

# Quantitative Risk Management

## MATH-471

Working results of Assignment 1

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## Question 1

1)

According to lecture slides, we know that,

$$L(t, t + \Delta) = -\lambda S(e^X - 1)$$

Let  $T$  be a standard Student's t-distributed variable generated by Matlab with freedom in  $f = 3, 10, 50$  degrees. However, the mean and variance of  $X_{1,t+\Delta}$  is provided, which is  $\mu = 0$  and  $\sigma = 0.01$ , thus, we need to introduce a constant  $\alpha$  to rescale  $T$  to make it fulfill the problem's requirement, which is,

$$\begin{aligned} X &= \alpha T \\ \Rightarrow \text{Var}[X] &= \alpha^2 \text{Var}[T] \\ \Rightarrow \alpha &= \sqrt{\frac{\text{Var}[X]}{\text{Var}[T]}} \\ \Rightarrow \alpha &= \frac{0.01}{\sqrt{\frac{f}{f-2}}} \end{aligned}$$

Hence, by using Matlab, we can find the empirical distribution of losses in different distribution.

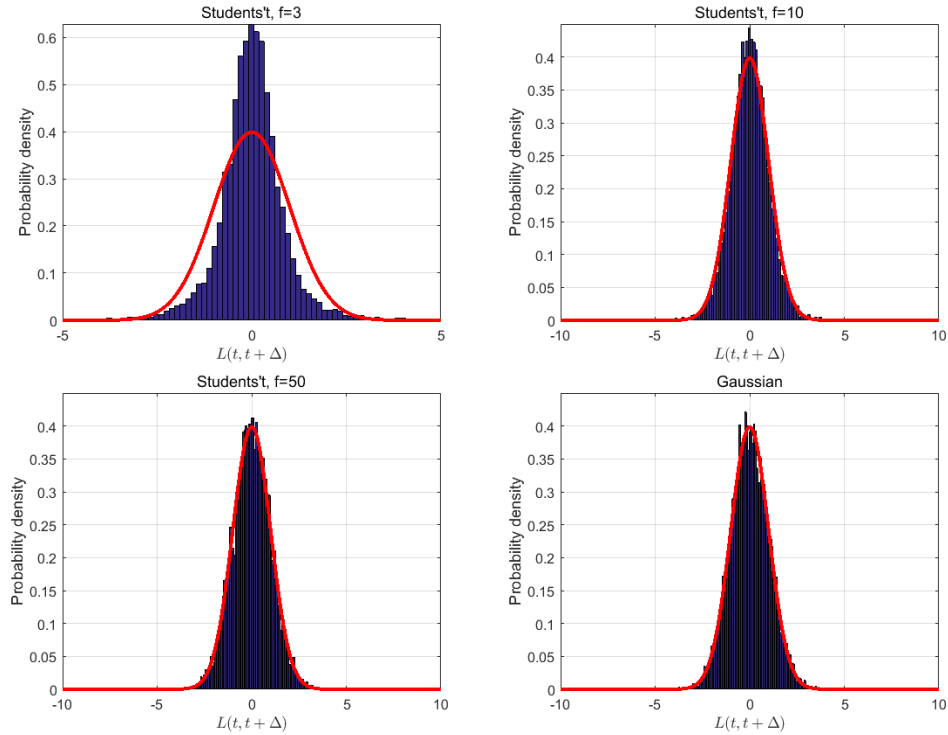


Figure 1: empirical distribution of  $L(t, t + \Delta)$

To compute the mean and variance of  $L(t, t + \Delta)$ , we check  $X_{1,t+\Delta}$ , which is actually small, thus, we can use the following approximation,

$$L(t, t + \Delta) = L^\delta(t, t + \Delta) = -\lambda S X$$

Thus, the mean and variance of  $L(t, t + \Delta)$  can be computed easily,

$$\begin{aligned} E[L^\delta(t, t + \Delta)] &= -\lambda S E[X] = 0 \\ \text{Var}[L^\delta(t, t + \Delta)] &= \lambda^2 S^2 \text{Var}[X] \\ &= 1^2 \times 100^2 \times 0.01^2 \\ &= 1 \end{aligned}$$

By the way, although the distributions of  $L$  above look like normal distribution, none of them is normal distribution because of the primary relation of  $L$  and  $X$ ,  $L(t, t + \Delta) = -\lambda S(e^X - 1)$ , which means that  $L$  is smaller than  $\lambda S$ , while normal distribution is unbounded. Therefore,  $L(t, t + \Delta)$  is not normal distribution.

