

# Stock\_Return\_Correlation

November 29, 2020

## 1 How Correlated Are Two Stocks Returns Over Time?

Using pandas, seaborn, and a stock module I developed, this notebook graphs the correlation between returns with different windows between two stocks

```
[15]: import stock_class as stock
import pandas as pd
import numpy as np
import seaborn as sns
sns.set()

stock1 = "MSFT"
stock2 = "SPY"

test1 = stock.Stock(stock1)
test2 = stock.Stock(stock2)
```

## 2 Calculate Daily Returns

```
[17]: daily_returns1 = test1.returns['D']['Returns']
daily_returns2 = test2.returns['D']['Returns']

returns1 = pd.merge(daily_returns1, daily_returns2, on='Date')
returns1.columns = [stock1, stock2]
returns1.tail()
```

```
[17]:
```

	MSFT	SPY
Date		
2020-11-18	-1.318376	-1.203482
2020-11-19	0.634829	0.421017
2020-11-20	-0.955653	-0.684782
2020-11-24	1.784779	1.611372
2020-11-25	0.004673	-0.154176

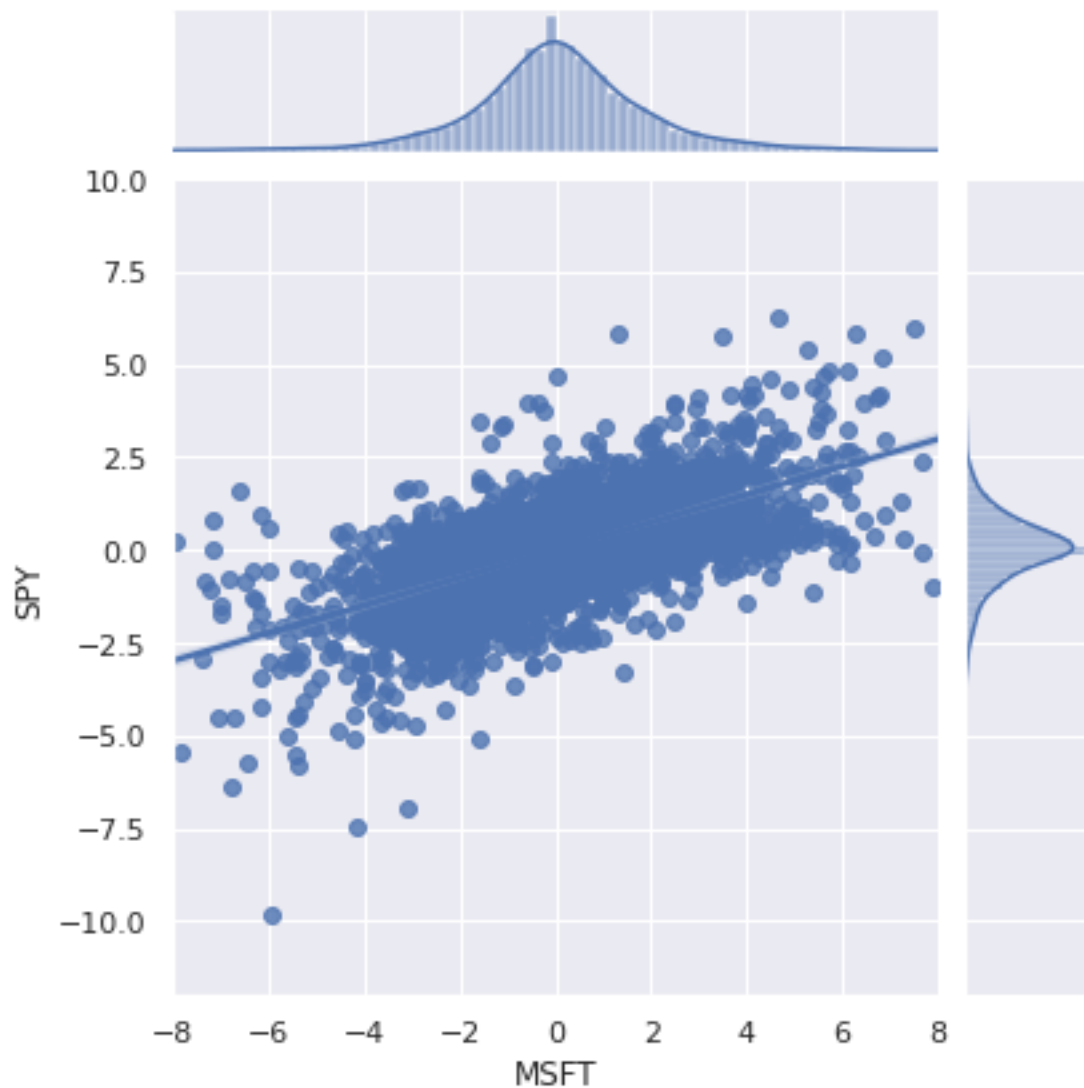
## 2.1 Graph the Returns Against Each Other

The slope of the regression line shows how correlated the two stocks daily returns are.

