

Dimension reduction numerical methods for Bermudan options

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1. Dimension reduction approach
2. Fourier cosine method
3. Bermudan option pricing

- ▶ a dimension reduction approach, built on a combination of Monte Carlo and Fourier Cosine-based methods, for options in high-dimensional models
- ▶ realistic jump-diffusion models with stochastic variance and multi-factor stochastic interest rates applicable to foreign exchange options

- ▶ spot price with jumps

$$\frac{dS(t)}{S(t^-)} = (r - \lambda\delta) dt + \sigma dW_S(t) + dJ(t)$$

r : instantaneous interest rate

$W_S(t)$: Wiener process for spot price

$J(t)$: jump process, $J(t) = \sum_{j=0}^{N(t)} (y_j - 1)$

$N(t)$: number of jumps

y : jump amplitude, $\delta = \mathbb{E}[y - 1]$

λ : jump intensity

- ▶ spot price with jumps

$$\frac{dS(t)}{S(t^-)} = (r - \lambda\delta) dt + \sqrt{\nu(t)} dW_S(t) + dJ(t)$$

- ▶ stochastic volatility (CIR)

$$d\nu(t) = \kappa_\nu(\bar{\nu} - \nu(t)) dt + \sigma_\nu\sqrt{\nu(t)} dW_\nu(t)$$

κ_ν : mean-reversion rate

$\bar{\nu}$: mean volatility

σ_ν : volatility of volatility

$W_\nu(t)$: volatility Wiener process

- ▶ spot price with jumps

$$\frac{dS(t)}{S(t^-)} = (r(t) - \lambda\delta) dt + \sqrt{\nu(t)} dW_S(t) + dJ(t)$$

- ▶ multi-factor stochastic interest rates

$$r(t) = r(0) e^{-\kappa_r t} + \kappa_r \int_0^t \bar{r}(s) e^{-\kappa_r(t-s)} ds + \sum_{i=1}^m X_i(t)$$

$$dX_i(t) = -\kappa_{r_i} X_i(t) dt + \sigma_{r_i} dW_{r_i}(t)$$

κ_{r_i} : mean-reversion rate

$\bar{r}(t)$: mean interest rate

σ_{r_i} : volatility

$W_{r_i}(t)$: interest rate Wiener process

- ▶ spot price with jumps

$$\frac{dS(t)}{S(t^-)} = (r(t) - q(t) - \lambda\delta) dt + \sqrt{\nu(t)} dW_S(t) + dJ(t)$$

- ▶ stochastic volatility

$$d\nu(t) = \kappa_\nu(\bar{\nu} - \nu(t)) dt + \sigma_\nu\sqrt{\nu(t)} dW_\nu(t)$$

- ▶ multi-factor stochastic interest rates

$$r(t) = \gamma_r(t) + \sum_{i=1}^m X_i(t)$$

$$dX_i(t) = -\kappa_{r_i} X_i(t) dt + \sigma_{r_i} dW_{r_i}(t)$$

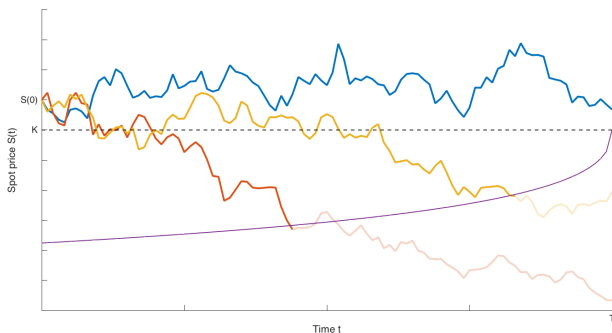
$$q(t) = \gamma_q(t) + \sum_{j=1}^n Y_j(t)$$

$$dY_j(t) = -\kappa_{q_j} Y_j(t) dt + \sigma_{q_j} dW_{q_j}(t)$$

Abstract

- ▶ Early exercise: Bermudan and American options, barriers
- ▶ Put option with exercise payoff $\Phi = (K - S_t)^+ \quad 0 \leq t \leq T$
- ▶ Optimal exercise boundary

$$V_0 = \sup_{\tau \in \mathcal{T}} \mathbb{E} [D(0, \tau) (K - S_\tau)^+], \quad D(0, \tau) = \exp \left(- \int_0^\tau r(s) ds \right)$$



The approach involves

1. applying conditional Monte Carlo on the variance factor
2. solving the conditional value using the Fourier Cosine method
3. enforcing the optimality condition at each early exercise date using the bundling technique

Numerical results indicate that the approach offers very efficient computation of the prices and hedging parameters.

