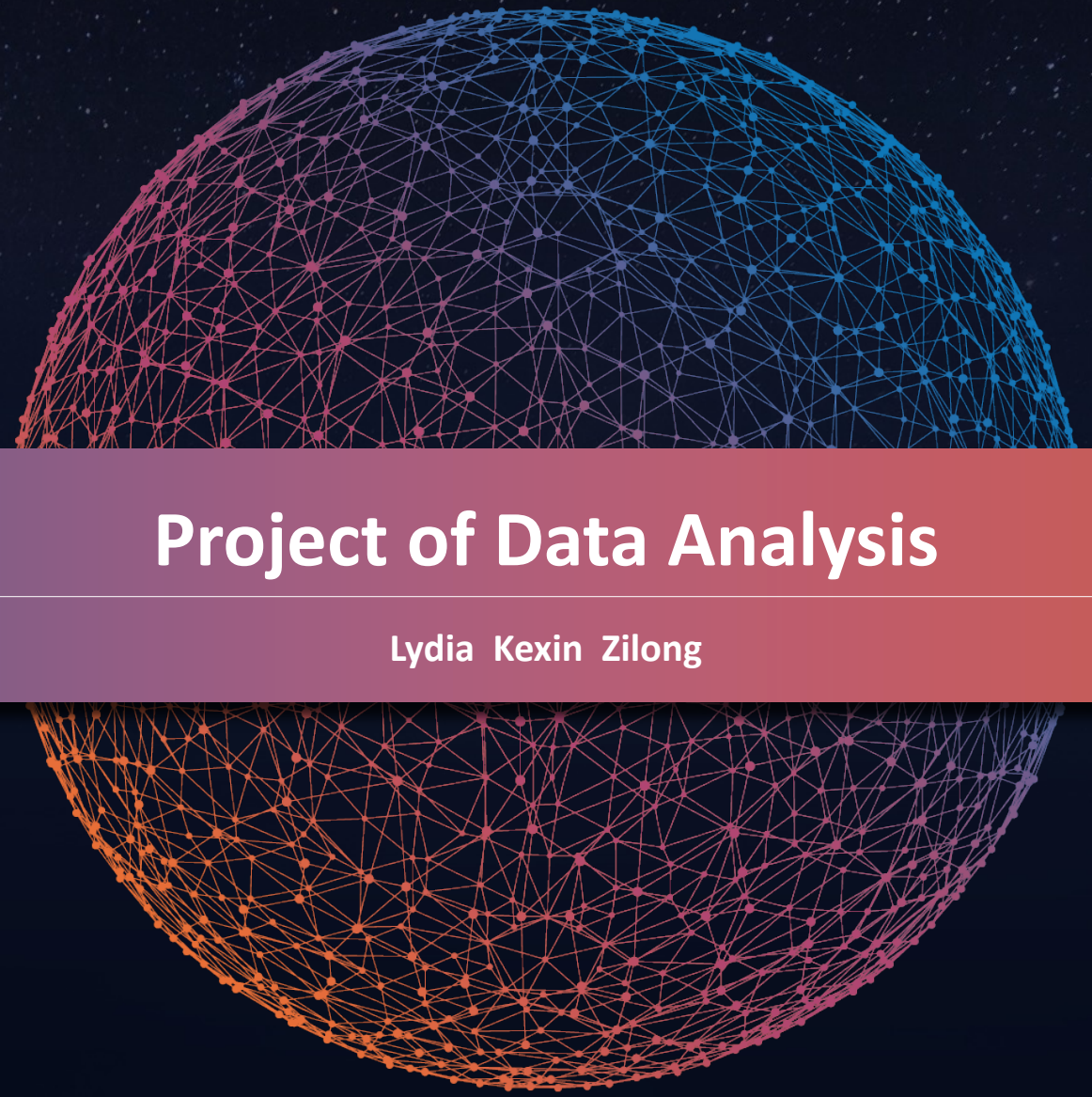

Project of Data Analysis

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Contents

1

Background of stocks and index

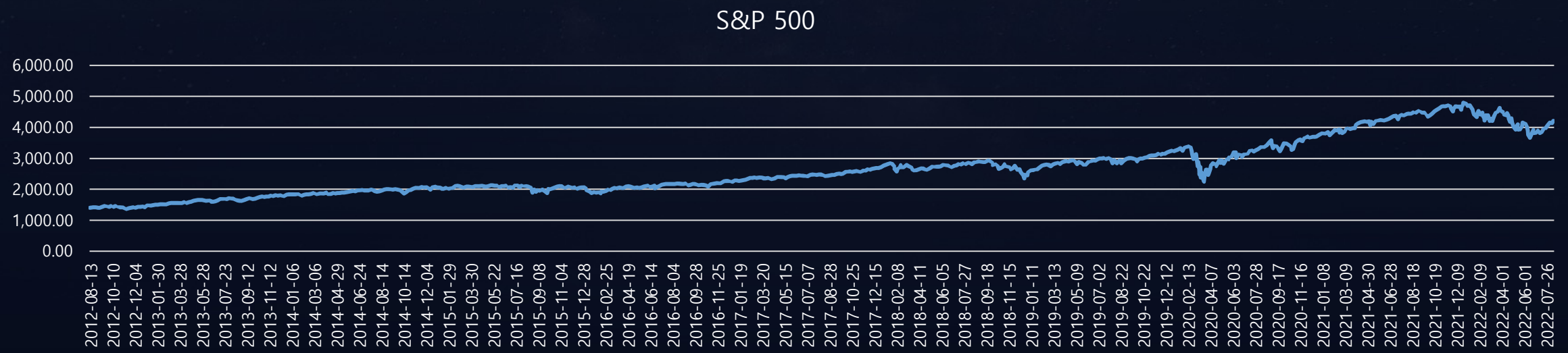
1-1 S&P 500

1-2 JNJ.N

1-3 PFE.N

1-1 S&P 500

- ✓ Containing 500 stocks in US stock market.
- ✓ One of the most authoritative index of US market, even in the world.
- ✓ The chosen stocks would be changed if they are not good or representative.
- ✓ This index can reflect the whole economic situation of US.



- We can see S&P500 has increased a lot steadily in last 10 years with two drops in Covid 19 period and 2022
- In last 10 years, the index increased by almost 2 times of its value in 2012.

1-2 JNJ.N

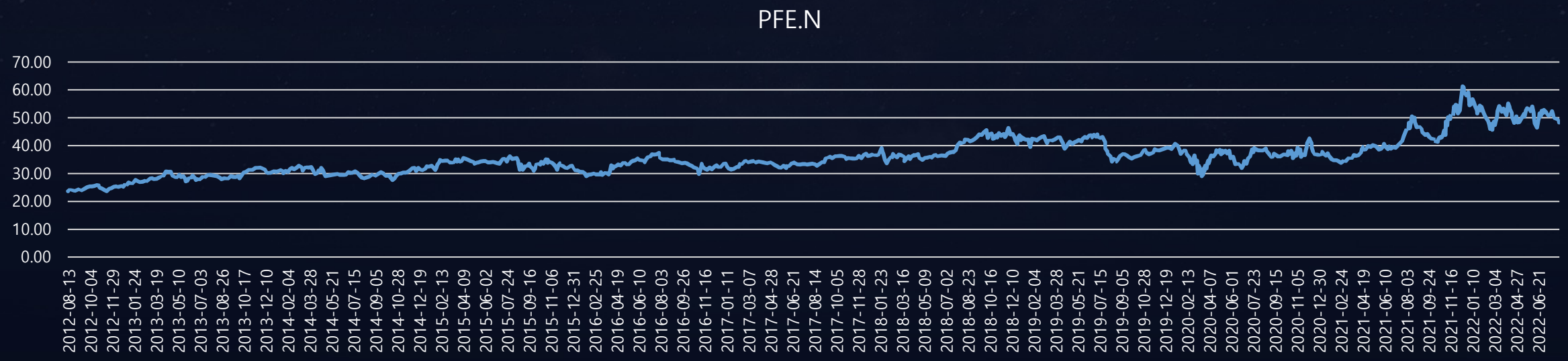
- ✓ One of the the most comprehensive and powerful medical company in the world.
- ✓ Containing various kinds of products, including care products, medicine, vaccine and medical equipment.
- ✓ Ranking 107 in the Fortune 500 in 2022.

