

Log normal Distribution

Normal and Lognormal

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

$$Y \sim LN(\mu, \sigma^2)$$

$$X = \ln(Y)$$

$$Y = e^X$$

$$E(X) = \mu$$

$$E(Y) = e^{\mu + \frac{1}{2}\sigma^2}$$

$$V(X) = \sigma^2$$

$$V(Y) = \text{~~scribbled out~~}$$

$$= [e^{\sigma^2} - 1] e^{2\mu + \sigma^2}$$

Sum of Normals

$$X_1 \sim N(\mu_1, \sigma_1^2)$$

$$X_2 \sim N(\mu_2, \sigma_2^2)$$

$$X_1 + X_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

~~Product of Normals~~

Product of Lognormals

$$Y_1 \sim \text{LN}(\mu_1, \sigma_1^2)$$

$$Y_2 \sim \text{LN}(\mu_2, \sigma_2^2)$$

$$Y_1 \cdot Y_2 = e^{x_1} \cdot e^{x_2} = e^{x_1 + x_2}$$

$$Y_1 \cdot Y_2 \sim \text{LN}(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

Looking up probabilities

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

$$P(X \leq x)$$

$$= P\left(\underbrace{\frac{X - \mu}{\sigma}}_{\substack{\text{std.} \\ \text{Normal}}} \leq \frac{x - \mu}{\sigma}\right) = N\left(\frac{x - \mu}{\sigma}\right)$$

ie, $\Phi\left(\frac{x - \mu}{\sigma}\right)$
Normal table.

$$Y \sim \text{LN}(\mu, \sigma^2)$$

$$\mathbb{P}(Y \leq y)$$

$$= \mathbb{P}(\underbrace{\ln(Y)}_{\text{Normal}} \leq \ln(y))$$

$$\approx N\left(\frac{\ln(y) - \mu}{\sigma}\right)$$

Lognormal model of Stock Prices

$$S_t = S_0 e^{(r-\delta)t \pm \sigma \sqrt{t}}$$

Binomial pricing.

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$$\ln\left(\frac{S_t}{S_0}\right) = (r - \delta)t \pm \sigma\sqrt{t}$$

$$\sim N((r-\delta)t, \sigma^2 t)$$

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That means,

$$\frac{S_t}{S_0} \sim \text{LN}((r-\delta)t, \sigma^2 t)$$

but then we have

$$E\left(\frac{S_t}{S_0}\right) = e^{\mu + \frac{1}{2}\sigma^2} \quad (\text{formula})$$

$$= e^{(r-\delta)t + \frac{1}{2}\sigma^2 t}$$

We want this to be

$$E\left(\frac{S_t}{S_0}\right) = e^{(r-\delta)t}$$

Adjustment.

Let

$$\ln\left(\frac{S_t}{S_0}\right) \sim N\left((r-\delta)t - \frac{1}{2}\sigma^2 t, \sigma^2 t\right)$$

then

$$\boxed{\frac{S_t}{S_0} \sim \text{LN}\left((r-\delta)t - \frac{1}{2}\sigma^2 t, \sigma^2 t\right)}$$

~~Black-Scholes~~
~~Call Option Pricing~~

$$E\left(\frac{S_t}{S_0}\right) = e^{r + \frac{1}{2}\sigma^2} \quad (\text{formula})$$

$$= e^{(r-\delta)t - \frac{1}{2}\sigma^2 t + \frac{1}{2}\sigma^2 t}$$

$$= e^{(r-\delta)t}$$

If

$$\ln\left(\frac{S_t}{S_0}\right) \sim N\left((r-\delta)t - \frac{1}{2}\sigma^2 t, \sigma^2 t\right)$$

$$= \ln(S_t) - \ln(S_0)$$

Then

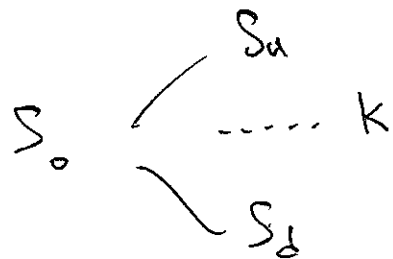
$$\ln(S_t) \sim N\left(\ln(S_0) + (r-\delta - \frac{1}{2}\sigma^2)t, \sigma^2 t\right)$$

$$\boxed{S_t \sim \text{LN}\left(\ln(S_0) + (r-\delta - \frac{1}{2}\sigma^2)t, \sigma^2 t\right)}$$

LN model of stock prices.

$$E(S_t) = e^{\ln(S_0) + (r-\delta)t} = S_0 e^{(r-\delta)t}$$

Probability that $S_t < K$



Call price = 0 if
 $S_t < K$,

$$P(S_t < K)$$

$$S_t \sim LN(\ln(S_0) + (r - \delta - \frac{1}{2}\sigma^2)t, \sigma^2 t)$$

$$= N\left(\frac{\ln(K) - \mu}{\sigma}\right) \quad (\text{formula})$$

$$= N\left(\frac{\ln(K) - \ln(S_0) - (r - \delta - \frac{1}{2}\sigma^2)t}{\sigma\sqrt{t}}\right)$$

$$= N \left(- \frac{\ln(S_0/K) + (r - \delta - \frac{1}{2}\sigma^2)t}{\sigma\sqrt{t}} \right)$$

$$= N(-d_2)$$

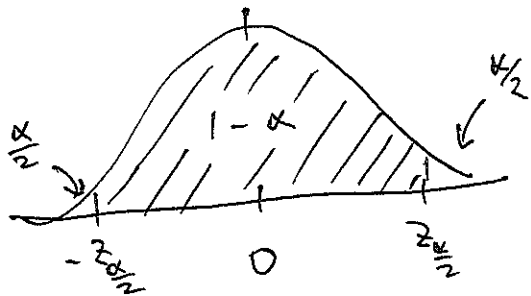
$$P(S_t \geq K)$$

$$= 1 - P(S_t < K) = 1 - N(d_2)$$

$$= N(d_2)$$

Confidence Intervals for S_t

Standard Normal



$$\ln(S_t) \sim N\left(\ln(S_0) + (r - \delta - \frac{1}{2}\sigma^2)t, \sigma^2 t\right)$$

$$P\left(-z_{\frac{\alpha}{2}} \leq \frac{\ln(S_t) - \mu}{\sigma_1} \leq z_{\frac{\alpha}{2}}\right)$$

$$= 1 - \alpha$$

$$P\left(\mu - z_{\frac{\alpha}{2}} \sigma_1 \leq \ln(S_t) \leq \mu + z_{\frac{\alpha}{2}} \sigma_1\right) = 1 - \alpha$$

$$\ln(S_t) \in \underbrace{\ln(S_0) + (r - \delta)t - \frac{1}{2}\sigma^2 t}_{\mu} \pm \underbrace{z_{\frac{\alpha}{2}} \sigma_1 \sqrt{t}}_{\sigma_1} \quad \text{with } (1 - \alpha)100\% \text{ probability.}$$

S_t is within

$$S_0 e^{(r-\delta-\frac{1}{2}\sigma^2)t} \pm z_{\frac{\alpha}{2}} \sigma \sqrt{t} \quad \text{with } (1-\alpha)100\%$$

$$z_{\frac{\alpha}{2}} = 1.96$$

$$\text{if } (1-\alpha)100 = 95\%$$

Conditional Expectation

Value of Call is 0 if $S_T < K$.

Value of Put is 0 if $S_T > K$.

What is

$$E(S_T | S_T < K) = ?$$

$$S_T \sim LN$$

$$= \frac{\int_0^K x f_{S_T}(x) dx}{\int_0^K f_{S_T}(x) dx}$$

$$p(S_T < K) = N(-d_2)$$

pdf of Lognormal

$$Y \sim LN(\mu, \sigma^2)$$

$$\ln Y \equiv X \sim N(\mu, \sigma^2)$$

or

~~or~~

$$\underbrace{P(Y \leq y)}_{\text{CDF of LN}} = \underbrace{P(\ln Y \leq \ln(y))}_X$$

CDF of Normal.

$$F_Y(y) = F_X(\ln y)$$

~~or~~

$$f_Y(y) = f_X(\ln y) \cdot \frac{1}{y}$$

$$= \left[\frac{1}{y \sqrt{2\pi} \sigma} e^{-\frac{(\ln y - \mu)^2}{2\sigma^2}} \right]$$

pdf of Lognormal.

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

$$\int_0^K x f_{S_T}(x) dx$$

$$= \int_0^K x \frac{1}{x\sqrt{2\pi}\sigma} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}} dx$$

$$= \int_0^K \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}} dx \quad \leftarrow f_N(\ln x)$$

$$\text{let } u = \ln x, \quad du = \frac{1}{x} dx \quad dx = \cancel{x} du = e^u du$$

$$= \int_0^{\ln(K)} \frac{1}{\sqrt{2\pi}\sigma} \underbrace{e^{-\frac{(u-\mu)^2}{2\sigma^2}} e^u}_{\star} du \quad (1)$$

$$\star = e^{-\frac{1}{2\sigma^2}(u-\mu)^2 + u}$$

Take the exponent.

Complete the square

$$= \frac{(u-\mu)^2 - 2\sigma^2 u}{2\sigma^2}$$

$$= -\frac{1}{2\sigma^2} [u^2 - 2u\mu + \mu^2 - 2\sigma^2 u]$$

$$= -\frac{1}{2\sigma^2} [u^2 - 2u(\mu + \sigma^2) + \mu^2]$$

$$= -\frac{1}{2\sigma^2} [u^2 - 2u(\mu + \sigma^2) + \underbrace{(\mu + \sigma^2)^2 - (\mu + \sigma^2)^2}_{\text{new}} + \mu^2]$$

$$= -\frac{1}{2\sigma^2} \left[\mu - 2\mu(\mu + \sigma^2) + \underbrace{(\mu + \sigma^2)^2 + (\mu + \sigma^2)^2}_{\text{new}} + \mu^2 \right]$$

$$= -\frac{1}{2\sigma^2} \left[\{ \mu - (\mu + \sigma^2) \}^2 - (\mu + \sigma^2)^2 + \mu^2 \right]$$

Go back to

$$\star = e^{-\frac{\{ \mu - (\mu + \sigma^2) \}^2}{2\sigma^2} + \frac{(\mu + \sigma^2)^2 - \mu^2}{2\sigma^2}}$$



$$\frac{\mu^2 + 2\mu\sigma^2 + \sigma^4 - \mu^2}{2\sigma^2} = +\mu + \frac{\sigma^2}{2}$$

Back to the integral. (1)

$$\int_0^K \frac{1}{\sqrt{2\pi} \sigma_0} e^{-\frac{(u-\mu)^2}{2\sigma_0^2}} e^u du$$

$$= \int_0^K \frac{1}{\sqrt{2\pi} \sigma_0} e^{-\frac{\{u - (\mu - \sigma_0^2)\}^2}{2\sigma_0^2}} \cdot e^{+\mu + \frac{\sigma_0^2}{2}} du$$

$$= \underbrace{e^{+\mu + \frac{\sigma_0^2}{2}}}_{(3)} \cdot \underbrace{\int_0^K \frac{1}{\sqrt{2\pi} \sigma_0} e^{-\frac{\{u - (\mu - \sigma_0^2)\}^2}{2\sigma_0^2}} du}_{(4) \text{ Normal with mean } \mu - \sigma_0^2} \quad (2)$$

$$P(N < K)$$

$$S_T \sim \text{LN} \left(\underbrace{\ln S_0 + (r - \delta - \frac{1}{2}\sigma^2)T}_{\mu}, \underbrace{\sigma^2 T}_{\sigma^2} \right)$$

$$(3) = e^{+\mu + \frac{\sigma^2}{2}} = e^{+\ln S_0 + (r - \delta - \frac{1}{2}\sigma^2)T + \frac{\sigma^2 T}{2}}$$

$$= S_0 \cdot e^{(r - \delta)T}$$

$$(4) = P(N < K)$$

$$N \sim N(\mu - \sigma_0^2, \sigma_0^2)$$

$$\mu = \ln(S_0) + (r - \delta - \frac{1}{2}\sigma^2)T$$

$$\sigma_0^2 = \sigma^2 T$$

$$= N\left(\frac{\ln(K) - (\mu - \sigma_0^2)}{\sigma_0}\right)$$

$$= N\left(\frac{\ln(K) - \ln(S_0) - (r - \delta - \frac{1}{2}\sigma^2)T + \sigma^2 T}{\sigma\sqrt{T}}\right)$$

$$= N(-d_1)$$

Finally ,

$$E(S_T | S_T < K)$$

$$= \frac{\int_0^K x f_{S_T}(x) dx}{\int_0^K f_{S_T}(x) dx}$$

$$= \left(\frac{N(-d_1)}{N(-d_2)} S_0 e^{(r-d)T} \right)$$

How about $E(S_T | S_T > k)$?

$$E(S_T) = E \left[E(S_T | \text{~~the~~ } A) \right]$$

$$= E(S_T | S_T > k) \cdot P(S_T > k)$$

$$+ E(S_T | S_T < k) \cdot P(S_T < k)$$

$$\underbrace{e^{\mu + \frac{1}{2}\sigma^2}}_{S_0 e^{(r-\delta)T}} = E(S_T | S_T > k) \cdot \cancel{N(d_2)} N(d_2)$$

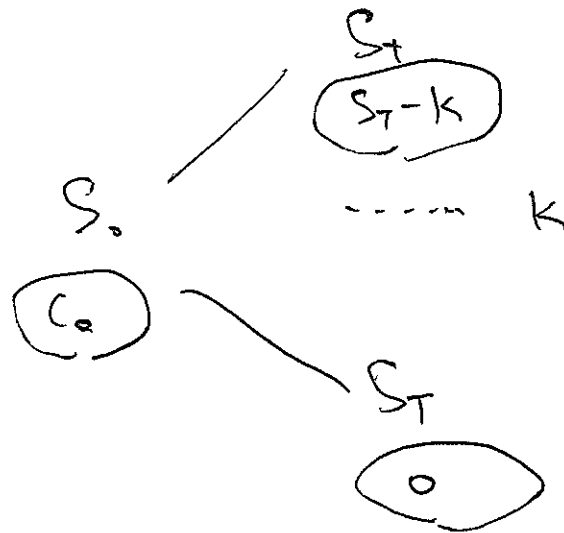
$$S_0 e^{(r-\delta)T} \frac{N(-d_1)}{N(-d_2)} \cdot N(-d_2)$$

$$E(S_T | S_T > k) = \frac{S_0 e^{(r-\delta)T} (1 - N(-d_1))}{N(d_2)}$$

$$= \boxed{S_0 e^{(r-\delta)T} \frac{N(d_1)}{N(d_2)}}$$

Black - Scholes Formula

Call option



$$C_0 = PV(E[\text{Call values}])$$

$$= e^{-rT} E[\text{Call Values}]$$

$$C_0 = e^{-rT} E[\text{Call Values}]$$

$$= e^{-rT} E \left\{ E[\text{Call Value} \mid \text{if } S_T > k \text{ or not}] \right\}$$

$$= e^{-rT} \left\{ E[S_T - k \mid S_T > k] \cdot P(S_T > k) \right. \\ \left. + E[0 \mid S_T \leq k] \cdot P(S_T \leq k) \right\}$$

~~$$= e^{-rT} \left\{ S_0 e^{(r-\delta)T} N(d_1) - K e^{-\delta T} N(d_2) \right\}$$~~

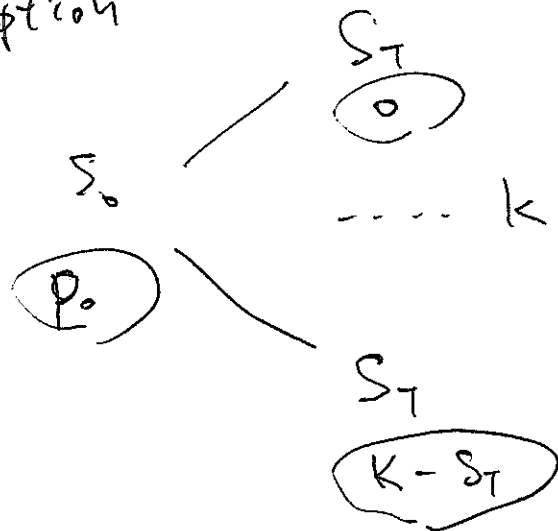
$$= e^{-rT} \{ E[S_T | S_T > k] - E[k | S_T > k] \} P(S_T > k)$$

$$= e^{-rT} \left\{ S_0 e^{(r-\delta)T} \frac{N(d_1)}{N(d_2)} - k \right\} N(d_2)$$

$$= \boxed{S_0 e^{-\delta T} N(d_1) - k e^{-rT} N(d_2)}$$

B-S call.

Put option



$$P_0 = e^{-rT} \left\{ 0 + E(K - S_T \mid S_T < K) \cdot P(S_T < K) \right\}$$

$$= e^{-rT} \left\{ K - E(S_T \mid S_T < K) \right\} P(S_T < K)$$

$$P_0 = e^{-rT} \left\{ K - S_0 e^{(r-s)T} \frac{N(-d_1)}{N(-d_2)} \right\} N(-d_2)$$

$$= \boxed{K e^{-rT} N(-d_2) - S_0 e^{(r-s)T} N(-d_1)}$$

Estimating Parameters of Lognormal

$$S_t \sim LN \left(\ln(S_0) + (r - \delta - \frac{1}{2}\sigma^2)T, \sigma^2 T \right)$$

$$E \left[\ln \left(\frac{S_h}{S_0} \right) \right] = (r - \delta - \frac{1}{2}\sigma^2)h$$

$$V \left[\ln \left(\frac{S_h}{S_0} \right) \right] = \sigma^2 h$$

Use daily ^{log} returns $\ln \left(\frac{S_{t+h}}{S_t} \right)$ and look at Sample mean
Sample Var.