## Question 2

1)

According to lecture slides, we know that:

$$\begin{array}{ll} Z_{1,t} = \log(S_t) & X_{1,t+\Delta} = \log(S_{t+\Delta}) - \log(S_t) \\ Z_{2,t} = r_t & \implies X_{2,t+\Delta} = r_{t+\Delta} - r_t \\ Z_{3,t} = \sigma_t & X_{3,t+\Delta} = \sigma_{t+\Delta} - \sigma_t \end{array}$$

As the risk factor changes  $X_{i,t+\Delta}$  is generated according to normal distribution. It is possible that  $r_{t+\Delta}$  and  $\sigma_{t+\Delta}$  being negative. But we claim that this possibility is extremely small, given the extremely small standard deviation of  $X_{i,t+\Delta}$  and small number of samples (10000). For example, we can calculate the probability that  $r_{t+\Delta} < 0$  as follow (given  $r_t = 0.05$ ):

$$\Pr(X_{2,t+\Delta} < -0.05) \xrightarrow[\text{standard}]{\text{to}} \Pr\left(\frac{X_{2,t+\Delta}}{10^{-4}} < \frac{-0.05}{10^{-4}}\right) = \Phi(-500)$$

which is small enough to be ignored. If we do meet negative values then we set them to their absolute value. Due to the low probability of this event, the whole distribution will not be affected significantly. Following figure displays the empirical distribution:

2)

The linearized loss is given by:

$$L^\delta(t, t + \Delta) = -\partial_S C^{BS} S_t X_{1,t+\Delta} - \partial_r C^{BS} X_{2,t+\Delta} - \partial_\sigma C^{BS} X_{3,t+\Delta}$$

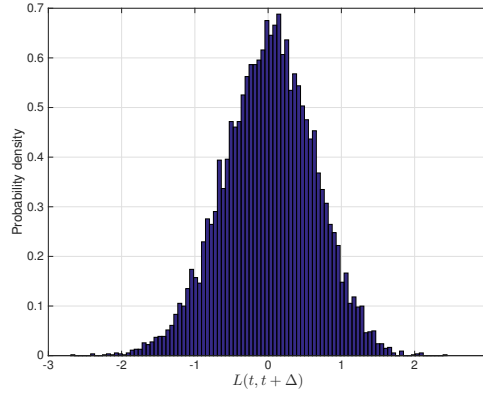


Figure 2: empirical distribution of  $L(t, t + \Delta)$

where

$$\begin{aligned}\partial_S C^{BS} &= \Phi(d_1) \\ \partial_r C^{BS} &= KTe^{-rT}\Phi(d_2) \\ \partial_\sigma C^{BS} &= S\phi(d_1)\sqrt{T}\end{aligned}$$

in which  $d_1$  and  $d_2$  are the same to that defined in lecture slides. Following figure illustrates the empirical distribution of linearized loss: To determine which of the

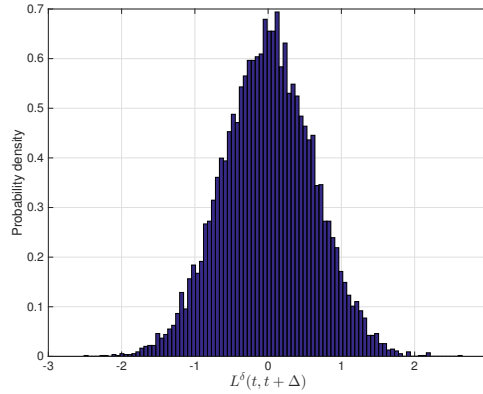


Figure 3: empirical distribution of  $L^\delta(t, t + \Delta)$

three risk factors contribute most to  $L^\delta(t, t + \Delta)$ , we can compare variances of the three terms used to calculate  $L^\delta(t, t + \Delta)$ :

