# Statistical Finance (STAT W4290)

# Assignment 1

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#### Question 1

(a)

Let investment amount at t be  $P_t$ . Set  $P_0 = 1000$ .

Given that  $\log (1 + R_{0,1}) \sim N(0.001, 0.015^2)$ ,

$$P(P_1 < 990) = P\left(\frac{P_1}{P_0} < \frac{990}{P_0}\right)$$

$$= P\left(1 + R_{0,1} < \frac{990}{1000}\right)$$

$$= P\left(\log\left(1 + R_{0,1}\right) < \log\frac{990}{1000}\right)$$

$$= 0.2306557$$

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1 > pnorm(log(990/1000), mean=0.001, sd=0.015)
2 [1] 0.2306557
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(b)

$$\begin{split} P(P_5 < 990) &= P\left(\frac{P_5}{P_0} < \frac{990}{1000}\right) \\ &= P\left(1 + R_{0,5} < \frac{990}{1000}\right) \\ &= P\left((1 + R_{0,1})(1 + R_{1,2})(1 + R_{2,3})(1 + R_{3,4})(1 + R_{4,5}) < \frac{990}{1000}\right) \\ &= P\left(\log\left((1 + R_{0,1})(1 + R_{1,2})(1 + R_{2,3})(1 + R_{3,4})(1 + R_{4,5})\right) < \log\frac{990}{1000}\right) \\ &= P\left(\log\left((1 + R_{0,1})... + \log\left((1 + R_{4,5})\right) < \log\frac{990}{1000}\right) \end{split}$$

Now, given that daily log returns are independent,

$$\log (1 + R_{0.1}) \dots + \log (1 + R_{4.5}) \sim N(0.005, 5 * 0.015^2)$$

Then,

$$P\left(\log(1+R_{0,1})...+\log(1+R_{4,5})<\log\frac{990}{1000}\right)=0.3268189$$

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1 > pnorm(log(990/1000), mean=0.005, sd=sqrt(5) * 0.015)
2 [1] 0.3268189
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Question 4

(a)

$$R_2 = \frac{P_2 + D_2}{P_1} - 1$$
$$= \frac{54 + 0.2}{52} - 1$$
$$= 0.04230769$$

(b)

$$R_4(3) = \frac{P_4 + D_4}{P_3} * \frac{P_3 + D_3}{P_2} * \frac{P_2 + D_2}{P_1} - 1$$

$$= \frac{59 + 0.25}{53} * \frac{53 + 0.2}{54} * \frac{54 + 0.2}{52} - 1 = 0.1479588$$

(c)

$$r_3 = \log 1 + R_3$$

$$= \log \frac{P_3 + D_3}{P_2}$$

$$= \log \frac{53 + 0.2}{54}$$

$$= -0.01492565$$

Trivial R code omitted.

## Question 6

(a)

$$X_k = X_0 \exp{(r_1 + \ldots + r_k)}$$
 
$$\log{X_k} - \log{X_0} = r_1 + \ldots + r_k$$

Then,

$$\log X_k - \log X_0 \sim N(k\mu, k\sigma^2)$$

$$P(X_2 > 1.3X_0) = P\left(\frac{X_2}{X_0} > 1.3\right)$$
  
=  $P(\log X_2 - \log X_0 > \log 1.3)$ 

Given that  $\log X_2 - \log X_0 \sim N(2\mu, 2\sigma^2)$ 

$$P(\log X_2 - \log X_0 > \log 1.3) = 1 - P(\log X_2 - \log X_0 < \log 1.3)$$

(b)

Recall that suppose X is a random variable with PDF  $f_X(x)$  and Y = g(X) for g is a strictly increasing function. Since g is strictly increasing, it has an inverse, which we denote by h. Then Y is also a random variable and its CDF is:

$$F_Y(y) = P(Y \le y) = P(g(X) \le y) = P(X \le h(y) = F_X(h(y))$$

Differentiating, we find the PDF of Y

$$f_Y(y) = f_X(h(y))h'(y)$$

In this case,  $r \sim N(\mu, \sigma^2)$ 

$$f_R(r) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(r-\mu)^2}{2\sigma^2}\right)$$

Since  $Y = X_1 = X_0 \exp R = g(R)$ ,

$$h(Y) = R = \log \frac{X_1}{X_0} = \log X_1 - \log X_0$$

$$h'(Y) = \frac{\delta R}{\delta X_1} = \frac{1}{X_1}$$

Then,

$$f_Y(y) = f_{X_1}(x) = \frac{1}{x} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(\log x - \log X_0 - \mu)^2}{2\sigma^2}\right)$$

(c)

$$X_k = X_0 \exp r_1 + \dots + r_k = X_0 \exp R$$

Then,  $R \sim N(k\mu, k\sigma^2)$ 

Then,

$$f_{X_k}(x) = \frac{1}{x} \frac{1}{\sqrt{2\pi k\sigma}} \exp\left(-\frac{(\log x - \log X_0 - k\mu)^2}{2k\sigma^2}\right)$$

Thus transformation from R to  $X_k$  is monotonic. Then, we find the 0.9 quantile of  $R \sim N(k\mu, k\sigma^2)$ . Denote this value with  $r_{0.9}$ . Then, the 0.9 quantile of  $X_k$  is simply  $X_0 \exp r_{0.9}$ 

