Time-Varying Double Barriers under Time-Dependent Volatility[a]

- More general models allow a time-varying $\sigma(t)$ (p. 312).
- Let the two barriers $L(t)$ and $H(t)$ be functions of time.[b]
- They do not have to be differentiable or even continuous.
- Still, we can price double-barrier options in $O(n^2)$ time or less with trinomial trees.
- Continuously monitored double-barrier knock-out options with time-varying barriers are called hot dog options.[c]

[a] Y. Zhang (R05922052) (2019).
[b] So the barriers are continuously monitored.
[c] El Babsiri & Noel (1998).

General Local-Volatility Models and Their Trees

- Consider the general local-volatility model

$$\frac{dS}{S} = (r_t - q_t)\, dt + \sigma(S, t)\, dW,$$

where $L \leq \sigma(S, t) \leq U$ for some positive L and U.

- This model has a unique (weak) solution.[a]
- The positive lower bound is justifiable because prices fluctuate.

[a] Achdou & Pironneau (2005).

General Local-Volatility Models and Their Trees (continued)

- The upper-bound assumption is also reasonable.
- Even on October 19, 1987, the CBOE S&P 100 Volatility Index (VXO) was about 150%, the highest ever.[a]
- An efficient quadratic-sized tree for this range-bounded model is straightforward.[b]
- Pick any $\sigma' \geq U$.
- Grow the trinomial tree with the node spacing $\sigma'\sqrt{\Delta t}$.[c]
- The branching probabilities are guaranteed to be valid.

[a] Caprio (2012).
[b] Lok (D99922028) & Lyuu (2016, 2017, 2020).
[c] Haahtela (2010).

General Local-Volatility Models and Their Trees (concluded)

- The same idea can be applied to price double-barrier options.
- Pick any

$$\sigma' \geq \max\left[\max_{S, 0 \leq t \leq T} \sigma(S, t), \sqrt{2}\,\sigma(S_0, 0)\right].$$

- Grow the trinomial tree with the node spacing $\sigma' \sqrt{\Delta t}$.
- Apply the mean-tracking idea to the first period and Eqs. (100)–(105) on p. 760 to obtain the probabilities

Merton's Jump-Diffusion Model

- Empirically, stock returns tend to have fat tails, inconsistent with the Black-Scholes model's assumptions.
- Stochastic volatility and jump processes have been proposed to address this problem.
- Merton's (1976) jump-diffusion model is our focus.

Merton's Jump-Diffusion Model (continued)

- This model superimposes a jump component on a diffusion component.
- The diffusion component is the familiar geometric Brownian motion.
- The jump component is composed of lognormal jumps driven by a Poisson process.
  - It models the *rare* but *large* changes in the stock price because of the arrival of important new information.[a]

[a]Derman & M. B. Miller (2016), "There is no precise, universally accepted definition of a jump, but it usually comes down to magnitude, duration, and frequency."

Merton's Jump-Diffusion Model (continued)

- Let S_t be the stock price at time t.
- The risk-neutral jump-diffusion process for the stock price follows[a]

$$\frac{dS_t}{S_t} = (r - \lambda \bar{k})\, dt + \sigma\, dW_t + k\, dq_t. \tag{107}$$

- Above, σ denotes the volatility of the diffusion component.

---

[a]Derman & M. B. Miller (2016), "[M]ost jump-diffusion models simply assume risk-neutral pricing without convincing justification."

Merton's Jump-Diffusion Model (continued)

- The jump event is governed by a compound Poisson process q_t with intensity λ, where k denotes the magnitude of the *random* jump.
  - The distribution of k obeys
  $$\ln(1+k) \sim N\left(\gamma, \delta^2\right)$$
  with mean $\bar{k} \stackrel{\Delta}{=} E(k) = e^{\gamma+\delta^2/2} - 1$.
  - Note that $k > -1$.
  - Note also that k is not related to dt.
- The model with $\lambda = 0$ reduces to the Black-Scholes model.

Merton's Jump-Diffusion Model (continued)

- The solution to Eq. (107) on p. 798 is

$$S_t = S_0 e^{(r-\lambda\bar{k}-\sigma^2/2)\,t+\sigma W_t} U(n(t)), \tag{108}$$

where

$$U(n(t)) = \prod_{i=0}^{n(t)} (1+k_i)\,.$$

  - k_i is the magnitude of the ith jump with $\ln(1+k_i) \sim N(\gamma,\delta^2)$.
  - $k_0 = 0$.
  - $n(t)$ is a Poisson process with intensity λ.

Merton's Jump-Diffusion Model (concluded)

- Recall that $n(t)$ denotes the number of jumps that occur up to time t.
- It is known that $E[\, n(t)\,] = \text{Var}[\, n(t)\,] = \lambda t$.
- As $k_i > -1$, stock prices will stay positive.
- The geometric Brownian motion, the lognormal jumps, and the Poisson process are assumed to be independent.

Tree for Merton's Jump-Diffusion Model[a]

- Define the S-logarithmic return of the stock price S' as

$$\ln(S'/S).$$

- Define the logarithmic distance between stock prices S' and S as

$$|\ln(S') - \ln(S)| = |\ln(S'/S)|.$$

[a] Dai (B82506025, R86526008, D8852600), C. Wang (F95922018), Lyuu, & Y. Liu (2010).

Tree for Merton's Jump-Diffusion Model (continued)

- Take the logarithm of Eq. (108) on p. 800:

$$M_t \triangleq \ln\left(\frac{S_t}{S_0}\right) = X_t + Y_t, \tag{109}$$

where

$$X_t \triangleq \left(r - \lambda\bar{k} - \frac{\sigma^2}{2}\right) t + \sigma W_t, \tag{110}$$

$$Y_t \triangleq \sum_{i=0}^{n(t)} \ln(1 + k_i). \tag{111}$$

- It decomposes the S_0-logarithmic return of S_t into the diffusion component X_t and the jump component Y_t.

Tree for Merton's Jump-Diffusion Model (continued)

- Motivated by decomposition (109) on p. 803, the tree construction divides each period into a diffusion phase followed by a jump phase.
- In the diffusion phase, X_t is approximated by the BOPM.
- So X_t makes an up move to $X_t + \sigma\sqrt{\Delta t}$ with probability p_u or a down move to $X_t - \sigma\sqrt{\Delta t}$ with probability p_d.

