

# MF921 Topics in Dynamic Asset Pricing

## Week 4

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# Background

Recall The Double Exponential Jump Diffusion Model:

$$\frac{dS(t)}{S(t^-)} = \mu dt + \sigma dW(t) + d \left( \sum_{i=1}^{N(t)} (V_i - 1) \right)$$

- $W(t)$ : Brownian motion under the real-world measure.
- $N(t)$ : Poisson process with rate  $\lambda$ .
- $V_i$ : multiplicative jump sizes, i.i.d. random variables.
- $Y = \log(V)$ , the jump sizes follow double exponential law:

$$f_Y(y) = p\eta_1 e^{-\eta_1 y} \mathbf{1}_{y \geq 0} + q\eta_2 e^{\eta_2 y} \mathbf{1}_{y < 0}$$

with parameters:

- $p, q \geq 0, p + q = 1$ : probabilities of upward/downward jumps.
- $\eta_1 > 1$ : rate for upward jumps.
- $\eta_2 > 0$ : rate for downward jumps.

# Background Con.

For option pricing, we switch to a risk-neutral measure  $P^*$ , so that the discounted price process is a martingale:

$$E^{P^*}[e^{-rt}S(t)] = S(0)$$

Under  $P^*$ , the dynamics adjust:

$$\frac{dS(t)}{S(t^-)} = (r - \lambda^*(t)\zeta^*)dt + \sigma dW^*(t) + d\left(\sum_{i=1}^{N^*(t)} (V_i^* - 1)\right)$$

where:

- $W^*(t)$ : Brownian motion under  $P^*$ ,
- $N^*(t)$ : Poisson process with intensity  $\lambda^*$ ,
- $V^* = e^{Y^*}$ : jump multiplier with new parameters  $(p^*, q^*, \eta_1^*, \eta_2^*)$ ,
- $\zeta^* = E^{P^*}[V^*] - 1 = \frac{p^*\eta_1^*}{\eta_1^*-1} + \frac{q^*\eta_2^*}{\eta_2^*+1} - 1$  is mean percentage jump size.

The log-price process:

$$X(t) = \log\left(\frac{S(t)}{S(0)}\right) = \left(r - \frac{1}{2}\sigma^2 - \lambda^*\zeta^*\right)t + \sigma W^*(t) + \sum_{i=1}^{N^*(t)} Y_i^*, \quad X(0) = 0$$

# Some Useful Formulas Con

Moment Generating Function of the log-price process,  $X(t)$ :

$$\mathbb{E}^* [e^{\theta X(t)}] = \exp\{G(\theta)t\}$$

Where the function  $G(\cdot)$  is defined as:

$$G(x) = x \left( r - \frac{1}{2}\sigma^2 - \lambda\zeta \right) + \frac{1}{2}x^2\sigma^2 + \lambda \left( \frac{p\eta_1}{\eta_1 - x} + \frac{q\eta_2}{\eta_2 + x} - 1 \right)$$

**Note:** Lemma 3.1 in Kou and Wang (2003) shows that the equation  $G(x) = \alpha, \forall \alpha > 0$ , has exactly four roots:  $\beta_{1,\alpha}$ ,  $\beta_{2,\alpha}$ ,  $-\beta_{3,\alpha}$ , and  $-\beta_{4,\alpha}$ , where:

$$0 < \beta_{1,\alpha} < \eta_1 < \beta_{2,\alpha} < \infty$$

$$0 < \beta_{3,\alpha} < \eta_2 < \beta_{4,\alpha} < \infty$$

These roots determine the structure of Laplace transforms for first passage times.

# Some Useful Formulas Con

Infinitesimal Generator of the log-price process,  $X(t)$ :

$$(\mathcal{L}V)(x) = \frac{1}{2}\sigma^2 V''(x) + \left(r - \frac{1}{2}\sigma^2 - \lambda\zeta\right) V'(x) + \lambda \int_{-\infty}^{\infty} (V(x+y) - V(x)) f_Y(y) dy$$

The generator describes how expectations of functions of  $X(t)$  evolve in time:

$$\frac{d}{dt} \mathbb{E}[V(X_t)] = \mathbb{E}[(\mathcal{L}V)(X_t)]$$

They provide the mathematical foundation to derive option pricing formulas.

# Lookback Options

Consider a lookback put option with an initial "prefixed maximum"  $M \geq S(0)$ :

$$\begin{aligned} LP(T) &= \mathbb{E}^{\mathbb{P}^*} \left[ e^{-rT} \left( \max\{M, \max_{0 \leq t \leq T} S(t)\} - S(T) \right) \right] \\ &= \mathbb{E}^{\mathbb{P}^*} \left[ e^{-rT} \max\{M, \max_{0 \leq t \leq T} S(t)\} \right] - S(0) \end{aligned}$$

You need the joint distribution of  $\max S(t)$  and  $S(T)$ , which is complicated for jump processes. Laplace transforms convert a complicated path integral over time into a function of roots of  $G(x)$  which we can solve algebraically.

