Quant Finance Bootcamp

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Mini-Project 1

Create two profitable investment portfolios:

1) A ***high*** risk portfolio
2) A ***low*** risk portfolio

0.1 Selection of Arbitrary Indices

```
stock_indices = ['TSLA','NVDA','AMD','PLTR','ZM','SPCE','COIN','RIVN','LCID','ARKK',
                 'JNJ','PG','KO','MCD','WMT','PEP','DUK','NEE','TGT','VZ']
data_close = yf.download(stock_indices, period = fetch_period)['Close']
```

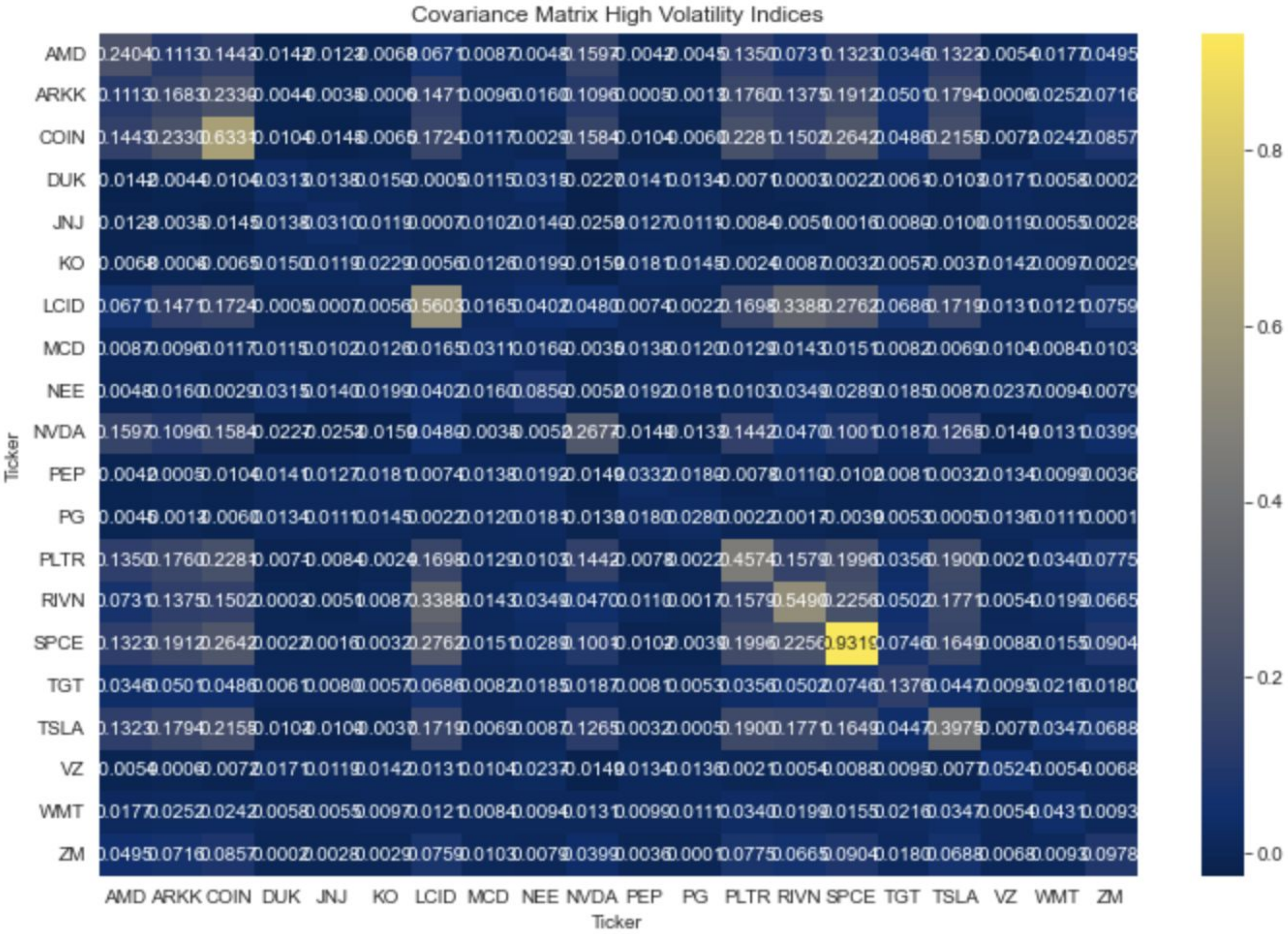
0.1.1 Handpicked Low volatility and High volatility indices

```
stock_indices_1 = ['TSLA', 'AMD', 'NVDA', 'PLTR', 'ZM']
```

```
stock_indices_2 = ['JNJ', 'PG', 'KO', 'MCD', 'WMT']
```

For each, compute the daily percentage return

Follow a strategy similar to that of Lect. 2, to finding ``appropriate weight”
… to diversify the investments


Covariance Matrix High Volatility Indices
Ticker
AMD
ARKK
COIN
DUK
JNJ
KO
LCID
MCD
NEE
NVDA
PEP
PG
PLTR
RIVN
SPCE
TGT
TSLA
VZ
WMT
ZM
0.8
0.6
0.4
0.2
0.0

0.2 Apply a threshold

Applying a threshold:

1) If std>0.3 ⇒ high volatility
2) If std<0.3 ⇒ low volatility

```
High Volatility Stocks, total of 11 (> 30% annualized):
['AMD', 'ARKK', 'COIN', 'LCID', 'NVDA', 'PLTR', 'RIVN', 'SPCE', 'TGT', 'TSLA', 'ZM']

Low Volatility Stocks, total of 9 (<= 30% annualized):
['DUK', 'JNJ', 'KO', 'MCD', 'NEE', 'PEP', 'PG', 'VZ', 'WMT']
```

Results, with equal weights of 1/n for each index

```
Annual Return: 46.94%, Volatility: 55.41%

Annual Return: 21.79%, Volatility: 18.14%
```

Solving Quadratic Program

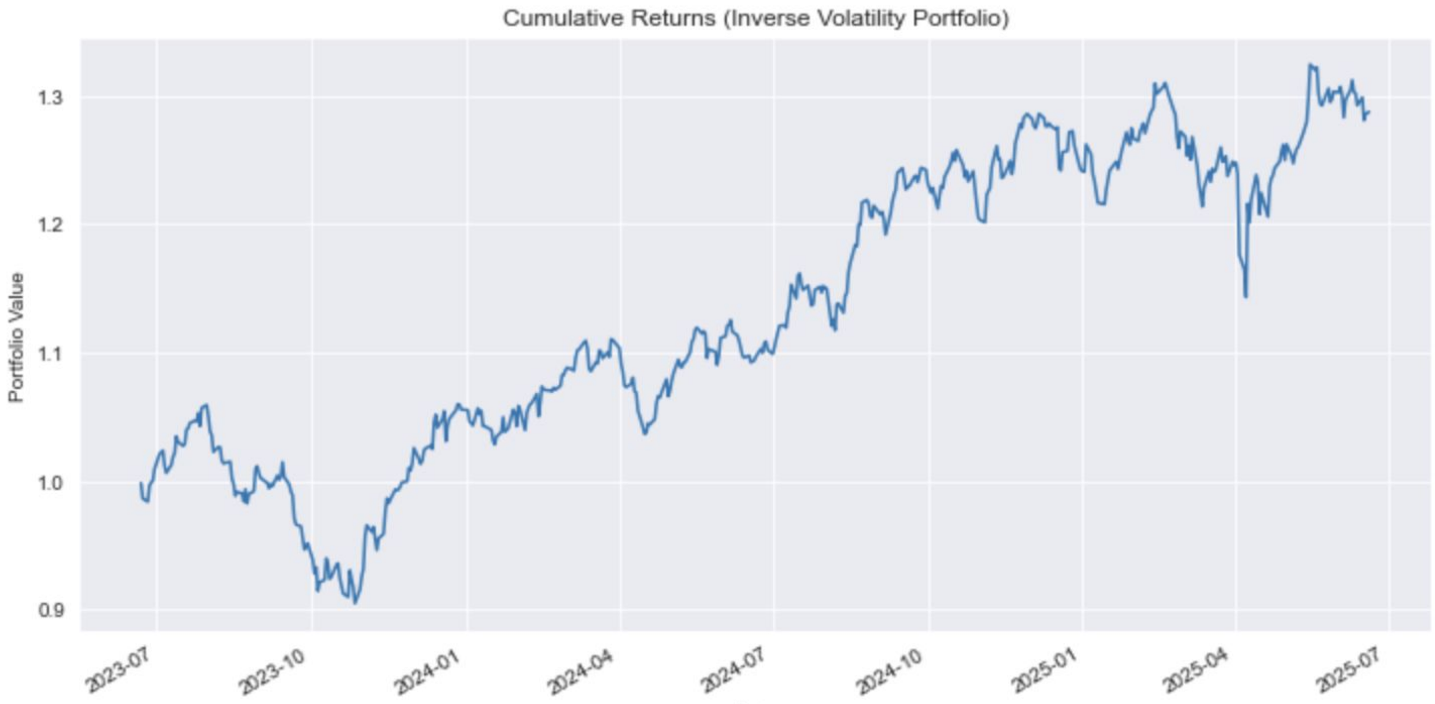
High Volatility Indices: Drops overall volatility to `26.694%`

