

MF921 Topics in Dynamic Asset Pricing

Week 4

Yuanhui Zhao

Boston University

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 λ .
- 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 λ^* ,
- $V^* = e^{Y^*}$: 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, $X(t)$:

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

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.

Option Pricing Under a Double Exponential Jump Diffusion Model

S.G. Kou
Hui Wang

Proof of two Theorems. The Laplace transform of lookback option and barrier option.

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 $\theta \in (-\eta_2, \eta_1)$, $\mathbb{E}^{\mathbb{P}^*}[e^{\theta X(t)}] < \infty$, 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:

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

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:

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

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

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 the Theorem:

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

This yields the Laplace transform we obtained in the Theorem.

Barrier Options

Consider the up-and-in call (UIC) option with the barrier level H ($H > S(0)$):

$$UIC = E^{\mathbb{P}^*} [e^{-rT} (S(T) - K)^+ I_{\{\max_{0 \leq t \leq T} S(t) \geq H\}}]$$

For any given probability P , define:

$$\Psi(\mu, \sigma, \lambda, p, \eta_1, \eta_2; a, b, T) := P[Z(T) \geq a, \max_{0 \leq t \leq T} Z(t) \geq b]$$

where under P , $Z(t)$ is a double exponential jump diffusion process with drift μ , volatility σ , and jump rate λ , i.e., $Z(t) = \mu t + \sigma W(t) + \sum_{i=1}^{N(t)} Y_i$, and Y has a double exponential distribution with density $f_Y(y) \sim p \cdot \eta_1 e^{-\eta_1 y} 1_{\{y \geq 0\}} + q \cdot \eta_2 e^{y \eta_2} 1_{\{y < 0\}}$.

Theorem:

The price of the UIC option is obtained as:

$$\begin{aligned} \text{UIC} = & S(0) \Psi \left(r + \frac{1}{2} \sigma^2 - \lambda \zeta, \sigma, \tilde{\lambda}, \tilde{p}, \tilde{\eta}_1, \tilde{\eta}_2; \log \left(\frac{K}{S(0)} \right), \log \left(\frac{H}{S(0)} \right), T \right) \\ & - K e^{-rT} \cdot \Psi \left(r - \frac{1}{2} \sigma^2 - \lambda \zeta, \sigma, \lambda, p, \eta_1, \eta_2; \log \left(\frac{K}{S(0)} \right), \log \left(\frac{H}{S(0)} \right), T \right) \end{aligned}$$

where $\tilde{p} = (p/(1 + \zeta)) \cdot (\eta_1/(\eta_1 - 1))$, $\tilde{\eta}_1 = \eta_1 - 1$, $\tilde{\eta}_2 = \eta_2 + 1$, $\tilde{\lambda} = \lambda(\zeta + 1)$, with $\zeta = E^{P^*}[V] - 1 = \frac{p\eta_1}{\eta_1 - 1} + \frac{q\eta_2}{\eta_2 + 1} - 1$. The Laplace transforms of Ψ is computed explicitly in Kou and Wang (2003).

Theorem 3.1 in Kou and Wang (2003):

For any $\alpha \in (0, \infty)$, let $\beta_{1,\alpha}$ and $\beta_{2,\alpha}$ be the only two positive roots of the equation

$$\alpha = G(\beta),$$

where $0 < \beta_{1,\alpha} < \eta_1 < \beta_{2,\alpha} < \infty$. Then we have the following results concerning the Laplace transforms of τ_b and X_{τ_b} :

$$\mathbb{E}[e^{-\alpha\tau_b}] = \frac{\eta_1 - \beta_{1,\alpha}}{\eta_1} \frac{\beta_{2,\alpha}}{\beta_{2,\alpha} - \beta_{1,\alpha}} e^{-b\beta_{1,\alpha}} + \frac{\beta_{2,\alpha} - \eta_1}{\eta_1} \frac{\beta_{1,\alpha}}{\beta_{2,\alpha} - \beta_{1,\alpha}} e^{-b\beta_{2,\alpha}}$$

