

Finite Difference for Pricing Options

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Program of Talk

- Introducing FD and Discretization
- Application of FD for BS-Equation
 - Theta Method
 - Computational Issues
- Pricing of arithmetic average option as a special case of an option on a traded account (Vecer, 2001, JoCF, Vol. 4 No. 4)
- Practical Implementation

Why use Finite Differences ?

- In small number of dimensions, FD may be faster than MC (even than fancy MC)
- In FD, effort and accuracy always scale in the same way, in MC scaling may jump (from $1/n^{1/2}$ to $1/n^{3/2}$, for example)
- Handle early exercise, discrete sampling, and complex boundaries and barriers
- FD are ideally suited for simultaneous solutions of multiple instruments

Disadvantages

- The driving factors must be Markovian
- The number of dimensions must be small
 - This is a DATA issue, not a speed issue
- Practical number of max dimensions: 3

The general Pricing Equation

- The pricing equation is a PIDE: Parabolic partial integro-differential equation in reverse time.
- Parabolic: Information propagates across all states instantaneously.
- Integro: There may be source terms containing integrals, but the integrals should not depend on the path of the underlying processes.
- Reverse time: Information “concentrates” as time goes by (the opposite of Physics)

The general Pricing Equation

$$\begin{aligned}
 & \text{Convection} && \text{Diffusion} \\
 & \overbrace{\frac{\partial V}{\partial t} + a \frac{\partial V}{\partial S} + b \frac{\partial V}{\partial r} + c \frac{\partial V}{\partial I}} & + & \overbrace{d \frac{\partial^2 V}{\partial S^2} + e\rho \frac{\partial^2 V}{\partial S \partial r} + f \frac{\partial^2 V}{\partial r^2}} = \\
 & \uparrow \quad \nearrow & & \\
 & \text{Parabolic directions} & & \\
 & \uparrow & & \\
 & \text{Hyperbolic direction} & & \text{Source} \\
 & & & \overbrace{= rV - \lambda \left(\underbrace{\int \eta(s)V(s)ds}_{\text{Convolution}} - V \right)} \\
 & & & \underbrace{\hspace{10em}}_{\text{Jump}}
 \end{aligned}$$

$$V = V(t, S, r, I)$$

The BS discretization

– Original BM :

$$dS = (r - q)S dt + \sigma S dz$$

– PDE $V = V(S, t)$

$$\frac{\partial V}{\partial t} + (r - q)S \frac{\partial V}{\partial S} + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} = rV$$

The Essential FD discretization

Central in space coordinates:

$$\frac{\partial V}{\partial S} = \frac{V(S + \Delta S) - V(S - \Delta S)}{2\Delta S} + O(\Delta S^2)$$

$$\frac{\partial^2 V}{\partial S^2} = \frac{V(S + \Delta S) - 2V(S) + V(S - \Delta S)}{\Delta S^2} + O(\Delta S^2)$$

Implementing space discretization

- Construct a grid of equally spaced points

$$\{S_i\} = \{S_0, S_1, S_2, \dots, S_I\}$$

$$S_{i+1} = S_i + \Delta S$$

- Define $V = V(i\Delta S, j\Delta t) = V_i^j$

$$V_i = V(S_i)$$

$$V_{i+1} = V(S_i + \Delta S)$$

$$V_{i-1} = V(S_i - \Delta S)$$

Implementing space discretization

- Replace $V(S)$, $V(S + \Delta S)$, $V(S - \Delta S)$ with $V(S_i)$, $V(S_i + \Delta S)$ and $V(S_i - \Delta S)$ in

$$\frac{\partial V}{\partial t} + (r - q)S \frac{V(S + \Delta S) - V(S - \Delta S)}{2\Delta S} + \frac{1}{2} \sigma^2 S^2 \frac{V(S + \Delta S) - 2V(S) + V(S - \Delta S)}{\Delta S^2} = Vr$$

- If we focus on interior points, $\{1, 2, \dots, I-1\}$, this gives us I ODEs, one for each interior grid point.