# Lookback Options Con.

## Theorem:

Using the notations  $\beta_{1,\alpha+r}$  and  $\beta_{2,\alpha+r}$  as in early slide, the Laplace transform of the lookback put is given by:

$$\hat{L}(T) = \int_0^\infty e^{-\alpha T} \text{LP}(T) dT = \frac{S(0)A_\alpha}{C_\alpha} \left( \frac{S(0)}{M} \right)^{\beta_{1,\alpha+r}-1} + \frac{S(0)B_\alpha}{C_\alpha} \left( \frac{S(0)}{M} \right)^{\beta_{2,\alpha+r}-1} + \frac{M}{\alpha+r} - \frac{S(0)}{\alpha}$$

For all  $\alpha > 0$ ; here:

$$A_\alpha = \frac{(\eta_1 - \beta_{1,\alpha+r})\beta_{2,\alpha+r}}{\beta_{1,\alpha+r} - 1}$$

$$B_\alpha = \frac{(\beta_{2,\alpha+r} - \eta_1)\beta_{1,\alpha+r}}{\beta_{2,\alpha+r} - 1}$$

$$C_\alpha = (\alpha + r)\eta_1(\beta_{2,\alpha+r} - \beta_{1,\alpha+r})$$

# Proof

Lemma :  $\lim_{y \rightarrow \infty} e^y \mathbb{P}^*[M_X(T) \geq y] = 0, \forall T \geq 0. M_X(T) := \max_{0 \leq t \leq T} X(t)$

[Proof]

Given  $\theta \in (-\eta_2, \eta_1)$ ,  $\mathbb{E}^*[e^{\theta X(t)}] < \infty$ , by stationary independent increments we can get that the process  $\{e^{\theta X(t) - G(\theta)t}; t \geq 0\}$  is a martingale.

Observe that  $G(x)$  is continuous and  $G(1) = r > 0$ , thus we can fix an  $\theta \in (1, \eta_1)$  such that  $G(\theta) > 0$ . Let  $\tau_y = \inf\{t \geq 0 : X(t) \geq y\}$ . By Optional Sampling Theorem:

$$1 = \mathbb{E}^*[M_{\tau_y \wedge T}] \mathbb{E}^*[e^{\theta X(\tau_y \wedge T)} e^{-G(\theta)(\tau_y \wedge T)}] \geq e^{\theta y} e^{-G(\theta)T} \mathbb{P}^*(\tau_y \leq T)$$

Thus  $e^{\theta y} \mathbb{P}^*(\tau_y \leq T) \leq e^{G(\theta)T}$ . Since  $\theta > 1$ , then we have:

$$e^y \mathbb{P}^*(M_X(T) \geq y) = e^{(1-\theta)y} [e^{\theta y} \mathbb{P}^*(\tau_y \leq T)] \leq e^{(1-\theta)y} e^{G(\theta)T} \xrightarrow{y \rightarrow \infty} 0$$

This will use to justify the boundary term vanishing in the integration-by-parts step later.



Given  $s = S(0)$  and  $M$  are constants,  $\max_{0 \leq t \leq T} S(t) = se^{M_X(T)}$ , the lookback put as:

$$LP(T) = \mathbb{E}^{\mathbb{P}^*} \left[ e^{-rT} \max\{M, se^{M_X(T)}\} \right] - s$$

Letting  $z = \log(M/s) \geq 0$ , define:

$$\begin{aligned} L(s, M; T) &:= \mathbb{E}^{\mathbb{P}^*} \left[ e^{-rT} \max\{M, se^{M_X(T)}\} \right] \\ &= s \mathbb{E}^{\mathbb{P}^*} \left[ e^{-rT} \max\{e^z, e^{M_X(T)}\} \right] \\ &= s \mathbb{E}^{\mathbb{P}^*} \left[ e^{-rT} \left( e^{M_X(T)} - e^z \right) \mathbf{1}_{\{M_X(T) \geq z\}} \right] + se^z e^{-rT} \end{aligned}$$

# Proof Con

Integration by parts:

$$\begin{aligned}\mathbb{E}^{\mathbb{P}^*} \left[ e^{-rT} e^{M_X(T)} \mathbf{1}_{\{M_X(T) \geq z\}} \right] &= e^{-rT} \int_z^\infty e^y d(1 - \mathbb{P}^*[M_X(T) \geq y]) \\&= -e^{-rT} \int_z^\infty e^y d\mathbb{P}^*[M_X(T) \geq y] \\&= -e^{-rT} \left\{ \left( -e^y \mathbb{P}^*[M_X(T) \geq y] \right) \Big|_0^\infty - \int_z^\infty \mathbb{P}^*[M_X(T) \geq y] e^y dy \right\} \\&= -e^{-rT} \left\{ -e^z \mathbb{P}^*[M_X(T) \geq z] - \int_z^\infty \mathbb{P}^*[M_X(T) \geq y] e^y dy \right\} \\&= \mathbb{E}^{\mathbb{P}^*} \left[ e^{-rT} e^z \mathbf{1}_{\{M_X(T) \geq z\}} \right] + e^{-rT} \int_z^\infty e^y \mathbb{P}^*[M_X(T) \geq y] dy;\end{aligned}$$

