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 gammas (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

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

- Its delta is

$$N'(x - \sigma\sqrt{\tau})/(S\sigma\sqrt{\tau}).$$

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

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

  holds for all $i > 0$, where θ is a parameter of interest.
  - A common requirement is Lipschitz continuity.[a]
- Then formulas for the Greeks become integrals.
- As a result, we avoid ϵ, finite differences, and resimulation.

[a]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

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

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]

---

[a] Lyuu, Teng (`R91723054`), & S. Wang (2013).
[b] Lyuu, Teng (`R91723054`), & Tzeng (2014).
[c] Cao (1985); Ho & Cao (1985).

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Biases in Pricing Continuously Monitored Options with Monte Carlo

- We are asked to price a continuously monitored up-and-out call with barrier H.
- The Monte Carlo method samples the stock price at n discrete time points $t_1, t_2, \ldots, t_n$.
- A sample path

$$S(t_0), S(t_1), \ldots, S(t_n)$$

  is produced.
  - Here, $t_0 = 0$ is the current time, and $t_n = T$ is the expiration time of the option.

Biases in Pricing Continuously Monitored Options with Monte Carlo (continued)

- If all of the sampled prices are below the barrier, this sample path pays $\max(S(t_n) - X, 0)$.
- Repeating these steps and averaging the payoffs yield a Monte Carlo estimate.

```
C := 0;
for i = 1, 2, 3, ..., N do
    P := S; hit := 0;
    for j = 1, 2, 3, ..., n do
        P := P × e^{(r − σ^2/2)(T/n) + σ √(T/n) ξ};
        if P ≥ H then
            hit := 1;
            break;
        end if
    end for
    if hit = 0 then
        C := C + max(P − X, 0);
    end if
end for
return C e^{−rT} / N;
```

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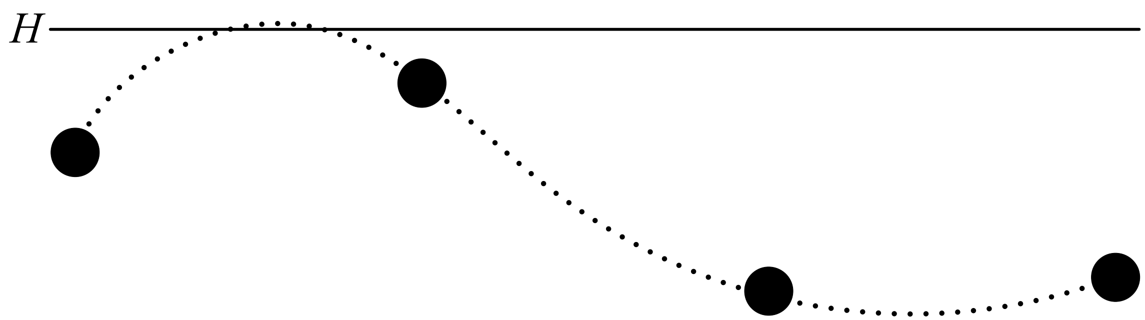
Biases in Pricing Continuously Monitored Options with Monte Carlo (continued)

- This estimate is biased.[a]
  - Suppose none of the sampled prices on a sample path equals or exceeds the barrier H.
  - It remains possible for the continuous sample path that passes through them to hit the barrier between sampled time points (see plot on next page).

[a]Shevchenko (2003).


H

Biases in Pricing Continuously Monitored Options with Monte Carlo (concluded)

- The bias can certainly be lowered by increasing the number of observations along the sample path.
- However, even daily sampling may not suffice.
- The computational cost also rises as a result.

Brownian Bridge Approach to Pricing Barrier Options

- We desire an unbiased estimate which can be calculated efficiently.
- The above-mentioned payoff should be multiplied by the probability p that a continuous sample path does *not* hit the barrier conditional on the sampled prices.
- This methodology is called the Brownian bridge approach.
- Formally, we have

$$p \stackrel{\Delta}{=} \text{Prob}[\, S(t) < H, 0 \leq t \leq T \mid S(t_0), S(t_1), \ldots, S(t_n)\,].$$

Brownian Bridge Approach to Pricing Barrier Options (continued)

- As a barrier is hit over a time interval if and only if the maximum stock price over that period is at least H,

$$p = \text{Prob}\left[\max_{0 \leq t \leq T} S(t) < H \mid S(t_0), S(t_1), \ldots, S(t_n)\right].$$

- Luckily, the conditional distribution of the maximum over a time interval given the beginning and ending stock prices is known.

Brownian Bridge Approach to Pricing Barrier Options (continued)

Lemma 23 *Assume S follows $dS/S = \mu\, dt + \sigma\, dW$ and define*

$$\zeta(x) \stackrel{\Delta}{=} \exp\left[-\frac{2 \ln(x/S(t)) \ln(x/S(t+\Delta t))}{\sigma^2 \Delta t} \right].$$

(1) If $H > \max(S(t), S(t+\Delta t))$, then

$$\text{Prob}\left[\max_{t \le u \le t+\Delta t} S(u) < H \,\middle|\, S(t), S(t+\Delta t) \right] = 1 - \zeta(H).$$

(2) If $h < \min(S(t), S(t+\Delta t))$, then

$$\text{Prob}\left[\min_{t \le u \le t+\Delta t} S(u) > h \,\middle|\, S(t), S(t+\Delta t) \right] = 1 - \zeta(h).$$

Brownian Bridge Approach to Pricing Barrier Options (continued)

- Lemma 23 gives the probability that the barrier is not hit in a time interval, given the starting and ending stock prices.
- For our up-and-out call,[a] choose $n = 1$.
- As a result,

$$p = \begin{cases} 1 - \exp\left[-\frac{2\ln(H/S(0))\ln(H/S(T))}{\sigma^2 T} \right], & \text{if } H > \max(S(0), S(T)), \\ 0, & \text{otherwise.} \end{cases}$$

[a] So $S(0) < H$.

