In [227]:
```
# Import libraries
import numpy as np
import pandas as pd
import scipy
from scipy import special
import scipy.stats as scs
from scipy.stats import norm
from pathlib import Path
from scipy.sparse import csr_matrix
import math
import matplotlib.pyplot as plt
```

In [149]:
```
Nout = 100000  # number of out-of-sample scenarios
Nin = 5000     # number of in-sample scenarios
Ns = 5         # number of idiosyncratic scenarios for each systemic

C = 8          # number of credit states

# Read and parse instrument data
instr_data = np.array(pd.read_csv('instrum_data.csv', header=None))
instr_id = instr_data[:, 0]     # ID
driver = instr_data[:, 1]       # credit driver
beta = instr_data[:, 2]         # beta (sensitivity to credit driver)
recov_rate = instr_data[:, 3]   # expected recovery rate
value = instr_data[:, 4]        # value
prob = instr_data[:, 5:(5 + C)] # credit-state migration probabilities
exposure = instr_data[:, 5 + C:5 + 2 * C]  # credit-state migration ex
retn = instr_data[:, 5 + 2 * C] # market returns

K = instr_data.shape[0]         # number of CPs

# Read matrix of correlations for credit drivers
rho = np.array(pd.read_csv('credit_driver_corr.csv', sep='\t', header=
# Cholesky decomp of rho (for generating correlated Normal random numb
sqrt_rho = np.linalg.cholesky(rho)

print('======= Credit Risk Model with Credit-State Migrations ======='
print('============== Monte Carlo Scenario Generation ==============='
print(' ')
print(' ')
print(' Number of out-of-sample Monte Carlo scenarios = ' + str(Nout))
print(' Number of in-sample Monte Carlo scenarios = ' + str(Nin))
print(' Number of counterparties = ' + str(K))
print(' ')

# Find credit-state for each counterparty
# 8 = AAA, 7 = AA, 6 = A, 5 = BBB, 4 = BB, 3 = B, 2 = CCC, 1 = default
```

```
CS = np.argmax(prob, axis=1) + 1

# Account for default recoveries
exposure[:, 0] = (1 - recov_rate) * exposure[:, 0]

# Compute credit-state boundaries
CS_Bdry = scipy.special.ndtri((np.cumsum(prob[:, 0:C - 1], 1)))
```

```
======= 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
```

In [170]:

```
# -------- Insert your code here -------- #
filename_save_out = "filename_save_out"
if Path(filename_save_out+'.npz').is_file():
    Losses_out = scipy.sparse.load_npz(filename_save_out + '.npz')
else:
    # Generating Scenarios

    # -------- Insert your code here -------- #
    # Generate dependent variable: correlated normal systemic risk
    np.random.seed(42)
    # system risk is Nout * number of credit driver
    # system risk is identical across all counterparties, but
    Z_sys = np.random.normal(0, 1, (Nout, rho.shape[0]))
    # Apply Cholesky decomposition for correlation
    Y_sys = Z_sys @ sqrt_rho.T

    # Generate independent variable: idiosyncratic risk
    Z_idio = np.random.normal(0, 1, (Nout, K))

    # Combine systemic and idiosyncratic risks
    sigma = np.sqrt(1 - beta**2)
    # driver index from 1
    W = beta * Y_sys[:, driver.astype(int)-1] + sigma * Z_idio


    ###### Calculate credit state ######
    credit_state = np.sum(W[:, :, np.newaxis] > CS_Bdry[np.newaxis, :,

    ###### Credit state to Loss Out ######
    Losses_out = np.zeros((Nout, K))
    for k in range(K):
        #for each credit state in column k, find the correct exposure
        exposure_k = exposure[k, credit_state[:, k] - 1] #This is LOSS
```

```
        # print(exp_k)
        #loss_k = value[k] - exposure_k  # Loss per counterparty
        Losses_out[:, k] = exposure_k

print("Losses_out matrix:")
print(Losses_out)
Losses_out = csr_matrix(Losses_out)

# print(np.min(W))
# print(np.min(credit_state))
# unique, counts = np.unique(credit_state, return_counts=True)
# print(unique, " ", counts)

# print(np.sum(Losses_out < 0), " greater than zero: ", np.sum(Losses_
```

```
(100000, 50)
Losses_out matrix:
[[     0.      0.      0. ...      0.      0.      0.]
 [     0.      0.      0. ...      0.      0.      0.]
 [ 11484.      0.      0. ... 170311.      0.      0.]
 ...
 [     0.      0.      0. ...      0.      0.      0.]
 [     0.      0.      0. ...      0.      0.      0.]
 [     0.      0.      0. ...      0.      0.  56464.]]
```

Out-of-Sample : Compute VaR and CVaR

In [151]:
```
# Normal approximation computed from out-of-sample scenarios
mu_l = np.mean(Losses_out, axis=0).reshape((K))
var_l = np.cov(Losses_out.toarray(), rowvar=False) # Losses_out as a s
# print(var_l.shape)

# Compute portfolio weights
portf_v = sum(value)  # portfolio value
w0 = []
w0.append(value / portf_v)   # asset weights (portfolio 1)
w0.append(np.ones((K)) / K)  # asset weights (portfolio 2)
x0 = []
x0.append((portf_v / value) * w0[0])  # asset units (portfolio 1)
x0.append((portf_v / value) * w0[1])  # asset units (portfolio 2)


# Quantile levels (99%, 99.9%)
alphas = np.array([0.99, 0.999])

VaRout = np.zeros((2, alphas.size))
VaRinN = np.zeros((2, alphas.size))
CVaRout = np.zeros((2, alphas.size))
CVaRinN = np.zeros((2, alphas.size))
```

