

Analytical formula for an Asian option

Alexandre Humeau

April 6, 2014

1 Payoff

Let us consider an Asian european option (call or put). The payoff of such option in T is

$$(\omega (\bar{S} - K))^+ \quad (1)$$

where

$$\bar{S} = \frac{1}{n} \sum_{i=1}^n S_{t_i} \quad (2)$$

with $0 = t_0 < t_1 < t_2 < \dots < t_n \leq T$.

2 Model

Let us assume that the stock price S follows a GBM under the risk neutral probability

$$\frac{dS_t}{S_t} = rdt + \sigma dW_t \quad (3)$$

Then

$$\forall i \in [1, n], S_{t_i} = S_0 e^{(r - \frac{\sigma^2}{2})t_i + \sigma W_{t_i}} \quad (4)$$

2.1 Moment matching method

2.1.1 Motivations

As we want to find a formula in the Black-Scholes world for the Asian option, let us try to fit a Black-Scholes lognormal underlying for \bar{S} .

$$\frac{d\bar{S}_t}{\bar{S}_t} = \bar{\mu}dt + \bar{\sigma}dW_t \quad (5)$$

2.1.2 Calculation

$$\begin{aligned} \mathbb{E} [\bar{S}] &= S_0 e^{\bar{\mu}T} \\ &= \frac{1}{n} \sum_{i=1}^n \mathbb{E} [S_{t_i}] \\ &= \frac{1}{n} \sum_{i=1}^n S_0 e^{rt_i} \end{aligned} \quad (6)$$

Then

$$\bar{\mu} = \frac{1}{T} \ln \left(\frac{1}{n} \sum_{i=1}^n e^{rt_i} \right) \quad (7)$$

$$\begin{aligned}
Var(\bar{S}) &= S_0^2 e^{2\bar{\mu}T} \left(e^{\bar{\sigma}^2 T} - 1 \right) \\
&= \frac{1}{n^2} \left(\sum_{i=1}^n Var(S_{t_i}) + 2 \sum_{i < j=1}^n Cov(S_{t_i}, S_{t_j}) \right) \\
&= \frac{1}{n^2} \left(\sum_{i=1}^n S_0^2 e^{2rt_i} \left(e^{\sigma^2 t_i} - 1 \right) + 2 \sum_{i < j=1}^n Cov(S_{t_i}, S_{t_j}) \right)
\end{aligned} \tag{8}$$

where

$$\begin{aligned}
Cov(S_{t_i}, S_{t_j}) &= \mathbb{E}[S_{t_i} S_{t_j}] - \mathbb{E}[S_{t_i}] \mathbb{E}[S_{t_j}] \\
&= \mathbb{E}[S_{t_i} \mathbb{E}[S_{t_j} | S_{t_i}]] - \mathbb{E}[S_{t_i}] \mathbb{E}[S_{t_j}] \\
&= \mathbb{E} \left[S_{t_i}^2 \mathbb{E} \left[e^{\left(r - \frac{\sigma^2}{2}\right)(t_j - t_i) + \sigma(W_{t_j} - W_{t_i})} \middle| S_{t_i} \right] \right] - \mathbb{E}[S_{t_i}] \mathbb{E}[S_{t_j}] \\
&= e^{r(t_j - t_i)} \mathbb{E}[S_{t_i}^2] - S_0^2 e^{r(t_i + t_j)} \\
&= e^{r(t_j - t_i)} S_0^2 e^{(2r + \sigma^2)t_i} - S_0^2 e^{r(t_i + t_j)} \\
&= S_0^2 e^{r(t_i + t_j)} \left(e^{\sigma^2 t_i} - 1 \right)
\end{aligned} \tag{9}$$

Then,

$$Var(\bar{S}) = \frac{1}{n^2} \left(\sum_{i=1}^n S_0^2 e^{2rt_i} \left(e^{\sigma^2 t_i} - 1 \right) + 2 \sum_{i < j=1}^n S_0^2 e^{r(t_i + t_j)} \left(e^{\sigma^2 t_i} - 1 \right) \right) \tag{10}$$

Thus,

$$e^{2\bar{\mu}T} \left(e^{\bar{\sigma}^2 T} - 1 \right) = \frac{1}{n^2} \left(\sum_{i=1}^n e^{2rt_i} \left(e^{\sigma^2 t_i} - 1 \right) + 2 \sum_{i < j=1}^n e^{r(t_i + t_j)} \left(e^{\sigma^2 t_i} - 1 \right) \right) \tag{11}$$

Then,

$$\left(e^{\bar{\sigma}^2 T} - 1 \right) = \frac{\frac{1}{n^2} \left(\sum_{i=1}^n e^{2rt_i} \left(e^{\sigma^2 t_i} - 1 \right) + 2 \sum_{i < j=1}^n e^{r(t_i + t_j)} \left(e^{\sigma^2 t_i} - 1 \right) \right)}{\left(\frac{1}{n} \sum_{i=1}^n e^{rt_i} \right)^2} \tag{12}$$

In conclusion

$$\bar{\sigma}^2 T = \ln \left(1 + \frac{\frac{1}{n^2} \sum_{i,j=1}^n e^{r(t_i + t_j)} \left(e^{\sigma^2 \min(t_i, t_j)} - 1 \right)}{\left(\frac{1}{n} \sum_{i=1}^n e^{rt_i} \right)^2} \right) \tag{13}$$