

Multivariate option pricing models: some extensions of the α VG model

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Actuarial and Financial Statistics workshop, Eindhoven

August 29th-30th, 2011

Time change in finance

- time-changed Brownian motion $W(T(t))$ in finance: first proposed by Clark (1973) \Rightarrow Business clock $T(t)$ (positive stochastic process) quantifies the information arrival rate
 - Motivation: information flow directly affects evolution of the price: when low amount of available information, slow trading and price process evolves slowly
 - time change T : characteristics
 - no loss of information over time \Rightarrow **non decreasing** process
 - amount of new information independent on the amount of information previously released \Rightarrow **independent increments**
 - amount of released information during $[t, t + dt]$ only depends on the length of that interval dt \Rightarrow **stationary increments**
- $\Rightarrow T \equiv \text{subordinator}$ (non-decreasing Lévy process)

Lévy processes

Definition

$X = \{X_t, t \geq 0\}$ defined on $(\Omega, \mathcal{F}, \mathbb{P})$ is a **Lévy process** if

- X starts at 0: $X_0 = 0$ a.s.;
- X has independent increments;
- X has stationary increments.

$\Rightarrow X_{t+s} - X_s \sim$ infinitely divisible distribution and has $(\phi(u))^t$ as CF,
where $\phi(u)$ is the CF of X_1 .

Definition

Lévy-Khintchine representation of an infinitely divisible distribution CF:

$$\log(\phi_X(u)) = i\gamma u - \frac{\sigma^2}{2}u^2 + \int_{-\infty}^{+\infty} (\exp(iux) - 1 - iux\mathbf{1}_{|x|<1}) \nu(dx)$$

where $\gamma \in \mathbb{R}$, $\sigma^2 \geq 0$ and ν is a measure on $\mathbb{R} \setminus \{0\}$ satisfying
 $\int_{-\infty}^{+\infty} \inf \{1, x^2\} \nu(dx) < \infty$



Example: the VG process as time-changed Brownian motion (BM)

The Gamma process

- CF of $\text{Gamma}(a, b)$ with $a > 0, b > 0$:

$$\phi_{\text{Gamma}}(u; a, b) = \left(1 - \frac{iu}{b}\right)^{-a}$$

- **Scaling property:** if $X \sim \text{Gamma}(a, b)$ then

$$cX \sim \text{Gamma}(a, b/c), c > 0 \quad (1)$$

$$X_t \sim \text{Gamma}(at, b) \quad (2)$$

- If $X_i \sim \text{Gamma}(a_i, b)$ are N independent r.v. then

$$\sum_{i=1}^N X_i \sim \text{Gamma}\left(\sum_{i=1}^N a_i, b\right) \quad (3)$$

Example: the VG process as time-changed Brownian motion (Cont)

The VG process

- VG(σ, ν, θ) process \equiv Gamma time-changed BM with drift

$$X_t^{\text{VG}}(\sigma, \nu, \theta) = \theta G_t + \sigma W_{G_t}$$

where $G = \{G_t, t \geq 0\} \sim \text{Gamma}(t/\nu, 1/\nu)$ process and

$W = \{W_t, t \geq 0\}$ is a standard Brownian motion

- CF of VG(σ, ν, θ) with $\sigma > 0, \nu > 0, \theta \in \mathbb{R}$:

$$\phi_{\text{VG}}(u; \sigma, \nu, \theta) = \left(1 - iu\theta\nu + \frac{u^2\sigma^2\nu}{2}\right)^{-\frac{1}{\nu}}$$

| | VG(σ, ν, θ) | VG($\sigma, \nu, 0$) |
|----------|--|------------------------|
| mean | θ | 0 |
| variance | $\sigma^2 + \nu\theta^2$ | σ^2 |
| skewness | $\frac{\theta\nu(3\sigma^2 + 2\nu\theta^2)}{(\sigma^2 + \nu\theta^2)^{\frac{3}{2}}}$ | 0 |
| kurtosis | $3\left(1 + 2\nu - \frac{\nu\sigma^4}{(\sigma^2 + \nu\theta^2)^2}\right)$ | $3(1 + \nu)$ |

Multivariate Lévy models as time changed BM

- ① multivariate BM subordinated by an univariate time change (Madan and Senata, 1990).

Unique business clock \Rightarrow independence can not be captured

- ② α VG model (Semeraro, 2008):

extend multivariate time changed BM by considering a subordinator = sum of idiosyncratic and common Gamma subordinators:

$$G_t^{(i)} = X_t^{(i)} + \alpha_i Z_t$$

Original model: constraints on the Gamma subordinator parameters such that $G_1^{(i)} \sim \text{Gamma}$. CFs: independent of common subordinator settings \Rightarrow calibration requires multivariate derivatives

- ③ multivariate Lévy two factors models (Luciano and Semeraro, 2010):

extend the α VG model to other subordinator distributions

Some extensions of the α VG model

- ① **relax the constraints** imposed on the subordinator parameters in the original model
- ② consider **Sato processes** instead of Lévy processes

The α VG model

$$\mathbf{S}_t = \begin{pmatrix} S_t^{(1)} \\ S_t^{(2)} \\ \dots \\ S_t^{(N)} \end{pmatrix} = \begin{pmatrix} \frac{S_0^{(1)} \exp((r-q_1)t + Y_t^{(1)})}{\mathbb{E}[\exp(Y_t^{(1)})]} \\ \frac{S_0^{(2)} \exp((r-q_2)t + Y_t^{(2)})}{\mathbb{E}[\exp(Y_t^{(2)})]} \\ \dots \\ \frac{S_0^{(N)} \exp((r-q_N)t + Y_t^{(N)})}{\mathbb{E}[\exp(Y_t^{(N)})]} \end{pmatrix}$$

$$\mathbf{Y}_t = \begin{pmatrix} Y_t^{(1)} \\ Y_t^{(2)} \\ \dots \\ Y_t^{(N)} \end{pmatrix} = \begin{pmatrix} \theta_1 G_t^{(1)} + \sigma_1 W_{G_t^{(1)}}^{(1)} \\ \theta_2 G_t^{(2)} + \sigma_2 W_{G_t^{(2)}}^{(2)} \\ \dots \\ \theta_N G_t^{(N)} + \sigma_N W_{G_t^{(N)}}^{(N)} \end{pmatrix} \quad \mathbf{G}_t = \begin{pmatrix} G_t^{(1)} \\ G_t^{(2)} \\ \dots \\ G_t^{(N)} \end{pmatrix} = \begin{pmatrix} X_t^{(1)} + \alpha_1 Z_t \\ X_t^{(2)} + \alpha_2 Z_t \\ \dots \\ X_t^{(N)} + \alpha_N Z_t \end{pmatrix}$$

where $W^{(i)}$'s are independent standard BM, $\alpha_i > 0$,

$Z_1 \sim \text{Gamma}(c_1, c_2)$, $c_1, c_2 > 0$ and $X_1^{(i)} \sim \text{Gamma}(a_i, b_i)$, $a_i, b_i > 0$ are independent r.v. and are independent of the $W^{(i)}$'s.

