

MARKET RISK MANAGEMENT: MEASUREMENT: MONTE CARLO SIMULATION

- ▶ Real Data
- ▶ Monte Carlo Simulation

REAL DATA

Returns

Distribution

Stylized Facts

ASSET RETURNS

► *Returns Discrete Compounding*

$$r_t = (S_t - S_{t-1})/S_{t-1} \quad (3.1)$$

► *Returns Continuous Compounding*

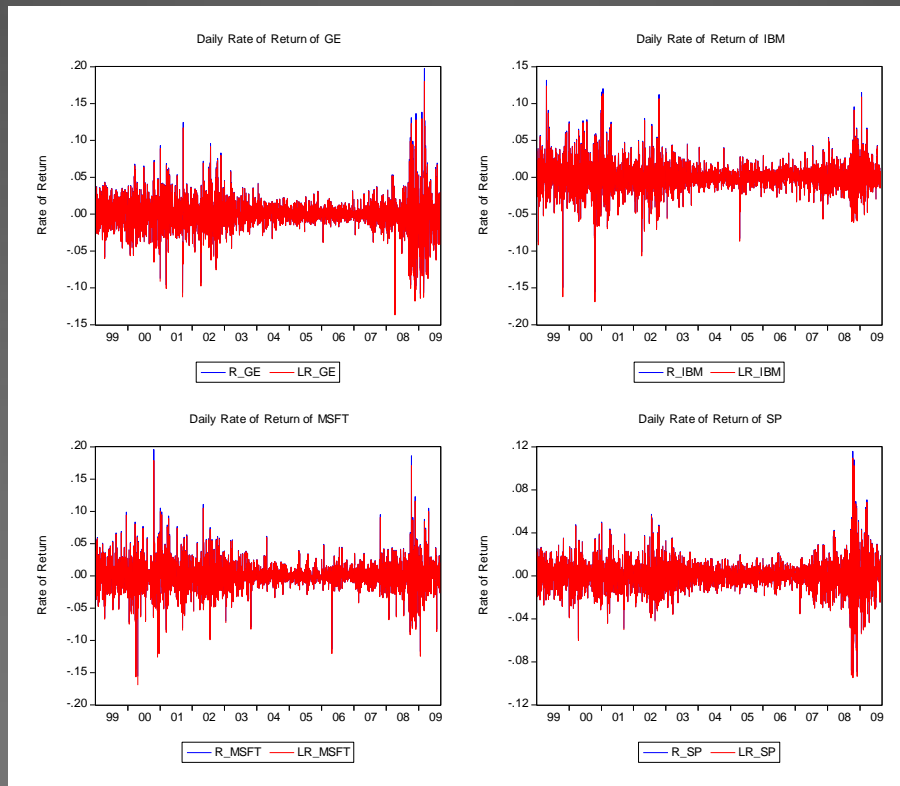
$$R_t = \ln[S_t / S_{t-1}] \quad (3.2)$$

► Equation (3.1) and (3.2) are related by

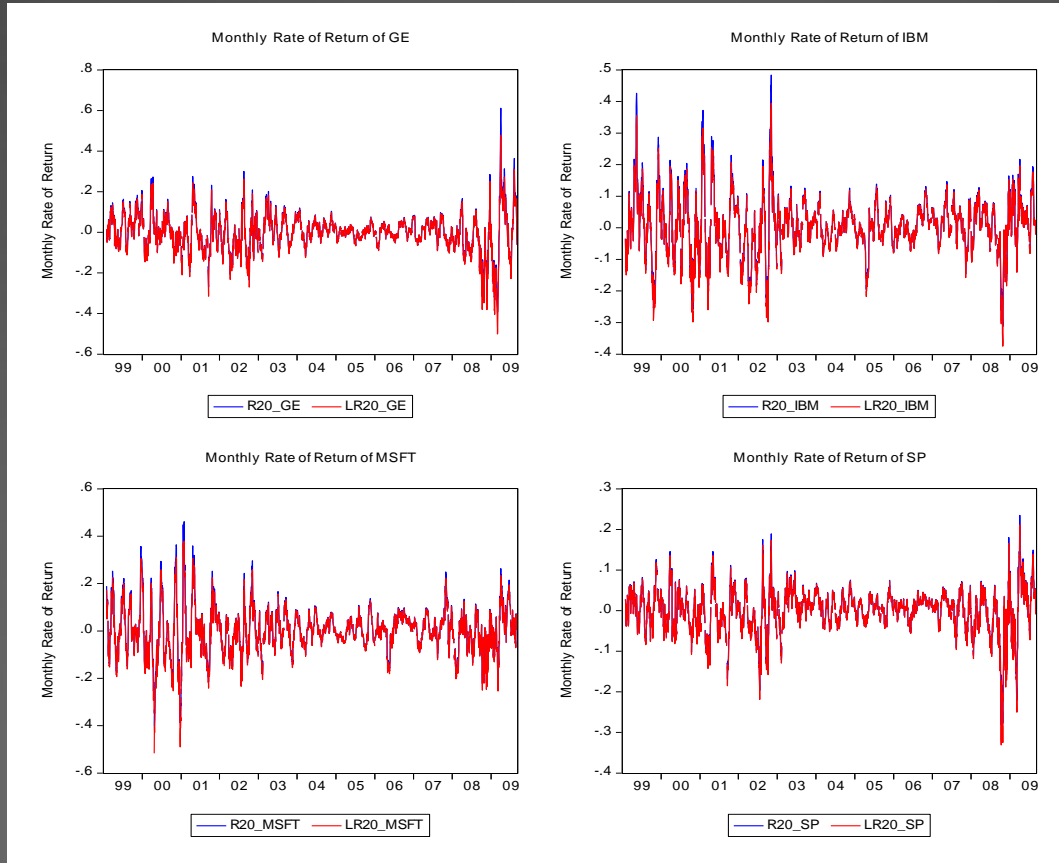
$$R_t = \ln[1 + (S_t - S_{t-1})/S_{t-1}] = \ln[1 + r_t]$$

if r_t is small $\ln[1 + r_t] \approx r_t$

DAILY RETURNS



MONTHLY RETURNS



ASSET RETURNS

- ▶ One advantage of using log returns is given by time aggregation
For example, the two-day return is equal to

$$\begin{aligned}R_{02} &= \ln[S_2 / S_0] = \ln[(S_2 / S_1) \times (S_1 / S_0)] = \ln[S_2 / S_1] + \ln[S_1 / S_0] \\ &= R_{01} + R_{12}\end{aligned}$$

More generally:

$$R_{t,t+k} = \ln[S_{t+k} / S_t] = \sum R_{t+i}$$

- ▶ Expected returns and variance for R_{02} :

$$E(R_{02}) = E(R_{01}) + E(R_{12})$$

$$V(R_{02}) = V(R_{01}) + V(R_{12}) + 2\text{Cov}(R_{01}, R_{12})$$

ASSET RETURNS

- ▶ Efficient Market Hypothesis:
 - ▶ Current prices convey all relevant information about the asset
 - ▶ Any change in the asset price is due to new news which are impossible to predict
 - ▶ This implies that changes in asset prices are unpredictable

- ▶ Random Walk

$$s_t = \ln[S_t]$$

$$s_t = s_{t-1} + \varepsilon_t \quad \varepsilon_t \sim \phi(\mu, \sigma^2)$$

$$\Delta s_t = R_t = \varepsilon_t$$

- ▶ If the distribution of ε_t is constant over time ε_t (and R_t) are independently and identically distributed (i.i.d.)