Brownian Bridge Approach to Pricing Barrier Options (continued)

The following algorithms works for up-and-out and down-and-out calls.

1: $C := 0$;
2: **for** $i = 1, 2, 3, \ldots, N$ **do**
3: $\quad P := S \times e^{(r-q-\sigma^2/2)\,T+\sigma\sqrt{T}\;\xi(\,)}$;
4: $\quad$ **if** $(S < H$ and $P < H)$ or $(S > H$ and $P > H)$ **then**
5: $\quad\quad C := C + \max(P - X, 0) \times \left\{ 1 - \exp\left[-\frac{2\ln(H/S) \times \ln(H/P)}{\sigma^2 T} \right] \right\}$;
6: $\quad$ **end if**
7: **end for**
8: `return` Ce^{-rT}/N;

Brownian Bridge Approach to Pricing Barrier Options (concluded)

- The idea can be generalized.
- For example, we can handle more complex barrier options.
- Consider an up-and-out call with barrier H_i for the time interval $(t_i, t_{i+1}]$, $0 \leq i < n$.
- This option thus contains n barriers.
- Multiply the probabilities for the n time intervals to obtain the desired probability adjustment term.

Variance Reduction

- The statistical efficiency of Monte Carlo simulation can be measured by the variance of its output.
- If this variance can be lowered without changing the expected value, fewer replications are needed.
- Methods that improve efficiency in this manner are called variance-reduction techniques.
- Such techniques become practical when the added costs are outweighed by the reduction in sampling.

Variance Reduction: Antithetic Variates

- We are interested in estimating $E[\, g(X_1, X_2, \ldots, X_n) \,]$.
- Let Y_1 and Y_2 be random variables with the same distribution as $g(X_1, X_2, \ldots, X_n)$.
- Then

$$\mathrm{Var}\left[\, \frac{Y_1 + Y_2}{2} \,\right] = \frac{\mathrm{Var}[\, Y_1 \,]}{2} + \frac{\mathrm{Cov}[\, Y_1, Y_2 \,]}{2}.$$

  - $\mathrm{Var}[\, Y_1 \,]/2$ is the variance of the Monte Carlo method with two independent replications.
- The variance $\mathrm{Var}[\, (Y_1 + Y_2)/2 \,]$ is smaller than $\mathrm{Var}[\, Y_1 \,]/2$ when Y_1 and Y_2 are negatively correlated.

Variance Reduction: Antithetic Variates (continued)

- For each simulated sample path X, a second one is obtained by *reusing* the random numbers on which the first path is based.
- This yields a second sample path Y.
- Two estimates are then obtained: One based on X and the other on Y.
- If N independent sample paths are generated, the antithetic-variates estimator averages over $2N$ estimates.

Variance Reduction: Antithetic Variates (continued)

- Consider process $dX = a_t\, dt + b_t \sqrt{dt}\, \xi$.
- Let g be a function of n samples $X_1, X_2, \ldots, X_n$ on the sample path.
- We are interested in $E[\, g(X_1, X_2, \ldots, X_n)\,]$.
- Suppose one simulation run has realizations $\xi_1, \xi_2, \ldots, \xi_n$ for the normally distributed fluctuation term ξ.
- This generates samples $x_1, x_2, \ldots, x_n$.
- The estimate is then $g(\boldsymbol{x})$, where $\boldsymbol{x} \stackrel{\Delta}{=} (x_1, x_2 \ldots, x_n)$.

Variance Reduction: Antithetic Variates (concluded)

- The antithetic-variates method does not sample n more numbers from ξ for the second estimate $g(\boldsymbol{x}')$.
- Instead, generate the sample path $\boldsymbol{x}' \stackrel{\Delta}{=} (x'_1, x'_2 \ldots, x'_n)$ from $-\xi_1, -\xi_2, \ldots, -\xi_n$.
- Compute $g(\boldsymbol{x}')$.
- Output $(g(\boldsymbol{x}) + g(\boldsymbol{x}'))/2$.
- Repeat the above steps for as many times as required by accuracy.

Variance Reduction: Conditioning

- We are interested in estimating $E[X]$.
- Suppose here is a random variable Z such that $E[X \mid Z = z]$ can be efficiently and precisely computed.
- $E[X] = E[E[X \mid Z]]$ by the law of iterated conditional expectations.
- Hence the random variable $E[X \mid Z]$ is also an unbiased estimator of $E[X]$.

