Approximate Basket Options Valuation for Local Volatility Jump-Diffusion Models

Harry Zheng
Imperial College London
(joint work with Guoping Xu, Citigroup)

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Introduction

- A basket option is an exotic option whose payoff depends on value of a portfolio of assets.
- Basket options are difficult to price and hedge due to lack of analytic characterization of distribution of sum of correlated random variables.
- Monte Carlo normally used, which is simple and accurate but time-consuming. Other methods include numerical PDE, lower and upper bounds, analytic approximations, see Lord (2006).
- Most work assume that underlying asset prices follow geometric Brownian motions. Basket value is sum of correlated lognormal variables.

Model Formulation

- $(\Omega, P, \mathcal{F}, \mathcal{F}_t)$ risk-neutral probability space, $\mathcal{F}_t$ natural filtration generated by correlated Brownian motions $W_1, \ldots, W_n$ with correlation matrix (ρ_{ij}) and independent Poisson processes $N_0, \ldots, N_n$ with intensities $\lambda_0 \ldots, \lambda_n$. Brownian motions and Poisson processes are independent to each other.

- Portfolio n assets and discounted asset prices $S_1, \ldots, S_n$ satisfy SDE

$$\frac{dS_i(t)}{S_i(t)} = \sigma_i dW_i(t) + h_i^0 d[N_0(t) - \lambda_0 t] + h_i^1 d[N_i(t) - \lambda_i t], \tag{1}$$

  for $i = 1, \ldots, n$, where σ_i volatilities, h_i^0, h_i^1 percentage jump sizes of assets i at time of jumps of Poisson processes N_0 and N_i, respectively. All coefficients constant.

Basket Options

- Discounted basket value at time T given by

$$S(T) = \sum_{i=1}^{n} w_i S_i(T)$$

where w_i positive constant weights, which can be written as

$$S(T) = \sum_{i=1}^{n} a_i e^{\sigma_i W_i + c_i^0 N_0 + c_i^1 N_i} \tag{2}$$

where $a_i = w_i S_i(0) e^{(-\frac{1}{2}\sigma_i^2 - h_i^0 \lambda_0 - h_i^1 \lambda_i)T}$, $c_i^0 = \ln(1 + h_i^0)$, $c_i^1 = \ln(1 + h_i^1)$, $W_i \sim N(0, T)$, and $N_i \sim Pos(\lambda_i T)$, $i = 1, \ldots, n$.

- Basket call option price at time 0 given by

$$C_0 = \mathbf{E}[S(T) - K)^+]$$

where K discounted exercise price, T maturity time, E risk-neutral expectation.

Approximation Methods

- For $h_i^0 = h_i^1 = 0$, $S(T)$ is sum of lognormal rvs.
- Idea is to find a simple random variable to approximate $S(T)$ and then to use it to get a closed-form pricing formula. Approximating variable is required to match some moments of $S(T)$.
- Levy (1992) uses a lognormal variable, Posner and Milevsky (1998) a shifted lognormal variable, Milevsky and Posner (1998) a reciprocal gamma variable. Error can only be estimated by numerical analysis.
- Curran (1994) introduces conditioning variable and conditional moment matching. Option price is decomposed into two parts: one can be calculated exactly and the other approximately by conditional moment matching method. Conditioning approach can also be used to find bounds of the basket option (Rogers and Shi (1995)).

Curran (1994) Work

- Assume asset prices S_i GBMs.
- Find a conditioning rv Λ which has strong correlation with $S(T)$ and satisfies

$$\Lambda \geq c \Longrightarrow S(T) \geq K$$

  for some constant c.
- Basket option price can be decomposed as

$$\mathbf{E}[(S(T)-K)^+] = \mathbf{E}[(S(T)-K)1_{[\Lambda \geq c]}] + \mathbf{E}[(S(T)-K)^+ 1_{[\Lambda < c]}].$$

- Choose Λ a lognormal variable (geometric average) to find closed-form expression for first part and use lognormal variable to find approximate value of second part.
- It's not known what conditioning variables should be used for JD asset price models.

