

Geometric Stopping of a Random Walk and Its Applications to Valuing Equity-linked Death Benefits

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AQFC 2017: The Fifth Asian Quantitative Finance Conference
24-26 April, 2017, Seoul, Republic of Korea

Source: A joint paper with Hans U. Gerber and Elias S.W. Shiu.

Support from RGC and Society of Actuaries' CAE Research Grants is acknowledged.

Motivation

- ▶ To value guarantees and options in Variable Annuities
- ▶ Variable Annuities
 - = Investment Funds (Mutual Funds)
 - +
 - Rider(s) : Guaranteed Minimum Benefits

Mathematical problem

- ▶ How to calculate

$$E[v^{(K_x+1)}b(S(K_x), M_S(K_x))].$$

where v is the discount factor per unit time, K_x denotes the curtate future life time r.v., $b(.,.)$ is a benefit function, $S(t)$ denotes the price of a stock or stock index at time t , and $M_S(t)$ is the running maximum of the stock price.

Random walk

- ▶ $X(t) = X_1 + \cdots + X_t, \quad X(0) = 0$
- ▶ X_1, X_2, \dots are i.i.d. r.v.'s, with $\Pr\{X_t = 1\} = p_1,$
 $\Pr\{X_t = 0\} = p_0, \Pr\{X_t = -1\} = p_{-1}, p_1 + p_0 + p_{-1} = 1.$

Geometric distribution

Let τ be an independent r.v. with a geometric distribution (say parameter π), such that

$$\Pr\{\tau = t\} = (1 - \pi)\pi^t, \quad t = 0, 1, 2, \dots . \quad (1)$$

Its probability generating function (pgf) is

$$E[z^\tau] = \frac{1 - \pi}{1 - \pi z}. \quad (2)$$

The pgf of $X(\tau)$

$$\begin{aligned} E \left[z^{X(\tau)} \right] &= E \left[E \left[z^{X(\tau)} \mid \tau \right] \right] \\ &= E \left[E \left[z^{X(1)} \right]^\tau \right] \\ &= E \left[(p_1 z + p_0 + p_{-1} z^{-1})^\tau \right] \\ &= \frac{1 - \pi}{1 - \pi(p_1 z + p_0 + p_{-1} z^{-1})}. \end{aligned} \quad (3)$$

This is a rational function of z , which we can expand by partial fractions. Let

$$0 < \alpha < 1 < \beta < \infty$$

denote the zeros of the denominator in (3), i.e. the solutions of the quadratic equation

$$\pi p_1 z^2 - (1 - \pi p_0)z + \pi p_{-1} = 0. \quad (4)$$

The pgf of $X(\tau)$

$$E \left[z^{X(\tau)} \right] = C \frac{\alpha}{z - \alpha} - C \frac{\beta}{z - \beta}, \quad (5)$$

with

$$C = \frac{1 - \pi}{\pi} \frac{1}{p(\beta - \alpha)} = \frac{(1 - \alpha)(\beta - 1)}{\beta - \alpha}. \quad (6)$$

To identify the distribution of $X(\tau)$, we rewrite (5) as

$$E \left[z^{X(\tau)} \right] = C \frac{\alpha/z}{1 - \alpha/z} + C \frac{1}{1 - z/\beta}. \quad (7)$$

The distribution of $X(\tau)$

$$\begin{aligned}\Pr\{X(\tau) = j\} &= C\alpha^{-j}, & j = -1, -2, \dots, \\ \Pr\{X(\tau) = j\} &= C\beta^{-j}, & j = 0, 1, 2, \dots .\end{aligned}\quad (8)$$

Thus $X(\tau)$ has a two-sided geometric distribution.

The record highs and lows of the random walk



$$M(t) = \max\{0, X(1), \dots, X(t)\} \quad (9)$$

denote the running maximum and, similarly, $m(t)$ the running minimum after t steps.