Variance Reduction: Conditioning (concluded)

- As
$$\text{Var}[\,E[\,X \mid Z\,]\,] \leq \text{Var}[\,X\,],$$
$E[\,X \mid Z\,]$ has a smaller variance than observing X directly.
- First obtain a random observation z on Z.
- Then calculate $E[\,X \mid Z = z\,]$ as our estimate.
  - There is no need to resort to simulation in computing $E[\,X \mid Z = z\,]$.
- The procedure can be repeated a few times to reduce the variance.

Control Variates

- Use the analytic solution of a similar yet simpler problem to improve the solution.
- Suppose we want to estimate $E[\,X\,]$ and there exists a random variable Y with a known mean $\mu \stackrel{\Delta}{=} E[\,Y\,]$.
- Then $W \stackrel{\Delta}{=} X + \beta(Y - \mu)$ can serve as a "controlled" estimator of $E[\,X\,]$ for any constant β.
  - However β is chosen, W remains an unbiased estimator of $E[\,X\,]$ as

$$E[\,W\,] = E[\,X\,] + \beta E[\,Y - \mu\,] = E[\,X\,].$$

Control Variates (continued)

- Note that

$$\mathrm{Var}[\,W\,] = \mathrm{Var}[\,X\,] + \beta^2\,\mathrm{Var}[\,Y\,] + 2\beta\,\mathrm{Cov}[\,X, Y\,], \tag{110}$$

- Hence W is less variable than X if and only if

$$\beta^2\,\mathrm{Var}[\,Y\,] + 2\beta\,\mathrm{Cov}[\,X, Y\,] < 0. \tag{111}$$

Control Variates (concluded)

- The success of the scheme clearly depends on both β and the choice of Y.
  - For example, arithmetic average-rate options can be priced by choosing Y to be the otherwise identical geometric average-rate option's price and $\beta = -1$.
- This approach is much more effective than the antithetic-variates method.

Choice of Y

- In general, the choice of Y is ad hoc,[a] and experiments must be performed to confirm the wisdom of the choice.
- Try to match calls with calls and puts with puts.[b]
- On many occasions, Y is a discretized version of the derivative that gives μ.
  - Discretely monitored geometric average-rate option vs. the continuously monitored geometric average-rate option given by formulas (50) on p. 401.

---

[a] But see Dai (B82506025, R86526008, D8852600), Chiu (R94922072), & Lyuu (2015).

[b] Contributed by Ms. Teng, Huei-Wen (R91723054) on May 25, 2004.

Optimal Choice of β

- For some choices, the discrepancy can be significant, such as the lookback option.[a]
- Equation (110) on p. 826 is minimized when

$$\beta = -\text{Cov}[\,X, Y\,]/\text{Var}[\,Y\,].$$

  - It is called beta in the book.
- For this specific β,

$$\text{Var}[\,W\,] = \text{Var}[\,X\,] - \frac{\text{Cov}[\,X, Y\,]^2}{\text{Var}[\,Y\,]} = \left(1 - \rho_{X,Y}^2\right)\text{Var}[\,X\,],$$

where $\rho_{X,Y}$ is the correlation between X and Y.

[a] Contributed by Mr. Tsai, Hwai (`R92723049`) on May 12, 2004.

Optimal Choice of β (continued)

- Note that the variance can never be increased with the optimal choice.
- Furthermore, the stronger X and Y are correlated, the greater the reduction in variance.
- For example, if this correlation is nearly perfect (± 1), we could control X almost exactly.

Optimal Choice of β (continued)

- Typically, neither $\mathrm{Var}[\,Y\,]$ nor $\mathrm{Cov}[\,X, Y\,]$ is known.
- Therefore, we cannot obtain the maximum reduction in variance.
- We can guess these values and hope that the resulting W does indeed have a smaller variance than X.
- A second possibility is to use the simulated data to estimate these quantities.
  - How to do it efficiently in terms of time and space?

Optimal Choice of β (concluded)

- Observe that $-\beta$ has the same sign as the correlation between X and Y.
- Hence, if X and Y are positively correlated, $\beta < 0$, then X is adjusted downward whenever $Y > \mu$ and upward otherwise.
- The opposite is true when X and Y are negatively correlated, in which case $\beta > 0$.
- Suppose a suboptimal $\beta + \epsilon$ is used instead.
- The variance increases by only $\epsilon^2 \mathrm{Var}[\,Y\,]$.[a]

[a] Han & Lai (2010).

A Pitfall

- A potential pitfall is to sample X and Y *independently*.
- In this case, $\text{Cov}[\,X, Y\,] = 0$.
- Equation (110) on p. 826 becomes

$$\text{Var}[\,W\,] = \text{Var}[\,X\,] + \beta^2 \,\text{Var}[\,Y\,].$$

- So whatever Y is, the variance is *increased*!
- Lesson: X and Y must be correlated.

Problems with the Monte Carlo Method

- The error bound is only probabilistic.
- The probabilistic error bound of $\sqrt{N}$ does not benefit from regularity of the integrand function.
- The requirement that the points be independent random samples are wasteful because of clustering.
- In reality, pseudorandom numbers generated by completely deterministic means are used.
- Monte Carlo simulation exhibits a great sensitivity on the seed of the pseudorandom-number generator.