$$\frac{dV_i}{dt} = -\frac{(r - q)S}{2\Delta S} (V_{i+1} - V_{i-1}) - \frac{1}{2} \frac{\sigma^2 S^2}{\Delta S^2} (V_{i+1} - 2V_i + V_{i-1}) + V_i r$$

The Finite Difference Problem

- This is a tridiagonal *rectangular* system

$$\frac{dV_i}{dt} = \left(\frac{(r-q)S}{2\Delta S} - \frac{1}{2} \frac{\sigma^2 S^2}{\Delta S^2} \right) V_{i-1} + \left(\frac{\sigma^2 S^2}{\Delta S^2} + r \right) V_i + \left(-\frac{(r-q)S}{2\Delta S} - \frac{1}{2} \frac{\sigma^2 S^2}{\Delta S^2} \right) V_{i+1}$$

- The boundaries are at S_0 and S_I
 - If we keep V_0 and V_I as unknowns, we don't have enough equations.
 - We can clear V_0 and V_I using reasonable assumptions: The first and last columns go away and the system becomes square.
 - We can add two additional equations at the top and bottom: This also makes the system square.

The Finite Difference Problem

- When the proper assumptions about boundaries are introduced, the system is written as follows:

$$\frac{dV}{dt} = AV$$

- V is a vector
 - A is the *discretization matrix*.
- The finite difference problem is the formulation and implementation of a scheme for the time-discretization of this system

The Finite Difference problem

- Difference between European and Early exercise options:
 - In pricing a European option, we have a Finite Difference problem as described.
 - In pricing options with early exercise (American or Bermudan), we have a Linear Complementarity Problem, of which this formulation is a part.

Effect of the convolution integral

- The convolution integral produces a source term and does not compromise the feasibility of the solution.
 - It may cause the discretization matrix to become full.
 - There are ways of dealing with the convolution integral, such that the discretization matrix remains sparse (iterative methods.)

Mechanics of FD

- Pricing equation must be solved in the direction of information flow (from the future to the past)
- Two equivalent alternatives:
 - Reverse time and advance in the positive direction (good for analysis)
 - Keep physical time and advance in the negative direction (better for implementation)

The Mechanics of FD

- The set of ODEs $\frac{dV}{dt} = AV$ is discretized in time.

- Define

$$V^j = V(j\Delta t)$$

- The FD implementation leads to

$$A_{lhs} V^j = A_{rhs} V^{j+1}$$

- A_{lhs} and A_{rhs} are (large and usually sparse) matrices
- The particulars of these matrices depends on the time solution scheme.

The Time Solution Scheme

- Explicit Finite Difference
- Implicit Finite Difference
- Mixed Explicit/Implicit Scheme (CN)

Time Derivative

$$\frac{\partial V}{\partial t} \approx \frac{V(S_i, t_{j+1}) - V(S_i, t_j)}{\Delta t}$$

The Time Solution Scheme

At an arbitrary node $V = V(S_i, t_j)$ $i = 1, K, N, j = 0, K, M$ in the grid we introduce the following difference approximations to the terms in the BS-PDE:

$$\frac{\partial V}{\partial S} \approx (1 - \Theta) \frac{V(S_{i+1}, t_j) - V(S_{i-1}, t_j)}{2\Delta S} + \Theta \frac{V(S_{i+1}, t_{j+1}) - V(S_{i-1}, t_{j+1})}{2\Delta S}$$

$$\begin{aligned} \frac{\partial^2 V}{\partial S^2} \approx & (1 - \Theta) \frac{V(S_{i+1}, t_j) - 2V(S_i, t_j) + V(S_{i-1}, t_j)}{\Delta S^2} \\ & + \Theta \frac{V(S_{i+1}, t_{j+1}) - 2V(S_i, t_{j+1}) + V(S_{i-1}, t_{j+1})}{\Delta S^2} \end{aligned}$$

The Time Solution Scheme

The parameter θ determines the time at which the partial derivatives are evaluated