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Dimension reduction approach

1. Conditional expectation

$$\begin{aligned}V(S_0, 0) &= \mathbb{E}[D(0, T) \Phi(S_T)] \\ &= \mathbb{E}\left[\mathbb{E}[D(0, T) \Phi(S_T) \mid \mathcal{G}_T]\right]\end{aligned}$$

- ▶ filtration $\{\mathcal{G}_t, 0 \leq t \leq T\}$ generated by the processes $\{W_\nu, W_{r_1}, \dots, W_{r_m}, W_{q_1}, \dots, W_{q_n}\}$ (all except W_S)

2. Inner expectation: PDE methods

- ▶ Feynman-Kac link between \mathbb{E} and PDE
- ▶ analytical solution using Fourier transforms
- ▶ dimension reduction to 1

3. Outer expectation: Monte Carlo simulation

$$V(S(0), 0) = \mathbb{E} \left[\mathbb{E} [D(0, T) \Phi(S(T)) \mid \mathcal{G}_T] \right]$$

- ▶ Using Feynman-Kac formula

$$V(S(0), 0) = \mathbb{E} \left[U(S(0), 0; \mathcal{G}_T) \right]$$

where $U(\cdot)$ is the unique solution to the conditional PIDE

$$\begin{aligned} \frac{\partial U}{\partial t} + \frac{a_{11}^2}{2} \nu(t) S^2 \frac{\partial^2 U}{\partial S^2} + (r(t) - q(t) - \lambda \delta) S \frac{\partial U}{\partial S} \\ - (r(t) + \lambda) U + \lambda \int_0^\infty U(Sy) g(y) dy = 0 \end{aligned}$$

with terminal condition

$$U(S(T), T; \mathcal{G}_T) = \Phi(S(T))$$

Dimension reduction

► $z(t) = \log S(t)$, $u(z, \cdot) = U(S, \cdot)$, $v(z, \cdot) = V(S, \cdot)$

► Fourier transform $\hat{u}(\xi)$ of conditional PIDE

$$\begin{aligned} \frac{\partial \hat{u}}{\partial t} + \frac{a_{11}^2}{2} \nu(t) (i\xi)^2 \hat{u} + (r(t) - q(t) - \lambda\delta - \frac{a_{11}^2}{2}) (i\xi) \hat{u} \\ - (r(t) + \lambda) \hat{u} + \lambda \Gamma(\xi) \hat{u} = 0 \end{aligned}$$

► ODE can be solved in 1 timestep

$$\begin{aligned} \hat{v}(\xi, t) = \mathbb{E} \left[\hat{\Phi}(\xi) \exp \left(-\xi^2 \int_0^T \frac{a_{11}^2}{2} \nu(t) dt + i\xi \int_0^T \left(r(t) - q(t) - \lambda\delta - \frac{\nu(t)}{2} \right) dt \right. \right. \\ \left. \left. + i\xi \sum_j a_{1j} \int_0^T \sqrt{\nu(t)} dW_j(t) - \int_0^T (r(t) + \lambda) dt + \lambda T \Gamma(\xi) \right) \right] \end{aligned}$$

► Dimension reduction, $\mathbb{E} \left[\exp \left(\int_0^T r(t) dt \right) \right]$

$$\hat{v}(\xi, t) = \mathbb{E} \left[\hat{\Phi}(\xi) \exp \left(-G\xi^2 + iF\xi + H + \lambda T \Gamma(\xi) \right) \right]$$

