

Secarios Setup

data

`instrum_data.csv`: instrument-specific parameters for Monte-Carlo loss simulation

`credit_driver_corr.csv`: correlation matrix for the systemic credit drivers

Portfolio1:

One unit invested in each of 100 bonds

Portfolio 2:

Equal value in dollar invested in each of 100 bonds

Scenarios:

`MC1`: 5000 in-sample cases (1000 systemic * 5 idiosyncratic for each systemic). Assume non-normal loss distribution

`MC2`: 5000 in-sample cases (5000 systemic * 1 idiosyncratic for each systemic). Assume non-normal loss distribution

`Out_of_sample`: 10,000 in-sample cases (10,000 systemic * 1 idiosyncratic for each systemic). Assume non-normal loss distribution. The True distribution.

Tasks:

1. For each portfolio, compare VaR and CVaR at 99% and 99.9% for `MC1` v.s. `Out_of_sample`, `MC2` v.s. `Out_of_sample`, which shows sampling error (caused by random noise in the finite sample).
2. Assume normal loss distribution for the above 3 scenarios (other remain same), denote the 3 new scenarios as `in-sample N1`, `in-sample N2`, `in-sample No`.

For each portfolio, compare VaR and CVaR at 99% and 99.9% for `in-sample N1` v.s. `Out_of_sample`, `in-sample N2` v.s. `Out_of_sample`, and `in-sample No` v.s. `Out_of_sample`, which shows model error (caused by assuming loss distribution normal).

Numerical Results

Portfolio 1:

Out-of-sample: VaR 99.0% = \$37319329.44, CVaR 99.0% = \$44771037.69

In-sample MC1: VaR 99.0% = \$37312227.91, CVaR 99.0% = \$44052010.50

In-sample MC2: VaR 99.0% = \$37021021.95, CVaR 99.0% = \$43675987.66

In-sample No: VaR 99.0% = \$26223851.31, CVaR 99.0% = \$29112906.46

In-sample N1: VaR 99.0% = \$26261723.39, CVaR 99.0% = \$29159080.79

In-sample N2: VaR 99.0% = \$26148477.23, CVaR 99.0% = \$29032176.05

Out-of-sample: VaR 99.9% = \$53666663.60, CVaR 99.9% = \$59629799.43

In-sample MC1: VaR 99.9% = \$54245958.38, CVaR 99.9% = \$50150230.00

In-sample MC2: VaR 99.9% = \$53603776.76, CVaR 99.9% = \$50102162.49

In-sample No: VaR 99.9% = \$32736461.01, CVaR 99.9% = \$35096852.88

In-sample N1: VaR 99.9% = \$32793048.30, CVaR 99.9% = \$35160223.21

In-sample N2: VaR 99.9% = \$32649012.50, CVaR 99.9% = \$35005028.19

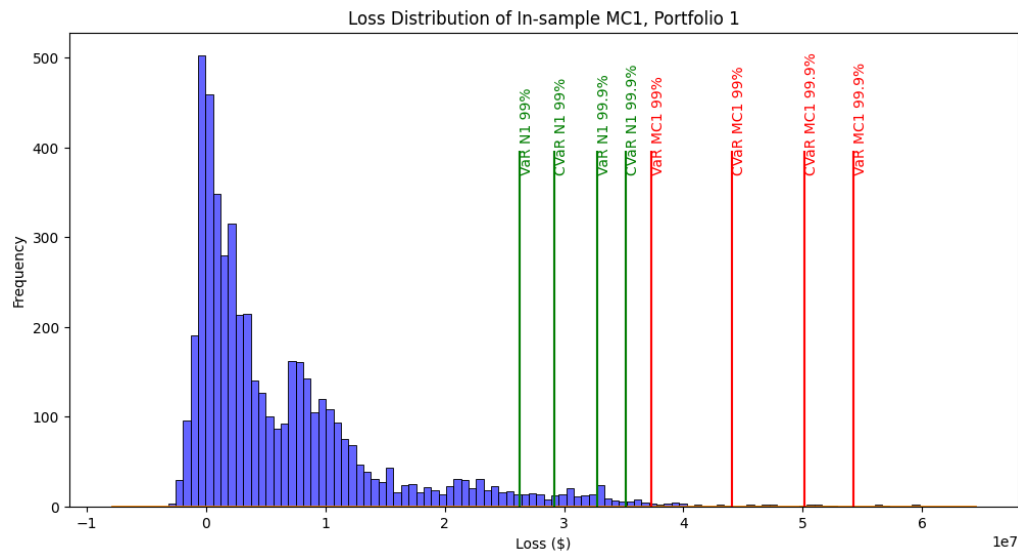
Portfolio 2:

Out-of-sample: VaR 99.0% = \$27539969.69, CVaR 99.0% = \$33553300.76
In-sample MC1: VaR 99.0% = \$27420303.04, CVaR 99.0% = \$33082724.38
In-sample MC2: VaR 99.0% = \$27326046.95, CVaR 99.0% = \$32873719.73
In-sample No: VaR 99.0% = \$21179147.31, CVaR 99.0% = \$23349885.38
In-sample N1: VaR 99.0% = \$21133038.09, CVaR 99.0% = \$23301791.43
In-sample N2: VaR 99.0% = \$21084626.07, CVaR 99.0% = \$23248883.97

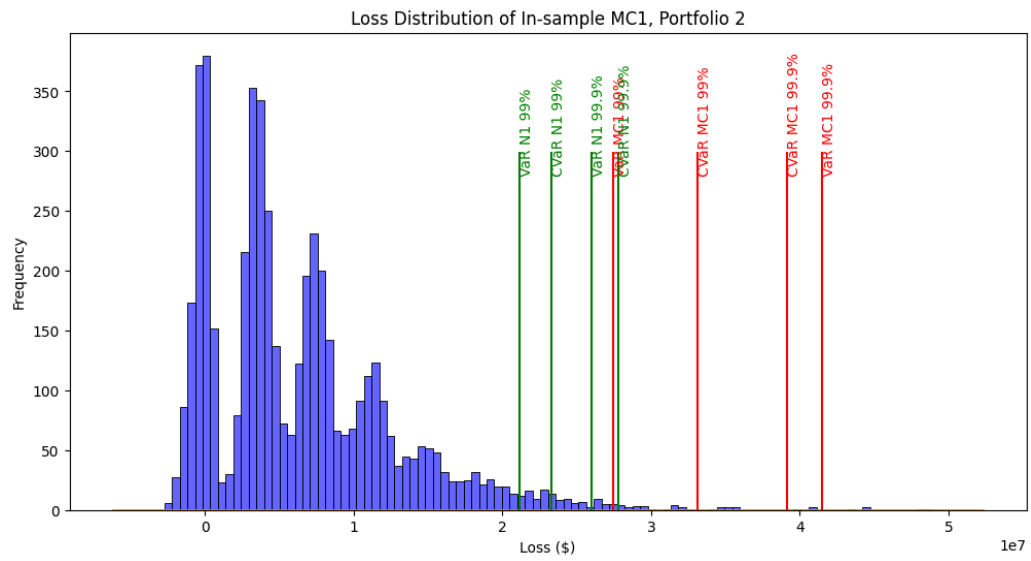
Out-of-sample: VaR 99.9% = \$41139936.55, CVaR 99.9% = \$46182956.20
In-sample MC1: VaR 99.9% = \$41461345.21, CVaR 99.9% = \$39141759.58
In-sample MC2: VaR 99.9% = \$41227565.17, CVaR 99.9% = \$39039429.78
In-sample No: VaR 99.9% = \$26072501.38, CVaR 99.9% = \$27846019.79
In-sample N1: VaR 99.9% = \$26021918.12, CVaR 99.9% = \$27793814.98
In-sample N2: VaR 99.9% = \$25963372.32, CVaR 99.9% = \$27731596.35

