

ARM

LIS

$$\therefore \mathbb{E} S_1 = e^{r_1} = p e^d + q e^{-d} \quad (q = 1 - p)$$

$$\mathbb{E} S_2 = e^{2r_1 + r_2} = p e^{2d} + q e^{-2d}$$

$$A = e^{r_1} = p(e^d - e^{-d}) + e^{-d}$$

$$B = e^{2r_1 + r_2} = p(e^{2d} - e^{-2d}) + q e^{-2d}$$

$$A = p\alpha + q\alpha^{-1} \quad \alpha = e^d > 0, 1$$

$$B = p\alpha^2 + q\alpha^{-2}$$

Use the last $A = p(\alpha - \alpha^{-1}) + \alpha^{-1}$

$$pB = \frac{(A - \alpha^{-1})(\alpha^2 - \alpha^{-2})}{\alpha - \alpha^{-1}}$$

$$\begin{aligned} \text{So } B &= \frac{A - \alpha^{-1}}{\alpha - \alpha^{-1}} (\alpha^2 - \alpha^{-2}) + \alpha^{-2} \\ &= (A - \alpha^{-1})(\alpha + \alpha^{-1}) + \alpha^{-2} \end{aligned}$$

$$\begin{aligned} B\alpha^2 &= (A\alpha - 1)(\alpha^2 + 1) + 1 \\ &= A\alpha^3 \end{aligned}$$

$$\Rightarrow (1+B)\alpha = A(\alpha^2 + 1)$$

$$\Rightarrow A\alpha^2 - (B+1)\alpha + A = 0$$

$$\alpha = \frac{B+1 \pm \sqrt{(B+1)^2 - 4A^2}}{2A}$$

Notice $B > A^2$. The larger root > 0 , quadratic positive at $\alpha = 1$ and product of roots ≈ 1 . So we take the larger root

$$\alpha = e^d = \frac{B+1 + \sqrt{(B+1)^2 - 4A^2}}{2A}$$

How does this vary with h ?

Both A, B close to 1 for small h .

$$A \approx 1 + rh$$

$$B \approx 1 + (2r + \sigma^2)h$$

$$\begin{aligned} \text{So } (B+A)^2 - 4A^2 &\approx (2 + (2r + \sigma^2)h)^2 - 4(1 + rh)^2 \\ &= 4(2r + \sigma^2)h - 8rh + O(h^2) \\ &= 4\sigma^2 h + O(h^2) \end{aligned}$$

$$\text{Thus } x = e^{\sigma} \approx \frac{2 + \sqrt{4\sigma^2 h}}{2} = 1 + \sigma\sqrt{h}$$

$$\text{So } \boxed{\sigma \approx \sqrt{\frac{1}{h}}}$$

So here spatial steps much bigger than time steps.

This illustrates the major drawback of binomial pricing: the time step has to be much smaller than the space step.

If $T=1$, you want $\Delta \approx 10^{-3}$, we need $\sim 10^6$ time steps... slow, big.

It is much better to use a PDE method.

Crank-Nicolson is the method of choice when it can be used.

- not so good for higher-dimensional problems...

For example, we have log-Brownian stocks, $S^1, \dots, S^n$ and when we stop we receive

$$(K - \min_{1 \leq i \leq n} \{S_t^i\})^+$$

L16

What more can we dig out here?

We can actually solve the infinite horizon problem explicitly. How? We expect to find that

$$V(s) = \sup_{0 \leq \tau} E(e^{-r\tau} (K - S_\tau)^+ | S_0 = s)$$

will solve some ODE, and that $V(s^*) = K - s^*$ for some critical value s^* at which we will exercise the option.

L16 What we shall have is that $(\tau_c := \inf\{u: S_u \leq a\})$

$$M_t = e^{-r(t \wedge \tau_c)} V_c(S_{t \wedge \tau_c}) = \mathbb{E}[e^{-r\tau_c} (K - S_{\tau_c})^+ | \mathcal{F}_t]$$

is a martingale, and $V_c(a) = (K - a)^+$

Now we do Ito on M_t ,

$$dM_t = -r e^{-rt} V_a(S_t) dt + e^{-rt} \left\{ V_a'(S_t) dS + \frac{1}{2} V_a''(S_t) dS dS \right\}$$

(where $dS = S(\sigma dB + r dt)$) ($t < \tau_c$)

$$= (\text{something}) dB + e^{-rt} dt \left\{ -r V_a + r S V_a' + \frac{1}{2} \sigma^2 S^2 V_a'' \right\}$$

~~is~~ vanishes, since martingale.

So we have to solve

$$\boxed{\frac{1}{2} \sigma^2 S^2 V_a'' + r S V_a' - r V_a = 0}$$

There 2 LI solutions of form S^θ , where θ solves:

$$\frac{1}{2} \sigma^2 \theta(\theta-1) + r\theta - r = 0$$

which has roots $\theta=1$, the other is

$$\boxed{\theta = -\frac{2r}{\sigma^2}}$$

$e^{-rt} S_t$ a martingale ✓

So have $V_a(s) = AS + BS^{-2r/\sigma^2}$

clearly $V_a(s) \rightarrow 0 \Rightarrow s \rightarrow \infty \Rightarrow A = 0$

We also have boundary condition

$$V_a(a) = B a^{-\alpha} = K - a \quad (\alpha = 2r/\sigma^2)$$

($a < K$)

$$\Rightarrow \boxed{B = (K - a) a^\alpha}$$

$\Rightarrow V_a(s) = (K - a) a^\alpha s^{-\alpha}$ is the value of S
for this stopping rule.

