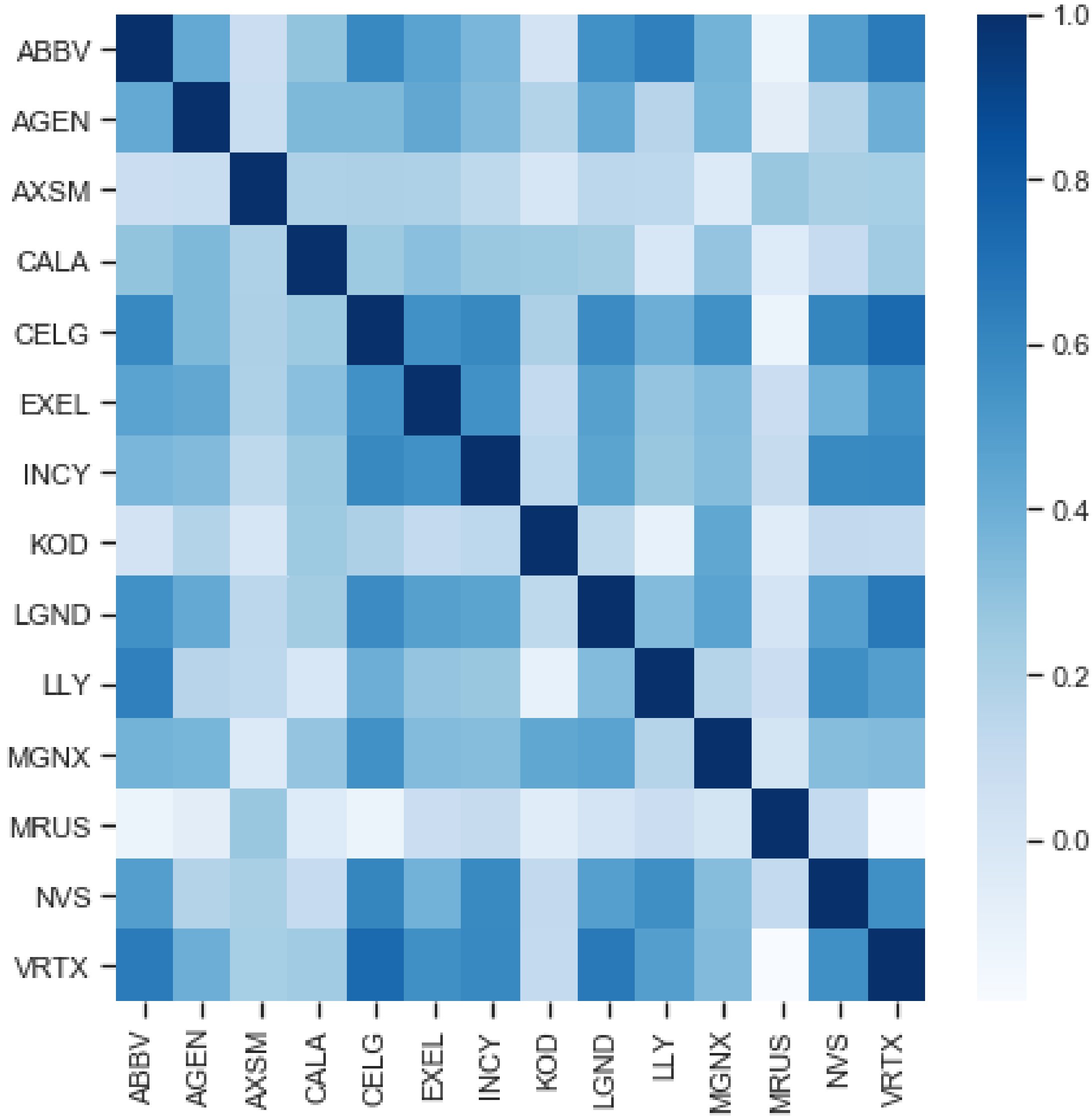


[17]:
```
ax = sns.PairGrid(stock_rets)
ax.map_upper(plt.scatter, color='purple')
ax.map_lower(sns.kdeplot, color='blue')
ax.map_diag(plt.hist, bins=30)
for i in range(nplot) :
    for j in range(nplot) :
        ax.axes[i, j].locator_params(axis='x', nbins=6, tight=True)
```



