MIE1622 Assignment 3

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Submission Date: March 28th, 2021

1. Implement portfolio credit risk simulation model in Python

Please see credit_risk_simul.py for coding.

Note: simulation result (loss matrix) of out-of-sample is saved as scen_out.npz and imported after, in order to lessen runtime. I have also included the Jupyter Notebook version with outputs for your ease of grading.

2. Analysis of Results

2.1 Output of VaR and CVaR for Different Portfolio and Simulation Methods

See *Figure 1.1* in Appendix for the output.

2.2 Loss Distribution Plots

See *Figure 2.1, 2.2* in Appendix for the plots of loss distribution of portfolio 1 for out-of-sample and associated normal distribution with VaR and CVaR of them and mean losses from 100 trials illustrated.

See *Figure 2.3, 2.4* in Appendix for similar plots but for portfolio 2.

See *Figure 3.1*, *3.2* in Appendix for VaR and CVaR standard deviation from the 100 trials.

2.3 Analysis of Sample Error and Model Error

Figure 2.1, *2.2* show that the VaR and CVaR (mean) of non-normal approximations are close to the true loss distribution for portfolio 1, thus sampling error is insignificant. *Figure 2.3*, *2.4* show that the differences between CVaR (mean) of non-normal approximations and CVaR of true loss distribution become significant for 99.9% for portfolio 2. In this case, the non-normal approximations have significantly smaller CVaR. From the true loss distribution of each portfolio, it is showed that portfolio 2 has a more volatile distribution. Therefore, sampling error larger for CVaR than VaR. In addition, sampling error increases when the true distribution is more volatile, or for higher percentile of CVaR and VaR.

Figure 2.1, *2.2*, *2.3*, *2.4* show that the differences of both VaR and CVaR between normal approximation and true loss distribution are very significant. Model error is more significant than sampling error. The VaR and CVaR for normal approximations are consistently smaller. Model error increases for higher percentile of VaR and CVaR.

Figure 3.1, *3.2* show that the standard deviation of VaR and CVaR are smaller for normal approximations. With higher percentile of VaR and CVaR, their standard deviation become more significant. Non-normal approximations have lower bias but higher variance, while normal approximations have higher bias but lower variance.

3. Discussion of Minimizing Impacts of Sampling and Model Errors

3.1 Consequences of Reporting In-Sample VaR and CVaR

In-sample VaR and CVaR can significantly underestimate the risk level of the portfolio and cause the decision-makers selecting a portfolio that in fact exceeds risk limit, which violates regulation. This can result in catastrophic capital loss that is higher than expected or even cannot be afforded, which can cause insufficient capital amount for depositors. If this happens, the bank goes bankruptcy.

3.2 Suggestion of Techniques Minimizing Impacts of Sampling and Model Errors

Sampling error can be lowered by taking many trials and then taking mean. As from *Figure 3.1*, *3.2*, the standard deviation of different individual trial can be significant. In addition, sample size can be increased to lower sampling error.

Model error can be lowered by applying more appropriate model (e.g. log-normal distribution). The true distributions, as showed in *Figure 2.1*, *2.2*, *2.3*, *2.4*, have high third and fourth moments, thus normal distribution is not a good option.

In addition, both sampling error and model errors can be lowered by using lower percentile of VaR and CVaR.

Moreover, with the same amount of sampling and model errors, their impact can be lowered by incorporating the idea of factor of safety, which magnifies the computed risk amount by designed scale depending on the simulation process, to compensate for the potential significant underestimation of risk.

4. Appendix

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======= Credit Risk Model with Credit-State Migrations =======
============== Monte Carlo Scenario Generation ===============


 Number of out-of-sample Monte Carlo scenarios = 100000
 Number of in-sample Monte Carlo scenarios = 5000
 Number of counterparties = 100


Portfolio 1:

Out-of-sample: VaR 99.0% = $37657626.48, CVaR 99.0% = $44907154.17
In-sample MC1: VaR 99.0% = $37015760.15, CVaR 99.0% = $44424377.87
In-sample MC2: VaR 99.0% = $37061999.47, CVaR 99.0% = $44582603.83
In-sample No: VaR 99.0% = $26172445.16, CVaR 99.0% = $29063168.38
In-sample N1: VaR 99.0% = $26059648.65, CVaR 99.0% = $28935951.81
In-sample N2: VaR 99.0% = $26187380.83, CVaR 99.0% = $29076528.57

Out-of-sample: VaR 99.9% = $54052314.68, CVaR 99.9% = $61329351.51
In-sample MC1: VaR 99.9% = $53464338.88, CVaR 99.9% = $60734262.16
In-sample MC2: VaR 99.9% = $53547487.71, CVaR 99.9% = $61490609.51
In-sample No: VaR 99.9% = $32688815.07, CVaR 99.9% = $35050569.77
In-sample N1: VaR 99.9% = $32543512.37, CVaR 99.9% = $34893485.71
In-sample N2: VaR 99.9% = $32700199.25, CVaR 99.9% = $35060666.77