・We can see that the JNJ.N has increased a lot steadily in last 10 years with a drop and a quick rebound in Covid 19 period.

・In last 10 years, the stock increased by almost 1.5 times of its value in 2012.

1-3 PFE.N

- ✓ A basic, innovative medical company which focuses on its patients.
- ✓ The vaccine of Covid-19 made by PFE.N is very famous in the world.
- ✓ Ranking 1 in the medical companies in 2022.



· We can see that PFE.N dropped during 2020 because of the pandemic and increased a lot during 2021 because the vaccine were made.

· In last 10 years, the stock increased by almost 1 time of its value in 2012.

2

Univariate Series

2-1 Serial Correlation of Returns

2-2 Serial Correlation of Squared Returns

2-3 Zero Mean

2-4 Volatility Variation

2-5 Returns Analysis

2-6 Correlation Between Variance and Returns

2-7 Skewness

2-8 Volatility Clustering

2-1 Serial Correlation

Fact : Return series are not independent and identically distributed (iid), although they show little serial correlation.

$$Corr(R_t, R_{t-\tau}) \approx 0,\ \tau = 1, \ldots 100$$

```python
def corr(lst1,lst2):
    a=len(lst1)
    b=len(lst2)
    if a>b:
        lst1=lst1[:b]
        a=b
    elif a<b:
        lst2=lst2[:a]
        b=a
    av_1=sum(lst1)/a
    av_2=sum(lst2)/b
    cov=sum([(x-av_1)*(y-av_2)for x,y in zip(lst1,lst2)])
    sq=(sum([(x-av_1)**2 for x in lst1])*sum([(y-av_2)**2 for y in lst2]))**0.5
    return cov/sq
```

Defining a corr function in Python

```
In [57]: cor=[]

In [60]: for i in range(1,101):
             lst=lst0[i:]
             cor.append(corr(lst,lst0))

In [61]: cor

Out[61]: [0.02093012206410876,
          -0.02217694306323787,
          0.016535710417195,
          0.04295273239111863,
          -0.024892165151931954,
          -0.07307457846231424,
          0.023411646753522863,
          0.025134288297975503,
          0.023343258623786525,
          -0.024897814353422507,
          -0.004984234185886553,
          -0.006242845344166463,
          0.041746626962982904,
          -0.08337505802862685,
          0.006880440630297455,
          0.014863621698385149,
          0.023627414459571474,
          0.007199817784332009,
          -0.01765758974183279,
```

Output Result in Python

2-2 Serial Correlation of Squared Returns

Fact : Series of absolute or squared returns show profound serial correlation.

In [84]:
```
cor=[]
for i in range(1,101):
    lst=lst0[i:]
    cor.append(corr([x**2 for x in lst0],[x**2 for x in lst]))
```

In [85]:
```
cor
```

```
0.13974288924707914,
0.10308320968748973,
0.12063205430733971,
0.0947723559082946,
0.13765913942265165,
0.0645795564461952,
0.12619886108166103,
0.18365360951724807,
0.14826851725878745,
0.16207872197758033,
0.11339866755345031,
0.16302385403870714,
0.14185538027181058,
0.1806785250882353,
0.14454861496617744,
0.10890389911297471,
0.20007161178482943,
0.08775405663771042,
0.13079170098596227,
```

2-2 Serial Correlation of Squared Returns

Results

S&P 500

cor(R(t)_sq, R(t-1)_sq):	43.962%
cor(R(t)_sq, R(t-2)_sq):	43.326%
cor(R(t)_sq, R(t-3)_sq):	32.914%
cor(R(t)_sq, R(t-4)_sq):	31.336%
cor(R(t)_sq, R(t-5)_sq):	26.359%
cor(R(t)_sq, R(t-6)_sq):	29.293%
cor(R(t)_sq, R(t-7)_sq):	34.671%
cor(R(t)_sq, R(t-8)_sq):	36.383%
cor(R(t)_sq, R(t-9)_sq):	22.146%
cor(R(t)_sq, R(t-10)_sq):	32.983%
cor(R(t)_sq, R(t-11)_sq):	18.482%
cor(R(t)_sq, R(t-12)_sq):	12.297%
cor(R(t)_sq, R(t-13)_sq):	16.717%
cor(R(t)_sq, R(t-14)_sq):	16.643%
cor(R(t)_sq, R(t-15)_sq):	10.066%
cor(R(t)_sq, R(t-16)_sq):	10.529%
cor(R(t)_sq, R(t-17)_sq):	6.556%
cor(R(t)_sq, R(t-18)_sq):	13.282%
cor(R(t)_sq, R(t-19)_sq):	4.905%
cor(R(t)_sq, R(t-20)_sq):	9.223%
cor(R(t)_sq, R(t-21)_sq):	6.262%
cor(R(t)_sq, R(t-22)_sq):	4.644%
cor(R(t)_sq, R(t-23)_sq):	4.277%
cor(R(t)_sq, R(t-24)_sq):	6.810%
cor(R(t)_sq, R(t-25)_sq):	3.824%
cor(R(t)_sq, R(t-26)_sq):	6.049%
cor(R(t)_sq, R(t-27)_sq):	3.721%
cor(R(t)_sq, R(t-28)_sq):	3.698%
cor(R(t)_sq, R(t-29)_sq):	2.719%

JNJ.N

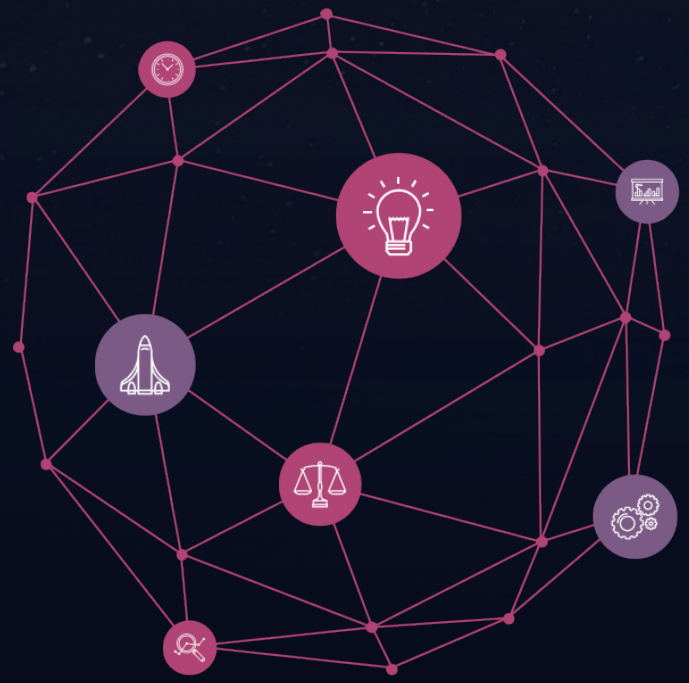
cor(R(t)_sq, R(t-1)_sq):	15.368%
cor(R(t)_sq, R(t-2)_sq):	28.789%
cor(R(t)_sq, R(t-3)_sq):	20.900%
cor(R(t)_sq, R(t-4)_sq):	19.791%
cor(R(t)_sq, R(t-5)_sq):	24.856%
cor(R(t)_sq, R(t-6)_sq):	13.574%
cor(R(t)_sq, R(t-7)_sq):	25.252%
cor(R(t)_sq, R(t-8)_sq):	11.142%
cor(R(t)_sq, R(t-9)_sq):	20.883%
cor(R(t)_sq, R(t-10)_sq):	9.722%
cor(R(t)_sq, R(t-11)_sq):	13.209%
cor(R(t)_sq, R(t-12)_sq):	13.321%
cor(R(t)_sq, R(t-13)_sq):	6.370%
cor(R(t)_sq, R(t-14)_sq):	10.229%
cor(R(t)_sq, R(t-15)_sq):	8.325%
cor(R(t)_sq, R(t-16)_sq):	9.691%
cor(R(t)_sq, R(t-17)_sq):	4.547%
cor(R(t)_sq, R(t-18)_sq):	3.868%
cor(R(t)_sq, R(t-19)_sq):	4.795%
cor(R(t)_sq, R(t-20)_sq):	4.478%
cor(R(t)_sq, R(t-21)_sq):	3.665%
cor(R(t)_sq, R(t-22)_sq):	1.840%
cor(R(t)_sq, R(t-23)_sq):	2.737%
cor(R(t)_sq, R(t-24)_sq):	1.379%
cor(R(t)_sq, R(t-25)_sq):	2.311%
cor(R(t)_sq, R(t-26)_sq):	0.397%
cor(R(t)_sq, R(t-27)_sq):	0.118%
cor(R(t)_sq, R(t-28)_sq):	2.390%
cor(R(t)_sq, R(t-29)_sq):	1.498%