Dimension reduction

$$G = \frac{a_{1,1}^2}{2} \int_0^T \nu(t) dt + \frac{1}{2} \sum_{k=2}^{h-1} \int_0^T \left(\sum_{j=1}^m a_{(j+1),k} \beta_{d_j}(t) - \sum_{j=1}^l a_{(j+m+1),k} \beta_{f_j}(t) + a_{1,k} \sqrt{\nu(t)} \right)^2 dt$$

$$\begin{aligned} F = & -\frac{1}{2} \int_0^T \nu(t) dt + a_{1,h} \int_0^T \sqrt{\nu(t)} dW_\nu(t) \\ & + \sum_{j=1}^m a_{(j+1),h} \int_0^T \beta_{d_j}(t) dW_\nu(t) - \sum_{j=1}^l a_{(j+m+1),h} \int_0^T \beta_{f_j}(t) dW_\nu(t) \\ & + \sum_{j=1}^l \rho_{s,f_j} \int_0^T \beta_{f_j}(t) \sqrt{\nu(t)} dt - \sum_{k=2}^{h-1} \sum_{j=1}^m \int_0^T a_{1,k} a_{(j+1),k} \beta_{d_j}(t) \sqrt{\nu(t)} dt \\ & - \sum_{k=2}^{h-1} \int_0^T \sum_{j=1}^m a_{(j+1),k} \beta_{d_j}(t) \left(\sum_{j=1}^m a_{(j+1),k} \beta_{d_j}(t) - \sum_{j=1}^l a_{(j+m+1),k} \beta_{f_j}(t) \right) dt \\ & + \int_0^T (\gamma_d(t) - \gamma_f(t)) dt - \lambda \delta T \end{aligned}$$

$$H = -\sum_{j=1}^m a_{(j+1),h} \int_0^T \beta_{d_j}(t) dW_\nu(t) - \int_0^T \gamma_d(t) dt + \frac{1}{2} \sum_{k=2}^{h-1} \int_0^T \left(\sum_{j=1}^m a_{(j+1),k} \beta_{d_j}(t) \right)^2 dt - \lambda T$$

$$\begin{aligned}\hat{v}(\xi, t) &= \mathbb{E} \left[\hat{\Phi}(\xi) \exp \left(-G\xi^2 + iF\xi + H + \lambda T \Gamma(\xi) \right) \right] \\ &= \mathbb{E} \left[\hat{\Phi}(\xi) \hat{L}(\xi) \right]\end{aligned}$$

- ▶ Inverse transform (convolution theorem)

$$v(z(0), 0) = \mathbb{E} \left[\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} \phi(x) L(z-x) dx \right]$$

- ▶ Solution: integrate L , expand $e^{\lambda T \Gamma(\xi)}$ in Taylor series

$$V(S(0), 0) = \mathbb{E} \left[\sum_{n=0}^{\infty} \frac{(\lambda T)^n}{n!} \left(S(0) e^{F+G+H+W_n} \mathcal{N}(d_{1,n}) - K e^H \mathcal{N}(d_{2,n}) \right) \right]$$

Bermudan options

t_n : exercise date timesteps $n = 0, \dots, N$, $t_N = T$

$$z(t) = \log \frac{S(t)}{K}$$

$$\phi(z) = [K(1 - e^z)]^+, \text{ exercise payoff}$$

$v_m(z, t_n)$: value conditional on variance path $m = 1, \dots, M$

$c_m(z, t_n)$: continuation value

- ▶ At maturity, $v_m(z, t_N) = \phi(z) \forall m$
- ▶ At prior exercise dates,

$$v_m(z, t_n) = \max(\phi(z), c_m(z, t_n))$$

$$c_m(z, t_n) = \int_{-\infty}^{+\infty} v_m(x, t_{n+1}) L_m(z, x) dx$$

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If $f(x)$ is an even function periodic on $[-\pi, \pi]$

$$f(x) = \sum_{k=0}^{\infty} A_k \cos(kx)$$
$$A_k = \frac{2}{\pi} \int_0^{\pi} f(x) \cos(kx) dx$$

If $f(x)$ decays rapidly as $x \rightarrow \pm\infty$, for a period $[a, b]$:

$$f(x) = \sum_{k=0}^{\infty} A_k \cos\left(\frac{k\pi}{b-a}(x-a)\right)$$
$$A_k = \frac{2}{b-a} \int_a^b f(x) \cos\left(\frac{k\pi}{b-a}x\right) dx$$

Fourier cosine method

(Fang, Oosterlee, 2008)