(d)

$$X_k^2 = X_0^2 \exp(2(r_1 + \dots + r_k)) = X_0^2 \prod_{i=1}^k \exp(2r_i)$$

Then, the expectation  $E(X_k^2)$  can be found by (since each  $r_i$  is iid)

$$\begin{split} E(X_k^2) &= X_0^2 \int_{-\infty}^{\infty} \left( \prod_{i=1}^k \exp{(2r_i)} p(r_i) dr_i \right) \\ &= X_0^2 \left( \int_{-\infty}^{\infty} \exp{(2r)} \frac{1}{\sqrt{2\pi}\sigma} \exp{-\frac{(r-\mu)^2}{2\sigma^2}} dr \right)^k \\ &= X_0^2 \left( \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} \exp{\left(2r - \frac{(r-\mu)^2}{2\sigma^2}\right)} dr \right)^k \\ &= X_0^2 \left( \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} \exp{\left(\left(2 + \frac{2\mu}{2\sigma^2}\right)r - \frac{r^2}{2\sigma^2} - \frac{\mu^2}{2\sigma^2}\right)} dr \right)^k \\ &= X_0^2 \left( \frac{1}{\sqrt{2\pi}\sigma} \exp{\left(-\frac{\mu^2}{2\sigma^2}\right)} \int_{-\infty}^{\infty} \exp{\left(\left(2 + \frac{2\mu}{2\sigma^2}\right)r - \frac{r^2}{2\sigma^2}\right)} dr \right)^k \end{split}$$

Working on the inner exponent,

$$\begin{split} \left(2 + \frac{2\mu}{2\sigma^2}\right)r - \frac{r^2}{2\sigma^2} &= -\frac{1}{2\sigma^2}\left(r^2 - 2\sigma^2\left(2 + \frac{\mu}{\sigma^2}\right)r\right) \\ &= -\frac{1}{2\sigma^2}\left(r^2 - 2(2\sigma^2 + \mu)r\right) \\ &= -\frac{1}{2\sigma^2}\left(r^2 - 2(2\sigma^2 + \mu)r + (2\sigma^2 + \mu)^2 - (2\sigma^2 + \mu)^2\right) \\ &= -\frac{1}{2\sigma^2}\left(\left(r - (2\sigma^2 + \mu)\right)^2 - (2\sigma^2 + \mu)^2\right) \end{split}$$

Continuing where we left off earlier,

$$\begin{split} E(X_k^2) &= X_0^2 \left(\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{\mu^2}{2\sigma^2}\right) \int_{-\infty}^{\infty} \exp\left(\left(2 + \frac{2\mu}{2\sigma^2}\right)r - \frac{r^2}{2\sigma^2}\right) dr\right)^k \\ &= X_0^2 \left(\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{\mu^2}{2\sigma^2}\right) \exp\frac{(2\sigma^2 + \mu)^2}{2\sigma^2} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}(r - (2\sigma^2 + \mu))^2\right) dr\right)^k \\ &= X_0^2 \left(\frac{1}{\sqrt{2\pi}\sigma} \exp\frac{(4\sigma^4 + 4\sigma^2\mu)^2}{2\sigma^2} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}r^2\right) dr\right)^k \end{split}$$

Recall that

$$\int_{-\infty}^{\infty} \exp\left(-ax^2\right) = \sqrt{\frac{\pi}{a}}$$

Then,

$$E(X_k^2) = X_0^2 \left( \frac{1}{\sqrt{2\pi}\sigma} \sqrt{2\pi}\sigma \exp(2\mu + 2\sigma^2) \right)^k$$
$$= X_0^2 \exp(2k\mu + 2k\sigma^2)$$

(e)

$$Var(X_k) = E(X_k^2) - E(X_k)^2$$

(I'm running late for the assignment and had no time to typeset this). Using basically the same stuff as (d) except replace  $X_k^2$  with  $X_k$ 

$$E(X_k) = X_0 \exp\left(\frac{k\sigma^2}{2} + k\mu\right)$$

Then,

$$Var(X_k) = X_0^2 \exp(2k\mu + 2k\sigma^2) - X_0^2 \exp\left(\frac{2k\sigma^2}{2} + 2k\mu\right)$$
$$= X_0^2 \left(\exp(2k\mu + 2k\sigma^2) - \exp\left(\frac{2k\sigma^2}{2} + 2k\mu\right)\right)$$

## Question 7

Given that  $\log(1 + R_t) \sim N(0.0002, 0.03^2)$ ,  $\log(1 + R_{0,20}) \sim N(20 * 0.0002, 20 * 0.03^2)$ 

$$\begin{split} P(P_{20} > 100) &= P\left(\frac{P_{20}}{P_0} > \frac{100}{P_0}\right) \\ &= P\left(1 + R_{0,20} > \frac{100}{97}\right) \\ &= P\left(\log\left(1 + R_1\right) + \log\left(1 + R_2\right) + \dots + \log\left(1 + R_{20}\right) > \log\frac{100}{97}\right) \\ &= 1 - P\left(\log\left(1 + R_1\right) + \log\left(1 + R_2\right) + \dots + \log\left(1 + R_{20}\right) < \log\frac{100}{97}\right) \\ &= 0.4218295 \end{split}$$

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1 > 1 - pnorm(log(100/97), mean=20*0.0002, sd=sqrt(20) * 0.03)
2 [1] 0.4218295
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