The α VG model: CF's

- CF of \mathbf{Y}_t :

$$\begin{aligned}\phi_{\mathbf{Y}}(\mathbf{u}, t) = \mathbb{E} [\exp(i\mathbf{u}'\mathbf{Y}_t)] &= \prod_{i=1}^N \phi_{X_1^{(i)}} \left(u_i \theta_i + i \frac{1}{2} \sigma_i^2 u_i^2, t \right) \\ &\quad \phi_{Z_1} \left(\sum_{i=1}^N \alpha_i \left(u_i \theta_i + i \frac{1}{2} \sigma_i^2 u_i^2 \right), t \right)\end{aligned}$$

- marginal CF's

$$\phi_{Y^{(i)}}(u, t) = \left(1 - i \frac{u \theta_i + i \frac{1}{2} \sigma_i^2 u^2}{b_i} \right)^{-a_i t} \left(1 - i \frac{\alpha_i}{c_2} \left(u \theta_i + i \frac{1}{2} \sigma_i^2 u^2 \right) \right)^{-c_1 t}$$

- $c_2 = 1$ (by space scaling property (1))
- On average, business time grows as the real time:

$$\mathbb{E} [G_t^{(i)}] = t \Rightarrow \frac{a_i}{b_i} = 1 - \alpha_i \frac{c_1}{c_2} \quad (4) \Rightarrow$$

$$\mathbf{b}_i \left(1 - \alpha_i \frac{c_1}{c_2} \right) > \mathbf{0} \quad (5)$$

The α VG model: correlation

$$\rho_{ij} = \frac{\text{Cov}\left(Y_t^{(i)}, Y_t^{(j)}\right)}{\sqrt{\text{Var}\left(Y_t^{(i)}\right) \text{Var}\left(Y_t^{(j)}\right)}}$$

where

$$\begin{cases} \text{Cov}\left(Y_t^{(i)}, Y_t^{(j)}\right) = \theta_i \theta_j \alpha_i \alpha_j \frac{c_1}{c_2^2} t \\ \text{Var}\left(Y_t^{(i)}\right) = \left(\theta_i^2 \left(\frac{a_i}{b_i^2} + \alpha_i^2 \frac{c_1}{c_2^2}\right) + \sigma_i^2 \left(\frac{a_i}{b_i} + \alpha_i \frac{c_1}{c_2}\right)\right) t \end{cases}$$

⇒ time independent correlations

The original α VG model

Original α VG model:

impose $\mathbf{b}_i = \frac{c_2}{\alpha_i}$ $\forall i$ such that

$$G_1^{(i)} \stackrel{(3)}{\sim} \text{Gamma}\left(a_i + c_1, \frac{c_2}{\alpha_i}\right) \stackrel{(4)}{\equiv} \text{Gamma}\left(\frac{c_2}{\alpha_i}, \frac{c_2}{\alpha_i}\right) \Rightarrow$$

$$\phi_{Y^{(i)}}(u, t) = \left(1 - i \frac{\alpha_i}{c_2} \left(u\theta_i + i \frac{1}{2}\sigma_i^2 u^2\right)\right)^{-\frac{c_2}{\alpha_i}t}$$

$$\Rightarrow Y_1^{(i)} \sim \mathbf{VG}\left(\sigma_i, \frac{\alpha_i}{c_2}, \theta_i\right)$$

\Rightarrow CFs independent of the common subordinator setting

$$\rho_{ij} = \frac{\theta_i \theta_j \alpha_i \alpha_j}{\sqrt{\left(\frac{\theta_i^2}{b_i} + \sigma_i^2\right) \left(\frac{\theta_j^2}{b_j} + \sigma_j^2\right)}} c_1 \propto c_1.$$

The generalized α VG model

Generalized α VG model:

relax the constraints on the b_i 's \Rightarrow

$$\begin{aligned}\phi_{Y^{(i)}}(u, t) &= \left(1 - i\frac{u\theta_i + i\frac{1}{2}\sigma_i^2 u^2}{b_i}\right)^{-a_i t} \left(1 - i\frac{\alpha_i}{c_2} (u\theta_i + i\frac{1}{2}\sigma_i^2 u^2)\right)^{-c_1 t} \\ &= (\phi_{Y^{(i)}}(u, 1))^t\end{aligned}$$

\Rightarrow CFs depend on the whole parameter set

$Y_t^{(i)} \sim$ Lévy process (but not necessarily VG)

Towards the Sato two factors models

Extend the two factors Lévy model to the class of Sato processes:

- Sato processes typically lead to a significantly better fit of option prices in both the strike and time to maturity dimensions in the univariate case (Carr, Geman, Madan and Yor, 2007)

Sato processes

Definition

X is **self-decomposable** if $X \stackrel{d}{=} cX + X_c$, $\forall 0 < c < 1$, where X_c is independent of X .

Self-decomposable distributions are infinitely divisible distributions with a Lévy-Khintchine representation

$$\log \Phi_X(u) = i\gamma u - \frac{\sigma^2}{2}u^2 + \int_{-\infty}^{+\infty} (\exp(iux) - 1 - iux\mathbf{1}_{|x|<1}) \frac{h(x)}{|x|} dx$$

where $h(x) \geq 0$ is decreasing for $x > 0$ and increasing for $x < 0$.

The probability law of the Sato process at time t is obtained by scaling the self-decomposable law of X at unit time:

$$X_t \stackrel{d}{=} t^\gamma X,$$

where γ = self-similar exponent. Sato processes have independent but time inhomogeneous increments.

The Sato VG process

- From the Lévy density of the VG process,

$$\nu_{\text{VG}}(dx) = \begin{cases} \frac{C \exp(Gx)}{|x|} dx & x < 0, \\ \frac{C \exp(-Mx)}{|x|} dx & x > 0, \end{cases}$$

the VG probability law at unit time is self-decomposable for all acceptable VG parameter sets $\{\sigma, \nu, \theta\}$.