Conditioning Variable for JD Models

- From (2) we have

$$\begin{aligned} S(T) &= \sum_{i=1}^{n} a_i e^{\sigma_i W_i + c_i^0 N_0 + c_i^1 N_i} \\ &\geq c_1 + m_0 N_0 + m_2 N + \sigma W \end{aligned}$$

where $N_0 \sim Pos(\lambda_0 T)$ and

$$N = \sum_{i=1}^{n} N_i \sim Pos(\lambda T) \quad \text{and} \quad W = \frac{1}{\sigma} \sum_{i=1}^{n} a_i \sigma_i W_i \sim N(0,1)$$

and $\lambda = \sum_{i=1}^{n} \lambda_i$, $\sigma^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} a_i a_j \rho_{ij} \sigma_i \sigma_j T$, c_1, m_0, m_2 some constant. N_0, N and W independent to each other.

- Choose $X = (N_0, N, W)$ and define $\Lambda = m_0 N_0 + m_2 N + \sigma W$ and $c = K - c_1$ then $S(T) \geq K$ whenever $\Lambda \geq c$. This choice is to extract maximal information from normal and Poisson variables.

Bounds

- Method of finding lower and upper bounds of basket option price in Rogers and Shi (1995) and Nielsen and Sandmann (2003) works for JD model (1) by conditioning on $\{\Lambda \geq c\}$. This leads to

$$\mathrm{LB} \leq \mathbf{E}[(S(T) - K)^+] \leq \mathrm{UB}$$

  where

$$\begin{aligned}\mathrm{LB} &= \mathbf{E}\left[(\mathbf{E}[S(T)|X] - K)^+\right] \\ \mathrm{UB} &= LB + \frac{1}{2}\mathbf{E}\left[\mathrm{var}(S(T)|X)1_{[\Lambda<c]}\right]^{\frac{1}{2}}\mathbf{E}[1_{[\Lambda<c]}]^{\frac{1}{2}}.\end{aligned}$$

- Numerical tests show that lower bound is in general very tight whereas upper bound has large deviations to exact value.
- Curran (1994) used lower bound to approximate basket option price.

Errors

- Denote by $A^X = \mathbf{E}[S(T)|X]$. Error between lower bound and exact value is given by

$$\begin{aligned} & \mathbf{E}[(S(T)-K)^+] - LB \\ = & \mathbf{E}[(S(T)-K)^+ 1_{[\Lambda<c]}] - \mathbf{E}[(A^X-K)^+ 1_{[\Lambda<c]}]. \end{aligned}$$

- Error is caused by replacing $S(T)1_{[\Lambda<c]}$ with $A^X 1_{[\Lambda<c]}$.
- A simple calculation shows that

$$\mathbf{E}[S(T)1_{[\Lambda<c]}] = \mathbf{E}[A^X 1_{[\Lambda<c]}] \tag{3}$$

$$\mathrm{Var}(S(T)1_{[\Lambda<c]}) = \mathrm{Var}(A^X 1_{[\Lambda<c]}) + \mathbf{E}[\mathrm{Var}(S(T)|X)1_{[\Lambda<c]}]. \tag{4}$$

- If we can find a random variable which matches first two moments of $S(T)1_{[\Lambda<c]}$ then we may reduce error and improve accuracy.

A New Approximation

- Let Y be rv independent of $S(T)$ and X and satisfy

$$\mathbf{E}[S(T)1_{[\Lambda<c]}] = \mathbf{E}[(A^X + Y)1_{[\Lambda<c]}] \quad (5)$$

$$\mathrm{Var}(S(T)1_{[\Lambda<c]}) = \mathrm{Var}((A^X + Y)1_{[\Lambda<c]}) \quad (6)$$

- After some calculation we can show Y must satisfy

$$\mathbf{E}[Y] = 0 \quad \text{and} \quad \mathbf{E}[Y^2] = \frac{\mathbf{E}[\mathrm{Var}(S(T)|X)1_{[\Lambda<c]}]}{\mathbf{E}[1_{[\Lambda<c]}]} \equiv y_0^2. \quad (7)$$

- $Y \sim N(0, y_0^2)$ will do. We choose discrete rv Z to avoid integration:

$$P(Z = -\sqrt{3}y_0) = 1/6, \quad P(Z = 0) = 2/3, \quad P(Z = \sqrt{3}y_0) = 1/6.$$

- We approximate $C(T, K)$ by

$$C^A(T, K) := \mathbf{E}[(S(T) - K)1_{[\Lambda \geq c]}] + \mathbf{E}[(A^X + Z - K)^+ 1_{[\Lambda<c]}] \quad (8)$$