Plots

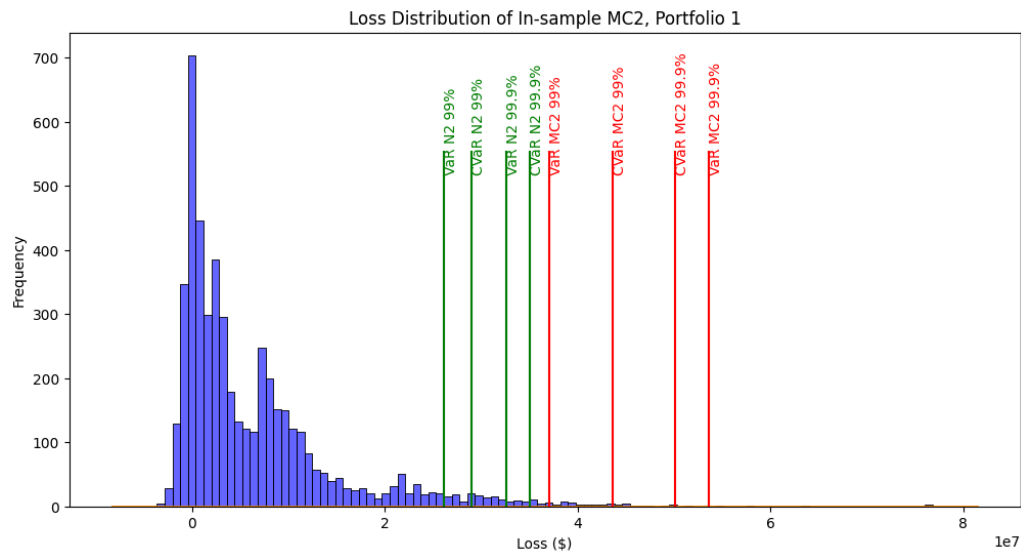
MC1, portf1



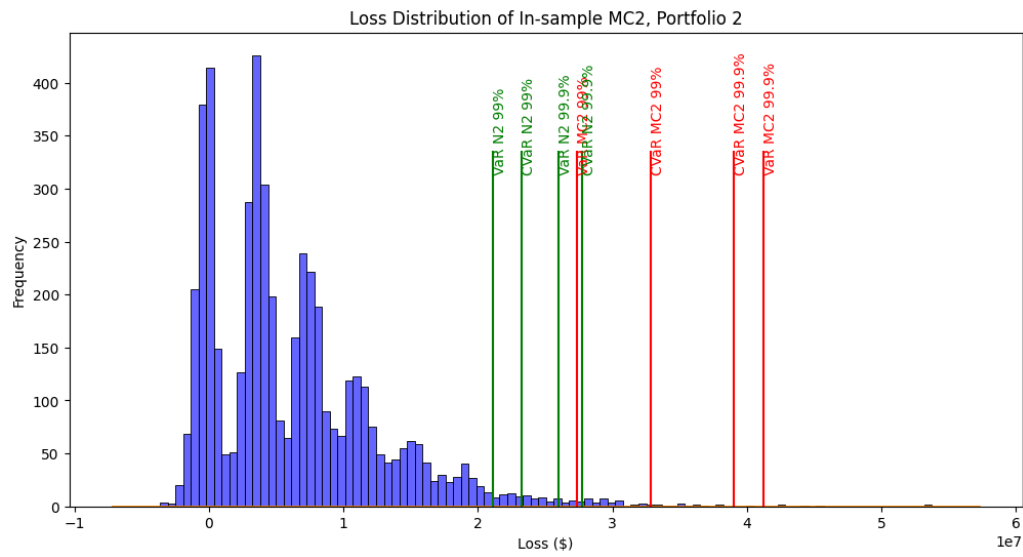
MC1, portf2



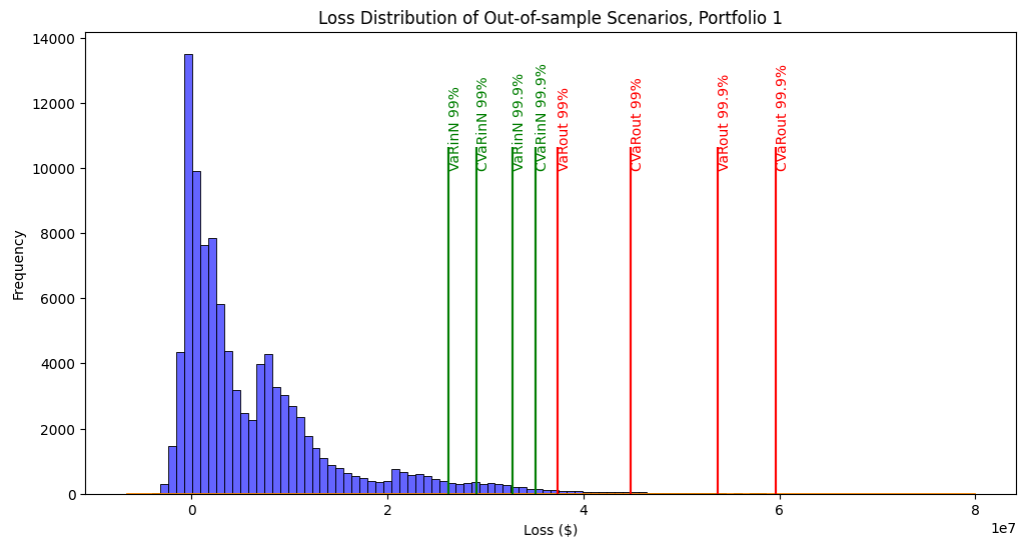
MC2, portf1



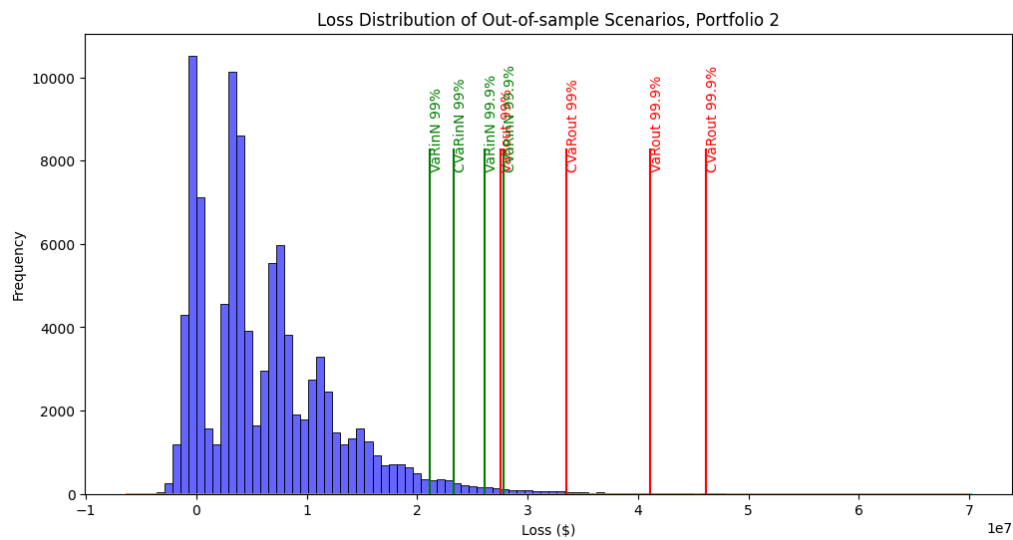
MC2, portf2



Out of sample, portf1



Out of sample, portf2



Sampling error

index	Sampling Error (% difference)
99% VaR, MC1, Portfolio 1	-0.019029101290303947
99% CVaR, MC1, Portfolio 1	-1.6060096623488433
99% VaR, MC2, Portfolio 1	-0.7993377434061169
99% CVaR, MC2, Portfolio 1	-2.4458893246664544
99.9% VaR, MC1, Portfolio 1	1.0794313287625517
99.9% CVaR, MC1, Portfolio 1	-15.897369305506686
99.9% VaR, MC2, Portfolio 1	-0.11718045800036678
99.9% CVaR, MC2, Portfolio 1	-15.977979185767008
99% VaR, MC1, Portfolio 2	-0.4345199235075166
99% CVaR, MC1, Portfolio 2	-1.4024741767046889
99% VaR, MC2, Portfolio 2	-0.7767719070097984
99% CVaR, MC2, Portfolio 2	-2.025377584002839
99.9% VaR, MC1, Portfolio 2	0.7812570663586335
99.9% CVaR, MC1, Portfolio 2	-15.246309890870965
99.9% VaR, MC2, Portfolio 2	0.2130013648166657
99.9% CVaR, MC2, Portfolio 2	-15.467884707576527

- Both MC1 and MC2 underestimate extreme losses
- CVaR has larger negative errors than VaR, especially at 99.9% confidence.
- MC2 generally has slightly smaller errors than MC1, suggesting that using more systemic scenarios (5000 vs. 1000) provides a better estimate.

Model error - normal to out of sample

index	Model Error (% difference): Normal to outOfSample
99% VaR, N1, Portfolio 1	-29.629701870733022
99% CVaR, N1, Portfolio 1	-34.8706612830648
99% VaR, N2, Portfolio 1	-29.933153611260906