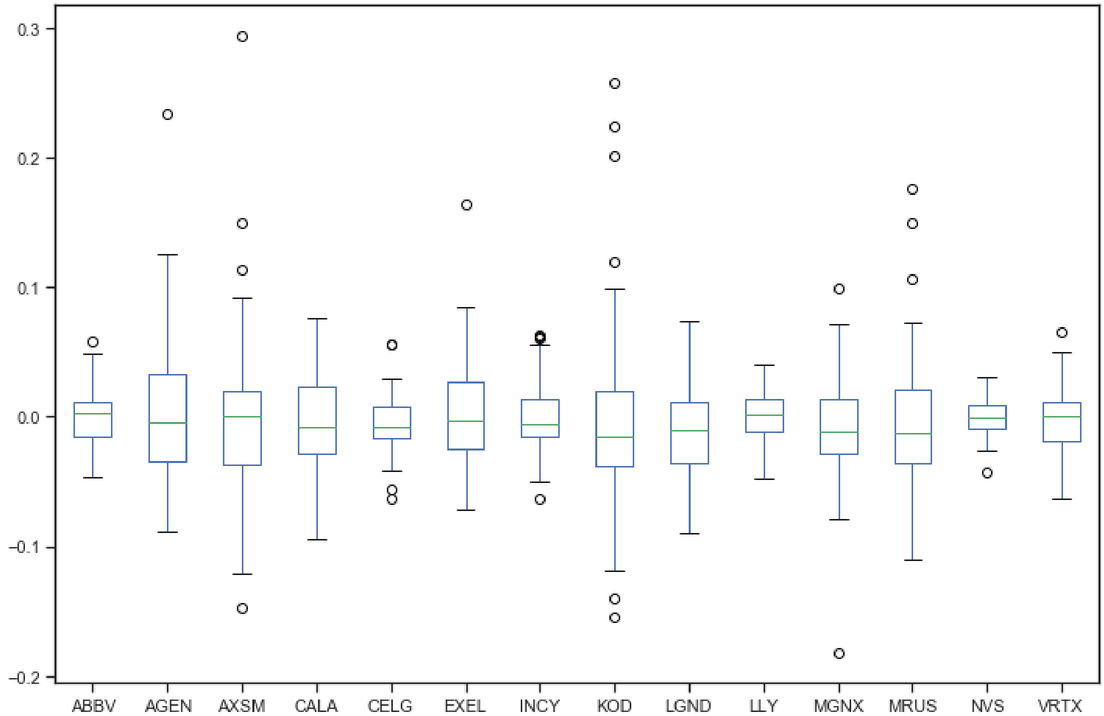
[18]:
```
plt.figure(figsize=(7,7))
corr = stock_rets.corr()

# plot the heatmap
sns.heatmap(corr,
        xticklabels=corr.columns,
        yticklabels=corr.columns,
            cmap="Blues")
```

[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1e1c7bbacc0>



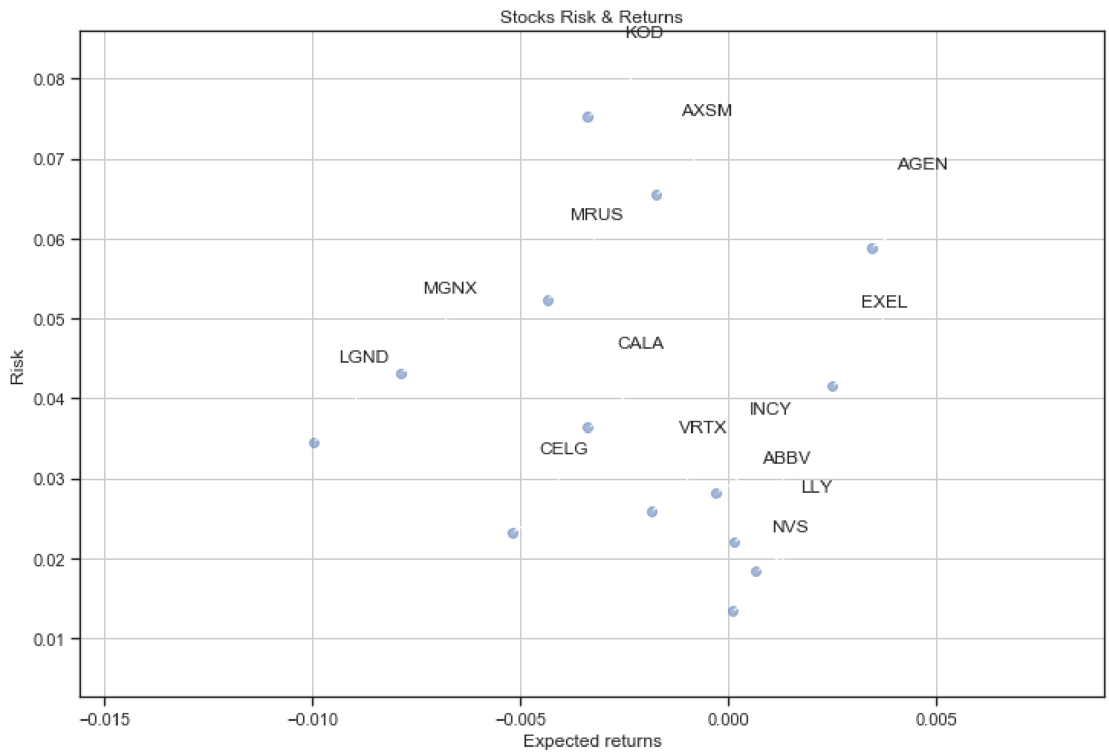
[19]:
```
# Box plot
stock_rets.plot(kind='box',figsize=(12,8))
```