$\theta = 0$ implicit FD

$\theta = 1$ explicit FD

$\theta = 0.5$ CN

Plugging in and collecting terms we end up

The Solution Scheme for BS

with $s_i = i\Delta s$ and the notation $V_i^j = V(s_i, t_j)$ we reach at

$$\begin{aligned} & -[(1-\Theta) \cdot 0.5 \cdot (\sigma^2 i^2 - (r-q)i)\Delta t]V_{i-1}^j \\ & + [1 + r(1-\Theta)\Delta t + (1-\Theta)\sigma^2 i^2 \Delta t]V_i^j \\ & - [(1-\Theta) \cdot 0.5 \cdot (\sigma^2 i^2 + (r-q)i)\Delta t]V_{i+1}^j = \\ & \quad [\Theta \cdot 0.5 \cdot (\sigma^2 i^2 - (r-q)i)\Delta t]V_{i-1}^{j+1} \\ & \quad - [\Theta\Delta t\sigma^2 i^2 - 1 + r\Theta\Delta t]V_i^{j+1} \\ & \quad + [\Theta \cdot 0.5 \cdot (\sigma^2 i^2 + (r-q)i)\Delta t]V_{i+1}^{j+1} \end{aligned}$$

Solving Sparse Systems

- Time advancement leads to a sequence of linear systems

$$AV^{j+1} = b$$

- A is very large (in 2D it has order of 10^8 elements)
- Solution approaches:
 - Direct solvers
 - Iterative solvers

Solving Sparse Systems

- Definition: A direct solver reaches the solution in a finite number of computational steps.
- Naive direct solvers:
 - In 1D with tridiagonal structure, the LU algorithm is extremely efficient.
 - In several dimensions there are efficient direct solvers if you use fractional steps or factored schemes. In this case, the solution is a sequence of tridiagonal problems.

Solving Sparse Systems

- Sophisticated direct solvers:
 - Strategy: Factor matrix A into upper and lower diagonal product (LU decomposition). This can now be solved directly by upward and downward sweeps.
 - Problem with the strategy: In order for strategy to work, L and U must be sparse. Naive decomposition will fill up the U and L !