Matrix Computation

To set up a philosophy against physics is rash;
philosophers who have done so
have always ended in disaster.
— Bertrand Russell

Definitions and Basic Results

- Let $A \stackrel{\Delta}{=} [\, a_{ij} \,]_{1 \leq i \leq m, 1 \leq j \leq n}$, or simply $A \in \boldsymbol{R}^{m \times n}$, denote an $m \times n$ matrix.
- It can also be represented as $[\, a_1, a_2, \ldots, a_n \,]$ where $a_i \in \boldsymbol{R}^m$ are vectors.
  - Vectors are column vectors unless stated otherwise.
- A is a square matrix when $m = n$.
- The rank of a matrix is the largest number of linearly independent columns.

Definitions and Basic Results (continued)

- A square matrix A is said to be symmetric if $A^{\mathrm{T}} = A$.
- A real $n \times n$ matrix

$$A \triangleq [\, a_{ij} \,]_{i,j}$$

  is diagonally dominant if $|\, a_{ii} \,| > \sum_{j \neq i} |\, a_{ij} \,|$ for $1 \leq i \leq n$.
  - Such matrices are nonsingular.
- The identity matrix is the square matrix

$$I \triangleq \mathrm{diag}[\, 1, 1, \ldots, 1 \,].$$

Definitions and Basic Results (concluded)

- A matrix has full column rank if its columns are linearly independent.
- A real symmetric matrix A is positive definite if

$$x^{\mathrm{T}} A x = \sum_{i,j} a_{ij} x_i x_j > 0$$

  for any nonzero vector x.
- A matrix A is positive definite if and only if there exists a matrix W such that $A = W^{\mathrm{T}} W$ and W has full column rank.

Cholesky Decomposition

- Positive definite matrices can be factored as

$$A = LL^{\mathrm{T}},$$

called the Cholesky decomposition.

  – Above, L is a lower triangular matrix.

Generation of Multivariate Distribution

- Let $\boldsymbol{x} \stackrel{\Delta}{=} [\,x_1, x_2, \ldots, x_n\,]^{\mathrm{T}}$ be a vector random variable with a positive definite covariance matrix C.
- As usual, assume $E[\,\boldsymbol{x}\,] = \mathbf{0}$.
- This covariance structure can be matched by $P\boldsymbol{y}$.
  - $C = PP^{\mathrm{T}}$ is the Cholesky decomposition of C.[a]
  - $\boldsymbol{y} \stackrel{\Delta}{=} [\,y_1, y_2, \ldots, y_n\,]^{\mathrm{T}}$ is a vector random variable with a covariance matrix equal to the identity matrix.

---

[a]What if C is not positive definite? See Lai (R93942114) & Lyuu (2007).

Generation of Multivariate Normal Distribution

- Suppose we want to generate the multivariate normal distribution with a covariance matrix $C = PP^{\mathrm{T}}$.
  - First, generate independent standard normal distributions $y_1, y_2, \ldots, y_n$.
  - Then
$$P[\, y_1, y_2, \ldots, y_n \,]^{\mathrm{T}}$$
    has the desired distribution.
  - These steps can then be repeated.

Multivariate Derivatives Pricing

- Generating the multivariate normal distribution is essential for the Monte Carlo pricing of multivariate derivatives (pp. 748ff).
- For example, the rainbow option on k assets has payoff

$$\max(\max(S_1, S_2, \ldots, S_k) - X, 0)$$

at maturity.

- The closed-form formula is a multi-dimensional integral.[a]

[a] Johnson (1987); Chen (D95723006) & Lyuu (2009).

Multivariate Derivatives Pricing (concluded)

- Suppose $dS_j/S_j = r\,dt + \sigma_j\,dW_j$, $1 \leq j \leq k$, where C is the correlation matrix for $dW_1, dW_2, \ldots, dW_k$.
- Let $C = PP^{\mathrm{T}}$.
- Let ξ consist of k independent random variables from $N(0,1)$.
- Let $\xi' = P\xi$.
- Similar to Eq. (109) on p. 791,

$$S_{i+1} = S_i e^{(r-\sigma_j^2/2)\,\Delta t + \sigma_j \sqrt{\Delta t}\;\xi'_j}, \quad 1 \leq j \leq k.$$

Least-Squares Problems

- The least-squares (LS) problem is concerned with

$$\min_{x \in R^n} \| Ax - b \|,$$

where $A \in \boldsymbol{R}^{m \times n}$, $b \in \boldsymbol{R}^m$, and $m \geq n$.

- The LS problem is called regression analysis in statistics and is equivalent to minimizing the mean-square error.
- Often written as

$$Ax = b.$$

Polynomial Regression

- In polynomial regression, $x_0 + x_1 x + \cdots + x_n x^n$ is used to fit the data $\{ (a_1, b_1), (a_2, b_2), \ldots, (a_m, b_m) \}$.
- This leads to the LS problem,

$$\begin{bmatrix} 1 & a_1 & a_1^2 & \cdots & a_1^n \\ 1 & a_2 & a_2^2 & \cdots & a_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & a_m & a_m^2 & \cdots & a_m^n \end{bmatrix} \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}.$$

- Consult p. 273 of the textbook for solutions.

American Option Pricing by Simulation

- The continuation value of an American option is the conditional expectation of the payoff from keeping the option alive now.
- The option holder must compare the immediate exercise value and the continuation value.
- In standard Monte Carlo simulation, each path is treated independently of other paths.
- But the decision to exercise the option cannot be reached by looking at one path alone.

