

MIE 1622

Assignment 3

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1. Matlab Output

===== 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% = \$86743504.86, CVaR 99.0% = \$128220213.73
In-sample MC1: VaR 99.0% = \$86444104.00, CVaR 99.0% = \$126500930.48
In-sample MC2: VaR 99.0% = \$85866679.44, CVaR 99.0% = \$126718534.12
In-sample No: VaR 99.0% = \$48051037.47, CVaR 99.0% = \$54130280.88
In-sample N1: VaR 99.0% = \$47792854.60, CVaR 99.0% = \$53830174.36
In-sample N2: VaR 99.0% = \$47816190.68, CVaR 99.0% = \$53860637.95

Out-of-sample: VaR 99.9% = \$187452990.62, CVaR 99.9% = \$225852522.86
In-sample MC1: VaR 99.9% = \$178566442.98, CVaR 99.9% = \$217605157.40
In-sample MC2: VaR 99.9% = \$179018432.28, CVaR 99.9% = \$222060134.51
In-sample No: VaR 99.9% = \$61755081.71, CVaR 99.9% = \$66721894.72
In-sample N1: VaR 99.9% = \$61402393.07, CVaR 99.9% = \$66334953.98
In-sample N2: VaR 99.9% = \$61441796.23, CVaR 99.9% = \$66380180.39

Portfolio 2:

Out-of-sample: VaR 99.0% = \$76598055.34, CVaR 99.0% = \$120061070.75
In-sample MC1: VaR 99.0% = \$76715076.33, CVaR 99.0% = \$118699833.66
In-sample MC2: VaR 99.0% = \$75706574.80, CVaR 99.0% = \$118827896.30
In-sample No: VaR 99.0% = \$44247367.34, CVaR 99.0% = \$49790065.09
In-sample N1: VaR 99.0% = \$44008654.82, CVaR 99.0% = \$49513589.92
In-sample N2: VaR 99.0% = \$44064432.89, CVaR 99.0% = \$49580693.73

Out-of-sample: VaR 99.9% = \$181135281.27, CVaR 99.9% = \$223667939.03
In-sample MC1: VaR 99.9% = \$174328285.80, CVaR 99.9% = \$215369740.61
In-sample MC2: VaR 99.9% = \$175891080.35, CVaR 99.9% = \$220507133.47
In-sample No: VaR 99.9% = \$56741911.49, CVaR 99.9% = \$61270360.42
In-sample N1: VaR 99.9% = \$56418073.07, CVaR 99.9% = \$60915669.47
In-sample N2: VaR 99.9% = \$56499382.02, CVaR 99.9% = \$61006231.68

2. Results Analysis

The distribution plots for 3 scenarios under 2 portfolio cases are included in the appendix.

Table 2.1 Sample Error for VaR 99% under non-Normal distribution

	MC1	MC2
Portfolio 1	0.35%	1.01%
Portfolio 2	0.15%	1.16%

Table 2.2 Sample Error for VaR 99.9% under non-Normal distribution

	MC1	MC2
Portfolio 1	4.74%	4.50%
Portfolio 2	3.76%	2.90%

Table 2.3 Sample Error for VaR 99% under Normal distribution

	MC1	MC2
Portfolio 1	44.92%	44.85%
Portfolio 2	42.55%	42.47%

Table 2.4 Sample Error for VaR 99.9% under Normal distribution

	MC1	MC2
Portfolio 1	67.23%	67.22%
Portfolio 2	68.85%	68.81%

2.1 Out of Sample vs In Sample under non Normal distribution

As we can see from table 2.1 and 2.2, the sampling error is relatively larger for VaR 99.9% than for VaR 99%. Based on the matlab outputs from section 1, the in-sample results underestimates the losses compared to the out of sample results. For example, for portfolio 1, the VaR 99.9% of out of sample is at \$187452990.62 whereas for MC1, the VaR 99.9% is at \$178566442.98, underestimating the losses by 4.74%. The overall comparison shows that true distribution has a flatter tail than both in sample distributions.

2.2 2.2 Out of Sample vs In Sample under Normal distribution

As we can see from table 2.3 and 2.4, the sampling error is extremely large under normal distribution assumption while the error for VaR99.9% is worse. The in sample results under normal distribution significantly underestimates the losses compared to true distribution. Overall, simulation results are relatively more precise under non Normal distribution assumption. Similar conditions also hold for CVaR.

3. Discuss possible strategies for minimizing impacts of sampling and model errors:

3.1 If you report the in-sample VaR and CVaR to decision-makers in your bank, what consequences for the bank capital requirements it may have?

Based on the analysis in section 2, both VaR and CVaR are underestimated by the simulation models. Reporting in-sample VaR/CVaR can cause the bank to take more risks than there actually is and essentially leads to less returns.

3.2 Can you suggest techniques for minimizing impacts of sampling and model errors?

To minimize sampling error, the suggestion is to increase simulation size as close as to true distribution. Improve the hardware used for simulation to speed up the simulation so that multiple models can be tested. Also, we can use regression from the results of out of sample distribution to regress the error when doing in-sample scenarios.