- CF of VG Sato process at time t :

$$X_t^{\text{VG Sato}}(\sigma, \nu, \theta, \gamma) = t^\gamma X_1^{\text{VG}}(\sigma, \nu, \theta)$$

$$\begin{aligned}\phi_{\text{VG Sato}}(u, t; \sigma, \nu, \theta, \gamma) &= \phi_{\text{VG}}(u, 1; t^\gamma \sigma, \nu, t^\gamma \theta) \\ &= \left(1 - i u \nu \theta t^\gamma + \frac{\sigma^2 \nu t^{2\gamma} u^2}{2}\right)^{\frac{-1}{\nu}}.\end{aligned}$$

The Sato α VG model

$$\mathbf{Y}_t = \begin{pmatrix} Y_t^{(1)} \\ Y_t^{(2)} \\ \dots \\ Y_t^{(N)} \end{pmatrix} = \begin{pmatrix} \theta_1 t^{\gamma_1} G^{(1)} + \sigma_1 t^{\gamma_1} W_{G^{(1)}}^{(1)} \\ \theta_2 t^{\gamma_2} G^{(2)} + \sigma_2 t^{\gamma_2} W_{G^{(2)}}^{(2)} \\ \dots \\ \theta_N t^{\gamma_N} G^{(N)} + \sigma_N t^{\gamma_N} W_{G^{(N)}}^{(N)} \end{pmatrix}$$

$$\mathbf{G} = \begin{pmatrix} G^{(1)} \\ G^{(2)} \\ \dots \\ G^{(N)} \end{pmatrix} = \begin{pmatrix} X^{(1)} + \alpha_1 Z \\ X^{(2)} + \alpha_2 Z \\ \dots \\ X^{(N)} + \alpha_N Z \end{pmatrix}$$

where $W^{(i)}$'s are independent standard BM, $\alpha_i > 0$,
 $Z \sim \text{Gamma}(c_1, c_2)$, $c_1, c_2 > 0$ and $X^{(i)} \sim \text{Gamma}(a_i, b_i)$,
 $a_i, b_i > 0$ are independent random variables and are independent of
the $W^{(i)}$'s.

The Sato α VG model (Cont)

- CF of \mathbf{Y}_t :

$$\begin{aligned}\phi_{\mathbf{Y}}(\mathbf{u}, t) = \mathbb{E} [\exp(\mathbf{i}\mathbf{u}'\mathbf{Y}_t)] &= \prod_{i=1}^N \phi_{X^{(i)}} \left(u_i \theta_i t^{\gamma_i} + \mathbf{i} \frac{1}{2} \sigma_i^2 t^{2\gamma_i} u_i^2 \right) \\ &\phi_{Z_1} \left(\sum_{i=1}^N \alpha_i \left(u_i \theta_i t^{\gamma_i} + \mathbf{i} \frac{1}{2} \sigma_i^2 t^{2\gamma_i} u_i^2 \right) \right).\end{aligned}$$

- marginal CF's

$$\phi_{Y^{(i)}}(u, t) = \left(1 - \mathbf{i} \frac{u \theta_i t^{\gamma_i} + \mathbf{i} \frac{1}{2} \sigma_i^2 t^{2\gamma_i} u^2}{b_i} \right)^{-a_i} \left(1 - \mathbf{i} \frac{\alpha_i}{c_2} \left(u \theta_i t^{\gamma_i} + \mathbf{i} \frac{1}{2} \sigma_i^2 t^{2\gamma_i} u^2 \right) \right)^{-c_1}$$

- $c_2 = 1$

- $\mathbb{E} [G^{(i)}] = 1 \Rightarrow \frac{a_i}{b_i} = 1 - \alpha_i \frac{c_1}{c_2} \Rightarrow b_i \left(1 - \alpha_i \frac{c_1}{c_2} \right) > 0$

The Sato α VG model: correlations

$$\rho_{ij} = \frac{\text{Cov}\left(Y_t^{(i)}, Y_t^{(j)}\right)}{\sqrt{\text{Var}\left(Y_t^{(i)}\right) \text{Var}\left(Y_t^{(j)}\right)}}$$

where

$$\text{Cov}\left(Y_t^{(i)}, Y_t^{(j)}\right) = \theta_i \theta_j \alpha_i \alpha_j \frac{c_1}{c_2^2} t^{\gamma_i + \gamma_j}$$

and

$$\text{Var}\left[Y_t^{(i)}\right] = \left(\theta_i^2 \left(\frac{a_i}{b_i^2} + \alpha_i^2 \frac{c_1}{c_2^2}\right) + \sigma_i^2 \left(\frac{a_i}{b_i} + \alpha_i \frac{c_1}{c_2}\right)\right) t^{2\gamma_i}$$

$$\Rightarrow \rho_{ij}^{\text{Sato}} = \rho_{ij}^{\text{Lévy}}$$

The original Sato α VG model

- Original Sato α VG model:

impose $\mathbf{b}_i = \frac{\mathbf{c}_2}{\alpha_i}$ $\forall i$ such that $G^{(i)} \sim \text{Gamma}(b_i, b_i) \Rightarrow$

$$\phi_{Y^{(i)}}(u, t) = \left(1 - i \frac{u \theta_i t^{\gamma_i} + i \frac{1}{2} \sigma_i^2 t^{2\gamma_i} u^2}{b_i} \right)^{-b_i}$$

$$\Rightarrow Y_t^{(i)} \sim \mathbf{VG\ Sato} \left(\sigma_i, \frac{1}{b_i}, \theta_i, \gamma_i \right)$$

\Rightarrow CFs independent of the common subordinator setting

$$\rho_{ij} = \frac{\theta_i \theta_j \alpha_i \alpha_j}{\sqrt{\left(\frac{\theta_i^2}{b_i} + \sigma_i^2\right) \left(\frac{\theta_j^2}{b_j} + \sigma_j^2\right)}} c_1 \propto c_1.$$

The generalized Sato α VG model

- Generalized Sato α VG model:

relax the constraints on the b_i 's \Rightarrow

$$\begin{aligned}\phi_{Y^{(i)}}(u, t) &= \left(1 - i \frac{u\theta_i t^{\gamma_i} + i \frac{1}{2} \sigma_i^2 t^{2\gamma_i} u^2}{b_i}\right)^{-a_i} \\ &\quad \left(1 - i \frac{\alpha_i}{c_2} (u\theta_i t^{\gamma_i} + i \frac{1}{2} \sigma_i^2 t^{2\gamma_i} u^2)\right)^{-c_1}\end{aligned}$$