In [252]:
```
print("True distribution - Mean of each bond:\n",mu_l)
print("True distribution - Variance of each bond:\n",mu_l)
```

```
True distribution - Mean of each bond:
 [[1.88587207e+03 3.22791589e+03 1.03516508e+04 2.67234644e+05
  7.49915495e+03 5.26435236e+03 1.19433688e+04 9.57220372e+02
  6.89706833e+02 1.53450502e+05 1.01791951e+04 3.75803827e+04
  8.66116969e+02 2.92991463e+03 1.96099442e+03 1.02557283e+03
  6.40077599e+04 5.18454192e+04 8.12490324e+03 3.71860485e+03
  1.39434576e+03 1.78367315e+02 3.22028287e+03 1.54495065e+03
  5.88946800e+01 9.13480414e+01 3.15031027e+04 6.88225380e+03
  2.00161355e+04 6.16416807e+03 1.66822744e+03 1.18825211e+04
  2.68548926e+04 1.83087274e+06 6.85991577e+03 1.28494926e+03
  1.68996033e+02 9.83839185e+02 1.19741234e+03 3.66120927e+04
  3.49493173e+02 3.08240562e+04 9.52324482e+02 1.51287005e+04
  5.25815806e+03 3.16049891e+03 8.43355873e+04 5.32855281e+03
  2.73948712e+03 3.10482520e+02 3.25372037e+03 1.94848713e+05
  2.43527130e+04 6.66193807e+03 5.26711640e+05 3.14279402e+03
  1.11301915e+05 2.41895488e+04 2.13058505e+03 4.17209646e+04
  1.75498978e+03 1.22787134e+04 1.53826710e+04 5.30664805e+04
  6.88673430e+03 2.79470333e+05 1.17160796e+03 1.07156081e+03
  1.35716141e+06 5.94511927e+04 6.99913629e+03 2.52519826e+03
  1.95063715e+04 1.10045712e+03 1.16714972e+03 4.00303958e+02
  1.87590528e+05 1.04177559e+04 1.11037472e+04 3.82530328e+04
  1.94668551e+03 1.45851759e+05 2.77653426e+03 1.20272188e+05
  6.37278313e+03 1.59686681e+03 7.03167944e+03 2.66742846e+03
```

```
 6.37278213e+03 1.59686681e+03 7.02167044e+02 2.66742846e+03
 7.38702900e+01 7.65473841e+04 1.13386476e+04 7.89859680e+01
 1.08808526e+03 2.10295825e+04 3.95907114e+04 2.50973045e+03
 1.50252443e+03 8.00372889e+04 9.16995264e+02 1.22026021e+04]]
True distribution - Variance of each bond:
 [[1.88587207e+03 3.22791589e+03 1.03516508e+04 2.67234644e+05
 7.49915495e+03 5.26435236e+03 1.19433688e+04 9.57220372e+02
 6.89706833e+02 1.53450502e+05 1.01791951e+04 3.75803827e+04
 8.66116969e+02 2.92991463e+03 1.96099442e+03 1.02557283e+03
 6.40077599e+04 5.18454192e+04 8.12490324e+03 3.71860485e+03
 1.39434576e+03 1.78367315e+02 3.22028287e+03 1.54495065e+03
 5.88946800e+01 9.13480414e+01 3.15031027e+04 6.88225380e+03
 2.00161355e+04 6.16416807e+03 1.66822744e+03 1.18825211e+04
 2.68548926e+04 1.83087274e+06 6.85991577e+03 1.28494926e+03
 1.68996033e+02 9.83839185e+02 1.19741234e+03 3.66120927e+04
 3.49493173e+02 3.08240562e+04 9.52324482e+02 1.51287005e+04
 5.25815806e+03 3.16049891e+03 8.43355873e+04 5.32855281e+03
 2.73948712e+03 3.10482520e+02 3.25372037e+03 1.94848713e+05
 2.43527130e+04 6.66193807e+03 5.26711640e+05 3.14279402e+03
 1.11301915e+05 2.41895488e+04 2.13058505e+03 4.17209646e+04
 1.75498978e+03 1.22787134e+04 1.53826710e+04 5.30664805e+04
 6.88673430e+03 2.79470333e+05 1.17160796e+03 1.07156081e+03
 1.35716141e+06 5.94511927e+04 6.99913629e+03 2.52519826e+03
 1.95063715e+04 1.10045712e+03 1.16714972e+03 4.00303958e+02
 1.87590528e+05 1.04177559e+04 1.11037472e+04 3.82530328e+04
 1.94668551e+03 1.45851759e+05 2.77653426e+03 1.20272188e+05
 6.37278213e+03 1.59686681e+03 7.02167044e+02 2.66742846e+03
 7.38702900e+01 7.65473841e+04 1.13386476e+04 7.89859680e+01
 1.08808526e+03 2.10295825e+04 3.95907114e+04 2.50973045e+03
 1.50252443e+03 8.00372889e+04 9.16995264e+02 1.22026021e+04]]
```

In [158]:

```
for portN in range(2):
    # Compute VaR and CVaR
    for q in range(alphas.size):
        alf = alphas[q]
        # --------- Insert your code here --------- #

        #Losses_out is 100000*100 and x0[portN] is 100*1
        Losses_port = np.sort(Losses_out @ x0[portN])

        VaRout[portN, q] = Losses_port[int(math.ceil(Nout * alf)) - 1]
        VaRinN[portN, q] = np.mean(Losses_port) + scs.norm.ppf(alf) *
        CVaRout[portN, q] = (1 / (Nout * (1 - alf))) * ((math.ceil(Nou
        CVaRinN[portN, q] = np.mean(Losses_port) + (scs.norm.pdf(scs.r
print("VaRout:", VaRout)
print("CVaRout:", CVaRout)
```

```
VaRout: [[37282631.02       54519973.36000001]
 [27420869.74348778 41440595.66747013]]
CVaRout: [[45038705.41803996 62980086.24459998]
 [33729733.8562785  48613020.30341443]]
```

