

# Computational Finance

Exercises for participants of all programs

## C-Exercise 01 (4 Points)

- (a) Write a Python function

```
S = CRR_stock(S_0, r, sigma, T, M)
```

that returns the stock price matrix  $S \in \mathbb{R}^{(M+1) \times (M+1)}$  in the CRR-model with initial stock price  $S(0) > 0$ , interest rate  $r > 0$  and volatility  $\sigma > 0$  to a time horizon  $T > 0$  with  $M \in \mathbb{N}$  time steps.

*Reminder:* In the stock price matrix  $S$  of the CRR-model  $S_{ji} = S(0)u^j d^{i-j}$  denotes the stock price at time  $t_i$  after  $j$  upward and hence  $i - j$  downward movements (see Section 2.4).

- (b) Now we want to price call options in the CRR-model. Write a Python function

```
V_0 = CRR_EuCall (S_0, r, sigma, T, M, K)
```

that computes and returns an approximation to the price of an European call option with strike  $K > 0$  and maturity  $T > 0$  in the Black-Scholes model with initial stock price  $S(0) > 0$ , interest rate  $r > 0$  and volatility  $\sigma > 0$  using the CRR-model as presented in the course and  $M \in \mathbb{N}$  time steps.

- (c) We want to compare the CRR model to the true price in the BS-model. To this end implement the BS-Formula for European call options as a Python function:

```
V_0 = BlackScholes_EuCall (t, S_t, r, sigma, T, K)
```

- (d) Compare the results by plotting the error of the CRR model against the BS-price in a common graph. Use the following parameters

$$S(0) = 100, r = 0.03, \sigma = 0.3, T = 1, M = 100, K = 70, \dots, 200.$$

### Black-Scholes formula

The fair price of a European Call option with strike  $K > 0$  in the Black-Scholes model at time  $0 \leq t \leq T$  with stock price  $S(t)$  is given by:

$$C(t, S(t), r, \sigma, T, K) = S(t)\Phi(d_1) - Ke^{-r(T-t)}\Phi(d_2).$$

Here,  $\Phi$  denotes the cumulative distribution function of the standard normal distribution and

$$d_1 := \frac{\log\left(\frac{S(t)}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}}, \quad d_2 := d_1 - \sigma\sqrt{T-t}.$$

**C-Exercise 02** (4 points)

Let  $s_1, \dots, s_N$  denote a time series of, e.g., stock prices on days  $1, \dots, N$ . The *logarithmic return* (log-return) of the stock on day  $n \in \{2, \dots, N\}$  is given by

$$l_n := \log\left(\frac{s_n}{s_{n-1}}\right) = \log(s_n) - \log(s_{n-1}).$$

Assuming 250 trading days per year, the *annualized empirical mean* of log-returns is given by

$$\hat{\mu} = \frac{250}{N-1} \sum_{k=2}^N l_k$$

and the *annualized empirical standard deviation* of log-returns is given by

$$\hat{\sigma} = \sqrt{\frac{250}{N-2} \sum_{k=2}^N \left(l_k - \frac{\hat{\mu}}{250}\right)^2}.$$

- (a) Write a Python function

```
log_returns(data)
```

that computes and returns the time series of log-returns for the time series given in `data`.

- (b) In the Material folder you find the file `time_series_dax_2024.csv` containing a time series of daily DAX data. Import this time series and test your function with it. This includes to

- apply the function to the imported time series,
- visualize the time series of log-returns in a plot,
- compute and display the annualized empirical mean and standard deviation of the log-returns.

- (c) Simulate a time series of log-returns with the assumption that these are normal distributed. Use your result of the empirical mean and standard deviation as parameters. Plot this simulated log-returns in the same figure as the log-returns from the data (in different colors).

- (d) What differences do you observe between the two time series? What do you conclude? (Write a short answer as comment at the end of your program.)

*Hint:* Use the data from the column ‘Close’ and pay attention to correct symbols indicating the separator between columns and the decimal point.

*Useful Python commands:* `numpy.diff`, `numpy.log`, `numpy.genfromtxt`, `numpy.mean`, `numpy.var`, `numpy.random.normal`, `print`, `str`

**T-Exercise 03 (4 Points)**

In the course we fixed the relation  $u = \frac{1}{d}$  in the specification of the binomial model that is used as an approximation to the Black-Scholes model. For even  $M \in \mathbb{N}$ , this implies  $S(0)u^{\frac{M}{2}}d^{\frac{M}{2}} = S(0)$ . Replace the condition (1.3), i.e.  $u = \frac{1}{d}$ , by

- (a)  $q = 0.5$ ,
- (b)  $S(0)u^{\frac{M}{2}}d^{\frac{M}{2}} = S(0)e^{rT}$ ,
- (c)  $S(0)u^{\frac{M}{2}}d^{\frac{M}{2}} = K$ .

and compute the value of the parameters  $u, d$  and  $q$  for each case (*maths students*) resp. only for (a) (*QF students*). Discuss the potential benefit of the alternative conditions and in what scenario they may be useful.

**T-Exercise 04 (Convergence of the binomial model to the Black-Scholes model) (for math only)**

For  $M \in \mathbb{N}$ , denote by  $(S_t^M)_{t \in \{t_0, \dots, t_M\}}$  the stock price process in a binomial model with  $M$  timesteps that approximates the Black-Scholes model with parameters  $r > 0$ ,  $S_0 > 0$ ,  $\mu \in \mathbb{R}$ ,  $\sigma > 0$  and time horizon  $T > 0$ .

- (a) Show that  $\log(S_{t_M}^M) \xrightarrow{M \rightarrow \infty} Z$  in law, where the random variable  $Z$  is normally distributed with mean  $\log(S_0) + (\mu - \frac{1}{2}\sigma^2)T$  and variance  $\sigma^2T$ .
- (b) Conclude that the initial prices of European put and call options with maturity  $T$  and strike  $K > 0$  in the binomial model with  $M$  timesteps approximating the risk-neutral dynamics of the Black-Scholes model converge to the corresponding Black-Scholes prices as  $M \rightarrow \infty$ .

Without proof, you can use

**Slutsky's Theorem:** Let  $(A_n)_{n \in \mathbb{N}}$ ,  $(B_n)_{n \in \mathbb{N}}$  and  $(X_n)_{n \in \mathbb{N}}$  be sequences of random variables such that  $A_n \xrightarrow{n \rightarrow \infty} A$ ,  $B_n \xrightarrow{n \rightarrow \infty} B$  in probability and  $X_n \xrightarrow{n \rightarrow \infty} X$  in law. Then  $A_n X_n + B_n \xrightarrow{n \rightarrow \infty} AX + B$  in law.

Please include your name(s) as comment in the beginning of the file.

Do not forget to include comments in your Python-programs.

**Submit until:** Thu, 02.05.2024, 12:00