$$\mathbb{E}[e^{-\alpha\tau_b} \mathbf{1}_{\{X_{\tau_b} - b > y\}}] = e^{-\eta_1 y} \frac{(\eta_1 - \beta_{1,\alpha})(\beta_{2,\alpha} - \eta_1)}{\eta_1(\beta_{2,\alpha} - \beta_{1,\alpha})} [e^{-b\beta_{1,\alpha}} - e^{-b\beta_{2,\alpha}}] \text{ for all } y \geq 0$$

$$\mathbb{E}[e^{-\alpha\tau_b} \mathbf{1}_{\{X_{\tau_b} = b\}}] = \frac{\eta_1 - \beta_{1,\alpha}}{\beta_{2,\alpha} - \beta_{1,\alpha}} e^{-b\beta_{1,\alpha}} + \frac{\beta_{2,\alpha} - \eta_1}{\beta_{2,\alpha} - \beta_{1,\alpha}} e^{-b\beta_{2,\alpha}}$$

The definition of τ_b are same and definition of X equivalent to Z here.

Proof Con.

Based on the Theorem 3.1, we can get explicit formula of the Laplace transform for $\Psi(\mu, \sigma, \lambda, p, \eta_1, \eta_2; a, b, T)$ (write as $\Psi(a, b, T)$ for simplicity). Define the Laplace transform in T :

$$\Phi_\alpha(a, b) := \int_0^\infty e^{-\alpha T} \Psi(a, b, T) dT = \int_0^\infty e^{-\alpha T} \mathbb{E}[1_{\{\tau_b \leq T\}} 1_{\{X(T) \geq a\}}] dT$$

We first use Fubini Theorem and strong Markov property can rewrite the formula, then split by overshoot and use tail-integration eventuality we will end up with the following:

$$\begin{aligned} \Phi_\alpha(a, b) = & A_1 e^{-\beta_{1,\alpha}(a-b)} \left(\mathbb{E} \left[e^{-\alpha \tau_b} 1_{\{X_{\tau_b} = b\}} \right] + \beta_{1,\alpha} \int_0^{a-b} e^{\beta_{1,\alpha} y} \mathbb{E} \left[e^{-\alpha \tau_b} 1_{\{X_{\tau_b} - b > y\}} \right] dy \right) \\ & + B_1 e^{-\beta_{2,\alpha}(a-b)} \left(\mathbb{E} \left[e^{-\alpha \tau_b} 1_{\{X_{\tau_b} = b\}} \right] + \beta_{2,\alpha} \int_0^{a-b} e^{\beta_{2,\alpha} y} \mathbb{E} \left[e^{-\alpha \tau_b} 1_{\{X_{\tau_b} - b > y\}} \right] dy \right) \end{aligned}$$

where:

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

Back to the proof of the Theorem for Barrier option. First rewrite UIC as:

$$\begin{aligned}
 UIC &= E^{\mathbb{P}^*} [e^{-rT} (S(T) - K)^+ I_{\{\max_{0 \leq t \leq T} S(t) \geq H\}}] \\
 &= E^{\mathbb{P}^*} \left[e^{-rT} S(T) \mathbf{1}_{\{S(T) \geq K, \max_{0 \leq t \leq T} S(t) \geq H\}} \right] \\
 &\quad - K e^{-rT} \mathbb{P}^* \left[S(T) \geq K, \max_{0 \leq t \leq T} S(t) \geq H \right] \\
 &= I - K e^{-rT} \cdot II
 \end{aligned}$$

Since the log-price $X(t) = \log(S(t)/S(0))$:

$$S(T) \geq K \iff X(T) \geq \log \frac{K}{S(0)}, \quad \max_{0 \leq t \leq T} S(t) \geq H \iff \max_{0 \leq t \leq T} X(t) \geq \log \frac{H}{S(0)}.$$

Based on the definition of $\Psi(\mu, \sigma, \lambda, p, \eta_1, \eta_2; a, b, T)$:

$$II = \Psi \left(r - \frac{1}{2} \sigma^2 - \lambda \zeta, \sigma, \lambda, p, \eta_1, \eta_2; \log \left(\frac{K}{S(0)} \right), \log \left(\frac{H}{S(0)} \right), T \right)$$

Proof Con.