Monte Carlo approximation

In [259]:
```
# Perform 100 trials
N_trials = 100

VaRinMC1 = {}
VaRinMC2 = {}
VaRinN1 = {}
VaRinN2 = {}
CVaRinMC1 = {}
CVaRinMC2 = {}
CVaRinN1 = {}
CVaRinN2 = {}
PorfMC1_mean = {}
PorfMC2_mean = {}
PorfMC1_std = {}
PorfMC2_std = {}

for portN in range(2):
    PorfMC1_mean[portN] = np.zeros(N_trials)
    PorfMC2_mean[portN] = np.zeros(N_trials)
    PorfMC1_std[portN] = np.zeros(N_trials)
    PorfMC2_std[portN] = np.zeros(N_trials)
    for q in range(alphas.size):
        VaRinMC1[portN, q] = np.zeros(N_trials)
        VaRinMC2[portN, q] = np.zeros(N_trials)
        VaRinN1[portN, q] = np.zeros(N_trials)
        VaRinN2[portN, q] = np.zeros(N_trials)
        CVaRinMC1[portN, q] = np.zeros(N_trials)
        CVaRinMC2[portN, q] = np.zeros(N_trials)
        CVaRinN1[portN, q] = np.zeros(N_trials)
        CVaRinN2[portN, q] = np.zeros(N_trials)
```

In [260]:
```



for tr in range(1, N_trials + 1):
    ########### Monte Carlo approximation 1 ###########

    # -------- Insert your code here -------- #

    Z_sys = np.random.normal(0, 1, (np.int32(np.ceil(Nin / Ns)), rho.s
    # Apply Cholesky decomposition for correlation
    # 5 idiosyncratic scenarios for each systemic
    # Repeat 5 times each row -> 5000*50,
    Y_sys = np.repeat(Z_sys @ sqrt_rho.T , repeats=5, axis=0)

    # Generate independent variable: idiosyncratic risk
    # Z_idio size 5000*100
    Z_idio = np.random.normal(0, 1, (Nin, K))
```

```
    # Combine systemic and idiosyncratic risks
    sigma = np.sqrt(1 - beta**2)

    # driver index from 1
    W = beta * Y_sys[:, driver.astype(int)-1] + sigma * Z_idio

    ###### Calculate credit state ######
    credit_state = np.sum(W[:, :, np.newaxis] > CS_Bdry[np.newaxis, :,
    # print(credit_state.shape)

    ###### Credit state to Loss Out ######
    Losses_inMC1 = np.zeros((Nin, K))
    for k in range(K):
        #for each credit state in column k, find the correct exposure
        exposure_k = exposure[k, credit_state[:, k] - 1] #This is LOSS
        # print(exp_k)
        #loss_k = value[k] - exposure_k  # Loss per counterparty
        Losses_inMC1[:, k] = exposure_k

    Losses_inMC1 = csr_matrix(Losses_inMC1)


    ############     Monte Carlo approximation 2 ###########

    #     -------- Insert your code here -------- #

    # Calculated losses for MC2 approximation (5000 x 100)
    # Losses_inMC2
    # Apply Cholesky decomposition for correlation
    Y_sys = np.random.normal(0, 1, (Nin, rho.shape[0])) @ sqrt_rho.T

    # Generate independent variable: idiosyncratic risk
    # Z_idio size 5000*100
    Z_idio = np.random.normal(0, 1, (Nin, K))

    # Combine systemic and idiosyncratic risks
    sigma = np.sqrt(1 - beta**2)

    # driver index from 1
    W = beta * Y_sys[:, driver.astype(int)-1] + sigma * Z_idio

    ###### Calculate credit state ######
    credit_state = np.sum(W[:, :, np.newaxis] > CS_Bdry[np.newaxis, :,
    # print(credit_state.shape)

    ###### Credit state to Loss Out ######
    Losses_inMC2 = np.zeros((Nin, K))
    for k in range(K):
        #for each credit state in column k, find the correct exposure
        exposure_k = exposure[k, credit_state[:, k] - 1] #This is LOSS
```

```
            # print(exp_k)
            #loss_k = value[k] - exposure_k  # Loss per counterparty
            Losses_inMC2[:, k] = exposure_k

        # print("Losses_inMC2 with shape", Losses_inMC2.shape,":")
        # print(Losses_inMC2)
        Losses_inMC2 = csr_matrix(Losses_inMC2)


        # Compute VaR and CVaR

        for portN in range(2):
            for q in range(alphas.size):
                alf = alphas[q]
                # -------- Insert your code here -------- #
                # Compute portfolio loss
                portf_loss_inMC1 = np.sort(Losses_inMC1 @ x0[portN])
                portf_loss_inMC2 = np.sort(Losses_inMC2 @ x0[portN])

                mu_MC1 = np.mean(Losses_inMC1, axis=0).reshape((K))
                var_MC1 = np.cov(Losses_inMC1.toarray(), rowvar=False)
                mu_MC2 = np.mean(Losses_inMC2, axis=0).reshape((K))
                var_MC2 = np.cov(Losses_inMC2.toarray(), rowvar=False)

                # Compute portfolio mean loss mu_p_MC1 and portfolio stand
                # Compute portfolio mean loss mu_p_MC2 and portfolio stand
                # Compute VaR and CVaR for the current trial

                mu_p_MC1 = np.mean(portf_loss_inMC1)
                sigma_p_MC1 = np.std(portf_loss_inMC1)
                mu_p_MC2 = np.mean(portf_loss_inMC2)
                sigma_p_MC2 = np.std(portf_loss_inMC2)

                PorfMC1_mean[portN][tr - 1]  = mu_p_MC1
                PorfMC2_mean[portN][tr - 1]  = mu_p_MC2
                PorfMC1_std[portN][tr - 1]  = sigma_p_MC1
                PorfMC2_std[portN][tr - 1]  = sigma_p_MC2

                VaRinMC1[portN, q][tr - 1] = portf_loss_inMC1[int(math.cei
                VaRinMC2[portN, q][tr - 1] = portf_loss_inMC2[int(math.cei
                VaRinN1[portN, q][tr - 1] =  mu_p_MC1 + scs.norm.ppf(alf)
                VaRinN2[portN, q][tr - 1] =  mu_p_MC2 + scs.norm.ppf(alf)

                CVaRinMC1[portN, q][tr - 1] = (1 / (Nin * (1 - alf))) * ((
                CVaRinMC2[portN, q][tr - 1] = (1 / (Nin * (1 - alf))) * ((
                CVaRinN1[portN, q][tr - 1] =  mu_p_MC1 + (scs.norm.pdf(scs
                CVaRinN2[portN, q][tr - 1] =  mu_p_MC2 + (scs.norm.pdf(scs
```