Low Volatility Indices: Drops overall volatility to `11.96%`

1. Consider weights inversely proportional to the std

Overall Portfolio: `Annual Return: 27.38%, Volatility: 19.80%`

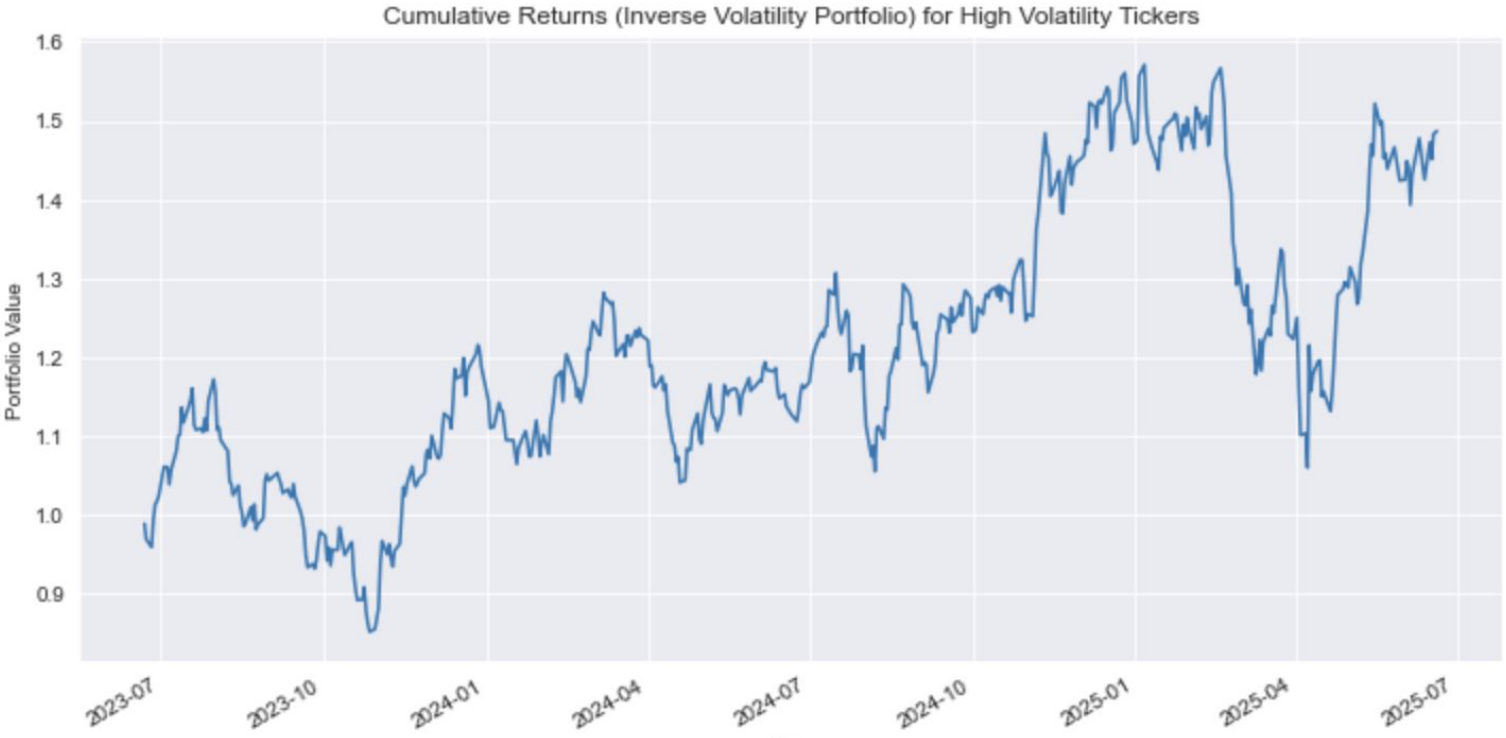
`Total return over 2 years: 28.75%`



.... w/ High volatility indices

<u>High Volatility Portfolio:</u> `Annual Return: 51.83%, Volatility: 48.95%`

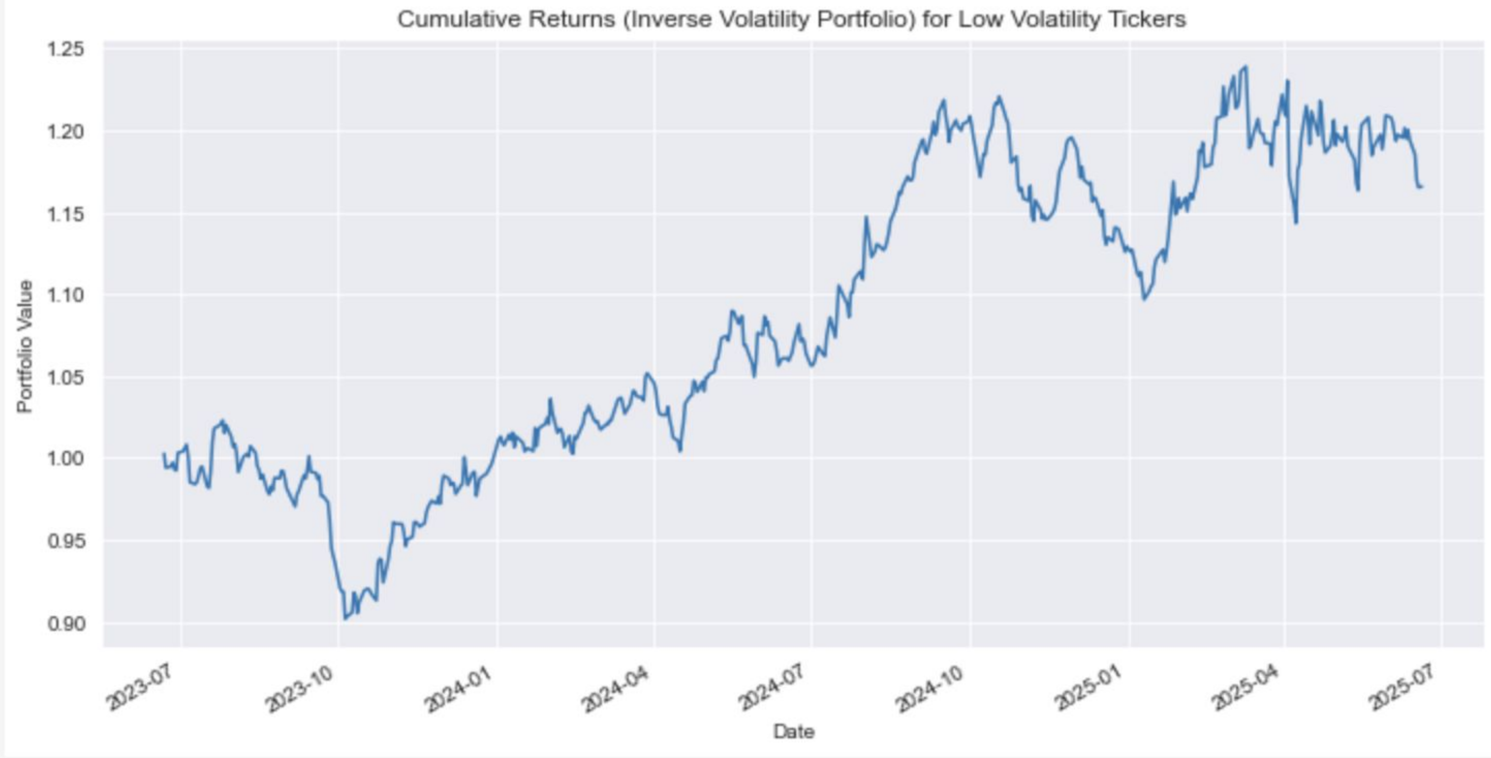
`Total return over 2 years: 48.70%`



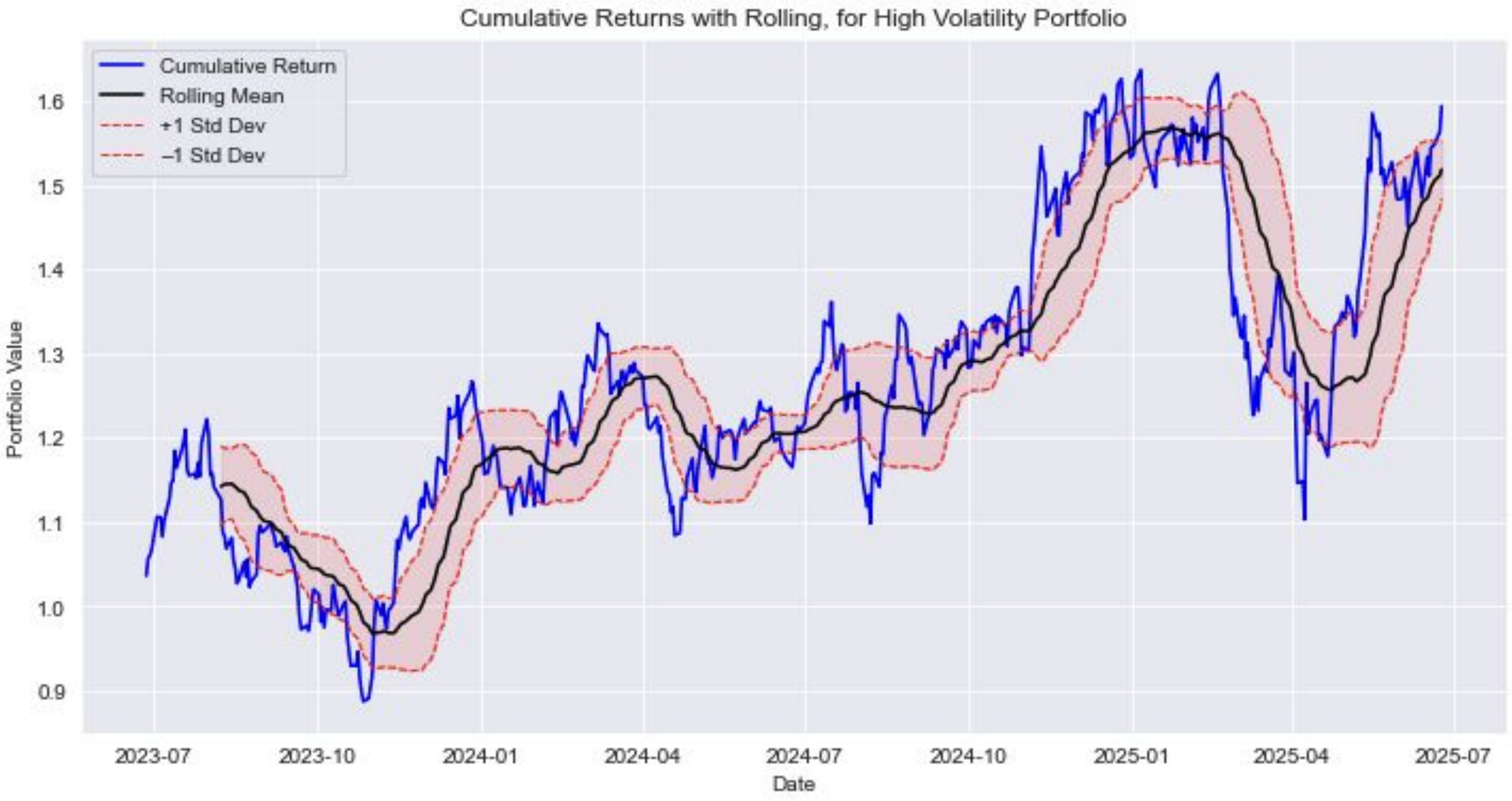
.... w/ Low volatility indices

Low Volatility Portfolio: Annual Return: 17.00%, Volatility: 17.74%

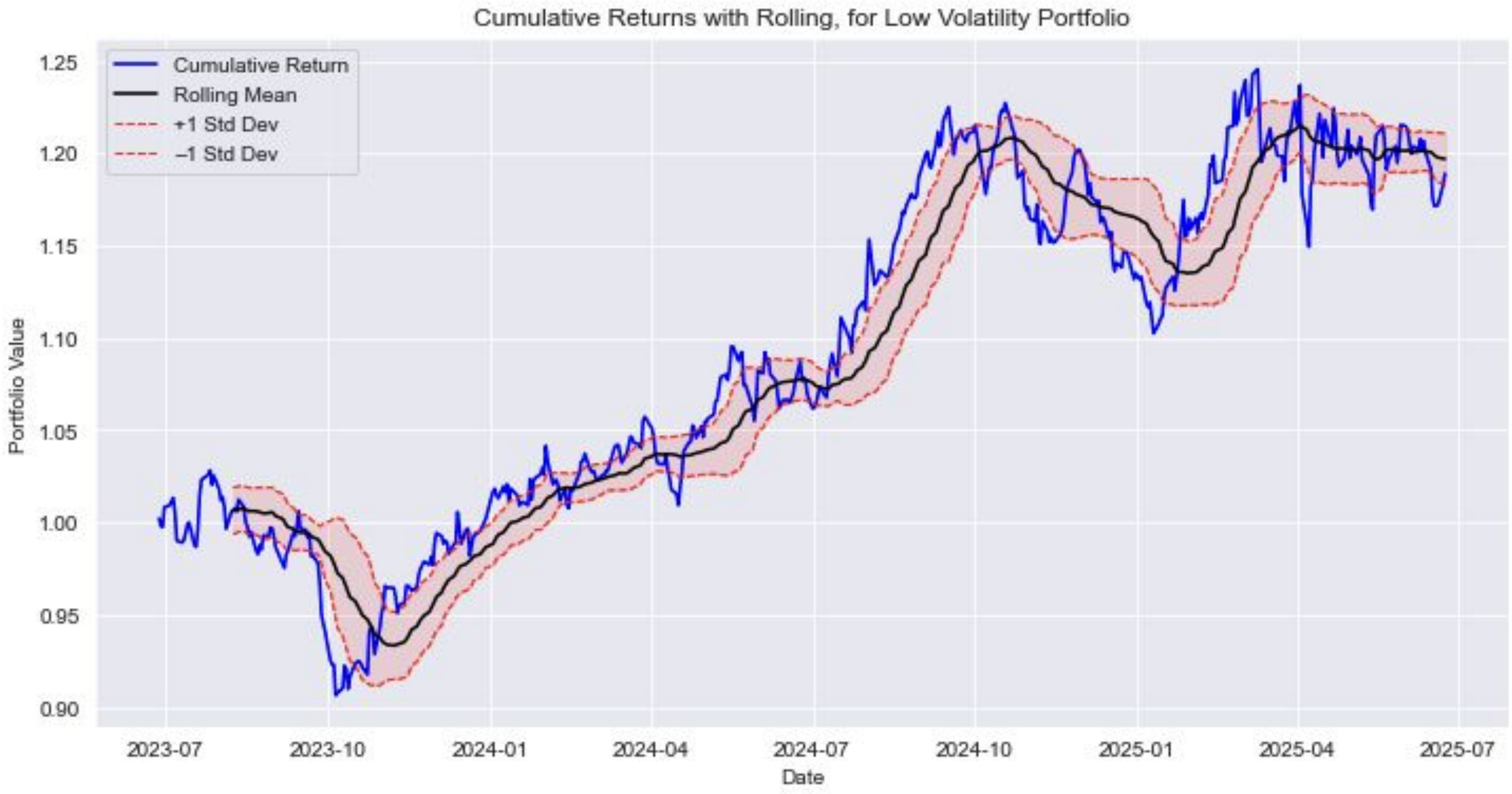
Total return over 2 years: 16.57%



Volatility with Rolling Mean – High Volatility