A slope of 1.0, means the stocks are perfectly correlated. To see an example of this, you can change the second stock in the code to match the first.

```
[11]: sns.jointplot(x=stock1, y=stock2, data=returns1, kind='reg', xlim=[-8, 8],  
    ↪ ylim=[-12, 10])
```

```
[11]: <seaborn.axisgrid.JointGrid at 0x7fd99ee85e80>
```



### 3 Calculate Monthly Returns

```
[18]: monthly_returns1 = test1.returns['M']['Returns']
monthly_returns2 = test2.returns['M']['Returns']

returns2 = pd.merge(monthly_returns1, monthly_returns2, on='Date')
returns2.columns = [stock1, stock2]
returns2.tail()
```

```
[18]:
```

	MSFT	SPY
Date		
2020-04-30	13.632616	12.698352
2020-06-30	11.311047	1.363760
2020-07-31	0.737066	5.889217
2020-08-31	10.275194	6.979671
2020-09-30	-6.739680	-3.744362

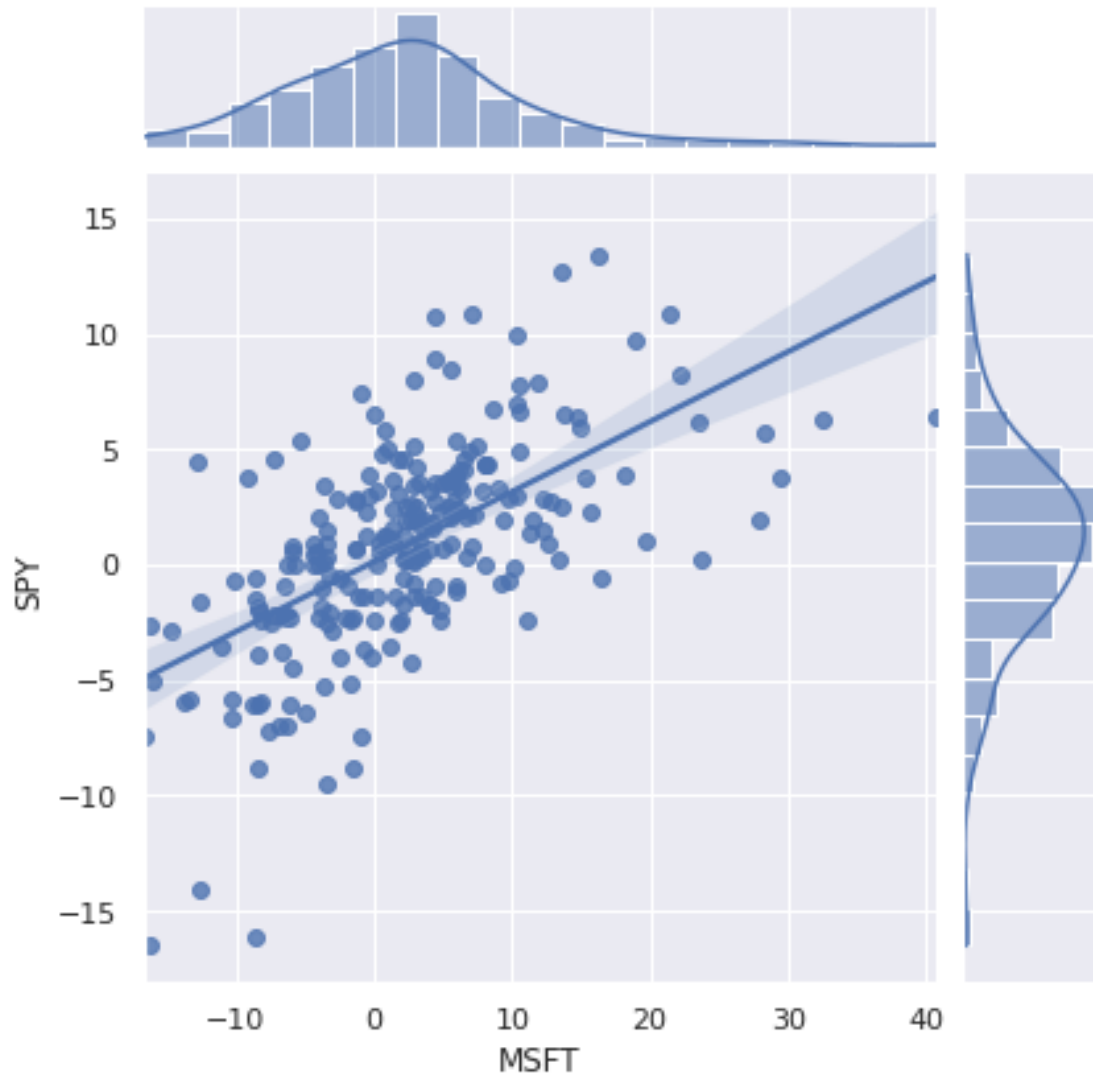
#### 3.1 Graph the Returns Against Each Other

The slope of the regression line shows how correlated the two stocks Monthly returns are.