Joint distribution in the trinomial tree model

Suppose $X(t) = X_1 + \dots + X_t$,

where X_i takes three values: $-1, 0, 1$

and $P(X_i = 1) = P(X_i = -1) = p/2$, $P(X_i = 0) = q$ with $p + q = 1$.

We assume that X_1, X_2, \dots is an i.i.d. sequence. Since the random walk $X(t)$ is symmetric, the reflection principle is true (the proof is the same as that for simple symmetric random walk).

$$P(\{X(t) = j, M(t) \geq k\}) = P(X(t) = 2k - j)$$

Joint distribution in the trinomial tree model

Now we assume that the random walk is not symmetric,

that is $P(X_i = 1) = p_1$, $P(X_i = -1) = p_{-1}$, $P(X_i = 0) = p_0$, with $p_1 + p_{-1} + p_0 = 1$. Let

$$\Lambda_t = \left(\frac{1}{2(p_{-1}p_1)^{1/2} + p_0} \right)^t (p_{-1}/p_1)^{X(t)/2}.$$

Then Λ_t is a martingale under P and $E[\Lambda_t] = 1$.

Joint distribution in the trinomial tree model

Let $dQ/dP|_{\mathcal{F}_t} = \Lambda_t$, where $\mathcal{F}_t = \sigma\{X_1, \dots, X_t\}$.

Then under Q , X_1, \dots, X_t, \dots is i.i.d symmetric random walk;

$$Q(X_1 = 1) = E_Q[I_{(X_1=1)}] = E_P[\Lambda_1 I_{(X_1=1)}] = \frac{(p_{-1}p_1)^{1/2}}{2(p_{-1}p_1)^{1/2} + p_0}$$

,
similarity,

$$Q(X_1 = -1) = \frac{(p_{-1}p_1)^{1/2}}{2(p_{-1}p_1)^{1/2} + p_0}$$

Joint distribution in the trinomial tree model

$$Q(X_1 = 0) = \frac{p_0}{2(p_{-1}p_1)^{1/2} + p_0}$$

X_1, X_2, \dots are independent under Q , because

$$\Lambda_t = \prod_{i=1}^t \left[\frac{(p_{-1}p_1)^{X_i/2}}{2(p_{-1}p_1)^{1/2} + p_0} \right].$$

Joint distribution in the trinomial tree model

$$P(X(t) = j, M(t) \geq k) = E_P[I_A],$$

where $A = \{X(t) = j, M(t) \geq k\}$.

$$E_P[I_A] = E_Q[I_A \Lambda_t^{-1}] = (2(p_{-1}p_1)^{1/2} + p_0)^t (p_1/p_{-1})^{j/2} Q(A), \quad (10)$$

and $Q(A) = Q(X(t) = 2k - j)$ because, under Q , X_1, X_2, \dots is a symmetric random walk.

Joint distribution in the trinomial tree model

$$\begin{aligned} Q(X(t) = 2k - j) &= E_Q[l_{(X(t)=2k-j)}] = E_P[\Lambda_t l_{(X(t)=2k-j)}] \\ &= (2(p_{-1}p_1)^{1/2} + p_0)^{-t} (p_{-1}/p_1)^{(2k-j)/2} P(X(t) = 2k - j). \end{aligned} \tag{11}$$

From (10) and (11)

$$P(X(t) = j, M(t) \geq k) = (p_{-1}/p_1)^{k-j} P(X(t) = 2k - j).$$

Joint distribution in the trinomial tree model

Since τ is independent of $X(t)$, we have

$$P(X(\tau) = j, M(\tau) \geq k) = (p_{-1}/p_1)^{k-j} P(X(\tau) = 2k - j).$$

From this we can obtain the joint probability function of $X(\tau)$ and $M(\tau)$.