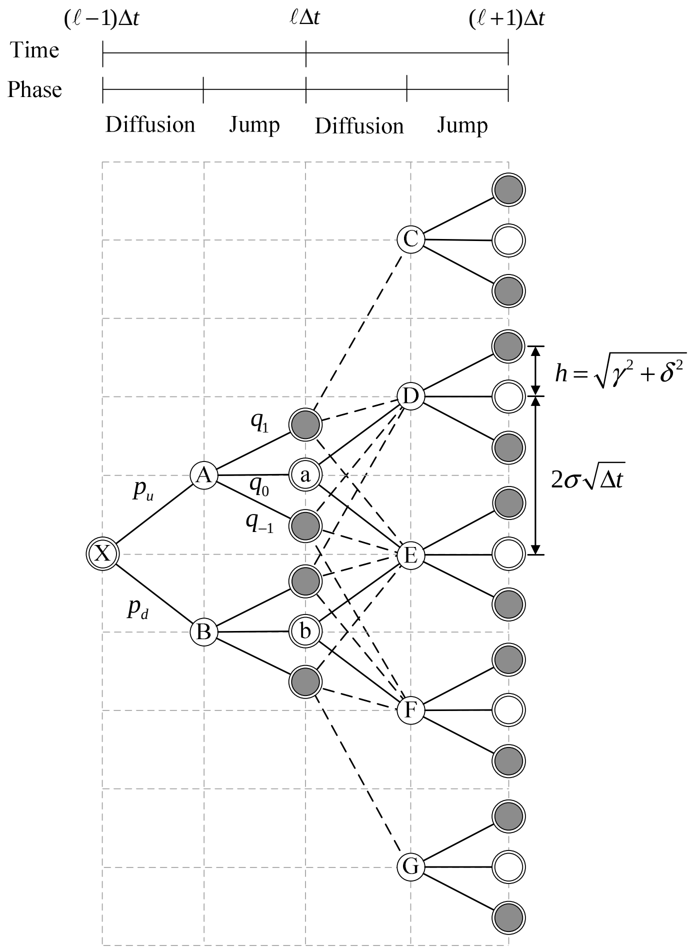
Tree for Merton's Jump-Diffusion Model (continued)

- According to BOPM,

$$p_u = \frac{e^{\mu \Delta t} - d}{u - d},$$
$$p_d = 1 - p_u,$$

  except that $\mu = r - \lambda \bar{k}$ here.

- The diffusion component gives rise to diffusion nodes.
- They are spaced at $2\sigma\sqrt{\Delta t}$ apart such as the white nodes A, B, C, D, E, F, and G on p. 806.



White nodes are *diffusion nodes*. Gray nodes are *jump nodes*. In the diffusion phase, the solid black lines denote the binomial structure of BOPM; the dashed lines denote the trinomial structure. Only the double-circled nodes will remain after the construction. Note that a and b are diffusion nodes because no jump occurs in the jump phase.

Tree for Merton's Jump-Diffusion Model (continued)

- In the jump phase, $Y_{t+\Delta t}$ is approximated by moves from *each* diffusion node to $2m$ jump nodes that match the first $2m$ moments of the lognormal jump.
- The m jump nodes above the diffusion node are spaced at $h \stackrel{\Delta}{=} \sqrt{\gamma^2 + \delta^2}$ apart.
- Note that h is independent of Δt.

Tree for Merton's Jump-Diffusion Model (concluded)

- The same holds for the m jump nodes below the diffusion node.
- The gray nodes at time $\ell\Delta t$ on p. 806 are jump nodes.
  - We set $m = 1$ on p. 806.
- The size of the tree is $O(n^{2.5})$.

Multivariate Contingent Claims

- They depend on two or more underlying assets.
- The basket call on m assets has the terminal payoff

$$\max\left(\sum_{i=1}^{m}\alpha_i S_i(\tau)-X,0\right),$$

where α_i is the percentage of asset i.

- Basket options are essentially options on a portfolio of stocks (or index options).[a]
- Option on the best of two risky assets and cash has a terminal payoff of $\max(S_1(\tau),S_2(\tau),X)$.

[a]Except that membership and weights do *not* change for basket options (Bennett, 2014).

Multivariate Contingent Claims (concluded)[a]

Name	Payoff
Exchange option	$\max(S_1(\tau) - S_2(\tau), 0)$
Better-off option	$\max(S_1(\tau), \ldots, S_k(\tau), 0)$
Worst-off option	$\min(S_1(\tau), \ldots, S_k(\tau), 0)$
Binary maximum option	$I\{\max(S_1(\tau), \ldots, S_k(\tau)) > X\}$
Maximum option	$\max(\max(S_1(\tau), \ldots, S_k(\tau)) - X, 0)$
Minimum option	$\max(\min(S_1(\tau), \ldots, S_k(\tau)) - X, 0)$
Spread option	$\max(S_1(\tau) - S_2(\tau) - X, 0)$
Basket average option	$\max((S_1(\tau) + \cdots + S_k(\tau))/k - X, 0)$
Multi-strike option	$\max(S_1(\tau) - X_1, \ldots, S_k(\tau) - X_k, 0)$
Pyramid rainbow option	$\max(\mid S_1(\tau) - X_1 \mid + \cdots + \mid S_k(\tau) - X_k \mid - X, 0)$
Madonna option	$\max(\sqrt{(S_1(\tau) - X_1)^2 + \cdots + (S_k(\tau) - X_k)^2} - X, 0)$

[a] Lyuu & Teng (R91723054) (2011).

Correlated Trinomial Model[a]

- Two risky assets S_1 and S_2 follow
$$\frac{dS_i}{S_i} = r\,dt + \sigma_i\,dW_i$$
in a risk-neutral economy, $i = 1, 2$.
- Let
$$\begin{aligned} M_i &\stackrel{\Delta}{=} e^{r\,\Delta t}, \\ V_i &\stackrel{\Delta}{=} M_i^2(e^{\sigma_i^2\,\Delta t} - 1). \end{aligned}$$
  - $S_i M_i$ is the mean of S_i at time Δt.
  - $S_i^2 V_i$ the variance of S_i at time Δt.

[a] Boyle, Evnine, & Gibbs (1989).

Correlated Trinomial Model (continued)

- The value of $S_1 S_2$ at time Δt has a joint lognormal distribution with mean $S_1 S_2 M_1 M_2 e^{\rho\sigma_1\sigma_2\Delta t}$, where ρ is the correlation between dW_1 and dW_2.
- Next match the 1st and 2nd moments of the approximating discrete distribution to those of the continuous counterpart.
- At time Δt from now, there are 5 distinct outcomes.

Correlated Trinomial Model (continued)

- The five-point probability distribution of the asset prices is

Probability	Asset 1	Asset 2
p_1	$S_1 u_1$	$S_2 u_2$
p_2	$S_1 u_1$	$S_2 d_2$
p_3	$S_1 d_1$	$S_2 d_2$
p_4	$S_1 d_1$	$S_2 u_2$
p_5	S_1	S_2

- As usual, impose $u_i d_i = 1$.

