THE ERDŐS INSTITUTE

Quant Finance Bootcamp Final Projects

Alborz Ranjbar

Summer 2025

Project 1

Objective:

- building two stock portfolios using current data: one high-risk and one low-risk with more stable performance."

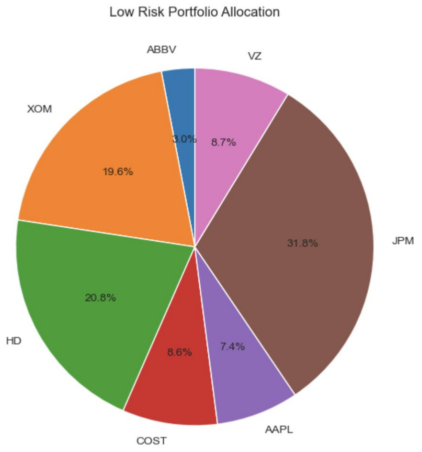
Approach (lower risk):

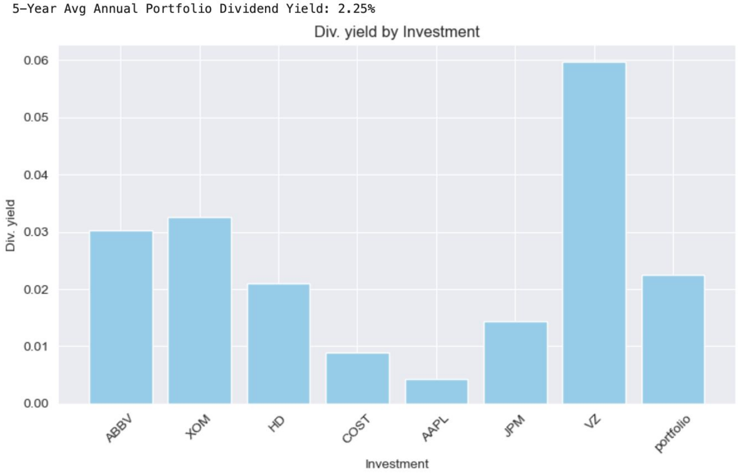
- Portfolio tickers: ABBV, XOM, HD, COST, AAPL, JPM, VZ
- Seven stocks were selected to help diversify risk, acknowledging that more holdings support but don't guarantee lower risk.
- Stocks span different sectors to reduce sector-specific correlation and risk.
- Companies providing essential goods and services, like Costco and Verizon, were chosen for portfolio stability.
- A five-year time horizon was set to mitigate short-term volatility.
- From a broader pool, stocks with higher dividends and returns were selected to balance income and growth.
- Having these points in mind we optimized the portfolio for minimal volatility and still got great potential annualized return and dividend yield

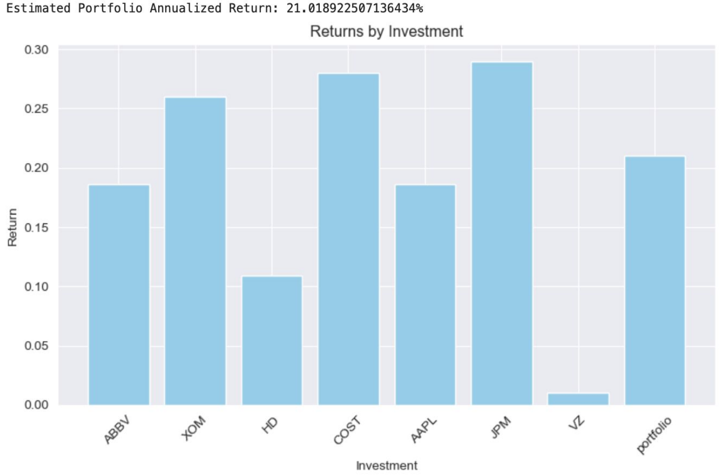
Approach (higher risk):

- Portfolio tickers: TSLA, PLTR, NVDA
- Lower number of stocks from less sectors exposes the portfolio to sector specific downturns
- Time horizon was taken to be 1 year
- These stocks showed high correlation in the past year
- We optimized the portfolio for maximal return but got close to zero dividend yield and extremely high volatility