ASSET RETURNS

- ▶ Autocovariance function: $Cov(R_t, R_{t-i})$
- ▶ Autocorrelation function: $Corr(R_t, R_{t-i}) \equiv \rho(R_t, R_{t-i})$
- ▶ If we assume that returns are uncorrelated and i.i.d.

$$\rho(R_t, R_{t-i}) \approx 0 \quad \text{for } i = 1, 2, 3, \dots, T$$

then:

$$E(R_{01}) = E(R_{12}) = E(R_{23}) = \dots \quad \rightarrow \quad E(R_{02}) = 2E(R_{01})$$

$$V(R_{01}) = V(R_{12}) = V(R_{23}) = \dots \quad \rightarrow \quad V(R_{02}) = 2V(R_{01})$$

or more in general, over T days

$$E(R_T) = E(R_{01})T \equiv E(R_1)T \quad (3.5)$$

$$V(R_T) = V(R_{01})T \equiv V(R_1)T \quad (3.6)$$

$$SD(R_T) = SD(R_{01})\sqrt{T} \equiv SD(R_1)\sqrt{T} \quad (3.7)$$

ASSET RETURNS

▶ When returns are uncorrelated (autocorrelation is zero for all lags), the volatility increases as the horizon increases, following the square root of time

▶ Autocorrelation function:

$$\text{if } \rho(R_t, R_{t-i}) > 0$$

movements in one direction one day are followed by movements in the same direction → trend

$$\text{if } \rho(R_t, R_{t-i}) < 0$$

movements in one direction one day are followed by movements in the opposite direction → mean reversion

STYLIZED FACTS OF ASSET RETURNS: MEAN AND STANDARD DEVIATION

- ▶ The standard deviation of returns dominates the mean of returns at short horizons such as daily
 - ▶ If we test the null hypothesis that the mean daily return is equal to zero, we fail to reject it!
 - ▶ Standard deviation of daily return is much higher than the mean

STYLIZED FACTS OF ASSET RETURNS: AUTOCORRELATION

- ▶ Daily returns have very little autocorrelation

$$\rho(R_t, R_{t-i}) \approx 0 \quad \text{for } i = 1, 2, 3, \dots, T$$



Returns are impossible to predict from their own past



Market efficiency!!!

STYLIZED FACTS OF ASSET RETURNS: SKEWNESS

- ▶ Stock market exhibits occasional very large drops but not equally large up-moves → the distribution of asset returns is not symmetric

Skewness: scaled third moment

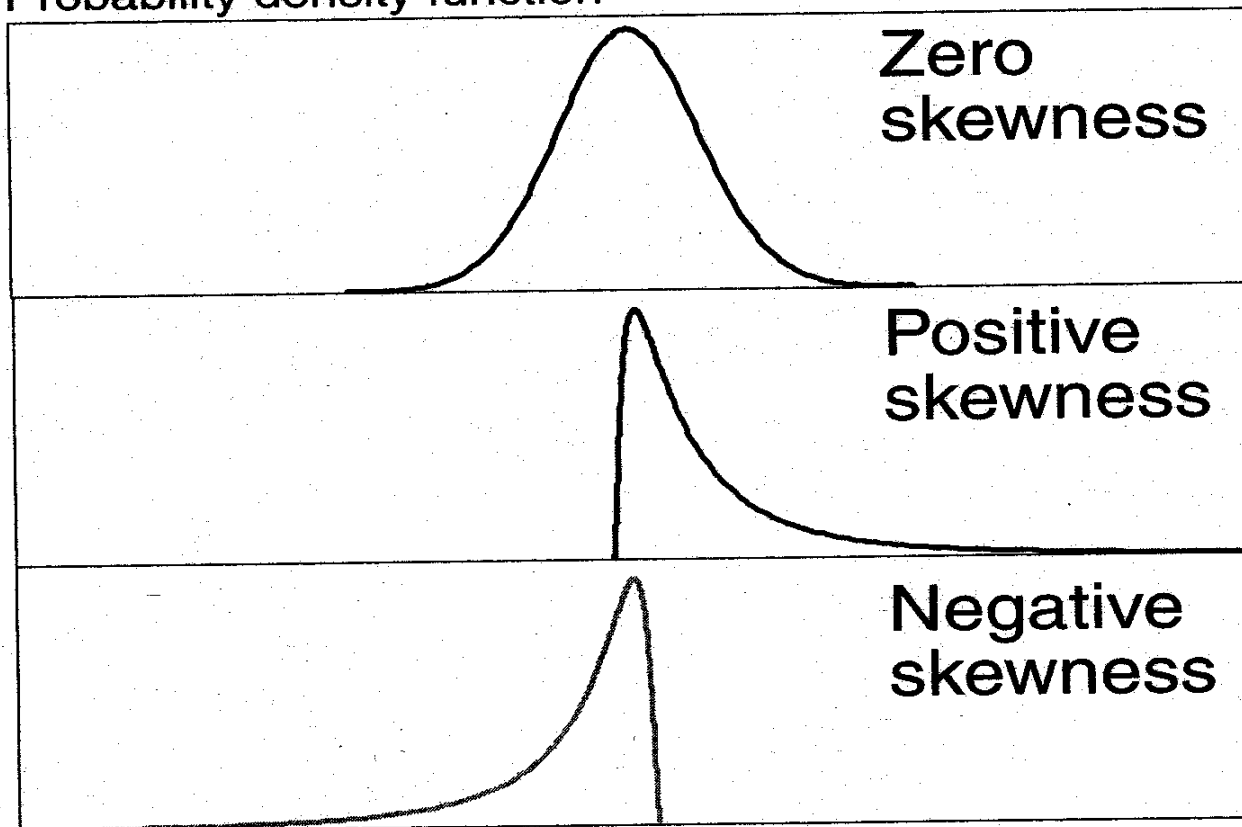
$$\gamma = \left(\int_{-\infty}^{+\infty} [x - E(x)]^3 f(x) dx \right) / \sigma^3 \quad (2.12)$$

- ▶ FX market tends to show less evidence of skewness

STYLIZED FACTS OF ASSET RETURNS: SKEWNESS

FIGURE 2-3 Effect of Skewness

Probability density function



STYLIZED FACTS OF ASSET RETURNS: KURTOSIS

- ▶ The unconditional distribution of daily returns has fatter tails than the normal distribution → higher probability of large losses

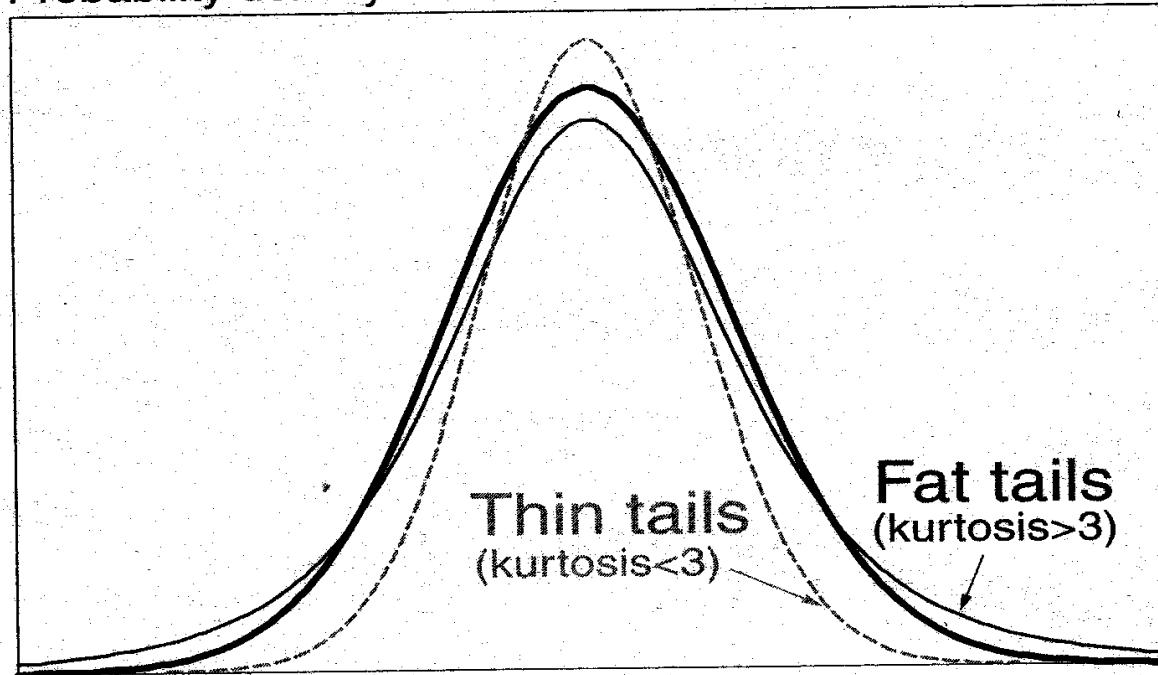
Kurtosis: scaled fourth moment

$$\delta = \left(\int_{-\infty}^{+\infty} [x - E(x)]^4 f(x) dx \right) / \sigma^4 \quad (2.13)$$