In [261]:

```
# Display VaR and CVaR

for portN in range(2):
    print('\nPortfolio {}:\n'.format(portN + 1))
    for q in range(alphas.size):
        alf = alphas[q]
        print('Out-of-sample: VaR %4.1f%% = $%6.2f, CVaR %4.1f%% = $%6
        100 * alf, VaRout[portN, q], 100 * alf, CVaRout[portN, q]))
        print('In-sample MC1: VaR %4.1f%% = $%6.2f, CVaR %4.1f%% = $%6
        100 * alf, np.mean(VaRinMC1[portN, q]), 100 * alf, np.mean(CVa
        print('In-sample MC2: VaR %4.1f%% = $%6.2f, CVaR %4.1f%% = $%6
        100 * alf, np.mean(VaRinMC2[portN, q]), 100 * alf, np.mean(CVa
        print('In-sample No: VaR %4.1f%% = $%6.2f, CVaR %4.1f%% = $%6.
        100 * alf, VaRinN[portN, q], 100 * alf, CVaRinN[portN, q]))
        print('In-sample N1: VaR %4.1f%% = $%6.2f, CVaR %4.1f%% = $%6.
        100 * alf, np.mean(VaRinN1[portN, q]), 100 * alf, np.mean(CVaR
        print('In-sample N2: VaR %4.1f%% = $%6.2f, CVaR %4.1f%% = $%6.
        100 * alf, np.mean(VaRinN2[portN, q]), 100 * alf, np.mean(CVaR
```

```
Portfolio 1:

Out-of-sample: VaR 99.0% = $37282631.02, CVaR 99.0% = $45038705.42
In-sample MC1: VaR 99.0% = $37199183.26, CVaR 99.0% = $44573729.30
In-sample MC2: VaR 99.0% = $37185325.95, CVaR 99.0% = $44550141.17
In-sample No: VaR 99.0% = $26162490.95, CVaR 99.0% = $29053311.75
In-sample N1: VaR 99.0% = $26231617.31, CVaR 99.0% = $29123024.33
In-sample N2: VaR 99.0% = $26182559.60, CVaR 99.0% = $29069417.23

Out-of-sample: VaR 99.9% = $54519973.36, CVaR 99.9% = $62980086.24
In-sample MC1: VaR 99.9% = $53667406.01, CVaR 99.9% = $60367350.91
In-sample MC2: VaR 99.9% = $53614630.41, CVaR 99.9% = $60711359.62
In-sample No: VaR 99.9% = $32679080.84, CVaR 99.9% = $35040915.27
In-sample N1: VaR 99.9% = $32749528.68, CVaR 99.9% = $35111842.05
In-sample N2: VaR 99.9% = $32690215.57, CVaR 99.9% = $35048812.04


Portfolio 2:

Out-of-sample: VaR 99.0% = $27420869.74, CVaR 99.0% = $33729733.86
In-sample MC1: VaR 99.0% = $27436853.28, CVaR 99.0% = $33238940.71
In-sample MC2: VaR 99.0% = $27292814.67, CVaR 99.0% = $33422077.88
In-sample No: VaR 99.0% = $21087794.13, CVaR 99.0% = $23255162.77
In-sample N1: VaR 99.0% = $21052901.27, CVaR 99.0% = $23210506.97
In-sample N2: VaR 99.0% = $21089218.70, CVaR 99.0% = $23253053.43

Out-of-sample: VaR 99.9% = $41440595.67, CVaR 99.9% = $48613020.30
In-sample MC1: VaR 99.9% = $40547046.28, CVaR 99.9% = $45747478.94
In-sample MC2: VaR 99.9% = $40839008.02, CVaR 99.9% = $47508667.76
```

```
In-sample No: VaR 99.9% = $25973552.72, CVaR 99.9% = $27744318.26
In-sample N1: VaR 99.9% = $25916651.89, CVaR 99.9% = $27679441.00
In-sample N2: VaR 99.9% = $25967011.02, CVaR 99.9% = $27734889.31
```

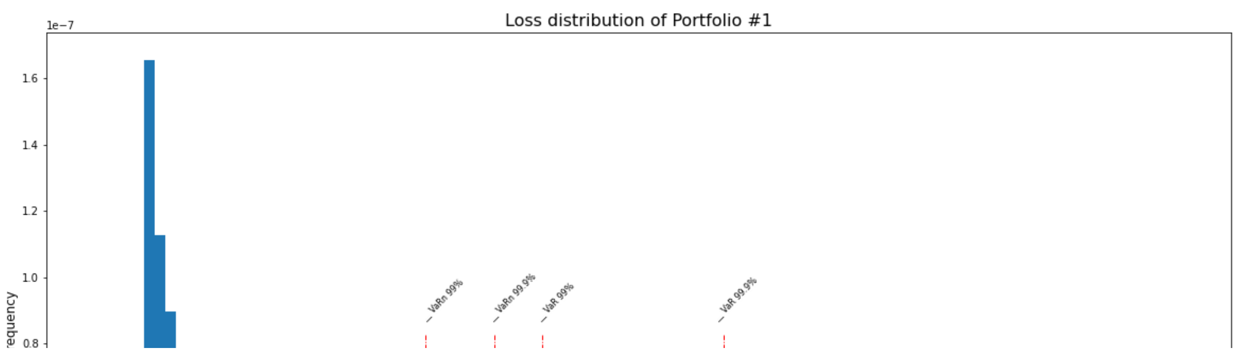
In [297]:

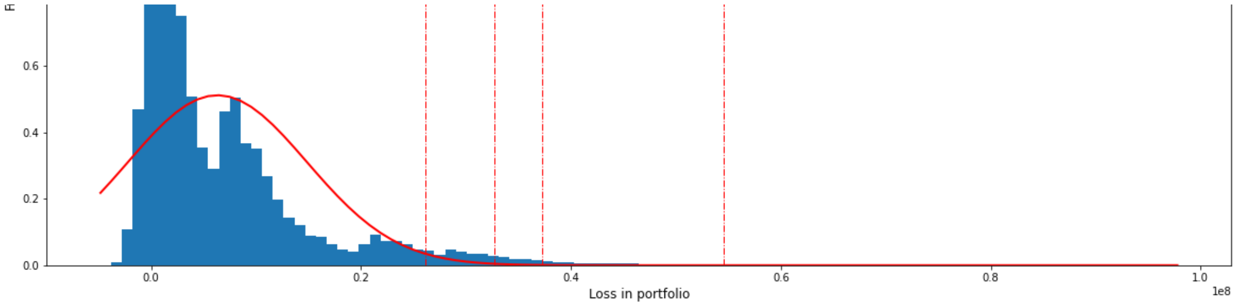
```
#Display Mean and std
for portN in range(2):
    print('\nPortfolio {}:\n'.format(portN + 1))
    print('Out-of-sample: Mean = ', np.mean(Losses_out @ x0[portN]), '
    print('In-sample MC1 average of 100 trials: Mean = ', np.mean(Porf
    print('In-sample MC2 average of 100 trials: Mean = ', np.mean(Porf



# Plot results (6 plots, 2 portfolios & 3 scenarios)
# # Figure (1):
# # -------- Insert your code here -------- #
# # Figure (2):
# # -------- Insert your code here -------- #
# # Build tables for errors
# # MC  approximations (16 rows)
# df_mc = pd.DataFrame({})
# # -------- Insert your code here -------- #
# # Normal approximations (16 rows)
# df_N = pd.DataFrame({})
# # -------- Insert your code here -------- #
```

```
Portfolio 1:

Out-of-sample: Mean =  6316746.7493652  Std =  8530858.356532618
In-sample MC1 average of 100 trials: Mean =  6381848.654341359  Std =
8532588.300593285
In-sample MC2 average of 100 trials: Mean =  6364022.93721756  Std =
8519162.971568126

Portfolio 2:

Out-of-sample: Mean =  6208613.948005141  Std =  6395939.466982296
In-sample MC1 average of 100 trials: Mean =  6240744.568389106  Std =
6367128.867495955
In-sample MC2 average of 100 trials: Mean =  6234299.158832099  Std =
6385510.8296006145
```

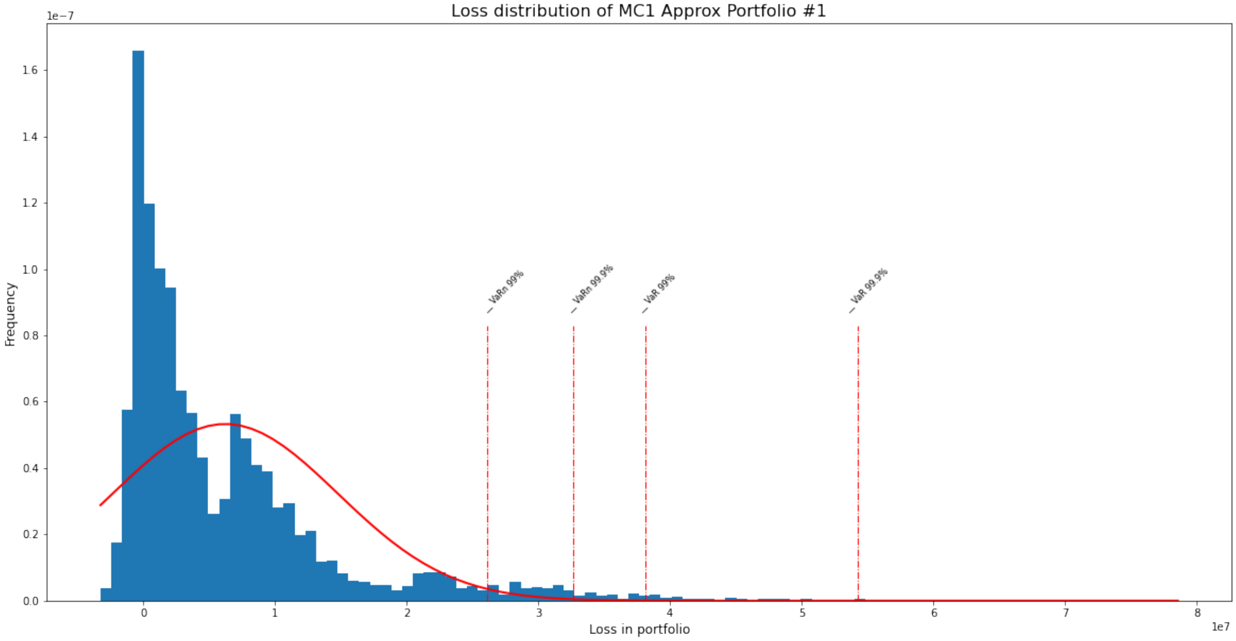
In [235]:
```
def plot_result(s, VaR_99, VaRn_99, VaR_999,VaRn_999, porf_name):
    #from posixpath import normpath
    fig = plt.figure(figsize=(20,10))
    mu, sigma = np.mean(s), np.std(s) # mean and standard deviation
    count, bins, ignored = plt.hist(s, 100, density=True) # In your pl
    # Plot the Normal curve
    norm = 1/(sigma * np.sqrt(2 * np.pi)) * np.exp( - (bins - mu)**2 /
    norm = norm * sum(count) / sum(norm)
    #Normal Distribution curve
    plt.plot(bins, norm, linewidth=2, color='r')
    # VaR red line
    # [0,max(count)/2]: height of VaR line
    plt.plot([VaR_99,VaR_99],[0,max(count)/2],color='r',linewidth=1,li
    plt.plot([VaRn_99,VaRn_99],[0,max(count)/2],color='r',linewidth=1,
    plt.text(0.98*VaR_99, max(count)/1.9, '__ VaR 99%',fontsize=8, rot
    plt.text(0.98*VaRn_99, max(count)/1.9, '__ VaRn 99%',fontsize=8, r

    plt.plot([VaR_999,VaR_999],[0,max(count)/2],color='r',linewidth=1,
    plt.plot([VaRn_999,VaRn_999],[0,max(count)/2],color='r',linewidth=
    plt.text(0.98*VaR_999, max(count)/1.9, '__ VaR 99.9%',fontsize=8,
    plt.text(0.98*VaRn_999, max(count)/1.9, '__ VaRn 99.9%',fontsize=8
    """
    Note: This is just a very simple example, the graph required for t
    - Plot Distribution example page
    """
    plt.xlabel('Loss in portfolio',fontsize=12)
    plt.ylabel('Frequency',fontsize=12)
    plt.title(porf_name,fontsize=16)
    plt.show()
```