$$Var_1 = (\partial_S C^{BS})^2 S_t^2 Var[X_{1,t+\Delta}] = 0.4134$$

$$Var_2 = (\partial_r C^{BS})^2 Var[X_{2,t+\Delta}] = 2.8727 \times 10^{-5}$$

$$Var_3 = (\partial_\sigma C^{BS})^2 Var[X_{3,t+\Delta}] = 0.0014$$

Hence we can conclude that the risk factor  $Z_{1,t}$ , i.e., the stock price contributes most to the linearized loss.

## Question 3

We have that  $x \sim \mathcal{N}(\mu, \sigma^2)$ , then:

$$\mathbb{E}[e^x] = \int_{-\infty}^{+\infty} e^x f(x) dx = \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} e^x dx$$

We know that:

$$\begin{aligned} e^{-\frac{(x-\mu)^2}{2\sigma^2}} e^x &= e^{-\frac{(x-\mu)^2}{2\sigma^2} + x} \\ &= e^{-\frac{(x-\mu)^2 - 2\sigma^2 x}{2\sigma^2}} \\ &= e^{-\frac{(x^2 - 2x\mu + \mu^2) - 2\sigma^2 x}{2\sigma^2}} \\ &= e^{-\frac{(x^2 - 2x(\mu + \sigma^2) + \mu^2)}{2\sigma^2}} \\ &= e^{-\frac{(x^2 - 2x(\mu + \sigma^2) + \mu^2 + (\mu + \sigma^2)^2 - (\mu + \sigma^2)^2)}{2\sigma^2}} \\ &= e^{\frac{(\mu + \sigma^2)^2}{2\sigma^2}} e^{-\frac{\mu}{2\sigma^2}} e^{-\frac{(x^2 - 2x(\mu + \sigma^2) + (\mu + \sigma^2)^2)}{2\sigma^2}} \\ &= e^{\frac{(\mu + \sigma^2)^2}{2\sigma^2}} e^{-\frac{\mu}{2\sigma^2}} e^{-\frac{(x - \mu - \sigma^2)^2}{2\sigma^2}} \end{aligned}$$

Let  $X = x - \sigma^2$  then we have:

$$\begin{aligned} \mathbb{E}[e^x] &= e^{\frac{(\mu + \sigma^2)^2}{2\sigma^2}} e^{-\frac{\mu}{2\sigma^2}} \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x - \mu - \sigma^2)^2}{2\sigma^2}} dx \\ &= e^{\frac{(\mu + \sigma^2)^2}{2\sigma^2}} e^{-\frac{\mu}{2\sigma^2}} \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(X - \mu)^2}{2\sigma^2}} dX \\ &= e^{\frac{(\mu + \sigma^2)^2}{2\sigma^2}} e^{-\frac{\mu}{2\sigma^2}} \times 1 = e^{\mu + \frac{1}{2}\sigma^2} \end{aligned}$$

## Appendix

Following are our codes for solving the questions of this assignment. In addition, for commented and runnable codes for above problems, please refer to:

<https://github.com/FINEPFL/Quant-Risk-Manage-MATH-471>

```
1 % This is a script for solving assignment 1 of Quantitative Risk
   % Management
2 % course at EPFL 2017. If you meet any problem when evaluating or
   % running
3 % the code, please feel free to drop an email to the authors.
```

```

4 %
   *****

5 % Author:
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7 %       Tianxiao Ma,   tianxiao.ma@epfl.ch
8 %
   *****

9 % Here we acknowlege that all following contents are working results of
10 % ourselves, w.r.t. EPFL honor code.
11 clear; clc
12
13 S_t = 100; lambda = 1; d = 1; mu_X = 0; SD_X = 0.01; f = [3, 10, 50]; N
    = 10000;
14
15 alpha = SD_X ./ sqrt(f ./ (f-2));
16 T(:, 1) = trnd (f(1, 1), N, 1);
17 T(:, 2) = trnd (f(1, 2), N, 1);
18 T(:, 3) = trnd (f(1, 3), N, 1);
19 T(:, 4) = randn (N, 1);
20
21 X(:, 1) = alpha(:, 1) * T(:, 1);
22 X(:, 2) = alpha(:, 2) * T(:, 2);
23 X(:, 3) = alpha(:, 3) * T(:, 3);
24 X(:, 4) = SD_X * T(:, 4);
25
26 L_t = lambda * S_t * (exp(X)-1);
27
28 figure(1)
29 %subplot(2, 2, 1)
30 [N_1, X] = hist(L_t(:, 1), 150);
31 bar(X, N_1/(sum(N_1)*diff(X(1:2))), 1);
32 x = -10:0.1:10;
33 y = normpdf(x, 0, 1);
34 hold on
35 plot(x,y, 'r', 'linewidth', 3);
36 axis([-5 5 -inf inf]);
37 hold off
38 grid on;
39 xlabel('L(t,t+\Delta)', 'interpreter', 'latex', 'fontsize', 15)
40 ylabel('Probability density')
41 title('Students't, f=3');
42 set(gca, 'fontsize', 12)
43
44 figure(2)
45 %subplot(2, 2, 2)
46 [N_2, X] = hist(L_t(:, 2), 100);
47 bar(X, N_2/(sum(N_2)*diff(X(1:2))), 1);
48 hold on
49 plot(x,y, 'r', 'linewidth', 3);
50 hold off
51 grid on;
52 xlabel('L(t,t+\Delta)', 'interpreter', 'latex', 'fontsize', 15)
53 ylabel('Probability density')
54 title('Students't, f=10');

```

```

55 set(gca, 'fontsize', 12)
56
57 figure(3)
58 %subplot(2, 2, 3)
59 [N_3, X] = hist(L_t(:, 3), 100);
60 bar(X, N_3/(sum(N_3)*diff(X(1:2))), 1);
61 hold on
62 plot(x,y, 'r', 'linewidth', 3);
63 hold off
64 grid on;
65 xlabel('L(t,t+\Delta)', 'interpreter', 'latex', 'fontsize', 15)
66 ylabel('Probability density')
67 title('Students''t, f=50');
68 set(gca, 'fontsize', 12)
69
70 figure(4)
71 %subplot(2, 2, 4)
72 [N_4, X] = hist(L_t(:, 4), 100);
73 bar(X, N_4/(sum(N_4)*diff(X(1:2))), 1);
74 hold on
75 plot(x,y, 'r', 'linewidth', 3);
76 hold off
77 grid on;
78 xlabel('L(t,t+\Delta)', 'interpreter', 'latex', 'fontsize', 15)
79 ylabel('Probability density')
80 title('Gaussian');
81 set(gca, 'fontsize', 12)

1 clearvars; close all; clc
2
3 %% Question 2
4 S_t = 100; r_t = 0.05; sigma_t = 0.2;
5
6 u_1_tpd = 0;
7 std_1_tpd = 0.01;
8
9 u_2_tpd = 0;
10 std_2_tpd = 0.0001;
11
12 u_3_tpd = 0;
13 std_3_tpd = 0.001;
14
15 corr_1_3 = -0.5;
16
17 % generating data for calculating loss -- L and L_\Delta
18 N = 10000;
19 MU = [u_1_tpd; u_2_tpd; u_3_tpd]';
20
21 % X2_tpd is independent with X1_tpd and X3_tpd, cor(X1_tpd, X3_tpd) =
    -0.5,
22 % then we build the correlation matrix, then map it to covariace matrix
23 % since it is required by the mvnrnd function
24 cor_mat = [ 1 0 -0.5;
25             0 1 0;
26            -0.5 0 1];