Example for Stock Option

European Put Option

$$S = 50$$

$$S_{MAX} = S_N = 2 \cdot X$$

$$X = 50$$

$$S_{MIN} = S_0 = 0$$

$$r = 0.1$$

$$\sigma = 0.4$$

$$T = 5/12$$

Analytical Value: 4.076

Example for Stock Option

A) Approach with Matrix Inversion

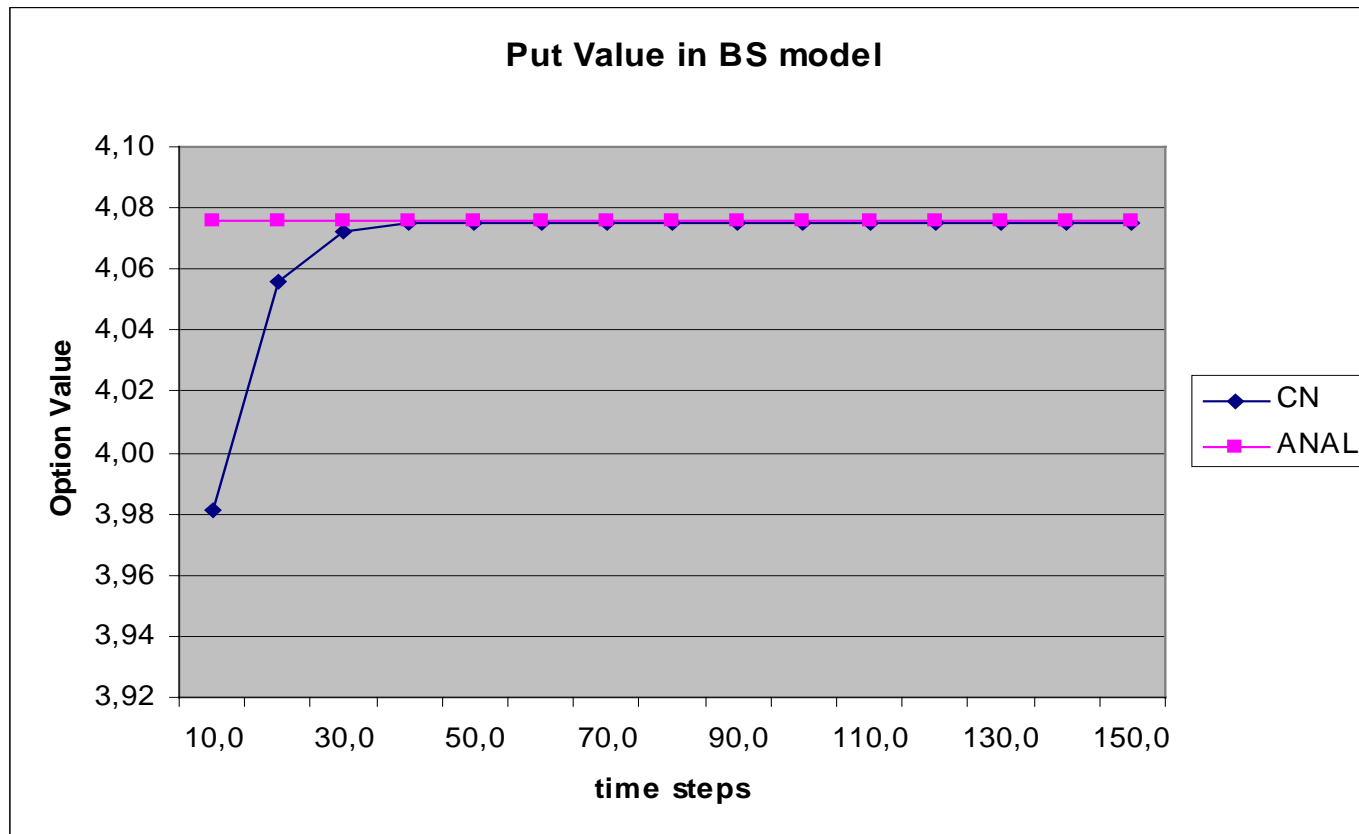
see sheet finite_sem1.xls $N = 20$ $M = 10$

B) Approach with LUAlgorithm

see sheet finite_sem2.xls $N = 200$ $M =$
variable

Delta, Gamma, Theta are evaluated by Cubic
Spline Interpolation

Stock Put Option



Example for Interest Rate Option

Term structure model in continuous time

HW Model short rate model

$$dr = (\phi(t) - ar)dt + \sigma dz$$

yields a PDE with $P = P(r_i, t_j)$ for the zero bond

$$\frac{\partial P}{\partial t} + (\phi(t) - ar) \frac{\partial P}{\partial r} + \frac{1}{2} \sigma^2 \frac{\partial^2 P}{\partial r^2} = rP$$

Example for Interest Rate Option

For this model closed form bond prices are given

$$P(t, T) = A(t, T) \cdot e^{-r(t)B(t, T)}$$

$$B(t, T) = \frac{1}{a} \left(1 - e^{-a(T-t)} \right)$$

$$\ln A(t, T) = \ln \frac{P(0, T)}{P(0, t)} + B(t, T) \cdot f(0, t) - \frac{1}{4a^3} \sigma^2 \left(e^{-aT} - e^{-at} \right)^2 \left(e^{2at} - 1 \right)$$

The Solution Scheme for HW

with $\phi(t) = \phi^j$ and the notation $\alpha = \Delta t / \Delta r^2$ we reach

$$\begin{aligned} & \left[\alpha(1-\Theta) \cdot 0.5 \cdot (\sigma^2 - (\phi^j - ar_i)\Delta r) \right] P_{i-1}^j \\ & - \left[1 + r_i \Delta t (1-\Theta) + \alpha(1-\Theta) \sigma^2 \right] P_i^j \\ & + \left[\alpha(1-\Theta) \cdot 0.5 \cdot (\sigma^2 + (\phi^j - ar_i)\Delta r) \right] P_{i+1}^j = \\ & - \left[\alpha \cdot \Theta \cdot 0.5 \cdot (\sigma^2 - (\phi^{j+1} - ar_i)\Delta r) \right] P_{i-1}^{j+1} \\ & + \left[\alpha \cdot \Theta \sigma^2 - 1 + r_i \Delta t \Theta \right] P_i^{j+1} \\ & - \left[\alpha \cdot \Theta \cdot 0.5 \cdot (\sigma^2 + (\phi^{j+1} - ar_i)\Delta r) \Delta t \right] P_{i+1}^{j+1} \end{aligned}$$