Now we maximise over a (take logs diff)

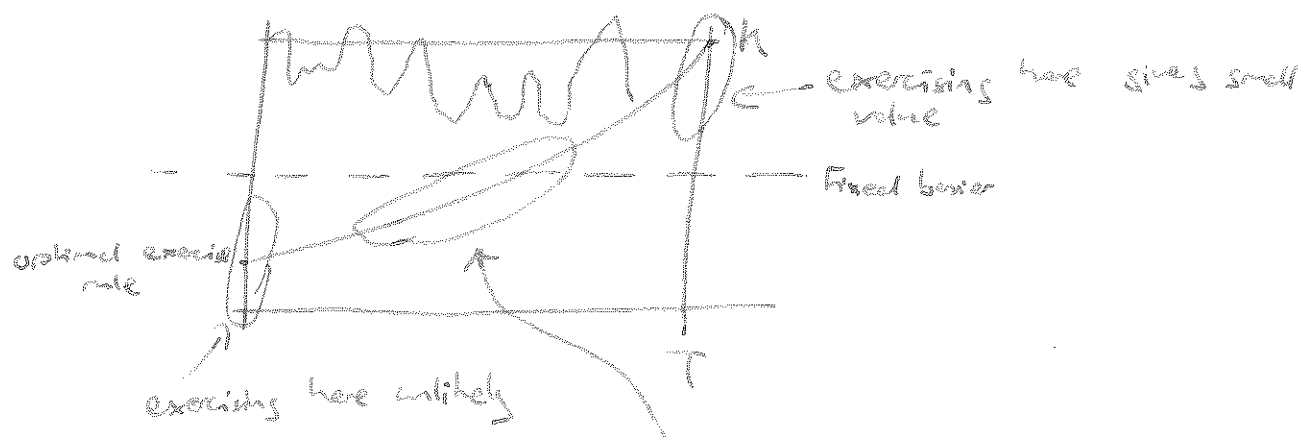
$$\Rightarrow \frac{1}{K-a} = \frac{\alpha}{a} \Rightarrow \boxed{a = \frac{\alpha K}{1+\alpha}}, \quad \alpha = \frac{2r}{\sigma^2}$$

a is the optimal barrier, ~~enter~~ unsurprisingly, $a \propto K$, as it has to be by scaling.

So we can easily calculate this, as a check and as a guide: the value we obtain for infinite horizon must be $\geq$ value for finite horizon, and exercise boundary must always be $\geq \frac{aK}{1+\alpha}$.

(?! What if we try to use a constant boundary with a finite horizon?

This was tried by Bjerkedal + Stensland in 1992, and they showed that with the best choice of the fixed barrier, the value was very nearly optimal for a wide range of realistic parameter values.



Likely to exercise in the middle, where exercise boundary is approximately constant.

Exercise Suppose we propose to stop at

$$\tau \equiv \inf \{t : \log S_t \leq a + bt\} \wedge T$$

(i.e. add a slope to $B_1 + S_t$ idea)

Find an expression for the value of the option if we use this rule. (Difficult)

A different approach

In a classical optimal stopping problem, we get reward Z_τ when we stop at stopping time $\tau \leq T$.

116 Theorem The value of the optimal stopping problem (assuming $\sup |Z_t| \in L^p$ for some $p > 1$) is

$$Y_0^* = \sup_{0 \leq \tau \leq T} E(Z_\tau) \\ = \min_{M \in \mathcal{M}_0} E\left[\sup_{0 \leq t \leq T} (Z_t - M_t)\right]$$

where $\mathcal{M}_0$ is the class of UI martingales, $M_0 = 0$.

Proof $\forall M \in \mathcal{M}_0$, stopping time τ , $EM_\tau = 0$

$$\text{so } E Z_\tau = E[Z_\tau - M_\tau] \\ \leq E\left[\sup_{0 \leq t \leq T} (Z_t - M_t)\right]$$

$$\text{so } \sup_{0 \leq \tau \leq T} E[Z_\tau] \leq E\left[\sup_{0 \leq t \leq T} (Z_t - M_t)\right]$$

since RHS does not depend on τ

$$\text{Hence } \sup_{0 \leq \tau \leq T} E[Z_\tau] \leq \inf_{M \in \mathcal{M}_0} E\left[\sup_{0 \leq t \leq T} (Z_t - M_t)\right]$$

since LHS does not depend on M

For the converse, we will use a result from optimal stopping theory.

The process

$$V_t^* = \text{ess sup}_{t \leq \tau \leq T} E(Z_\tau | \mathcal{F}_t)$$

is a supermartingale ($\text{ess sup} = \sup\{\text{up to } 1\}$), and has Doob-Meyer decomposition

$$V_t^* = Y_0^* + M_t^* - A_t^*$$

where A^* is a previsible increasing process, and M^* is in $\mathcal{M}_0$.

Now we get

$$\begin{aligned} \sup_{0 \leq t \leq T} (Z_t - M_t^*) &= \sup_{0 \leq t \leq T} (V_t^* - M_t^*) \\ &= \sup_{0 \leq t \leq T} (Y_0^* - A_t^*) \quad (\text{by optimality of } V^*) \\ &= Y_0^*, \text{ since } A^* \text{ increasing.} \end{aligned}$$

Therefore, $E[\sup_{0 \leq t \leq T} (Z_t - M_t^*)] \leq Y_0^*$

But $Y_0^* = \sup_{\tau \leq T} E[Z_\tau] \leq E[\sup_{0 \leq t \leq T} (Z_t - M_t^*)] \leq Y_0^*$

$\Rightarrow$ have equality

□

Why might this be useful?

- offers a simple simulation route to American Option pricing!

(since $\sup_{0 \leq t \leq T} (Z_t - M_t)$ does not depend on stopping rule, it is 'easier' to find a good martingale than a good stopping rule.)