```

```

27 var_map = [std_1_tpd; std_2_tpd; std_3_tpd] *...
28             [std_1_tpd; std_2_tpd; std_3_tpd]';
29 cov_mat = cor_mat .* var_map;
30 R = mvnrnd(MU, cov_mat, N);
31 corr(R(:, 1), R(:, 3)) % verify the correlation is -0.5
32 corr(R(:, 1), R(:, 2)) % verify the correlation is 0
33 corr(R(:, 3), R(:, 2)) % verify the correlation is 0
34
35 % as the r_tpd and sigma_tpd could be zero, we force then to its
    absolute
36 % value. However, the probability of this event is extremely small.
37 neg_r_tpd_idx = find(R(:, 2) + r_t < 0);
38 neg_sigma_tpd_idx = find(R(:, 3) + sigma_t < 0);
39
40 % convert the negative values to its absolute value
41 R(neg_r_tpd_idx, 2) = - r_t - R(neg_r_tpd_idx, 2);
42 R(neg_sigma_tpd_idx, 3) = - sigma_t - R(neg_sigma_tpd_idx, 3);
43
44 % def parameters and helper functions for calculation
45 t = 0; T = 1; K = 100; Delta = 1/252;
46 get_d1 = @(t, T, K, S, r, sigma) (log(S./K) + (r + 0.5*sigma.^2) * (T-t
    ))/...
47                                     (sigma * sqrt(T-t))
    ;
48 get_d2 = @(t, T, K, S, r, sigma) (get_d1(t, T, K, S, r, sigma) - ...
49                                     sigma * sqrt(T-t))
    ;
50
51 get_C_bs = @(t, T, K, S, r, sigma) (S*normcdf(get_d1(t, T, K, S, r,
    sigma)))...
52     - exp(-r*(T-t)) * K * normcdf(get_d2(t, T, K, S, r,
    sigma));
53
54 d1_t = get_d1(t, T, K, S_t, r_t, sigma_t);
55 d2_t = get_d2(t, T, K, S_t, r_t, sigma_t);
56 C_bs_t = get_C_bs(t, T, K, S_t, r_t, sigma_t);
57
58 % in matrix R we have X1_tpd, X2_tpd and X3_tpd respectively.
59 % tpd means t plus delat
60 t = Delta;
61 S_tpd = exp(R(:, 1) + log(S_t));
62 r_tpd = R(:, 2) + r_t;
63 sigma_tpd = R(:, 3) + sigma_t;
64
65 for i=1:N
66 C_bs_tpd(i) = get_C_bs(t, T, K, S_tpd(i), r_tpd(i), sigma_tpd(i));
67 end
68 L_t_tpd = -(C_bs_tpd - C_bs_t);
69
70 % get handles from hist to make the hist to pdf and integral to 1
71 [N, X] = hist(L_t_tpd, 95);
72 bar(X, N/(sum(N)*diff(X(1:2))), 1)
73 grid on;
74 xlabel('L(t,t+Δ)', 'interpreter', 'latex', 'fontsize', 15)
75 ylabel('Probability density')
76 set(gca, 'fontsize', 12)

```



```

77
78 % calculate  $\Delta$ , rho and vega
79  $\Delta$  = normcdf(d1_t)
80 rho = K * T * exp(-r_t * T) * normcdf(d2_t)
81 vega = S_t * normpdf(d1_t) * sqrt(T)
82 % calculate contribution to linear loss of each term
83 var1 = ( $\Delta$ )^2 * S_t^2 * var(R(:, 1))
84 var2 = (rho)^2 * var(R(:, 2))
85 var3 = (vega)^2 * var(R(:, 3))
86
87 % calculate linearized loss
88 lized_L_t_tpd = -( $\Delta$  * S_t * R(:, 1) + rho * R(:, 2) + vega * R(:, 3));
89 figure(2)
90 [N_, X_] = hist(lized_L_t_tpd, 95);
91 bar(X_, N_/(sum(N_)*diff(X_(1:2))), 1)
92 grid on
93 xlabel('L $^\delta(t, t + \Delta)$ ', 'interpreter', 'latex', 'fontsize', 15)
94 ylabel('Probability density')
95 set(gca, 'fontsize', 12)

```