In [306]:
```
plot_result(Losses_out @ x0[0], VaRout[0, 0], VaRinN[0,0], VaRout[0, 1]

#MC1
plot_result(Losses_inMC1 @ x0[0], VaRinMC1[0, 0][99], VaRinN1[0, 0][99]

#MC2
plot_result(Losses_inMC2 @ x0[0], VaRinMC2[0, 0][99], VaRinN2[0, 0][99]
```

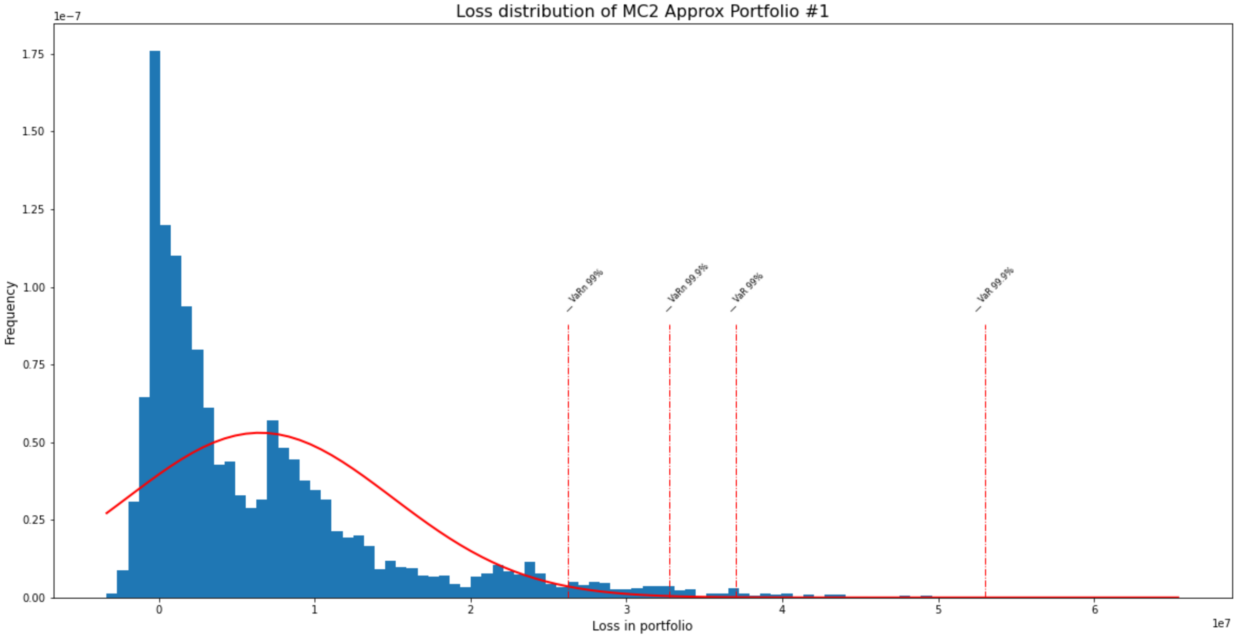




Loss distribution of MC1 Approx Portfolio #1

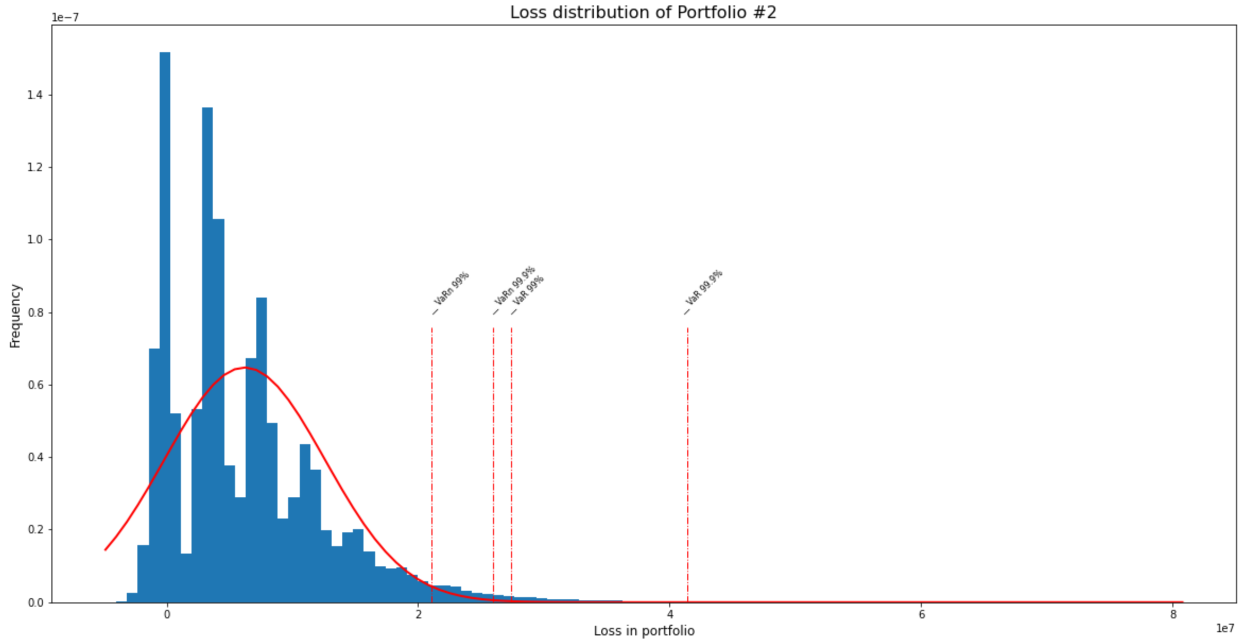


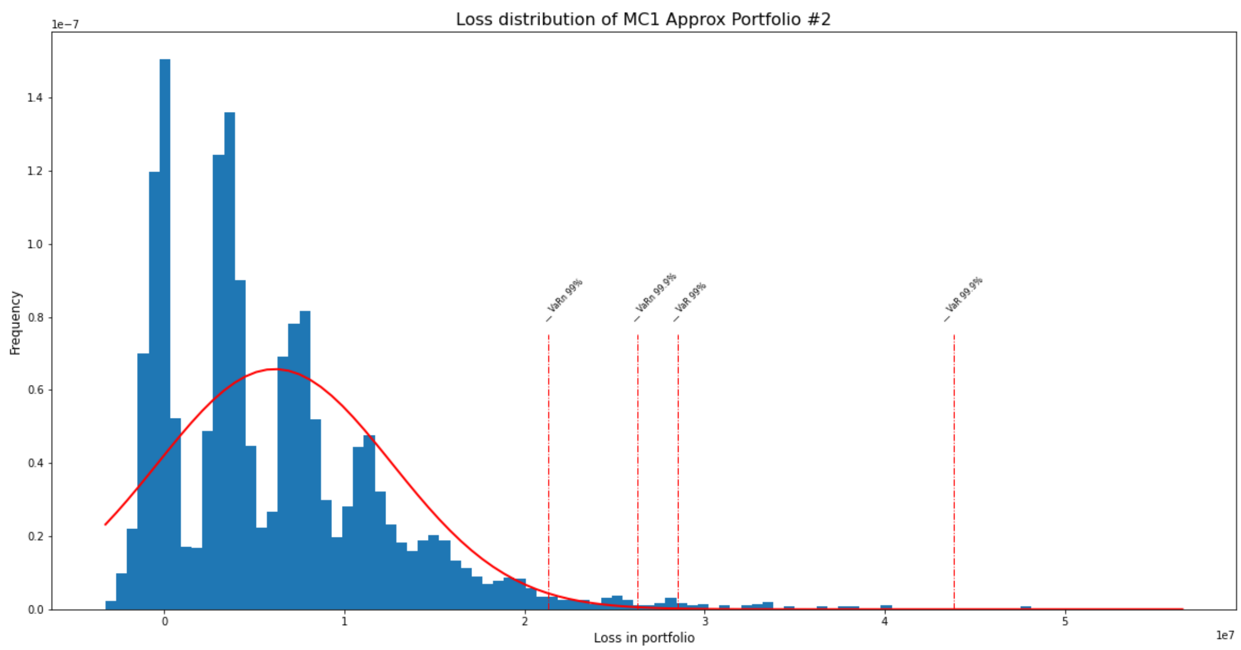