Volatility with Rolling Mean – Low Volatility



Sharpe Ratio:

I also considered optimizing according to the Sharpe Ratio

– here I had to make an assumption on the value of R_b (risk-free return)

This yielded very good total returns, both for low and high volatility portfolios

Other Approaches:

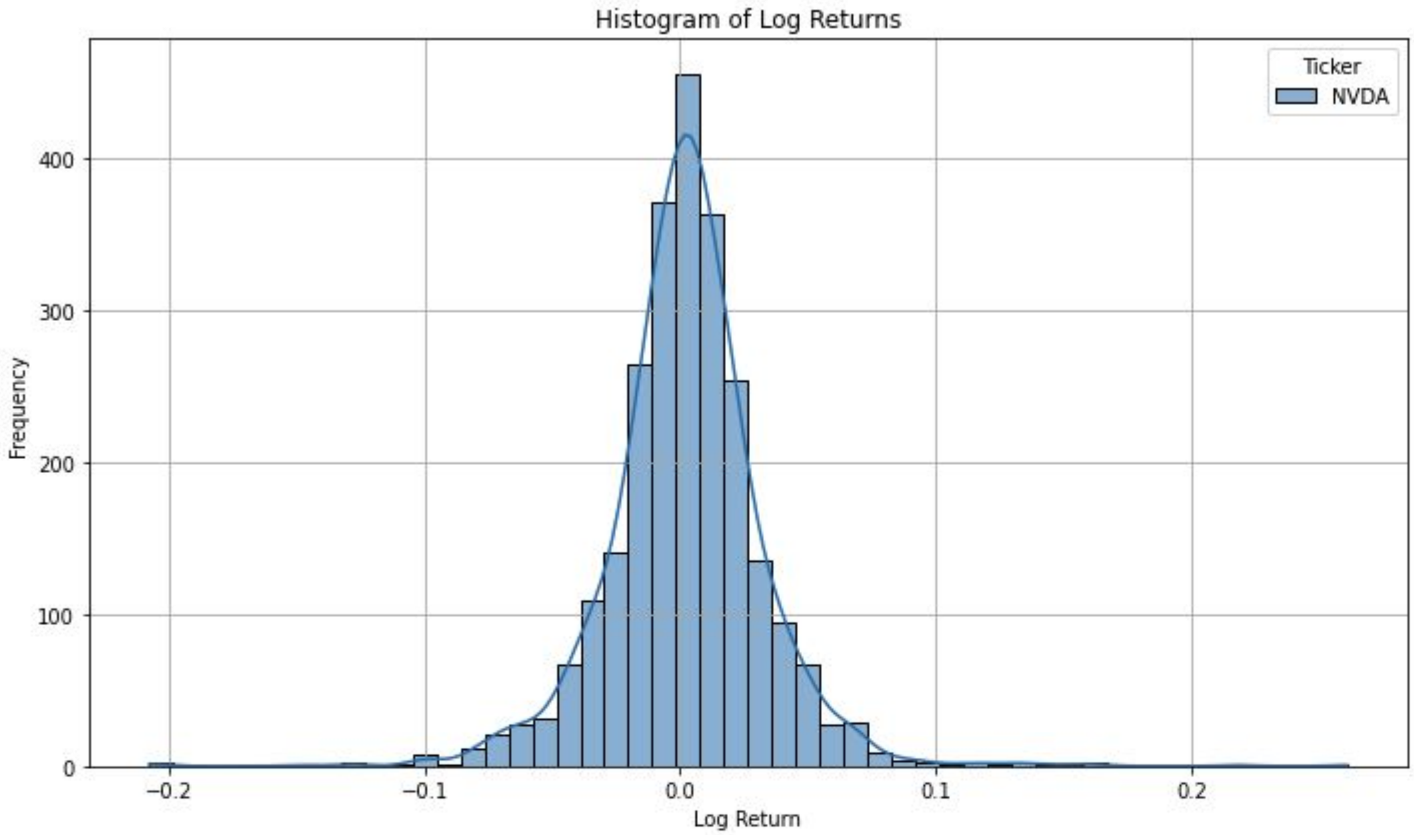
1) Correlation-Based Diversification:
   - <u>High risk</u>: correlated high-growth stocks
   - <u>Low risk</u>: low-correlation assets
2) Sector base approaches (group sector indices)
3) Volatility Targeting Portfolios
4) Barbell Strategy

Mini-Project 2

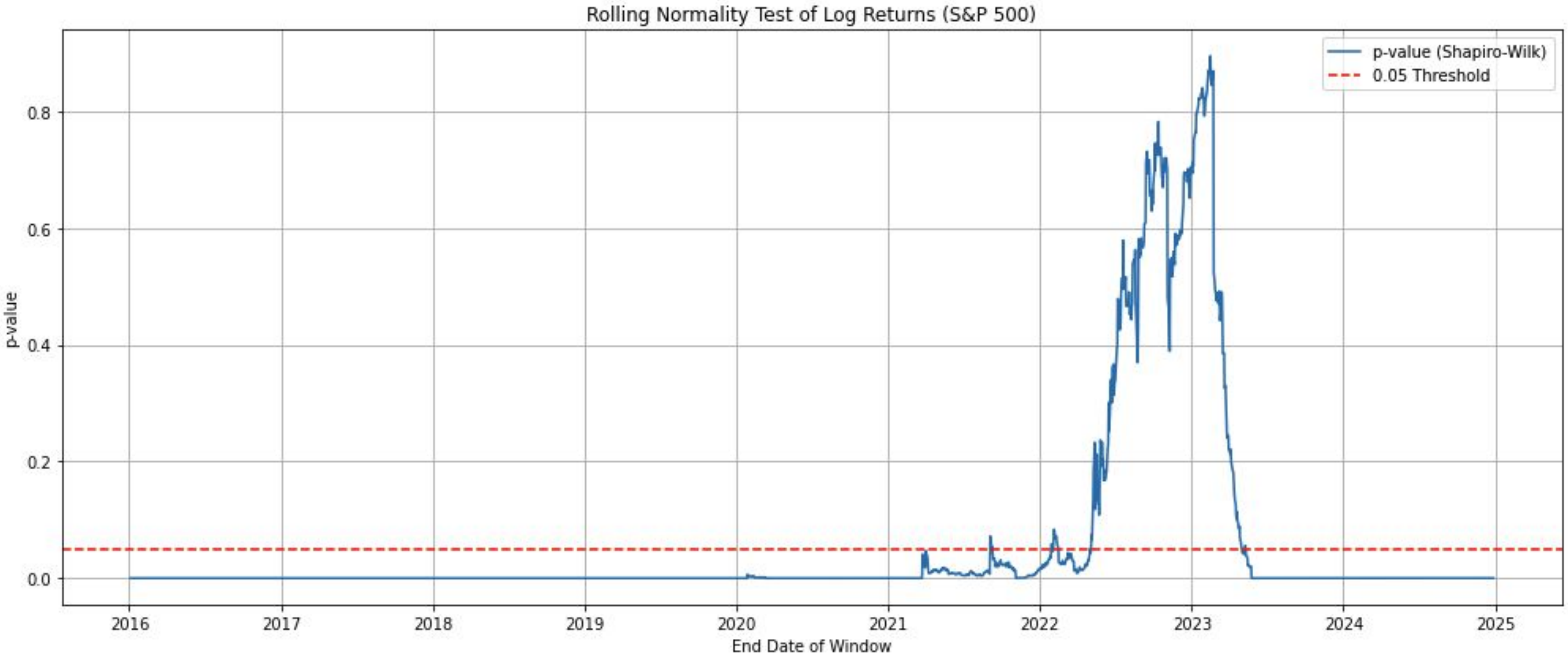
Hypothesis Testing of Standard Assumptions

Are financial time series truly normally distributed?