Plug back into  $L(s, M; T)$ :

$$\begin{aligned}L(s, M; T) &= s \mathbb{E}^{\mathbb{P}^*} \left[ e^{-rT} \left( e^{M_X(T)} - e^z \right) \mathbf{1}_{\{M_X(T) \geq z\}} \right] + s e^z e^{-rT} \\&= s e^{-rT} \int_z^\infty e^y \mathbb{P}^*[M_X(T) \geq y] dy + M e^{-rT}\end{aligned}$$

Then take Laplace in maturity and use Fubini Theorem:

$$\begin{aligned}\int_0^\infty e^{-\alpha T} L(s, M; T) dT &= s \int_0^\infty e^{-\alpha T} e^{-rT} \int_z^\infty e^y \mathbb{P}^*[M_X(T) \geq y] dy dT + \frac{M}{\alpha + r} \\ &= s \int_z^\infty e^y \int_0^\infty e^{-(\alpha+r)T} \mathbb{P}^*[M_X(T) \geq y] dT dy + \frac{M}{\alpha + r}\end{aligned}$$

Follows from Kou and Wang (2003) that:

$$\int_0^\infty e^{-(\alpha+r)T} \mathbb{P}^*[M_X(T) \geq y] dT = A_1 e^{-y\beta_{1,\alpha+r}} + B_1 e^{-y\beta_{2,\alpha+r}}$$

$$A_1 = \frac{1}{\alpha + r} \frac{\eta_1 - \beta_{1,\alpha+r}}{\eta_1} \cdot \frac{\beta_{2,\alpha+r}}{\beta_{2,\alpha+r} - \beta_{1,\alpha+r}}, \quad B_1 = \frac{1}{\alpha + r} \frac{\beta_{2,\alpha+r} - \eta_1}{\eta_1} \cdot \frac{\beta_{1,\alpha+r}}{\beta_{2,\alpha+r} - \beta_{1,\alpha+r}}.$$

# Proof Con

Note that  $\beta_{2,\alpha+r} > \eta_1 > 1$ ,  $\beta_{1,\alpha+r} > \beta_{1,r} = 1$ . Therefore: Note that  $\beta_{2,\alpha+r} > \eta_1 > 1$ ,  $\beta_{1,\alpha+r} > \beta_{1,r} = 1$ . Therefore,

$$\begin{aligned}\int_0^\infty e^{-\alpha T} L(s, M; T) dT &= s \int_z^\infty e^y A_1 e^{-y\beta_{1,\alpha+r}} dy + s \int_z^\infty e^y B_1 e^{-y\beta_{2,\alpha+r}} dy + \frac{M}{\alpha+r} \\ &= s A_1 \frac{e^{-z(\beta_{1,\alpha+r}-1)}}{\beta_{1,\alpha+r}-1} + s B_1 \frac{e^{-z(\beta_{2,\alpha+r}-1)}}{\beta_{2,\alpha+r}-1} + \frac{M}{\alpha+r} \\ &= s \frac{A_\alpha}{C_\alpha} e^{-z(\beta_{1,\alpha+r}-1)} + s \frac{B_\alpha}{C_\alpha} e^{-z(\beta_{2,\alpha+r}-1)} + \frac{M}{\alpha+r}.\end{aligned}$$

This yields the Laplace transform we obtained in Theorem 1.

$$\begin{aligned}\int_0^\infty e^{-\alpha T} L(s, M; T) dT &= s \int_z^\infty e^y A_1 e^{-y\beta_{1,\alpha+r}} dy + s \int_z^\infty e^y B_1 e^{-y\beta_{2,\alpha+r}} dy + \frac{M}{\alpha+r} \\ &= s A_1 \frac{e^{-z(\beta_{1,\alpha+r}-1)}}{\beta_{1,\alpha+r}-1} + s B_1 \frac{e^{-z(\beta_{2,\alpha+r}-1)}}{\beta_{2,\alpha+r}-1} + \frac{M}{\alpha+r} \\ &= s \frac{A_\alpha}{C_\alpha} e^{-z(\beta_{1,\alpha+r}-1)} + s \frac{B_\alpha}{C_\alpha} e^{-z(\beta_{2,\alpha+r}-1)} + \frac{M}{\alpha+r}\end{aligned}$$

This yields the Laplace transform we obtained in the Theorem.