Final Project

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Part1

I left risk free rate in the systematic bucket.

First, I used the data from 2023, performed OLS regression on the daily return of each stock with respect to the daily return of SPY to obtain the alpha and beta coefficients.

At the end of 2023, when purchasing the stocks, I calculated the weight of each stock in the portfolio based on the number of shares held and the stock price: in a portfolio composed of *m* stocks, the weight of stock *i* is denoted as $w_i = \frac{price_i * holding_i}{\sum_{j=1}^{m} price_j * holding_j}$.

During the holding period, the weight of each stock in the portfolio is recalculated daily based on changes in stock prices.

Since directly summing multi-period simple returns can introduce compounding errors, I used Carino method to apply logarithmic returns to ensure consistency with the compounding relationship across dates and accurately attributes total returns to each day.

Return Attribution:

Total return over the holding period:

$$R_{portfolio} = (1 + r_p^{(1)})\left(1 + r_p^{(2)}\right)\cdots\left(1 + r_p^{(n)}\right) - 1$$

Carino scaling factor *k*:

$$k = \frac{\ln(1 + R_{portfolio})}{R_{portfolio}}$$

Daily attribution weight k_i:

$$k_i = \frac{\ln(1 + r_p^{(i)})}{r_p^{(i)} \cdot k}$$

Systematic return contribution (factor SPY) on day *i*:

$$SysAttrib_i = F^{(i)} \cdot \left(\sum_{j=1}^{m} \beta_j \, w_j^{(i-1)}\right) \cdot k_i$$

where $F^{(i)}$ is daily return of SPY in day i.
idiosyncratic return contribution

$$ResAttrib_i = r_p^{(i)} - SysAttrib_i$$

Realized Risk Attribution:

$$\sigma_p = std(\left\{r_p^{(i)}\right\}_{i=1}^{n})$$

$$cSD_{sys} = \beta_{sys} \cdot \sigma_p, \qquad cSD_{idio} = \beta_{idio} \cdot \sigma_p$$

Result:

Total Portfolio

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	-0.035969	0.204731
1	Return Attribution	0.244039	-0.039309	0.204731
2	Vol Attribution	0.007207	-0.000131	0.007076

Portfolio A

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	-0.095555	0.136642
1	Return Attribution	0.242621	-0.105980	0.136642
2	Vol Attribution	0.007056	0.000348	0.007404

Portfolio B

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	-0.028626	0.203526
1	Return Attribution	0.234259	-0.030733	0.203526
2	Vol Attribution	0.006411	0.000442	0.006854

Portfolio C

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	0.022337	0.281172
1	Return Attribution	0.255627	0.025546	0.281172
2	Vol Attribution	0.007230	0.000678	0.007908

Analysis

1. For all portfolios, the bulk of both return and risk was driven by SPY (systematic), reflecting high average betas.
2. Portfolios A and B suffered return drag from negative idiosyncratic performance, while C benefited from stock-specific gains. Portfolio C is the only portfolio with a positive alpha, which means it's the only portfolio that outperformed the market. However, it also had the highest total volatility, suggesting it may contain more aggressive or volatile stocks.
3. Volatility attribution shows idiosyncratic risk is negligible (<10 bps) in all cases, reaffirming that diversifying across multiple stocks reduced stock-specific variance.

Part2

I left risk free rate in the systematic bucket.

Firstly I calculated arithmetic mean value of risk free rate as the expected risk free rate for the holding period and arithmetic mean value of SPY's return prior to the holding period as the expected return of the SPY. Therefore,

expected risk free rate = 0.0009849959688576415

expected return of the SPY = 0.0001973138615264867

Then I calculated optimal maximum Sharpe Ratio portfolio for each sub portfolio and rerun the attribution from Part 1 using the new optimal portfolios. The results are as bellow:

Result:

Optimal Total Portfolio Attribution

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	-0.029040	0.241423(increased)
1	Return Attribution	0.273015	-0.031591	0.241423
2	Vol Attribution	0.007677	0.000208	0.007886

Optimal A Portfolio Attribution

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	-0.053660	0.224511(increased)
1	Return Attribution	0.284686	-0.060175	0.224511
2	Vol Attribution	0.007845	0.001252	0.009097

Optimal B Portfolio Attribution

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	-0.069802	0.186744(decreased)
1	Return Attribution	0.263700	-0.076955	0.186744
2	Vol Attribution	0.007204	0.000182	0.007386