Correlated Trinomial Model (continued)

- The probabilities must sum to one, and the means must be matched:

$$
\begin{aligned}
1 &= p_1 + p_2 + p_3 + p_4 + p_5, \\
S_1 M_1 &= (p_1 + p_2)\, S_1 u_1 + p_5 S_1 + (p_3 + p_4)\, S_1 d_1, \\
S_2 M_2 &= (p_1 + p_4)\, S_2 u_2 + p_5 S_2 + (p_2 + p_3)\, S_2 d_2.
\end{aligned}
$$

Correlated Trinomial Model (concluded)

- Let $R \stackrel{\Delta}{=} M_1 M_2 e^{\rho\sigma_1\sigma_2\Delta t}$.
- Match the variances and covariance:

$$
\begin{aligned}
S_1^2 V_1 &= (p_1 + p_2)\left[(S_1 u_1)^2 - (S_1 M_1)^2\right] + p_5\left[S_1^2 - (S_1 M_1)^2\right] \\
&\quad + (p_3 + p_4)\left[(S_1 d_1)^2 - (S_1 M_1)^2\right], \\
S_2^2 V_2 &= (p_1 + p_4)\left[(S_2 u_2)^2 - (S_2 M_2)^2\right] + p_5\left[S_2^2 - (S_2 M_2)^2\right] \\
&\quad + (p_2 + p_3)\left[(S_2 d_2)^2 - (S_2 M_2)^2\right], \\
S_1 S_2 R &= (p_1 u_1 u_2 + p_2 u_1 d_2 + p_3 d_1 d_2 + p_4 d_1 u_2 + p_5)\, S_1 S_2.
\end{aligned}
$$

- The solutions appear on p. 246 of the textbook.

Correlated Trinomial Model Simplified[a]

- Let $\mu_i' \stackrel{\Delta}{=} r - \sigma_i^2/2$ and $u_i \stackrel{\Delta}{=} e^{\lambda\sigma_i\sqrt{\Delta t}}$ for $i = 1, 2$.
- The following simpler scheme is good enough:

$$\begin{aligned}
p_1 &= \frac{1}{4}\left[\frac{1}{\lambda^2} + \frac{\sqrt{\Delta t}}{\lambda}\left(\frac{\mu_1'}{\sigma_1} + \frac{\mu_2'}{\sigma_2}\right) + \frac{\rho}{\lambda^2}\right],\\
p_2 &= \frac{1}{4}\left[\frac{1}{\lambda^2} + \frac{\sqrt{\Delta t}}{\lambda}\left(\frac{\mu_1'}{\sigma_1} - \frac{\mu_2'}{\sigma_2}\right) - \frac{\rho}{\lambda^2}\right],\\
p_3 &= \frac{1}{4}\left[\frac{1}{\lambda^2} + \frac{\sqrt{\Delta t}}{\lambda}\left(-\frac{\mu_1'}{\sigma_1} - \frac{\mu_2'}{\sigma_2}\right) + \frac{\rho}{\lambda^2}\right],\\
p_4 &= \frac{1}{4}\left[\frac{1}{\lambda^2} + \frac{\sqrt{\Delta t}}{\lambda}\left(-\frac{\mu_1'}{\sigma_1} + \frac{\mu_2'}{\sigma_2}\right) - \frac{\rho}{\lambda^2}\right],\\
p_5 &= 1 - \frac{1}{\lambda^2}.
\end{aligned}$$

[a] Madan, Milne, & Shefrin (1989).

Correlated Trinomial Model Simplified (continued)

- All of the probabilities lie between 0 and 1 if and only if

$$-1+\lambda\sqrt{\Delta t}\,\left|\frac{\mu_1'}{\sigma_1}+\frac{\mu_2'}{\sigma_2}\right| \leq \rho \leq 1-\lambda\sqrt{\Delta t}\,\left|\frac{\mu_1'}{\sigma_1}-\frac{\mu_2'}{\sigma_2}\right|, \tag{112}$$

$$1 \leq \lambda. \tag{113}$$

- We call a multivariate tree (correlation-) optimal if it guarantees valid probabilities as long as

$$-1+O(\sqrt{\Delta t})<\rho<1-O(\sqrt{\Delta t}),$$

such as the above one.[a]

[a] W. Kao (R98922093) (2011); W. Kao (R98922093), Lyuu, & Wen (D94922003) (2014).

Correlated Trinomial Model Simplified (continued)

- But this model cannot price 2-asset 2-barrier options accurately.[a]
- Few multivariate trees are both optimal and able to handle multiple barriers.[b]
- An alternative is to use orthogonalization.[c]

---

[a]See Y. Chang (B89704039, R93922034), Hsu (R7526001, D89922012), & Lyuu (2006); W. Kao (R98922093), Lyuu, & Wen (D94922003) (2014) for solutions.

[b]See W. Kao (R98922093), Lyuu, & Wen (D94922003) (2014) for an exception.

[c]Hull & White (1990); Dai (B82506025, R86526008, D8852600), C. Wang (F95922018), & Lyuu (2013).

Correlated Trinomial Model Simplified (concluded)

- Suppose we allow each asset's volatility to be a function of time.[a]
- There are k assets.
- Can you build an optimal multivariate tree that can handle two barriers on each asset in time $O(n^{k+1})$?[b]

---

[a] Recall p. 311.

[b] See Y. Zhang (R05922052) (2019) for a complete solution.

Extrapolation

- It is a method to speed up numerical convergence.
- Say $f(n)$ converges to an unknown limit f at rate of $1/n$:

$$f(n) = f + \frac{c}{n} + o\left(\frac{1}{n}\right). \tag{114}$$

- Assume c is an unknown constant independent of n.
  - Convergence is basically monotonic and smooth.

Extrapolation (concluded)

- From two approximations $f(n_1)$ and $f(n_2)$ and ignoring the smaller terms,

$$f(n_1) = f + \frac{c}{n_1},$$
$$f(n_2) = f + \frac{c}{n_2}.$$

- A better approximation to the desired f is

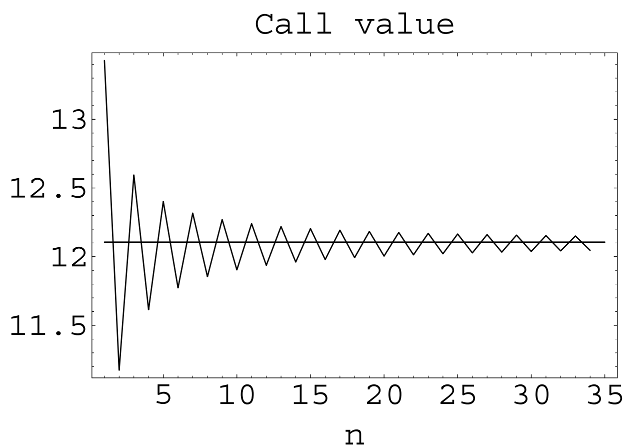
$$f = \frac{n_1 f(n_1) - n_2 f(n_2)}{n_1 - n_2}. \tag{115}$$

- This estimate should converge faster than $1/n$.[a]
- The Richardson extrapolation uses $n_2 = 2n_1$.