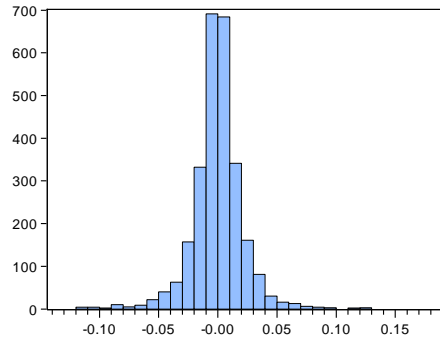
STYLIZED FACTS OF ASSET RETURNS: KURTOSIS

FIGURE 2-4 Effect of Kurtosis

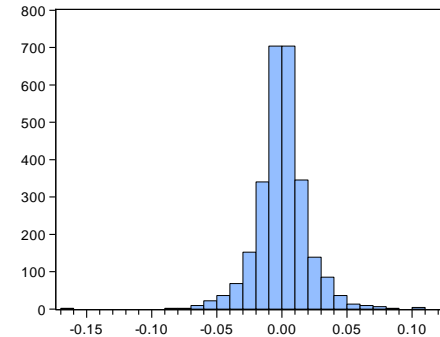
Probability density function



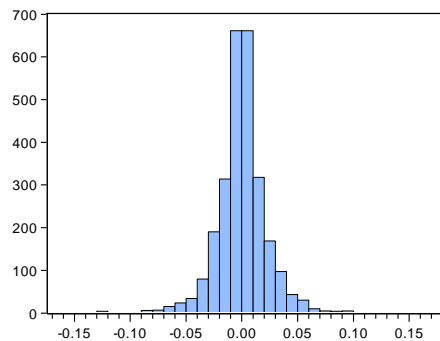
DESCRIPTIVE STATISTICS



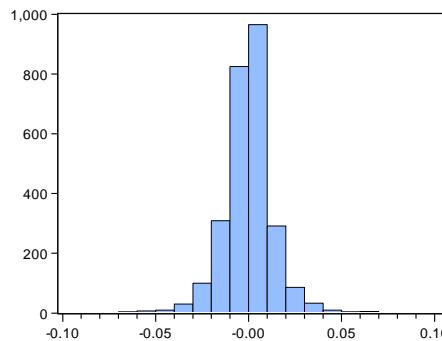
Series: LR_GE	
Sample 1/04/1999 9/04/2009	
Observations 2685	
Mean	-0.000220
Median	0.000000
Maximum	0.180051
Minimum	-0.136655
Std. Dev.	0.022167
Skewness	0.035824
Kurtosis	10.13080
Jarque-Bera	5689.229
Probability	0.000000



Series: LR_IBM	
Sample 1/04/1999 9/04/2009	
Observations 2685	
Mean	0.000133
Median	0.000000
Maximum	0.123710
Minimum	-0.168902
Std. Dev.	0.020183
Skewness	-0.073004
Kurtosis	9.997292
Jarque-Bera	5480.019
Probability	0.000000



Series: LR_MSFT	
Sample 1/04/1999 9/04/2009	
Observations 2685	
Mean	-6.02e-05
Median	0.000000
Maximum	0.178863
Minimum	-0.169442
Std. Dev.	0.023055
Skewness	-0.038153
Kurtosis	10.07949
Jarque-Bera	5607.737
Probability	0.000000

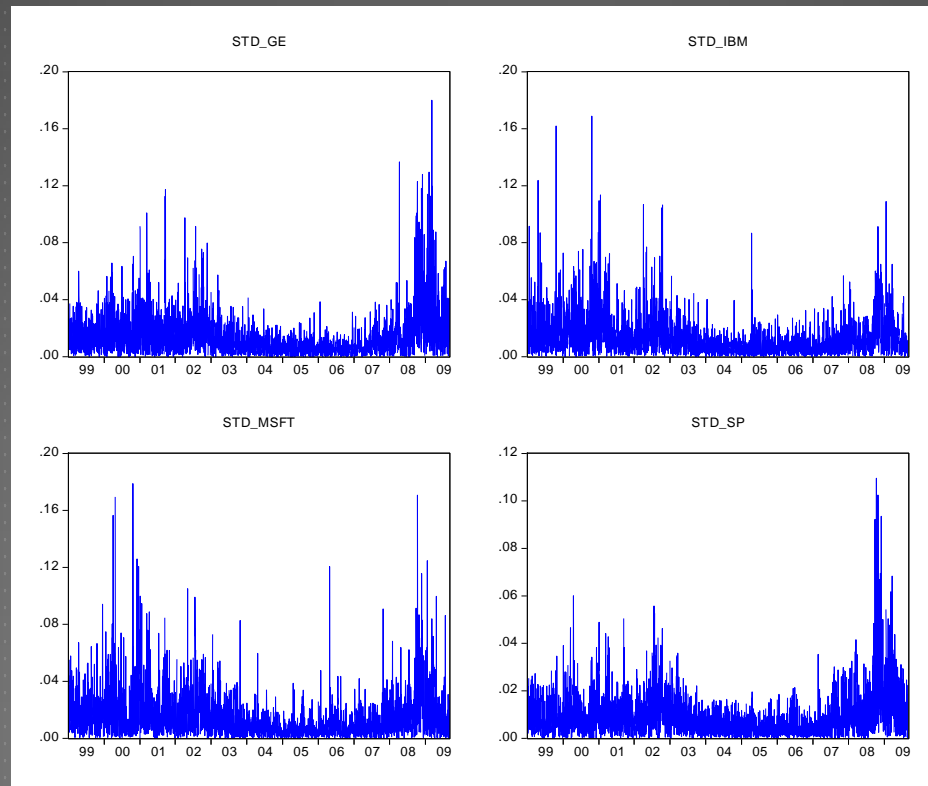


Series: LR_SP	
Sample 1/04/1999 9/04/2009	
Observations 2685	
Mean	-7.05e-05
Median	0.000425
Maximum	0.109572
Minimum	-0.094695
Std. Dev.	0.013889
Skewness	-0.092863
Kurtosis	10.40657
Jarque-Bera	6141.011
Probability	0.000000

STANDARD DEVIATION

- ▶ The standard deviation of returns dominates the mean of returns at short horizons. It is not possible to reject zero mean in short horizon.
- ▶ Standard deviations seem to be more volatile over time. It reaches the peak of 11% around the collapse of Lehman Brothers in September 2008.

STANDARD DEVIATIONS



STYLIZED FACTS OF ASSET RETURNS: SQUARED RETURNS

- ▶ Squared returns \rightarrow variance

$$\sigma^2 = E(x^2) - [E(x)]^2$$

$$\Delta s_t = R_t = \varepsilon_t \quad \varepsilon_t \sim \phi(0, \sigma^2) \quad E(R_t) = 0$$