Example for Interest Rate Option

With $\phi(t)$ known to be

$$\phi(t) = \frac{\partial f(0, t)}{\partial t} + af(0, t) + \frac{\sigma^2}{2a} (1 - e^{-2at})$$

In this formulation we have now time dependent coefficients at the grid nodes

Payoff of a Put Option on a zero bond

is $MAX[X - P(t, T), 0]$ (Caplet)

Example for Interest Rate Option

Let the curve be

$$r(t) = 0.08 - 0.05 \cdot e^{-0.18t}$$

Option Maturity 5.5 years

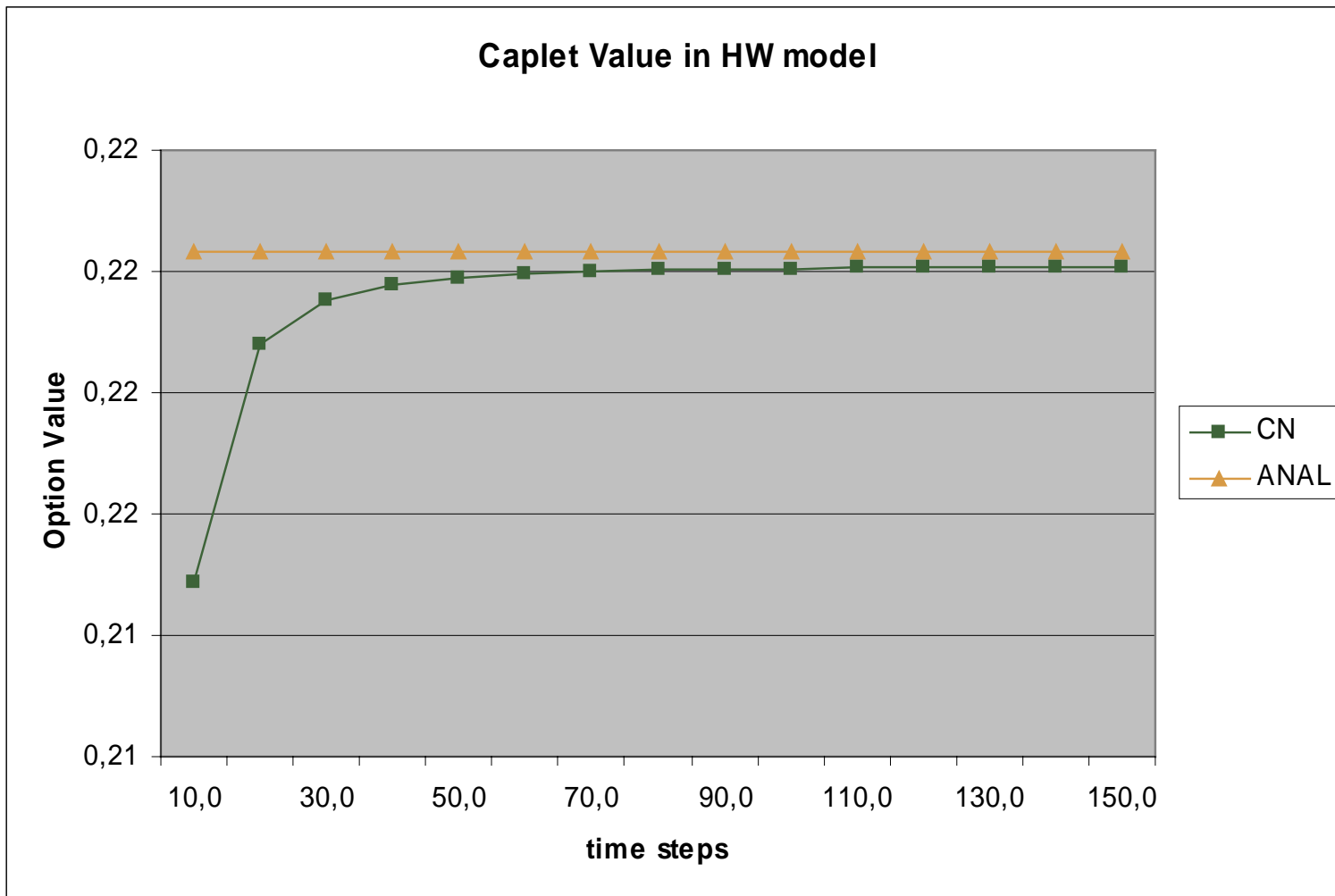
Bond Maturity 6 years

Strike = ATM Forward Bond = 0.9605

$\alpha = 0.15$ Notional = 100, space steps = 200

$\sigma = 0.01$ Analytical Value = 0,2160793

Interest Rate Option



Arithmetic Asian Option

- Asian Options are a Subclass of the general case of the option on a traded account
- We are interested in valuing
Discrete Arithmetic Asian Options

Arithmetic Asian Option

Option on a trading account with trading strategy q_t and asset S_t is modelled:

$$dX_t^q = q_t dS_t + \mu(X_t^q - q_t S_t)dt; \quad X_0^q = X_0$$

$$dS_t = S_t(rdt + \sigma dw_t)$$

$$q_t \in [\alpha_t, \beta_t]$$

In case of Passport Option $\alpha_t = -1, \beta_t = 1$

In case of Asian Option $\alpha_t = \beta_t$

In case of European Call Option $\alpha_t = 1, \beta_t = 1$

Arithmetic Asian Option

The risk-neutral value is the at time t with payoff at Time T $MAX[X_T^q, 0]$ is