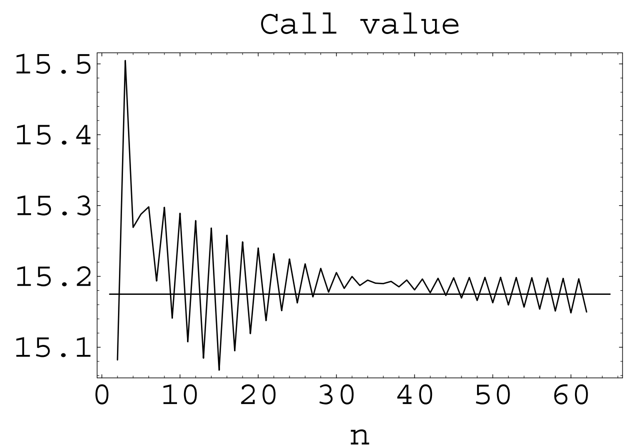
[a]It is identical to the forward rate formula (22) on p. 150!

Improving BOPM with Extrapolation

- Consider standard European options.
- Denote the option value under BOPM using n time periods by $f(n)$.
- It is known that BOPM convergences at the rate of $1/n$, consistent with Eq. (114) on p. 820.
- The plots on p. 302 (redrawn on next page) show that convergence to the true option value oscillates with n.
- Extrapolation is inapplicable at this stage.



Call value
13
12.5
12
11.5
5
10
15
20
25
30
35
n



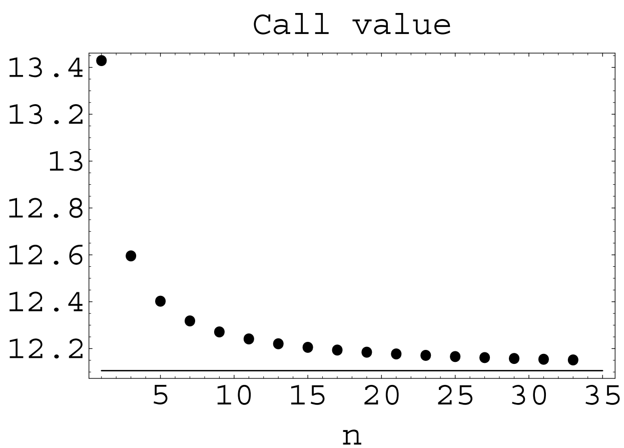
Call value
15.5
15.4
15.3
15.2
15.1
0
10
20
30
40
50
60
n

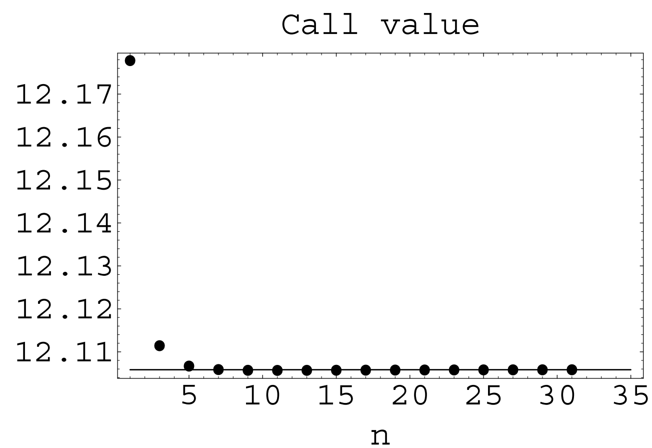
Improving BOPM with Extrapolation (concluded)

- Take the at-the-money option in the left plot on p. 823.
- The sequence with odd n turns out to be monotonic and smooth (see the left plot on p. 825).[a]
- Apply extrapolation (115) on p. 821 with $n_2 = n_1 + 2$, where n_1 is odd.
- Result is shown in the right plot on p. 825.
- The convergence rate is amazing.
- See Exercise 9.3.8 (p. 111) of the text for ideas in the general case.

---

[a] This can be proved (L. Chang & Palmer, 2007).