The Least-Squares Monte Carlo Approach

- The continuation value can be estimated from the cross-sectional information in the simulation by using least squares.[a]
- The result is a function (of the state) for estimating the continuation values.
- Use the function to estimate the continuation value for each path to determine its cash flow.
- This is called the least-squares Monte Carlo (LSM) approach.

[a] Longstaff & Schwartz (2001).

The Least-Squares Monte Carlo Approach (concluded)

- The LSM is provably convergent.[a]
- The LSM can be easily parallelized.[b]
  - Partition the paths into subproblems and perform LSM on each of them independently.
  - The speedup is close to linear (i.e., proportional to the number of cores).
- Surprisingly, accuracy is not affected.

---

[a] Clément, Lamberton, & Protter (2002); Stentoft (2004).

[b] Huang (B96902079, R00922018) (2013); Chen (B97902046, R01922005) (2014); Chen (B97902046, R01922005), Huang (B96902079, R00922018) & Lyuu (2015).

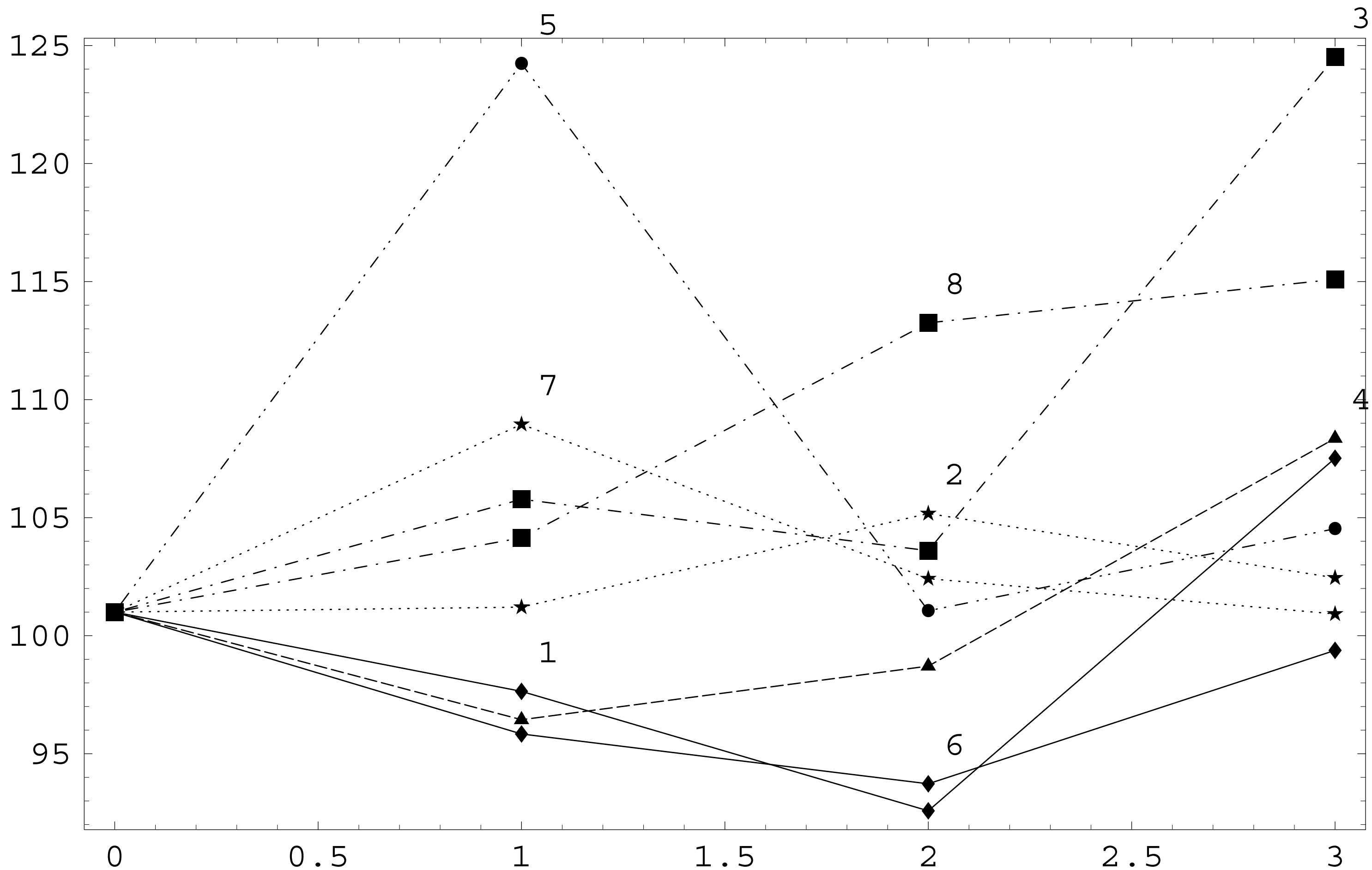
A Numerical Example

- Consider a 3-year American put on a non-dividend-paying stock.
- The put is exercisable at years 0, 1, 2, and 3.
- The strike price $X = 105$.
- The annualized riskless rate is $r = 5\%$.
- The current stock price is 101.
  - The annual discount factor hence equals 0.951229.
- We use only 8 price paths to illustrate the algorithm.