PFE.N

cor(R(t)_sq, R(t-1)_sq):	0.217578
cor(R(t)_sq, R(t-2)_sq):	0.230499
cor(R(t)_sq, R(t-3)_sq):	0.161515
cor(R(t)_sq, R(t-4)_sq):	0.167271
cor(R(t)_sq, R(t-5)_sq):	0.195588
cor(R(t)_sq, R(t-6)_sq):	0.123975
cor(R(t)_sq, R(t-7)_sq):	0.14864
cor(R(t)_sq, R(t-8)_sq):	0.082621
cor(R(t)_sq, R(t-9)_sq):	0.149731
cor(R(t)_sq, R(t-10)_sq):	0.100079
cor(R(t)_sq, R(t-11)_sq):	0.112183
cor(R(t)_sq, R(t-12)_sq):	0.065015
cor(R(t)_sq, R(t-13)_sq):	0.057697
cor(R(t)_sq, R(t-14)_sq):	0.102384
cor(R(t)_sq, R(t-15)_sq):	0.059568
cor(R(t)_sq, R(t-16)_sq):	0.059187
cor(R(t)_sq, R(t-17)_sq):	0.051221
cor(R(t)_sq, R(t-18)_sq):	0.030478
cor(R(t)_sq, R(t-19)_sq):	0.064987
cor(R(t)_sq, R(t-20)_sq):	0.047643
cor(R(t)_sq, R(t-21)_sq):	0.040597
cor(R(t)_sq, R(t-22)_sq):	0.025262
cor(R(t)_sq, R(t-23)_sq):	0.017412
cor(R(t)_sq, R(t-24)_sq):	0.05484
cor(R(t)_sq, R(t-25)_sq):	0.046325
cor(R(t)_sq, R(t-26)_sq):	0.019237
cor(R(t)_sq, R(t-27)_sq):	0.069425
cor(R(t)_sq, R(t-28)_sq):	0.077342
cor(R(t)_sq, R(t-29)_sq):	0.053264

2-3 Zero Mean Test

Fact : The standard deviation of returns completely dominates the mean of returns at short horizons: it is impossible to reject statistically zero mean



Testing Process:

- Using the data to calculate the mean and standard deviation.
- Using the mean and std to produce a normal distribution.
- Finding the 95% confidential range of the normal distribution.
- Calculating the 2.5% and 97.5% percentile of the distribution.
- Finding that 0 is in the range.

2-3 Zero Mean Test

S&P 500

mean	0.000473	
std	0.009444	
95% conf	low	-0.01804
	high	0.018983
So mean could be 0.		

JNJ.N

mean	0.00041	
std	0.009983	
95% conf	low	-0.01916
	high	0.019975
So mean could be 0.		

PFE.N

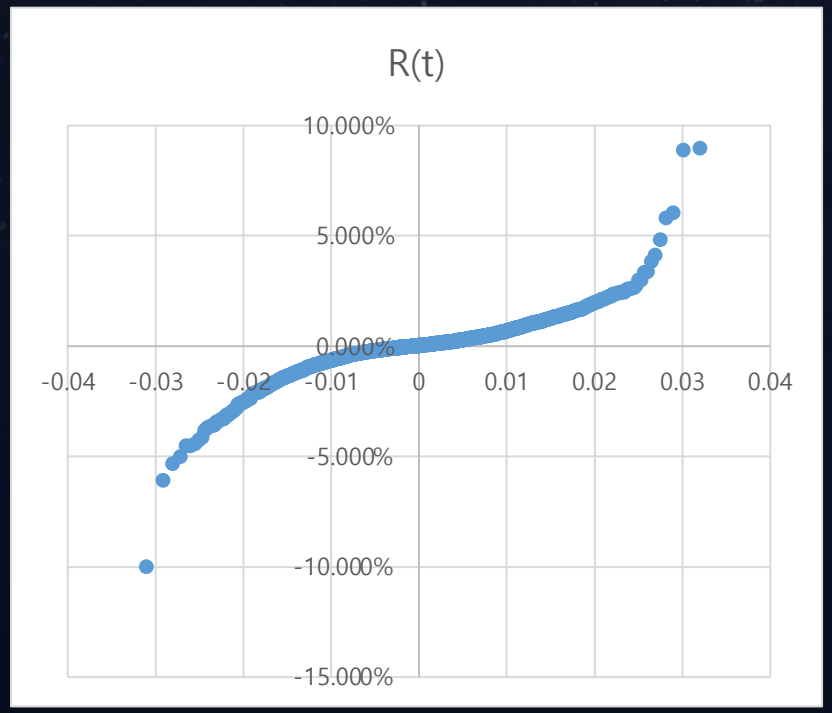
mean	0.000292	
std	0.012093	
95% conf	low	-0.02341
	high	0.023994
So mean could be 0.		

Conclusion

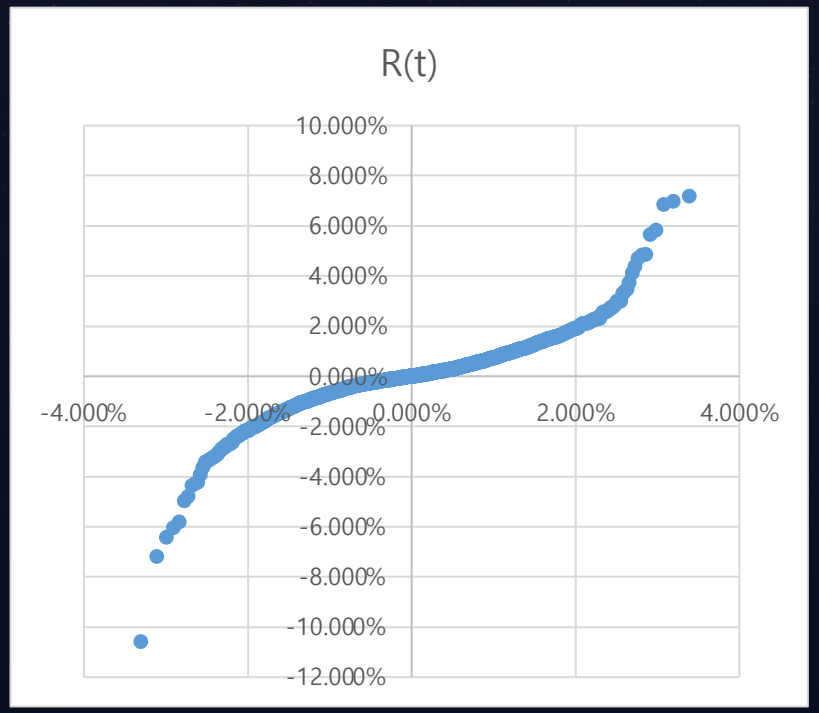
The standard deviation of returns completely dominates the mean of ret urns at short horizons: It is impossible to reject statistically zero mean