Call value
13.4
13.2
13
12.8
12.6
12.4
12.2
5 10 15 20 25 30 35
n

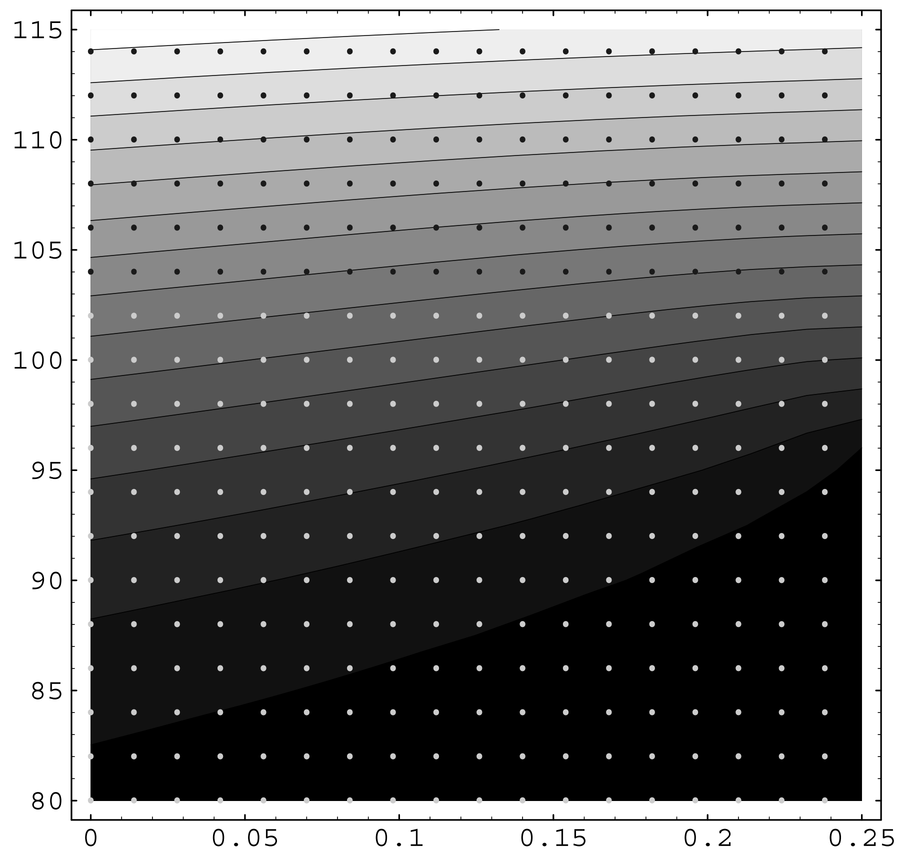

Call value
12.17
12.16
12.15
12.14
12.13
12.12
12.11
5 10 15 20 25 30 35
n

Numerical Methods

All science is dominated
by the idea of approximation.
— Bertrand Russell

Finite-Difference Methods

- Place a grid of points on the space over which the desired function takes value.
- Then approximate the function value at each of these points (p. 829).
- Solve the equation numerically by introducing difference equations in place of derivatives.


115
110
105
100
95
90
85
80
0
0.05
0.1
0.15
0.2
0.25

Example: Poisson's Equation

- It is $\partial^2\theta/\partial x^2 + \partial^2\theta/\partial y^2 = -\rho(x,y)$, which describes the electrostatic field.
- Replace second derivatives with finite differences through central difference.
- Introduce evenly spaced grid points with distance of Δx along the x axis and Δy along the y axis.
- The finite-difference form is

$$-\rho(x_i, y_j) = \frac{\theta(x_{i+1}, y_j) - 2\theta(x_i, y_j) + \theta(x_{i-1}, y_j)}{(\Delta x)^2} + \frac{\theta(x_i, y_{j+1}) - 2\theta(x_i, y_j) + \theta(x_i, y_{j-1})}{(\Delta y)^2}.$$

Example: Poisson's Equation (concluded)

- In the above, $\Delta x \stackrel{\Delta}{=} x_i - x_{i-1}$ and $\Delta y \stackrel{\Delta}{=} y_j - y_{j-1}$ for $i, j = 1, 2, \ldots$.
- When the grid points are evenly spaced in both axes so that $\Delta x = \Delta y = h$, the difference equation becomes

$$\begin{aligned} -h^2 \rho(x_i, y_j) &= \theta(x_{i+1}, y_j) + \theta(x_{i-1}, y_j) \\ &\quad + \theta(x_i, y_{j+1}) + \theta(x_i, y_{j-1}) - 4\theta(x_i, y_j). \end{aligned}$$

- Given boundary values, we can solve for the x_is and the y_js within the square $[\pm L, \pm L]$.
- From now on, $\theta_{i,j}$ will denote the finite-difference approximation to the exact $\theta(x_i, y_j)$.

Explicit Methods

- Consider the diffusion equation $D(\partial^2\theta/\partial x^2) - (\partial\theta/\partial t) = 0$, $D > 0$.
- Use evenly spaced grid points (x_i, t_j) with distances Δx and Δt, where $\Delta x \triangleq x_{i+1} - x_i$ and $\Delta t \triangleq t_{j+1} - t_j$.
- Employ central difference for the second derivative and forward difference for the time derivative to obtain

$$\left.\frac{\partial\theta(x,t)}{\partial t}\right|_{t=t_j} = \frac{\theta(x,t_{j+1}) - \theta(x,t_j)}{\Delta t} + \cdots, \tag{116}$$

$$\left.\frac{\partial^2\theta(x,t)}{\partial x^2}\right|_{x=x_i} = \frac{\theta(x_{i+1},t) - 2\theta(x_i,t) + \theta(x_{i-1},t)}{(\Delta x)^2} + \cdots . \tag{117}$$

Explicit Methods (continued)

- Next, assemble Eqs. (116) and (117) into a single equation at (x_i, t_j).
- But we need to decide how to evaluate x in the first equation and t in the second.
- Since central difference around x_i is used in Eq. (117), we might as well use x_i for x in Eq. (116).
- Two choices are possible for t in Eq. (117).
- The first choice uses $t = t_j$ to yield the following finite-difference equation,

$$\frac{\theta_{i,j+1} - \theta_{i,j}}{\Delta t} = D \, \frac{\theta_{i+1,j} - 2\theta_{i,j} + \theta_{i-1,j}}{(\Delta x)^2}. \tag{118}$$

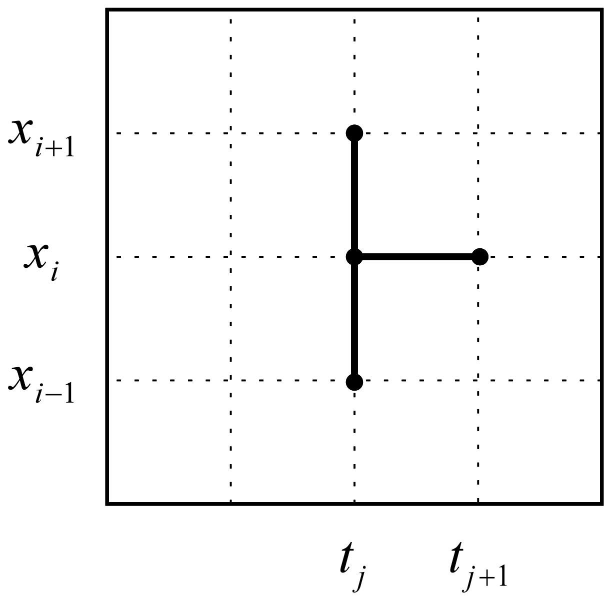
Explicit Methods (continued)

- The stencil of grid points involves four values, $\theta_{i,j+1}$, $\theta_{i,j}$, $\theta_{i+1,j}$, and $\theta_{i-1,j}$.
- Rearrange Eq. (118) on p. 833 as

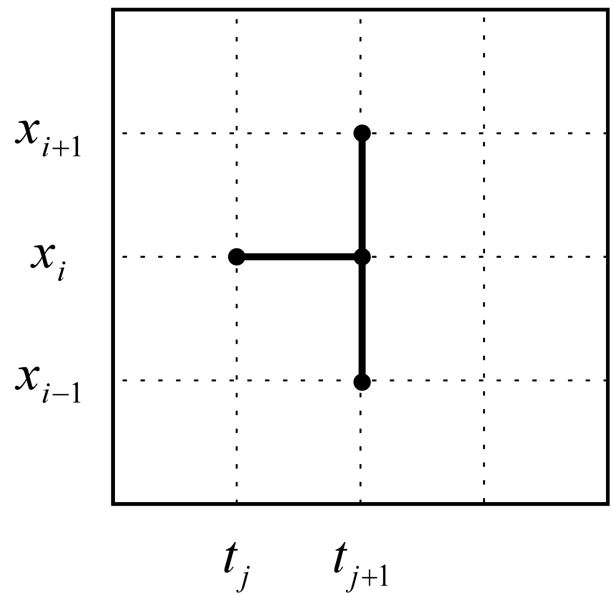
$$\theta_{i,j+1} = \frac{D\Delta t}{(\Delta x)^2}\,\theta_{i+1,j} + \left(1 - \frac{2D\Delta t}{(\Delta x)^2}\right)\theta_{i,j} + \frac{D\Delta t}{(\Delta x)^2}\,\theta_{i-1,j}.$$

- We can calculate $\theta_{i,j+1}$ from $\theta_{i,j}, \theta_{i+1,j}, \theta_{i-1,j}$, at the previous time t_j (see exhibit (a) on next page).