For the first term, we can use a change of numeraire argument. More precisely, introduce a new probability $\tilde{\mathbb{P}}$ defined as:

$$\left. \frac{d\tilde{\mathbb{P}}}{d\mathbb{P}^*} \right|_{t=T} = e^{-rT} \frac{S(T)}{S(0)} = e^{-rT} e^{X(T)} = \exp \left\{ \left(-\frac{1}{2} \sigma^2 - \lambda \zeta \right) T + \sigma W(T) + \sum_{i=1}^{N(T)} Y_i \right\}$$

Note that this is a well-defined probability as $\mathbb{E}^{\mathbb{P}^*}[e^{-rt}(S(t)/S(0))] = 1$. Then we reparametrize everything we need under $\tilde{\mathbb{P}}$. The Brownian part by Girsanov is $\tilde{W}(t) = W(t) - \sigma t$. The diffusion drift shifts by $+\sigma^2$, $\tilde{\mu} = r + \frac{1}{2}\sigma^2 - \lambda\zeta$. The modified jump rate and the jump distribution:

$$\text{New rate : } \tilde{\lambda} = \lambda \mathbb{E}^{\mathbb{P}^*}[e^Y] = \lambda(1 + \zeta), \quad \text{where } \zeta = \mathbb{E}^{\mathbb{P}^*}[e^Y] - 1 = \frac{p\eta_1}{\eta_1 - 1} + \frac{q\eta_2}{\eta_2 + 1} - 1$$

$$\text{New jump density: } \tilde{f}_Y(y) = \frac{e^y}{\mathbb{E}^{\mathbb{P}^*}[e^Y]} f_Y(y) = \tilde{p}\tilde{\eta}_1 e^{-\tilde{\eta}_1 y} \mathbf{1}_{y \geq 0} + \tilde{q}\tilde{\eta}_2 e^{\tilde{\eta}_2 y} \mathbf{1}_{y < 0}$$

$$\text{With: } \tilde{\eta}_1 = \eta_1 - 1, \quad \tilde{\eta}_2 = \eta_2 + 1, \quad \tilde{p} = p \left(\frac{p\eta_1}{\eta_1 - 1} + \frac{q\eta_2}{\eta_2 + 1} \right)^{-1} \frac{\eta_1}{\eta_1 - 1}, \quad \tilde{q} = q \left(\frac{p\eta_1}{\eta_1 - 1} + \frac{q\eta_2}{\eta_2 + 1} \right)^{-1} \frac{\eta_2}{\eta_2 + 1}$$

For I:

$$\begin{aligned} I &= S(0) \mathbb{E}^{\mathbb{P}^*} \left[e^{-rT} \frac{S(T)}{S(0)} \cdot \mathbf{1}_{\{S(T) \geq K, \max_{0 \leq t \leq T} S(t) \geq H\}} \right] \\ &= S(0) \tilde{\mathbb{P}} \left[S(T) \geq K, \min_{0 \leq t \leq T} S(t) \leq H \right] \\ &= S(0) \Psi \left(r + \frac{1}{2} \sigma^2 - \lambda \zeta, \sigma, \tilde{\lambda}, \tilde{p}, \tilde{\eta}_1, \tilde{\eta}_2; \log \left(\frac{K}{S(0)} \right), \log \left(\frac{H}{S(0)} \right), T \right) \end{aligned}$$

Pricing Path-Dependent Options with Jump Risk via Laplace Transforms

Steven Kou
Giovanni Petrella
Hui Wang

Derive the Laplace transforms for casepricing of European call and put options. Derive the two dimensional Laplace transform for barrier option.

European call and put options

The price of a European call and put with maturity T and strike K , is given:

$$C_T(k) = e^{-rT} \mathbb{E}^{\mathbb{P}^*} [(S(T) - K)^+] = e^{-rT} \mathbb{E}^{\mathbb{P}^*} \left[(S(0)e^{X(T)} - e^{-k})^+ \right]$$
$$P_T(k') = e^{-rT} \mathbb{E}^{\mathbb{P}^*} [(K - S(T))^+] = e^{-rT} \mathbb{E}^{\mathbb{P}^*} \left[(e^{k'} - S(0)e^{X(T)})^+ \right]$$