Optimal C Portfolio Attribution

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	0.011513	0.288082(increased)
1	Return Attribution	0.274086	0.013996	0.288082
2	Vol Attribution	0.006846	0.002063	0.008908

Systematic vs Idiosyncratic Attribution:

	Initial Systematic	Initial Idiosyncratic	Optimal Systematic	Optimal Idiosyncratic
Total	0.2440	-0.0393	0.2730	-0.0316
A	0.2426	-0.1060	0.2847	-0.0602
B	0.2343	-0.0307	0.2637	-0.0770
C	0.2556	0.0255	0.2741	0.0140

Volatility Attribution:

Initial Systematic	Initial Idiosyncratic	Optimal Systematic	Optimal Idiosyncratic

Total	0.0072	-0.0001	0.0077	0.0002
A	0.0071	0.0003	0.0078	0.0013
B	0.0064	0.0004	0.0072	0.0002
C	0.0072	0.0007	0.0068	0.0021

Analysis

1. Total portfolio, A and C clearly benefited, with A turning from a net drag into a strong gain; B underperformed because optimization overweighted stocks with high beta but poor idiosyncratic outcomes.
2. Optimization increased systematic exposure (beta) at the expense of amplifying idiosyncratic outcomes—good for A/C, but costly for B.

Part3

Quantitative risk management in finance frequently requires modeling returns that exhibit significant deviations from normality, such as skewness and kurtosis. Two distributions particularly adept at capturing these complexities are the Normal Inverse Gaussian (NIG) and the Skew Normal (SN) distributions.

Normal Inverse Gaussian (NIG)

The NIG distribution is characterized by four parameters: location, scale, asymmetry, and tail heaviness. Its flexibility in modeling skewed and fat-tailed distributions makes it exceptionally suitable for capturing financial returns, which often exhibit pronounced skewness and excess kurtosis.

One critical property of the NIG distribution is its ability to model heavy tails and asymmetry simultaneously. In financial markets, asset returns frequently display these characteristics, driven by asymmetric investor reactions to good and bad news. The presence of heavy tails means extreme outcomes are more common than the Normal distribution would predict, which is vital for risk management purposes. By using NIG, risk managers can more accurately estimate Value at Risk (VaR) and Expected Shortfall (ES), crucial metrics for measuring potential financial losses under extreme conditions.

For instance, during market downturns, stock returns typically exhibit significant negative skewness and fat tails. The NIG distribution allows risk managers to fit empirical return distributions closely, improving the estimation of tail risk and aiding in better-informed hedging and risk mitigation strategies.

Skew Normal (SN)

The Skew Normal distribution extends the standard Normal distribution by adding a shape parameter that controls skewness. While simpler than the NIG, it efficiently models asymmetry without necessarily heavy tails. This makes the SN distribution useful for financial assets exhibiting skewness but relatively moderate tail behaviors compared to NIG.

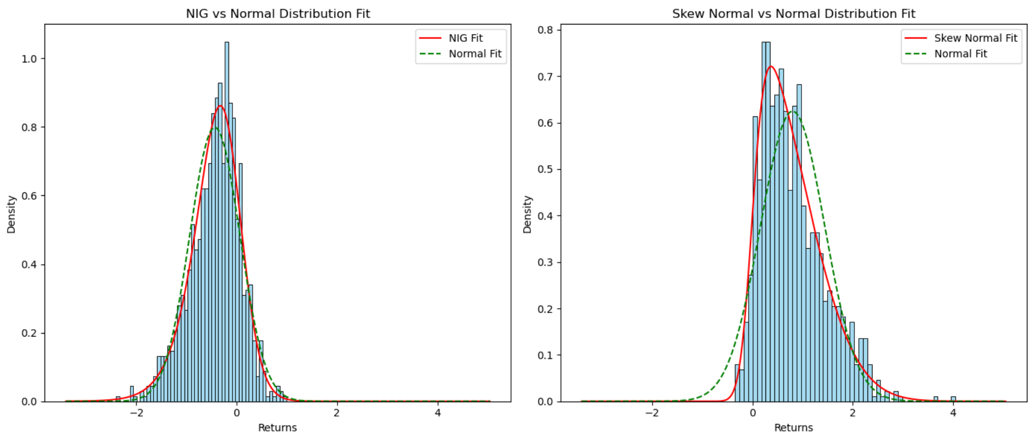
One practical property of the SN distribution is its computational simplicity and interpretability. In scenarios where skewness is the primary deviation from normality, using SN can significantly enhance model fit without overcomplicating the analysis. This is particularly relevant for portfolios where skewness arises from predictable structural market biases rather than extreme shocks.