[19]: <matplotlib.axes._subplots.AxesSubplot at 0x1e1c7d439b0>

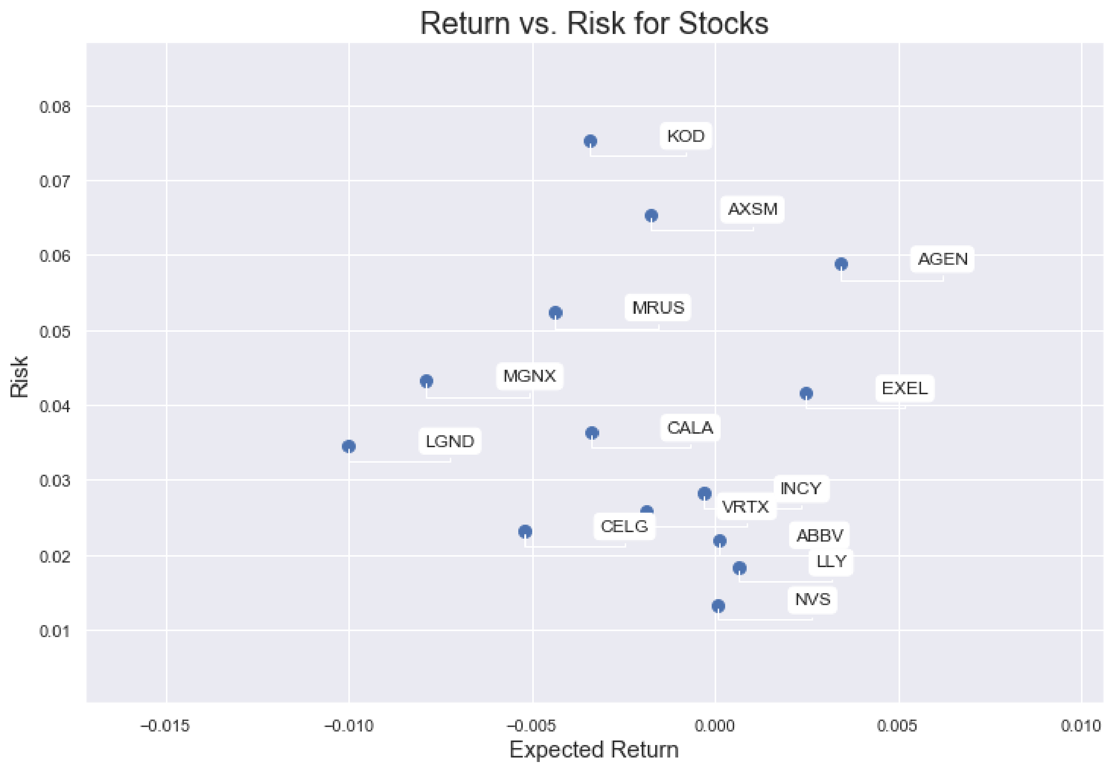


[20]:

```
rets = stock_rets.dropna()

plt.figure(figsize=(12,8))
plt.scatter(rets.mean(), rets.std(),alpha = 0.5)

plt.title('Stocks Risk & Returns')
plt.xlabel('Expected returns')
plt.ylabel('Risk')
plt.grid(which='major')

for label, x, y in zip(rets.columns, rets.mean(), rets.std()):
    plt.annotate(
        label,
        xy = (x, y), xytext = (50, 50),
        textcoords = 'offset points', ha = 'right', va = 'bottom',
        arrowprops = dict(arrowstyle = '-', connectionstyle = 'arc3,rad=-0.3'))
```