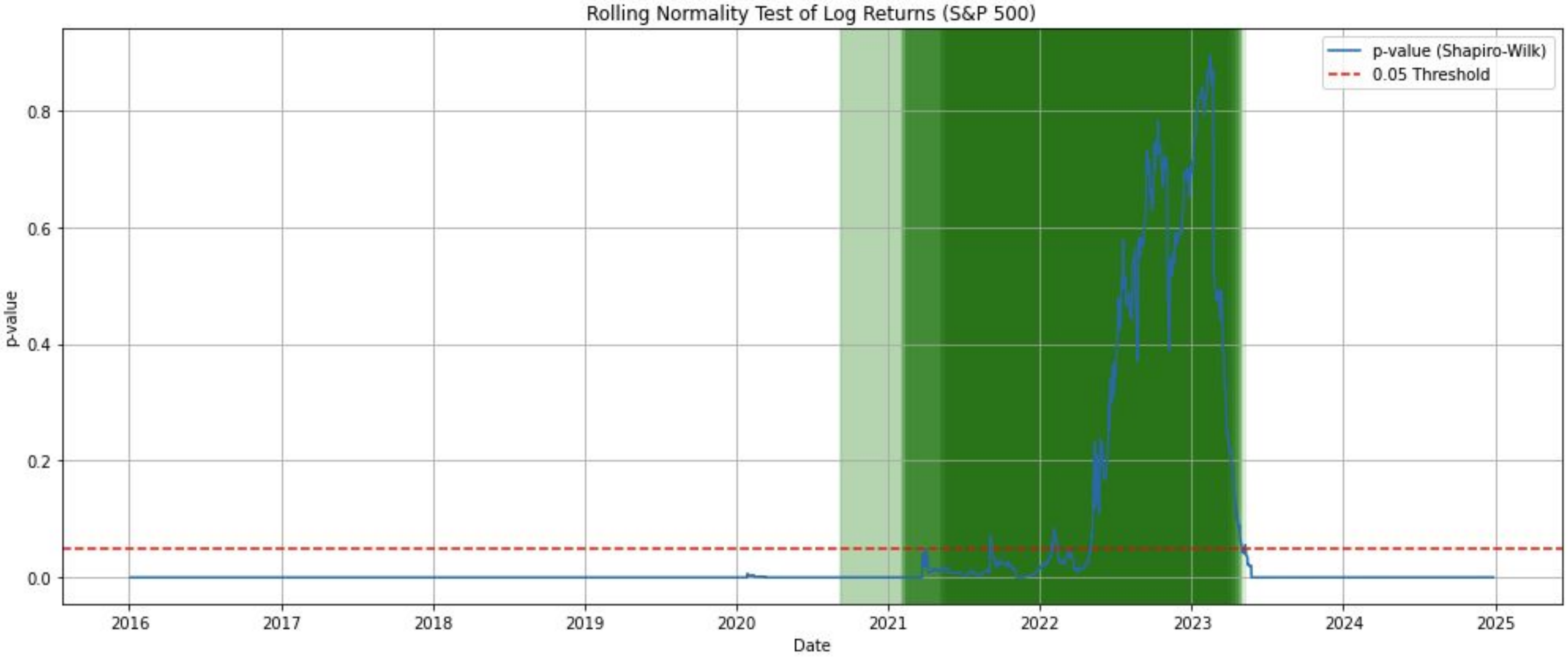
NVDA – log returns histogram



Rolling Shapiro-Wilk Test



Rolling Shapiro-Wilk Test



Comments

– Smaller the rolling windows ⇒ more ”normality” instances

– If period was to two years ⇒ we would get longer instances (shaded green)

– This is consistent with the CLT and the "non-rolling" Shapiro-Wilk test,

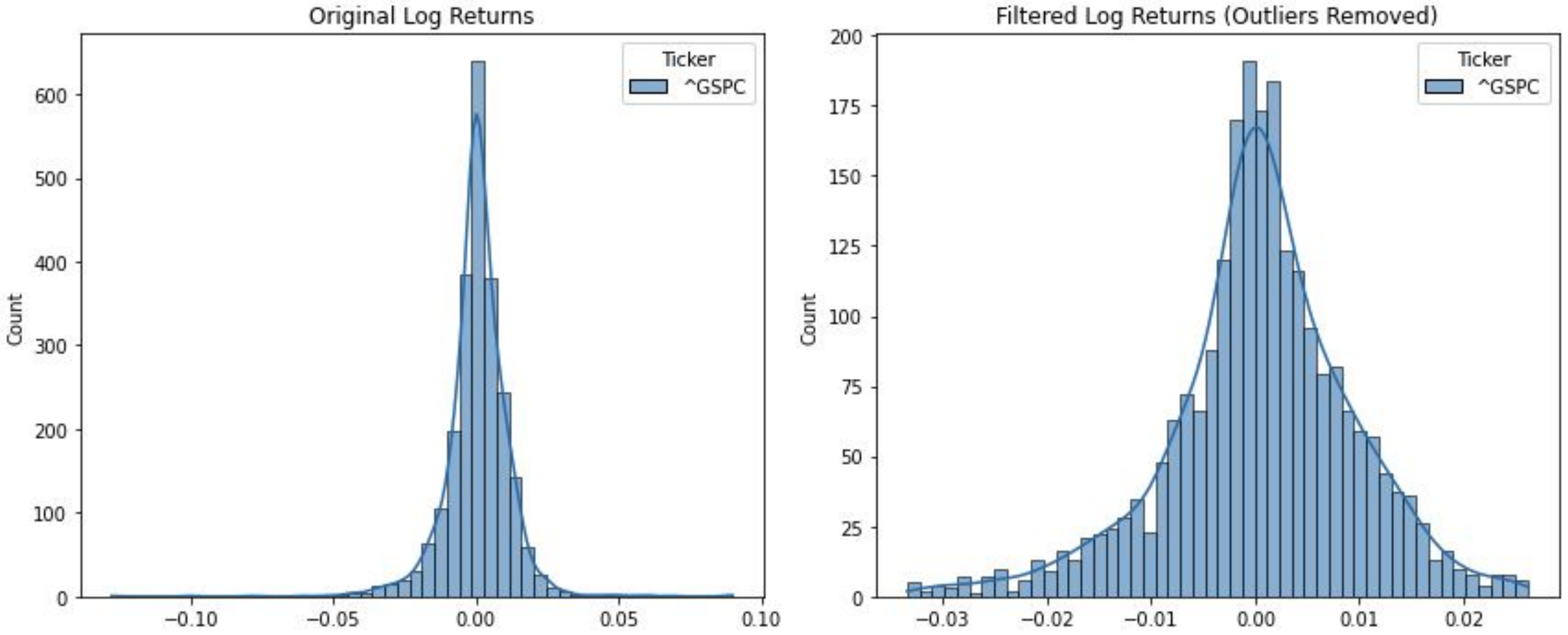
... more of the total log-returns were deduced to be normally distributed

– Around 2020, we would not pass the test (... Covid pandemic)

D’Agostino and Pearson’s test

```
Normality Test Results (D'Agostino and Pearson's Test):
============================================================
Original Log Returns: p-value = 0.0000
Statistically significant evidence that the data is NOT normally distributed.
------------------------------------------------------------
Filtered Log Returns: p-value = 0.0000
Statistically significant evidence that the data is NOT normally distributed.
------------------------------------------------------------
```