Consider a currency pair that frequently demonstrates predictable skewness in its returns due to persistent economic imbalances or policy biases. Employing the SN distribution in this context allows risk managers to incorporate skewness into risk models easily, improving forecasts and asset allocation decisions while maintaining computational efficiency.

Why These Distributions Matter in Risk Management:

Both NIG and SN distributions address critical shortcomings of the Normal distribution, especially skewness and tail risks, fundamental to robust risk management:

1. Better Risk Quantification: Accurate modeling of extreme market movements (tail risks) prevents underestimating losses, a common pitfall in models based solely on Normal distributions. As the picture below, normal distribution cannot fit extreme market movements.



2. Improved Stress Testing: These distributions provide realistic scenarios for stress testing, enabling managers to evaluate portfolios under extreme but plausible market conditions.
3. Enhanced Portfolio Allocation: By capturing skewness and kurtosis, these distributions support more accurate allocation of capital and diversification strategies, ensuring portfolios are constructed to withstand shocks effectively.

In conclusion, the Normal Inverse Gaussian and Skew Normal distributions are invaluable tools in quantitative risk management, providing a more nuanced understanding of market dynamics and improved foresight into potential risks. By aligning risk modeling with empirical realities, these distributions help financial institutions maintain resilience and stability in volatile markets.

Part4

I fitted each stock to the Normal, Generalized T, Normal Inverse Gaussian, and the Skew Normal. Because the task says "Make the assumed return on each stock to be 0%", I used **discrete return($r_{i,t} = P_{i,t}/P_{i,t-1} - 1$)** here, and **subtract the mean value from each stock's return rate to make it zero-mean**, then **set the mean parameter to 0 when fitting distributions**. To prevent overfitting in the case of small samples, I adopted AICC instead of AIC/BIC as the criterion for determining the best distribution. Therefore, I chose the one with **the smallest AICC** as best fitted model for each stock.

As there are too many stocks, the best fit Distribution selection result is too long, I put this part at the end of my answer (Appendix).

I calculated the 1-day VaR and ES (95% confidence level) for each portfolio and the total portfolio using a Gaussian Copula and the fitted models. I also did the same assuming a multivariate normal. When fitting multivariate normal model, I **used the centered return matrix(which means the return of each stock is zero-mean) to calculate correlation matrix**.

VaR and ES Results (1-day, 95% confidence level, reported as return):

Portfolio	Gaussian Copula (fitted marginals)	Multivariate Normal
A	VaR 1.374% ES 1.811%	VaR 1.422% ES 1.793%
B	VaR 1.247% ES 1.633%	VaR 1.323% ES 1.652%
C	VaR 1.283% ES 1.662%	VaR 1.377% ES 1.725%
Total	VaR 1.266% ES 1.647%	VaR 1.317% ES 1.670%

Analysis

(1) The fitted distribution approach generally provides more accurate risk estimates by capturing the non-normal characteristics of returns (skewness and kurtosis). The multivariate normal tends to underestimate tail risk in some cases, as shown by the lower ES values from the fitted models for some portfolios.

(2) In risk management, adopting models that better capture tail risk (like the Fitted/Copula method) is typically more conservative and prudent, especially when markets might experience extreme volatility. Although the Fitted/Copula method is theoretically more accurate, it has higher computational complexity. For Portfolios A and B, the simplified Multivariate Normal method provides very similar results and may be more efficient in practical applications.

In summary, while the two methods produce relatively close numerical results, the Gaussian Copula with fitted distributions approach is theoretically more accurate and better able to capture market non-linearities and extreme risks. For portfolios with more complex risk characteristics, using more sophisticated models may produce significantly different risk estimates, which is crucial for risk management decisions.

Part5

First, I built a Monte Carlo simulation framework that generates correlated random returns using:

- The best-fit distributions for each asset
- The historical correlation structure between assets (using Spearman rank correlation)
- Cholesky decomposition to ensure proper correlation

Then, I calculated Expected Shortfall (ES) at a 95% confidence level.