[21]:
```
rets = stock_rets.dropna()
area = np.pi*20.0

sns.set(style='darkgrid')
plt.figure(figsize=(12,8))
plt.scatter(rets.mean(), rets.std(), s=area)
plt.xlabel("Expected Return", fontsize=15)
plt.ylabel("Risk", fontsize=15)
plt.title("Return vs. Risk for Stocks", fontsize=20)

for label, x, y in zip(rets.columns, rets.mean(), rets.std()) :
    plt.annotate(label, xy=(x,y), xytext=(50, 0), textcoords='offset points',
                arrowprops=dict(arrowstyle='-',␣
↪connectionstyle='bar,angle=180,fraction=-0.2'),
                bbox=dict(boxstyle="round", fc="w"))
```



[22]:
```
rest_rets = rets.corr()
pair_value = rest_rets.abs().unstack()
pair_value.sort_values(ascending = False)
```

[22]:
```
VRTX  VRTX    1.000000
NVS   NVS     1.000000
AGEN  AGEN    1.000000
AXSM  AXSM    1.000000
CALA  CALA    1.000000
CELG  CELG    1.000000
EXEL  EXEL    1.000000
INCY  INCY    1.000000
KOD   KOD     1.000000
LGND  LGND    1.000000
LLY   LLY     1.000000
MGNX  MGNX    1.000000
MRUS  MRUS    1.000000
ABBV  ABBV    1.000000
CELG  VRTX    0.735707
VRTX  CELG    0.735707
      LGND    0.664595
LGND  VRTX    0.664595
ABBV  VRTX    0.654258
```

```
VRTX  ABBV    0.654258
LLY   ABBV    0.634248
ABBV  LLY     0.634248
CELG  NVS     0.607962
NVS   CELG    0.607962
ABBV  CELG    0.598175
CELG  ABBV    0.598175
VRTX  INCY    0.597989
INCY  VRTX    0.597989
CELG  INCY    0.592354
INCY  CELG    0.592354
                …
MRUS  INCY    0.102754
INCY  MRUS    0.102754
LLY   KOD     0.101754
KOD   LLY     0.101754
AGEN  AXSM    0.087025
AXSM  AGEN    0.087025
ABBV  AXSM    0.074573
AXSM  ABBV    0.074573
LLY   MRUS    0.073959
MRUS  LLY     0.073959
EXEL  MRUS    0.071352
MRUS  EXEL    0.071352
      AGEN    0.065702
AGEN  MRUS    0.065702
KOD   MRUS    0.057635
MRUS  KOD     0.057635
      CALA    0.038613
CALA  MRUS    0.038613
AXSM  MGNX    0.029837
MGNX  AXSM    0.029837
KOD   ABBV    0.024933
ABBV  KOD     0.024933
MGNX  MRUS    0.020743
MRUS  MGNX    0.020743
LGND  MRUS    0.015236
MRUS  LGND    0.015236
LLY   CALA    0.006927
CALA  LLY     0.006927
KOD   AXSM    0.002330
AXSM  KOD     0.002330
Length: 196, dtype: float64
```

[23]:

```
# Normalized Returns Data
Normalized_Value = ((rets[:] - rets[:].min()) /(rets[:].max() - rets[:].min()))
Normalized_Value.head()
```

[23]:
```
                 ABBV      AGEN      AXSM      CALA      CELG      EXEL  \
2018-10-05  0.496934  0.260546  0.411413  0.912454  0.405407  0.250824
2018-10-08  0.485389  0.173144  0.184530  0.631872  0.552197  0.238152
2018-10-09  0.417127  0.139580  0.200659  0.705798  0.461232  0.332349
2018-10-10  0.289753  0.196344  0.270291  0.754223  0.286939  0.000000
2018-10-11  0.195230  0.404217  0.443488  1.000000  0.181198  0.229940

                 INCY       KOD      LGND       LLY      MGNX      MRUS  \
2018-10-05  0.367630  0.440288  0.548427  0.743807  0.536610  0.280429
2018-10-08  0.389629  0.280529  0.377737  0.584142  0.548552  0.236645
2018-10-09  0.663593  0.346809  0.254886  0.539971  0.595148  0.181917
2018-10-10  0.301162  0.326862  0.000000  0.334588  0.492468  0.155004
2018-10-11  0.240395  0.425845  0.311657  0.000000  0.560285  0.392362

                  NVS      VRTX
2018-10-05  0.526441  0.469781
2018-10-08  0.540520  0.381482
2018-10-09  0.551555  0.506596
2018-10-10  0.470083  0.107777
2018-10-11  0.227780  0.459374
```