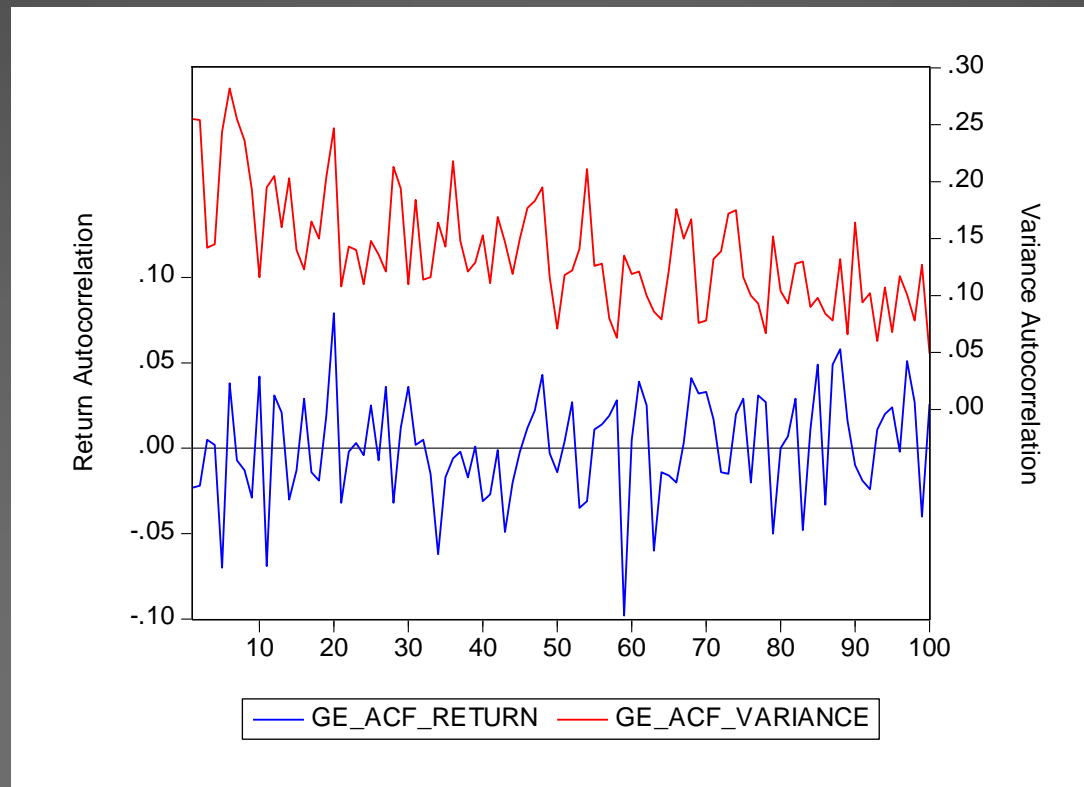
$$\sigma^2 = E(x^2)$$

- ▶ Squared returns exhibit positive autocorrelation

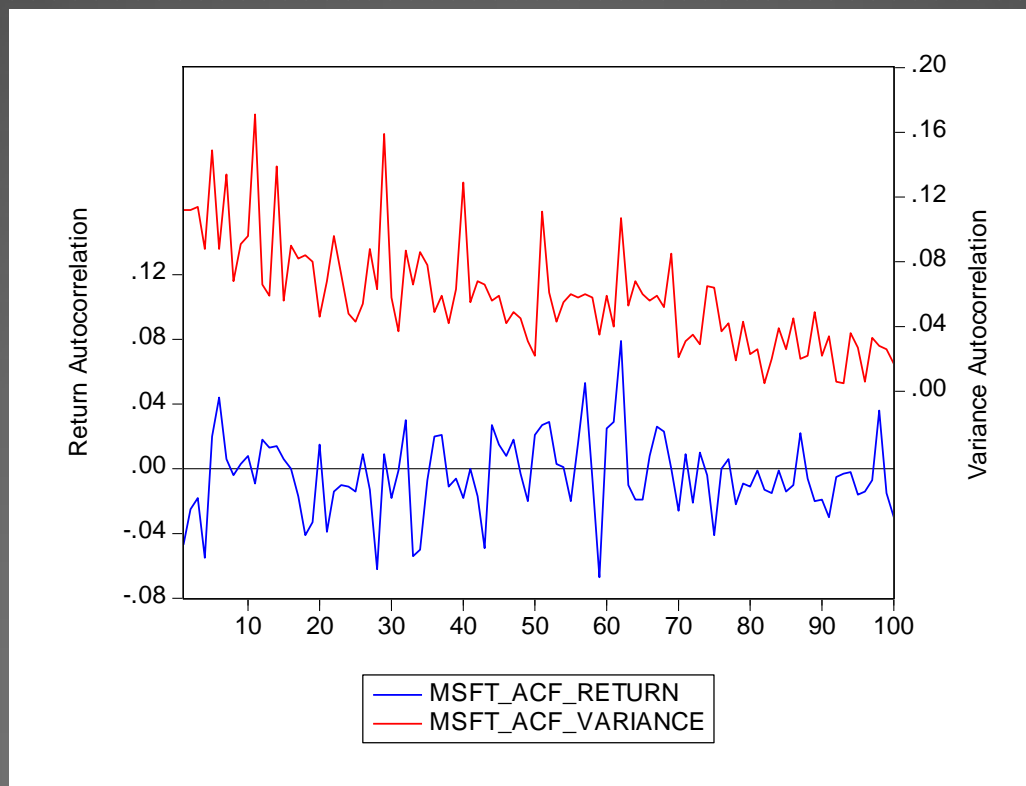
$$\rho(R_t^2, R_{t-i}^2) > 0 \quad \text{for } i = 1, 2, 3, \dots, T$$

- ▶ The autocorrelations of squared returns tend to be positive for short lags and decay exponentially to zero as the number of lags increases.

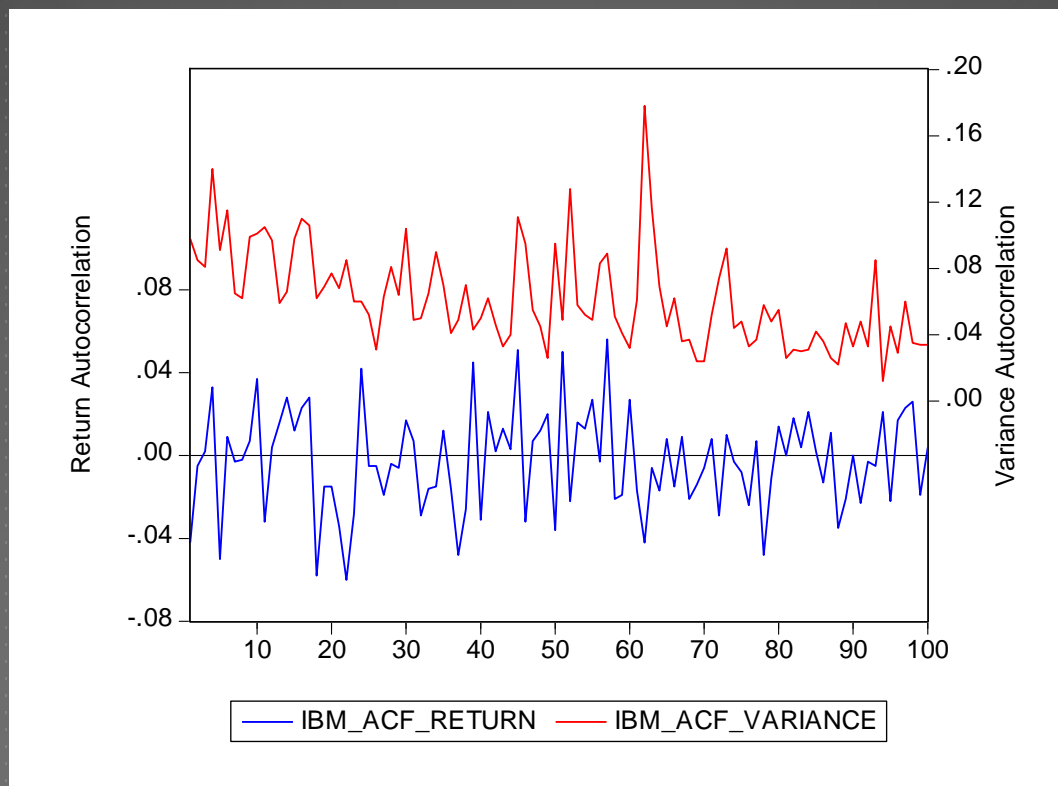
AUTOCORRELATION FUNCTIONS: GE



ACF: MSFT



ACF: IBM



ACF: S&P 500



STYLIZED FACTS OF ASSET RETURNS: LEVERAGE EFFECT

- ▶ Equity and equity indices display negative correlation between variance and returns



Leverage effect

A drop in the stock price will increase the leverage of the firm and therefore the risk (variance)

STYLIZED FACTS OF ASSET RETURNS: CORRELATION BETWEEN ASSETS

- ▶ Correlation between assets is not constant over time – i.e. it changes

Empirical evidence shows that assets are more correlated during crashes!!!