Then

$$\mathrm{LB} \leq C^A(T, K) \leq \mathrm{UB}.$$

Time	Vol	M's	MC (stdev)	PEA	LB	UB	RG	LN
1	0.2	0.9	19.49 (0.01)	19.48	19.46	20.09	18.10	18.73
		1	14.34 (0.01)	14.34	14.32	15.03	13.36	13.83
		1.1	10.28 (0.01)	10.28	10.26	11.04	9.79	10.06
	0.5	0.9	25.01 (0.02)	24.97	24.84	26.66	23.00	24.61
		1	20.55 (0.02)	20.49	20.36	22.39	18.81	20.03
		1.1	16.84 (0.02)	16.76	16.64	18.87	15.43	16.60
	0.8	0.9	32.62 (0.02)	32.42	32.05	35.82	28.57	32.49
		1	28.77 (0.03)	28.50	28.15	32.34	24.88	28.65
		1.1	25.42 (0.03)	25.10	24.77	29.40	21.79	25.33
3	0.2	0.9	28.95 (0.04)	28.98	28.80	32.32	25.51	27.94
		1	24.71 (0.04)	24.72	24.55	28.10	21.56	23.81
		1.1	21.06 (0.04)	21.05	20.90	24.48	18.30	20.29
	0.5	0.9	38.80 (0.03)	39.03	37.95	47.46	31.90	38.38
		1	35.32 (0.02)	35.37	34.41	44.10	28.49	34.92
		1.1	32.23 (0.02)	32.13	31.28	41.14	25.58	31.85
	0.8	0.9	51.53 (0.07)	51.91	49.33	65.65	36.99	52.07
		1	48.87 (0.05)	48.81	46.51	63.48	33.96	49.42
		1.1	46.44 (0.07)	46.05	43.96	61.58	31.34	47.00
RMSE				**0.18**	1.06	7.30	7.02	0.53

Table 1: Basket option values and bounds with varying maturity T, volatility σ, and moneyness $K/S(0)$. Data: number of assets $n = 2$, correlation of Brownian motions $\rho_{12} = 0.3$, jump intensities $\lambda_0 = 2$, $\lambda_1 = 1$, $\lambda_2 = 0.5$, jump sizes $h_i^0 = h_i^1 = -0.2$, and interest rate $r = 0.05$.

Introduction to Local Volatility Basket Options

- To price basket options for general asset price processes one may study directly the basket value and its associated stochastic process which may contain stochastic volatilities and/or stochastic jump intensities and sizes. Dupire (1994) shows that any diffusion model with stochastic volatility can be replaced by a LV model without changing European option price.

- We discuss European basket options pricing for a LV JD model. Main idea is to reduce a multi-dimensional LV JD model to a *one-dimensional* SV JD model, then to derive a forward PIDE for basket options price with an *unknown* conditional expectation, or LV function, and finally to apply the asymptotic expansion method to approximate LV function.

- Numerical tests show that method discussed here, asymptotic expansion method, performs very well for most cases in comparison with the Monte Carlo method and the Partial Exact Approximation method discussed in Xu and Zheng (2009).

Local Volatility Model Formulation

- Assume a portfolio is composed of n assets and the risk-neutral asset prices S_i satisfy SDEs:

$$dS_i(t) = \sigma_i(t, S_i(t-))dW_i(t) + S_i(t-)(dZ(t) - \lambda m dt), \tag{9}$$

where W_i are standard Brownian motions with correlation matrix (ρ_{ij}), Z is a compound Poisson process

$$Z(t) := \sum_{l=1}^{N(t)} (e^{Y_l} - 1)$$

with N a Poisson process with intensity λ and $\{Y_l\}$ iid normal variables with mean η and variance γ^2, $m = \mathbf{E}[e^{Y_l} - 1] = e^{\eta + \frac{1}{2}\gamma^2} - 1$, σ_i bounded LV functions. Assume $\{W_i\}$, N, and $\{Y_l\}$ are independent of each other.

- Basket value $S(t)$ at time t is defined by

$$S(t) = \sum_{i=1}^{n} w_i S_i(t).$$

Equivalent Stochastic Volatility Model

- Define

$$V(t)^2 := \sum_{i,j=1}^{n} w_i w_j \sigma_i(t, S_i(t)) \sigma_j(t, S_j(t)) \rho_{ij}$$

$$W(t) := \int_0^t \frac{1}{V(u)} \sum_{i=1}^{n} w_i \sigma_i(u, S_i(u)) dW_i(u)$$

Then W standard Brownian motion.