2-4 Returns Analysis

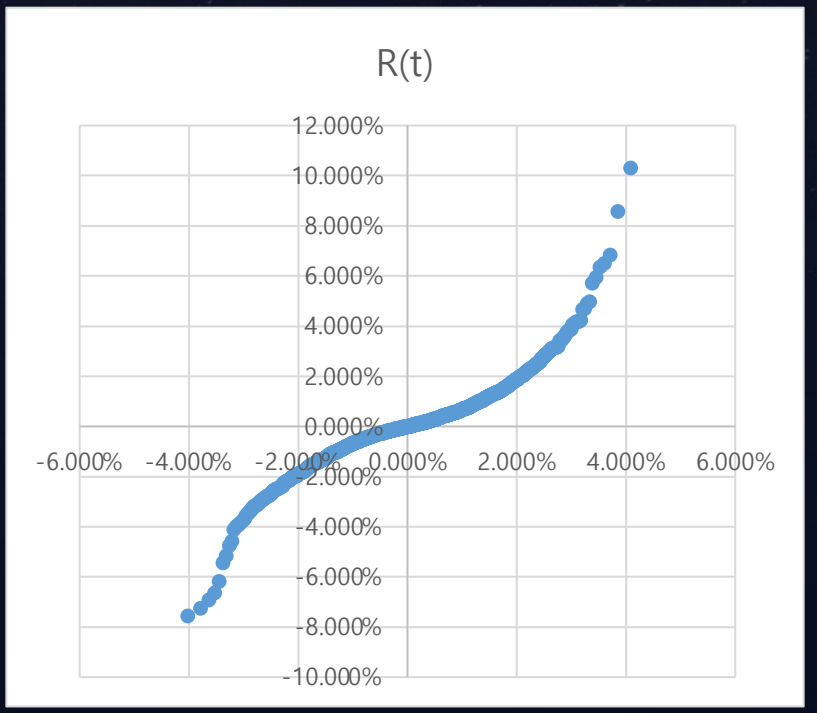
S&P 500



J&J



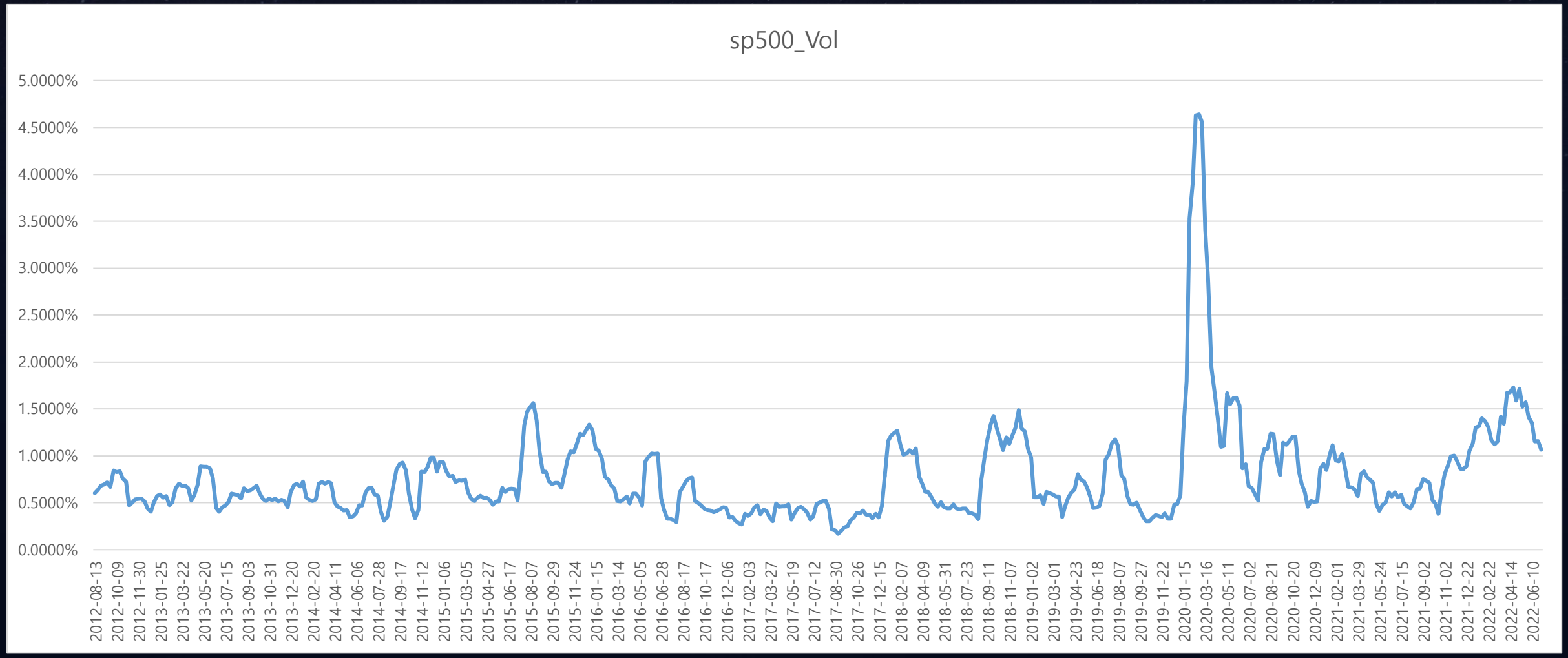
PFE



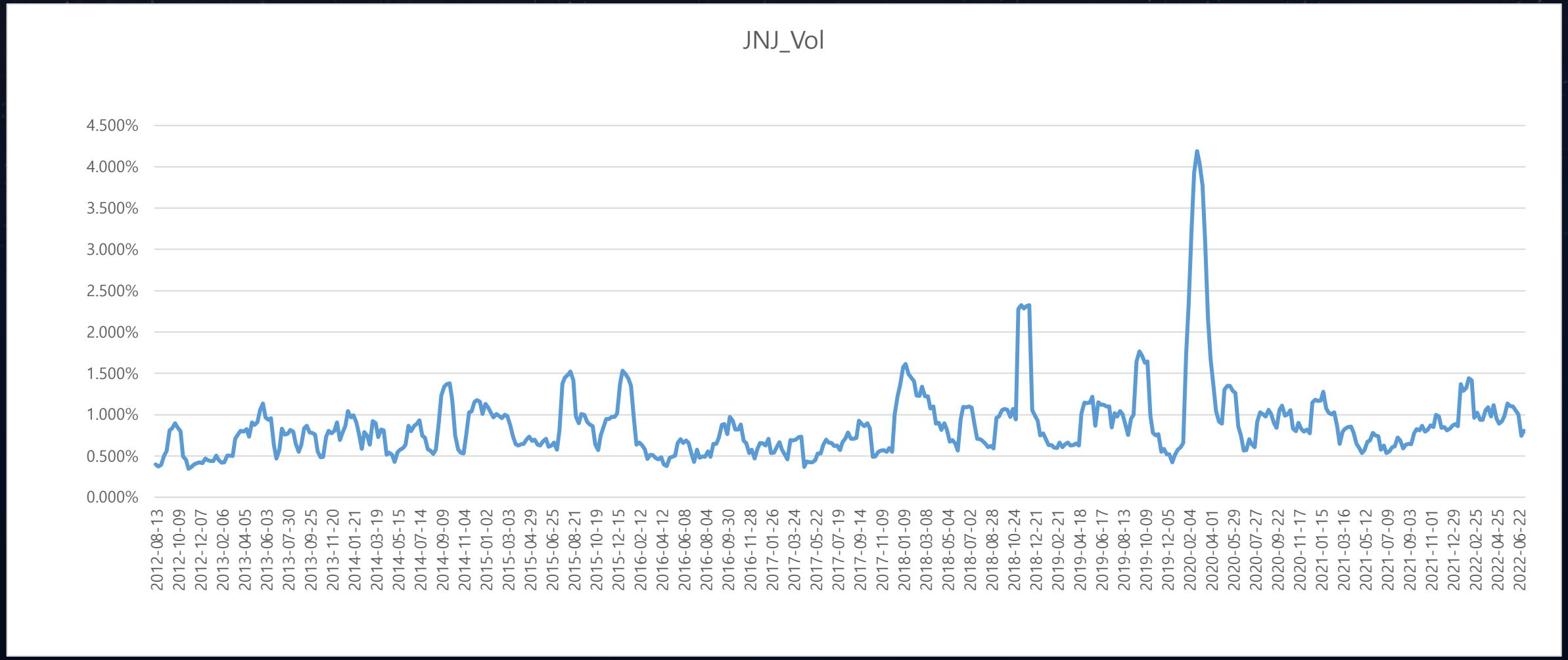
	S&P	JNJ	PFE
kurtosis	16.8545339	13.1018243	7.5935781