Covariance: $E(xy) = E[(x - E(x)) \times (y - E(y))]$

if $E(x) = 0$ and $E(y) = 0$

$$E(xy) = E(x \times y)$$

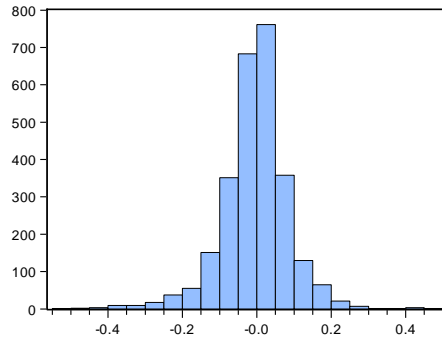
$$\text{Cov}(R_{i,t}, R_{j,t}) = E(R_{i,t} R_{j,t})$$

Covariance between asset returns may be estimated by the product of the returns

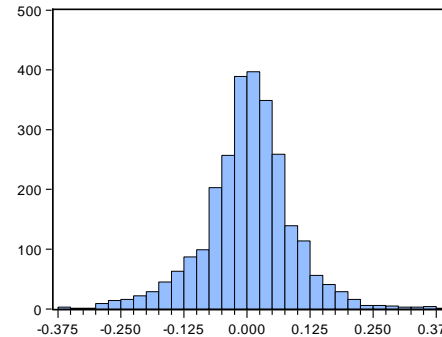
STYLIZED FACTS OF ASSET RETURNS: RETURN HORIZON

- ▶ As the return horizon increases, the unconditional return distribution changes and looks increasingly like a normal distribution

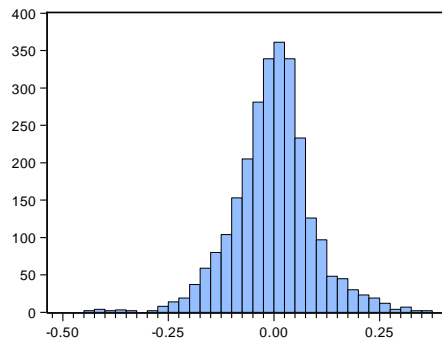
MONTHLY RETURNS



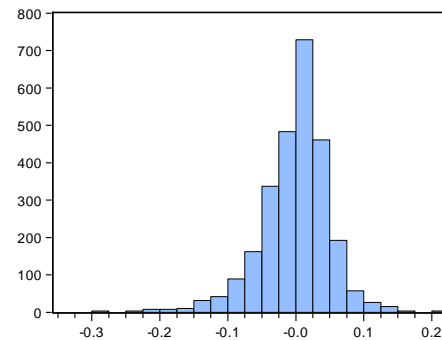
Series: LR20_GE	
Sample 1/04/1999 9/04/2009	
Observations 2666	
Mean	-0.004451
Median	0.000671
Maximum	0.476976
Minimum	-0.501140
Std. Dev.	0.090029
Skewness	-0.530171
Kurtosis	6.670863
Jarque-Bera	1621.768
Probability	0.000000



Series: LR20_IBM	
Sample 1/04/1999 9/04/2009	
Observations 2666	
Mean	0.002613
Median	0.006851
Maximum	0.394383
Minimum	-0.374981
Std. Dev.	0.088664
Skewness	-0.170139
Kurtosis	4.846287
Jarque-Bera	391.5204
Probability	0.000000

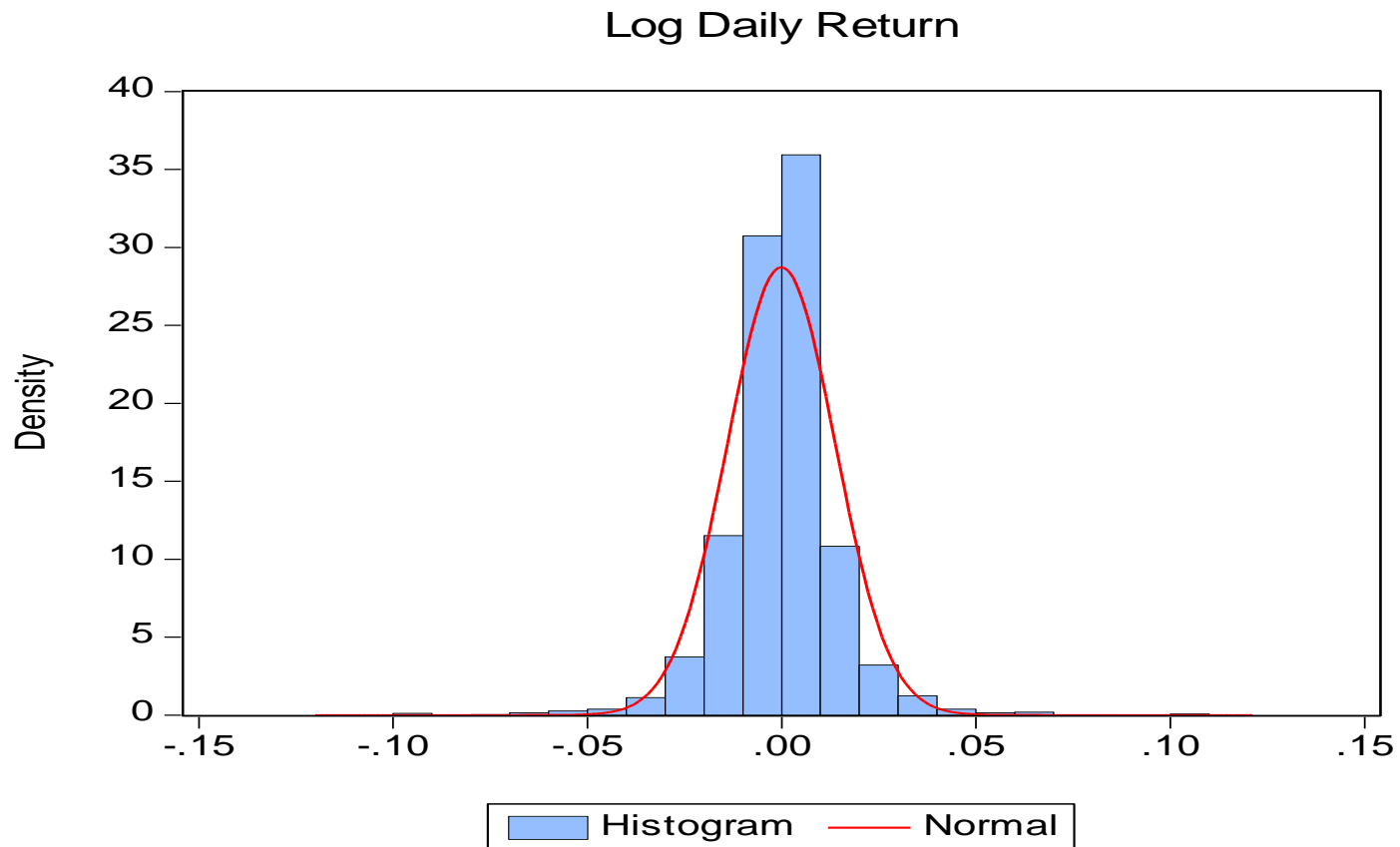


Series: LR20_MSFT	
Sample 1/04/1999 9/04/2009	
Observations 2666	
Mean	-0.002154
Median	0.001239
Maximum	0.379105
Minimum	-0.516659
Std. Dev.	0.095490
Skewness	-0.218652
Kurtosis	5.407270
Jarque-Bera	664.9651
Probability	0.000000



Series: LR20_SP	
Sample 1/04/1999 9/04/2009	
Observations 2666	
Mean	-0.001600
Median	0.006013
Maximum	0.211030
Minimum	-0.330730
Std. Dev.	0.052726
Skewness	-1.046314
Kurtosis	7.324474
Jarque-Bera	2563.822
Probability	0.000000

UNCONDITIONAL DISTRIBUTION DAILY RETURNS S&P500



MONTE CARLO & SIMULATION



RANDOM VARIABLES



MONTE CARLO SIMULATION

- ▶ Monte Carlo simulation involve creating artificial random variables, whose time path is not predictable.
- ▶ Any variable whose value changes over time in an unpredictable way is said to follow a *stochastic process*
- ▶ A *Markov process* is a particular type of stochastic process where only the present value of a variable is relevant for predicting the future.