- Basket value S follows SDE

$$dS(t) = V(t)dW(t) + S(t-)(dZ(t) - \lambda m dt) \tag{10}$$

with initial price $S(0) = \sum_{i=1}^{n} w_i S_i(0)$.

- $V(t)$ is a SV which depends on individual asset prices, not just the basket price, and (10) is a SV JD asset price model.

Forward PIDE

Andersen and Andreasen (2000) show that European call option price $C(T,K)$ at time 0 as a function of maturity $T>0$ and exercise price $K\geq 0$ satisfies a forward PIDE:

$$\begin{aligned} C_T(T,K) &= \lambda m K C_K(T,K) + \frac{1}{2}\sigma(T,K)^2 C_{KK}(T,K) \\ &\quad + \lambda\int_{-\infty}^{\infty} C(T,Ke^{-y})e^{y}\phi_{\eta,\gamma^2}(y)dy - \lambda(1+m)C(T,K) \qquad (11) \end{aligned}$$

with initial condition $C(0,K)=(S(0)-K)^+$ and LV function σ , defined by

$$\begin{aligned} \sigma(T,K)^2 &= \mathbf{E}[V(T)^2|S(T)=K] \\ &= \sum_{i,j=1}^{n} w_i w_j \rho_{ij}\mathbf{E}[\sigma_i(T,S_i(T))\sigma_j(T,S_j(T))|S(T)=K]. \qquad (12) \end{aligned}$$

Note σ is an *unkonwn* LV function.

Approximation of LV Function

- Main difficulty is how to compute conditional expectation (12) as asset prices S_i have no closed-form expressions.
- If $\sigma_i(t,S) = \sigma_i S$ for all (t,S), then there is a closed form solution to SDE (9) and there are some efficient approximation techniques for basket value process S, see Xu and Z (2009).
- Piterbarg (2007) uses Taylor formula to approximate $\sigma_i(T, S_i(T))$ to first order wrt $S_i(T)$ at point $S_i(0)$ to get

$$\sigma_i(T, S_i(T)) \approx p_i + q_i(S_i(T) - S_i(0))$$

  where $p_i = \sigma_i(T, S_i(0))$ and $q_i = \frac{\partial}{\partial S_i}\sigma_i(T, S_i(0))$.
- We use same first order approximation to get

$$\sigma_i(T, S_i(T))\sigma_j(T, S_j(T)) \ \approx \ p_i p_j + p_j q_i(S_i(T) - S_i(0)) + p_i q_j(S_j(T) - S_j(0)).$$

- We may approximate LV function as

$$\sigma(T,K)^2 \approx \sum_{i,j=1}^{n} w_i w_j \rho_{ij} p_i p_j (1 + \varphi_i(T,K) + \varphi_j(T,K))$$

where

$$\varphi_i(T,K) = \frac{q_i}{p_i} \mathbf{E}[S_i(T) - S_i(0) | S(T) = K].$$

- To obtain analytical approximation to $\mathbf{E}[S_i(T) - S_i(0)|S(T) = K]$, we use asymptotic expansion approach related to small diffusion and small jump intensity and size, see Benhamou et al. (2009).

- Perturbation and its purpose are different. We use asymptotic expansion to find *unknown* LV function and then use it in forward PIDE, while Benhamou et al. (2009) use a different asymptotic expansion to a process with a *known* LV function and then find options value directly.

Perturbation of SDEs

- Assume $\epsilon \in [0,1]$ and define

$$dS_i^\epsilon(t) = -\lambda m^\epsilon S_i^\epsilon(t-)dt + \epsilon\sigma_i(t, S_i^\epsilon(t))dW_i(t) + S_i^\epsilon(t-)dZ^\epsilon(t)$$

with $S_i^\epsilon(0) = S_i(0)$, where $m^\epsilon = \mathbf{E}[e^{\epsilon Y_1} - 1] = e^{\epsilon\eta + \frac{1}{2}\epsilon^2\gamma^2} - 1$ and $Z^\epsilon(t) = \sum_{l=1}^{N(t)}(e^{\epsilon Y_l} - 1)$. Note that $S_i^1(T) = S_i(T)$.

