Financial Mathematics

MATH 5870/6870[1]
Fall 2021

Le Chen

lzc0090@auburn.edu

Last updated on

August 15, 2021

Auburn University
Auburn AL

[1] Based on Robert L. McDonald's *Derivatives Markets*, 3rd Ed, Pearson, 2013.

Chapter 18. The Lognormal Distribution

Chapter 18. The Lognormal Distribution

Definition 18.1-1 A random variable X is said to have the *normal distribution* (or *normally distributed*) with mean μ and variance σ^2, if the probability density function (pdf) is given by

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}.$$

We write

$$X \sim N(\mu, \sigma^2).$$

$N(0, 1)$ is called the *standard normal distribution*.

Definition 18.1-2 The *cumulative distribution function (cdf) of the standard normal distribution* is denoted by $\Phi(\cdot)$, namely,

$$\Phi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y^2}\, dy.$$

Let $Z \sim N(0,1)$ and $a > 0$. By symmetry of the density, we have the following useful formulas:

1.
$$\mathbb{P}(-a \leq Z \leq a) = 2\Phi(a) - 1.$$

For example,
$$\mathbb{P}(|Z| \leq 0.3) = 2 \cdot \Phi(0.3) - 1 = 2 \times 0.6179 - 1 = 0.2358.$$

2.
$$\mathbb{P}(Z > a) = \mathbb{P}(Z < -a) = \Phi(-a) = 1 - \Phi(a)$$

3.
$$\mathbb{P}(0 < Z \leq a) = \mathbb{P}(Z < a) - \mathbb{P}(Z \leq 0) = \Phi(a) - \frac{1}{2}.$$

Let $Z \sim N(0,1)$ and $a > 0$. By symmetry of the density, we have the following useful formulas:

1.
$$\mathbb{P}(-a \leq Z \leq a) = 2\Phi(a) - 1.$$
For example,
$$\mathbb{P}(|Z| \leq 0.3) = 2 \cdot \Phi(0.3) - 1 = 2 \times 0.6179 - 1 = 0.2358.$$

2.
$$\mathbb{P}(Z > a) = \mathbb{P}(Z < -a) = \Phi(-a) = 1 - \Phi(a)$$

3.
$$\mathbb{P}(0 < Z \leq a) = \mathbb{P}(Z < a) - \mathbb{P}(Z \leq 0) = \Phi(a) - \frac{1}{2}.$$

Let $Z \sim N(0,1)$ and $a > 0$. By symmetry of the density, we have the following useful formulas:

1. $$\mathbb{P}\left(-a \leq Z \leq a\right) = 2\Phi(a) - 1.$$

   For example,

   $$\mathbb{P}\left(|Z| \leq 0.3\right) = 2 \cdot \Phi(0.3) - 1 = 2 \times 0.6179 - 1 = 0.2358.$$

2. $$\mathbb{P}\left(Z > a\right) = \mathbb{P}(Z < -a) = \Phi(-a) = 1 - \Phi(a)$$

3. $$\mathbb{P}\left(0 < Z \leq a\right) = \mathbb{P}(Z < a) - \mathbb{P}(Z \leq 0) = \Phi(a) - \frac{1}{2}.$$

Let $Z \sim N(0,1)$ and $a > 0$. By symmetry of the density, we have the following useful formulas:

1.
$$\mathbb{P}\left(-a \leq Z \leq a\right) = 2\Phi(a) - 1.$$

For example,

$$\mathbb{P}\left(|Z| \leq 0.3\right) = 2 \cdot \Phi(0.3) - 1 = 2 \times 0.6179 - 1 = 0.2358.$$

2.
$$\mathbb{P}\left(Z > a\right) = \mathbb{P}(Z < -a) = \Phi(-a) = 1 - \Phi(a)$$

3.
$$\mathbb{P}\left(0 < Z \leq a\right) = \mathbb{P}(Z < a) - \mathbb{P}(Z \leq 0) = \Phi(a) - \frac{1}{2}.$$

Standardization

$$X \sim N\left(\mu, \sigma^2\right) \quad \Longleftrightarrow \quad Z = \frac{X - \mu}{\sigma} \sim N(0,1)$$

or equivalently

$$Z \sim N\left(0, 1\right) \quad \Longleftrightarrow \quad X = \mu + \sigma Z \sim N(\mu, \sigma^2)$$

Example 18.1-1 Assume the lifetime of a brand of light bulb follows a normal distribution with mean of 4 years and standard deviation of 0.4 years. What is the probability that it stop working before 5 years.