Portfolio 2:

Out-of-sample: VaR 99.0% = $27289731.80, CVaR 99.0% = $33803495.59
In-sample MC1: VaR 99.0% = $27176488.40, CVaR 99.0% = $33062294.59
In-sample MC2: VaR 99.0% = $27237787.27, CVaR 99.0% = $33323942.83
In-sample No: VaR 99.0% = $21085595.71, CVaR 99.0% = $23254126.05
In-sample N1: VaR 99.0% = $20998347.41, CVaR 99.0% = $23153957.69
In-sample N2: VaR 99.0% = $21058643.45, CVaR 99.0% = $23220229.05

Out-of-sample: VaR 99.9% = $42777957.51, CVaR 99.9% = $48370686.98
In-sample MC1: VaR 99.9% = $40261069.72, CVaR 99.9% = $46005470.00
In-sample MC2: VaR 99.9% = $40637187.19, CVaR 99.9% = $47276227.68
In-sample No: VaR 99.9% = $25973973.05, CVaR 99.9% = $27745687.71
In-sample N1: VaR 99.9% = $25857599.90, CVaR 99.9% = $27618758.74
In-sample N2: VaR 99.9% = $25931365.70, CVaR 99.9% = $27697406.42
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Figure 1.1: Output of VaR and CVaR for Different Portfolio and Simulation Methods