- If we define

$$S_i^{(k)}(t) = \frac{\partial^k S_i^\epsilon(t)}{\partial \epsilon^k}\bigg|_{\epsilon=0}$$

then the first order asymptotic expansion around $\epsilon = 0$ for $S_i^\epsilon(T)$ is

$$S_i^\epsilon(T) \approx S_i^{(0)}(T) + S_i^{(1)}(T)\epsilon. \tag{13}$$

- After some computation, we have $S_i^{(0)}(T) \equiv S_i(0)$ and

$$S_i^{(1)}(T) = -\lambda\eta S_i(0)T + \int_0^T \sigma_i(t, S_i(0))dW_i(t) + S_i(0)\sum_{l=1}^{N(T)} Y_l.$$

- The asset value $S_i(T)$ at time T may be approximated by

$$S_i(T) = S_i^1(T) \approx S_i(0) + S_i^{(1)}(T)$$

and basket value by

$$S(T) \approx S_c(T) := S(0) + \sum_{i=1}^{n} w_i S_i^{(1)}(T). \tag{14}$$

- We chosen $\epsilon = 1$ in (13) to get approximation above, similar approach used in Ju (2002) for Asian options and Kawai (2003) for swaptions.

- Conditional on $N(T) = k$, variable $S_i^{(1)}(T)$, written as $S_i^{(1)}(T, k)$, normal variable with mean $(-\lambda T + k)\eta S_i(0)$ and variance $\int_0^T \sigma_i^2(t, S_i(0))dt + k\gamma^2 S_i(0)^2$, variable $S_c(T)$, written as $S_c(T, k)$, normal variable with mean $\mu_c(k) = (1 - \lambda T\eta + k\eta)S(0)$, variance

$$\sigma_c(k)^2 = \sum_{i,j=1}^{n} w_i w_j \left[\left(\int_0^T \sigma_i(t, S_i(0))\sigma_j(t, S_j(0))dt \right)\rho_{ij} + k\gamma^2 S_i(0)S_j(0) \right].$$

Approximation of LV Function

After lengthy computation, we can approximate LV function $\sigma(T,K)$ in (12) by

$$\sigma(T,K)^2 \approx a(T) + b(T)K - c(T)S(0), \tag{15}$$

where

$$\begin{aligned}
a(T) &= \sum_{i,j=1}^{n} w_i w_j \rho_{ij} p_i p_j \\
b(T) &= \sum_{i,j=1}^{n} \sum_{k=0}^{\infty} \frac{P(N(T)=k)}{\sigma_c(k)^2} w_i w_j \rho_{ij} p_i p_j \left(\frac{q_i}{p_i} C_i(k) + \frac{q_j}{p_j} C_j(k) \right) \\
c(T) &= \sum_{i,j=1}^{n} \sum_{k=0}^{\infty} \frac{P(N(T)=k)}{\sigma_c(k)^2} w_i w_j \rho_{ij} p_i p_j \left(\frac{q_i}{p_i} C_i(k) + \frac{q_j}{p_j} C_j(k) \right) (1 - \lambda T \eta + k\eta),
\end{aligned}$$

and $C_i(k)$ is the covariance of $S_i^{(1)}(T,k)$ and $S_c(T,k)$, given by

$$C_i(k) = \sum_{j=1}^{n} w_j \left[\rho_{ij} \left(\int_0^T \sigma_i(t, S_i(0)) \sigma_j(t, S_j(0)) dt \right) + k\gamma^2 S_i(0) S_j(0) \right].$$

Numerical Test

- MC method provides the benchmark results.
- AE (Asymptotic Expansion) method is to solve PIDE (11) with approximate LV function (15) and explicit-implicit finite difference method of Cont and Voltchkova (2005).
- CV (Control Variate) method approximates basket value $S(T)$ with a tractable variable $S_c(T)$ and finds a closed form pricing formula from

$$\mathbf{E}[(S_c(T) - K)^+] = \sum_{k=0}^{\infty} P(N(T) = k)\mathbf{E}[(S_c(T, k) - K)^+]. \quad (16)$$

  This approach is similar to Benhamou et al. (2009), with difference that we only expand to first order while Benhamou et al. to second order.
- number of assets $n = 4$, weights $w_i = 0.25$, correlation of Brownian motions $\rho_{ij} = 0.3$, initial asset prices $S_i(0) = 100$, exercise price $K = 100$. We choose a CEV model

$$\sigma_i(t, S) = \alpha S^{\beta}, \quad Y_l \sim N(\eta, \gamma^2) \quad \eta = -0.3,\ \gamma = 0.35.$$