[24]:
```
Normalized_Value.corr()
```

[24]:
```
          ABBV      AGEN      AXSM      CALA      CELG      EXEL      INCY  \
ABBV  1.000000  0.427637  0.074573  0.285213  0.598175  0.465816  0.356005
AGEN  0.427637  1.000000  0.087025  0.342340  0.345060  0.436806  0.337058
AXSM  0.074573  0.087025  1.000000  0.189099  0.199882  0.196105  0.135618
CALA  0.285213  0.342340  0.189099  1.000000  0.254609  0.310993  0.265098
CELG  0.598175  0.345060  0.199882  0.254609  1.000000  0.553212  0.592354
EXEL  0.465816  0.436806  0.196105  0.310993  0.553212  1.000000  0.552299
INCY  0.356005  0.337058  0.135618  0.265098  0.592354  0.552299  1.000000
KOD   0.024933  0.173264 -0.002330  0.253076  0.197497  0.109840  0.137852
LGND  0.554322  0.428031  0.144460  0.234095  0.577354  0.479638  0.457564
LLY   0.634248  0.159665  0.137731 -0.006927  0.400445  0.282657  0.267662
MGNX  0.376768  0.364712 -0.029837  0.282364  0.553380  0.334307  0.319333
MRUS -0.127805 -0.065702  0.266485 -0.038613 -0.128139  0.071352  0.102754
NVS   0.488510  0.172740  0.210610  0.106105  0.607962  0.378964  0.588543
VRTX  0.654258  0.398961  0.222292  0.241100  0.735707  0.557054  0.597989

           KOD      LGND       LLY      MGNX      MRUS       NVS      VRTX
ABBV  0.024933  0.554322  0.634248  0.376768 -0.127805  0.488510  0.654258
AGEN  0.173264  0.428031  0.159665  0.364712 -0.065702  0.172740  0.398961
AXSM -0.002330  0.144460  0.137731 -0.029837  0.266485  0.210610  0.222292
CALA  0.253076  0.234095 -0.006927  0.282364 -0.038613  0.106105  0.241100
CELG  0.197497  0.577354  0.400445  0.553380 -0.128139  0.607962  0.735707
EXEL  0.109840  0.479638  0.282657  0.334307  0.071352  0.378964  0.557054
INCY  0.137852  0.457564  0.267662  0.319333  0.102754  0.588543  0.597989
```

```
KOD   1.000000  0.132109 -0.101754  0.443014 -0.057635  0.114513  0.111953
LGND  0.132109  1.000000  0.334433  0.464213  0.015236  0.482527  0.664595
LLY  -0.101754  0.334433  1.000000  0.167876  0.073959  0.560906  0.489926
MGNX  0.443014  0.464213  0.167876  1.000000  0.020743  0.319734  0.339228
MRUS -0.057635  0.015236  0.073959  0.020743  1.000000  0.110201 -0.196105
NVS   0.114513  0.482527  0.560906  0.319734  0.110201  1.000000  0.559522
VRTX  0.111953  0.664595  0.489926  0.339228 -0.196105  0.559522  1.000000
```

[25]:

```
normalized_rets = Normalized_Value.corr()
normalized_pair_value = normalized_rets.abs().unstack()
normalized_pair_value.sort_values(ascending = False)
```