Loss distribution of MC2 Approx Portfolio #1

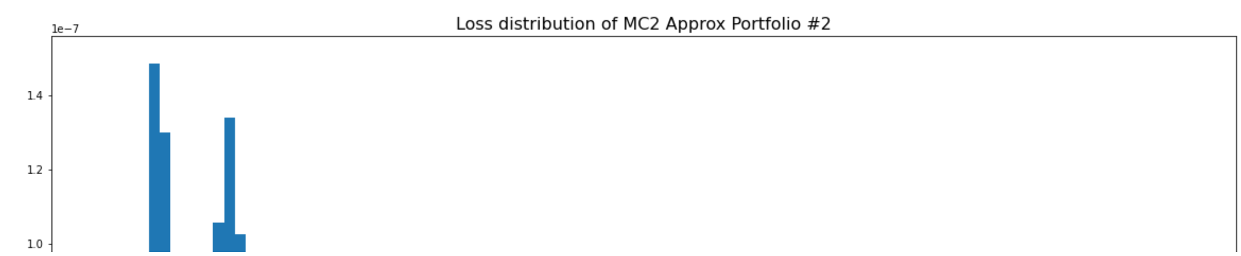


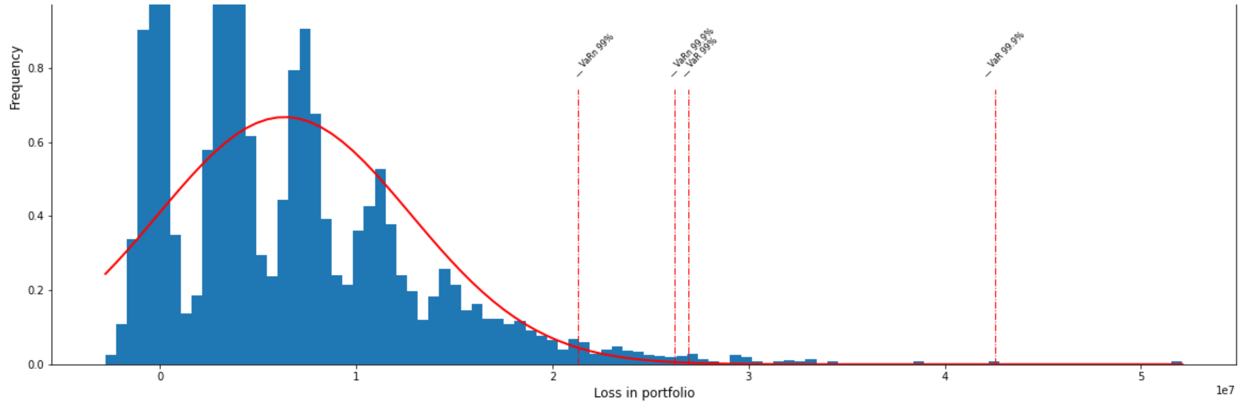
In [304]:
```
plot_result(Losses_out @ x0[1], VaRout[1, 0], VaRinN[1,0], VaRout[1, 1
#MC1
```

```
plot_result(Losses_inMC1 @ x0[1], VaRinMC1[1, 0][99], VaRinN1[1, 0][99

#MC2
plot_result(Losses_inMC2 @ x0[1], VaRinMC2[1, 0][99], VaRinN2[1, 0][99
```









