

An Efficient Monte Carlo for Discrete Variance Contracts

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1 Model specification

Nicolas Merener and Leonardo Vicchi proposed in [1] an efficient Monte Carlo method for the valuation of a financial contract with payoff dependent on discretely realized variance. Here we focus on the implementation of the method with the Heston model. Let's denote

- T : the maturity of the contract.
- S_t : the underlying at time $t \geq 0$.
- V_t : the stochastic volatility of S_t at time $t \geq 0$.
- N : the number of days deals in the contract.
- M : the number of Monte Carlo iterations.
- r : the rate of return of the asset.
- d : the dividend.
- κ : the rate of which V_t reverts to theta.
- θ : long variance (or long run average price).
- σ : volatility of the volatility.
- ρ : correlation factor between Z and W .
- K : the strike.
- $B(0, T) = e^{-rT}$: the discount factor.
- Let $x \mapsto g(x)$ be the function of a payoff (Variance Swap: $g(x) = (10,000 x - K^2)$).
- Let $(Z_t, t \geq 0)$ and $(W_t, t \geq 0)$ two independants Brownian Motion.

The Heston model reads:

$$\begin{aligned} dS_t &= (r - d) S_t dt + \sqrt{V_t} S_t dZ_t \\ dV_t &= \kappa (\theta - V_t) dt + \sigma \sqrt{V_t} \left(\rho dZ_t + \sqrt{1 - \rho^2} dW_t \right). \end{aligned}$$

Let's denote by $\Delta = \frac{T}{N}$ the discretization step over a deterministic time grid $t_0 < t_1 < \dots < t_N$ on $[0, T]$ with $t_i = i\Delta$, $\forall i \in \{0, \dots, N\}$. The Euler Full Truncation Scheme reads:

$$\begin{aligned} \hat{S}_{i+1} &= \hat{S}_i e^{\Delta(r-d-\hat{V}_i/2) + \sqrt{\hat{V}_i} \sqrt{\Delta} Z_{i+1}} \\ \tilde{V}_{i+1} &= \tilde{V}_i + \kappa (\theta - \tilde{V}_i^+) \Delta + \sigma \sqrt{\tilde{V}_i^+} \sqrt{\Delta} \left(\rho Z_{i+1} + \sqrt{1 - \rho^2} W_{i+1} \right) \\ \hat{V}_{i+1} &= \tilde{V}_{i+1}^+. \end{aligned}$$

2 The algorithm

The price of a discrete realized variance contracts under such model is computed as the expectation of a deterministic function of discretely recorded variance defined as

$$RV(Z, W) = \sum_{i=0}^{N-1} \left(\log \frac{S_{i+1}}{S_i} \right)^2.$$

Their method combines deterministic integration with random sampling and Monte Carlo simulation for the pricing of such contracts:

$$\begin{aligned} C &= B(0, T) \mathbb{E} [g(RV(Z, W))] \\ &= B(0, T) \mathbb{E} [\mathbb{E} [g(RV(Z, W)) \mid (\|Z\|_2^2, \langle v, W \rangle)]] \\ &= B(0, T) \int_{\mathbb{R}} \int_{\mathbb{R}} \mathbb{E} [g(RV(Z, W)) \mid (\|Z\|_2^2, \langle v, W \rangle) = (z, w)] f_{\|Z\|_2^2}(z) f_{\langle v, W \rangle}(w) dz dw \end{aligned}$$

With

- $\|Z\|_2^2 = \sum_{i=0}^{N-1} Z_i^2$, the Euclidean norm of Z , being a χ^2 distribution of degree N .
- $\|V\|_1 = \sum_{i=0}^{N-1} V_i$, the one norm of V .
- $v = \nabla_W \|V\|_1$ evaluated at $\{Z = 0, W = 0\}$, the optimal integration direction.
- $\langle v, W \rangle = \sum_{i=0}^{N-1} v_i W_i$, the scalar product of v and W , being a standard normal random variable.
- $f_{\langle v, W \rangle}(w) = \frac{1}{\sqrt{2\pi}} e^{-\frac{w^2}{2}}$, the probability density function of the standard normal distribution.
- $f_{\|Z\|_2^2}(z) = \frac{1}{2^{\frac{N}{2}} \Gamma(\frac{N}{2})} z^{\frac{N}{2}-1} e^{-\frac{z}{2}}$, the probability density function of the χ^2 of degree N distribution.

We now combine deterministic integration over the values of the components of $(\|Z\|_2^2, \langle v, W \rangle)$ with Monte Carlo sampling conditional on $(\|Z\|_2^2, \langle v, W \rangle)$ with a proportional allocation of paths. Namely $M' = M f_{\|Z\|_2^2}(z) f_{\langle v, W \rangle}(w)$:

$$\mathbb{E} [g(RV(Z, W)) \mid (\|Z\|_2^2, \langle v, W \rangle) = (z, w)] \approx \frac{1}{M'} \sum_{k=1}^{M'} g(RV(Z_{\|Z\|_2^2=z}^{(k)}, W_{\langle v, W \rangle=w}^{(k)})),$$

with $Z_{\|Z\|_2^2=z}^{(k)}$ sampled as:

$$Z_{\|Z\|_2^2=z}^{(k)} = \sqrt{z} \frac{\xi}{\|\xi\|_2}, \quad \xi \sim \mathcal{N}(0, 1).$$

and $W_{\langle v, W \rangle=w}^{(k)}$ sampled as:

$$W_{\langle v, W \rangle=w}^{(k)} = v_k w + (1 - v_k^2) \Lambda, \quad \Lambda \sim \mathcal{N}(0, 1).$$

The estimator \hat{C} of C now reads:

$$\hat{C} = B(0, T) \int_{\mathbb{R}} \int_{\mathbb{R}} \frac{1}{M'} \sum_{k=1}^{M'} g(RV(Z_{\|Z\|_2^2=z}^{(k)}, W_{\langle v, W \rangle=w}^{(k)})) f_{\|Z\|_2^2}(z) f_{\langle v, W \rangle}(w) dz dw,$$

(noticing that $M' = M f_{\|Z\|_2^2}(z) f_{\langle v, W \rangle}(w)$),

$$= B(0, T) \int_{\mathbb{R}} \int_{\mathbb{R}} \frac{1}{M} \sum_{k=1}^{M'} g(RV(Z_{\|Z\|_2^2=z}^{(k)}, W_{\langle v, W \rangle=w}^{(k)})) dz dw$$

We now approximate the two integrals with 40 equally spaced steps on the real line, ranging from -4 to 4 for the standard normal distribution: $w_i = -4 + i\Delta w$ with $\Delta w = \frac{8}{40}$, $\forall i \in \{0, \dots, 40\}$. And 30 equally

spaced steps on the positive real half line, ranging from 0 to $15\sqrt{N}$ for the χ^2 distribution: $z_j = j\Delta z$ with $\Delta z = \frac{15\sqrt{N}}{30}$, $\forall j \in \{0, \dots, 30\}$:

$$C \approx B(0, T) \frac{\Delta z \Delta w}{M} \sum_{i=0}^{40} \sum_{j=0}^{30} \sum_{k=1}^{\lfloor M f_{||Z||_2^2}(z_j) f_{\langle v, W \rangle}(w_i) \rfloor} g(RV \left(Z_{||Z||_2^2=z}^{(k)}, W_{\langle v, W \rangle=w}^{(k)} \right)).$$

References

- [1] N.Merener L.Vicchi An efficient Monte Carlo method for discrete variance contracts. *The Journal of Computational Finance.*, 16 (4), 2013.