By the change of numeraire argument w.r.t $S(t)$:

$$C_T(k) = S(0)\tilde{\Psi}_C(k) - e^{-k}e^{-rT}\Psi_C(k)$$
$$P_T(k') = e^{k'}e^{-rT}\Psi_P(k') - S(0)\tilde{\Psi}_P(k')$$

where:

$$\Psi_C(k) = \mathbb{P}^*(S(T) \geq e^{-k}), \quad \tilde{\Psi}_C(k) = \tilde{\mathbb{P}}(S(T) \geq e^{-k})$$
$$\Psi_P(k') = \mathbb{P}^*(S(T) < e^{k'}), \quad \tilde{\Psi}_P(k') = \tilde{\mathbb{P}}(S(T) < e^{k'})$$

European call and put options Con.

Lemma. The Laplace transform with respect to k of $C_T(k)$ and with respect to k' for the put option $P_T(k')$ are given by:

$$\tilde{f}_C(\xi) := \int_{-\infty}^{\infty} e^{-\xi k} C_T(k) dk = e^{-rT} \frac{S(0)^{\xi+1}}{\xi(\xi+1)} \exp(G(\xi+1)T), \quad \xi > 0$$

$$\tilde{f}_P(\xi) := \int_{-\infty}^{\infty} e^{-\xi k'} P_T(k') dk' = e^{-rT} \frac{S(0)^{-\xi-1}}{\xi(\xi-1)} \exp(G(-(\xi-1))T), \quad \xi > 1$$

The Laplace transforms with respect to k of $\Psi_C(k)$ and k' of $\Psi_P(k')$ are:

$$\tilde{f}_{\Psi_C}(\xi) := \int_{-\infty}^{\infty} e^{-\xi k} \Psi_C(k) dk = \frac{S(0)^{\xi}}{\xi} \exp(G(\xi)T), \quad \xi > 0$$

$$\tilde{f}_{\Psi_P}(\xi) := \int_{-\infty}^{\infty} e^{-\xi k'} \Psi_P(k') dk' = e^{-rT} \frac{S(0)^{-\xi}}{\xi} \exp(G(-\xi)T), \quad \xi > 0$$

European call and put options Con.

Proof:

The Laplace transform for the call option is:

$$\hat{f}_C(\xi) = e^{-rT} \int_{-\infty}^{\infty} e^{-\xi k} \mathbb{E}^{\mathbb{P}^*} \left[(S(0)e^{X(T)} - e^{-k})^+ \right] dk$$

Applying the Fubini theorem yields for every $\xi > 0$:

$$\begin{aligned} \hat{f}_C(\xi) &= e^{-rT} \mathbb{E}^{\mathbb{P}^*} \left[\int_{-\infty}^{\infty} e^{-\xi k} (S(0)e^{X(T)} - e^{-k})^+ dk \right] \\ &= e^{-rT} \mathbb{E}^{\mathbb{P}^*} \left[\int_{-X(T) - \log S(0)}^{\infty} e^{-\xi k} (S(0)e^{X(T)} - e^{-k}) dk \right] \\ &= e^{-rT} \mathbb{E}^{\mathbb{P}^*} \left[S(0)e^{X(T)} e^{\xi(X(T) + \log S(0))} \frac{1}{\xi} - e^{(\xi+1)(X(T) + \log S(0))} \frac{1}{\xi+1} \right] \\ &= e^{-rT} \frac{S(0)^{\xi+1}}{\xi(\xi+1)} \mathbb{E}^{\mathbb{P}^*} \left[e^{(\xi+1)X(T)} \right] \stackrel{\text{MGF}}{=} e^{-rT} \frac{S(0)^{\xi+1}}{\xi(\xi+1)} e^{G(\xi+1)T} \end{aligned}$$

Similary, we can get the Laplace transform for the put option.

European call and put options Con.