Risk-neutral value

$$v(z, t_n) = e^{-r\Delta t} \int_{\mathbb{R}} v(x, t_{n+1}) f(x|z) dx$$

Apply Fourier cosine expansion to density $f(x|z)$

$$f(x|z) = \sum_{k=0}^{\infty} A_k(z) \cos\left(\frac{k\pi}{b-a}(x-a)\right)$$

$$\begin{aligned} v(z, t_n) &\approx e^{-r\Delta t} \sum_{k=0}^{\infty} A_k(z) \left[\int_a^b v(x, t_{n+1}) \cos\left(\frac{k\pi}{b-a}(x-a)\right) dx \right] \\ &= e^{-r\Delta t} \sum_{k=0}^{\infty} A_k(z) C_k(t_n) \end{aligned}$$

$$\begin{aligned} A_k(z) &= \frac{2}{b-a} \int_a^b f(x|z) \cos\left(\frac{k\pi}{b-a}(x-a)\right) dx \\ &= \frac{2}{b-a} \operatorname{Re} \left\{ e^{-ik\pi \frac{a}{b-a}} \int_a^b f(x|z) \exp\left(i \frac{k\pi}{b-a} x\right) dx \right\} \\ &\approx \frac{2}{b-a} \operatorname{Re} \left\{ e^{-ik\pi \frac{a}{b-a}} \hat{f}\left(\frac{k\pi}{b-a}; z\right) \right\} \end{aligned}$$

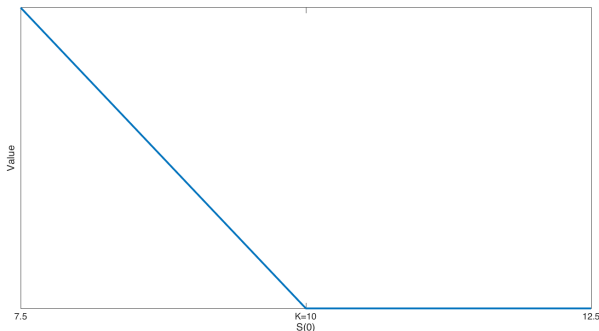
- ▶ Integral involving density f replaced with characteristic function \hat{f}

Value coefficient

$$C_k(t_n) = \int_a^b v(x, t_{n+1}) \cos\left(\frac{k\pi}{b-a}(x-a)\right) dx$$

At maturity,

$$C_k(T) = \int_a^b \phi(x) \cos\left(\frac{k\pi}{b-a}(x-a)\right) dx$$

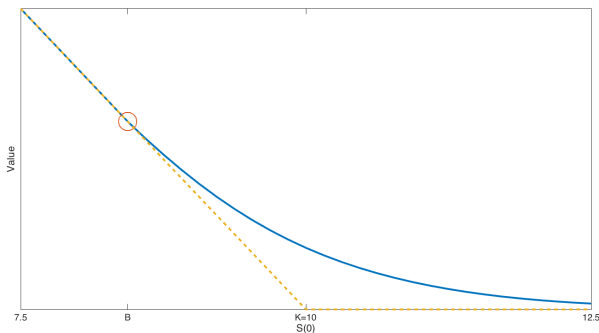


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Value coefficient

At prior exercise dates, separate at optimal exercise barrier $B(t_n)$

$$v_m(z, t_n) = \max(\phi(z), c_m(z, t_n)) \quad v(z, t_n) = \phi(z) \text{ for } z \leq B(t_n)$$

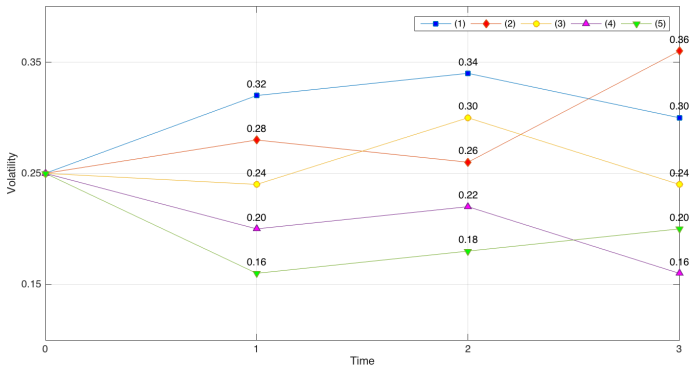


$$C_k(t_n) = \int_a^{B(t_n)} \phi(x) \cos\left(\frac{k\pi}{b-a}(x-a)\right) dx + \int_{B(t_n)}^b v(x, t_{n+1}) \cos\left(\frac{k\pi}{b-a}(x-a)\right) dx$$