$$V^{[\alpha, \beta]}(t, S, X) = MAX_{q \in [\alpha, \beta]} e^{-r(T-t)} E[MAX[X_T^q, 0] | \mathcal{F}_t]$$

Change of variable

$$Z_t^q = \frac{X_t^q}{S_t}$$

Arithmetic Asian Option

Using Ito's lemma and Girsanov's theorem
we get a SDE

$$dZ_t^q = (q_t - Z_t^q)(r - \mu)dt + (q_t - Z_t^q)\sigma d\tilde{w}_t$$

Introducing $u(t, Z_t) = \text{MAX}_{q \in [\alpha, \beta]} \tilde{E}[\text{MAX}[Z_T^q, 0] | \mathfrak{F}_t]$

This leads to the PDE

$$\frac{\partial u}{\partial t} + \text{MAX}_{q \in [\alpha, \beta]} \left[(r - \mu)(q - z) \frac{\partial u}{\partial z} + \frac{1}{2} (q - z)^2 \sigma^2 \frac{\partial^2 u}{\partial z^2} \right] = 0$$

Arithmetic Asian Option

Asian Options

with $d(tS_t) = tdS_t + S_t dt$ we get $\frac{1}{T} \int_0^T S_t dt = \int_0^T \left(1 - \frac{t}{T}\right) dS_t + S_0$

So the fixed strike call payoff $\text{MAX}[\bar{S} - K, 0]$

is modelled by the strategy $q_t = 1 - t/T$

and initial value $X_0 = S_0 - K$

where the traded account is evolving as

$$dX = q_t dS_t$$

Arithmetic Asian Option

Diskrete Asian Options with n average points

The strategy is approximated by a step function

$$q_t = 1 - \frac{1}{n} INT \left[n \frac{t}{T} \right]$$

So we get for the discrete fixed strike call

$$MAX \left(\frac{1}{n} \sum_{k=1}^n S_{(k/n)T} - K, 0 \right)$$

The discrete fixed strike put is similar.