The Laplace transforms with respect to k of $\Psi_C(k)$:

$$\begin{aligned}\hat{f}_{\Psi_C}(\xi) &= \int_{-\infty}^{\infty} e^{-\xi k} \mathbb{E}^{\mathbb{P}^*} \left[\mathbf{1}_{\{S(T) \geq e^{-k}\}} \right] dk \\&= \int_{-\infty}^{\infty} e^{-\xi k} \mathbb{E}^{\mathbb{P}^*} \left[\mathbf{1}_{\{k \geq -\log S(T)\}} \right] dk \\&= \mathbb{E}^{\mathbb{P}^*} \left[\int_{-\log S(T)}^{\infty} e^{-\xi k} dk \right] \\&= \frac{1}{\xi} \mathbb{E}^{\mathbb{P}^*} \left[S(T)^{\xi} \right] = \frac{S(0)^{\xi}}{\xi} \mathbb{E}^{\mathbb{P}^*} \left[e^{\xi X(T)} \right] \stackrel{\text{MGF}}{=} \frac{S(0)^{\xi}}{\xi} e^{G(\xi)T}\end{aligned}$$

Similary, we can get the Laplace transform for $\Psi_P(k')$.

Rewrite the pricing formula of up-and-in call option(UIC) in early slide:

$$UIC(k, T) = E^{\mathbb{P}^*} \left[e^{-rT} (S(T) - e^{-k})^+ I[\tau_b < T] \right]$$

where $H > S(0)$ is the barrier level, $k = -\log(K)$ the transformed strike and $b = \log(H/S(0))$. In previous paper, we obtain:

$$UIC(k, T) = S(0)\tilde{\Psi}_{UI}(k, T) - Ke^{-rT}\Psi_{UI}(k, T)$$

where:

$$\Psi_{UI}(k, T) = P^*(S(T) \geq e^{-k}, \tau_b < T), \quad \tilde{\Psi}_{UI}(k, T) = \tilde{P}(S(T) \geq e^{-k}, \tau_b < T)$$

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Theorem: For ξ and α such that $0 < \xi < \eta_1 - 1$ and $\alpha > \max(G(\xi + 1) - r, 0)$ (such a choice of ξ and α is possible for all small enough ξ as $G(1) - r = -\delta < 0$). The Laplace transform with respect to k and T of $UIC(k, T)$ is given by

$$\begin{aligned}\tilde{f}_{UIC}(\xi, \alpha) &= \int_0^\infty \int_{-\infty}^\infty e^{-\xi k - \alpha T} UIC(k, T) dk dT \\ &= \frac{H^{\xi+1}}{\xi(\xi+1)} \frac{1}{r + \alpha - G(\xi+1)} \left(A(r + \alpha) \frac{\eta_1}{\eta_1 - (\xi+1)} + B(r + \alpha) \right)\end{aligned}$$

where

$$\begin{aligned}A(h) &:= E^{\mathbb{P}^*} \left[e^{-h\tau_b} \mathbf{1}_{\{X(\tau_b) > b\}} \right] = \frac{(\eta_1 - \beta_{1,h})(\beta_{2,h} - \eta_1)}{\eta_1(\beta_{2,h} - \beta_{1,h})} \left[e^{-b\beta_{1,h}} - e^{-b\beta_{2,h}} \right] \\ B(h) &:= E^{\mathbb{P}^*} \left[e^{-h\tau_b} \mathbf{1}_{\{X(\tau_b) = b\}} \right] = \frac{\eta_1 - \beta_{1,h}}{\beta_{2,h} - \beta_{1,h}} e^{-b\beta_{1,h}} + \frac{\beta_{2,h} - \eta_1}{\beta_{2,h} - \beta_{1,h}} e^{-b\beta_{2,h}}\end{aligned}$$

with $b = \log(H/S(0))$.

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If $0 < \xi < \eta_1$ and $\alpha > \max(G(\xi), 0)$ (again this choice of ξ and α is possible for all ξ small enough as $G(0) = 0$), then the Laplace transform with respect to k and T of $\Psi_{UI}(k, T)$ is:

$$\begin{aligned}\tilde{f}_{\Psi_{UI}}(\xi, \alpha) &= \int_0^\infty \left(\int_{-\infty}^\infty e^{-\xi k - \alpha T} \Psi_{UI}(k, T) dk \right) dT \\ &= \frac{H^\xi}{\xi} \frac{1}{\alpha - G(\xi)} \left(A(\alpha) \frac{\eta_1}{\eta_1 - \xi} + B(\alpha) \right)\end{aligned}$$

The Laplace transforms with respect to k and T of $\tilde{\Psi}_{UI}(k, T)$ is given similarly with \tilde{G} replacing G and the functions \tilde{A} and \tilde{B} defined similarly.