\Rightarrow CFs depend on the whole parameter set

The generalized Sato α VG model

Under the generalized Sato model, $Y_t^{(i)} \sim \text{Sato}$

Proof.

$$\begin{aligned}\phi_{Y^{(i)}}(u, 1) &= \left(1 - i\frac{u\theta_i + i\frac{1}{2}\sigma_i^2 u^2}{b_i}\right)^{-a_i} \left(1 - i\frac{\alpha_i}{c_2} (u\theta_i + i\frac{1}{2}\sigma_i^2 u^2)\right)^{-c_1} \\ &= \phi_{\mathbf{VG}}\left(u; \sqrt{\frac{a_i}{b_i}}\sigma_i, \frac{1}{a_i}, \frac{a_i}{b_i}\theta_i\right) \phi_{\mathbf{VG}}\left(u; \sqrt{\frac{c_1}{c_2}\alpha_i}\sigma_i, \frac{1}{c_1}, \frac{c_1}{c_2}\alpha_i\theta_i\right)\end{aligned}$$

$\Rightarrow Y_1^{(i)} \stackrel{d}{=} U_1^{(i)} + U_2^{(i)}$, where $U_1^{(i)} \sim \mathbf{VG}\left(\sqrt{\frac{a_i}{b_i}}\sigma_i, \frac{1}{a_i}, \frac{a_i}{b_i}\theta_i\right)$ and
 $U_2^{(i)} \sim \mathbf{VG}\left(\sqrt{\frac{c_1}{c_2}\alpha_i}\sigma_i, \frac{1}{c_1}, \frac{c_1}{c_2}\alpha_i\theta_i\right)$ are independent VG r.v $\Rightarrow Y_1^{(i)}$'s
are self decomposable since they are the sum of 2 self
decomposable r.v. □

Calibration: original α VG model I

Original α VG model:

dissociate the calibration of the univariate option surfaces and the calibration of the correlations (Leoni and Schoutens 2008, Luciano and Semeraro 2010):

- ① simultaneous calibration of each option surface:

$$\text{MRMSE} = \sum_{i=1}^N \frac{\text{RMSE}^{(i)}}{N} = \sum_{i=1}^N \frac{1}{N} \sqrt{\frac{\sum_{j=1}^{M^{(i)}} (P_j^{(i)} - \hat{P}_j^{(i)})^2}{M^{(i)}}}$$

where

- $N \equiv$ number of underlying stocks
- $M^{(i)} \equiv$ number of quoted options for the i th stock
- $P_j^{(i)} \equiv$ j th market option price of the i th stock
- $\hat{P}_j^{(i)} \equiv$ j th model option price of the i th stock

$\Rightarrow \equiv N$ univariate option surface calibrations since CF's do not share any common parameter

Calibration: original α VG model II

- ② calibrate parameters which do not influence any marginal CF, i.e. c_1 on market implied or historical stock correlations (Moving Window or EWMA technique):

$$\text{RMSE}^{\rho} = \sqrt{\frac{1}{\frac{N^2-N}{2}} \sum_{i,j \neq i}^N (\rho_{ij} - \hat{\rho}_{ij})^2}$$

BUT: (5) $\Rightarrow c_1 < \frac{1}{\max_i \alpha_i}$ AND only 1 parameter to fit $\frac{N^2-N}{2}$ correlations

Calibration: generalized α VG model

Generalized α VG model

- Univariate option surfaces only: minimize

$$\sum_i \frac{\text{RMSE}^{(i)}}{N} = \sum_i \frac{\text{RMSE}^{(i)}(\theta_i, \sigma_i, \alpha_i, b_i | c_1)}{N}$$

and repeat for different values of $c_1 \Rightarrow \text{MRMSE}^*$.

- Univariate option surfaces + correlation:

$$\text{MRMSEJ} = \sum_{i=1}^N \frac{\text{RMSE}^{(i)}}{N} + \alpha^\rho \text{MRMSE}^* \sqrt{\frac{1}{\frac{N^2-N}{2}} \sum_{j,k \neq j}^N (\rho_{jk} - \hat{\rho}_{jk})^2}$$

where MRMSE^* = optimal value of MRMSE given by the calibration of the option surfaces and $\alpha^\rho \geq 0$ specifies the relative importance of the correlation matching

Numerical study: data I

- basket = 4 of the 10 largest (market cap) S&P500 components which satisfy:

$$D_i \leq K(1 - \exp(-r(t_{i+1} - t_i))), \quad i = 1, 2, \dots, n-1$$

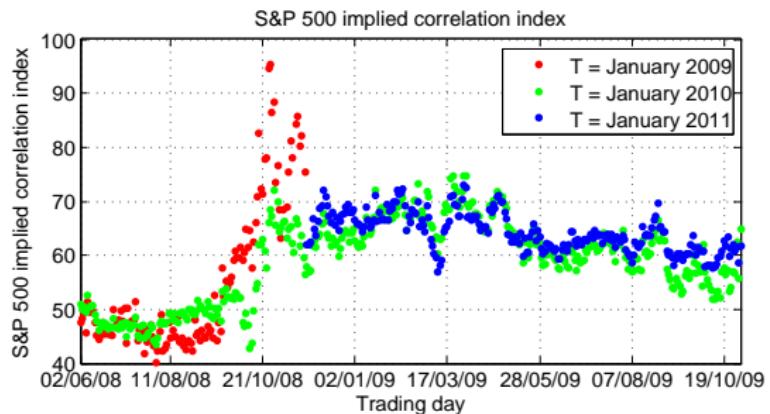
and

$$D_n \leq K(1 - \exp(-r(T - t_n)))$$

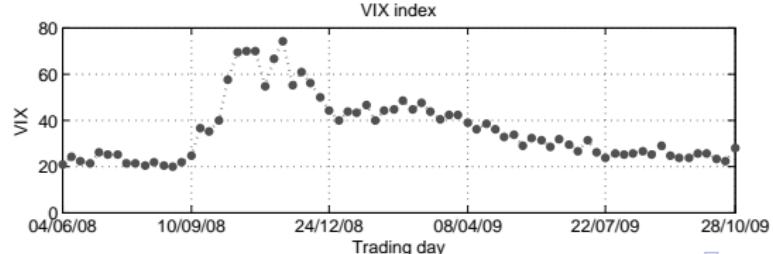
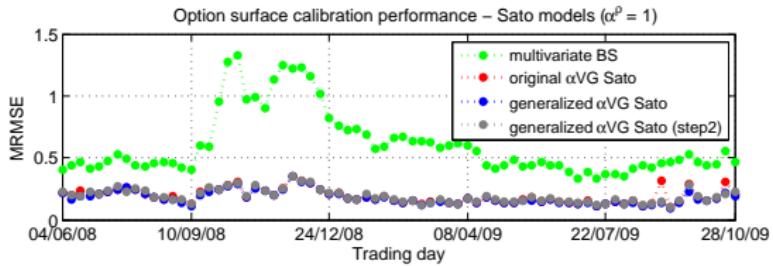
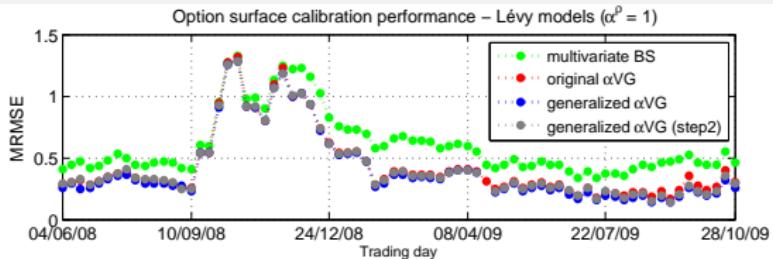
where D_i = dividend at i th ex-dividend dates t_i with
 $t_0 < t_1 < \dots < t_n < T$

- implied correlations: inferred from the S&P500 implied correlation index (= measure of the expected average correlation of price return): $\rho^{\text{CBOE}} \sim \rho \left(\frac{S_{T_\rho}^{(i)}}{S_{t_0}^{(i)}}, \frac{S_{T_\rho}^{(j)}}{S_{t_0}^{(j)}} \right)$
- infer $\rho(Y_{T_\rho}^{(i)}, Y_{T_\rho}^{(j)})$ by Taylor series expansions

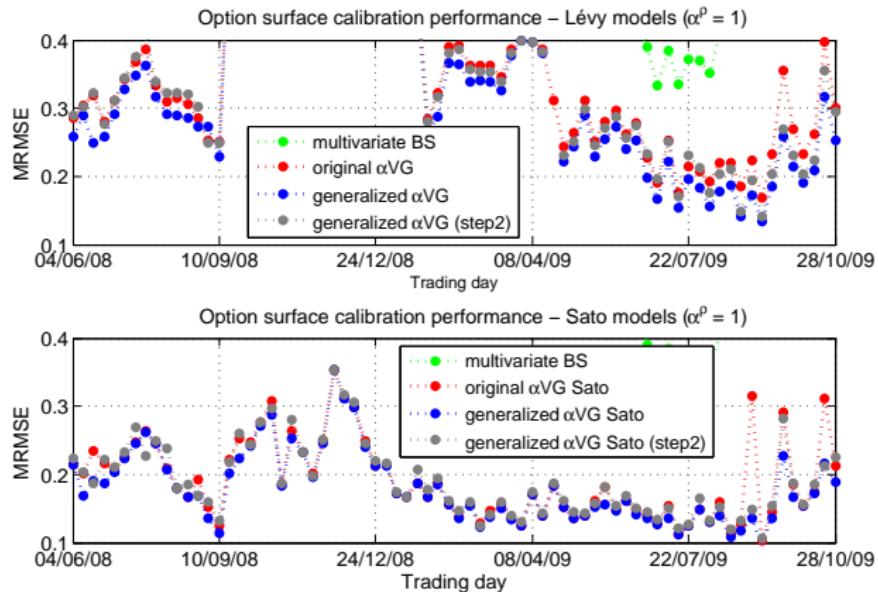
Numerical study: data II



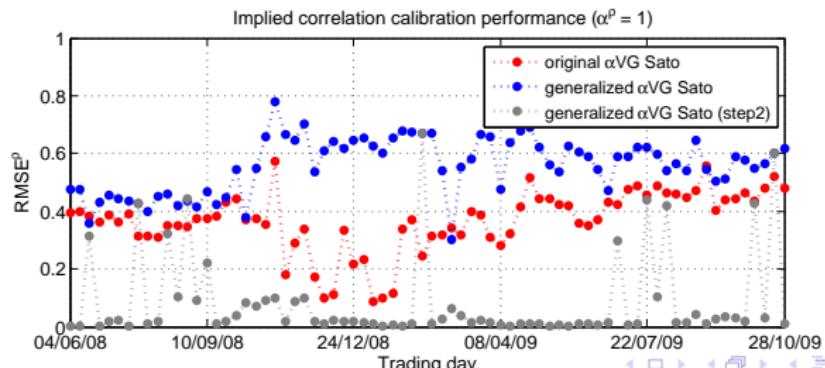
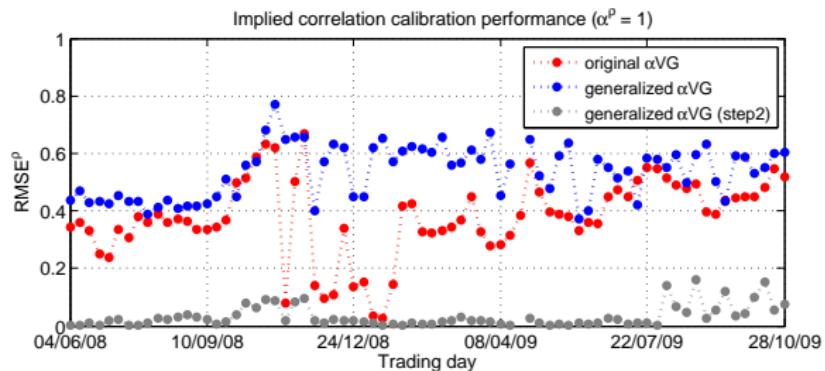
The α VG models: calibration performance (univariate option surfaces) I