Low Risk Results: A volatility rate of 13.9% was achieved

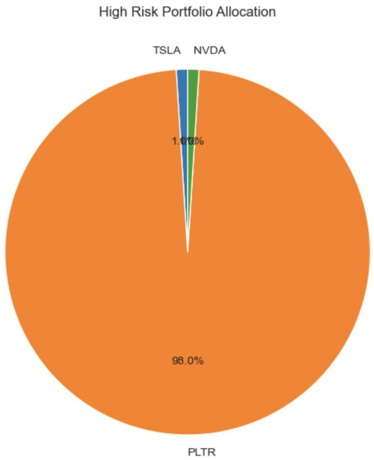


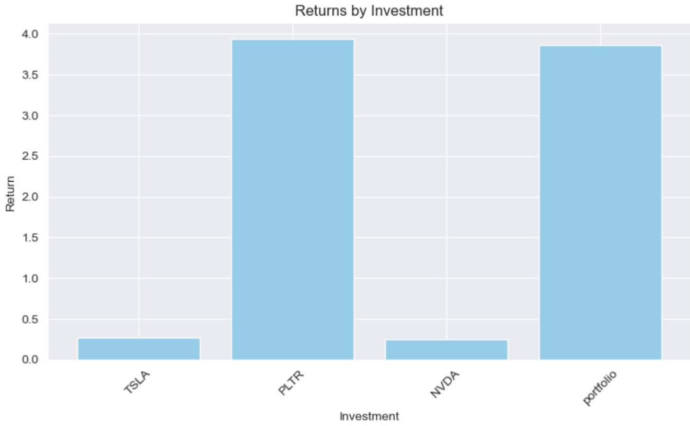




High Risk Results:

- Achieved a 386% return
- But a 70.8% volatility





Project 1

Future improvements:

- I haven't incorporated any ML models that can heavily help the analysis. So, I'd like to add such analysis in the future.
- It would also be nice to add some type of auto-hedging which further reduces the risk associated to our investment

Project 2

Objective:

- Examining whether log returns of stocks or indexes follow a normal distribution by testing for normality, analyzing the effect of removing outliers, and constructing a portfolio with more normally distributed returns. It also evaluates an existing portfolio over time to assess the stability of the normality assumption in real markets.

Approach:

- For this project we used three normality tests being Shapiro-Wilk's test, Pearson's test, and Kolmogorov-Smirnov's test
- Shapiro and Pearson return a statistics and a p-value which if $p < 0.05$ we can't reject the possibility of distribution being close to normal and the opposite holds for $p >= 0.05$
- Kolmogorov's test, tests for overall shape differences of the distributions as well
- I examined normality in the 30-day, 60-day, and 90-day periods in the past 720 days that the market was open
- In addition to the tests above, I used Q-Q plotting and plotting the histogram of each period's distribution to analyzed normality
- Finally we optimized weights of our portfolio of selected stocks to simultaneously maximize the p-value achieved from the three tests (i.e make portfolio more normal) in the 60-day and 90-day periods in the 720 days of market

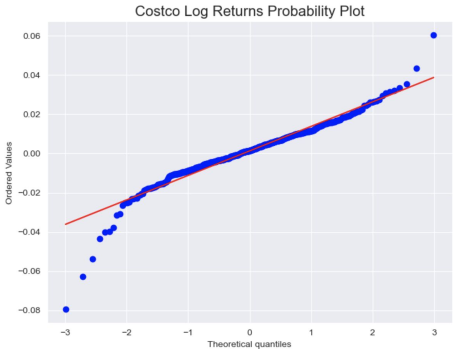
Project 2 results:

- for long periods of time it's close to impossible to have a stock that follows a normal distribution closely as expected
- for short periods of time like 30-day periods although our tests might return values that fall within the region where it signals the potential for being normal, the Q-Q plot and our histograms show that it almost always is not the case.
- In the sixty and ninety day periods we were able to get more normal-like behavior especially when we removed outliers in our data
- it's fair to say generally around the 3-6 months is when we can expect to see more normal-like behavior and for more than one year it's extremely unlikely.
- By removing the top and bottom 1% of data in each period the number of periods for which all the tests return higher than 0.05 p value increased considerably, showing the importance of the weight of the tails.
- We also saw that the low risk portfolio from proj. 1 was very far from being normal
- After optimizing a portfolio of the same tickers as in low risk portfolio for normality, we can see the heavy weighting of Costco suggests it may have the most normal returns in the periods analyzed. Further testing of its skewness, kurtosis, and comparison with other portfolio stocks could help validate this.