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Proof: Follow the pricing formula of UIC and the Fubini theorem:

$$\begin{aligned}
 \tilde{f}_{UIC}(\xi, \alpha) &= \int_0^\infty \int_{-\infty}^\infty e^{-\xi k - (r+\alpha)T} \mathbb{E}^{\mathbb{P}^*} \left[\left(S(T) - e^{-k} \right)^+ \mathbf{1}_{\{\tau_b < T\}} \right] dk dT \\
 &= \mathbb{E}^{\mathbb{P}^*} \left[\int_0^\infty e^{-(r+\alpha)T} \mathbf{1}_{\{\tau_b < T\}} \left(\int_{-\log S(T)}^\infty e^{-\xi k} \left(S(T) - e^{-k} \right) dk \right) dT \right] \\
 &= \frac{1}{\xi(\xi+1)} \mathbb{E}^{\mathbb{P}^*} \left[\int_0^\infty e^{-(r+\alpha)T} \mathbf{1}_{\{\tau_b < T\}} S(T)^{\xi+1} dT \right] \\
 (T = \tau_b + t \text{ with } t > 0) &= \frac{1}{\xi(\xi+1)} \mathbb{E}^{\mathbb{P}^*} \left[e^{-(r+\alpha)\tau_b} \int_0^\infty e^{-(r+\alpha)t} S(t + \tau_b)^{\xi+1} dt \right] \\
 &= \frac{1}{\xi(\xi+1)} \mathbb{E}^{\mathbb{P}^*} \left[e^{-(r+\alpha)\tau_b} \mathbb{E}^{\mathbb{P}^*} \left[\int_0^\infty e^{-(r+\alpha)t} S(t + \tau_b)^{\xi+1} dt \middle| \mathcal{F}_{\tau_b} \right] \right] \\
 (i) &= \frac{1}{\xi(\xi+1)} \mathbb{E}^{\mathbb{P}^*} \left[e^{-(r+\alpha)\tau_b} S(\tau_b)^{\xi+1} \int_0^\infty e^{-(r+\alpha)t} \mathbb{E}^{\mathbb{P}^*} \left[e^{(\xi+1)X(t)} \right] dt \right]
 \end{aligned}$$

Where i is based on $S(\tau_b + t)^{\xi+1} = (S(\tau_b))^{\xi+1} \cdot e^{(\xi+1)(X(\tau_b+t) - X(\tau_b))}$ and strong Markov property that $\mathbb{E}^{\mathbb{P}^*} \left[e^{(\xi+1)(X(\tau_b+t) - X(\tau_b))} \middle| \mathcal{F}_{\tau_b} \right] = \mathbb{E}^{\mathbb{P}^*} \left[e^{(\xi+1)X(t)} \right]$

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$$\begin{aligned}(\text{MGF}) &= \frac{1}{\xi(\xi+1)} \mathbb{E}^{\mathbb{P}^*} \left[e^{-(r+\alpha)\tau_b} S(\tau_b)^{\xi+1} \int_0^\infty e^{-(r+\alpha)t} e^{G(\xi+1)t} dt \right] \\&= \frac{1}{\xi(\xi+1)} \frac{1}{r+\alpha-G(\xi+1)} \mathbb{E}^{\mathbb{P}^*} \left[e^{-(r+\alpha)\tau_b} S(\tau_b)^{\xi+1} \right] \\&= \frac{1}{\xi(\xi+1)} \frac{1}{r+\alpha-G(\xi+1)} \left\{ \mathbb{E}^{\mathbb{P}^*} \left[e^{-(r+\alpha)\tau_b} H^{\xi+1} \mathbf{1}_{\{X(\tau_b) > b\}} \right] \mathbb{E}^{\mathbb{P}^*} \left[e^{(\xi+1)\chi^+} \right] \right. \\&\quad \left. + \mathbb{E}^{\mathbb{P}^*} \left[e^{-(r+\alpha)\tau_b} H^{\xi+1} \mathbf{1}_{\{X(\tau_b) = b\}} \right] \right\} \\&= \frac{H^{\xi+1}}{\xi(\xi+1)} \frac{1}{r+\alpha-G(\xi+1)} \left\{ A(r+\alpha) \frac{\eta_1}{\eta_1 - (\xi+1)} + B(r+\alpha) \right\}\end{aligned}$$