Remove Outliers – "^GSPC" index



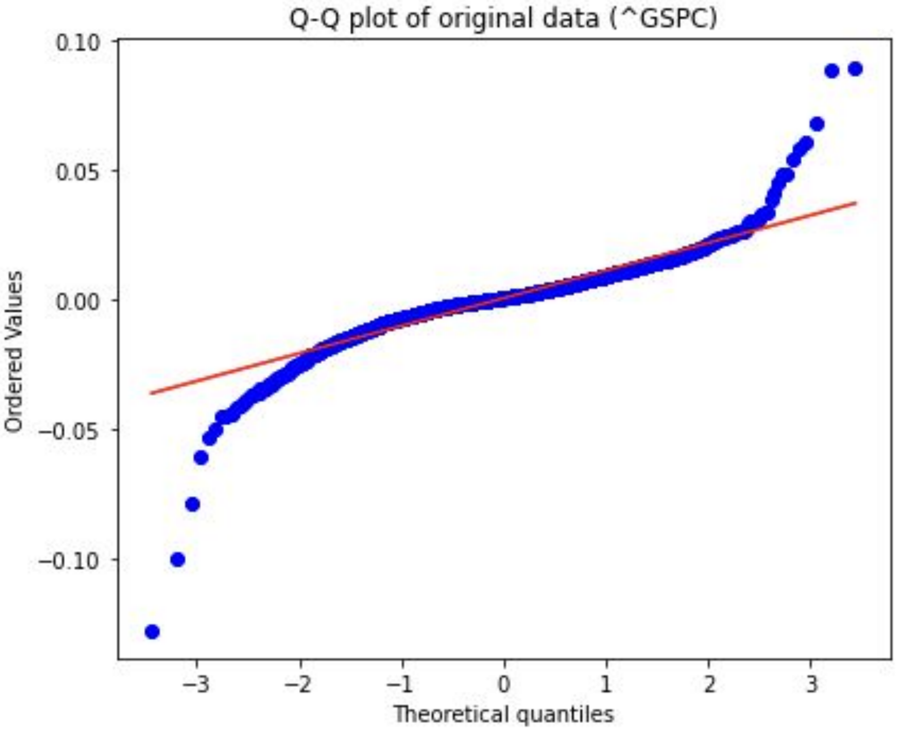
Would still not pass the test

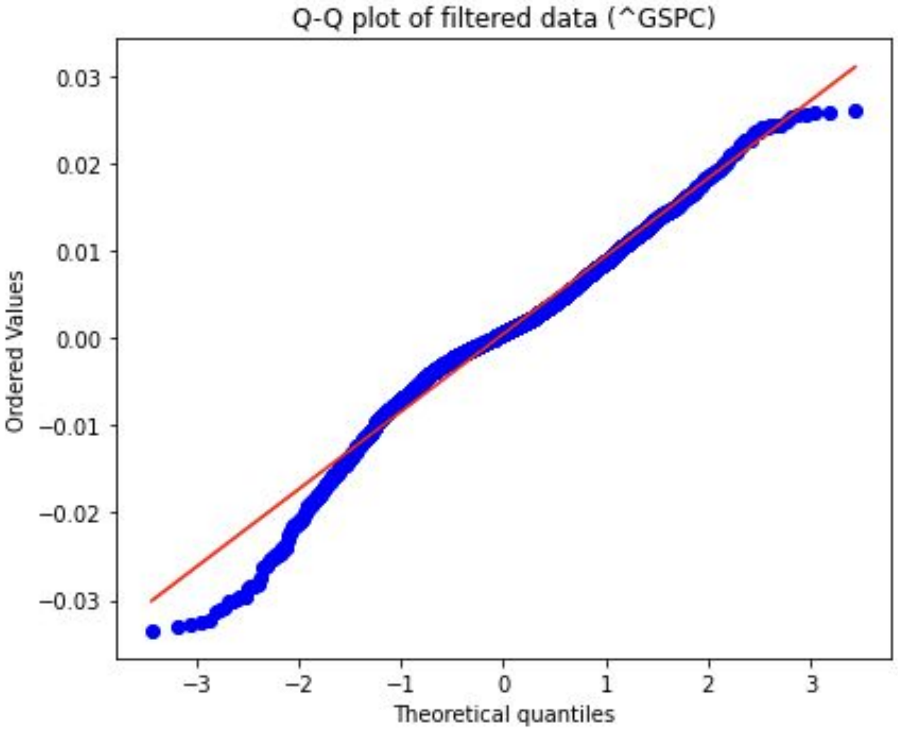
Seems like data actually follows a **Laplace** distribution… so let's test this

Kolmogorov-Smirnov Test

```
Laplace fit parameters: loc = 0.00060, scale = 0.00739
Kolmogorov-Smirnov test for Laplace:
D-statistic = 0.0257, p-value = 0.0855
  => The log returns fit a Laplace distribution

- - - - - - - - - - -

Laplace fit parameters: loc = 0.00060, scale = 0.00739
Kolmogorov-Smirnov test for Laplace:
D-statistic = 0.0303, p-value = 0.0277
  => The FILTERED log returns do NOT fit a Laplace distribution
```

Q-Q Plot with fitted Laplace distribution





Conclusion from this project

Laplace Distribution may be a better, more realistic assumption regarding the distribution of financial log return data, compared to the usual *Normal Distribution* assumption.

That is, extreme returns happen more frequently than what the Normal Distribution implies.

Portofolio from Project-1

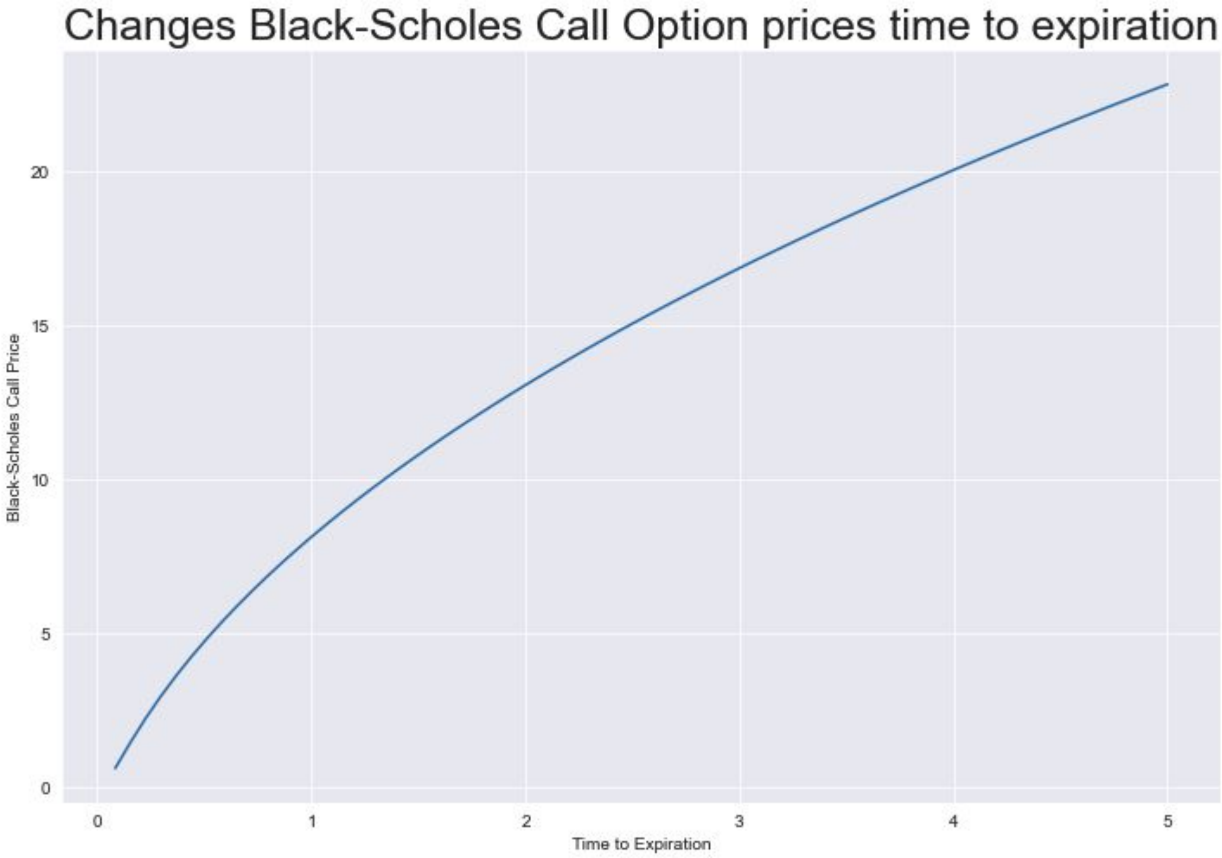
```
Normality Tests:
 - Shapiro-Wilk p-value: 0.0000
 - D'Agostino & Pearson p-value: 0.0000

Laplace Fit Test:
 - KS test p-value: 0.1048
 - Laplace fit parameters: loc = 0.00092, scale = 0.00656
```

```
Conclusions:
 - Shapiro-Wilk test: log returns reject normality -- data is NOT normal.
 - D'Agostino & Pearson test: log returns reject normality -- data is NOT normal.
 - KS test for Laplace: log returns do NOT reject Laplace fit -- it looks plausible.
```