Distributions of $M(\tau)$ and $m(\tau)$

Both $M(\tau)$ and $m(\tau)$ have geometric distributions:

$$\Pr\{M(\tau) \geq k\} = \beta^{-k}, \quad k = 0, 1, 2, \dots, \quad (12)$$

$$\Pr\{m(\tau) \leq k\} = \alpha^{-k}, \quad k = 0, -1, -2, \dots, \quad (13)$$

or,

$$\Pr\{M(\tau) = k\} = (\beta - 1)\beta^{-k-1}, \quad k = 0, 1, 2, \dots, \quad (14)$$

$$\Pr\{m(\tau) = k\} = (1 - \alpha)\alpha^{-k}, \quad k = 0, -1, -2, \dots \quad (15)$$

We note that $M(\tau) \geq k$ is the event that $X(n)$ reaches level k before or at time τ . Similarly, $m(\tau) \leq k$ is the event that $X(n)$ falls to level k before or at time τ .

Proof

Let k_1 be a negative integer and k_2 a positive integer. Let Π_1 be the probability that $X(t)$ reaches k_1 before or at time τ , and before $X(t) = k_2$. Similarly, Let Π_2 be the probability that $X(t)$ reaches k_2 before or at time τ , and before $X(t) = k_1$. It is verified that

$$\{z^{X(t)}I_{(\tau \geq t)}; t = 0, 1, 2, \dots\} \quad (16)$$

is a martingale for $z = \alpha$ and $z = \beta$.

Proof

Now we stop each of the two martingales the first time (before or at time τ) when $X(t) = k_1$, or $X(t) = k_2$, or else at time $\tau + 1$. Then the optional sampling theorem yields the equations

$$\Pi_1 \alpha^{k_1} + \Pi_2 \alpha^{k_2} = 1, \quad (17)$$

$$\Pi_1 \beta^{k_1} + \Pi_2 \beta^{k_2} = 1. \quad (18)$$

It follows that

$$\Pi_1 = \frac{\beta^{k_2} - \alpha^{k_2}}{\alpha^{k_1} \beta^{k_2} - \alpha^{k_2} \beta^{k_1}}, \quad (19)$$

$$\Pi_2 = \frac{\alpha^{k_1} - \beta^{k_1}}{\alpha^{k_1} \beta^{k_2} - \alpha^{k_2} \beta^{k_1}}. \quad (20)$$

In the limit $k_1 \rightarrow -\infty$ ($k_2 = k$), (20) becomes (12). Similarly, in the limit $k_2 \rightarrow \infty$ ($k_1 = k$), (19) becomes (13).

The distributions of $M(\tau)$ and $X(\tau) - m(\tau)$ are the same

We note that for each t , the r.v.'s $M(t)$ and $X(t) - m(t)$ have the same distribution. This follows from

$$\begin{aligned}M(t) &= \max\{0, X_1, X_1 + X_2, \dots, X_1 + X_2 + \dots + X_t\}, \\X(t) - m(t) &= \max\{0, X_t, X_t + X_{t-1}, \dots, X_t + X_{t-1} + \dots + X_1\}.\end{aligned}$$

Hence, the distributions of $M(\tau)$ and $X(\tau) - m(\tau)$ are the same; their probabilities are given by (14). Similarly, the distributions of $m(\tau)$ and $X(\tau) - M(\tau)$ are the same; their probabilities are given by (15).

The r.v.'s $M(\tau)$ and $X(\tau) - M(\tau)$ are independent

Because the conditional distribution of $X(\tau) - M(\tau)$, given $M(\tau)$, is the conditional distribution of $X(\tau)$, given $X(n) \leq 0$ for $n = 1, \dots, \tau$, and hence the same for all values of $M(\tau)$. To see this, consider the first time t when $X(t) = M(\tau)$; thus $\tau \geq t$ and $X(n) - X(t) \leq 0$ for $n = t, \dots, \tau$. Then observe that the conditional distribution of $\tau - t$ does not depend on t .