For the risk parity optimization, I set an objective function that minimizes the squared difference between actual risk contributions and equal target risk contributions. Besides, I added constraints so weights sum to 1.0 and stay between 0.0 and 1.0

Finally, I rerun the attribution from Part 1 using the new optimal portfolios and the previously fit CAPM beta.

Result:

A Portfolio Attribution

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	-0.035955	0.194483
1	Return Attribution	0.233480	-0.038997	0.194483

2	Vol Attribution	0.006688	0.000186	0.006874

B Portfolio Attribution

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	0.027481	0.256825
1	Return Attribution	0.225270	0.031555	0.256825
2	Vol Attribution	0.005892	0.000613	0.006505

C Portfolio Attribution

	Value	SPY	Alpha	Portfolio
0	TotalReturn	0.261373	0.072173	0.337944
1	Return Attribution	0.256651	0.081293	0.337944
2	Vol Attribution	0.007088	0.000914	0.008002

Compared to Parts 1 and 2:

Risk parity portfolios generally showed better risk-adjusted returns than initial portfolios

While maximum Sharpe ratio portfolios focused on optimizing return/volatility, risk parity better balanced risk contributions

Portfolio B showed much better performance under risk parity than under Sharpe optimization, suggesting it benefited more from balanced risk allocation

Portfolio C consistently performed well across all approaches

The risk parity approach using the sophisticated distribution models demonstrated that properly balancing risk exposure can achieve superior returns while controlling for tail risks better than traditional mean-variance optimization.

Appendix: Best Fit Distribution for Each Stock (using AICC criterion):

Symbol: SPY
  Best Fit Model: Normal
  Parameters: {'mu': 0, 'sigma': 0.00824684201271041}
  AICC: -1681.7190

Symbol: AAPL
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.01530745862896632, 'nu': 4.9860445001663125, 'p': 1.9249622298382667}
  AICC: -1476.4741

Symbol: NVDA
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.03274502032363604, 'nu': 1.2114900154735568, 'p': 2.9674313003029575}
AICC: -1087.0949

Symbol: MSFT
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.01901641997681056, 'nu': 4.989272373110831, 'p': 1.8728705320147596}
AICC: -1360.9526

Symbol: AMZN
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.023851332848633538, 'nu': 4.972577902767439, 'p': 1.794573879866977}
AICC: -1231.2825

Symbol: META
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.023643731731089267, 'nu': 0.607444047506583, 'p': 4.6394759804945815}
AICC: -1237.9332

Symbol: GOOGL
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.020564851962757105, 'nu': 1.4734632651309634, 'p': 2.4361636871764354}
AICC: -1288.8331

Symbol: AVGO
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.02091977689411296, 'nu': 4.949552718154032, 'p': 1.6502428467230452}
AICC: -1262.3853

Symbol: TSLA
Best Fit Model: NIG
Parameters: {'alpha': 72.90237910449495, 'beta': -817.6027543853693, 'mu': 0, 'delta': 0.0010000000001788578}
AICC: -inf

Symbol: GOOG

Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.021029981539260164, 'nu': 1.3708997608006492, 'p': 2.568314437358814}
  AICC: -1283.5285

Symbol: BRK-B
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.010033464951908305, 'nu': 4.984004261195996, 'p': 1.7983532267373108}
  AICC: -1665.2807

Symbol: JPM
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.011876176351860397, 'nu': 4.940174324198197, 'p': 1.4548318777773064}
  AICC: -1490.4601

Symbol: LLY
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.01535021628365197, 'nu': 2.227152151360406, 'p': 1.7144754431900742}
  AICC: -1359.8393

Symbol: V
  Best Fit Model: Normal
  Parameters: {'mu': 0, 'sigma': 0.009816409746842631}
  AICC: -1594.9549

Symbol: XOM
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.019076912895835966, 'nu': 4.991105508352455, 'p': 1.8989892708296672}
  AICC: -1363.8752

Symbol: UNH
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.01187162582274109, 'nu': 4.933968407769765, 'p': 1.463216695107931}
  AICC: -1490.9152

Symbol: MA
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.012272343482788946, 'nu': 4.971589224459633, 'p': 1.7763735885158431}

AICC: -1559.3637

Symbol: COST
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.011794727289863667, 'nu': 4.951873161204252, 'p': 1.530309223965936}
AICC: -1519.4953

Symbol: PG
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.010313461593275343, 'nu': 4.9733438320516115, 'p': 1.6767427413096743}
AICC: -1625.3615