MARKOV PROCESSES

- ▶ If markets are efficient, financial prices should display random walk pattern
- ▶ More generally, in finance it is often assumed that asset prices follow a Markov process → the entire distribution of the future price relies on the current price only → past history is irrelevant
- ▶ Wiener process: describes a variable whose change is measured over an interval Δt , such that the average change is zero and its variance is proportional to Δt

$$\Delta z \sim N(0, \Delta t) \quad (4.1)$$

or

$$\Delta z = \varepsilon \sqrt{\Delta t} \quad \varepsilon \sim N(0,1)$$

MARKOV PROCESSES

- ▶ Generalized Wiener process: it contains a constant trend a and volatility b

$$\Delta x = a\Delta t + b\Delta z \quad (4.2)$$

if $a = 0$ (no drift), the process is a Martingale \rightarrow expectation of the future value is the current value $E(x_T) = x_0$

- ▶ Ito process: trend (a) and volatility (b) depend on the current value of the underline variable and time

$$\Delta x = a(x,t)\Delta t + b(x,t)\Delta z \quad (4.4)$$

This is a Markov process because the distribution depends only on the current value of x

GEOMETRIC BROWNIAN MOTION

- ▶ An example of Ito process is the GBM

$$\Delta S = \mu S \Delta t + \sigma S \Delta z \quad (4.5)$$

- ▶ This process is geometric because trend and volatility are proportional to the current value of S .
- ▶ This process is particularly useful in modeling stock prices
 - μ represents the expected total rate of return (less dividend)
 - σ volatility

Example: A stock price process

Consider a stock that pays no dividends, has an expected return of 10% per annum, and volatility of 20% per annum. If the current price is \$100, what is the process for the change in the stock price over the next week? What if the current price is \$10?

The process for the stock price is

$$\Delta S = S(\mu \Delta t + \sigma \sqrt{\Delta t} \times \epsilon)$$

where ϵ is a random draw from a standard normal distribution. If the interval is one week, or $\Delta t = 1/52 = 0.01923$, the mean is $\mu \Delta t = 0.10 \times 0.01923 = 0.001923$ and $\sigma \sqrt{\Delta t} = 0.20 \times \sqrt{0.01923} = 0.027735$. The process is $\Delta S = \$100(0.001923 + 0.027735 \times \epsilon)$. With an initial stock price at \$100, this gives $\Delta S = 0.1923 + 2.7735\epsilon$. With an initial stock price at \$10, this gives $\Delta S = 0.01923 + 0.27735\epsilon$. The trend and volatility are scaled down by a factor of 10.

Example: A stock price process (continued)

Assume the price in one week is given by $S = \$100 \exp(R)$, where R has annual expected value of 10% and volatility of 20%. Construct a 95% confidence interval for S .

The standard normal deviates that corresponds to a 95% confidence interval are $\alpha_{\text{MIN}} = -1.96$ and $\alpha_{\text{MAX}} = 1.96$. In other words, we have 2.5% in each tail. The 95% confidence band for R is then $R_{\text{MIN}} = \mu \Delta t - 1.96\sigma \sqrt{\Delta t} = 0.001923 - 1.96 \times 0.027735 = -0.0524$ and $R_{\text{MAX}} = \mu \Delta t + 1.96\sigma \sqrt{\Delta t} = 0.001923 + 1.96 \times 0.027735 = 0.0563$. This gives $S_{\text{MIN}} = \$100 \exp(-0.0524) = \94.89 , and $S_{\text{MAX}} = \$100 \exp(0.0563) = \105.79 .

GEOMETRIC BROWNIAN MOTION

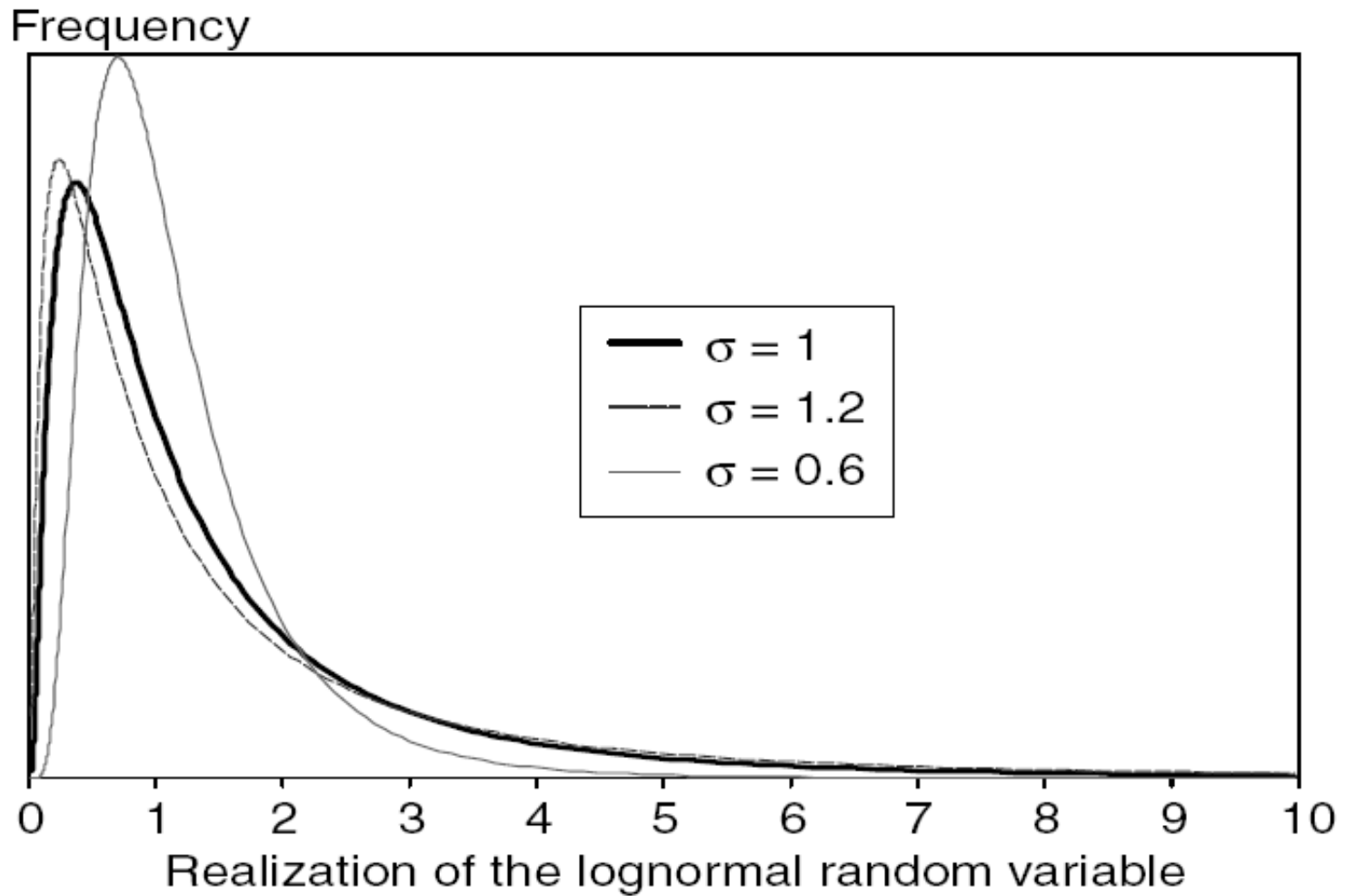
- ▶ This is an important model: used in Black-Scholes
- ▶ Volatility is proportional to $S \rightarrow$ the stock price will stay positive,
If the stock price falls \rightarrow its variance decreases \rightarrow it is very unlikely that there will be a down large movement that makes the stock negative
- ▶ At the limit, when $\Delta t \rightarrow 0$ (very small intervals/increments)

$$dS/S = d\ln(S)$$

- ▶ Given that $dS/S = d\ln(S)$ follows a Normal distribution $\rightarrow S$ follows a log-normal distribution

In fact if $Y = \ln(X)$ is normally distributed, then X follows a log-normal distribution

FIGURE 2-8 Lognormal Density Function



GEOMETRIC BROWNIAN MOTION

- ▶ The GBM implies that over an interval of time, $T - t = \tau$ the \ln of the final price is given by

$$\ln(S_T) = \ln(S_t) + (\mu - \sigma^2/2)\tau + \sigma\sqrt{\tau}\epsilon \quad (4.6)$$

- ▶ Should we choose a Normal distribution or a log-Normal for our price process? It depends on the time horizon
 - ▶ Short time periods (such as a day) it does not matter which of the two distributions we choose
 - ▶ Long horizons (such as years) it is better to adopt the log-normal
 - prices will not be negative