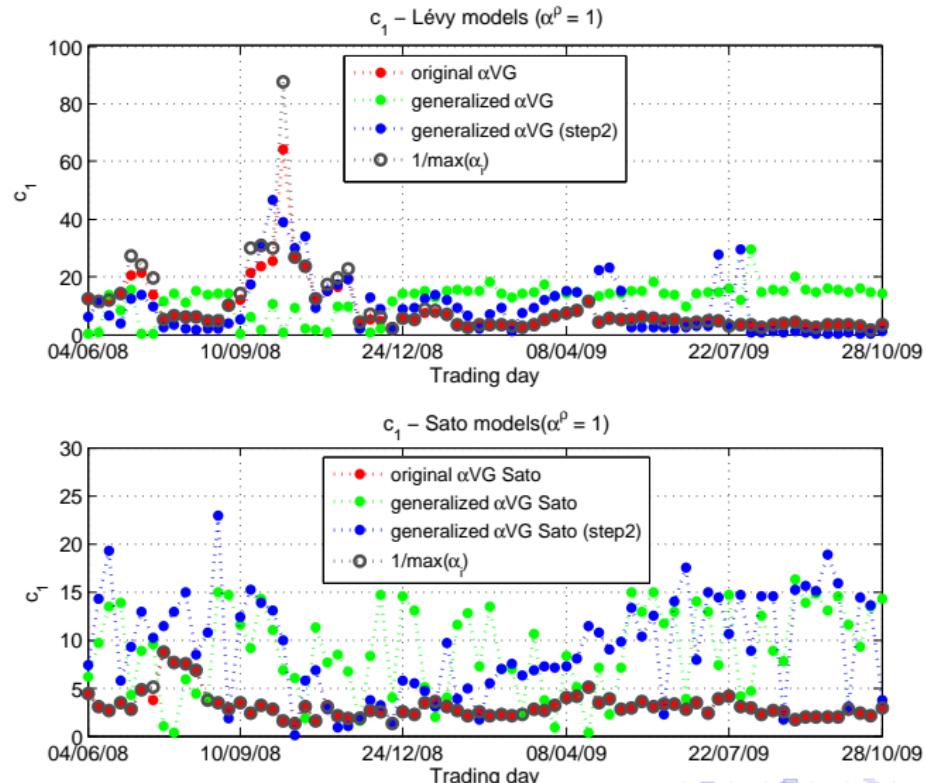
The α VG models: calibration performance (univariate option surfaces) II



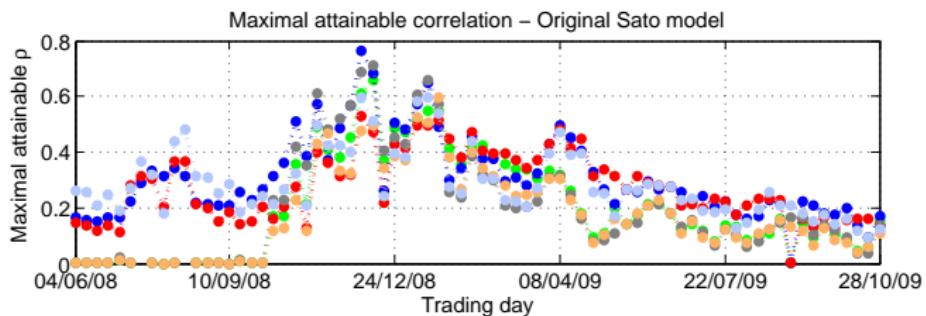
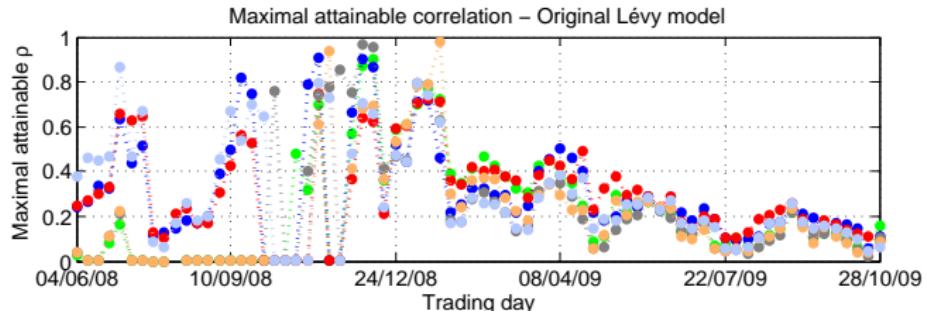
The α VG models: calibration performance (correlations) I



The α VG models: calibration performance (correlations) II

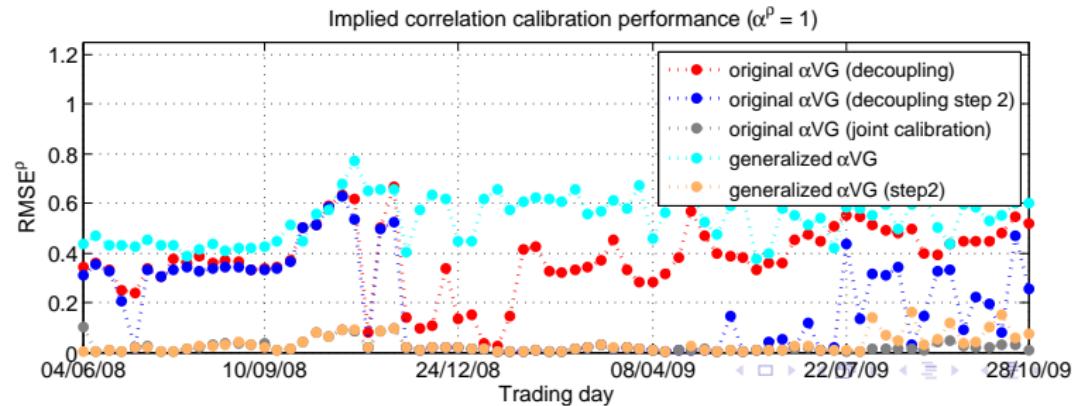
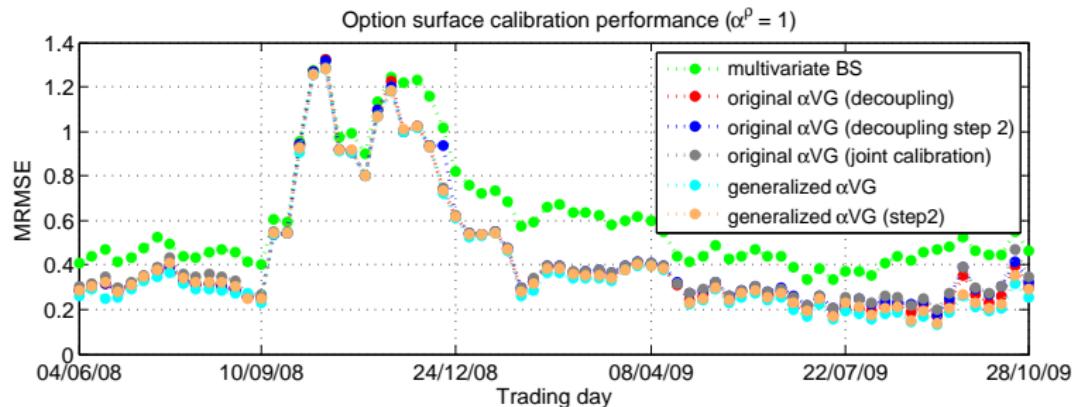