The r.v.'s $M(\tau)$ and $X(\tau) - M(\tau)$ are independent

$$\begin{aligned} & P(X(\tau) - M(\tau) = k | M(\tau)) \\ = & P(X(\tau) - M(\tau) = k | M(\tau) = X(t^*), \tau > t^*) \\ = & P(X(\tau) - X(t^*) = k | X(t) \leq X(t^*), t = 0, 1, \dots, \tau, \tau > t^*) \\ = & P(X(\tau) - X(t^*) = k | X(t) \leq X(t^*), t = t^*, t^* + 1, \dots, \tau, \tau > t^*) \\ = & P(X(\tau - t^*) = k | X(t) - X(t^*) \leq 0, t = t^*, \dots, \tau, \tau > t^*) \\ = & P(X(\tau - t^*) = k | X(t - t^*) \leq 0, t = t^*, \dots, \tau, \tau > t^*) \\ = & P(X(\tau^*) = k | X(0) \leq 0, \dots, X(\tau^*) \leq 0), \end{aligned}$$

where τ^* and τ have the same distribution.

The joint distribution of $X(\tau)$ and $M(\tau)$

$$\begin{aligned} & \Pr\{X(\tau) = j, M(\tau) = h\} \\ &= \Pr\{M(\tau) - X(\tau) = h - j, M(\tau) = h\} \\ &= \Pr\{M(\tau) - X(\tau) = h - j\} \Pr\{M(\tau) = h\} \\ &= \Pr\{m(\tau) = -(h - j)\} \Pr\{M(\tau) = h\} \\ &= (1 - \alpha) \alpha^{h-j} (\beta - 1) \beta^{-h-1}. \end{aligned} \tag{21}$$

Similarly, for $h = 0, -1, -2, \dots$ and $j \geq h$, we have

$$\begin{aligned} & \Pr\{X(\tau) = j, m(\tau) = h\} \\ &= \Pr\{X(\tau) - m(\tau) = j - h, m(\tau) = h\} \\ &= \Pr\{X(\tau) - m(\tau) = j - h\} \Pr\{m(\tau) = h\} \\ &= \Pr\{M(\tau) = j - h\} \Pr\{m(\tau) = h\} \\ &= (\beta - 1) \beta^{-(j-h)-1} (1 - \alpha) \alpha^{-h}. \end{aligned} \tag{22}$$

For $k = 0, 1, 2, \dots$ and $j \leq k$, we find that

$$\Pr\{X(\tau) = j, M(\tau) \geq k\} = C\alpha^{-j}\left(\frac{\alpha}{\beta}\right)^k. \quad (23)$$

Of course for $j \geq k$,

$$\Pr\{X(\tau) = j, M(\tau) \geq k\} = \Pr\{X(\tau) = j\} = C\beta^{-j}. \quad (24)$$

Similarly, for $k = 0, -1, -2, \dots$ and $j \geq k$ one shows that

$$\Pr\{X(\tau) = j, m(\tau) \leq k\} = C\beta^{-j}\left(\frac{\beta}{\alpha}\right)^k. \quad (25)$$

Of course

$$\Pr\{X(\tau) = j, m(\tau) \leq k\} = \Pr\{X(\tau) = j\} = C\alpha^{-j} \quad (26)$$

for $j \leq k$.

Remark

The proofs that $M(\tau)$ and $X(\tau) - M(\tau)$ are independent, and that $X(\tau) - m(\tau)$ has the same distribution as $m(\tau)$, are valid for a general random walk. It follows that

$$\begin{aligned}P_{X(\tau)}(z) &= \mathbb{E}[z^{X(\tau)}] = \mathbb{E}[z^{M(\tau)+X(\tau)-M(\tau)}] \\ &= \mathbb{E}[z^{M(\tau)}] \times \mathbb{E}[z^{X(\tau)-M(\tau)}] \\ &= \mathbb{E}[z^{M(\tau)}] \times \mathbb{E}[z^{m(\tau)}] = P_{M(\tau)}(z)P_{m(\tau)}(z). \quad (27)\end{aligned}$$

This formula is a version of the *Wiener-Hopf factorization*.