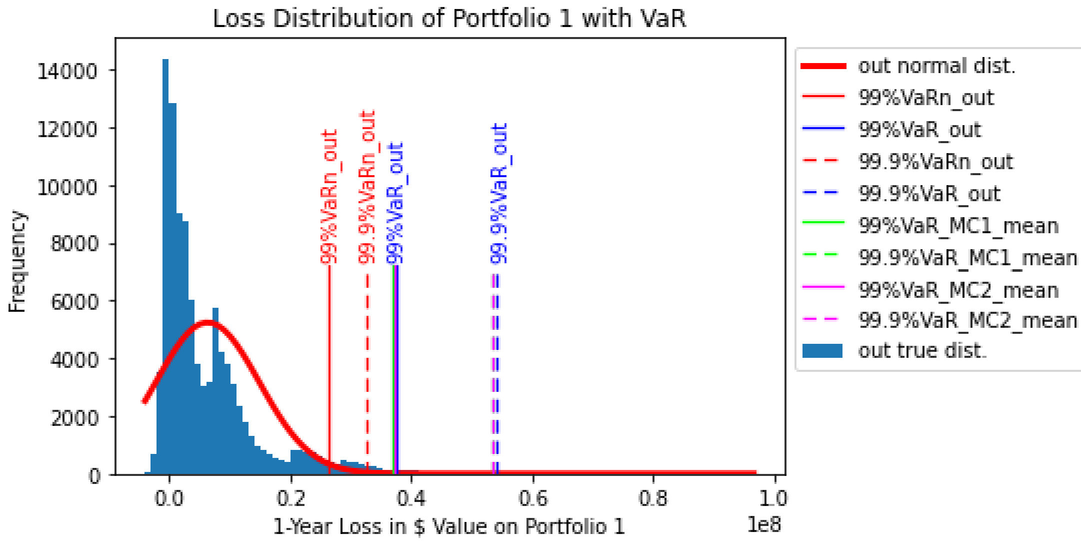

Figure 2.1: Loss Distribution of Portfolio 1 with VaR

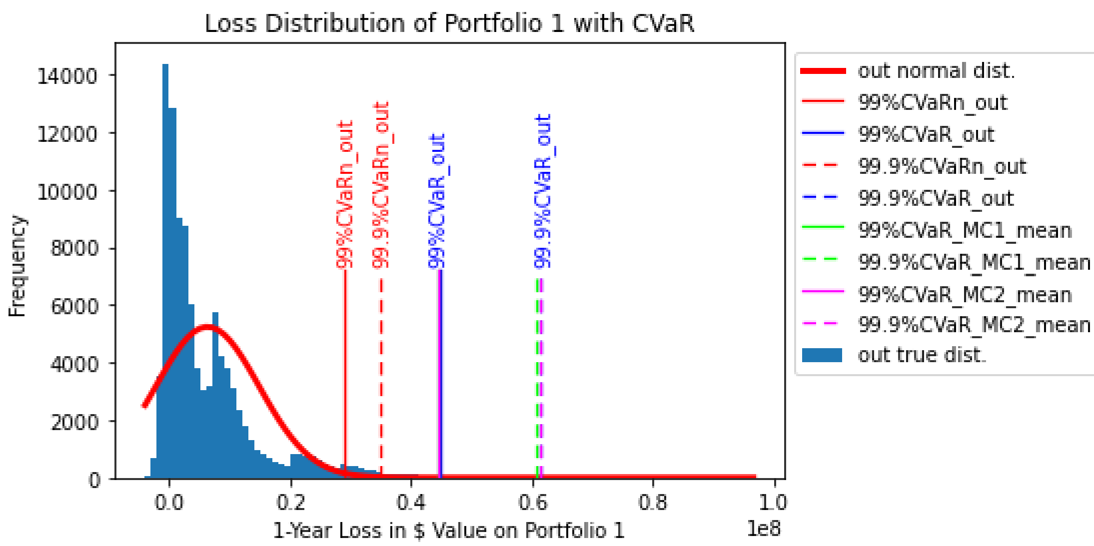

Figure 2.2: Loss Distribution of Portfolio 1 with CVaR

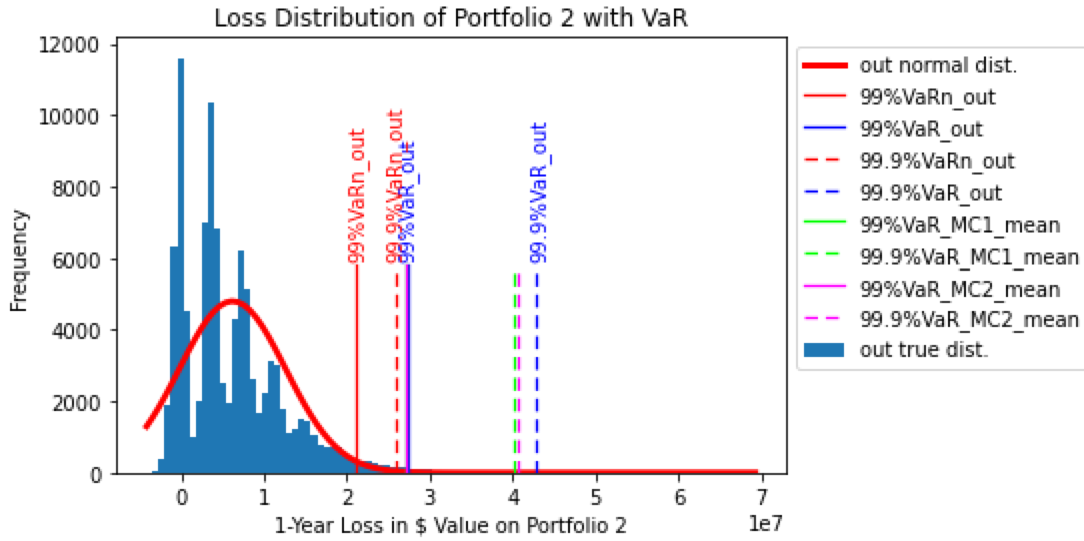

Figure 2.3: Loss Distribution of Portfolio 2 with VaR