Improvements:

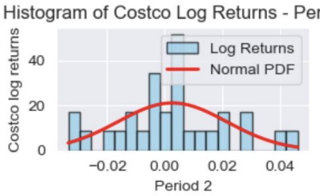
- Incorporating more sophisticated normality tests
- Again for finding normal-like periods we can come up with some ML-adjacent techniques to find such periods
- Test alternative maximizing functions for maximizing my p_value for creating my portfolio with close to normal behavior.

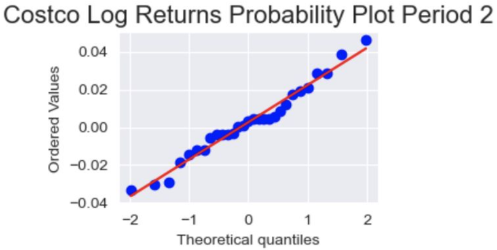
Q-Q plot of costco 2yr return:



Example of a 30-day period:

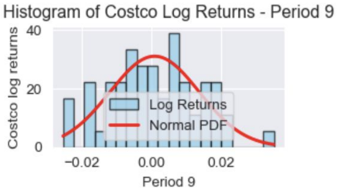
```
Costco log return distribution: D'Agostino and Pearson's test p-value = 0.7970 for period 2
2022-10-03 00:00:00 2022-11-11 00:00:00
→ No statistically significant evidence against normality.
Costco log return distribution: Shapiro-Wilk's test p-value = 0.7016 for period 2
2022-10-03 00:00:00 2022-11-11 00:00:00
→ No statistically significant evidence against normality.
Costco log return distribution: Kolmogorov-Smirnov's test p-value = 0.7055 for period 2
2022-10-03 00:00:00 2022-11-11 00:00:00
→ No statistically significant evidence against normality.
```





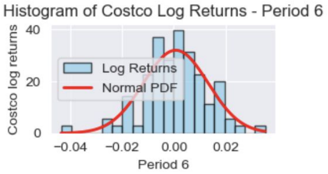
Example of a 60-day period:

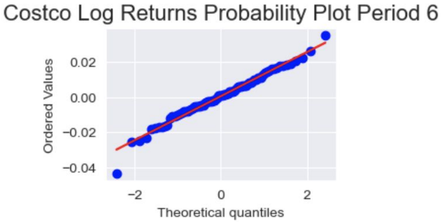
```
Costco log return distribution: D'Agostino and Pearson's test p-value = 0.9641 for period 9
2024-07-19 00:00:00 2024-10-11 00:00:00
→ Statistically significant evidence that the data is NOT normally distributed.
Costco log return distribution: Shapiro-Wilk's test p-value = 0.8622 for period 9
2024-07-19 00:00:00 2024-10-11 00:00:00
→ No statistically significant evidence against normality.
Costco log return distribution: Kolmogorov-Smirnov's test p-value = 0.9986 for period 9
2024-07-19 00:00:00 2024-10-11 00:00:00
→ No statistically significant evidence against normality.
```



Example of a 90-day period:

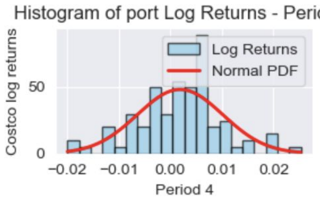
```
Costco log return distribution: D'Agostino and Pearson’s test p-value = 0.0632 for period 6
2024-06-05 00:00:00 2024-10-11 00:00:00
→ Statistically significant evidence that the data is NOT normally distributed.
Costco log return distribution: Shapiro-Wilk’s test p-value = 0.3825 for period 6
2024-06-05 00:00:00 2024-10-11 00:00:00
→ No statistically significant evidence against normality.
Costco log return distribution: Kolmogorov-Smirnov’s test p-value = 0.9166 for period 6
2024-06-05 00:00:00 2024-10-11 00:00:00
→ No statistically significant evidence against normality.
```