Stencils



(a)



(b)

Explicit Methods (concluded)

- Starting from the initial conditions at t_0, that is, $\theta_{i,0} = \theta(x_i, t_0)$, $i = 1, 2, \ldots$, we calculate

$$\theta_{i,1}, \quad i = 1, 2, \ldots .$$

- And then

$$\theta_{i,2}, \quad i = 1, 2, \ldots .$$

- And so on.

Stability

- The explicit method is numerically unstable unless

$$\Delta t \leq (\Delta x)^2/(2D).$$

  - A numerical method is unstable if the solution is highly sensitive to changes in initial conditions.
- The stability condition may lead to high running times and memory requirements.
- For instance, halving Δx would imply quadrupling $(\Delta t)^{-1}$, resulting in a running time 8 times as much.

Explicit Method and Trinomial Tree

- Recall that

$$\theta_{i,j+1} = \frac{D\Delta t}{(\Delta x)^2}\, \theta_{i+1,j} + \left(1 - \frac{2D\Delta t}{(\Delta x)^2}\right) \theta_{i,j} + \frac{D\Delta t}{(\Delta x)^2}\, \theta_{i-1,j}.$$

- When the stability condition is satisfied, the three coefficients for $\theta_{i+1,j}$, $\theta_{i,j}$, and $\theta_{i-1,j}$ all lie between zero and one and sum to one.
- They can be interpreted as probabilities.
- So the finite-difference equation becomes identical to backward induction on trinomial trees!

Explicit Method and Trinomial Tree (concluded)

- The freedom in choosing Δx corresponds to similar freedom in the construction of trinomial trees.
- The explicit finite-difference equation is also identical to backward induction on a binomial tree.[a]
  - Let the binomial tree take 2 steps each of length $\Delta t/2$.
  - It is now a trinomial tree.

[a] Hilliard (2014).

Implicit Methods

- Suppose we use $t = t_{j+1}$ in Eq. (117) on p. 832 instead.
- The finite-difference equation becomes

$$\frac{\theta_{i,j+1} - \theta_{i,j}}{\Delta t} = D\, \frac{\theta_{i+1,j+1} - 2\theta_{i,j+1} + \theta_{i-1,j+1}}{(\Delta x)^2}. \tag{119}$$

- The stencil involves $\theta_{i,j}$, $\theta_{i,j+1}$, $\theta_{i+1,j+1}$, and $\theta_{i-1,j+1}$.
- This method is implicit:
  - The value of any one of the three quantities at t_{j+1} cannot be calculated unless the other two are known.
  - See exhibit (b) on p. 835.

Implicit Methods (continued)

- Equation (119) can be rearranged as

$$\theta_{i-1,j+1} - (2+\gamma)\,\theta_{i,j+1} + \theta_{i+1,j+1} = -\gamma\theta_{i,j},$$

  where $\gamma \stackrel{\Delta}{=} (\Delta x)^2/(D\Delta t)$.

- This equation is unconditionally stable.
- Suppose the boundary conditions are given at $x = x_0$ and $x = x_{N+1}$.
- After $\theta_{i,j}$ has been calculated for $i = 1, 2, \ldots, N$, the values of $\theta_{i,j+1}$ at time t_{j+1} can be computed as the solution to the following tridiagonal linear system,

Implicit Methods (continued)

$$\begin{bmatrix} a & 1 & 0 & \cdots & \cdots & \cdots & 0 \\ 1 & a & 1 & 0 & \cdots & \cdots & 0 \\ 0 & 1 & a & 1 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & \cdots & 0 & 1 & a & 1 \\ 0 & \cdots & \cdots & \cdots & 0 & 1 & a \end{bmatrix} \begin{bmatrix} \theta_{1,j+1} \\ \theta_{2,j+1} \\ \theta_{3,j+1} \\ \vdots \\ \vdots \\ \vdots \\ \theta_{N,j+1} \end{bmatrix} = \begin{bmatrix} -\gamma\theta_{1,j} - \theta_{0,j+1} \\ -\gamma\theta_{2,j} \\ -\gamma\theta_{3,j} \\ \vdots \\ \vdots \\ -\gamma\theta_{N-1,j} \\ -\gamma\theta_{N,j} - \theta_{N+1,j+1} \end{bmatrix},$$

where $a \stackrel{\Delta}{=} -2 - \gamma$.

Implicit Methods (concluded)

- Tridiagonal systems can be solved in $O(N)$ time and $O(N)$ space.
  - Never invert a matrix to solve a tridiagonal system.
- The matrix above is nonsingular when $\gamma \geq 0$.
  - A square matrix is nonsingular if its inverse exists.

Crank-Nicolson Method

- Take the average of explicit method (118) on p. 833 and implicit method (119) on p. 840:

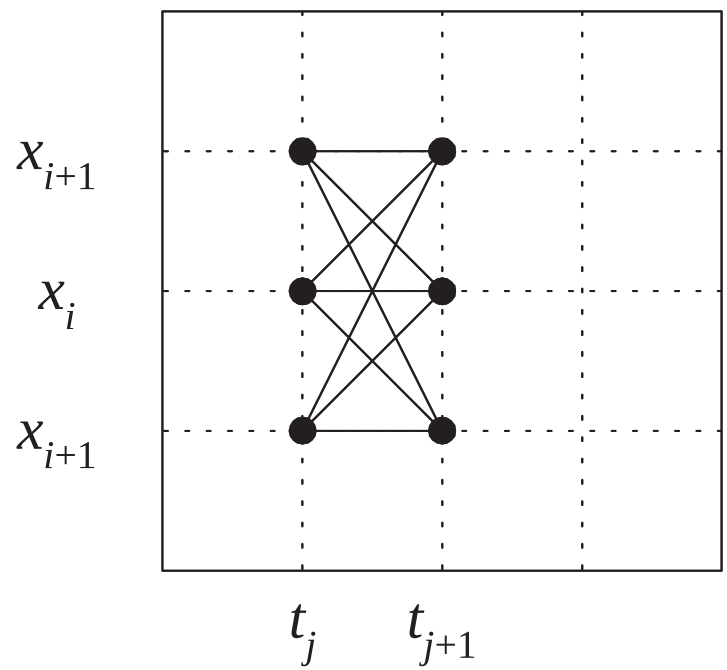
$$\frac{\theta_{i,j+1} - \theta_{i,j}}{\Delta t} = \frac{1}{2}\left(D\,\frac{\theta_{i+1,j} - 2\theta_{i,j} + \theta_{i-1,j}}{(\Delta x)^2} + D\,\frac{\theta_{i+1,j+1} - 2\theta_{i,j+1} + \theta_{i-1,j+1}}{(\Delta x)^2} \right).$$