A slope of less than 1.0 means that the stocks are not as correlated. This can be useful to balance out more volatile positions.

```
[9]: sns.jointplot(x=stock1, y=stock2, data=returns2, kind='reg')
```

```
[9]: <seaborn.axisgrid.JointGrid at 0x7fd99f0d7880>
```



## 4 Calculate Yearly Returns

```
[19]: yearly_returns1 = test1.returns['Y']['Returns']
      yearly_returns2 = test2.returns['Y']['Returns']

      returns3 = pd.merge(yearly_returns1, yearly_returns2, on='Date')
      returns3.columns = [stock1, stock2]
      returns3.tail()
```

```
[19]:      MSFT      SPY
      Date
```

2013-12-31	44.297942	32.307780
2014-12-31	27.564629	13.463820
2015-12-31	22.691904	1.234256
2018-12-31	20.219096	-5.247164
2019-12-31	57.558088	31.223856

## 4.1 Graph the Returns Against Each Other

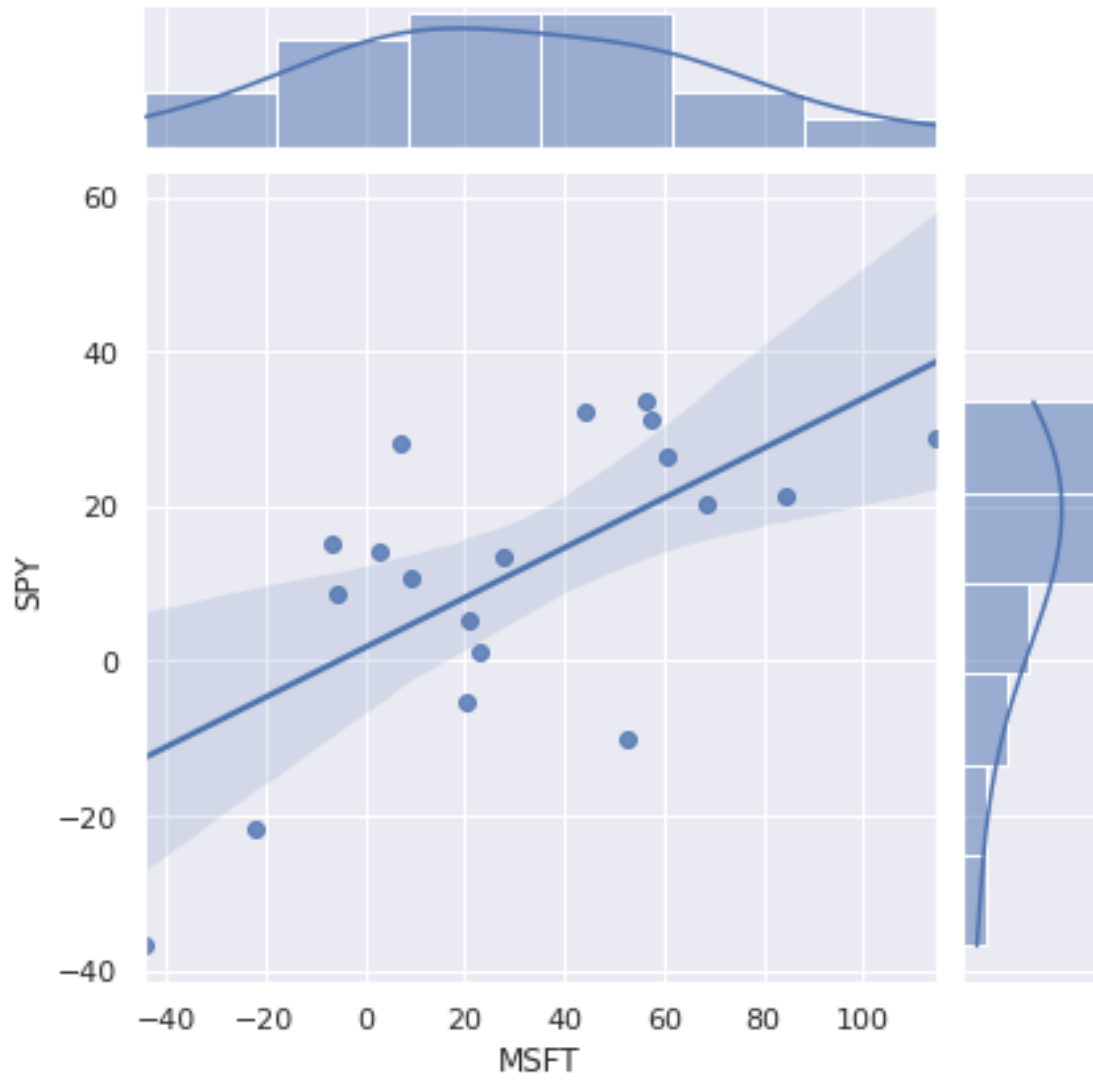
The slope of the regression line shows how correlated the two stocks yearly returns are.

A slope of greater than 1.0 means that the first stock is more than correlated with the second.

For example, if stock a goes up in price 2%, stock b will go up 6%, stocks with very high slopes might be very volatile.

```
[10]: sns.jointplot(x=stock1, y=stock2, data=returns3, kind='reg')
```

```
[10]: <seaborn.axisgrid.JointGrid at 0x7fd99f0dcd90>
```



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