Remark

If X_1 takes integer values from $-n$ to $+m$, then

$$\begin{aligned} P_{X(\tau)}(z) &= \frac{1 - \pi}{1 - \pi P_{X_1}(z)} = \frac{1 - \pi}{1 - \pi \sum_{j=-n}^m p_j z^j} \\ &= \frac{(1 - \pi)z^n}{g(z)}, \end{aligned} \tag{28}$$

where $g(z) = \left(1 - \pi \sum_{j=-n}^m p_j z^j\right) z^n$ is a polynomial of degree $m + n$.

Remark

Because $1 > \pi = \pi \sum_{j=-n}^m p_j$, we have

$$|z^n| > |g(z) - z^n|, \quad \text{for } |z| = 1. \quad (29)$$

Then by Rouché's Theorem, $g(z)$ has the same number of zeros inside the complex disk of radius 1 as the function z^n . Denote these n zeros of $g(z)$ as $\alpha_1, \dots, \alpha_n$. Denote the other zeros of $g(z)$, those with absolute value greater than 1, as β_1, \dots, β_m . Then, the pgf $P_{X(\tau)}(z)$ is proportional to

$$\begin{aligned} & \frac{z^n}{\left(\prod_{j=1}^n (z - \alpha_j)\right) \left(\prod_{j=1}^m (z - \beta_j)\right)} \\ = & \frac{1}{\left(\prod_{j=1}^n (1 - \alpha_j/z)\right) \left(\prod_{j=1}^m (z - \beta_j)\right)}. \end{aligned} \quad (30)$$

Remark

Note that $P_{M(\tau)}(1) = 1$ and $P_{m(\tau)}(1) = 1$. Because $M(\tau) \geq 0$, $P_{M(\tau)}(z)$ exists for each z with $|z| < 1$. Similarly, $P_{m(\tau)}(z)$ exists for each z with $|z| > 1$. Therefore

$$P_{M(\tau)}(z) = \frac{\prod_{j=1}^m (\beta_j - 1)}{\prod_{j=1}^m (\beta_j - z)}, \quad P_{m(\tau)}(z) = \frac{\prod_{j=1}^n (1 - \alpha_j)}{\prod_{j=1}^m (1 - \alpha_j/z)}. \quad (31)$$

Remark

In the special case of a simple random walk, from (5) and (6), we have

$$P_{X(\tau)}(z) = C \frac{(\beta - \alpha)z}{(z - \alpha)(\beta - z)} = \frac{\beta - 1}{\beta - z} \times \frac{(1 - \alpha)z}{z - \alpha}. \quad (32)$$

Indeed, the first factor of the RHS of (32) is the pgf of (14), and the second factor is the pgf of (15).

Applications

Let K_x denote the curtate future life time r.v. (measured in number of time units). Upon death, a benefit payment B is payable at time $K_x + 1$. We assume a constant rate of interest and denote by v the discount factor per unit time. The general goal is to calculate

$$E[v^{K_x+1}B] = \sum_{n=0}^{\infty} \Pr\{K_x = n\}v^{n+1}E[B|K_x = n], \quad (33)$$

the expectation of the discounted benefit payment.

We assume that K_x and $\{S(t); t = 0, 1, \dots\}$ are independent.

Reduced problem

The distribution of K_x can be approximated by a combination of geometric distributions:

$$\Pr\{K_x = n\} \approx \sum_{j=1}^m c_j (1 - \pi_j) \pi_j^n, \quad (34)$$

where $c_1, \dots, c_m, \pi_1, \dots, \pi_m$ are suitably chosen. As a consequence, it suffices to consider the reduced problem, where K_x in (33) is a geometrically distributed r.v. τ , that is, to calculate

$$E[v^{\tau+1}B] = \sum_{n=0}^{\infty} (1 - \pi) \pi^n v^{n+1} E[B|\tau = n]. \quad (35)$$

Reduced problem

We can simplify the problem by one more step:

$$\begin{aligned} E[v^{\tau+1}B] &= \frac{v(1-\pi)}{1-v\pi} \sum_{n=0}^{\infty} (1-v\pi)(v\pi)^n E[B|\tau=n] \\ &= \frac{v(1-\pi)}{1-v\pi} \tilde{E}[B] = E[v^{\tau+1}] \tilde{E}[B]. \end{aligned} \quad (36)$$

Formally, the discounting has been eliminated in the second expectation. But note that it is taken with respect to the geometric distribution with parameter $v\pi$ instead of π .