The α VG models: calibration performance (correlations) III



- ρ (Apple, Exxon)
- ρ (Apple, Microsoft)
- ρ (Apple, Intl)
- ρ (Exxon, Microsoft)
- ρ (Exxon, Intl)
- ρ (Microsoft, Intl)

Alternative calibrations of the original model



Choice of α^ρ

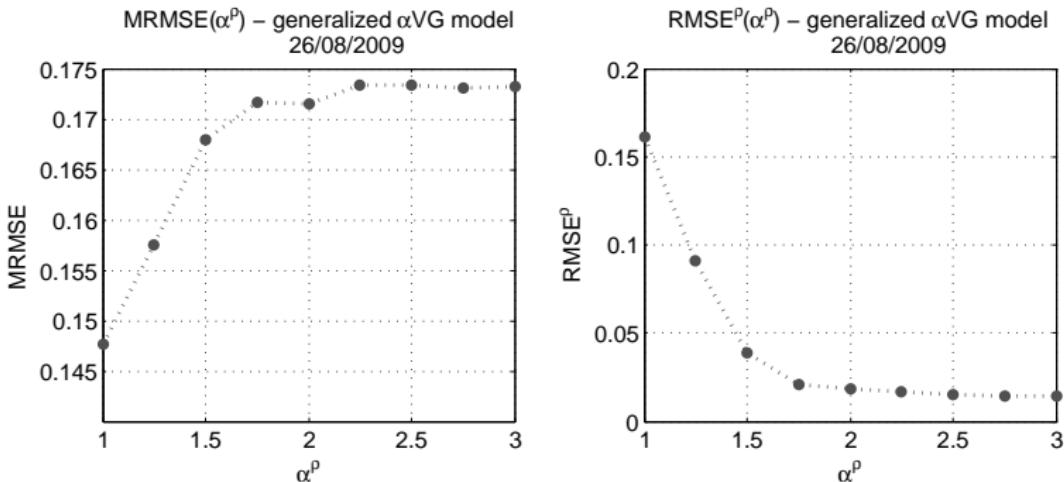


Figure: Influence of α^ρ for the generalized α VG model.

Multivariate exotic options: Rainbow options

- Worst-of call

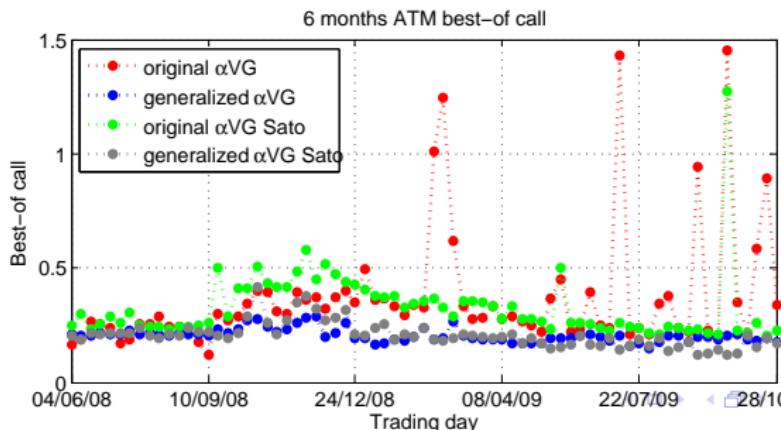
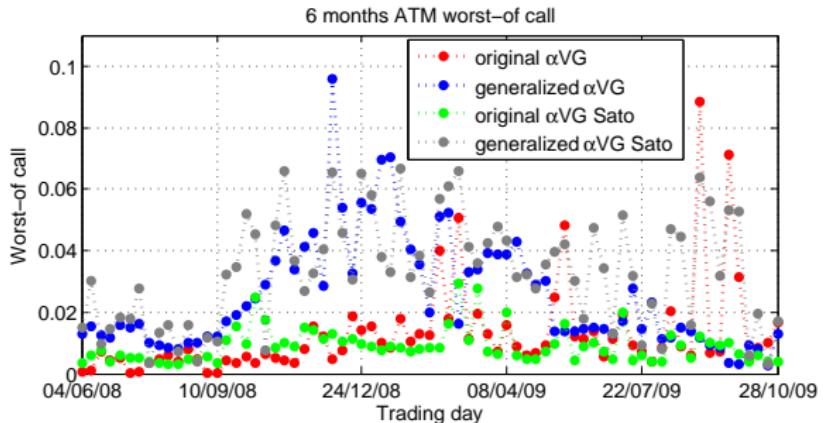
$$WC = \exp(-rT) \mathbb{E}_{\mathbb{Q}} \max \left(\min \left(\frac{S_T^{(1)} - S_0^{(1)}}{S_0^{(1)}}, \frac{S_T^{(2)} - S_0^{(2)}}{S_0^{(2)}}, \frac{S_T^{(3)} - S_0^{(3)}}{S_0^{(3)}}, \frac{S_T^{(4)} - S_0^{(4)}}{S_0^{(4)}} \right), 0 \right)$$

- Best-of call

$$BC = \exp(-rT) \mathbb{E}_{\mathbb{Q}} \max \left(\max \left(\frac{S_T^{(1)} - S_0^{(1)}}{S_0^{(1)}}, \frac{S_T^{(2)} - S_0^{(2)}}{S_0^{(2)}}, \frac{S_T^{(3)} - S_0^{(3)}}{S_0^{(3)}}, \frac{S_T^{(4)} - S_0^{(4)}}{S_0^{(4)}} \right), 0 \right)$$

\Rightarrow when ρ increases \Rightarrow asset prices tend to be the same \Rightarrow minimum of asset prices increases and maximum decreases