SIMULATION

Wiener Process

$$\Delta S = \varepsilon \sqrt{\Delta t} \quad \varepsilon \sim N(0,1) \quad S_{t+1} = S_t + \Delta S = S_t + \varepsilon_{t+1} \sqrt{\Delta t}$$

$$\Delta t = \frac{1}{252} \quad \text{daily} \implies 252 \text{ steps (simulating one year)}$$

Generalized Wiener Process

$$\Delta S = a\Delta t + b\varepsilon\sqrt{\Delta t} \quad S_{t+1} = S_t + \Delta S = S_t + a\Delta t + b\varepsilon_{t+1}\sqrt{\Delta t}$$

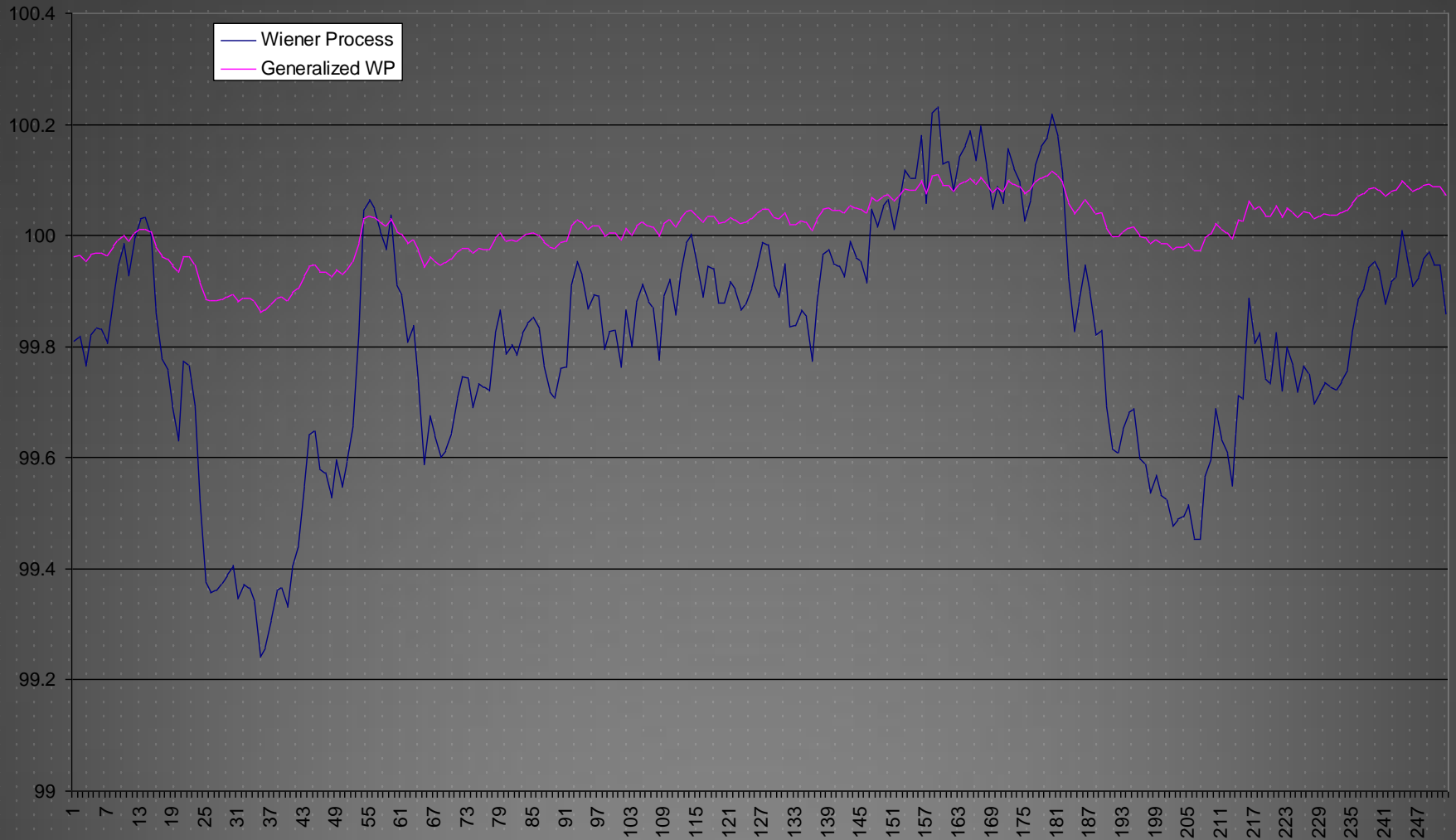
$a = 10\%$ per annum, $b = 20\%$ per annum

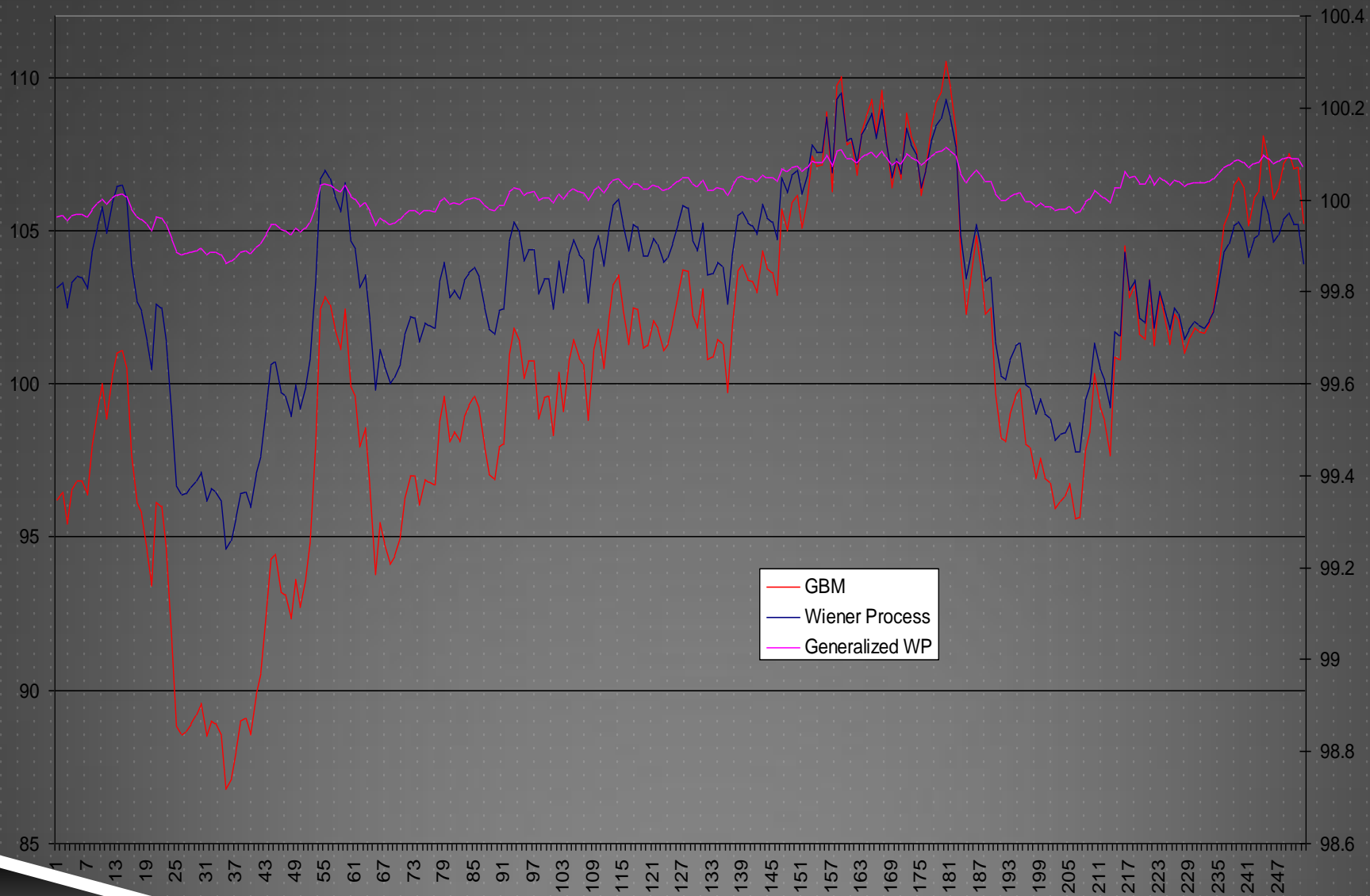
Geometric Brownian Motion

$$\Delta S = \mu S \Delta t + \sigma S \varepsilon \sqrt{\Delta t} \quad \frac{\Delta S}{S} = \mu \Delta t + \sigma \varepsilon \sqrt{\Delta t}$$

$$\frac{\Delta S}{S} \sim N(\mu \Delta t, \sigma^2 \Delta t) \quad (4.7)$$

$$S_{t+1} = S_t + \Delta S = S_t + S_t (\mu \Delta t + \sigma \varepsilon_{t+1} \sqrt{\Delta t})$$