The trinomial tree model

We assume the trinomial tree model, that is, that for some $a > 1$,

$$S(t) = S(0)a^{X(t)}, \quad t = 0, 1, 2, \dots, \quad (37)$$

where $\{X(t); t = 0, 1, 2, \dots\}$ is the random walk taking three possible values.

$0 < \alpha < 1 < \beta < \infty$ are now defined as the solution of the equation

$$\pi p_1 z^2 - (1 - \pi p_0)z + \pi p_{-1} = 0. \quad (38)$$

$$B = S(\tau)$$

By (36) and (3) with $z = a$, we have

$$\begin{aligned} E[v^{\tau+1}S(\tau)] &= \frac{v(1-\pi)}{1-v\pi} \tilde{E}[S(\tau)] \\ &= \frac{v(1-\pi)}{1-v\pi} S(0) \tilde{E}[a^{X(\tau)}] \\ &= S(0) \frac{v(1-\pi)}{1-v\pi(p_1a + p_0 + p_{-1}a^{-1})}. \end{aligned} \quad (39)$$

B a function of $S(K_x)$

$$B = b(S(K_x)) \quad (40)$$

for some function $b(s)$. Because of the factorization formula (36), we are to calculate

$$\begin{aligned} E[B] &= E[b(S(\tau))] \\ &= \sum_{j=-\infty}^{\infty} b(S(0)a^j) \Pr\{X(\tau) = j\} \\ &= \sum_{j=-\infty}^{-1} b(S(0)a^j) C \alpha^{-j} + \sum_{j=0}^{\infty} b(S(0)a^j) C \beta^{-j} \quad (41) \end{aligned}$$

by (8). Note that $E[B]$ is a function of $S(0)$; we shall use the symbol $\mathcal{E}_b(S(0))$ for it.

Out-of-the money put option

For a *put option* with exercise price K , $b(s) = (K - s)_+$. Then

$$E[(K - S(\tau))_+] = \sum_{j=-\infty}^{\ell} (K - S(0)a^j) \Pr\{X(\tau) = j\}, \quad (42)$$

where ℓ is the greatest integer j such that $K - S(0)a^j > 0$. For the *out-of-the money case*, $S(0) > K$ ($\ell < 0$), we find that

$$E[(K - S(\tau))_+] = C \left[K \frac{(1/\alpha)^\ell}{1 - \alpha} - S(0) \frac{(a/\alpha)^\ell}{1 - \alpha/a} \right], \quad (43)$$

where C is given by (6).

Out-of-the money call option

For a *call option* with exercise price K , $b(s) = (s - K)_+$. In the *out-of-the money case*, $S(0) \leq K$ ($\ell \geq 0$), we obtain

$$\begin{aligned} E[(S(\tau) - K)_+] &= \sum_{j=\ell+1}^{\infty} (S(0)a^j - K)C\beta^{-j} \\ &= C \left[S(0) \frac{(a/\beta)^{\ell+1}}{1 - a/\beta} - K \frac{(1/\beta)^{\ell+1}}{1 - 1/\beta} \right]. \quad (44) \end{aligned}$$

Put-call-parity

From

$$(K - S(\tau))_+ - (S(\tau) - K)_+ = K - S(\tau), \quad (45)$$

we see that

$$E[(K - S(\tau))_+] - E[(S(\tau) - K)_+] = K - E[(S(\tau))], \quad (46)$$

with

$$E[S(\tau)] = S(0) \frac{1 - \pi}{1 - \pi(pa + qa^{-1})}. \quad (47)$$

In-the money put option

$$\begin{aligned} E[(K - S(\tau))_+] &= E[(S(\tau) - K)_+] + K - E[(S(\tau))] \\ &= C \left[S(0) \frac{(a/\beta)^{\ell+1}}{1 - a/\beta} - K \frac{(1/\beta)^{\ell+1}}{1 - 1/\beta} \right] + K - E[(S(\tau))], \quad (48) \end{aligned}$$