Symbol: WMT
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.011111751744038282, 'nu': 4.99999868031108, 'p': 1.999998106824273}
AICC: -1640.3191

Symbol: HD
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.013744070033406093, 'nu': 4.9580442690267255, 'p': 1.5742508270742055}
AICC: -1455.3208

Symbol: NFLX
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.020269884694131192, 'nu': 4.923615347801984, 'p': 1.4158652628549615}
AICC: -1210.3934

Symbol: JNJ
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.009140474945061466, 'nu': 4.930013691682994, 'p': 1.4231883760339727}
AICC: -1610.1066

Symbol: ABBV
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.011634518711006231, 'nu': 4.940273743214992, 'p': 1.5195433022943265}
AICC: -1520.4006

Symbol: CRM
 Best Fit Model: Generalized_T
 Parameters: {'loc': 0, 'scale': 0.01911000109930598, 'nu': 4.947117564822764, 'p': 1.6347426370904161}
 AICC: -1305.4345

Symbol: BAC
 Best Fit Model: Generalized_T
 Parameters: {'loc': 0, 'scale': 0.017157616091049672, 'nu': 4.963516567037304, 'p': 1.5487868559744875}
 AICC: -1338.6324

Symbol: ORCL
 Best Fit Model: Generalized_T
 Parameters: {'loc': 0, 'scale': 0.01544051739836678, 'nu': 1.5029790482856384, 'p': 2.035532722320668}
 AICC: -1368.0558

Symbol: MRK
 Best Fit Model: Generalized_T
 Parameters: {'loc': 0, 'scale': 0.014485420508891263, 'nu': 4.992608012844015, 'p': 1.8993244689390565}
 AICC: -1501.2879

Symbol: CVX
 Best Fit Model: Generalized_T
 Parameters: {'loc': 0, 'scale': 0.015139415756760345, 'nu': 4.962864602870602, 'p': 1.6161499082056352}
 AICC: -1417.8782

Symbol: KO
 Best Fit Model: Generalized_T
 Parameters: {'loc': 0, 'scale': 0.009242225517366367, 'nu': 4.962138509385358, 'p': 1.7301428878853888}
 AICC: -1688.7392

Symbol: CSCO
 Best Fit Model: Generalized_T
 Parameters: {'loc': 0, 'scale': 0.011772223634838585, 'nu': 4.928682350896146, 'p': 1.5598510614003858}
 AICC: -1522.3536

Symbol: WFC
 Best Fit Model: Generalized_T

Parameters: {'loc': 0, 'scale': 0.01888456708847547, 'nu': 4.969505745539369, 'p': 1.6640400206346888}
AICC: -1320.1643

Symbol: ACN
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.016532246797346137, 'nu': 2.838505801097883, 'p': 2.157493880558818}
AICC: -1436.6996

Symbol: NOW
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.018192607714991683, 'nu': 7.217673937433716, 'p': 1.324293738164174}
AICC: -1258.7324

Symbol: MCD
Best Fit Model: Normal
Parameters: {'mu': 0, 'sigma': 0.008798208000282446}
AICC: -1649.4896

Symbol: PEP
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.010295886920931764, 'nu': 4.968927652661676, 'p': 1.6848917904050007}
AICC: -1627.6912

Symbol: IBM
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.01091877104553709, 'nu': 1.9385882021345973, 'p': 2.2070584921854546}
AICC: -1609.9793

Symbol: DIS
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.017425226677123037, 'nu': 4.961864674134142, 'p': 1.6282555804295176}
AICC: -1351.0609

Symbol: TMO
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.015828689634605153, 'nu': 4.974860023920766, 'p': 1.69541544215489}
AICC: -1415.6707

Symbol: LIN
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.011273959611947082, 'nu': 4.949424075569333, 'p': 1.4196717068240607}
  AICC: -1505.5802

Symbol: ABT
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.014816073140395623, 'nu': 4.999997035268142, 'p': 1.9999961600102405}
  AICC: -1498.2057

Symbol: AMD
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.03132331586721223, 'nu': 4.961906755382651, 'p': 1.6392931679933045}
  AICC: -1061.4769

Symbol: ADBE
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.02246461244404338, 'nu': 4.97477794303636, 'p': 1.7229232157403065}
  AICC: -1247.7560