Arithmetic Asian Option

This leads to the PDE for Asian Options

$$\frac{\partial u}{\partial t} + r(q_t - z) \frac{\partial u}{\partial z} + \frac{1}{2} (q_t - z)^2 \sigma^2 \frac{\partial^2 u}{\partial z^2} = 0$$

with boundary condition: $u(T, z) = \text{MAX}[z, 0]$

Again this has to be solved with a numerical method (FD).

The Asian Solution Scheme

At an arbitrary node $u = u(z_i, t_j)$ $i = 1, K, M, j = 0, K, N$
in the grid we introduce the following difference
approximations ($\Theta=1$ implicit, $\Theta=0$ explicit) :

$$\frac{\partial u}{\partial z} \approx \Theta \frac{u(z_{i+1}, t_j) - u(z_{i-1}, t_j)}{2\Delta z} + (1 - \Theta) \frac{u(z_{i+1}, t_{j+1}) - u(z_{i-1}, t_{j+1})}{2\Delta z}$$

$$\frac{\partial^2 u}{\partial z^2} \approx \Theta \frac{u(z_{i+1}, t_j) - 2u(z_i, t_j) + u(z_{i-1}, t_j)}{\Delta z^2} \\ + (1 - \Theta) \frac{u(z_{i+1}, t_{j+1}) - 2u(z_i, t_{j+1}) + u(z_{i-1}, t_{j+1})}{\Delta z^2}$$

The Solution Scheme Asian Options

with $q(t) = q^j$ and $u(z_i, t_j) = u_i^j$, $k = \Delta z^2 / \Delta t$

$$t_j = j\Delta t, z_i = z_0 + i\Delta z, z_0 = -1; z_M = 1$$

$$\begin{aligned} & \Theta \left[\sigma^2 (q^j - z_i)^2 - r(q^j - z_i)\Delta z \right] u_{i-1}^j \\ & - 2 \left[\sigma^2 \Theta (q^j - z_i)^2 + k \right] u_i^j \\ & + \Theta \left[\sigma^2 (q^j - z_i)^2 + r(q^j - z_i)\Delta z \right] u_{i+1}^j = \\ & - (1 - \Theta) \left[\sigma^2 (q^j - z_i)^2 - r(q^j - z_i)\Delta z \right] u_{i-1}^{j+1} \\ & + 2 \left[(1 - \Theta) \sigma^2 (q^j - z_i)^2 - k \right] u_i^{j+1} \\ & - (1 - \Theta) \left[\sigma^2 (q^j - z_i)^2 + r(q^j - z_i)\Delta z \right] u_{i+1}^{j+1} \end{aligned}$$

The Solution Scheme Asian Options

Payoff $u_i^N = \text{MAX}[z_i, 0]$

Boundary conditions and strategy:

Call: $u_0^j = 0, u_M^j = 2u_{M-1}^j - u_{M-2}^j \quad q_t = 1 - \frac{1}{n} \text{INT} \left[n \frac{t}{T} \right]$

Put: $u_0^j = 2u_{M-1}^j - u_{M-2}^j, u_M^j = 0 \quad q_t = \frac{1}{n} \text{INT} \left[n \frac{t}{T} \right] - 1$

Solution is given by $\text{Optvalue} = S \cdot u(z_0, 0)$

Results for Asian Options FD

Calculations with $N=200$, $M=200$, $MC=10000$
 $S=100$, $\text{vola}=0.2$, $r=0.05$, $T=1y$, $n=10$

Strike	MC	FD-Call-CN	MC	FD-Put-CN
90,0	12,98	12,98	0,81	0,81
92,5	11,04	11,05	1,25	1,25
95,0	9,26	9,27	1,85	1,85
97,5	7,65	7,66	2,62	2,62
100,0	6,23	6,23	3,57	3,57
102,5	4,99	4,99	4,71	4,71
105,0	3,94	3,94	6,04	6,04
107,5	3,06	3,07	7,54	7,54
110,0	2,35	2,35	9,20	9,20

Summary

- FD is flexible and fast
- FD is straightforward to implement
- Convergence properties are known

Literature

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