Solution. Let X be the lifetime of the light bulb. Then

$$X \sim N\left(4, 0.4^2\right) \quad \Longrightarrow \quad \mathbb{P}(X \leq 5) = \mathbb{P}\left(\frac{X-4}{0.4} \leq 2.5\right) = \Phi(2.5) = 0.99379.$$

$\square$

Example 18.1-1 Assume the lifetime of a brand of light bulb follows a normal distribution with mean of 4 years and standard deviation of 0.4 years. What is the probability that it stop working before 5 years.

Solution. Let X be the lifetime of the light bulb. Then

$$X \sim N\left(4, 0.4^2\right) \quad \Longrightarrow \quad \begin{aligned} \mathbb{P}(X \leq 5) &= \mathbb{P}\left(\frac{X-4}{0.4} \leq 2.5\right) \\ &= \Phi(2.5) \\ &= 0.99379. \end{aligned}$$

$\square$

Sums of normal random variables

Suppose we have n jointly distributed random variables X_i, $i = 1, \ldots, n$, with mean and variance $\mathbb{E}(X_i) = \mu_i$, $\mathrm{Var}(X_i) = \sigma_i^2$, and covariance $\mathrm{Cov}(X_i, X_j) = \sigma_{ij}$.

Remark 18.1-1

1. The covariance between two random variables measures their tendency to move together.
2. $\mathrm{Var}(X_i) = \mathrm{Cov}(X_i, X_i)$.
3. Let ρ_{ij} be the *correlation coefficient* of X_i and X_j, namely,

$$\rho_{ij} := \frac{\sigma_{ij}}{\sigma_i \sigma_j}.$$

   Hence, $\sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$.

Sums of normal random variables

Suppose we have n jointly distributed random variables X_i, $i = 1, \ldots, n$, with mean and variance $\mathbb{E}(X_i) = \mu_i$, $\mathrm{Var}(X_i) = \sigma_i^2$, and covariance $\mathrm{Cov}(X_i, X_j) = \sigma_{ij}$.

Remark 18.1-1

1. The covariance between two random variables measures their tendency to move together.
2. $\mathrm{Var}(X_i) = \mathrm{Cov}(X_i, X_i)$.
3. Let ρ_{ij} be the *correlation coefficient* of X_i and X_j, namely,

$$\rho_{ij} := \frac{\sigma_{ij}}{\sigma_i \sigma_j}.$$

   Hence, $\sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$.

Sums of normal random variables

Suppose we have n jointly distributed random variables X_i, $i = 1, \ldots, n$, with mean and variance $\mathbb{E}(X_i) = \mu_i$, $\mathrm{Var}(X_i) = \sigma_i^2$, and covariance $\mathrm{Cov}(X_i, X_j) = \sigma_{ij}$.

Remark 18.1-1

1. The covariance between two random variables measures their tendency to move together.
2. $\mathrm{Var}(X_i) = \mathrm{Cov}(X_i, X_i)$.
3. Let ρ_{ij} be the *correlation coefficient* of X_i and X_j, namely,

$$\rho_{ij} := \frac{\sigma_{ij}}{\sigma_i \sigma_j}.$$

Hence, $\sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$.

Sums of normal random variables

Suppose we have n jointly distributed random variables X_i, $i = 1, \ldots, n$, with mean and variance $\mathbb{E}(X_i) = \mu_i$, $\mathrm{Var}(X_i) = \sigma_i^2$, and covariance $\mathrm{Cov}(X_i, X_j) = \sigma_{ij}$.

Remark 18.1-1

1. The covariance between two random variables measures their tendency to move together.
2. $\mathrm{Var}(X_i) = \mathrm{Cov}(X_i, X_i)$.
3. Let ρ_{ij} be the *correlation coefficient* of X_i and X_j, namely,

$$\rho_{ij} := \frac{\sigma_{ij}}{\sigma_i \sigma_j}.$$

Hence, $\sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$.

