# FINTECH 545 HW3

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### PROBLEM 1

All tests passed in test\_risk\_management.py. The results from my library functions are compared to those in testfiles. And running the test file, the terminal would present:

- 1.1Arrays are approximately equal: True
- 1.2Arrays are approximately equal: True
- 1.3Arrays are approximately equal: True
- 1.4Arrays are approximately equal: True
- 2.1Arrays are approximately equal: True
- 2.2Arrays are approximately equal: True
- 2.3Arrays are approximately equal: True
- 3.1Arrays are approximately equal: True
- 3.2Arrays are approximately equal: True
- 3.3Arrays are approximately equal: True
- 3.4Arrays are approximately equal: True
- 4.1Arrays are approximately equal: True
- 5.1Arrays are approximately equal: True
- 5.2Arrays are approximately equal: True
- 5.3Arrays are approximately equal: True
- 5.4Arrays are approximately equal: True
- 5.5Arrays are approximately equal: True
- 7.1mu is approximately equal: True
- 7.1sigma is approximately equal: True
- 7.2mu is approximately equal: True
- 7.2sigma is approximately equal: True

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7.2nu is approximately equal: True
```

mu sigma nu Alpha B1 B2 B3

 $0\, \text{-}3.072982 \text{e-}07 \ 0.048547 \ 4.597745 \ 0.042634 \ 0.974735 \ 2.041119 \ 3.154833$ 

mu sigma nu Alpha B1 B2 B3

 $0\ 0.0\ 0.048548\ 4.598293\ 0.042634\ 0.974889\ 2.041192\ 3.154801$ 

 $8.1 VaR_absolute$  is approximately equal: True

8.1VaR\_diff\_from\_mean is approximately equal: True

 $8.2 VaR\_absolute$  is approximately equal: True

8.2VaR\_diff\_from\_mean is approximately equal: True

8.4ES\_absolute is approximately equal: True

8.4ES\_diff\_from\_mean is approximately equal: True

8.5ES\_absolute is approximately equal: True

 $8.5 ES\_diff\_from\_mean$  is approximately equal: True

Stock VaR95 ES95 VaR95\_Pct ES95\_Pct

 $0 \quad \text{A} \quad 94.314357 \ \ 117.854494 \ \ 0.047157 \ \ 0.058927$ 

1 B 108.31591 152.252229 0.036105 0.050751

2 Total 152.856258 200.801152 0.030571 0.04016

Stock VaR95 ES95 VaR95\_Pct ES95\_Pct

0 A 94.460376 118.289371 0.047230 0.059145

1 B 107.880427 151.218174 0.035960 0.050406

 $2\ \, \text{Total}\ \, 152.565684\ \, 199.704532\ \, 0.030513\ \, 0.039941$ 

## PROBLEM 2

#### Calculate VaR and ES:

- a. Using a normal distribution with an exponentially weighted variance (lambda=0.97); b. Using a MLE fitted T distribution
- c. Using a Historic Simulation

Notice the alpha is set as 0.05

Method	VaR (Absolute)	VaR (Relative)	ES (Absolute)	ES(Relative)
a	0.09117	0.09029	0.11411	0.113226
b	0.07648	0.07638	0.11322	0.113124
c	0.07825	0.07707	0.11633	0.115159

In method a, the VaR is calculated assuming a normal distribution with an exponentially weighted variance. The use of the exponentially weighted variance suggests that recent observations have more impact on the calculation than older ones. This can be particularly useful when there is evidence of changing volatility over time. The differences between VaR and ES may be due to the asymmetric nature of the tail risk in a normal distribution, where ES captures a more extreme tail by considering losses beyond the VaR level.

In method b, the VaR and ES are calculated using a Maximum Likelihood Estimation (MLE) fitted T distribution. The T distribution has fatter tails than the normal distribution, making it more flexible in capturing extreme events. The differences between VaR and ES can be influenced by the shape of the tails and the degrees of freedom parameter in the T distribution. Higher degrees of freedom would make the distribution approach a normal distribution, and lower degrees of freedom would result in fatter tails.

Lastly, historic Simulation calculates VaR based on historical data. The differences between VaR and ES may be attributed to the way extreme events are treated. VaR relies on a specified percentile of historical returns, while ES considers the average of losses beyond the VaR cutoff. ES, in this case, appears to be higher, indicating that the tail of the distribution is more severe than what is captured by the specified VaR level.

## PROBLEM 3

Using my risk management library, fit Generalized T models to stocks in portfolios A and B, and fit a normal distributions to stocks in portfolio C. Calculate the VaR and ES of each portfolio as well as total VaR and ES, using a copula:

Portfolio	VaR95	ES95	VaR95_Pct	ES95_Pct
A	7975.166758	10466.545891	0.026588	0.034894
В	6666.070491	8757.26401	0.022644	0.029748
С	5794.823141	7256.175144	0.021459	0.02687
Total	20217.65156	26096.123046	0.02339	0.030191

Comparing to the results from the last assignment:

Port/Method	Normal Monte	Delta Normal	Historical \$VaR
	Carlo \$VaR	\$VaR	
A	14178.28	15446.10	17065.30
В	7621.99	8094.60	10983.46
С	16338.76	18194.04	22186.52
Total	35018.05	39008.47	47618.78

#### Discussion:

The differences in results between the two methods (using the risk management library and the methods from the last assignment) can be attributed to variations in modeling assumptions, statistical techniques, and the treatment of risk factors. Let's discuss the key factors contributing to the differences:

### 1. Distributional Assumptions:

Risk Management Library:

Portfolio A and B: Generalized T models

Portfolio C: Normal distribution

Last Assignment:

Monte Carlo and Delta Normal methods assumed a normal distribution.

Historical Simulation used historical data without specifying a distribution.

The choice of distribution has a significant impact on VaR and ES calculations. The risk management library employs more sophisticated models (Generalized T models) that allow for heavier tails and better capture extreme events, whereas the last assignment relied on simpler assumptions, such as normality.

### 2. Modeling Techniques:

Risk Management Library:

Utilized copula modeling for dependency between stocks in portfolios A and B.

Last Assignment:

Monte Carlo, Delta Normal, and Historical Simulation did not explicitly model dependencies between stocks.

Considering dependencies between stocks in a portfolio is crucial for accurate risk measurement. The copula method in the risk management library takes into account the joint distribution of asset returns, capturing potential correlations that the previous methods might have overlooked.

#### 3. Tail Behavior:

Risk Management Library:

Generalized T models and copula methods likely capture tail events better than methods assuming normality.

Last Assignment:

Methods assuming normality may underestimate tail risk.

The Generalized T models and copula method are designed to handle fat-tailed distributions, which is important for accurately assessing the risk of extreme events.