

$$\textcircled{1} \quad X(t) = \log [S(t)/s(0)], \quad t > 0.$$

$$\text{for } S(t) = s(0) e^{\mu_{\text{m}} t + \sigma B(t)}$$

CHRISTIAN DRAPP

$$X(t) = \log [e^{\mu_{\text{m}} t + \sigma B(t)}] = \mu_{\text{m}} t + \sigma B(t)$$

### Properties

(i)  $P(X(0) = 0) = 1$ . This is trivial as  $B(0) \stackrel{\text{def}}{=} 0$ .

(ii) Stationary increments:

Let  $s, t \in [0, \infty)$ :

$$\begin{aligned} \text{Then } X(t) - X(s) &= \mu_{\text{m}} t + \sigma B(t) - \mu_{\text{m}} s - \sigma B(s) \\ &= \mu_{\text{m}}(t-s) + \sigma [B(t) - B(s)] \end{aligned}$$

Since  $B(t)$  has stationary increments,  $B(t) - B(s) = B(t-s)$

and so  $X(t) - X(s) = \mu_{\text{m}}(t-s) + \sigma B(t-s) = X(t-s)$

(iii) Independent Increments:

Let  $\{t_1, t_2, \dots, t_n\} \subset [0, \infty)$ .

$$\begin{aligned} \text{Then } X(t_{i+1}) - X(t_i) &= X(t_{i+1} - t_i) \\ \text{and } X(t_i) - X(t_{i-1}) &= X(t_i - t_{i-1}) \end{aligned} \quad \left. \begin{array}{l} \text{by (ii)} \\ \text{by (ii)} \end{array} \right\}$$

Suppose  $X(t_{i+1} - t_i)$  was dependent on  $X(t_i - t_{i-1})$ .

Since  $\mu_{\text{m}}(t_{i+1} - t_i)$  and  $\mu_{\text{m}}(t_i - t_{i-1})$  are deterministic, the dependence must come between  $\sigma B(t_{i+1} - t_i)$  and  $\sigma B(t_i - t_{i-1})$ . This contradicts the independent increments property of  $B(t)$ .

see reverse  
for remainder

## Properties (continued)

(iv) Normally distributed.

By construction,  $\beta(t) \sim N(0, t)$ .

By the properties normally distributed random variables,

$$\mu_m t + \sigma \beta(t) \sim N(\mu_m t, \sigma^2 t) \quad \text{and} \quad (1)$$

so  $X(t)$  is normally distributed  $\quad (1)$

(v)  $t \rightarrow X(t)$  is continuous almost surely (a.s.)

By construction,  $\beta(t)$  is continuous a.s.

$\mu_m t$  is linear so it is continuous a.s.,

and  $\sigma \beta(t)$  is continuous a.s. since  $\sigma$  is a constant.

If  $f$  and  $g$  are continuous a.s. then

$f + g$  is also continuous a.s. so

$X(t) = \mu_m t + \sigma \beta(t)$  is continuous a.s.

$X(t) = \mu_m t + \sigma \beta(t)$  satisfies:

$dX(t) = (\mu_m - \frac{\sigma^2}{2}) dt + \sigma d\beta(t)$ . This is the same answer we would get using Itô's Lemma, since  $X(t)$  is an Itô diffusion-drift process. To check:

$$d[\mu_m t + \sigma \beta(t)] = \mu_m dt + \sigma d\beta(t) + \frac{\sigma^2}{2} dt \quad \text{by Itô.}$$

$$\mu_m + \frac{\sigma^2}{2} = \mu_m - \frac{\sigma^2}{2} \quad \text{so both SDEs agree.}$$

$$\boxed{2} \textcircled{a} \quad S(t) = S(0) e^{\mu_{\text{inst}} t + \sigma \mathcal{B}(t)}$$

$$\Rightarrow dS(t) = d[S(0) e^{\mu_{\text{inst}} t + \sigma \mathcal{B}(t)}]$$

$$= S(0) e^{\mu_{\text{inst}} t + \sigma \mathcal{B}(t)} d[\mu_{\text{inst}} t + \sigma \mathcal{B}(t)]$$

$$= S(0) e^{\mu_{\text{inst}} t + \sigma \mathcal{B}(t)} \left[ \mu_{\text{inst}} dt + \sigma d\mathcal{B}(t) + \frac{\sigma^2}{2} dt \right]$$

$$= S(0) e^{\mu_{\text{inst}} t + \sigma \mathcal{B}(t)} \left[ (\mu_{\text{inst}} - \frac{\sigma^2}{2}) dt + \sigma d\mathcal{B}(t) \right]$$

$$\Rightarrow dS(t) = (\mu_{\text{inst}} - \frac{\sigma^2}{2}) S(t) dt + \sigma S(t) d\mathcal{B}(t)$$

Let  $\delta t$  satisfy:  $0 < \delta t \ll 1$ .

$$\Delta S(t) \equiv (\mu_{\text{inst}} - \frac{\sigma^2}{2}) S(t) \delta t + \sigma S(t) \sqrt{\delta t} \cdot \varepsilon$$

$$\boxed{E[\Delta S(t)] \equiv (\mu_{\text{inst}} - \frac{\sigma^2}{2}) S(t) \cdot \delta t}$$

$$V_a[\Delta S(t)] \equiv \sigma^2 S^2(t) \cdot \delta t \cdot \text{var}(\varepsilon) = \sigma^2 S^2(t) \cdot \delta t$$

$$\Rightarrow \boxed{S\text{dev}[\Delta S(t)] \equiv \sigma S(t) \sqrt{\delta t}}$$

For  $\delta t$  sufficiently small, the  $S\text{dev}[\Delta S(t)]$  will control the security's price fluctuations (in the short term). This is because for  $0 < \delta t \ll 1$ ,  $\sqrt{\delta t} > \delta t$  and so the second term in the SDE dominates.

$$\mathbb{E}[S(t)] = S_0 e^{\mu_{\text{inst}} t} \mathbb{E}[e^{\sigma B(t)}] \quad [2] \quad (b)$$

$$\mathbb{E}[e^{\sigma B(t)}] = \int_0^\infty \frac{1}{s \sigma \sqrt{2\pi t}} \cdot s \cdot e^{-\frac{\ln^2(s)}{2\sigma^2 t}} ds$$

$$= \int_0^\infty \frac{ds}{\sigma \sqrt{2\pi t}} e^{-\frac{\ln^2(s)}{2\sigma^2 t}}$$

Let  $s = e^x$ ,  $\ln(s) = x$ , and  $ds = e^x dx$

$$\text{then } \mathbb{E}[e^{\sigma B(t)}] = \int_0^\infty ds \frac{1}{\sigma \sqrt{2\pi t}} e^{-\frac{x^2}{2\sigma^2 t}} e^x dx$$

$$= \frac{1}{\sigma \sqrt{2\pi t}} \int_0^\infty e^{\frac{-1}{2\sigma^2}(x^2 - 2\sigma^2 xt)} dx$$

$$x^2 - 2\sigma^2 tx = (x - \sigma^2 t)^2 - \sigma^4 t^2 \quad \text{so substituting}$$

$$= \frac{1}{\sigma \sqrt{2\pi t}} \int_0^\infty e^{\frac{-1}{2\sigma^2}(x - \sigma^2 t)^2} e^{-\frac{1}{2\sigma^2}(-\sigma^4 t^2)} dx$$

$$= \frac{1}{\sigma \sqrt{2\pi t}} \cdot e^{\frac{\sigma^2 t^2}{2}}$$

$$= e^{\frac{\sigma^2 t^2}{2}}$$

$$\text{Hence } \mathbb{E}[S(t)] = S_0 e^{\mu_{\text{inst}} t} \cdot e^{\frac{\sigma^2 t^2}{2}}$$

$$\boxed{\mathbb{E}[S(t)] = S_0 e^{[\mu_{\text{inst}} + \frac{\sigma^2 t^2}{2}]t} = S_0 e^{(m-q)t}}$$

$$\mathbb{E}[S^2(t)] = S^2(0) e^{2\mu_m t} \mathbb{E}[e^{2\sigma B(t)}] \quad \boxed{2} (b)$$

$$\mathbb{E}[e^{2\sigma B(t)}] = e^{(2\sigma)^2 t / 2} \quad \text{by the}$$

calculation for  $\mathbb{E}[e^{\sigma B(t)}]$  taking  $\sigma \rightarrow 2\sigma$ ,

$$\begin{aligned} \text{so } \mathbb{E}[S^2(t)] &= S^2(0) e^{2\mu_m t} e^{2\sigma^2 t} \\ &= S^2(0) e^{(2\mu_m + \sigma^2)t} e^{\sigma^2 t} \end{aligned}$$

$$\begin{aligned} (\mathbb{E}[S(t)])^2 &= S^2(0) [e^{(\mu_m + \sigma^2/2)t}]^2 \\ &= S^2(0) e^{(2\mu_m + \sigma^2)t} \end{aligned}$$

$$\begin{aligned} \text{Var}[S(t)] &= \mathbb{E}[S^2(t)] - [\mathbb{E}S(t)]^2 \\ &= S^2(0) e^{(2\mu_m + \sigma^2)t} e^{-\sigma^2 t} \\ &\quad - S^2(0) e^{(2\mu_m + \sigma^2)t} \end{aligned}$$

$$\boxed{\text{Var}[S(t)] = S^2(0) e^{(2\mu_m + \sigma^2)t} [e^{-\sigma^2 t} - 1]}$$

[2] (b)

$$\text{Med}[S(t)] = k \quad \text{s.t.}$$

$$P\left(\frac{S(t)}{S(0)} > \frac{k}{S(0)}\right) = \frac{1}{2} = \frac{1}{\frac{k}{S(0)}} \int_{-\infty}^{\ln(k/S(0))} e^{-\frac{1}{2\sigma^2} [\ln(s) - \mu_{\ln} t]^2} ds$$

Letting  $ds = e^x dx$ ,  $s = e^x$ ,  $\ln(s) = x$ .

$$\frac{1}{2} = \int_{\ln(k/S(0))}^{\infty} \frac{1}{\sigma \sqrt{2\pi t}} e^{-x} e^{-\frac{1}{2\sigma^2} (x - \mu_{\ln} t)^2} e^x dx$$

$$\Rightarrow \frac{1}{2} = \frac{1}{\sigma \sqrt{2\pi t}} \int_{\ln(k/S(0))}^{\infty} e^{-\frac{1}{2\sigma^2} (x - \mu_{\ln} t)^2} dx$$

By symmetry, this integral is  $\frac{1}{2}$

$$\text{when } \ln\left(\frac{k}{S(0)}\right) = \mu_{\ln} t \text{ hence } k = S(0) e^{\mu_{\ln} t}$$

$$\text{So the median, } \text{Med}[S(t)] = S(0) e^{\mu_{\ln} t}$$

$$S(0) e^{\mu_{\ln} t} = S(0) e^{(\mu - \sigma^2/2)t - \sigma^2 t/2} = e^{-\sigma^2 t/2} E[S(t)]$$

$$③ S(t) = S(0) e^{\mu_{\text{const}} t + \sigma \mathcal{B}(t)}$$

Let  $K > 0$ ,

$$\mathbb{P}(S(t) > K) = \mathbb{P}\left(\frac{S(t)}{S(0)} > \frac{K}{S(0)}\right)$$

$$= \int_{\ln(K/S_0)}^{\infty} \frac{ds}{s \sqrt{2\pi \sigma^2 t}} \cdot e^{-\frac{(\ln(s) - \mu_{\text{const}} t)^2}{2\sigma^2 t}}$$

$$\text{Let } x = \ln s, e^x = s \Rightarrow ds = e^x dx$$

$$= \int_{\ln(K/S_0)}^{\infty} \frac{e^x dx}{e^x \sigma \sqrt{2\pi t}} \cdot e^{-\frac{(x - \mu_{\text{const}} t)^2}{2\sigma^2 t}} = \int_{\ln(K/S_0)}^{\infty} \frac{1}{\sqrt{2\pi (\sigma^2 t)}} e^{-\frac{(x - \mu_{\text{const}} t)^2}{2(\sigma^2 t)}}$$

This is a normal distribution integral, with

$\sigma^2 \rightarrow \sigma^2 t$ ,  $\mu \rightarrow \mu_{\text{const}} t$ , going from

$$\ln(K/S_0) \rightarrow \infty, \text{ i.e. it represents } \mathbb{P}(x > \ln(K/S_0))$$

when  $x \sim N(\mu_{\text{const}} t, \sigma^2 t)$ .

$$\text{i.e. } \mathbb{P}(S(t) > K) = \mathbb{P}(x > \ln(K/S_0))$$

$$= \mathbb{P}\left(\frac{x - \mu_{\text{const}} t}{\sigma \sqrt{t}} > \frac{\ln(K/S_0) - \mu_{\text{const}} t}{\sigma \sqrt{t}}\right)$$

$$= \mathbb{P}\left(\frac{x - \mu_{\text{const}} t}{\sigma \sqrt{t}} > -\frac{\ln(K/S_0) - \mu_{\text{const}} t}{\sigma \sqrt{t}}\right) = \mathbb{P}(Z > -d_{z,m})$$

$$N(z) = \mathbb{P}(Z < z) \text{ so } \mathbb{P}(Z > -d_{z,m}) = 1 - \mathbb{P}(Z < -d_{z,m})$$

Hence  $\mathbb{P}(Z > -d_{z,m}) = 1 - N(-d_{z,m}) = N(d_{z,m})$  by the properties of  $N(\cdot)$ .

$$\text{Likewise, } \mathbb{P}(S(t) < K) = 1 - \mathbb{P}(S(t) > K) = 1 - N(d_{z,m}) = N(-d_{z,m})$$

$$\therefore \mathbb{P}(S(t) > K) = N(d_{z,m}) \text{ and } \mathbb{P}(S(t) < K) = N(-d_{z,m}) \quad \square$$

(4) I agree. Let  $\sigma^2 > 2(m-q)$ .

$$\begin{aligned} \text{Then } \text{Med}[S(t)] &= e^{-\frac{\sigma^2}{2}t} \cdot E[S(t)] \\ &= S(0) \cdot e^{-\frac{\sigma^2}{2}t} e^{(m-q)t} \\ &= S(0) \cdot e^{-\frac{t}{2}(m-q-\sigma^2)} < S(0). \end{aligned}$$

$$\text{So } \sigma^2 > 2(m-q) \Rightarrow \text{Med}[S(t)] < S(0)$$

$$\begin{aligned} \text{Hence, } P(S(t) < S(0)) &= P(S(t) < \text{Med}[S(t)]) + P(\text{Med}[S(t)] < S(t) < S(0)) \\ &= \frac{1}{2} + P(\text{Med}[S(t)] < S(t) < S(0)) \end{aligned}$$

Since  $\text{Med}[S(t)] < S(0)$ ,  $P(\text{Med}[S(t)] < S(t) < S(0)) > 0$ .

And so  $P(S(t) < S(0)) > \frac{1}{2}$ .  $\square$

5 Show that  $E[S(t) | S(t) > k] = \frac{N(d_{1,m})}{N(d_{2,m})} E(S(t))$

where  $d_{2,m} = \frac{\ln(s_0/k) - \mu_{m,0}t}{\sigma\sqrt{t}}$  and

$$d_{1,m} = d_{2,m} + \sigma\sqrt{t}$$

$$E[S(t) | S(t) > k] = \int_0^\infty s P(s | s > k) ds$$

$$P(s | s > k) = \frac{P(s) \cdot \mathbb{1}(s > k)}{\int_0^\infty P(s) \cdot \mathbb{1}(s > k) ds}$$

$$\Rightarrow E[S(t) | S(t) > k] = \frac{\int_0^\infty s P(s) \cdot \mathbb{1}(s > k) ds}{\int_0^\infty P(s) \cdot \mathbb{1}(s > k) ds}$$

$$= \frac{\int_k^\infty s P(s) ds}{\int_k^\infty P(s) ds}$$

The denominator is simply  $P(S(t) > k) = N(d_{2,m})$  from problem (3)

$$\text{The numerator is } \int_k^\infty s \cdot \frac{ds}{s\sqrt{2\pi\sigma^2 t}} e^{-\frac{(\ln(s/s_0) - \mu_{m,0}t)^2}{2\sigma^2 t}}$$

Let  $x = \ln(s/s_0)$ ,  $s = s_0 e^x$ ,  $ds = s_0 e^x dx$ , yielding:

$$\int_{\ln(k/s_0)}^\infty \frac{s_0 e^x}{\sqrt{2\pi\sigma^2 t}} e^{-\frac{(x - \mu_{m,0}t)^2}{2\sigma^2 t}} dx = \frac{s_0}{\sqrt{2\pi\sigma^2 t}} \int_{\ln(k/s_0)}^\infty e^{\frac{-1}{2\sigma^2 t} [(x - \mu_{m,0}t)^2 - 2\sigma^2 t x]} dx$$

$$(x - \mu_{m,0}t)^2 - 2\sigma^2 t x = x^2 - 2\mu_{m,0}t x + \mu_{m,0}^2 t^2 - 2\sigma^2 t x$$

$$= x^2 - 2x(\mu_{m,0}t + \sigma^2 t) + \mu_{m,0}^2 t^2$$

$$= [x - (\mu_{m,0}t + \sigma^2 t)]^2 + \mu_{m,0}^2 t^2 - (\mu_{m,0}t + \sigma^2 t)^2$$

see reverse  
→

5 | continued

$$E[S(t) | S(t) > k] = \frac{1}{N(d_{2,m})} \cdot \frac{s_0}{\sqrt{2\pi\sigma^2 t}} \int_{\ln(k/s_0)}^{\infty} e^{-\frac{1}{2\sigma^2 t} [(x - \mu_{m,t})^2 - 2\sigma^2 t x]} dx$$

$$\begin{aligned} & \int_{\ln(k/s_0)}^{\infty} \exp \left\{ -\frac{1}{2\sigma^2 t} [ (x - \mu_{m,t})^2 - 2\sigma^2 t x ] \right\} dx \\ &= \int_{\ln(k/s_0)}^{\infty} \exp \left\{ -\frac{1}{2\sigma^2 t} [ x - (\mu_{m,t} + \sigma^2 t) ]^2 + \mu_{m,t}^2 t^2 - (\mu_{m,t} + \sigma^2 t)^2 \right\} dx \end{aligned}$$

$$\mu_{m,t}^2 t^2 - (\mu_{m,t} + \sigma^2 t)^2 = \mu_{m,t}^2 t^2 - \mu_{m,t}^2 t^2 - \sigma^4 t^2 - 2\mu_{m,t} \sigma^2 t$$

$$\Rightarrow \int_{\ln(k/s_0)}^{\infty} \exp \left\{ -\frac{1}{2\sigma^2 t} [ (x - (\mu_{m,t} + \sigma^2 t))^2 + \mu_{m,t}^2 t^2 - (\mu_{m,t} + \sigma^2 t)^2 ] \right\} dx$$

$$= e^{\frac{1}{2\sigma^2 t} [ 2\mu_{m,t} \sigma^2 t + \sigma^4 t^2 ]} \int_{\ln(k/s_0)}^{\infty} e^{\frac{-1}{2\sigma^2 t} (x - (\mu_{m,t} + \sigma^2 t))^2} dx$$

$$= e^{\mu_{m,t} + \frac{\sigma^2}{2} t} \cdot \int_{\ln(k/s_0)}^{\infty} e^{\frac{-1}{2\sigma^2 t} (x - (\mu_{m,t} + \sigma^2 t))^2} dx$$

$$\text{Let } \frac{x - [\mu_{m,t} + \sigma^2 t]}{\sigma \sqrt{t}} = z \Rightarrow \int_{\ln(k/s_0)}^{\infty} e^{-\frac{1}{2} z^2} \cdot \sigma \sqrt{t} dz$$

$$\text{where } K^* = \frac{\ln(k/s_0) - (\mu_{m,t} + \sigma^2 t)}{\sigma \sqrt{t}} = -d_{1,m}$$

$$\sqrt{2\pi} \cdot \sigma \sqrt{t} \cdot \int_{K^*}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} z^2} dz = \sqrt{\pi \sigma^2 t} N(-K^*)$$

$$\Rightarrow E[S(t) | S(t) > k] = \frac{1}{N(d_{2,m})} \cdot s_0 e^{\mu_{m,t} + \frac{\sigma^2}{2} t} \cdot N(-d_{1,m})$$

$$s_0 e^{\mu_{m,t} + \frac{\sigma^2}{2} t} = s_0 e^{(\mu - \sigma^2)t} = E[S(t)]$$

$$\Rightarrow E[S(t) | S(t) > k] = \frac{N(d_{1,m})}{N(d_{2,m})} E[S(t)] \quad \square$$