[25]:

```
VRTX  VRTX    1.000000
NVS   NVS     1.000000
AGEN  AGEN    1.000000
AXSM  AXSM    1.000000
CALA  CALA    1.000000
CELG  CELG    1.000000
EXEL  EXEL    1.000000
INCY  INCY    1.000000
KOD   KOD     1.000000
LGND  LGND    1.000000
LLY   LLY     1.000000
MGNX  MGNX    1.000000
MRUS  MRUS    1.000000
ABBV  ABBV    1.000000
CELG  VRTX    0.735707
VRTX  CELG    0.735707
      LGND    0.664595
LGND  VRTX    0.664595
ABBV  VRTX    0.654258
VRTX  ABBV    0.654258
LLY   ABBV    0.634248
ABBV  LLY     0.634248
CELG  NVS     0.607962
NVS   CELG    0.607962
ABBV  CELG    0.598175
CELG  ABBV    0.598175
VRTX  INCY    0.597989
INCY  VRTX    0.597989
CELG  INCY    0.592354
INCY  CELG    0.592354
                …
MRUS  INCY    0.102754
INCY  MRUS    0.102754
LLY   KOD     0.101754
KOD   LLY     0.101754
```

```
AGEN  AXSM    0.087025
AXSM  AGEN    0.087025
ABBV  AXSM    0.074573
AXSM  ABBV    0.074573
LLY   MRUS    0.073959
MRUS  LLY     0.073959
EXEL  MRUS    0.071352
MRUS  EXEL    0.071352
      AGEN    0.065702
AGEN  MRUS    0.065702
KOD   MRUS    0.057635
MRUS  KOD     0.057635
      CALA    0.038613
CALA  MRUS    0.038613
AXSM  MGNX    0.029837
MGNX  AXSM    0.029837
KOD   ABBV    0.024933
ABBV  KOD     0.024933
MGNX  MRUS    0.020743
MRUS  MGNX    0.020743
LGND  MRUS    0.015236
MRUS  LGND    0.015236
LLY   CALA    0.006927
CALA  LLY     0.006927
KOD   AXSM    0.002330
AXSM  KOD     0.002330
Length: 196, dtype: float64
```

[26]:

```
print("Stock returns: ")
print(rets.mean())
print('-' * 50)
print("Stock risks:")
print(rets.std())
```

```
Stock returns:
ABBV    0.000118
AGEN    0.003431
AXSM   -0.001757
CALA   -0.003385
CELG   -0.005209
EXEL    0.002482
INCY   -0.000291
KOD    -0.003397
LGND   -0.009992
LLY     0.000657
MGNX   -0.007873
MRUS   -0.004364
```

```
NVS      0.000080
VRTX    -0.001864
dtype: float64
--------------------------------------------------
Stock risks:
ABBV     0.022021
AGEN     0.058816
AXSM     0.065432
CALA     0.036324
CELG     0.023185
EXEL     0.041567
INCY     0.028192
KOD      0.075263
LGND     0.034577
LLY      0.018396
MGNX     0.043203
MRUS     0.052393
NVS      0.013347
VRTX     0.025864
dtype: float64
```

[27]:

```python
table = pd.DataFrame()
table['Returns'] = rets.mean()
table['Risk'] = rets.std()
table.sort_values(by='Returns')
```

[27]:

	Returns	Risk
LGND	-0.009992	0.034577
MGNX	-0.007873	0.043203
CELG	-0.005209	0.023185
MRUS	-0.004364	0.052393
KOD	-0.003397	0.075263
CALA	-0.003385	0.036324
VRTX	-0.001864	0.025864
AXSM	-0.001757	0.065432
INCY	-0.000291	0.028192
NVS	0.000080	0.013347
ABBV	0.000118	0.022021
LLY	0.000657	0.018396
EXEL	0.002482	0.041567
AGEN	0.003431	0.058816

[28]:

```python
table.sort_values(by='Risk')
```

[28]:

	Returns	Risk
NVS	0.000080	0.013347
LLY	0.000657	0.018396

```
ABBV  0.000118  0.022021
CELG -0.005209  0.023185
VRTX -0.001864  0.025864
INCY -0.000291  0.028192
LGND -0.009992  0.034577
CALA -0.003385  0.036324
EXEL  0.002482  0.041567
MGNX -0.007873  0.043203
MRUS -0.004364  0.052393
AGEN  0.003431  0.058816
AXSM -0.001757  0.065432
KOD  -0.003397  0.075263
```

[29]:
```
rf = 0.01
table['Sharpe Ratio'] = (table['Returns'] - rf) / table['Risk']
table
```

[29]:
```
       Returns      Risk  Sharpe Ratio
ABBV  0.000118  0.022021     -0.448765
AGEN  0.003431  0.058816     -0.111694
AXSM -0.001757  0.065432     -0.179680
CALA -0.003385  0.036324     -0.368482
CELG -0.005209  0.023185     -0.655988
EXEL  0.002482  0.041567     -0.180867
INCY -0.000291  0.028192     -0.365033
KOD  -0.003397  0.075263     -0.178010
LGND -0.009992  0.034577     -0.578186
LLY   0.000657  0.018396     -0.507891
MGNX -0.007873  0.043203     -0.413701
MRUS -0.004364  0.052393     -0.274157
NVS   0.000080  0.013347     -0.743256
VRTX -0.001864  0.025864     -0.458699
```