99% CVaR, N2, Portfolio 1	-35.15411402414807
99.9% VaR, N1, Portfolio 1	-38.89493755677354
99.9% CVaR, N1, Portfolio 1	-41.03581842560233
99.9% VaR, N2, Portfolio 1	-39.16332726773562
99.9% CVaR, N2, Portfolio 1	-41.29608262830908
99% VaR, N1, Portfolio 2	-23.2641200233124
99% CVaR, N1, Portfolio 2	-30.552908653909412
99% VaR, N2, Portfolio 2	-23.43990822132181
99% CVaR, N2, Portfolio 2	-30.710590483880523
99.9% VaR, N1, Portfolio 2	-36.7477922825108
99.9% CVaR, N1, Portfolio 2	-39.81802537871482
99.9% VaR, N2, Portfolio 2	-36.89010120477152
99.9% CVaR, N2, Portfolio 2	-39.95274743708135

- All errors are negative, meaning the normal model underestimates risk compared to the non-normal model.
- CVaR Errors Are More Negative Than VaR Errors, Larger Errors at Higher Confidence Levels (99.9%)

Remarks

impact on bank capital requirements using in-sample estimates

- From the sampling error table, we see that in-sample Monte Carlo estimates (MC1, MC2) systematically underestimate VaR and CVaR relative to the out-of-sample benchmark.
- This means banks relying on MC1/MC2 for risk measurement may hold significantly less capital than required.
- Particularly at 99.9% confidence levels, underestimation of CVaR is severe, which is critical because regulatory capital frameworks (like Basel III) often require capital based on tail risk.

techniques to minimizing impacts of sampling and modeling error

- Incorporate larger out-of-sample datasets (like 100,000 scenarios instead of 5,000).
- Use non-normal distributions
- Combine historical simulations and empirical data with Monte Carlo for a robust risk model.