- After rearrangement,

$$\gamma\theta_{i,j+1} - \frac{\theta_{i+1,j+1} - 2\theta_{i,j+1} + \theta_{i-1,j+1}}{2} = \gamma\theta_{i,j} + \frac{\theta_{i+1,j} - 2\theta_{i,j} + \theta_{i-1,j}}{2}.$$

- This is an unconditionally stable implicit method with excellent rates of convergence.

Stencil



Numerically Solving the Black-Scholes PDE (90) on p. 678

- See text.
- Brennan and Schwartz (1978) analyze the stability of the implicit method.

Monte Carlo Simulation[a]

- Monte Carlo simulation is a sampling scheme.
- In many important applications within finance and without, Monte Carlo is one of the few feasible tools.
- When the time evolution of a stochastic process is not easy to describe analytically, Monte Carlo may very well be the only strategy that succeeds consistently.

[a]A top 10 algorithm (Dongarra & Sullivan, 2000).

The Big Idea

- Assume $X_1, X_2, \ldots, X_n$ have a joint distribution.
- $\theta \triangleq E[\, g(X_1, X_2, \ldots, X_n)\,]$ for some function g is desired.
- We generate
$$\left(x_1^{(i)}, x_2^{(i)}, \ldots, x_n^{(i)}\right), \quad 1 \leq i \leq N$$
independently with the same joint distribution as $(X_1, X_2, \ldots, X_n)$.
- Set
$$Y_i \triangleq g\left(x_1^{(i)}, x_2^{(i)}, \ldots, x_n^{(i)}\right).$$

The Big Idea (concluded)

- $Y_1, Y_2, \ldots, Y_N$ are independent and identically distributed random variables.
- Each Y_i has the same distribution as

$$Y \triangleq g(X_1, X_2, \ldots, X_n).$$

- Since the average of these N random variables, $\overline{Y}$, satisfies $E[\,\overline{Y}\,] = \theta$, it can be used to estimate θ.
- The strong law of large numbers says that this procedure converges almost surely.
- The number of replications (or independent trials), N, is called the sample size.

Accuracy

- The Monte Carlo estimate and true value may differ owing to two reasons:
  1. Sampling variation.
  2. The discreteness of the sample paths.[a]
- The first can be controlled by the number of replications.
- The second can be controlled by the number of observations along the sample path.

---

[a]This may not be an issue if the financial derivative only requires discrete sampling along the time dimension, such as the *discrete* barrier option.

Accuracy and Number of Replications

- The statistical error of the sample mean $\overline{Y}$ of the random variable Y grows as $1/\sqrt{N}$.
  - Because $\mathrm{Var}[\,\overline{Y}\,] = \mathrm{Var}[\,Y\,]/N$.
- In fact, this convergence rate is asymptotically optimal.[a]
- So the variance of the estimator $\overline{Y}$ can be reduced by a factor of $1/N$ by doing N times as much work.
- This is amazing because the same order of convergence holds independently of the dimension n.

[a] The Berry-Esseen theorem.

Accuracy and Number of Replications (concluded)

- In contrast, classic numerical integration schemes have an error bound of $O(N^{-c/n})$ for some constant $c > 0$.
  - n is the dimension.
- The required number of evaluations thus grows exponentially in n to achieve a given level of accuracy.
  - The curse of dimensionality.
- The Monte Carlo method is more efficient than alternative procedures for multivariate derivatives when n is large.

Monte Carlo Option Pricing

- For the pricing of European options on a dividend-paying stock, we may proceed as follows.
- Assume
$$\frac{dS}{S} = \mu\, dt + \sigma\, dW.$$
- Stock prices $S_1, S_2, S_3, \ldots$ at times $\Delta t, 2\Delta t, 3\Delta t, \ldots$ can be generated via

$$\begin{aligned} & S_{i+1} \\ = \quad & S_i e^{(\mu-\sigma^2/2)\,\Delta t+\sigma\sqrt{\Delta t}\;\xi}, \quad \xi \sim N(0,1), \qquad (120) \end{aligned}$$

by Eq. (84) on p. 616.

Monte Carlo Option Pricing (continued)

- If we discretize $dS/S = \mu \, dt + \sigma \, dW$ directly, we will obtain

$$S_{i+1} = S_i + S_i \mu \, \Delta t + S_i \sigma \sqrt{\Delta t} \; \xi.$$

- But this is locally normally distributed, not lognormally, hence biased.[a]
- In practice, this is not expected to be a major problem as long as Δt is sufficiently small.

[a]Contributed by Mr. Tai, Hui-Chin (R97723028) on April 22, 2009.

Monte Carlo Option Pricing (continued)

Non-dividend-paying stock prices in a risk-neutral economy can be generated by setting $\mu = r$ and $\Delta t = T$.

$C := 0$; {Accumulated terminal option value.}
for $i = 1, 2, 3, \ldots, N$ **do**
  $P := S \times e^{(r - \sigma^2/2)\, T + \sigma \sqrt{T}\, \xi}, \ \xi \sim N(0, 1)$;
  $C := C + \max(P - X, 0)$;
end for
`return` Ce^{-rT}/N;

Monte Carlo Option Pricing (concluded)

Pricing Asian options is also easy.

$C := 0;$

for $i = 1, 2, 3, \ldots, N$ **do**

    $P := S;\ M := S;$

    for $j = 1, 2, 3, \ldots, n$ **do**

        $P := P \times e^{(r-\sigma^2/2)(T/n)+\sigma\sqrt{T/n}\,\xi};$

        $M := M + P;$

    end for

    $C := C + \max(M/(n+1) - X, 0);$

end for

`return` $Ce^{-rT}/N;$

How about American Options?