A Numerical Example (continued)

Stock price paths

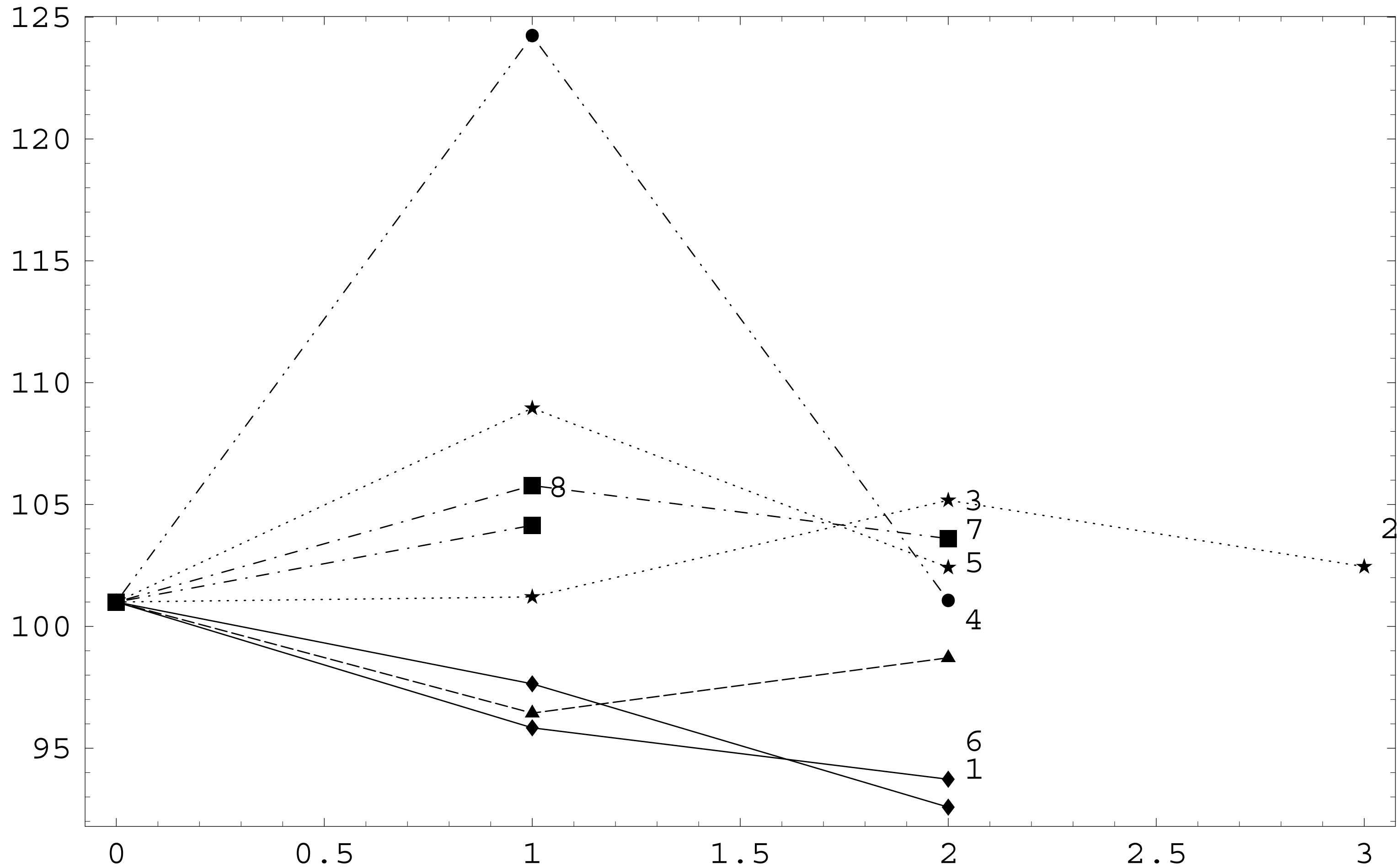
Path	Year 0	Year 1	Year 2	Year 3
1	**101**	**97.6424**	**92.5815**	107.5178
2	**101**	**101.2103**	105.1763	**102.4524**
3	**101**	105.7802	**103.6010**	124.5115
4	**101**	**96.4411**	**98.7120**	108.3600
5	**101**	124.2345	**101.0564**	**104.5315**
6	**101**	**95.8375**	**93.7270**	**99.3788**
7	**101**	108.9554	**102.4177**	**100.9225**
8	**101**	**104.1475**	113.2516	115.0994


125
120
115
110
105
100
95
0
0.5
1
1.5
2
2.5
3
5
3
8
7
4
2
1
6

A Numerical Example (continued)

- We use the basis functions $1, x, x^2$.
  - Other basis functions are possible.[a]
- The plot next page shows the final estimated optimal exercise strategy given by LSM.
- We now proceed to tackle our problem.
- The idea is to calculate the cash flow along each path, using information from *all* paths.

[a] Laguerre polynomials, Hermite polynomials, Legendre polynomials, Chebyshev polynomials, Gedenbauer polynomials, and Jacobi polynomials.