Rainbow options: model risk



Multivariate exotic options: Spread options

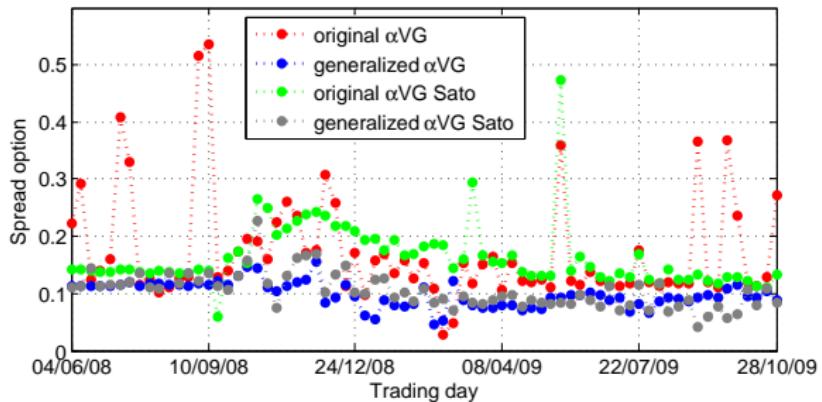
- Spread options

$$\text{Spread} = \exp(-rT) \mathbb{E}_{\mathbb{Q}} \max \left(\frac{S_T^{(1)}}{S_0^{(1)}} - \frac{S_T^{(2)}}{S_0^{(2)}}, 0 \right)$$

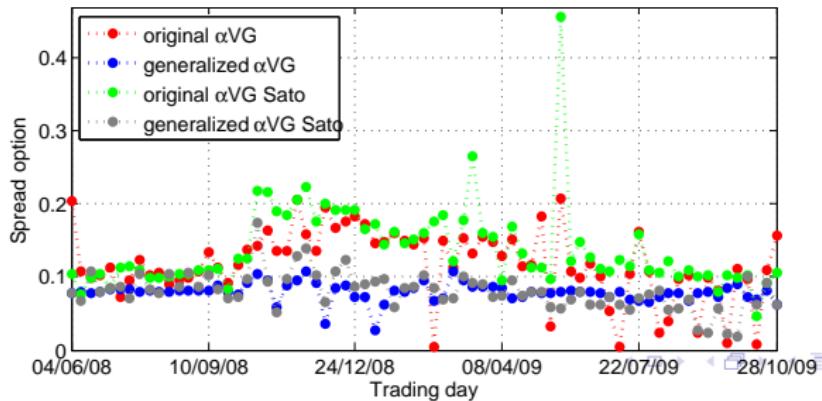
\Rightarrow when ρ increases \Rightarrow asset prices tend to be the same \Rightarrow spread decreases

Spread options: model risk

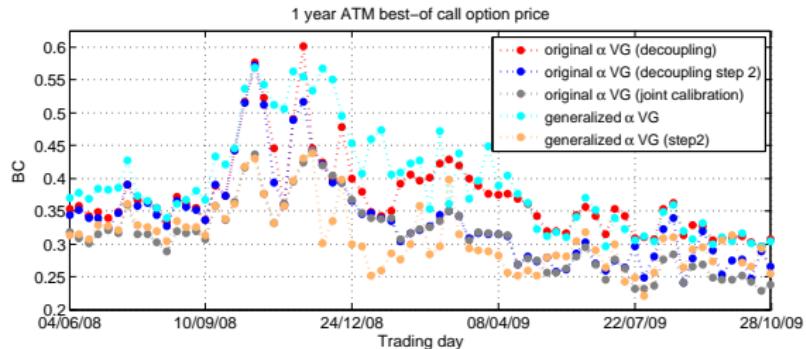
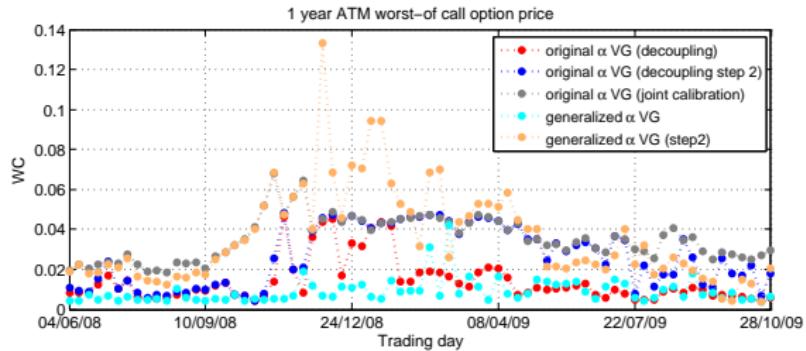
6 months Exxon Apple spread option



6 months Exxon Microsoft spread option



Alternative calibrations of the original model: impact on rainbow option prices



The generalized α VG model: conclusions

- generalized α VG model: CFs which remain of Lévy type but become dependent on the whole parameter set \Rightarrow
 - market-implied calibration does not require anymore the existence of a liquid market for multivariate derivatives
 - volatility (trading activity) depends on both the idiosyncratic and common subordinators \Rightarrow in line with empirical evidence of the presence of both individual and common business clocks
- generalized model: better fit of univariate option surfaces except during high volatility regime periods + correlation goodness of fit significantly improved by performing a second calibration (penalty term assessing the correlation goodness of fit)
- shortfall of the decoupling calibration procedure for the original α VG model: condition that the business time grows on average as the calendar time implies an upper bound on the common parameter c_1 which is a function of the α_i 's \Rightarrow decoupling calibration limits severely admissible value range of c_1

The α VG Sato models: Conclusions

- Sato processes \Rightarrow significantly better fit of univariate option surfaces (especially during high volatility regime)
- Similar correlation fit than the α VG models
- Test higher values of α^ρ to improve the correlation fit
- Significantly different multivariate exotic option prices under the original and generalized models

- [1] Carr, P., Geman, H., Madan, D.B. and Yor, M. (2007). Self-decomposability and Option Pricing. *Mathematical Finance*, **17:1**, 31-57.
- [2] Chicago Board Options Exchange (2009) CBOE S&P 500 Implied Correlation Index. *Working paper, Chicago*.
- [3] Leoni, P. and Schoutens, W. (2008) Multivariate smiling. *Wilmott magazine*
- [4] Luciano, E. and Semeraro, P. (2010) Multivariate time changes for Lévy asset models: Characterization and calibration. *Journal of Computational and Applied Mathematics*, **233**, 1937-1953.
- [5] Madan, D.B. and Senata, E. (1990) The Variance Gamma (V.G.) Model for Share Market Returns. *Journal of Business*, **63**, 511-524.
- [6] Semeraro, P. (2008) A multivariate Variance Gamma model for financial applications. *International Journal of Theoretical and Applied Finance*, **11**, 1-18.

Thank you for your attention