[30]:
```
table['Max Returns'] = rets.max()
```

[31]:
```
table['Min Returns'] = rets.min()
```

[32]:
```
table['Median Returns'] = rets.median()
```

[33]:
```
total_return = stock_rets[-1:].transpose()
table['Total Return'] = 100 * total_return
table
```

[33]:
```
       Returns      Risk  Sharpe Ratio  Max Returns  Min Returns  \
ABBV  0.000118  0.022021     -0.448765     0.057985    -0.045839
AGEN  0.003431  0.058816     -0.111694     0.233831    -0.088710
AXSM -0.001757  0.065432     -0.179680     0.293578    -0.147287
```

```
CALA -0.003385  0.036324     -0.368482     0.075862    -0.095000
CELG -0.005209  0.023185     -0.655988     0.056006    -0.063432
EXEL  0.002482  0.041567     -0.180867     0.164548    -0.071551
INCY -0.000291  0.028192     -0.365033     0.063346    -0.063346
KOD  -0.003397  0.075263     -0.178010     0.257400    -0.155000
LGND -0.009992  0.034577     -0.578186     0.074011    -0.090059
LLY   0.000657  0.018396     -0.507891     0.040656    -0.047909
MGNX -0.007873  0.043203     -0.413701     0.099398    -0.181597
MRUS -0.004364  0.052393     -0.274157     0.175549    -0.110269
NVS   0.000080  0.013347     -0.743256     0.030908    -0.042722
VRTX -0.001864  0.025864     -0.458699     0.065368    -0.063616

      Median Returns  Total Return
ABBV        0.002827      1.174272
AGEN       -0.003802     -0.418410
AXSM        0.000000     29.357798
CALA       -0.008147      4.155844
CELG       -0.008344      2.658972
EXEL       -0.003043      1.183122
INCY       -0.005289      2.103406
KOD        -0.015167      7.250755
LGND       -0.010718     -0.103062
LLY         0.001650      1.330999
MGNX       -0.011316      0.713719
MRUS       -0.012640      1.966497
NVS        -0.000224      0.645090
VRTX        0.000162      2.657669
```

[34]:
```python
table['Average Return Yearly'] = (1 + total_return)**(1 / number_of_years) - 1
table
```

[34]:
```
       Returns      Risk  Sharpe Ratio  Max Returns  Min Returns  \
ABBV  0.000118  0.022021     -0.448765     0.057985    -0.045839
AGEN  0.003431  0.058816     -0.111694     0.233831    -0.088710
AXSM -0.001757  0.065432     -0.179680     0.293578    -0.147287
CALA -0.003385  0.036324     -0.368482     0.075862    -0.095000
CELG -0.005209  0.023185     -0.655988     0.056006    -0.063432
EXEL  0.002482  0.041567     -0.180867     0.164548    -0.071551
INCY -0.000291  0.028192     -0.365033     0.063346    -0.063346
KOD  -0.003397  0.075263     -0.178010     0.257400    -0.155000
LGND -0.009992  0.034577     -0.578186     0.074011    -0.090059
LLY   0.000657  0.018396     -0.507891     0.040656    -0.047909
MGNX -0.007873  0.043203     -0.413701     0.099398    -0.181597
MRUS -0.004364  0.052393     -0.274157     0.175549    -0.110269
NVS   0.000080  0.013347     -0.743256     0.030908    -0.042722
VRTX -0.001864  0.025864     -0.458699     0.065368    -0.063616
```

	Median Returns	Total Return	Average Return Yearly
ABBV	0.002827	1.174272	0.003899
AGEN	-0.003802	-0.418410	-0.001397
AXSM	0.000000	29.357798	0.089593
CALA	-0.008147	4.155844	0.013665
CELG	-0.008344	2.658972	0.008786
EXEL	-0.003043	1.183122	0.003928
INCY	-0.005289	2.103406	0.006963
KOD	-0.015167	7.250755	0.023607
LGND	-0.010718	-0.103062	-0.000344
LLY	0.001650	1.330999	0.004417
MGNX	-0.011316	0.713719	0.002373
MRUS	-0.012640	1.966497	0.006512
NVS	-0.000224	0.645090	0.002146
VRTX	0.000162	2.657669	0.008782

[35]:
```
initial_value = df.iloc[0]
ending_value = df.iloc[-1]
table['CAGR'] = ((ending_value / initial_value) ** (252.0 / days)) -1
table
```

[35]:

	Returns	Risk	Sharpe Ratio	Max Returns	Min Returns	\
ABBV	0.000118	0.022021	-0.448765	0.057985	-0.045839	
AGEN	0.003431	0.058816	-0.111694	0.233831	-0.088710	
AXSM	-0.001757	0.065432	-0.179680	0.293578	-0.147287	
CALA	-0.003385	0.036324	-0.368482	0.075862	-0.095000	
CELG	-0.005209	0.023185	-0.655988	0.056006	-0.063432	
EXEL	0.002482	0.041567	-0.180867	0.164548	-0.071551	
INCY	-0.000291	0.028192	-0.365033	0.063346	-0.063346	
KOD	-0.003397	0.075263	-0.178010	0.257400	-0.155000	
LGND	-0.009992	0.034577	-0.578186	0.074011	-0.090059	
LLY	0.000657	0.018396	-0.507891	0.040656	-0.047909	
MGNX	-0.007873	0.043203	-0.413701	0.099398	-0.181597	
MRUS	-0.004364	0.052393	-0.274157	0.175549	-0.110269	
NVS	0.000080	0.013347	-0.743256	0.030908	-0.042722	
VRTX	-0.001864	0.025864	-0.458699	0.065368	-0.063616	

	Median Returns	Total Return	Average Return Yearly	CAGR
ABBV	0.002827	1.174272	0.003899	0.143792
AGEN	-0.003802	-0.418410	-0.001397	-0.134921
AXSM	0.000000	29.357798	0.089593	-0.286675
CALA	-0.008147	4.155844	0.013665	-0.132928
CELG	-0.008344	2.658972	0.008786	-0.130743
EXEL	-0.003043	1.183122	0.003928	0.342455
INCY	-0.005289	2.103406	0.006963	-0.105964
KOD	-0.015167	7.250755	0.023607	NaN
LGND	-0.010718	-0.103062	-0.000344	0.066964

LLY	0.001650	1.330999	0.004417	0.101140
MGNX	-0.011316	0.713719	0.002373	-0.176165
MRUS	-0.012640	1.966497	0.006512	NaN
NVS	-0.000224	0.645090	0.002146	0.025861
VRTX	0.000162	2.657669	0.008782	0.071424

[36]:
```
table.sort_values(by='Average Return Yearly')
```

[36]:

	Returns	Risk	Sharpe Ratio	Max Returns	Min Returns \
AGEN	0.003431	0.058816	-0.111694	0.233831	-0.088710
LGND	-0.009992	0.034577	-0.578186	0.074011	-0.090059
NVS	0.000080	0.013347	-0.743256	0.030908	-0.042722
MGNX	-0.007873	0.043203	-0.413701	0.099398	-0.181597
ABBV	0.000118	0.022021	-0.448765	0.057985	-0.045839
EXEL	0.002482	0.041567	-0.180867	0.164548	-0.071551
LLY	0.000657	0.018396	-0.507891	0.040656	-0.047909
MRUS	-0.004364	0.052393	-0.274157	0.175549	-0.110269
INCY	-0.000291	0.028192	-0.365033	0.063346	-0.063346
VRTX	-0.001864	0.025864	-0.458699	0.065368	-0.063616
CELG	-0.005209	0.023185	-0.655988	0.056006	-0.063432
CALA	-0.003385	0.036324	-0.368482	0.075862	-0.095000
KOD	-0.003397	0.075263	-0.178010	0.257400	-0.155000
AXSM	-0.001757	0.065432	-0.179680	0.293578	-0.147287

	Median Returns	Total Return	Average Return Yearly	CAGR
AGEN	-0.003802	-0.418410	-0.001397	-0.134921
LGND	-0.010718	-0.103062	-0.000344	0.066964
NVS	-0.000224	0.645090	0.002146	0.025861
MGNX	-0.011316	0.713719	0.002373	-0.176165
ABBV	0.002827	1.174272	0.003899	0.143792
EXEL	-0.003043	1.183122	0.003928	0.342455
LLY	0.001650	1.330999	0.004417	0.101140
MRUS	-0.012640	1.966497	0.006512	NaN
INCY	-0.005289	2.103406	0.006963	-0.105964
VRTX	0.000162	2.657669	0.008782	0.071424
CELG	-0.008344	2.658972	0.008786	-0.130743
CALA	-0.008147	4.155844	0.013665	-0.132928
KOD	-0.015167	7.250755	0.023607	NaN
AXSM	0.000000	29.357798	0.089593	-0.286675