125
120
115
110
105
100
95
0
0.5
1
1.5
2
2.5
3
8
3
7
5
4
6
1
2

A Numerical Example (continued)

Cash flows at year 3

Path	Year 0	Year 1	Year 2	Year 3
1	—	—	—	0
2	—	—	—	2.5476
3	—	—	—	0
4	—	—	—	0
5	—	—	—	0.4685
6	—	—	—	5.6212
7	—	—	—	4.0775
8	—	—	—	0

A Numerical Example (continued)

- The cash flows at year 3 are the exercise value if the put is in the money.
- Only 4 paths are in the money: 2, 5, 6, 7.
- Some of the cash flows may not occur if the put is exercised earlier, which we will find out step by step.
- Incidentally, the *European* counterpart has a value of

$$0.951229^3 \times \frac{2.5476 + 0.4685 + 5.6212 + 4.0775}{8} = 1.3680.$$

A Numerical Example (continued)

- We move on to year 2.
- For each state that is in the money at year 2, we must decide whether to exercise it.
- There are 6 paths for which the put is in the money: 1, 3, 4, 5, 6, 7 (p. 851).
- Only in-the-money paths will be used in the regression because they are where early exercise is relevant.
  - If there were none, we would move on to year 1.

A Numerical Example (continued)

- Let x denote the stock prices at year 2 for those 6 paths.
- Let y denote the corresponding discounted future cash flows (at year 3) if the put is not exercised at year 2.

A Numerical Example (continued)

Regression at year 2

Path	x	y
1	92.5815	0×0.951229
2	—	—
3	103.6010	0×0.951229
4	98.7120	0×0.951229
5	101.0564	0.4685×0.951229
6	93.7270	5.6212×0.951229
7	102.4177	4.0775×0.951229
8	—	—

A Numerical Example (continued)

- We regress y on 1, x, and x^2.
- The result is

$$f(x) = 22.08 - 0.313114 \times x + 0.00106918 \times x^2.$$

- $f(x)$ estimates the continuation value conditional on the stock price at year 2.
- We next compare the immediate exercise value and the continuation value.[a]

---

[a]The $f(102.4177)$ entry on the next page was corrected by Mr. Du, Yung-Szu (B79503054, R83503086) on May 25, 2017.

A Numerical Example (continued)

Optimal early exercise decision at year 2

Path	Exercise	Continuation
1	12.4185	$f(92.5815) = 2.2558$
2	—	—
3	1.3990	$f(103.6010) = 1.1168$
4	6.2880	$f(98.7120) = 1.5901$
5	3.9436	$f(101.0564) = 1.3568$
6	11.2730	$f(93.7270) = 2.1253$
7	2.5823	$f(102.4177) = 1.2266$
8	—	—

A Numerical Example (continued)

- Amazingly, the put should be exercised in all 6 paths: 1, 3, 4, 5, 6, 7.
- Now, any positive cash flow at year 3 should be set to zero or overridden for these paths as the put is exercised before year 3 (p. 851).
  - They are paths 5, 6, 7.
- The cash flows on p. 855 become the ones on next slide.

A Numerical Example (continued)

Cash flows at years 2 & 3

Path	Year 0	Year 1	Year 2	Year 3
1	—	—	12.4185	0
2	—	—	0	2.5476
3	—	—	1.3990	0
4	—	—	6.2880	0
5	—	—	3.9436	0
6	—	—	11.2730	0
7	—	—	2.5823	0
8	—	—	0	0

A Numerical Example (continued)

- We move on to year 1.
- For each state that is in the money at year 1, we must decide whether to exercise it.
- There are 5 paths for which the put is in the money: 1, 2, 4, 6, 8 (p. 851).
- Only in-the-money paths will be used in the regression because they are where early exercise is relevant.
  - If there were none, we would move on to year 0.

A Numerical Example (continued)

- Let x denote the stock prices at year 1 for those 5 paths.
- Let y denote the corresponding discounted future cash flows if the put is not exercised at year 1.
- From p. 863, we have the following table.

A Numerical Example (continued)

Regression at year 1

Path	x	y
1	97.6424	12.4185×0.951229
2	101.2103	2.5476×0.951229^2
3	—	—
4	96.4411	6.2880×0.951229
5	—	—
6	95.8375	11.2730×0.951229
7	—	—
8	104.1475	0

A Numerical Example (continued)

- We regress y on 1, x, and x^2.
- The result is

$$f(x) = -420.964 + 9.78113 \times x - 0.0551567 \times x^2.$$

- $f(x)$ estimates the continuation value conditional on the stock price at year 1.
- We next compare the immediate exercise value and the continuation value.

A Numerical Example (continued)

Optimal early exercise decision at year 1

Path	Exercise	Continuation
1	7.3576	$f(97.6424) = 8.2230$
2	3.7897	$f(101.2103) = 3.9882$
3	—	—
4	8.5589	$f(96.4411) = 9.3329$
5	—	—
6	9.1625	$f(95.8375) = 9.83042$
7	—	—
8	0.8525	$f(104.1475) = -0.551885$

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A Numerical Example (continued)

- The put should be exercised for 1 path only: 8.
  - Note that $f(104.1475) < 0$.
- Now, any positive future cash flow should be set to zero or overridden for this path.
  - But there is none.
- The cash flows on p. 863 become the ones on next slide.
- They also confirm the plot on p. 854.