Conclusion: All are Platykurtic (Heavy Tail)

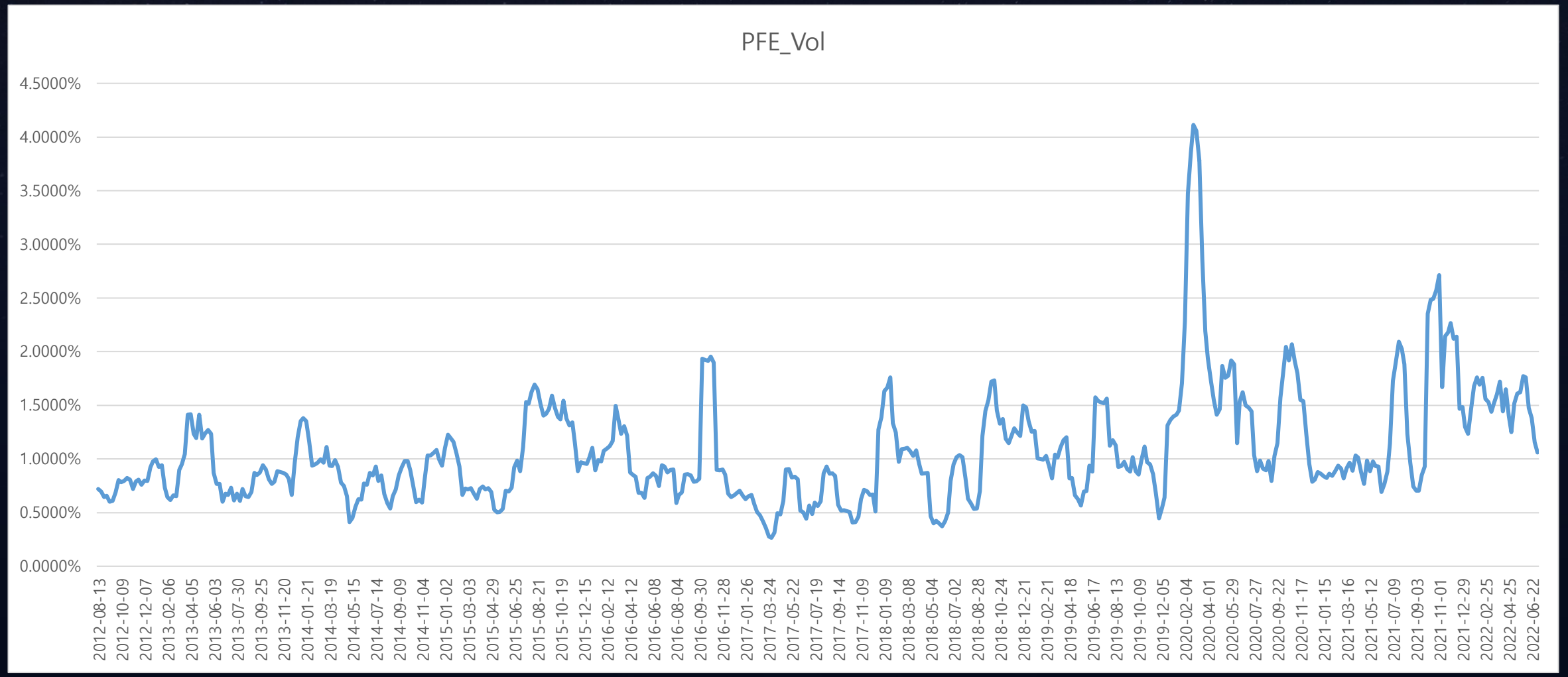
2-5 Volatility Variation



2-5 Volatility Variation



2-5 Volatility Variation



2-5 Volatility Analysis

	S&P 500	JNJ	PFE
min value	0.1689%	0.3439%	0.2647%
max value	4.6397%	4.1901%	4.1127%
average value	0.7715%	0.8778%	1.0714%

Analysis :

S&P 500 is less volatile than JNJ and PFE ;

PFE is the most volatile stock

2-6 & 2-7 Return Analysis

	S&P	JNJ	PFE
Correlation [return and var]	1.740%	-3.517%	-5.287%

2-6 Correlation between Variance and Returns

- ✓ JNJ and PFE display negative correlation between variance and returns
- ✓ S&P 500 displays positive correlation between variance and returns

	S&P	JNJ	PFE
skew	-0.2696	-0.4777	0.3154

2-7 Skewness

- ✓ Two distributions of the three stocks are negatively sk ewed

2-8 Volatility Clustering--Process

01
Initial choice of centers

Equidistant points

02
First label

Cluster all the data points into the centers based on absolute distance value

03
Re-choose centers

50 percentile of each cluster

04
Last Label

Repeat step 2 and 3 until the cetners become stable (equal to last round clustering centers)

05
Probability Matrix

The probability staying the initial label

2-8 Volatility Clustering--Python

Label process

```python
### relabel with new centers
def re_label(data,c) :

    label = []
    for i in data:
        lable_1,lable_2,lable_3 = abs(i - c[0]),abs(i - c[1]),abs(i - c[2])
        least = min(lable_1,lable_2,lable_3)
        if least == lable_1:
            label .append(1)
        elif least == lable_2:
            label .append(2)
        else:
            label.append(3)

    label_dict = dict(zip(data,label))

    return label_dict
```

Check the stable state

```python
### clustering , iteration
def cluster_center(v,c):
    last_c = c
    new_c = new_centers(re_label(v,c))
    while last_c != new_c :
        last_c = new_c.copy()
        new_c = new_centers(re_label(v,last_c))

    return new_c,re_label(v,last_c)
```

Example of the outcomes

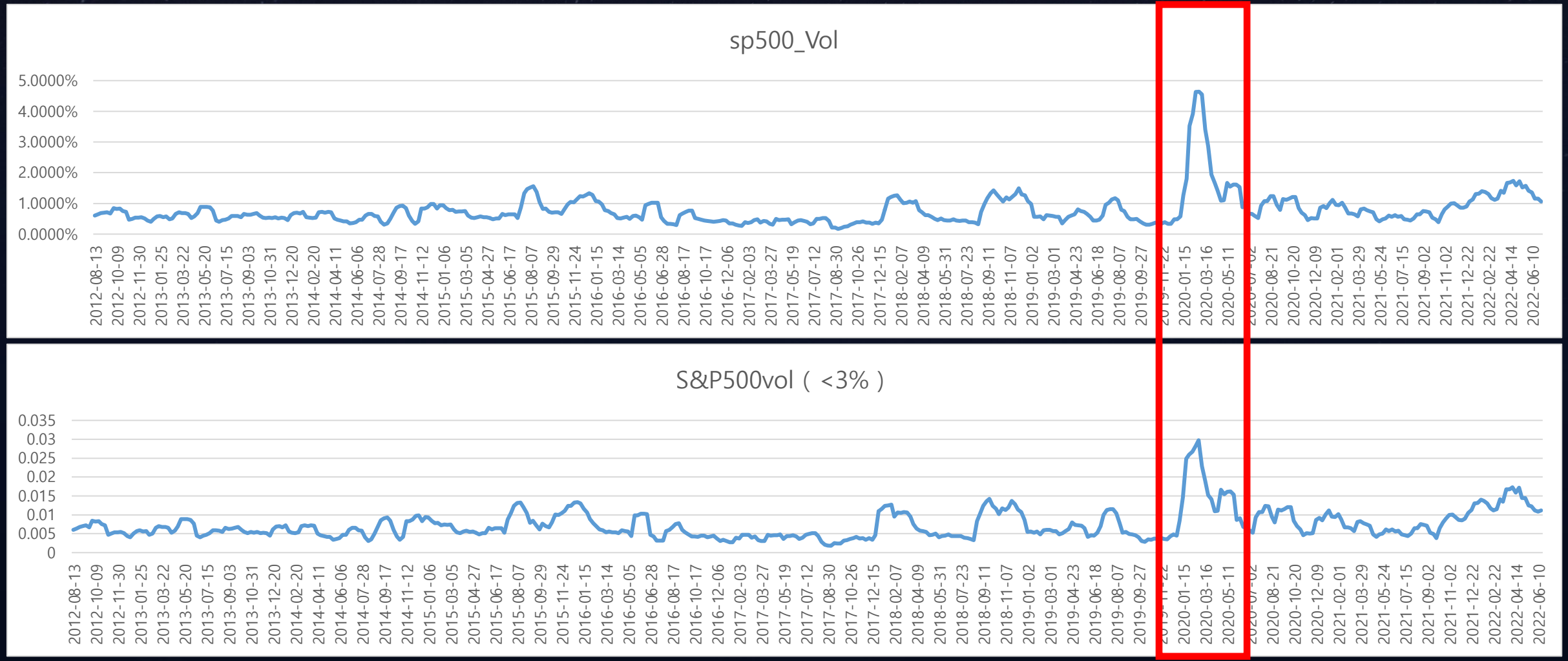
In [39]:
```
label_sp500_df
```

Out[39]:

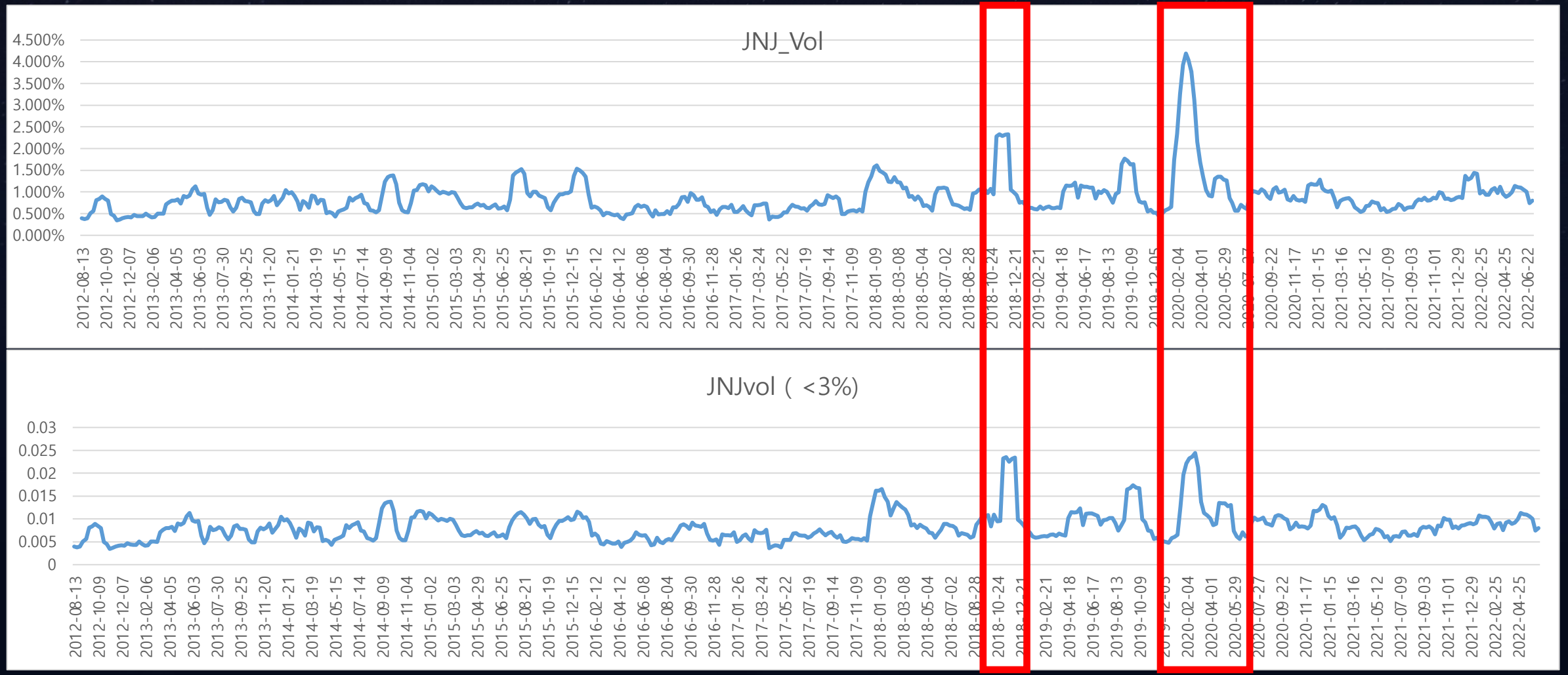
	sp500_first_label	sp500_last_label
0.006011	2	2
0.006391	2	2
0.006798	2	2
0.006964	2	2
0.007182	2	2
...	...	...
0.012448	3	3
0.012224	3	3
0.011144	3	3
0.010846	3	3
0.011193	3	3

464 rows × 2 columns

2-8 Volatility Clustering



2-5 Volatility Variation



2-8 Volatility Clustering--Probablity Matrix（Wrong）

S&P 500

(first,last)	1	2	3
1	100.000%	0.000%	0.000%
2	42.767%	57.233%	0.000%
3	0.000%	32.927%	67.073%

J&J

(first,last)	1	2	3
1	100.000%	0.000%	0.000%
2	45.890%	54.110%	0.000%
3	0.000%	67.526%	32.474%

PFE

(first,last)	1	2	3
1	100.000%	0.000%	0.000%
2	5.946%	94.054%	0.000%
3	0.000%	20.809%	79.191%

S&P 500 (<3%)

(first,last)	1	2	3
1	100.000%	0.000%	0.000%
2	42.675%	57.325%	0.000%
3	0.000%	30.539%	69.461%

J&J (<3%)

(first,last)	1	2	3
1	100.000%	0.000%	0.000%
2	27.211%	72.789%	0.000%
3	0.000%	31.053%	68.947%

PFE (<3%)

(first,last)	1	2	3
1	100.000%	0.000%	0.000%
2	7.222%	92.778%	0.000%
3	0.000%	23.494%	76.506%

S&P 500 (4 groups)

(first,last)	1	2	3	4
1	100.00%	0.00%	0.00%	0.00%
2	56.20%	43.80%	0.00%	0.00%
3	0.00%	66.67%	33.33%	0.00%
4	0.00%	0.00%	47.27%	52.73%

J&J (4 groups)

(first,last)	1	2	3	4
1	100.00%	0.00%	0.00%	0.00%
2	0.79%	99.21%	0.00%	0.00%
3	0.00%	25.00%	75.00%	0.00%
4	0.00%	0.00%	44.86%	55.14%

PFE (4 groups)

(first,last)	1	2	3	4
1	100.00%	0.00%	0.00%	0.00%
2	12.69%	87.31%	0.00%	0.00%
3	0.00%	71.43%	28.57%	0.00%
4	0.00%	0.00%	56.80%	43.20%

2-8 Volatility Clustering--Error Analysis

Initial Wrong Idea

$P_{n,m} = i / j$

i : the number of data whose last label is m

j : the number of data whose first label is n

After Correction

$P_{n,m} = i / j$

i : the number of data whose last label is n , and the data after has a last label of m

j : the number of data whose last label is n

2-8 Volatility Clustering--Probablity Matrix（Corrected）

S&P 500

(i,i+1)	1	2	3
1	87.20%	12.32%	0.47%
2	17.24%	73.79%	8.97%
3	1.83%	10.09%	88.07%

J&J

(i,i+1)	1	2	3
1	85.84%	13.72%	0.44%
2	14.35%	79.90%	5.74%
3	1.59%	19.05%	79.37%

PFE

(i,i+1)	1	2	3
1	80.263%	18.421%	1.316%
2	13.876%	77.990%	8.134%
3	0.000%	13.869%	86.131%

S&P 500 (<3%)

(i,i+1)	1	2	3
1	85.99%	12.56%	1.45%
2	19.86%	72.34%	7.80%
3	0.87%	10.43%	88.70%

J&J (<3%)

(i,i+1)	1	2	3
1	83.417%	15.075%	1.508%
2	19.394%	67.879%	12.727%
3	0.000%	18.321%	81.679%

PFE (<3%)

(i,i+1)	1	2	3
1	82.803%	15.287%	1.911%
2	12.683%	81.463%	5.854%
3	0.000%	11.811%	11.811%