- Standard Monte Carlo simulation is inappropriate for American options because of early exercise.
  - Given a sample path $S_0, S_1, \ldots, S_n$, how to decide which S_i is an early-exercise point?
  - What is the option price at each S_i if the option is not exercised?
- It is difficult to determine the early-exercise point based on one single path.
- But Monte Carlo simulation can be modified to price American options with small biases (pp. 919ff).[a]

---

[a] Longstaff & Schwartz (2001).

Delta and Common Random Numbers

- In estimating delta, it is natural to start with the finite-difference estimate
$$e^{-r\tau}\,\frac{E[\,P(S+\epsilon)\,]-E[\,P(S-\epsilon)\,]}{2\epsilon}.$$
  - $P(x)$ is the terminal payoff of the derivative security when the underlying asset's initial price equals x.
- Use simulation to estimate $E[\,P(S+\epsilon)\,]$ first.
- Use another simulation to estimate $E[\,P(S-\epsilon)\,]$.
- Finally, apply the formula to approximate the delta.
- This is also called the bump-and-revalue method.

Delta and Common Random Numbers (concluded)

- This method is not recommended because of its high variance.
- A much better approach is to use common random numbers to lower the variance:
$$e^{-r\tau}\, E\left[\, \frac{P(S+\epsilon)-P(S-\epsilon)}{2\epsilon} \,\right].$$
- Here, the *same* random numbers are used for $P(S+\epsilon)$ and $P(S-\epsilon)$.
- This holds for gamma and cross gamma.[a]

[a]For multivariate derivatives.

Problems with the Bump-and-Revalue Method

- Consider the binary option with payoff

$$\begin{cases} 1, & \text{if } S(T) > X, \\ 0, & \text{otherwise.} \end{cases}$$

- Then

$$P(S+\epsilon)-P(S-\epsilon) = \begin{cases} 1, & \text{if } S+\epsilon > X \text{ and } S-\epsilon < X, \\ 0, & \text{otherwise.} \end{cases}$$

- So the finite-difference estimate per run for the (undiscounted) delta is 0 or $O(1/\epsilon)$.
- This means high variance.

Problems with the Bump-and-Revalue Method (concluded)

- The price of the binary option equals

$$e^{-r\tau} N(x - \sigma\sqrt{\tau}).$$

  - It equals *minus* the derivative of the European call with respect to X.
  - It also equals $X\tau$ times the rho of a European call (p. 358).

- Its delta is

$$\frac{N'\left(x - \sigma\sqrt{\tau}\right)}{S\sigma\sqrt{\tau}}.$$

Gamma

- The finite-difference formula for gamma is

$$e^{-r\tau}\, E\left[\,\frac{P(S+\epsilon) - 2\times P(S) + P(S-\epsilon)}{\epsilon^2}\,\right].$$

- For a correlation option with multiple underlying assets, the finite-difference formula for the cross gamma $\partial^2 P(S_1, S_2, \dots)/(\partial S_1 \partial S_2)$ is:

$$e^{-r\tau}\, E\left[\,\frac{P(S_1+\epsilon_1, S_2+\epsilon_2) - P(S_1-\epsilon_1, S_2+\epsilon_2)}{4\epsilon_1\epsilon_2}\right.$$

$$\left.\frac{-P(S_1+\epsilon_1, S_2-\epsilon_2) + P(S_1-\epsilon_1, S_2-\epsilon_2)}{}\,\right].$$

Gamma (continued)

- Choosing an ϵ of the right magnitude can be challenging.
  - If ϵ is too large, inaccurate Greeks result.
  - If ϵ is too small, unstable Greeks result.
- This phenomenon is sometimes called the curse of differentiation.[a]

---

[a] Aït-Sahalia & Lo (1998); Bondarenko (2003).

Gamma (continued)

- In general, suppose (in some sense)

$$\frac{\partial^i}{\partial \theta^i} e^{-r\tau} E[\,P(S)\,] = e^{-r\tau} E\left[\,\frac{\partial^i P(S)}{\partial \theta^i}\,\right]$$

  holds for all $i > 0$, where θ is a parameter of interest.[a]

  – A common requirement is Lipschitz continuity.[b]

- Then Greeks become integrals.

- As a result, we avoid ϵ, finite differences, and resimulation.

---

[a] $\partial^i P(S)/\partial \theta^i$ may not be partial differentiation in the classic sense.

[b] Broadie & Glasserman (1996).

Gamma (continued)

- This is indeed possible for a broad class of payoff functions.[a]
  - Roughly speaking, any payoff function that is equal to a sum of products of differentiable functions and indicator functions with the right kind of support.
  - For example, the payoff of a call is

$$\max(S(T) - X, 0) = (S(T) - X) I_{\{\, S(T) - X \geq 0 \,\}}.$$

  - The results are too technical to cover here (see next page).

[a] Teng (R91723054) (2004); Lyuu & Teng (R91723054) (2011).

Gamma (continued)

- Suppose $h(\theta, x) \in \mathcal{H}$ with pdf $f(x)$ for x and $g_j(\theta, x) \in \mathcal{G}$ for $j \in \mathcal{B}$, a finite set of natural numbers.
- Then

$$\begin{aligned} & \frac{\partial}{\partial \theta} \int_{\Re} h(\theta, x) \prod_{j \in \mathcal{B}} \mathbf{1}_{\{g_j(\theta,x)>0\}}(x)\, f(x)\, dx \\ = \quad & \int_{\Re} h_\theta(\theta, x) \prod_{j \in \mathcal{B}} \mathbf{1}_{\{g_j(\theta,x)>0\}}(x)\, f(x)\, dx \\ & + \sum_{l \in \mathcal{B}} \left[h(\theta, x) J_l(\theta, x) \prod_{j \in \mathcal{B} \setminus l} \mathbf{1}_{\{g_j(\theta, x)>0\}}(x)\, f(x) \right]_{x=\chi_l(\theta)}, \end{aligned}$$

where

$$J_l(\theta, x) = \text{sign}\left(\frac{\partial g_l(\theta, x)}{\partial x_k} \right) \frac{\partial g_l(\theta, x)/\partial \theta}{\partial g_l(\theta, x)/\partial x} \text{ for } l \in \mathcal{B}.$$

Gamma (concluded)

- Similar results have been derived for Levy processes.[a]
- Formulas are also recently obtained for credit derivatives.[b]
- In queueing networks, this is called infinitesimal perturbation analysis (IPA).[c]

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[a] Lyuu, Teng (R91723054), & S. Wang (2013).
[b] Lyuu, Teng (R91723054), & Tseng (2014, 2018).
[c] Cao (1985); Y. C. Ho & Cao (1985).