λ			0.3			1		
T	α	β	MC (stdev)	AE (err%)	CV (err%)	MC (stdev)	AE (err%)	CV (err%)
1	0.1	1	6.99 (0.02)	7.00 (0.1)	8.4 (20.2)	15.23 (0.03)	15.28 (0.3)	18.20 (20.0)
	0.2		8.84 (0.01)	8.84 (0.0)	9.91 (12.1)	15.76 (0.05)	15.79 (0.2)	18.62 (18.2)
	0.5		15.89 (0.02)	15.62(1.7)	16.51 (3.9)	20.24 (0.04)	20.02 (1.1)	22.34 (10.4)
	0.1	0.8	6.45 (0.01)	6.45 (0.0)	8.13 (26.1)	15.14 (0.03)	15.17 (0.2)	18.09 (19.5)
	0.2		6.72 (0.01)	6.73 (0.2)	8.24 (22.6)	15.20 (0.04)	15.23 (0.2)	18.15 (19.4)
	0.5		8.83 (0.02)	8.83 (0.0)	9.89 (12.0)	15.75 (0.02)	15.79 (0.3)	18.62 (18.2)
	0.1	0.5	6.43 (0.01)	6.44 (0.2)	8.12 (26.3)	15.11 (0.03)	15.15 (0.3)	18.07 (19.6)
	0.2		6.44 (0.01)	6.44 (0.0)	8.12 (26.1)	15.12 (0.03)	15.16 (0.3)	18.07 (19.5)
	0.5		6.49 (0.01)	6.49 (0.0)	8.14 (25.4)	15.15 (0.05)	15.19 (0.3)	18.10 (19.5)
3	0.1	1	14.70 (0.02)	14.71 (0.1)	17.46 (18.8)	27.00 (0.07)	27.03 (0.1)	31.92 (18.2)
	0.2		16.85 (0.03)	16.79 (0.4)	19.11 (13.4)	28.08 (0.06)	28.04 (0.1)	32.93 (17.3)
	0.5		27.99 (0.04)	26.51 (5.3)	29.19 (4.3)	35.31 (0.06)	33.92 (3.9)	39.44 (11.7)
	0.1	0.8	14.27 (0.02)	14.29 (0.1)	17.12 (20.0)	26.64 (0.07)	26.74 (0.4)	31.63 (18.7)
	0.2		14.48 (0.02)	14.49 (0.1)	17.30 (19.5)	26.82 (0.07)	26.91 (0.3)	31.79 (18.5)
	0.5		16.81 (0.02)	16.80 (0.1)	19.09 (13.6)	28.07 (0.06)	28.09 (0.1)	32.92 (17.3)
	0.1	0.5	14.22 (0.01)	14.23 (0.1)	17.07 (20.0)	26.58 (0.04)	26.68 (0.4)	31.58 (18.8)
	0.2		14.23 (0.01)	14.25 (0.1)	17.07 (20.0)	26.62 (0.05)	26.69 (0.3)	31.59 (18.7)
	0.5		14.31 (0.02)	14.32 (0.1)	17.15 (20.0)	26.71 (0.06)	26.78 (0.3)	31.66 (18.5)
Average			(0.02)	(**0.5**)	(18.0)	(0.05)	(**0.5**)	(17.9)

Summary

- We discuss local volatility jump-diffusion asset price processes for which European basket option price can be approximated with reasonable accuracy and computed efficiently.
- Main difficulty is to compute conditional expectation when there is no closed form formulas for asset prices and basket value.
- Methods used are moment matching of conditioning random variables, asymptotic expansion of asset prices, smart Taylor expansion of local volatility functions, and implicit-explicit FD method for PIDE.
- Numerical tests (limited) show results are good compared with MC and other methods.
- Further research: (1) theoretical error bound estimation and analysis, (2) local volatility model with individual and common jumps, and (3) sensitivity and hedging.

References

Talk is based on following papers:

- Xu, G. and H. Zheng (2009). Approximate basket options valuation for a jump-diffusion model, *Insurance: Mathematics and Economics*, **45**, 188-194.
- Xu, G. and H. Zheng (2010). Basket options valuation for a local volatility jump-diffusion model with the asymptotic expansion method, *Insurance: Mathematics and Economics* **47**, 415-422.