Where $\chi^+ \sim \text{Exp}(\eta_1)$, and $A(h) := \mathbb{E}^{\mathbb{P}^*} [e^{-h\tau_b} \mathbf{1}_{\{X(\tau_b) > b\}}]$, $B(h) := \mathbb{E}^{\mathbb{P}^*} [e^{-h\tau_b} \mathbf{1}_{\{X(\tau_b) = b\}}]$. Kou-Wang compute $A(h)$ and $B(h)$ explicitly (via first-passage Laplace transforms) with $\beta_{1,h}, \beta_{2,h}$ being the two positive roots of $G(\beta) = h$:

$$\begin{aligned}A(h) &= \frac{(\eta_1 - \beta_{1,h})(\beta_{2,h} - \eta_1)}{\eta_1(\beta_{2,h} - \beta_{1,h})} (e^{-b\beta_{1,h}} - e^{-b\beta_{2,h}}) \\B(h) &= \frac{\eta_1 - \beta_{1,h}}{\beta_{2,h} - \beta_{1,h}} e^{-b\beta_{1,h}} + \frac{\beta_{2,h} - \eta_1}{\beta_{2,h} - \beta_{1,h}} e^{-b\beta_{2,h}}\end{aligned}$$

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For the Laplace transform of the probability Ψ_{UI} , apply the same trick we have:

$$\begin{aligned}\hat{f}_{\Psi_{UI}}(\xi, \alpha) &= \int_0^\infty \left[\int_{-\infty}^\infty e^{-\xi k - \alpha T} \cdot \mathbb{E}^{\mathbb{P}^*} \left\{ \mathbf{1}_{\{k > -\log(S(T)), \tau_b < T\}} \right\} dk \right] dT \\&= \mathbb{E}^{\mathbb{P}^*} \left\{ \int_{\tau_b}^\infty \left[\int_{-\log S(T)}^\infty e^{-\xi k - \alpha T} dk \right] dT \right\} \\&= \frac{1}{\xi} \mathbb{E}^{\mathbb{P}^*} \left\{ \int_{\tau_b}^\infty S(T)^\xi e^{-\alpha T} dT \right\} \\&= \frac{1}{\xi} \mathbb{E}^{\mathbb{P}^*} \left\{ e^{-\alpha \tau_b} \int_0^\infty \{S(t + \tau_b)\}^\xi e^{-\alpha t} dt \right\} \\&= \frac{1}{\xi} \mathbb{E}^{\mathbb{P}^*} \left\{ e^{-\alpha \tau_b} \mathbb{E}^{\mathbb{P}^*} \left[\int_0^\infty S(\tau_b + t)^\xi e^{-\alpha t} dt \middle| \mathcal{F}_{\tau_b} \right] \right\} \\&= \frac{1}{\xi} \frac{1}{\alpha - G(\xi)} \mathbb{E}^{\mathbb{P}^*} \left\{ e^{-\alpha \tau_b} [S(\tau_b)]^\xi \right\} \\&= \frac{1}{\xi} \frac{1}{\alpha - G(\xi)} \left\{ \mathbb{E}^{\mathbb{P}^*} \left[e^{-\alpha \tau_b} H^\xi \mathbf{1}_{[X(\tau_b) > b]} \right] \mathbb{E}^{\mathbb{P}^*} \left[e^{\xi X^+} \right] + \mathbb{E}^{\mathbb{P}^*} \left[e^{-\alpha \tau_b} H^\xi \mathbf{1}_{[X(\tau_b) = b]} \right] \right\} \\&= \frac{H^\xi}{\xi} \frac{1}{\alpha - G(\xi)} \left\{ A(\alpha) \frac{\eta_1}{\eta_1 - \xi} + B(\alpha) \right\}\end{aligned}$$