A Numerical Example (continued)

Cash flows at years 1, 2, & 3

Path	Year 0	Year 1	Year 2	Year 3
1	—	0	12.4185	0
2	—	0	0	2.5476
3	—	0	1.3990	0
4	—	0	6.2880	0
5	—	0	3.9436	0
6	—	0	11.2730	0
7	—	0	2.5823	0
8	—	0.8525	0	0

A Numerical Example (continued)

- We move on to year 0.
- The continuation value is, from p 870,

$$
\begin{aligned}
& (12.4185 \times 0.951229^2 + 2.5476 \times 0.951229^3 \\
& +1.3990 \times 0.951229^2 + 6.2880 \times 0.951229^2 \\
& +3.9436 \times 0.951229^2 + 11.2730 \times 0.951229^2 \\
& +2.5823 \times 0.951229^2 + 0.8525 \times 0.951229)/8 \\
= {} & 4.66263.
\end{aligned}
$$

A Numerical Example (concluded)

- As this is larger than the immediate exercise value of

$$105 - 101 = 4,$$

  the put should not be exercised at year 0.

- Hence the put's value is estimated to be 4.66263.
- Compare this with the European put's value of 1.3680 (p. 856).

Time Series Analysis

The historian is a prophet in reverse.
— Friedrich von Schlegel (1772–1829)

GARCH Option Pricing[a]

- Options can be priced when the underlying asset's return follows a GARCH process.
- Let S_t denote the asset price at date t.
- Let h_t^2 be the *conditional* variance of the return over the period $[\,t, t+1\,]$ given the information at date t.
  - "One day" is merely a convenient term for any elapsed time Δt.

---

[a]ARCH (autoregressive conditional heteroskedastic) is due to Engle (1982), co-winner of the 2003 Nobel Prize in Economic Sciences. GARCH (generalized ARCH) is due to Bollerslev (1986) and Taylor (1986). A Bloomberg quant said to me on Feb 29, 2008, that GARCH is seldom used in trading.

GARCH Option Pricing (continued)

- Adopt the following risk-neutral process for the price dynamics:[a]

$$\ln \frac{S_{t+1}}{S_t} = r - \frac{h_t^2}{2} + h_t \epsilon_{t+1}, \tag{112}$$

where

$$\begin{aligned} h_{t+1}^2 &= \beta_0 + \beta_1 h_t^2 + \beta_2 h_t^2 (\epsilon_{t+1} - c)^2, \qquad (113) \\ \epsilon_{t+1} &\sim N(0,1) \text{ given information at date } t, \\ r &= \text{daily riskless return}, \\ c &\geq 0. \end{aligned}$$

[a]Duan (1995).

GARCH Option Pricing (continued)

- The five unknown parameters of the model are c, h_0, β_0, β_1, and β_2.
- It is postulated that $\beta_0, \beta_1, \beta_2 \geq 0$ to make the conditional variance positive.
- There are other inequalities to satisfy (see text).
- The above process is called the nonlinear asymmetric GARCH (or NGARCH) model.

GARCH Option Pricing (continued)

- It captures the volatility clustering in asset returns first noted by Mandelbrot (1963).[a]
  - When $c = 0$, a large ϵ_{t+1} results in a large h_{t+1}, which in turns tends to yield a large h_{t+2}, and so on.
- It also captures the negative correlation between the asset return and changes in its (conditional) volatility.[b]
  - For $c > 0$, a positive ϵ_{t+1} (good news) tends to decrease h_{t+1}, whereas a negative ϵ_{t+1} (bad news) tends to do the opposite.

---

[a] "... large changes tend to be followed by large changes—of either sign—and small changes tend to be followed by small changes ..."

[b] Noted by Black (1976): Volatility tends to rise in response to "bad news" and fall in response to "good news."

GARCH Option Pricing (concluded)

- With $y_t \stackrel{\Delta}{=} \ln S_t$ denoting the logarithmic price, the model becomes

$$y_{t+1} = y_t + r - \frac{h_t^2}{2} + h_t \epsilon_{t+1}. \tag{114}$$

- The pair (y_t, h_t^2) completely describes the current state.
- The conditional mean and variance of y_{t+1} are clearly

$$E[\, y_{t+1} \,|\, y_t, h_t^2 \,] = y_t + r - \frac{h_t^2}{2}, \tag{115}$$

$$\mathrm{Var}[\, y_{t+1} \,|\, y_t, h_t^2 \,] = h_t^2. \tag{116}$$

GARCH Model: Inferences

- Suppose the parameters c, h_0, β_0, β_1, and β_2 are given.
- Then we can recover $h_1, h_2, \ldots, h_n$ and $\epsilon_1, \epsilon_2, \ldots, \epsilon_n$ from the prices

$$S_0, S_1, \ldots, S_n$$

  under the GARCH model (112) on p. 876.
- This property is useful in statistical inferences.

The Ritchken-Trevor (RT) Algorithm[a]

- The GARCH model is a continuous-state model.
- To approximate it, we turn to trees with *discrete* states.
- Path dependence in GARCH makes the tree for asset prices explode exponentially (why?).
- We need to mitigate this combinatorial explosion.

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[a] Ritchken & Trevor (1999).