Symbol: PM
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.012536931729873864, 'nu': 4.991815815704661, 'p': 1.8808581408606588}
  AICC: -1570.1167

Symbol: ISRG
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.017958932344902562, 'nu': 4.95441130168673, 'p': 1.5359841115515347}
  AICC: -1312.1888

Symbol: GE
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.018624347816777513, 'nu': 4.985192004568577, 'p': 1.93255941259095}
  AICC: -1379.9867

Symbol: GS

Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.016747325655170422, 'nu': 4.972816964054447, 'p': 1.6940138454281584}
AICC: -1387.4702

Symbol: INTU
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.020132672370175953, 'nu': 4.973093064674551, 'p': 1.6720148350271733}
AICC: -1291.2112

Symbol: CAT
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.018594120063627165, 'nu': 4.946601300962683, 'p': 1.6562857622431986}
AICC: -1321.2942

Symbol: QCOM
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.022373958509603078, 'nu': 2.063813591285017, 'p': 2.200339165977659}
AICC: -1259.4726

Symbol: TXN
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.01917024363471227, 'nu': 4.997030219354829, 'p': 2.0206368906931513}
AICC: -1380.4237

Symbol: VZ
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.01309637603536403, 'nu': 1.3704066133081347, 'p': 2.209696509962532}
AICC: -1465.9744

Symbol: AXP
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.016821849703462878, 'nu': 3.282711434796349, 'p': 1.7509800701881884}
AICC: -1367.2701

Symbol: T
Best Fit Model: Generalized_T

Parameters: {'loc': 0, 'scale': 0.013066832029851188, 'nu': 0.20738426479640465, 'p': 9.0365270559231}
AICC: -1411.4737

Symbol: BKNG
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.019539207111875567, 'nu': 4.999997921210902, 'p': 1.9999983032434012}
AICC: -1366.6300

Symbol: SPGI
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.013650859123692153, 'nu': 4.945754323802616, 'p': 1.5752774983854374}
AICC: -1456.3638

Symbol: MS
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.01644873824031853, 'nu': 4.95536894369843, 'p': 1.561595874882423}
AICC: -1362.2622

Symbol: RTX
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.011318065093309161, 'nu': 4.906343600272421, 'p': 1.3137516460825136}
AICC: -1460.5491

Symbol: PLTR
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.034509519752801615, 'nu': 4.925405518625597, 'p': 1.294052589254495}
AICC: -900.5627

Symbol: PFE
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.014414332056879588, 'nu': 4.953327771903989, 'p': 1.5501179827756355}
AICC: -1423.8468

Symbol: BLK
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.016863769603420797, 'nu': 4.989118064483039, 'p': 1.8898527137172279}

AICC: -1423.5777

Symbol: DHR
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.017071710002605992, 'nu': 4.965945392122249, 'p': 1.7806750100816826}
AICC: -1393.1993

Symbol: NEE
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.014593078351971173, 'nu': 4.922184119908457, 'p': 1.3893933510072063}
AICC: -1360.3965

Symbol: HON
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.013483545096325744, 'nu': 1.8734324841025063, 'p': 2.3906127900434266}
AICC: -1526.6173

Symbol: CMCSA
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.015837094216386655, 'nu': 0.8104068974650752, 'p': 3.728882483511914}
AICC: -1439.8832

Symbol: PGR
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.013735565299783804, 'nu': 0.29007695402087824, 'p': 6.417165902811609}
AICC: -1389.8301

Symbol: LOW
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.014246756568137847, 'nu': 4.960604540103765, 'p': 1.4588710702689207}
AICC: -1405.2986

Symbol: AMGN
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.015048438951674908, 'nu': 4.981671008193113, 'p': 1.7710944936469435}
AICC: -1457.8058

Symbol: UNP
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.013412110911056385, 'nu': 4.921233342971223, 'p': 1.5251697140354872}
AICC: -1447.6536

Symbol: TJX
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.012735955894125357, 'nu': 4.999999434718418, 'p': 2.000003111850278}
AICC: -1581.9702

Symbol: AMAT
Best Fit Model: Normal
Parameters: {'mu': 0, 'sigma': 0.02135165156587088}
AICC: -1207.9723

Symbol: UBER
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.028980656611102284, 'nu': 4.997334126091681, 'p': 2.0527949390220934}
AICC: -1178.9585

Symbol: C
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.015527272585234826, 'nu': 4.95476453468605, 'p': 1.4925928342501464}
AICC: -1371.6476