In-the money call option

$$\begin{aligned} E[(S(\tau) - K)_+] &= E[(K - S(\tau))_+] - K + E[(S(\tau))] \\ &= C \left[K \frac{(1/\alpha)^\ell}{1 - \alpha} - S(0) \frac{(a/\alpha)^\ell}{1 - \alpha/a} \right] - K + E[(S(\tau))], \quad (49) \end{aligned}$$

Expiry at time T

Suppose that $b(S(K_x))$ is payable at time $K_x + 1$, provided that $K_x < T$, where T is a positive integer. Because of (36), we want to determine

$$E[b(S(\tau))I_{(\tau < T)}] = E[b(S(\tau))] - E[b(S(\tau))I_{(\tau \geq T)}], \quad (50)$$

where I denotes the indicator function. Using the memoryless property of τ and the independence between τ and the stock price process, we see that

$$\begin{aligned} E[b(S(\tau))I_{(\tau \geq T)}] &= \Pr\{\tau \geq T\}E[b(S(\tau))|\tau \geq T] \\ &= \pi^T E[\mathcal{E}_b(S(T))], \end{aligned} \quad (51)$$

where $\mathcal{E}_b(s) = E[b(S(\tau))|S(0) = s]$ has been defined

The remaining task is to calculate

$$\begin{aligned} & E[\mathcal{E}_b(S(T))] \\ &= E[\mathcal{E}_b(S(T))I_{(S(T) \leq K)}] + E[\mathcal{E}_b(S(T))I_{(S(T) > K)}]. \quad (52) \end{aligned}$$

For $b(s) = I_{(s \leq K)}$,

$$\begin{aligned} E[\mathcal{E}_b(S(T))] &= C \frac{(1/\alpha)^\ell}{1-\alpha} E[\alpha^{X(T)}] \Pr\{S(T) > K; \alpha\} \\ &\quad + \Pr\{S(T) \leq K\} \\ &\quad - C \frac{(1/\beta)^{\ell+1}}{1-1/\beta} E[\beta^{X(T)}] \Pr\{S(T) \leq K; \beta\}. \end{aligned}$$

Esscher transform

We have used the formula

$$E[h^X | A] = E[h^X] \Pr\{A; h\}, \quad h > 0, \quad (53)$$

where the probability of the event A is calculated with respect to the Esscher transformed probabilities,

$$\Pr\{X = j; h\} = h^j \Pr\{X = j\} / E[h^X]. \quad (54)$$

Formula (53) has been used for $X = X(T)$ and $h = \beta, \alpha, a$.

Furthermore, we note that the generating function of the transformed probabilities is

$$E[z^X; h] = E[(hz)^X] / E[h^X], \quad (55)$$

which can be useful to determine the transformed probabilities.

Barrier options

First we consider a double barrier option with barriers $L < U$ and initial stock price $S(0)$ with $L < S(0) < U$. We may assume that

$$k_1 = \log_a\left(\frac{L}{S(0)}\right), \quad k_2 = \log_a\left(\frac{U}{S(0)}\right) \quad (56)$$

are integers.

Double barrier options

The probability that the stock price first hits the lower end L of the barrier interval, and that this takes place before or at time τ , is Π_1 given by (19). At that time, because of the memoryless property of the geometric distribution, the conditional expectation of B is $\mathcal{E}_b(L)$; here $\mathcal{E}_b(s)$ refers to the ordinary option. Similarly, the probability that the stock price first hits the upper end U of the barrier interval, and that this happens before or at time τ , is Π_2 given by (20). Then the conditional expectation of B is $\mathcal{E}_b(U)$.