S&P 500 (4 groups)

(i,i+1)	1	2	3	4
1	83.89%	13.33%	2.78%	0.00%
2	20.74%	71.11%	7.41%	0.74%
3	1.08%	15.05%	72.04%	10.75%
4	0.00%	0.00%	18.97%	81.03%

J&J (4 groups)

(i,i+1)	1	2	3	4
1	73.11%	22.69%	4.20%	0.00%
2	19.14%	63.58%	15.43%	1.23%
3	0.00%	20.13%	74.21%	5.66%
4	0.00%	0.00%	18.64%	81.36%

PFE (4 groups)

(i,i+1)	1	2	3	4
1	82.07%	15.86%	2.07%	0.00%
2	12.69%	79.70%	5.58%	1.52%
3	0.00%	14.56%	76.70%	8.74%
4	0.00%	3.70%	18.52%	77.78%

2-8 Volatility Clustering--4 Groups

Relabeling with Python

```
# 当前文件中每组的中位数值
initial_group_median.update(get_group_median(initial_info))

while True:
    # 根据中位数调整后的分组
    adjust_info = {}

    # 根据每组的中位数值 重新对所欲数据进行分组
    for data in all_data:
        # 设置当前数与四个中位数最小距离值
        min_group_name, min_distance = None, None

        for k, v in initial_group_median.items():
            # 遍历四个中位数 分别比较 得到离的最近中位数的分组名称
            distance_value = abs(data - v)

            if min_distance is None:
                min_group_name, min_distance = k, distance_value
            else:
                if distance_value < min_distance:
                    min_group_name, min_distance = k, distance_value
        # 将当前数据重新分组
        if adjust_info.get(min_group_name):
            adjust_info[min_group_name].append(data)
        else:
            adjust_info[min_group_name] = [data]

    # 对重新排序后的数据求中位数
    adjust_group_median = get_group_median(adjust_info)

    if initial_group_median == adjust_group_median:
        # 排序后中位数和上次中位数相同 不再继续
        print("%s的各分组最终的中位数是：%s" % (vol_name, adjust_group_median))
        break
    else:
        # 重新赋值 继续排序
        initial_group_median.update(adjust_group_median)
# 将最终数据按分组值进行排序
adjust_info_list = list(adjust_info.items())
```

To check whether clustering with 4 groups is reasonable

for label 4	S&P 500	JNJ	PFE
mean	1.7621%	1.7898%	2.1947%
median	1.4414%	1.4701%	1.9570%
25%percentile	1.3144%	1.3692%	1.7946%
75%percentile	1.6868%	1.7610%	2.2319%
min	1.2300%	1.2441%	1.7025%
max	4.7354%	4.2765%	4.1975%

The group of Label 4 contains volatility from about 1.2% to about 4%, which contains plenty of normal value of volatility,
contradicting with the expectation that the group 4 contains
only the outliers of the volatility.

3

Multivariate Series

3-1 Cross Correlations of Multivariate Series

3-2 Cross Correlations of the Absolute Returns

3-3 Variation of Correlations between Series

3-4 Coincidence of Extreme Returns

3-1&2 Cross Correlation

Q1−1&Q1−2 correlation of 10years	JNJ.N vs PFE.N	correlationship	53.855%
		correlationship (abs)	46.045%
correlation of 2020 Jan−Jun	JNJ.N vs PFE.N	correlationship	73.69%
		correlationship (abs)	70.77%
correlation of random asynchronous returns	JNJ.N vs PFE.N	correlationship	5.184%
		correlationship (abs)	−1.313%
correlation of 2018 returns	JNJ.N vs PFE.N	correlationship	56.282%
		correlationship (abs)	37.162%

Q1−1&Q1−2 correlation of 10years	S&P vs JNJ.N	correlationship	−2.595%
		correlationship (abs)	2.537%
	S&P vs PFE.N	correlationship	−1.730%
		correlationship (abs)	2.141%
	JNJ.N vs PFE.N	correlationship	53.855%
		correlationship (abs)	46.045%