$$\begin{aligned}C_k(t_n) &= \int_a^{B(t_n)} \phi(x) \cos\left(\frac{k\pi}{b-a}(x-a)\right) dx + \int_{B(t_n)}^b v(x, t_{n+1}) \cos\left(\frac{k\pi}{b-a}(x-a)\right) dx \\&= I_{\text{PAY},k}(B(t_n)) + \int_{B(t_n)}^b v(x, t_{n+1}) \cos\left(\frac{k\pi}{b-a}(x-a)\right) dx \\&\approx I_{\text{PAY},k}(B(t_n)) + \\&\quad \text{Re}\left\{ \sum_{j=0}^J C_j(t_{n+1}) \hat{f}\left(\frac{k\pi}{b-a}; 0\right) \int_{B(t_n)}^b e^{i\frac{j\pi}{b-a}x} \cos\left(\frac{k\pi}{b-a}(x-a)\right) dx \right\} \\&= I_{\text{PAY},k}(B(t_n)) + \text{Re}\left\{ \sum_{j=0}^J C_j(t_{n+1}) \hat{f}\left(\frac{k\pi}{b-a}; 0\right) I_{\text{CONT},k}(B(t_n)) \right\}\end{aligned}$$

- Solve $C_k(t_n)$ backwards in time using $C_k(t_{n+1})$

Simulation and bundling



$$v(z, t_n) = \sum_k' e^{-i \frac{k\pi}{b-a} z} \sum_{m=1}^M \frac{L_{k,m}(t_n) C_{k,m}(t_n)}{M}$$

$$L_{k,m}(t_n) = \exp \left(-G_m(t_n) \left(\frac{k\pi}{b-a} \right)^2 + i (F_m(t_n) - a) \frac{k\pi}{b-a} + H_m(t_n) \right)$$

$$C_{k,m}(t_n) = I_{\text{PAY},k}(B_m(t_n)) + \sum_j' C_{j,m}(t_{n+1}) \operatorname{Re} \{ A_{j,m}(t_n) I_{\text{CONT},j}(B_m(t_n)) \}$$

Price for multiple S and K

$$v(z, t_0) = \sum_k' e^{-i \frac{k\pi}{b-a} z} \sum_{m=1}^M \frac{L_{k,m}(t_0) C_{k,m}(t_0)}{M}$$

$$\bar{C}_k(t_0) = \sum_{m=1}^M \frac{L_{k,m}(t_0) C_{k,m}(t_0)}{M}$$

$$V(S(0), K, t_0) = \sum_k' \bar{C}_k(t_0) \left(\frac{S(0)}{K} \right)^{-i \frac{k\pi}{b-a}}$$

Algorithm

begin

Simulate M variance paths: $\nu_m(t)$, $m = 1, \dots, M$, $\nu_m(0) = \nu_0 \forall m$;

Partition the variance space into P partitions;

$\bar{C}_{k,p}(t_N) \leftarrow I_{\text{PAY},k}(0) \forall k, p$;

for $t_n \leftarrow t_{N-1}$ **to** t_1 **do**

for $p \leftarrow 1$ **to** P **do**

$\mathcal{M} \leftarrow$ index set of variance paths in partition p at time t_n ;

foreach m **in** \mathcal{M} **do**

 Determine early exercise boundary $z \leftarrow B_m(t_n)$;

 Calculate value coefficient $C_{k,m}(t_n) \leftarrow I_{\text{PAY},k}(z) +$

$$\text{Re} \left\{ \sum_{j=0}^J \bar{C}_{k,q}(t_{n+1}) L_{k,m}(t_n) I_{\text{CONT},k}(z) \right\}$$

$\bar{C}_{k,p}(t_n) \leftarrow \sum_{m \in \mathcal{M}} \frac{1}{|\mathcal{M}|} C_{k,m}(t_n)$;

$\bar{C}_k(t_0) \leftarrow \sum_{m=1}^M \frac{1}{M} L_{k,m}(t_0) C_{k,m}(t_1)$;

$V(S, K) = \sum_k' \bar{C}_k(t_0) \left(\frac{S}{K} \right)^{i \frac{k\pi}{b-a}}$;

Thank you!