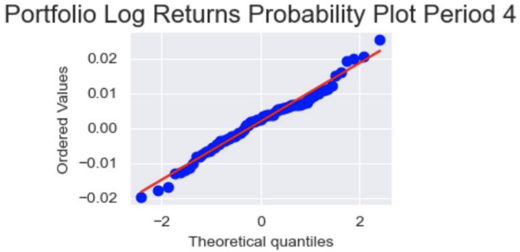




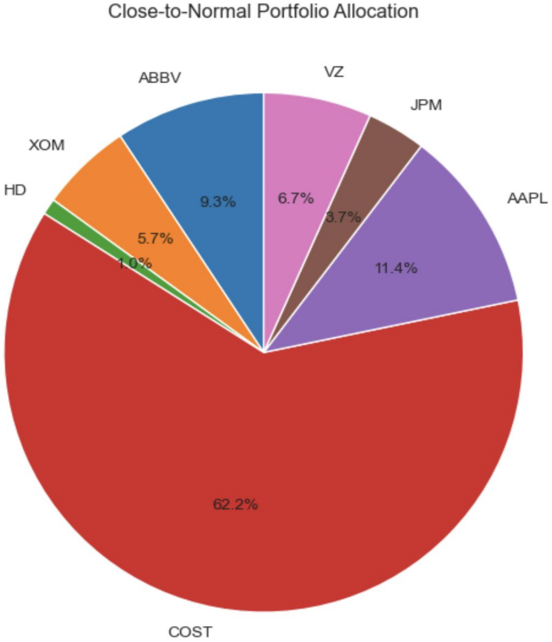
Example of a 90-day period for normal portfolio:

```
portfolio log return distribution: Shapiro-Wilk’s test p-value = 0.2214 for period 4
2023-09-18 00:00:00 2024-01-25 00:00:00
→ No statistically significant evidence against normality.
```





Portfolio allocation for normality:



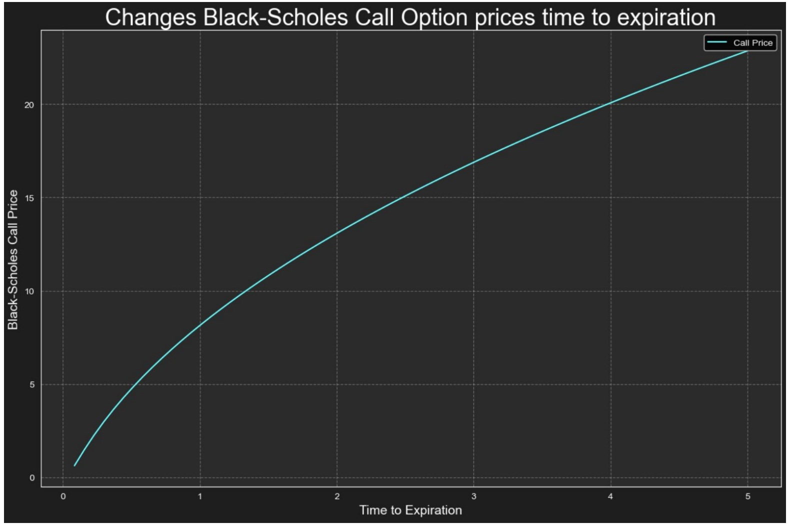
Project 3

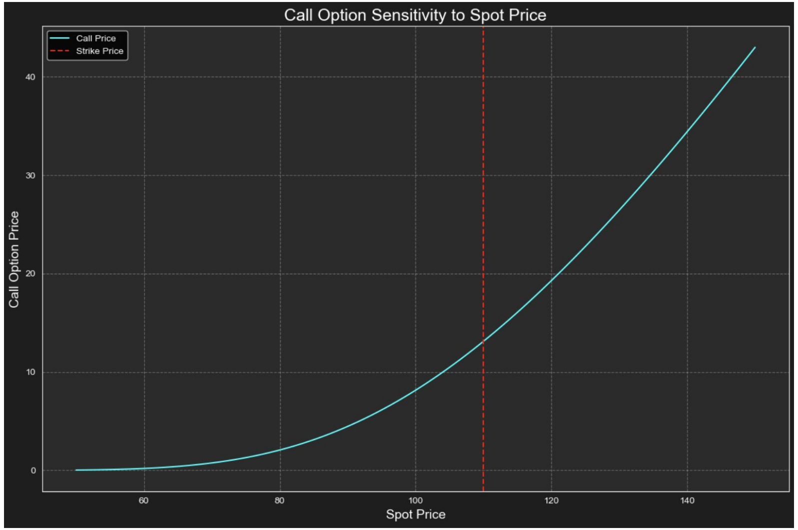
Objective:

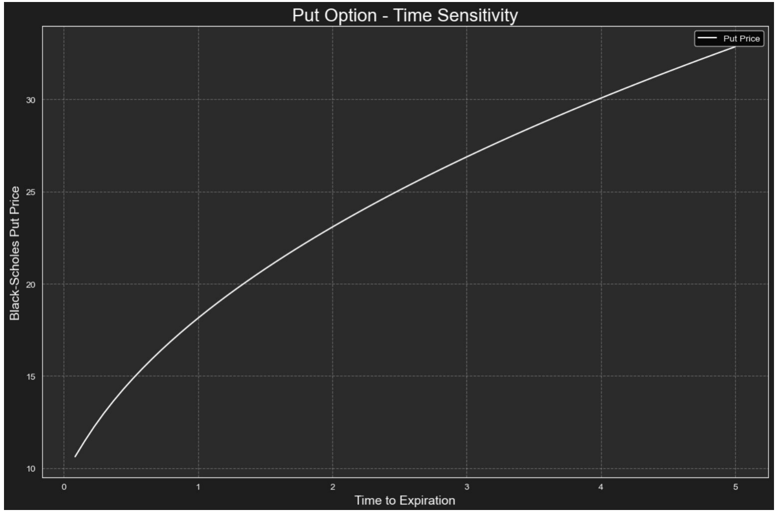
- In this project we will explore the time sensitivity and spot price sensitivity of call and put options

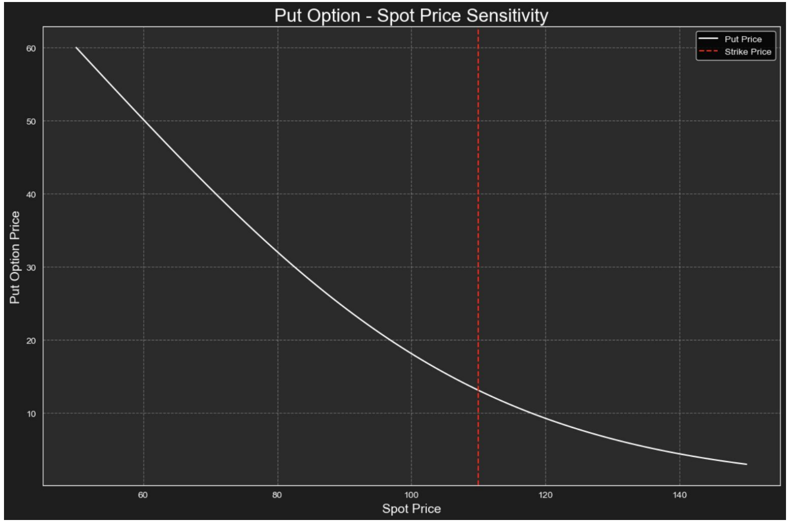
Observations:

- Call and put options are both affected by time and the underlying asset's price, but in different ways. As time passes, both types of options lose value due to time decay (theta), and this loss accelerates as expiration nears.
- Long-dated options decay more slowly, while short-dated options see a sharper drop in value.
- In terms of price sensitivity, a call option increases in value when the spot price rises (positive delta), especially when it's in the money, while its value drops near zero when the spot is far below the strike.
- a put option loses value when the spot price rises (negative delta); it gains value as the spot drops far below the strike, and becomes nearly worthless when the spot is much higher than the strike. Overall, calls and puts react in opposite ways to spot price changes but are both similarly impacted by the passage of time.


Changes Black-Scholes Call Option prices time to expiration
Call Price
Black-Scholes Call Price
Time to Expiration
0
5
10
15
20
0
1
2
3
4
5


Call Option Sensitivity to Spot Price
Call Price
Strike Price
Call Option Price
Spot Price
0
10
20
30
40
60
80
100
120
140


Put Option - Time Sensitivity
Put Price
Black-Scholes Put Price
Time to Expiration
10
15
20
25
30
0
1
2
3
4
5


Put Option - Spot Price Sensitivity
Put Price
Strike Price
Put Option Price
Spot Price
10
20
30
40
50
60
60
80
100
120
140

Project 4

Objective:

- Researching and applying a sigma-hedging technique i.e. a hedging strategy for a simulated stock path with varying standard deviation as opposed to a constant one.

Approach:

- Three ways of simulating stock paths with varying standard deviation being Custom method, Heston Model, and Garch(1,1).
- corresponding call_price functions of the Heston and garch were implemented.
- Next, no hedging, delta-hedging, and delta-vega-hedging strategies were implemented and compared.
- This process was done once with simulating paths from Heston and once from garch.

Observation:

Delta hedging outperforms no hedging, but adding Vega hedging further reduces losses and increases both average and maximum profits. This makes Delta-Vega hedging more effective for call sellers in volatile markets—provided the hedge asset (e.g., a helper stock) aligns well with the main stock. However, real-world factors, like option mispricing on the hedge asset, can impact its effectiveness.