Symbol: BSX
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.011369889694275489, 'nu': 4.941030229484167, 'p': 1.4262662009237714}
AICC: -1503.5143

Symbol: ETN
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.016363679689550614, 'nu': 4.957155557028648, 'p': 1.5214398714984538}
AICC: -1353.1781

Symbol: COP
Best Fit Model: Generalized_T

Parameters: {'loc': 0, 'scale': 0.02055178644897278, 'nu': 4.972140759912895, 'p': 1.8015233519736658}
AICC: -1306.2321

Symbol: BA
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.017462275137320998, 'nu': 4.962447061308917, 'p': 1.5721644663493042}
AICC: -1336.3281

Symbol: BX
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.0239188797371523, 'nu': 6.7918686098818295, 'p': 1.5857368241619652}
AICC: -1201.8200

Symbol: SYK
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.010407966645218819, 'nu': 4.923517680609638, 'p': 1.202916017635911}
AICC: -1454.2866

Symbol: PANW
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.019730312568587774, 'nu': 4.924228164813597, 'p': 1.3529559835881995}
AICC: -1201.2220

Symbol: ADP
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.010847013173949016, 'nu': 4.9255234082358035, 'p': 1.3650757781534222}
AICC: -1503.9405

Symbol: FI
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.011956723096751994, 'nu': 4.9226685972014135, 'p': 1.491296128970269}
AICC: -1494.9531

Symbol: ANET
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.022338137140195186, 'nu': 1.2134865424417638, 'p': 2.157578484187757}

AICC: -1166.0876

Symbol: GILD
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.015365048516505626, 'nu': 4.994693615386684, 'p': 1.852410352397351}
AICC: -1464.5674

Symbol: BMY
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.01240457605279423, 'nu': 4.956861380698167, 'p': 1.586907149365867}
AICC: -1508.8488

Symbol: SCHW
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.019551441884868848, 'nu': 4.915817351600227, 'p': 1.253610554156742}
AICC: -1163.1486

Symbol: TMUS
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.013328920194718203, 'nu': 4.97420508494574, 'p': 1.7403033227932971}
AICC: -1510.8669

Symbol: DE
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.019360325153597625, 'nu': 4.969054821781384, 'p': 1.773542358608103}
AICC: -1330.4073

Symbol: ADI
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.018776983093946598, 'nu': 4.973905135777706, 'p': 1.7806806097308863}
AICC: -1348.4940

Symbol: VRTX
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.013648261085663272, 'nu': 4.921940249890983, 'p': 1.4788180372270843}
AICC: -1427.0065

Symbol: SBUX
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.013164706827808865, 'nu': 4.924787715394479, 'p': 1.5761847524894879}
  AICC: -1471.0403

Symbol: MMC
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.011417230173547396, 'nu': 4.964482693885645, 'p': 1.6788426033326658}
  AICC: -1574.1838

Symbol: MDT
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.01403707254908002, 'nu': 4.967753706732421, 'p': 1.5873973278059659}
  AICC: -1449.3074

Symbol: CB
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.014109677016829095, 'nu': 4.972511433827679, 'p': 1.6997130284154025}
  AICC: -1473.9930

Symbol: LMT
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.009852892117616726, 'nu': 4.9264616847056875, 'p': 1.4699996672923188}
  AICC: -1586.0828

Symbol: KKR
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.023362259363535108, 'nu': 4.986003283057382, 'p': 1.7991489156921396}
  AICC: -1245.0833

Symbol: MU
  Best Fit Model: Generalized_T
  Parameters: {'loc': 0, 'scale': 0.024333811111965864, 'nu': 4.97302756567917, 'p': 1.6194750216934821}
  AICC: -1184.2358

Symbol: PLD
  Best Fit Model: Generalized_T

Parameters: {'loc': 0, 'scale': 0.019701811049126196, 'nu': 4.9815197172013885, 'p': 1.848394050141793}
AICC: -1337.5717

Symbol: LRCX
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.025236993133322797, 'nu': 4.975225479694659, 'p': 1.6820902650243292}
AICC: -1181.0339

Symbol: EQIX
Best Fit Model: Generalized_T
Parameters: {'loc': 0, 'scale': 0.016530537370596885, 'nu': 4.973599712905184, 'p': 1.6480093085917829}
AICC: -1383.9593