Double barrier options

Hence, by conditioning we find that

$$E[B] = \Pi_1 \mathcal{E}_b(L) + \Pi_2 \mathcal{E}_b(U). \quad (57)$$

Single barrier options

The *down-and-in* option becomes alive if the stock price hits the level L before or at time τ , the probability of which is given by (13) with $k = k_1$. Thus

$$E[B] = \alpha^{-k_1} \mathcal{E}_b(L). \quad (58)$$

In contrast, the *up-and-in* option becomes alive if the stock price hits the level U before or at time τ , the probability of which is given by (12) with $k = k_2$. Thus

$$E[B] = \beta^{-k_2} \mathcal{E}_b(U). \quad (59)$$

Knock-out barrier options

A *knock-out* option is alive at time 0 and is knocked out when the stock price hits the predetermined barrier(s). The payoff B of a knock-out option is the payoff of the corresponding ordinary option reduced by the payoff of the corresponding knock-in option. From this and (57) - (59) it follows that

$$E[B] = \mathcal{E}_b(S(0)) - \Pi_1 \mathcal{E}_b(L) - \Pi_2 \mathcal{E}_b(U) \quad (60)$$

for the knock-out double barrier option,

$$E[B] = \mathcal{E}_b(S(0)) - \Pi_1 \mathcal{E}_b(L) \quad (61)$$

for the *down-and-out* option, and

$$E[B] = \mathcal{E}_b(S(0)) - \Pi_2 \mathcal{E}_b(U) \quad (62)$$

for the *up-and-out* option.

Remark

For the single barrier options the expected payoff can also be obtained from (23) - (26). For example, for the up-and-in option, it is

$$\begin{aligned} & \sum_{j=-\infty}^{\infty} b(S(0)a^j) \Pr\{X(\tau) = j, M(\tau) \geq k_2\} \\ &= \sum_{j=-\infty}^{k_2} b(S(0)a^j) C \alpha^{-j} \left(\frac{\alpha}{\beta}\right)^{k_2} + \sum_{j=k_2+1}^{\infty} b(S(0)a^j) C \beta^{-j}. \end{aligned} \quad (63)$$

To see that this is the same as (59), use (41) and note that

$$\mathcal{E}_b(U) = \mathcal{E}_b(S(0)a^{k_2}).$$

Out-of-the-money fixed strike lookback call option

The payoff is

$$[S(0)a^{M(\tau)} - K]_+, \quad (64)$$

whose time-0 value, by (14), is

$$\begin{aligned} E[[S(0)a^{M(\tau)} - K]_+] &= \sum_{k=\ell+1} [S(0)a^k - K](\beta - 1)\beta^{-k-1} \\ &= S(0)\frac{\beta - 1}{\beta} \frac{(a/\beta)^{\ell+1}}{1 - a/\beta} - K(1/\beta)^{\ell+1}. \end{aligned} \quad (65)$$

In-the-money fixed strike lookback call option

The payoff is

$$\max(H, S(0)a^{M(\tau)}) - K. \quad (66)$$

By rewriting (66) as

$$H - K + [S(0)a^{M(\tau)} - H]_+ \quad (67)$$

and using (65) with K replaced by H , we find that the time-0 value of (66) is

$$H - K + S(0) \frac{\beta - 1}{\beta} \frac{(a/\beta)^{\ell+1}}{1 - a/\beta} - H(1/\beta)^{\ell+1}. \quad (68)$$

Floating strike lookback put option

The payoff at time τ is

$$\max(H, \max_{0 \leq t \leq \tau} S(t)) - S(\tau), \quad (69)$$

where $H \geq S(0)$. By comparing (69) with (66), we see that its time-0 value is (68) but with K replaced by $E[S(\tau)]$. The result is

$$H - E[S(\tau)] + S(0) \frac{\beta - 1}{\beta} \frac{(a/\beta)^{\ell+1}}{1 - a/\beta} - H(1/\beta)^{\ell+1}. \quad (70)$$