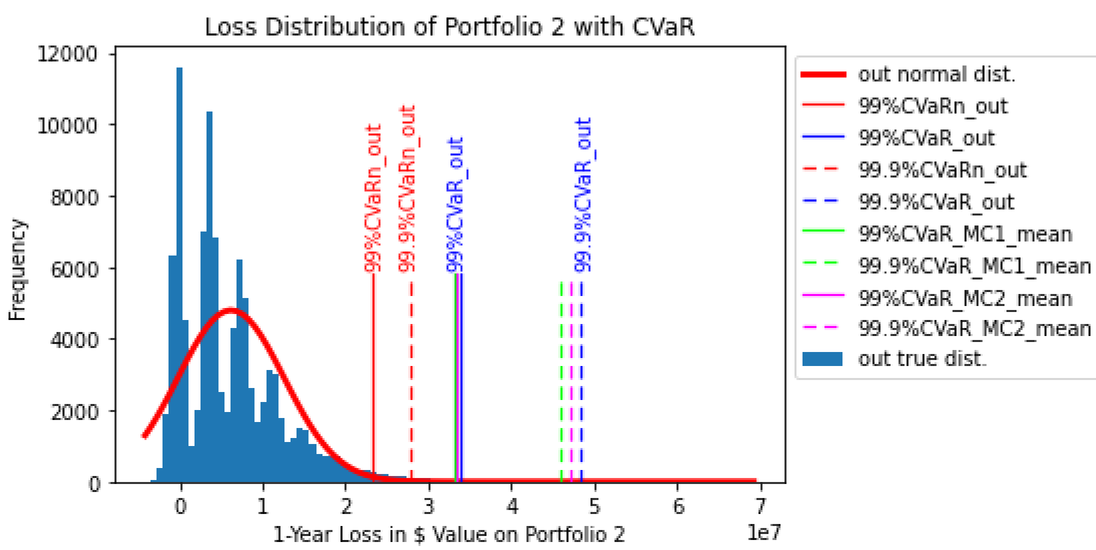

Figure 2.4: Loss Distribution of Portfolio 2 with CVaR

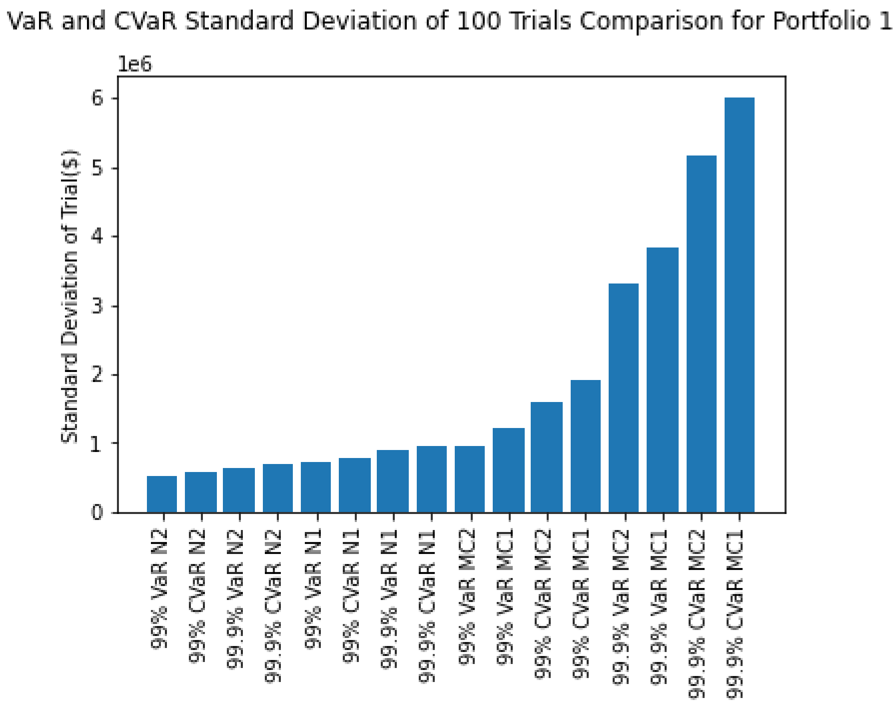

Figure 3.1: Loss Standard Deviation of 100 Trials for Portfolio 1

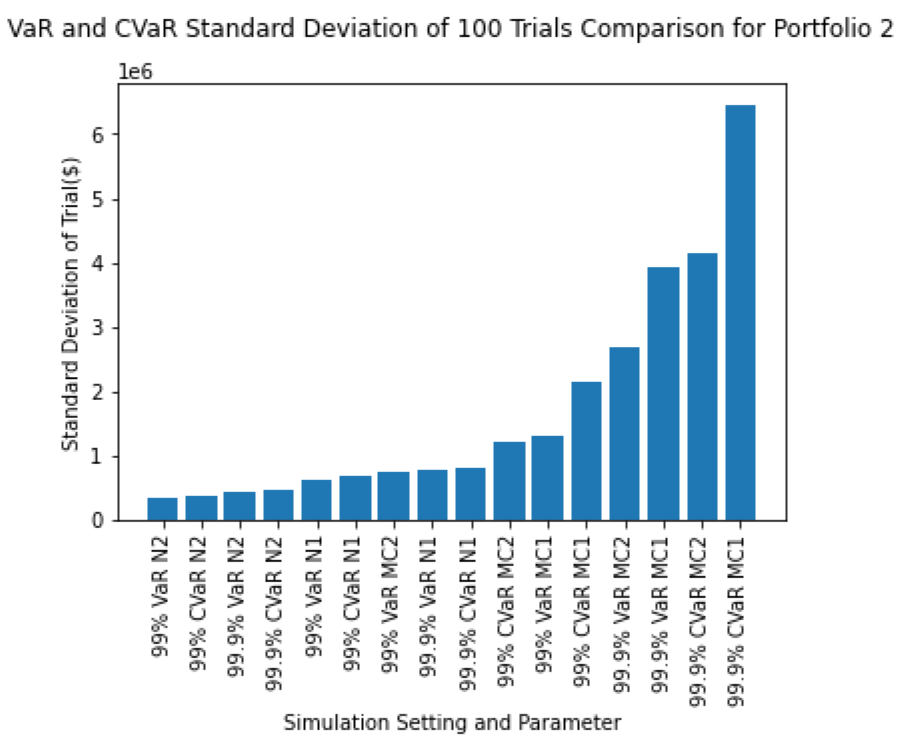

Figure 3.2: VaR and CVaR Standard Deviation of 100 Trials for Portfolio 2