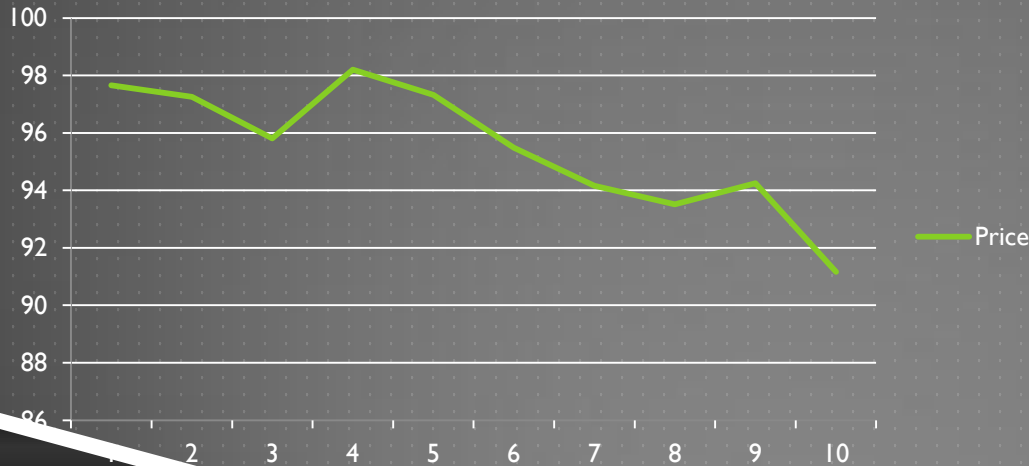
Drift (Annual) 10%
 Volatility (Annual) 40%
 Drift (daily) 0.04%
 Volatility (daily) 2.52%
 Drift (mean) 0.01%
 Initial Stock \$ 100.00

$$\ln(P_t/P_{t-1}) = \mu + \sigma z_t$$

	1	2	3	4	5	6	7	8	9	10
N(0,1)	-0.944415595	-0.16806	-0.59763	0.976508	-0.35888	-0.75882	-0.55818	-0.2774	0.309081	-1.32457
Log Return	-2.37%	-0.42%	-1.50%	2.47%	-0.90%	-1.90%	-1.40%	-0.69%	0.79%	-3.33%
Price	97.65613823	97.25118	95.80526	98.19965	97.32337	95.48777	94.16162	93.51316	94.25177	91.16516

$$\ln\left(\frac{P_t}{P_{t-1}}\right) \rightarrow N\left[\left(\alpha - \frac{\sigma^2}{2}\right)T, \sigma\sqrt{T}\right]$$

Price



SIMULATION

- ▶ Remember:

We can replicate a Monte Carlo experiment many times.
Each time we will generate a new path

Initial values may affect the results

Seed: it allows to generate the same random numbers

TERM STRUCTURE OF INTEREST RATE

- ▶ Bond prices display mean reversion to the face value

We can first model the yield (interest rate) and then the bond price

→ mean reversion in the yield

GBM do not display mean reversion

One factor models

$$\Delta r_t = \kappa(\theta - r_t)\Delta t + \sigma r_t^\gamma \Delta z_t \quad (4.8)$$

$\theta \geq 0$, is the long-run value of the interest rate r

$\kappa \in [0, 1]$, is the speed of mean reversion

$\gamma = 0$ → Vasicek Model (JFE - 1977)

$\gamma = 0.5$ → Cox, Ingersoll and Ross (CIR), (Econometrica 1985)

TERM STRUCTURE OF INTEREST RATE

- ▶ In C-I-R's model the stochastic term is proportional to $r^{1/2}$ indicating that, as the short term interest rate increases, its standard deviation increases
- ▶ In C-I-R's model interest rates are always positive. A negative value is implausible for nominal interest rates but not for real rates
- ▶ In Vasicek the short term interest rate can be negative: implausible for nominal but not for real rates
- ▶ Vasicek and C-I-R both accommodate rising, falling and single humped structure
- ▶ In both Vasicek and C-I-R the short term interest rate converges towards a long term interest rate which is constant and independent from r
- ▶ However, in practice, long rate is quite variable → two-factor models

BINOMIAL TREE

- ▶ Two steps: up or down
- ▶ Binomial model → Discrete version of a GBM

Divide the horizon T into n intervals: $\Delta t = T/n$

At each node the price can go up with probability p or down with probability $1 - p$

Option evaluation with binomial tree

$$u = e^{\sigma\sqrt{\Delta t}}, \quad d = (1/u), \quad p = \frac{e^{\mu\Delta t} - d}{u - d} \quad (4.11)$$

$$\begin{aligned} E \left[\frac{S_1}{S_0} \right] &= pu + (1 - p)d = \frac{e^{\mu\Delta t} - d}{u - d}u + \frac{u - e^{\mu\Delta t}}{u - d}d \\ &= \frac{e^{\mu\Delta t}(u - d) - du + ud}{u - d} = e^{\mu\Delta t} \end{aligned}$$

BINOMIAL TREE

TABLE 4-2 Binomial Tree

0	Step		
	1	2	3
			$u^3 S$
		$u^2 S$	\nearrow
	$u S$	\nearrow	\searrow
S	\nearrow	$u d S$	\nearrow
	\searrow	$u d S$	\searrow
	$d S$	\nearrow	$d^2 u S$
		\searrow	\nearrow
		$d^2 S$	\searrow
			$d^3 S$

IMPLEMENTING SIMULATIONS FOR VALUE AT RISK

1. Choose stochastic Process \rightarrow distribution and parameters
2. Generate pseudo-random variables at the target horizon, S_T
3. Calculate the value at the target horizon, $F_T(S_T)$
4. Repeat steps 2 and 3, K times $\rightarrow F_T^1, F_T^2, F_T^3, \dots, F_T^K$
5. Distribution of $F_T \rightarrow \text{VaR}$

IMPLEMENTING SIMULATIONS

- ▶ Simulations for option pricing: Risk-neutral approach → the price grows at the risk-free rate → model based simulation
- ▶ Simulations for VaR: physical distribution – i.e. the actual distribution
- ▶ Sampling variability: even with K large, the empirical distribution of S_T will only be an approximation of the true distribution
Monte Carlo: Independent draws → standard error is inversely related to \sqrt{K}

MULTIPLE SOURCES OF RISK

- ▶ N number of risk factors, $j = 1, 2, 3, \dots, N$

$$\Delta S_{j,t} = S_{j,t-1} \mu_j \Delta t + S_{j,t-1} \sigma_j \epsilon_{j,t} \sqrt{\Delta t} \quad (4.14)$$

- ▶ Risk factors are usually correlated

$$\begin{aligned} \epsilon_1 &= \eta_1 \\ \epsilon_2 &= \rho \eta_1 + (1 - \rho^2)^{1/2} \eta_2 \end{aligned} \quad (4.15)$$

$$V(\epsilon) = \begin{bmatrix} \sigma^2(\epsilon_1) & \text{Cov}(\epsilon_1, \epsilon_2) \\ \text{Cov}(\epsilon_1, \epsilon_2) & \sigma^2(\epsilon_2) \end{bmatrix} = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} = R$$

MULTIPLE SOURCES OF RISK

- ▶ If we have N risk factors, we have $N(N - 1)/2$ covariances
- ▶ A portfolio with 100 assets will have to consider 4,950 covariances!
- ▶ We only consider the main risk factors