Conclusion

✓ The return on the same date will be more correlated

? ABS returns are not stronger correlated

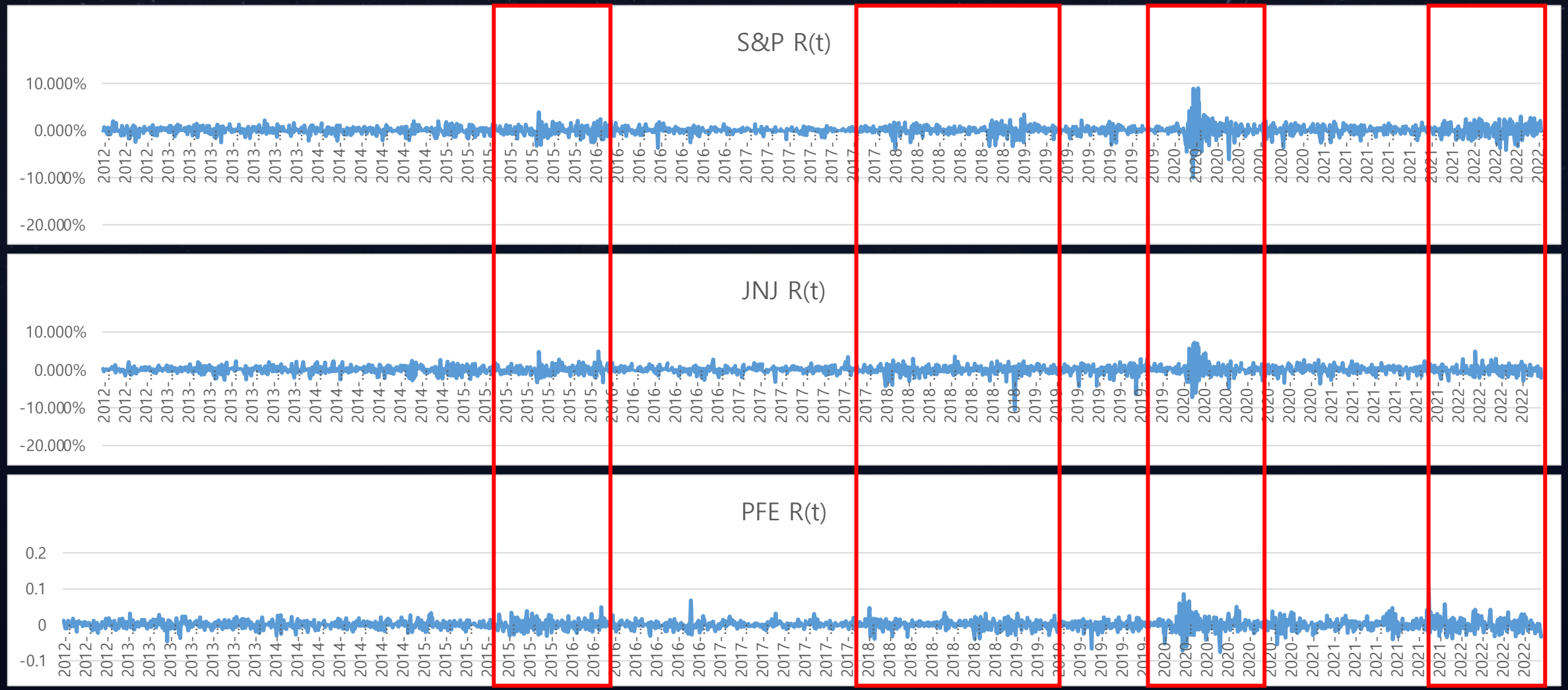
3-3 Variation of Cross Correlation

correlation varies over time	S&P vs JNJ.N	S&P vs PFE.N	JNJ.N vs PFE.N
window=100	−0.020750883	0.144193096	0.552898072
n=10	0.001174601	0.145337117	0.551066969
	−0.020790658	0.041191687	0.554753222
	−0.029647125	0.07109179	0.529773289
	0.033259131	0.121715595	0.550450384
	0.140605787	0.176105928	0.548513563
	0.118435646	0.056704742	0.631314143
	0.089095576	0.109553837	0.625100466
	0.156803735	0.155954121	0.585216703
	0.184108669	0.182326034	0.551151737
	0.18289615	0.077157608	0.615176654
	0.199320201	0.104701173	0.631728878
	0.11486564	0.113101383	0.619484476
	0.109352694	0.089881644	0.627948699
	0.02516021	0.02934676	0.641864664
	0.038820645	0.069506459	0.623256858
	−0.001318979	0.060029871	0.586412933
	0.0478537	0.068569203	0.578902587
	0.021765332	0.009451164	0.637713067
	−0.0242389	−0.067503175	0.6607676
	−0.025034696	0.094681026	0.622615265
	−0.075870289	−0.026828683	0.608534568
	−0.024249969	0.00540869	0.562803107
	−0.041099311	−0.005135624	0.556419314
	0.098151099	0.092241837	0.599654012
	0.085627872	0.012930651	0.614119424
	0.096265811	0.032633752	0.597135413
	0.072492086	−0.020827684	0.606266971
	0.021099721	0.000371936	0.581825266
	0.03562047	0.050192916	0.58172187
	−0.017764182	−0.056298587	0.55118658
	0.007930238	−0.010290793	0.539892022
	0.037069241	−0.005128862	0.536105754
	0.0426288	−0.008868749	0.534701784
	−0.039915581	−0.040965315	0.449100034
	0.008378232	−0.016720087	0.456359165
	0.073678429	−0.017138537	0.463253261
	0.071090185	−0.027213548	0.443200009
	0.096247187	−0.04239583	0.433481789
	0.093969607	−0.102480462	0.350680516
	0.146477374	0.011728709	0.400787013
	0.063306273	−0.006250073	0.360517723
	0.065724918	0.027077754	0.355936509
	0.080025759	0.048717891	0.363709526
	0.111732058	0.052049994	0.502012084
	0.076747547	0.15615796	0.539644136
	0.020792994	0.126045394	0.562475959

Window:100
n=10

It is obvious that the cross correlation is constantly changing

3-4 Coincidence



3-4 Coincidence

max 30

S&P500	R(t)	JNJ	R(t)	PFE	R(t)
		2014−10−08	2.431%		
2014−12−18	2.373%	2014−12−18	2.599%	2015−02−10	3.214%
2015−08−26	3.829%	2015−08−26	4.715%	2015−08−26	3.419%
2015−08−27	2.401%	2015−10−15	2.734%	2015−10−02	3.821%
2016−01−29	2.446%	2016−01−26	4.839%	2016−04−06	4.885%
2016−03−01	2.359%	2016−11−09	2.747%	2016−11−09	6.828%
2018−11−28	2.271%	2017−10−17	3.373%	2016−11−10	4.177%
2018−12−26	2.420%	2018−02−09	2.478%	2018−01−26	4.670%
2019−01−04	3.376%	2018−04−03	2.997%	2018−07−31	3.413%
		2018−07−17	3.483%		
		2019−10−30	2.840%		
		2019−11−15	2.994%		
2020−03−04	4.134%	2020−03−04	5.656%	2020−03−04	5.942%
2020−03−10	4.822%	2020−03−10	3.740%		
2020−03−13	8.881%	2020−03−13	6.841%	2020−03−13	8.582%
2020−03−17	5.823%	2020−03−17	7.177%	2020−03−17	6.354%
2020−03−24	8.968%	2020−03−24	6.984%	2020−03−24	4.159%
2020−03−26	6.054%	2020−03−26	5.832%	2020−03−26	6.506%
		2020−03−30	2.565%		
2020−04−02	2.257%	2020−04−02	3.314%	2020−04−02	3.467%
2020−04−08	3.349%	2020−04−08	4.118%		
2020−04−14	3.011%	2020−04−14	4.381%	2020−04−14	3.633%
2020−04−17	2.644%	2020−12−17	2.605%	2020−07−22	4.971%
2020−04−22	2.267%	2021−01−26	2.675%	2020−07−28	3.867%
2020−04−29	2.624%	2021−10−19	2.315%	2020−10−16	3.759%
2020−06−05	2.587%	2022−01−25	2.819%	2020−12−02	3.466%
2022−01−28	2.406%	2022−02−25	4.851%	2021−08−03	3.838%
2022−03−09	2.537%			2021−08−10	4.695%
2022−03−16	2.214%	2022−03−15	2.559%	2021−11−02	4.064%
2022−04−28	2.445%			2021−11−05	10.305%
2022−05−13	2.359%			2021−11−10	3.572%
2022−05−27	2.444%			2021−12−15	5.704%
2022−06−24	3.011%			2021−12−16	4.082%
2022−07−19	2.725%			2022−02−25	3.758%
2022−07−27	2.582%			2022−03−02	4.174%
		2022−04−06	2.568%	2022−04−07	4.240%
		2022−04−19	3.005%	2022−05−20	3.530%

min 30

S&P500	R(t)	JNJ	R(t)	PFE	R(t)
		2014−10−09	−2.735%	2013−04−30	−4.57%
2015−08−21	−3.237%	2015−08−21	−3.324%	2013−05−31	−3.68%
2015−09−01	−3.002%	2016−02−05	−3.287%	2014−01−24	−3.01%
2016−06−24	−3.658%	2017−04−18	−3.151%	2015−11−19	−3.11%
		2018−01−23	−4.353%	2016−08−03	−3.07%
		2018−01−31	−3.022%	2018−01−30	−3.18%
2018−02−08	−3.826%	2018−02−08	−3.926%	2018−02−08	−3.94%
		2018−03−22	−2.947%	2018−03−23	−3.17%
				2018−05−01	−3.36%
2018−10−10	−3.342%	2018−10−11	−2.865%	2018−10−11	−3.89%
2018−10−24	−3.135%	2018−11−21	−3.093%	2018−10−24	−3.74%
2018−12−04	−3.290%	2018−12−14	−10.578%	2019−07−30	−6.63%
2019−08−14	−2.973%	2019−05−29	−4.278%	2020−01−28	−5.16%
2020−02−25	−3.075%	2019−07−12	−4.235%		
		2019−08−23	−2.734%		
		2019−10−18	−6.422%		
2020−02−27	−4.517%	2020−02−27	−3.225%		
2020−03−03	−2.851%	2020−02−28	−3.392%		
2020−03−05	−3.451%	2020−03−03	−3.215%		
2020−03−09	−2.634%				
2020−03−11	−5.010%	2020−03−11	−7.200%	2020−03−11	−7.25%
2020−03−12	−9.994%	2020−03−12	−4.970%	2020−03−12	−6.92%
2020−03−16	−4.255%				
2020−03−18	−5.322%	2020−03−19	−6.040%	2020−03−19	−6.18%
2020−03−20	−4.433%	2020−03−20	−5.801%	2020−03−20	−4.75%
2020−03−27	−3.427%	2020−03−27	−2.731%	2020−05−07	−4.11%
2020−04−01	−4.515%				
2020−04−21	−3.116%				
2020−06−11	−6.075%	2020−06−11	−4.802%	2020−06−11	−7.57%
2020−09−03	−3.576%	2020−09−03	−2.822%		
2020−10−28	−3.593%	2020−10−28	−3.403%	2020−10−28	−5.43%
2022−04−22	−2.813%	2021−01−29	−3.630%	2020−11−17	−3.52%
2022−04−26	−2.855%	2021−02−26	−2.677%	2021−08−11	−3.98%
2022−04−29	−3.696%	2021−12−17	−2.802%	2021−08−24	−3.15%
2022−05−18	−4.123%	2022−06−28	−2.886%	2021−12−02	−3.05%
				2021−12−21	−3.45%
				2022−01−04	−3.81%
				2022−04−19	−3.25%
				2022−06−09	−3.21%
2022−06−10	−2.954%			2022−06−10	−3.56%
2022−06−16	−3.305%			2022−08−11	−3.38%

Many extreme returns on the three stocks even occurred on the same day

4

Problems and Reflections

Problems and Reflections

Why can the ABS return show stronger correlation?

Why are stock returns and volatility negatively correlated?

For Further Study

Why the PFE distribution is not negatively skewed?

We hope to relate to the events happened in reality to explain these problems in further study.


THANK YOU
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