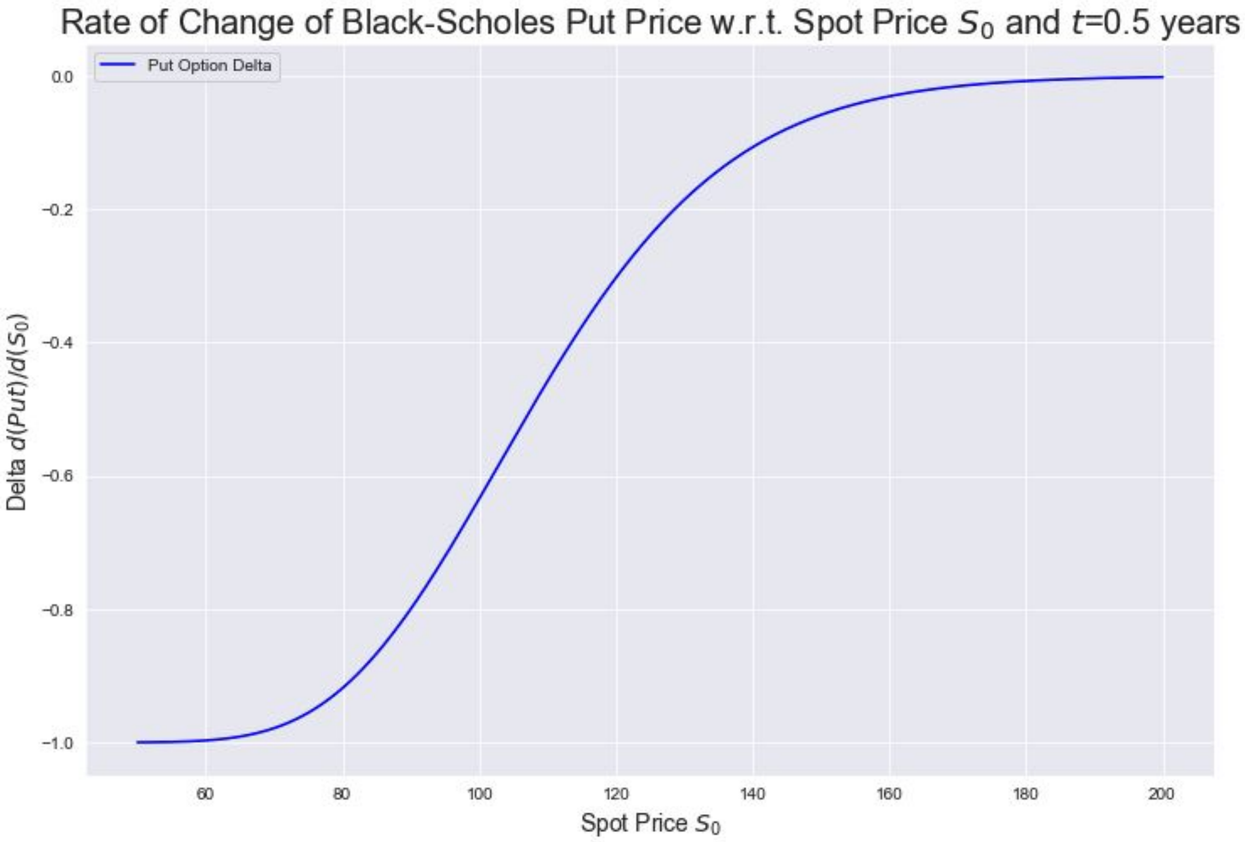
Mini-Project 3

Black-Scholes call and put options visuals

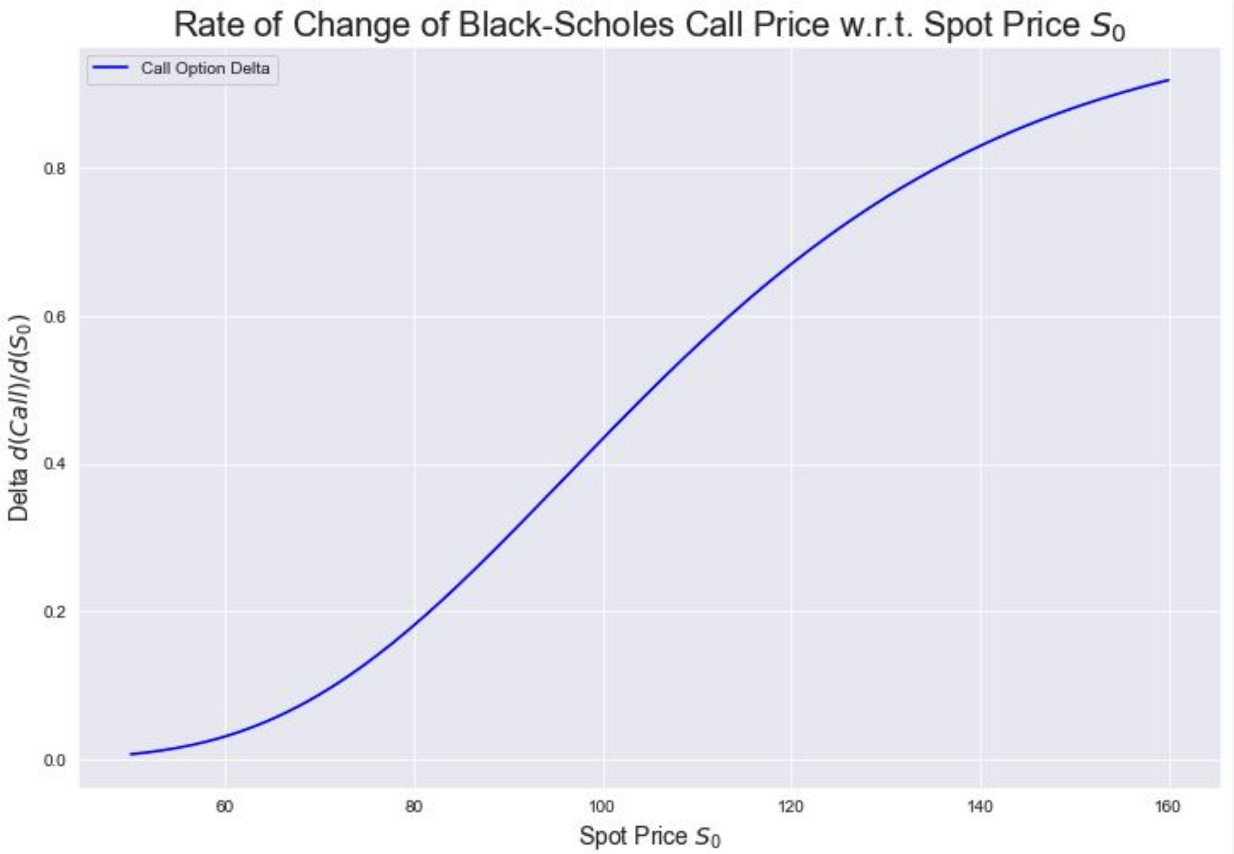
BS Call Price vs. Time to Expiration



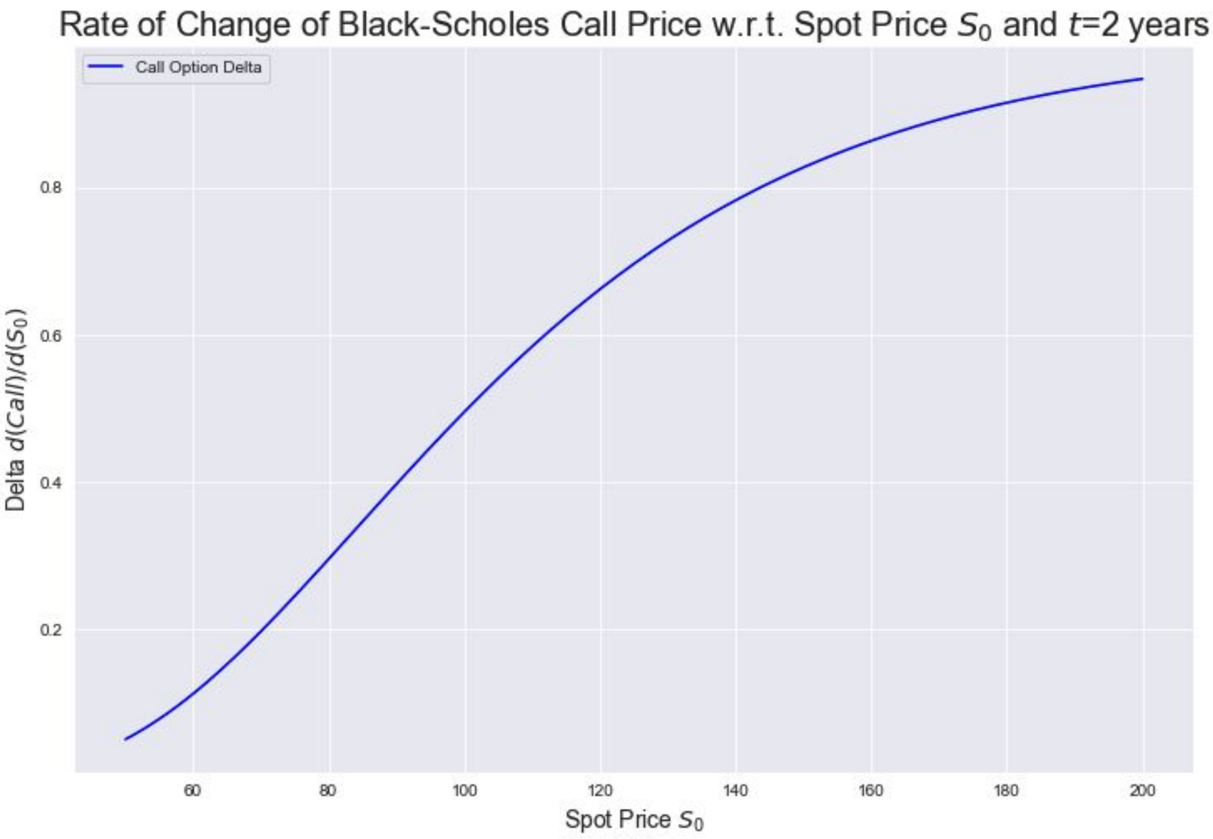
Rate of change dependence on S_0 – t=0.5



Rate of change dependence on S_0 – t=1

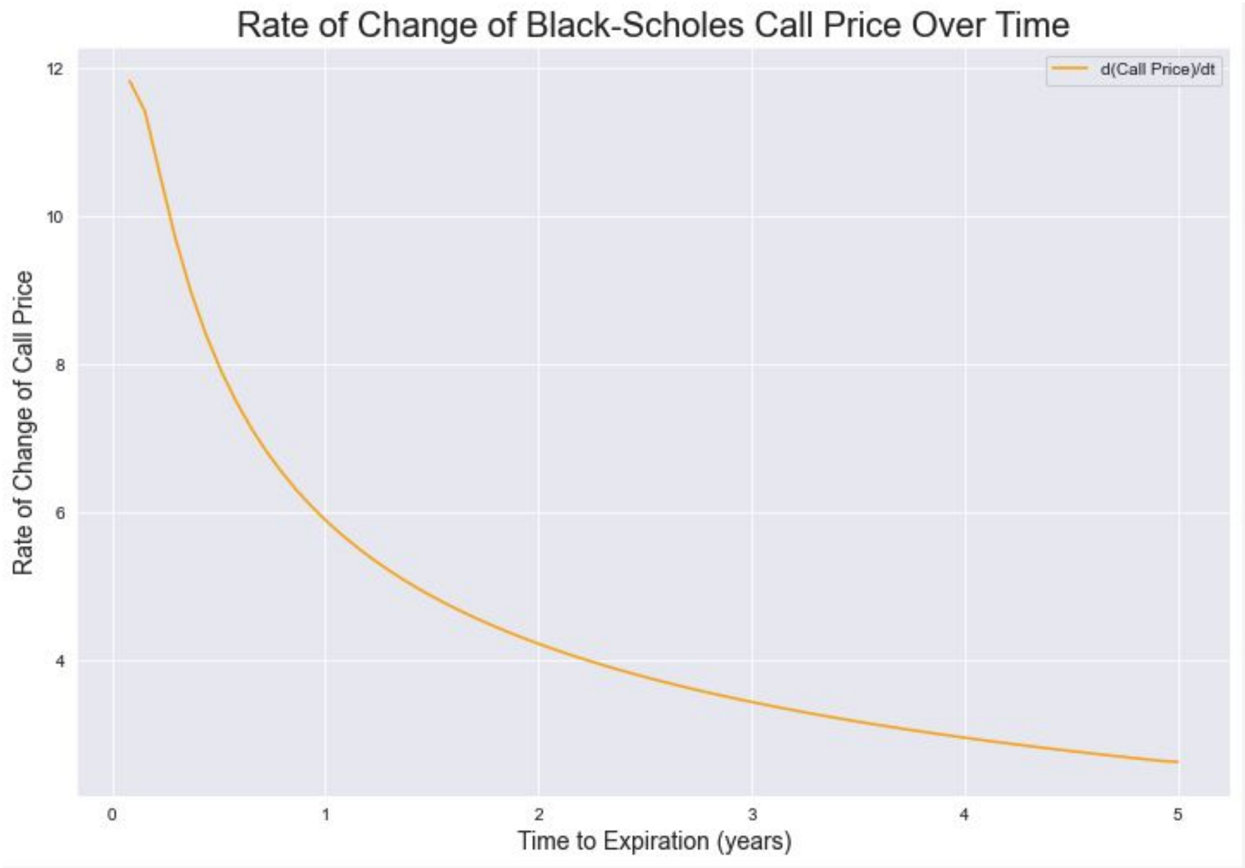


Rate of change dependence on S_0 – t=2

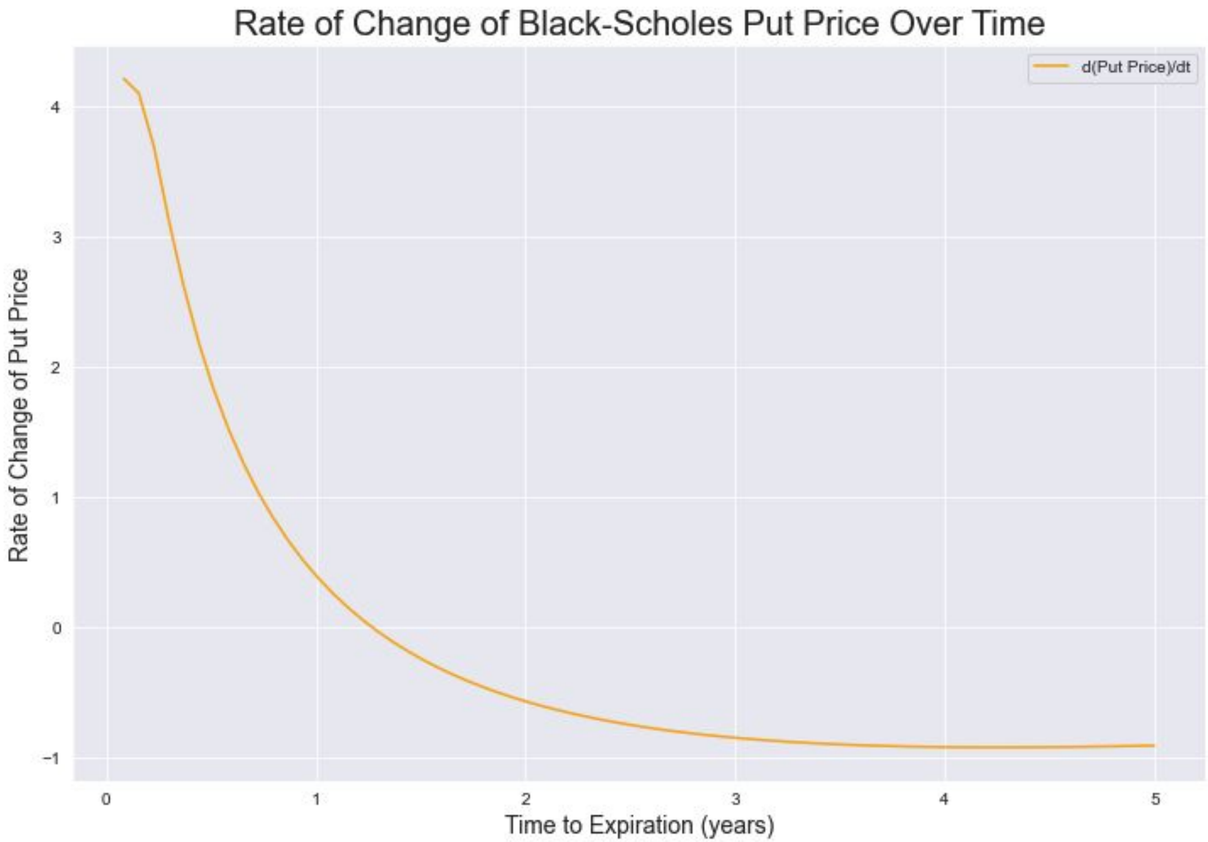


Rate of change dependence on S_0 – t=5

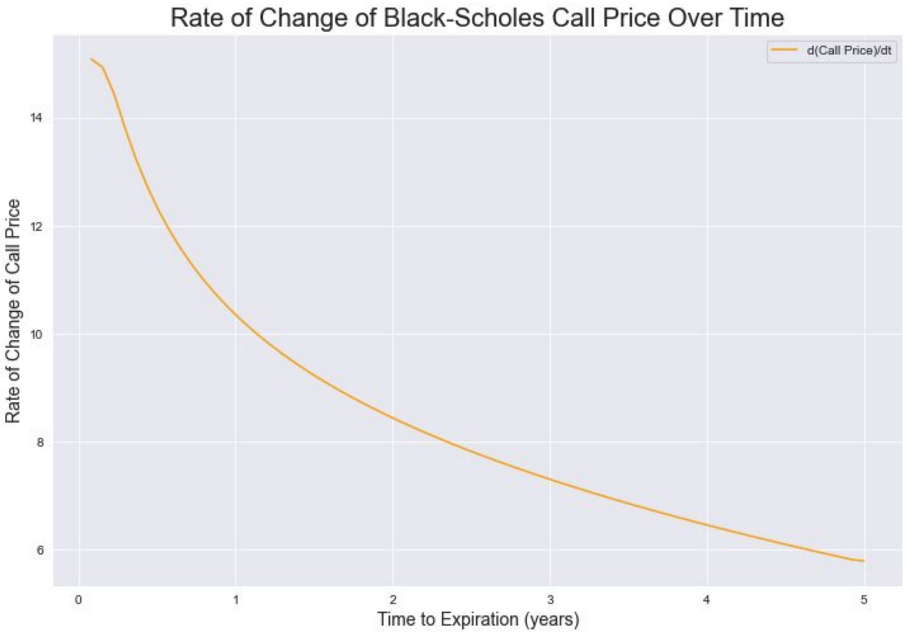
Rate of change (Call Price) – at r=0



Rate of change (Put Price) – at r=0



Rate of change – at r=0.1



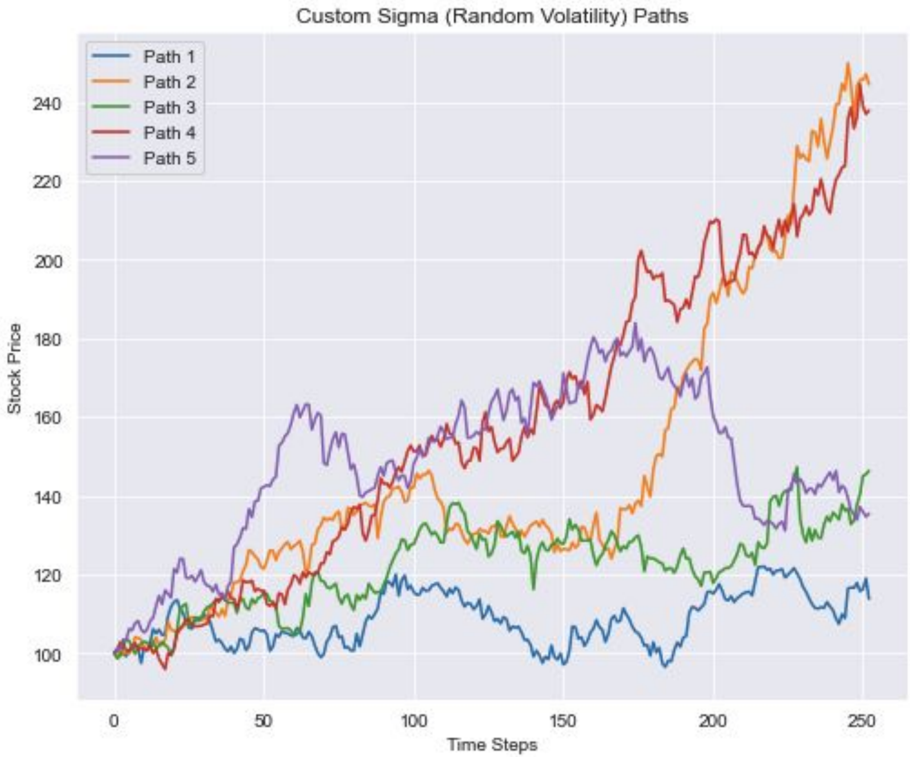
Mini-Project 4

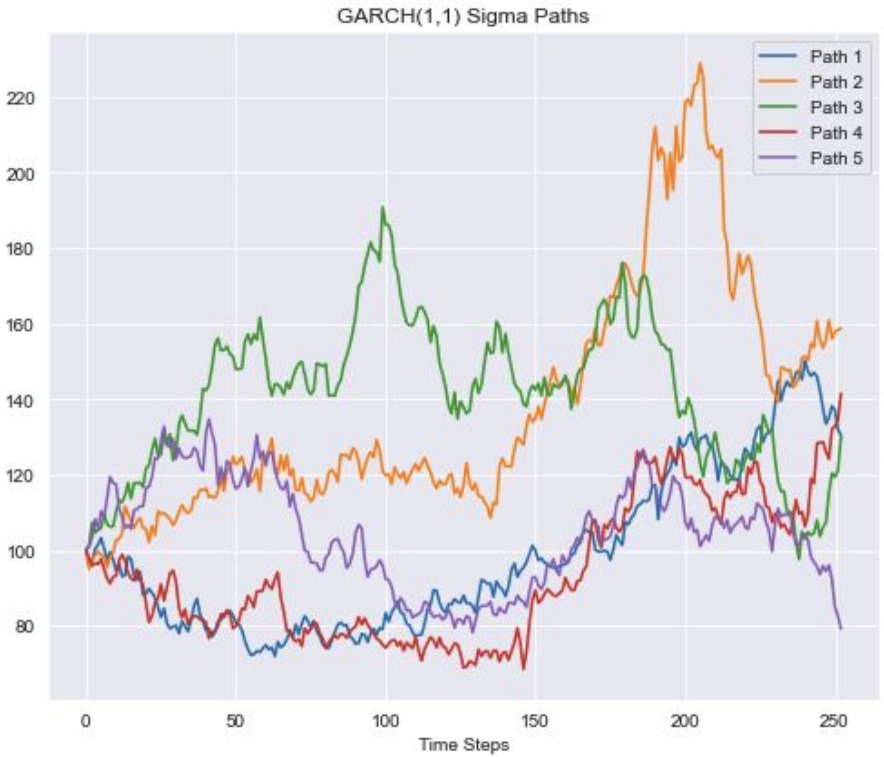
Effect of variable/stochastic volatility

– ***Heston*** model

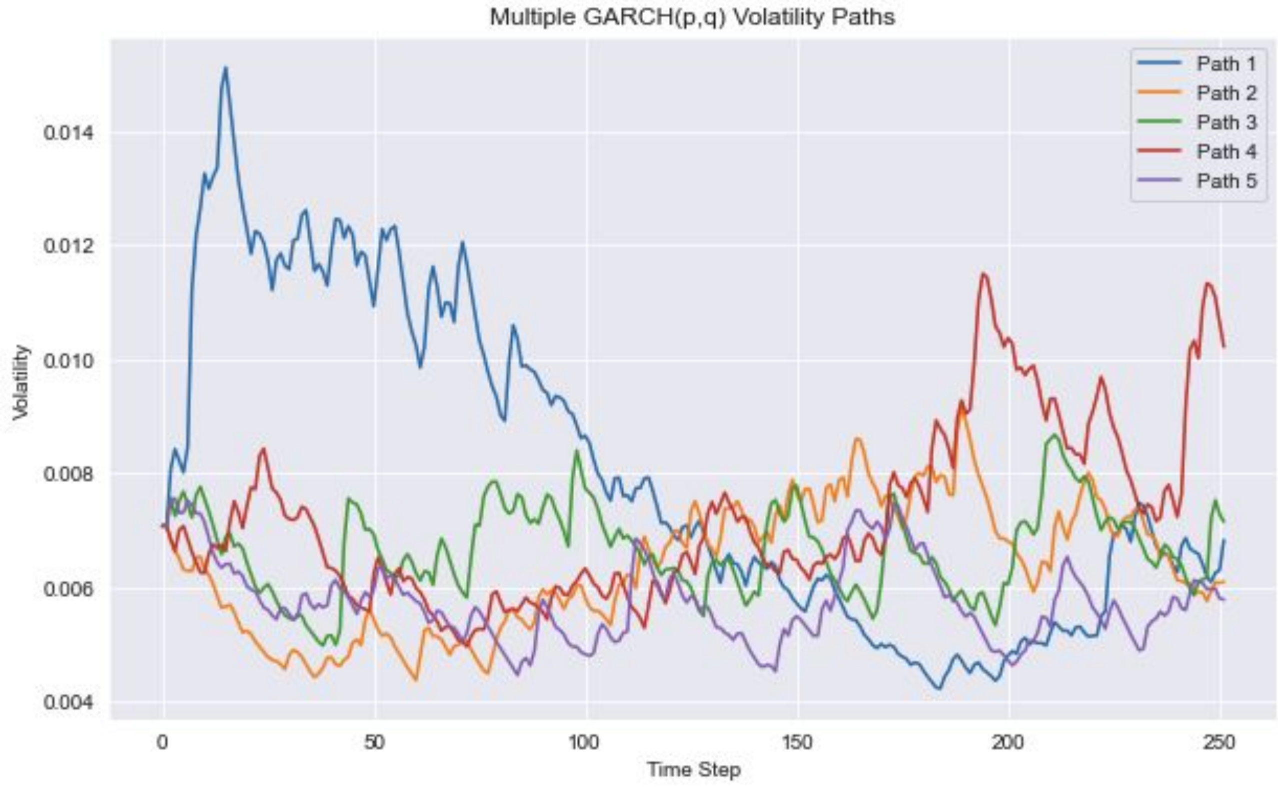
– ***GARCH*** model

GARCH(1,1) Model – σ paths

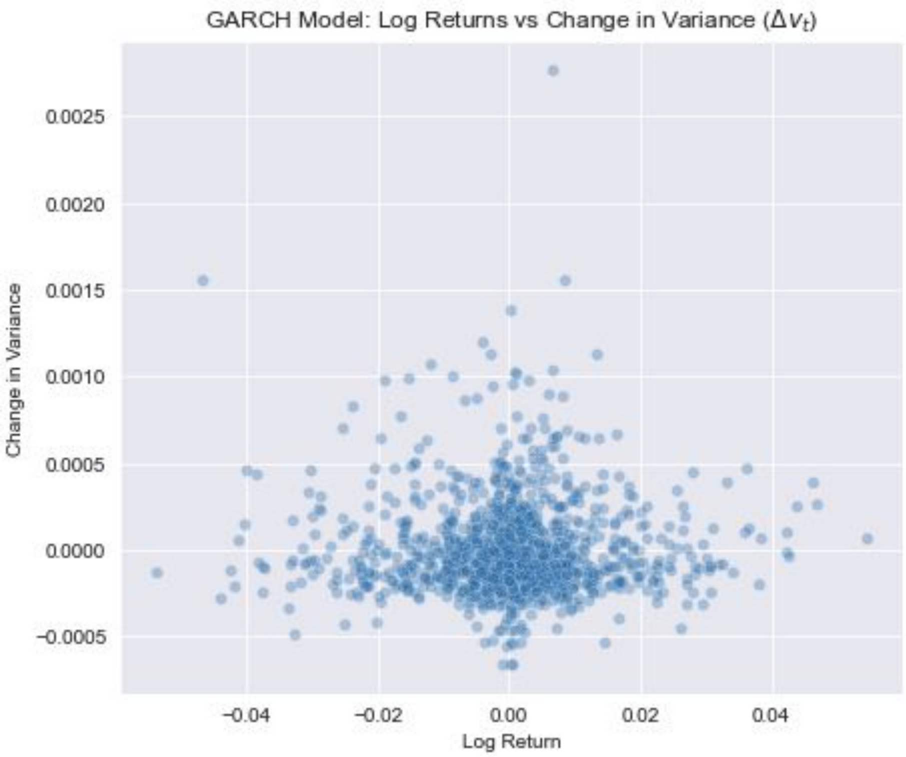


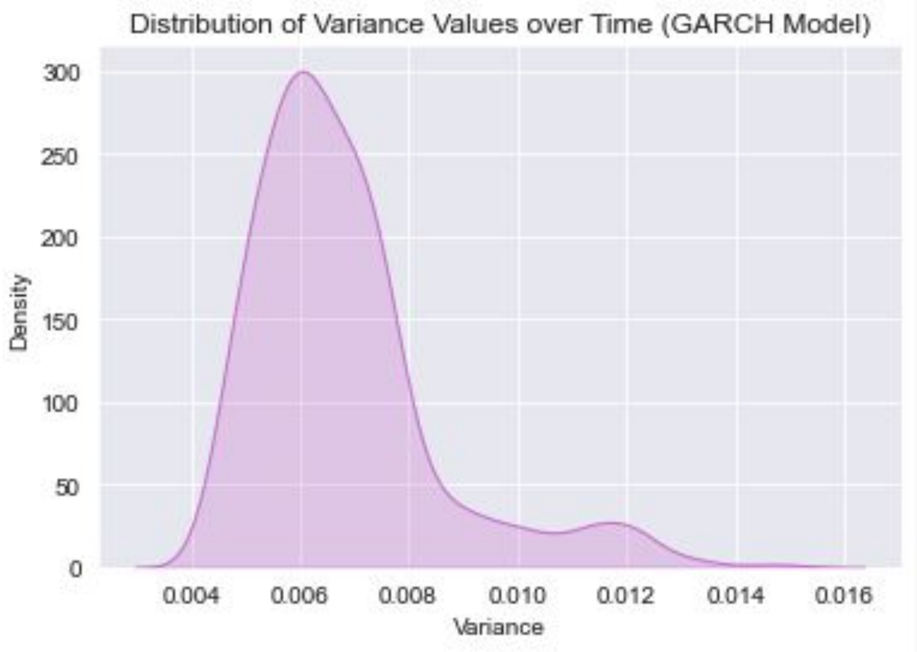


GARCH(2,1) Volatility Paths

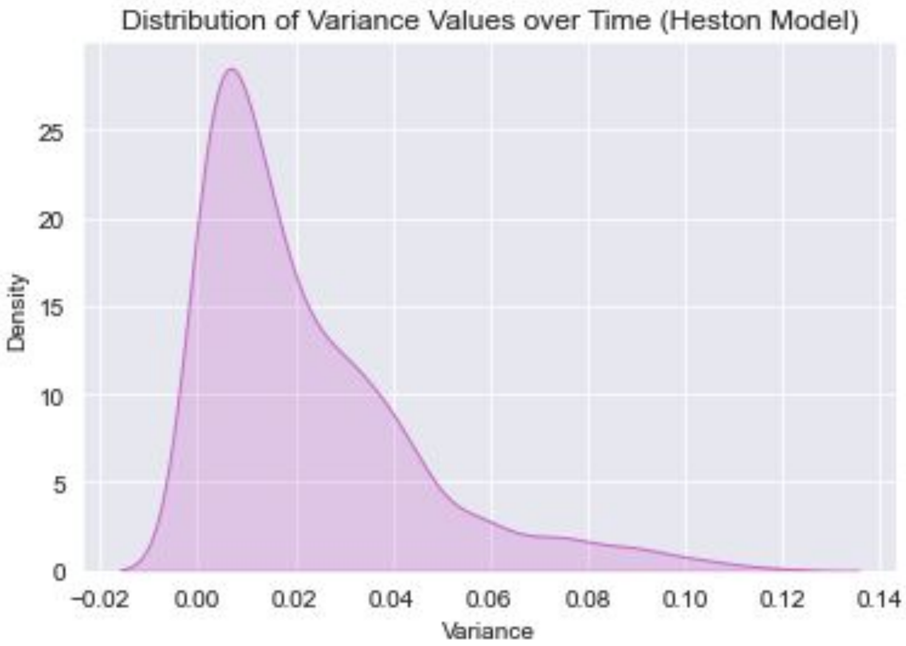


GARCH(2,1)


GARCH Model: Log Returns vs Change in Variance (Δv_t)
Change in Variance
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
−0.0005
−0.04
−0.02
0.00
0.02
0.04
Log Return


Distribution of Variance Values over Time (GARCH Model)
Density
300
250
200
150
100
50
0
0.004
0.006
0.008
0.010
0.012
0.014
0.016
Variance

Heston Model



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