Theorem 18.1-1 The weighted random variable $\sum_{i=1}^{n} a_i X_i$ have the following mean and variance:

$$\mathbb{E}\left(\sum_{i=1}^{n} a_i X_i\right) = \sum_{i=1}^{n} a_i \mu_i,$$

$$\operatorname{Var}\left(\sum_{i=1}^{n} a_i X_i\right) = \sum_{i=1}^{n} \sum_{j=1}^{n} a_i a_j \sigma_{ij}.$$

Theorem 18.1-2 If $X_i \sim N\left(\mu_i, \sigma_i^2\right)$, then

$$\sum_{i=1}^{n} a_i X_i \sim N\left(\sum_{i=1}^{n} a_i \mu_i, \sum_{i=1}^{n}\sum_{j=1}^{n} a_i a_j \sigma_{ij}\right)$$

Example 18.1-2 If $X_1 \sim N(\mu_1, \sigma_1^2)$ and $X_2 \sim N(\mu_2, \sigma_2^2)$, give the distribution of $aX_1 + bX_2$.

Solution.

$$aX_1 + bX_2 \sim N\left(a\mu_1 + b\mu_2, a^2\sigma_1^2 + b^2\sigma_2^2 + 2ab\,\sigma_{12}\right).$$

□

Example 18.1-2 If $X_1 \sim N(\mu_1, \sigma_1^2)$ and $X_2 \sim N(\mu_2, \sigma_2^2)$, give the distribution of $aX_1 + bX_2$.

Solution.

$$aX_1 + bX_2 \sim N\left(a\mu_1 + b\mu_2, a^2\sigma_1^2 + b^2\sigma_2^2 + 2ab\,\sigma_{12}\right).$$

□

Central Limit Theorem

Measurements lead to error. The error tends to be independent and is usually modeled by zero mean normal random variables thanks to the central limit theorem (CLT).

CLT usually can be phrased under different conditions. Here is one example:

Theorem 18.1-3 (Linderberg-Lévy CLT) Suppose $\{X_1, \cdots, X_n\}$ is a sequence of independent random variables having the same distribution (i.e., i.i.d.) with $\mathbb{E}(X_i) = \mu$ and $\text{Var}(X_i) = \sigma^2 < \infty$. Then

$$\frac{\sqrt{n}(\overline{X}_n - \mu)}{\sigma} \xrightarrow{d} N(0,1), \qquad \text{as } n \to \infty,$$

where

$$\overline{X}_n = \frac{X_1 + \cdots + X_n}{n}.$$

Central Limit Theorem

Measurements lead to error. The error tends to be independent and is usually modeled by zero mean normal random variables thanks to the central limit theorem (CLT).

CLT usually can be phrased under different conditions. Here is one example:

Theorem 18.1-3 (Linderberg-Lévy CLT) Suppose $\{X_1, \cdots, X_n\}$ is a sequence of independent random variables having the same distribution (i.e., i.i.d.) with $\mathbb{E}(X_i) = \mu$ and $\mathrm{Var}(X_i) = \sigma^2 < \infty$. Then

$$\frac{\sqrt{n}(\overline{X}_n - \mu)}{\sigma} \xrightarrow{d} N(0,1), \qquad \text{as } n \to \infty,$$

where

$$\overline{X}_n = \frac{X_1 + \cdots + X_n}{n}.$$

Central Limit Theorem

Measurements lead to error. The error tends to be independent and is usually modeled by zero mean normal random variables thanks to the central limit theorem (CLT).

CLT usually can be phrased under different conditions. Here is one example:

Theorem 18.1-3 (Linderberg-Lévy CLT) Suppose $\{X_1, \cdots, X_n\}$ is a sequence of independent random variables having the same distribution (i.e., i.i.d.) with $\mathbb{E}(X_i) = \mu$ and $\mathrm{Var}(X_i) = \sigma^2 < \infty$. Then

$$\frac{\sqrt{n}(\overline{X}_n - \mu)}{\sigma} \xrightarrow{d} N(0,1), \qquad \text{as } n \to \infty,$$

where

$$\overline{X}_n = \frac{X_1 + \cdots + X_n}{n}.$$