Further Improvements

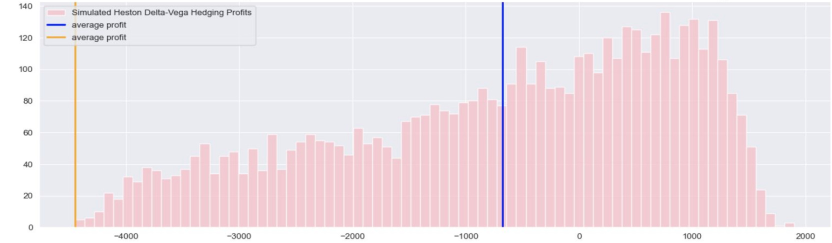
- I'd like to make the body of my comparison into a function at some point that also takes in the number of simulations and type of path simulator and corresponding variables and prints these results.
- I'd like to learn more about other types of sigma-hedging techniques and implement those as well.
- Lastly like previous projects I'd like to learn apply some ML models.

Project 4 results:

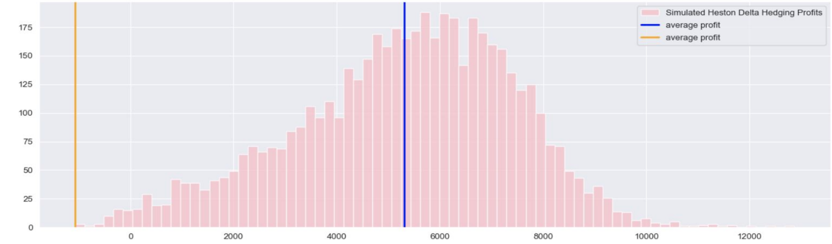
```
max profit for no-hedge method: -1.8769468887980256
min profit for no-hedge method: -20135.92885665923
expected profit for no-hedge method: -890.5019466521208
standard deviation for no-hedge profit: 1934.6073171919697
----------------------------------------------------------------------
max profit for delta-hedge method: 1900.7669858185232
min profit for delta-hedge method: -4448.274944773361
expected profit for delta-hedge method: -672.9901236223889
standard deviation for delta-hedge profit: 1526.6523780629618
----------------------------------------------------------------------
max profit for delta-vega-hedge method: 12868.232288581317
min profit for delta-vega-hedge method: -1071.7661722891341
expected profit for delta-vega-hedge method: 5311.6117691067775
standard deviation for delta-vega-hedge profit: 2126.2952080412906
```

Simulated Call Option Values, Heston Model with 5000 and 252 no hedges

Simulated Profits, Heston Model with 5000 number of simulations and 252 Delta hedges



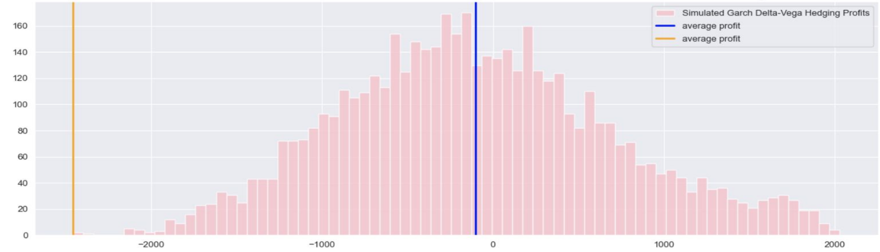
Simulated Call Option Values, Heston Model with 5000 and 252 Delta Vega hedges




```
max profit for no-hedge method: 12.535520803611233
min profit for no-hedge method: -2459.0759420528548
expected profit for no-hedge method: 0.0
standard deviation for no-hedge profit: 125.96678510125292
----------------------------------------------------------------------
max profit for delta-hedge method: 2028.4220212956511
min profit for delta-hedge method: -2456.710163351427
expected profit for delta-hedge method: -100.07159050106902
standard deviation for delta-hedge profit: 798.2596547860562
----------------------------------------------------------------------
max profit for delta-vega-hedge method: 1364.6440591057697
min profit for delta-vega-hedge method: -911.0121855912075
expected profit for delta-vega-hedge method: -29.399050949496157
standard deviation for delta-vega-hedge profit: 287.94176620221396
```

Simulated Call Option Values, Garch Model with 5000 and 252 no hedges

Simulated Profits, Garch Model with 5000 number of simulations and 252 Delta hedges



Simulated Call Option Values, Garch Model with 5000 and 252 Delta Vega hedges