Sampling Error and Model Error

sampling error = Z * sigma / sqrt(n) where Z is score value based on confidence interval. sigma is population standard deviation. n is the size of sample.

In [307]:
```
def calculate_sampling_error(sample, n):
    z_score = norm.ppf(0.975) # approx 1.96 for 95% CI
    sigma = np.std(sample)
    return z_score * (sigma / np.sqrt(n))


z_score = norm.ppf(0.975)
data = {
    "Out-of-Sample": [calculate_sampling_error(Losses_out @ x0[0], Nou
    "MC1": [z_score * (np.mean(PorfMC1_std[0]) / np.sqrt(Nin)), z_scor
#     "MC1": [z_score * (PorfMC1_std[0][99] / np.sqrt(Nin)), z_score *
    "MC2": [z_score * (np.mean(PorfMC2_std[0]) / np.sqrt(Nin)), z_scor
#     "MC2": [z_score * (PorfMC2_std[0][99] / np.sqrt(Nin)), z_score *
}

sampling_error = pd.DataFrame(data, index=["Portfolio 1", "Portfolio 2
sampling_error
```

Out[307]:

	Out-of-Sample	MC1	MC2
Portfolio 1	52873.836307	236506.935148	236134.810851
Portfolio 2	39641.715086	176484.564952	176994.077583

In [308]:
```
#Portfolio 1
data = {
    "VaR 99%": [np.abs(VaRout[0, 0] - VaRinN[0, 0]),
                np.abs(np.mean(VaRinN1[0, 0])-np.mean(VaRinMC1[0, 0]))
                np.abs(np.mean(VaRinN2[0, 0])-np.mean(VaRinMC2[0, 0]))
    "VaR 99.9%": [np.abs(VaRout[0, 1] - VaRinN[0, 1]),
                np.abs(np.mean(VaRinN1[0, 1])-np.mean(VaRinMC1[0, 1]))
                np.abs(np.mean(VaRinN2[0, 1])-np.mean(VaRinMC2[0, 1]))
    "CVaR 99%": [np.abs(CVaRout[0, 0] - CVaRinN[0, 0]),
                np.abs(np.mean(CVaRinN1[0, 0])-np.mean(CVaRinMC1[0, 0]
                np.abs(np.mean(CVaRinN2[0, 0])-np.mean(CVaRinMC2[0, 0]
    "CVaR 99.9%": [np.abs(CVaRout[0, 1] - CVaRinN[0, 1]),
                np.abs(np.mean(CVaRinN1[0, 1])-np.mean(CVaRinMC1[0, 1]
                np.abs(np.mean(CVaRinN2[0, 1])-np.mean(CVaRinMC2[0, 1]
}

model_error = pd.DataFrame(data, index=["True","MonteCarlo1", "MonteCa
model_error
```

Out[308]:

	VaR 99%	VaR 99.9%	CVaR 99%	CVaR 99.9%
True	1.112014e+07	2.184089e+07	1.598539e+07	2.793917e+07
MonteCarlo1	1.096757e+07	2.091788e+07	1.545070e+07	2.525551e+07
MonteCarlo2	1.100277e+07	2.092441e+07	1.548072e+07	2.566255e+07

In [309]:
```
#Portfolio 2
data = {
    "VaR 99%": [np.abs(VaRout[1, 0] - VaRinN[1, 0]),
                np.abs(np.mean(VaRinN1[1, 0])-np.mean(VaRinMC1[1, 0]))
                np.abs(np.mean(VaRinN2[1, 0])-np.mean(VaRinMC2[1, 0]))
    "VaR 99.9%": [np.abs(VaRout[1, 1] - VaRinN[1, 1]),
                np.abs(np.mean(VaRinN1[1, 1])-np.mean(VaRinMC1[1, 1]))
                np.abs(np.mean(VaRinN2[1, 1])-np.mean(VaRinMC2[1, 1]))
    "CVaR 99%": [np.abs(CVaRout[1, 0] - CVaRinN[1, 0]),
                np.abs(np.mean(CVaRinN1[1, 0])-np.mean(CVaRinMC1[1, 0]
                np.abs(np.mean(CVaRinN2[1, 0])-np.mean(CVaRinMC2[1, 0]
    "CVaR 99.9%": [np.abs(CVaRout[1, 1] - CVaRinN[1, 1]),
                np.abs(np.mean(CVaRinN1[1, 1])-np.mean(CVaRinMC1[1, 1]
                np.abs(np.mean(CVaRinN2[1, 1])-np.mean(CVaRinMC2[1, 1]
}

model_error = pd.DataFrame(data, index=["True","MonteCarlo1", "MonteCa
model_error
```

Out[309]:

	VaR 99%	VaR 99.9%	CVaR 99%	CVaR 99.9%
True	6.333076e+06	1.546704e+07	1.047457e+07	2.086870e+07
MonteCarlo1	6.383952e+06	1.463039e+07	1.002843e+07	1.806804e+07
MonteCarlo2	6.203596e+06	1.487200e+07	1.016902e+07	1.977378e+07

In [ ]: