

# Risk Neutral Valuation

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Version 2.2

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April 19-20, 2012



# Outline

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## Notation

Differential Equations  
Monte-Carlo Simulation

## Modeling

## Risk Neutral Valuation

Change of Measure / Drift  
Example: Black Scholes Model  
Example: Black-Scholes Model Monte-Carlo Option Pricer

NOTATION  
DIFFERENTIAL EQUATIONS

## Notation I

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### Integral:

$$\int_0^{t_n} f(t) \, dt \approx \sum_{i=0}^{n-1} f(t_i) \cdot \Delta t_i$$

### *Discrete Interpretation:*

- ▶ Integral is approximately the sum of  $f(t_i) \cdot \Delta t_i$ .
  
- ▶ For piecewise constant function  $f$ , constant on  $[t_i, t_{i+1})$  we have "—" above.

## Notation II

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**Differential Equation:** Define the function  $t \mapsto X(t)$  by specifying its change:

$$dX = f(t) dt \quad :\Leftrightarrow \quad X(T) = X(0) + \int_0^T f(t) dt$$

*Discrete Interpretation:*

- ▶  $f$  is the change of  $X$  per unit time (rate of change):  
 $\Delta X(t_i) = f(t_i) \cdot \Delta t_i \quad :\Leftrightarrow \quad \Delta X(t_i) / \Delta t_i = f(t_i).$

## Notation III

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**Differential Equation - Special Case:** Define the function  $X$  by specifying its *relative* change.

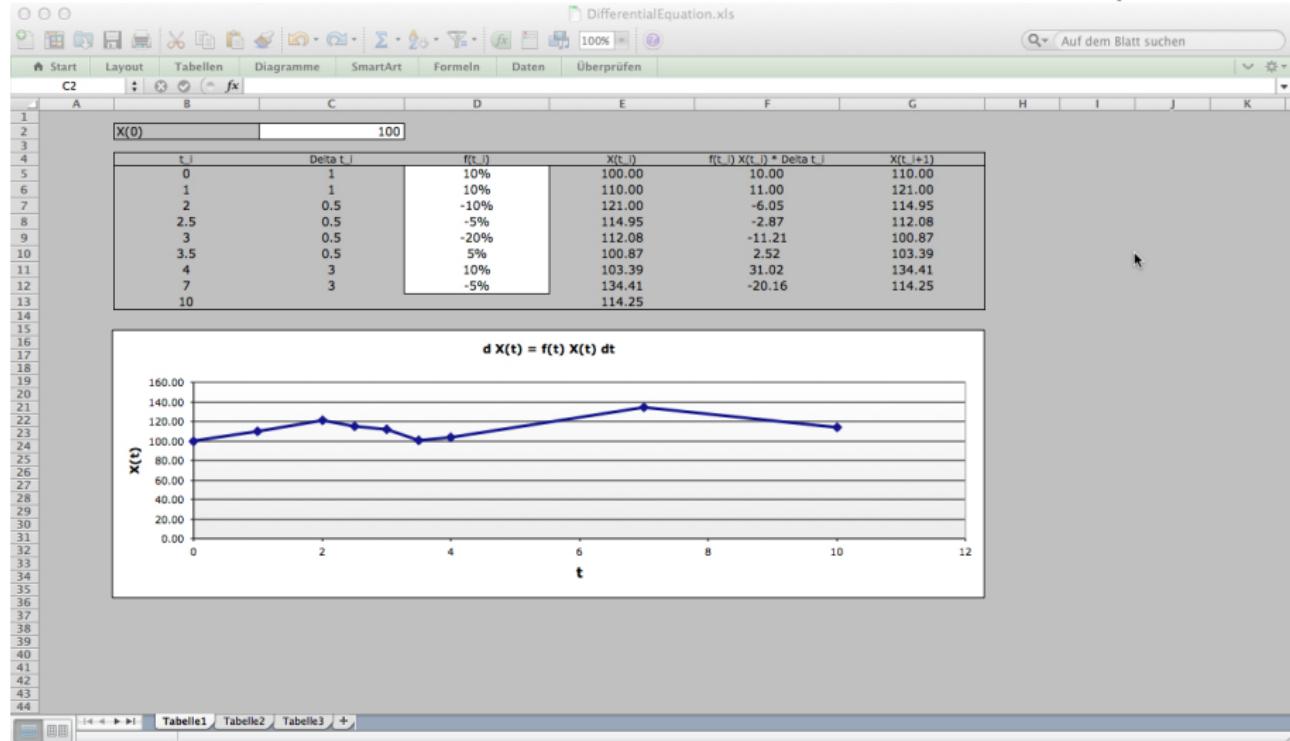
$$dX = f(t) \cdot X(t) dt \Leftrightarrow X(T) = X(0) + \int_0^T f(t) \cdot X(t) dt$$

*Discrete Interpretation:*

- $f$  is the *relative* change of  $X$  per time (percentage rate of change):  
 $\Delta X(t_i) = f(t_i) \cdot X(t_i) \cdot \Delta t_i \Leftrightarrow \frac{\Delta X(t_i)}{X(t_i)} / \Delta t_i = f(t_i).$

## Notation IV

### Exercise: Excel Sheet with Discretization of Differential Equation



## Notation V

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### State, Probability, Probability Measure:

$\Omega = \{ \omega_1, \omega_2, \dots, \omega_n \}$  (probability space)

$P(\{\omega_i\})$  (probability that we are in state  $\omega_i$ )

$P$  (probability measure)

### Probability of an State Configuration (Event):

$$P(\{\omega_1, \omega_2, \dots, \omega_k\}) = P(\{\omega_1\}) + P(\{\omega_2\}) + \dots + P(\{\omega_k\})$$

### Random Variable:

$X : \Omega \rightarrow \mathbb{R}$  Example:  $X(\omega_i)$  payment that depends on the state  $\omega_i$ .

### Expectation:

$$E^P(X) := \sum_{\omega_i \in \Omega} X(\omega_i) \cdot P(\{\omega_i\})$$

### Conditional Expectation:

$$E^P(X|F) := \frac{1}{P(F)} \sum_{\omega_i \in F} X(\omega_i) \cdot P(\{\omega_i\})$$

NOTATION  
MONTE-CARLO SIMULATION

## Notation VI

### Monte-Carlo Simulation

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#### Expectation:

$$E^P(X) := \sum_{\omega_i \in \Omega} X(\omega_i) \cdot P(\{\omega_i\})$$

#### Monte-Carlo Simulation: Numerical Approximation of Expectation:

Let

$$\tilde{\Omega} := \{ \tilde{\omega}_1, \tilde{\omega}_2, \dots, \tilde{\omega}_m \}$$

denote elements from  $\Omega$  - a *drawing from  $\Omega$ , i.e. a set of samples*. Some  $\tilde{\omega}_i$ 's may be the same and we may have more  $\tilde{\omega}_i$ 's than  $\Omega$  has elements. Our set of sample paths should have the following property:

*A path  $\omega \in \Omega$  occurs in  $\tilde{\Omega}$  approximately  $m \cdot P(\{\omega\})$  times.*

Then we have

$$E^P(X) := \sum_{\omega_i \in \Omega} X(\omega_i) \cdot P(\{\omega_i\}) \approx \frac{1}{m} \sum_{\tilde{\omega}_i \in \tilde{\Omega}} X(\tilde{\omega}_i)$$

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## Modeling

### Random Variable and Stochastic Processes

---

**Financial Product:** A stream of payments depending on events described in a contract.

#### Modeling:

*Value / Payment* → *Random Variable*

$$X : \Omega \rightarrow \mathbb{R}.$$

- ▶ Value of an asset (aka. underlying) at a fixed time  $t$  dep. on the states of the world.
- ▶ Payment of a financial product at a fixed time  $t$  dep. on state of underlying assets.
- ▶ Value of the financial product at a fixed time  $t$  depending on states of the assets.

## Modeling

### Random Variable and Stochastic Processes

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#### Modeling:

*Value Process / Payoff Stream*  $\rightarrow$  *Stochastic Process*

$:=$  family of random variables over time

$$S : [0, \infty) \times \Omega \rightarrow \mathbb{R}$$

$S(\omega)$  with  $\omega \in \Omega$  is a map  $[0, \infty) \rightarrow \mathbb{R}$ : the *path* of  $S$  in state  $\omega$ . Note: All random variables (at all times  $t$ ) are given over the same space  $(\Omega, \mathcal{F})$

$$\omega \in \Omega \quad \leftrightarrow \quad \text{path / history / chain of events}$$

## Modeling

### Random Variable and Stochastic Processes

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#### Modeling:

Information is modeled through the *filtration*:

- ▶ Family of  $\sigma$  algebras  $\mathcal{F}_t$ .
- ▶  $\mathcal{F}_t \subset \mathcal{F}_s$ ,  $t < s$ .
- ▶ Elements of  $\mathcal{F}_t$  are *the events, which may be known at time t*.

#### Measurable:

$$X \text{ is } \mathcal{F}_T \text{ measurable} \quad \leftrightarrow \quad X \text{ is known in time } T$$

#### Natural Condition (for stochastic process):

$$S(T) \text{ is } \mathcal{F}_T \text{ measurable.}$$

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### Random Variable and Stochastic Processes

**Example:** (Time discrete) stochastic process of coin toss at  $T_1, T_2, T_3$ .

**Modeling (e.g. a bet):**

$\Omega = \{(h, h, h), (h, h, t), (h, t, h), \dots, (t, t, t)\}$  - Prob' space (**head or tail**).

$X : \Omega \mapsto \mathbb{IR}$  - Bet with a single payoff

$S : \{T_1, T_2, T_3\} \times \Omega \mapsto \mathbb{IR}$   
 $S(T_k)$  paid at time  $T_k$ .  
} Bet with payments  
} - or evolution of value  
} (**stochastic process**)

Natural Condition (\*):  $S(T_k)$  may depend on events known on or before  $T_k$  only.

$$\Leftrightarrow S(T_k, (e_1, \dots, e_n)) = \text{const. } \forall e_i \in \{h, t\} \text{ mit } i > k$$

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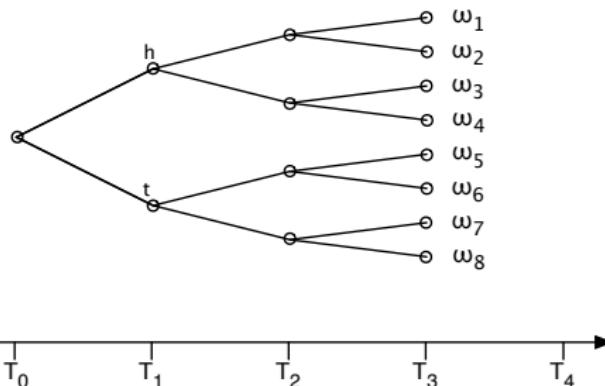
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## Modeling

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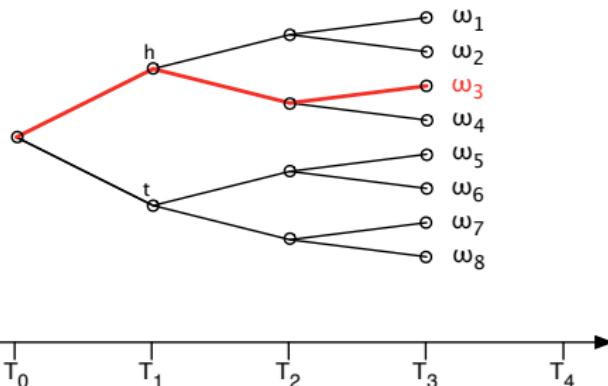
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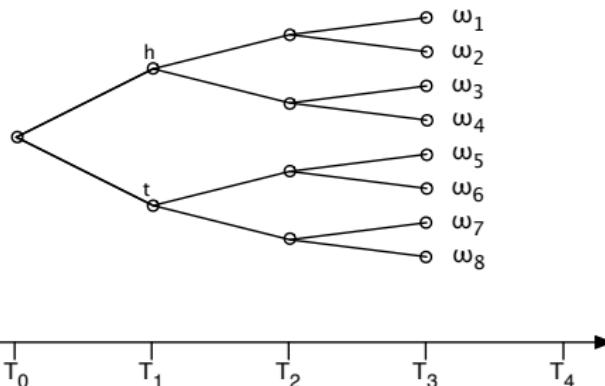
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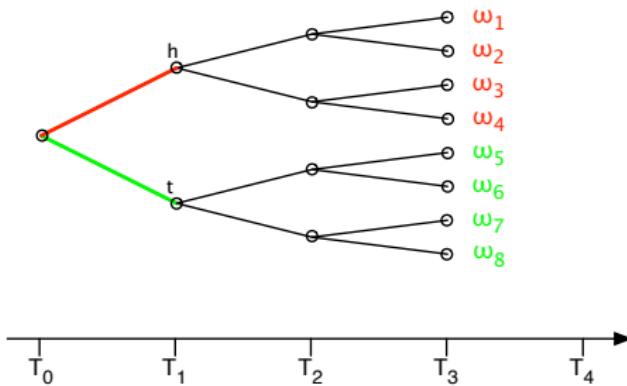
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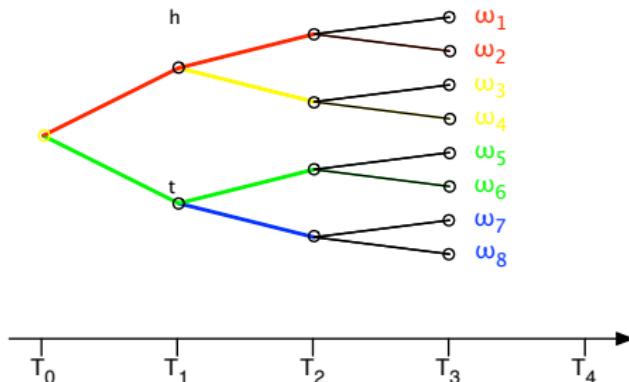
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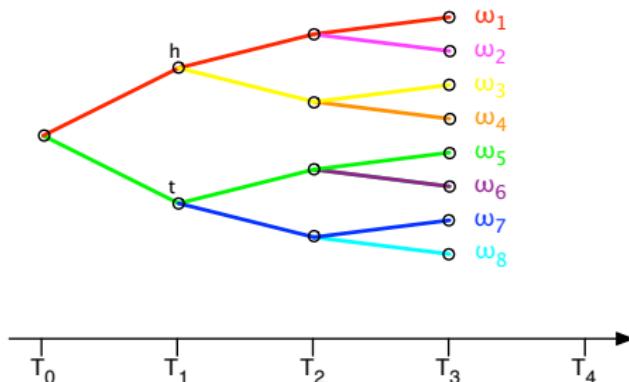
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## Modeling

### Random Variable and Stochastic Processes

---

#### Modeling:

Prototype of a stochastic process - building block of Itô processes:

#### Brownian Motion: $W$

- ▶  $W(t)$  defined over  $(\Omega, \mathcal{F}, P)$ .
- ▶  $W(0) = 0$ .
- ▶  $W(t)$  normal distribution with mean 0 and standard deviation  $\sqrt{t}$ .
- ▶  $W(t_2) - W(t_1)$  normal distribution with mean 0 and standard deviation  $\sqrt{t_2 - t_1}$  (i.i.d.).
- ▶  $W(\cdot, \omega)$  continuous (but nowhere differentiable) function  $[0, \infty) \rightarrow \mathbb{R}$  ( $P$ -a.s.).

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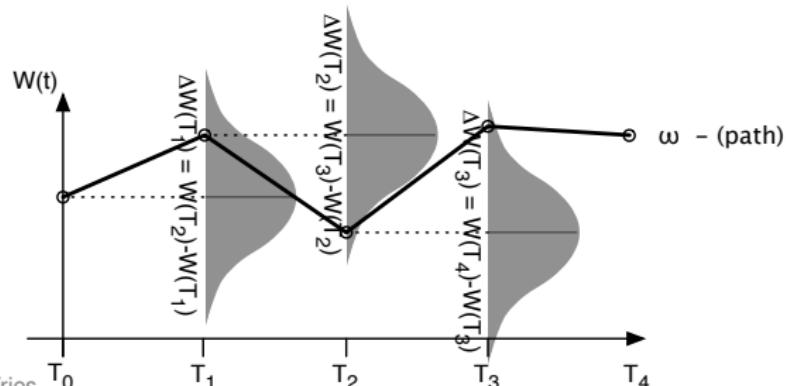
### Random Variable and Stochastic Processes

#### Construction of realizations at discrete times:

$$W(t_k) := \sum_{i=0}^{k-1} \Delta W(t_i) \quad (0 = t_0 < t_1 < \dots),$$

where

$$W(t_0) := 0 \quad , \quad \Delta W(t_i) = (W(t_{i+1}) - W(t_i)) \sim \mathcal{N}(0, \sqrt{t_{i+1} - t_i}) \text{ (i.i.d.)}.$$



## Modeling

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#### Infinitesimal Notation:

$$W(t) =: \int_0^t dW(\tau).$$

## Modeling

### Random Variable and Stochastic Processes

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#### Stochastic Differential Equation:

$$dS = \mu(t, S(t)) dt + \sigma(t, S(t)) dW(t)$$

#### Euler Discretization (e.g.):

$$\underbrace{\Delta \tilde{S}(t_i)}_{\tilde{S}(t_{i+1}) - \tilde{S}(t_i)} = \mu(t_i, \tilde{S}(t_i)) \cdot \underbrace{\Delta t_i}_{t_{i+1} - t_i} + \sigma(t_i, \tilde{S}(t_i)) \cdot \underbrace{\Delta W_i}_{\sim \mathcal{N}(0, \sqrt{\Delta t_i})},$$

i.e.

$$\tilde{S}(t_{i+1}) = \tilde{S}(t_i) + \mu(t_i, \tilde{S}(t_i)) \cdot (t_{i+1} - t_i) + \sigma(t_i, \tilde{S}(t_i)) \cdot \Delta W_i,$$

with  $\tilde{S}(0) = S(0)$ .

$\{\tilde{S}(t_i) \mid 0 = t_0 < t_1 < \dots\}$  is the *Euler discretization* of  $\{S(t) \mid t \geq 0\}$ .

## Modeling

### Random Variable and Stochastic Processes

**Example: log normal process for stock value  $S$ :**

$$dS(t) = \mu(t)S(t)dt + \sigma(t)S(t)dW(t) \Leftrightarrow \frac{dS(t)}{S(t)} = \mu(t)dt + \sigma(t)dW(t)$$

Euler Scheme:

$$\tilde{S}(t_{j+1}) = \tilde{S}(t_j) + \mu(t_j) \cdot \tilde{S}(t_j) \cdot \Delta t_j + \sigma(t_j) \cdot \tilde{S}(t_j) \cdot \underbrace{\Delta W_j}_{\sim \mathcal{N}(0, \sqrt{\Delta t_j})},$$

Log Euler Scheme:

$$\tilde{S}(t_{j+1}) = \tilde{S}(t_j) \cdot \exp \left( (\mu(t_j) - \frac{1}{2}\sigma(t_j)^2) \cdot \Delta t_j + \sigma(t_j) \cdot \underbrace{\Delta W_j}_{\sim \mathcal{N}(0, \sqrt{\Delta t_j})} \right),$$

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## Random Variable and Stochastic Processes

## Exercise: Excel Sheet with Monte-Carlo Simulation

The screenshot shows a Microsoft Excel spreadsheet titled "Monte Carlo Simulation.xls". The top menu bar includes "Start", "Layout", "Tabellen", "Diagramme", "SmartArt", "Formeln", "Daten", and "Überprüfen". The main area displays a table titled "Model Specification" with parameters:  $S(0)=100$ ,  $r=5\%$ ,  $\sigma=10\%$ , and  $\delta=0.01$ . Below this is a "Model" section with the equations for Riskless asset ( $dB = r B dt$ ) and Risky asset ( $dS = r S dt + \sigma S dW$ ). The data table starts at row 10, column C, showing simulated paths for  $S(t)$  over time from 0.00 to 1.00. A callout box highlights the "Monte Carlo Paths of S(t)" chart, which plots multiple colored lines representing the stochastic process of the asset price over time.

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### Product A: Weather Derivative

At time  $T_2 > 0$  measure amount of rain  $R(T_2)$  (in mm) fallen at a predetermined place for a predetermined period. Pay the Euro amount

$$A(T_2) := (R(T_2) - X) \cdot \frac{\text{€}}{\text{mm}}.$$

What determines the value  $A(T_1)$  of this contract at time  $T_1 < T_2$ ?

Note:  $R(T_2)$  is stochastic

⇒ Value depends on assessment of the probability of rain, risk, ...

### Product B: Equity Derivative

At time  $T_2$  measure the quoted value of IBM  $S(T_2)$  (in €). Pay the Euro amount

$$B(T_2) := (S(T_2) - X)$$

What determined the value  $B(T_1)$  of this contract at time  $T_1 < T_2$ ?

⇒ Product looks most similar to the first one.

### Replication:

The payoff of B can be replicated through products traded in  $T_1$ :

Let  $P(T_2; T_1)$  denote the value of a credit which has to be payed back in  $T_2$  by an amount of 1 ( $\rightarrow$  *Zero Bond*). In  $T_1$ :

Buy stock  $S(T_1)$  and  $X$  times a credit  $P(T_2; T_1)$   
(stock long, bond short).

Then

$$\text{Value in } T_2: \quad S(T_2) - X \quad = \quad B(T_2)$$

$$\text{Value in } T_1: \quad S(T_1) - X \cdot P(T_2; T_1) \quad \stackrel{!}{=} \quad B(T_1)$$

$\Rightarrow$  Value of replication portfolio is a “fair value” for the derivative.

### Discrete Time ( $T_1, T_2$ ), Two Assets ( $S, B$ ), Two States ( $\omega_1, \omega_2$ )

Given: In  $T_2$  we have two disjoint events (states)  $\omega_1$  and  $\omega_2$ , the payoff of a derivative product  $V(T_2, \omega_i)$  and two traded assets  $S$  und  $B$ .

Wanted: A portfolio  $\alpha S + \beta B$ , which replicates the value  $V(T_2)$  in  $T_2$  *for any state*.

⇒ Its value in  $T_1$  determines the (fair) value  $V(T_1)$  of  $V$   
→ *cost of replication*.

Solution:

$$\begin{array}{ccc} & \alpha \cdot S(T_2; \omega_1) + \beta \cdot B(T_2; \omega_1) \stackrel{!}{=} V(T_2; \omega_1) \\ \alpha \cdot S(T_1) + \beta \cdot B(T_1) & \xrightarrow{\hspace{1cm}} & \\ & \alpha \cdot S(T_2; \omega_2) + \beta \cdot B(T_2; \omega_2) \stackrel{!}{=} V(T_2; \omega_2) \end{array}$$

## Risk Neutral Valuation

Linear equation, two equations, two unknowns.

$$\begin{array}{ccc} \alpha \cdot S(T_2; \omega_1) + \beta \cdot B(T_2; \omega_1) & \stackrel{!}{=} & V(T_2; \omega_1) \\ \downarrow & & \downarrow \\ \alpha \cdot S(T_1) + \beta \cdot B(T_1) & & \\ \downarrow & & \downarrow \\ \alpha \cdot S(T_2; \omega_2) + \beta \cdot B(T_2; \omega_2) & \stackrel{!}{=} & V(T_2; \omega_2) \end{array}$$

Solvable

$$\Leftrightarrow S(T_2; \omega_1) \cdot B(T_2; \omega_2) - S(T_2; \omega_2) \cdot B(T_2; \omega_1) \neq 0$$

$$\stackrel{B \neq 0}{\Leftrightarrow} \frac{S(T_2; \omega_1)}{B(T_2; \omega_1)} \neq \frac{S(T_2; \omega_2)}{B(T_2; \omega_2)}$$

*Overhead:* For every derivative product  $V$ , the replication portfolio  $\alpha(t)$ ,  $\beta(t)$  has to be calculated (though every time step  $t$ ).

## Risk Neutral Valuation

Same example again - but consider everything divided by  $B$

$$\alpha \cdot \frac{S(T_1)}{B(T_1)} + \beta \cdot 1 \xrightarrow{\text{Diagram}} \begin{cases} p \rightarrow \alpha \cdot \frac{S(T_2; \omega_1)}{B(T_2; \omega_1)} + \beta \cdot 1 \stackrel{!}{=} \frac{V(T_2; \omega_1)}{B(T_2; \omega_1)} \\ 1-p \rightarrow \alpha \cdot \frac{S(T_2; \omega_2)}{B(T_2; \omega_2)} + \beta \cdot 1 \stackrel{!}{=} \frac{V(T_2; \omega_2)}{B(T_2; \omega_2)} \end{cases}$$

## Risk Neutral Valuation

Same example again - but consider everything divided by  $B$

$$\alpha \cdot \frac{S(T_1)}{B(T_1)} + \beta \cdot 1 \xrightarrow{\begin{array}{l} p \\ 1-p \end{array}} \begin{aligned} & \alpha \cdot \frac{S(T_2; \omega_1)}{B(T_2; \omega_1)} + \beta \cdot 1 \stackrel{!}{=} \frac{V(T_2; \omega_1)}{B(T_2; \omega_1)} \\ & \alpha \cdot \frac{S(T_2; \omega_2)}{B(T_2; \omega_2)} + \beta \cdot 1 \stackrel{!}{=} \frac{V(T_2; \omega_2)}{B(T_2; \omega_2)} \end{aligned}$$

In general

$$\frac{V(T_1)}{B(T_1)} \neq E^{\mathbb{P}} \left( \frac{V(T_2)}{B(T_2)} \right) \quad \text{and thus} \quad \frac{S(T_1)}{B(T_1)} \neq E^{\mathbb{P}} \left( \frac{S(T_2)}{B(T_2)} \right).$$

## Risk Neutral Valuation

Same example again - but consider everything divided by  $B$

$$\alpha \cdot \frac{S(T_1)}{B(T_1)} + \beta \cdot 1 \xrightarrow{\begin{array}{l} q \\ 1-q \end{array}} \begin{aligned} & \alpha \cdot \frac{S(T_2; \omega_1)}{B(T_2; \omega_1)} + \beta \cdot 1 \stackrel{!}{=} \frac{V(T_2; \omega_1)}{B(T_2; \omega_1)} \\ & \alpha \cdot \frac{S(T_2; \omega_2)}{B(T_2; \omega_2)} + \beta \cdot 1 \stackrel{!}{=} \frac{V(T_2; \omega_2)}{B(T_2; \omega_2)} \end{aligned}$$

## Risk Neutral Valuation

Same example again - but consider everything divided by  $B$

$$\alpha \cdot \frac{S(T_1)}{B(T_1)} + \beta \cdot 1 \xrightarrow{\begin{array}{l} q \\ 1-q \end{array}} \begin{aligned} & \alpha \cdot \frac{S(T_2; \omega_1)}{B(T_2; \omega_1)} + \beta \cdot 1 \stackrel{!}{=} \frac{V(T_2; \omega_1)}{B(T_2; \omega_1)} \\ & \alpha \cdot \frac{S(T_2; \omega_2)}{B(T_2; \omega_2)} + \beta \cdot 1 \stackrel{!}{=} \frac{V(T_2; \omega_2)}{B(T_2; \omega_2)} \end{aligned}$$

However, if  $\text{sign}\left(\frac{S(T_2; \omega_2)}{B(T_2; \omega_2)} - \frac{S(T_1)}{B(T_1)}\right) \neq \text{sign}\left(\frac{S(T_2; \omega_1)}{B(T_2; \omega_1)} - \frac{S(T_1)}{B(T_1)}\right)$  there exists a prob.-measure  $\mathbb{Q}$  s.th.

$$\frac{S(T_1)}{B(T_1)} = E^{\mathbb{Q}}\left(\frac{S(T_2)}{B(T_2)}\right) \quad \text{and thus} \quad \frac{V(T_1)}{B(T_1)} = E^{\mathbb{Q}}\left(\frac{V(T_2)}{B(T_2)}\right).$$

### Equivalent Martingale Measure

The measure  $\mathbb{Q}$  is the so called *equivalent martingale measure*. It does not depend on  $V$  (!) - this does not hold if one considers

$$V(T_1) \stackrel{!}{=} E(V(T_2)) \text{ in place of } \frac{V(T_1)}{B(T_1)} \stackrel{!}{=} E\left(\frac{V(T_2)}{B(T_2)}\right).$$

### Numéraire

The measure  $\mathbb{Q}$  depends on the reference quantity (here  $B$ ), the so called *numéraire*.

Here:

$$q \cdot \frac{S(T_2; \omega_1)}{B(T_2; \omega_1)} + (1 - q) \cdot \frac{S(T_2; \omega_2)}{B(T_2; \omega_2)} \stackrel{!}{=} \frac{S(T_1)}{B(T_1)} \quad \Rightarrow \quad q = \frac{\frac{S(T_2; \omega_1)}{B(T_2; \omega_1)} - \frac{S(T_1)}{B(T_1)}}{\frac{S(T_2; \omega_1)}{B(T_2; \omega_1)} - \frac{S(T_2; \omega_2)}{B(T_2; \omega_2)}}$$

### Universal Pricing Theorem:

$$\frac{V(0)}{N(0)} = E^{\mathbb{Q}^N} \left( \frac{V(T_n)}{N(T_n)} \mid \mathcal{F}_0 \right)$$

Assume  $V$  consists of finite number of payments

$X_i$  paid in  $T_i$ ,  $\Rightarrow$   $N$ -relative payment value:  $E^{\mathbb{Q}^N} \left( \frac{X_i}{N(T_i)} \mid \mathcal{F}_0 \right)$ .

Value

$$\Rightarrow E^{\mathbb{Q}^N} \left( \frac{V}{N} \mid \mathcal{F}_0 \right) = \sum_{i=1}^n E^{\mathbb{Q}^N} \left( \frac{X_i}{N(T_i)} \mid \mathcal{F}_0 \right)$$

### Monte-Carlo Simulation:

Sample space  $\tilde{\Omega} = \{\omega_1, \dots, \omega_m\}$ , e.g.  $m \approx 10000$

- ▶  $\frac{V(0)}{N(0)} = E^{\mathbb{Q}^N} \left( \frac{V}{N} \mid \mathcal{F}_0 \right) = \sum_{i=1}^n E^{\mathbb{Q}^N} \left( \frac{X_i}{N(T_i)} \mid \mathcal{F}_0 \right)$
- ▶  $E^{\mathbb{Q}^N} \left( \frac{X_i}{N(T_i)} \mid \mathcal{F}_0 \right) \approx \frac{1}{m} \sum_{\omega \in \tilde{\Omega}} \frac{X_i(\omega)}{N(T_i; \omega)}$

$$\begin{aligned}\Rightarrow V(0) &= N(0) \cdot E^{\mathbb{Q}^N} \left( \frac{V}{N} \mid \mathcal{F}_0 \right) \\ &\approx \frac{1}{m} \sum_{\omega \in \tilde{\Omega}} \sum_{i=1}^n X_i(\omega) \cdot \underbrace{\frac{N(0)}{N(T_i; \omega)}}_{\text{state price deflator / discount factor}}\end{aligned}$$

### Monte-Carlo Simulation

#### Advantages

- ▶ Pricing of path dependent options in a natural way.
- ▶ High dimensions possible (but slower convergence in high dimensions).
- ▶ Straight forward to implement.

#### Challenges

- ▶ Sensitivities (partial derivatives of option price w.r.t. model parameters) tend to be unstable (harder to get them stable).
- ▶ Pricing of Bermudan option needs additional effort.
- ▶ Calibration.

### Monte-Carlo Simulation

#### Alternatives

- ▶ Analytic pricing formulas - only for simple models and simple payoffs.
- ▶ Numerical integration - only for simple models and European style options.
- ▶ Lattice models (PDE, Tree, Markov Functional) - only for low dimensional models

# RISK NEUTRAL VALUATION CHANGE OF MEASURE / DRIFT

## Change of Drift Trick I

**Risk Neutral Pricing:** Find a measure  $\mathbb{Q}$  such that for all underlying assets  $S$  we have

$$E^{\mathbb{Q}} \left( \frac{S(T_{i+1})}{N(T_{i+1})} \mid \mathcal{F}_{T_i} \right) = \frac{S(T_i)}{N(T_i)},$$

then for a derivative the cost of replication  $V$  satisfies

$$E^{\mathbb{Q}} \left( \frac{V(T_{i+1})}{N(T_{i+1})} \mid \mathcal{F}_{T_i} \right) = \frac{V(T_i)}{N(T_i)}.$$

**Martingale Property:** (in place of  $\frac{S}{N}$  or  $\frac{V}{N}$  we simple write  $X$ )

$$E^{\mathbb{Q}}(X(T_{i+1}) \mid \mathcal{F}_{T_i}) = X(T_i) \quad \Leftrightarrow \quad E^{\mathbb{Q}}(\underbrace{X(T_{i+1}) - X(T_i)}_{=: \Delta X(T_i)} \mid \mathcal{F}_{T_i}) = 0$$

How to calculate the measure  $\mathbb{Q}$ ?

## Change of Drift Trick II

Never need to (explicitly) calculate the measure  $\mathbb{Q}$ :  
Conditional Expectation:

$$E^{\mathbb{Q}}(\Delta X(T_i) \mid \mathcal{F}_{T_i}) = \sum_{\omega \in \Omega} \Delta X(T_i, \omega) \cdot \mathbb{Q}(\{\omega\})$$

interpretation 1: the measure has changed from  $\mathbb{P}$  to  $\mathbb{Q}$ :

$$= \sum_{\omega \in \Omega} \Delta X(T_i, \omega) \cdot \underbrace{\frac{\mathbb{Q}(\{\omega\})}{\mathbb{P}(\{\omega\})}}_{\text{measure changed}} \mathbb{P}(\{\omega\})$$

interpretation 2: the values have changed:

$$= \sum_{\omega \in \Omega} \underbrace{\Delta X(T_i, \omega)}_{\text{value changed}} \frac{\mathbb{Q}(\{\omega\})}{\mathbb{P}(\{\omega\})} \cdot \mathbb{P}(\{\omega\})$$

## Change of Drift Trick III

**Question:** How does the process look like, if it has to satisfy the martingale property?

**Answer:** The drift is zero.

$$\left. \begin{array}{l} dX(t) = \mu dt + \sigma dW(t) \\ \text{and} \\ E^{\mathbb{Q}}(X(T_{i+1}) - X(T_i) \mid \mathcal{F}_{T_i}) = 0 \end{array} \right\} \Rightarrow \mu = 0$$

Note:  $X(T_{i+1}) - X(T_i) = \Delta X = \int_{T_i}^{T_{i+1}} dX(t).$

## Change of Drift Trick IV

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### Conclusion:

Instead of calculating the pricing measure ([martingale measure](#)), simply write down the process and calculate the correct drift.

change of measure  $\Leftrightarrow$  change of drift

A Monte-Carlo simulation of that process corresponds to a simulation under the pricing measure.

## Change of Drift Trick V

**Itô Lemma:** Main Tool to Calculate the Drift of Processes

Let  $X$  denote an Itô process with

$$dX(t) = \mu dt + \sigma dW.$$

Let  $g(t, x)$  denote some function  $g \in C^2([0, \infty] \times \mathbb{R})$ . Then we have that

$$Y(t) := g(t, X(t))$$

is an Itô process with

$$dY_t = \frac{\partial g}{\partial t}(t, X_t) dt + \frac{\partial g}{\partial x}(t, X_t) dX_t + \frac{1}{2} \frac{\partial^2 g}{\partial x^2}(t, X_t) \cdot (dX_t)^2,$$

where  $(dX_t)^2 = (dX_t) \cdot (dX_t)$  is given by formal expansion with

$$dt \cdot dt = 0,$$

$$dt \cdot dW = 0,$$

$$dW \cdot dt = 0,$$

$$dW \cdot dW = dt,$$

## Change of Drift Trick VI

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i.e.

$$\begin{aligned} (\mathrm{d}X_t)^2 &= (\mathrm{d}X_t) \cdot (\mathrm{d}X_t) = (\mu \, \mathrm{d}t + \sigma \, \mathrm{d}W) \cdot (\mu \, \mathrm{d}t + \sigma \, \mathrm{d}W) \\ &= \mu^2 \cdot \mathrm{d}t \cdot \mathrm{d}t + \mu \cdot \sigma \cdot \mathrm{d}t \cdot \mathrm{d}W + \mu \cdot \sigma \cdot \mathrm{d}W \cdot \mathrm{d}t + \sigma^2 \cdot \mathrm{d}W \cdot \mathrm{d}W \\ &= \sigma^2 \, \mathrm{d}t \end{aligned}$$

## Change of Drift Trick VII

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**Itô Lemma:** Example:

$$dX(t) = \mu X(t) dt + \sigma X(t) dW.$$

Consider logarithm of  $X$

$$Y(t) := \log(X(t))$$

then

$$dY(t) = \left(\mu - \frac{1}{2}\sigma^2\right) dt + \sigma dW.$$

# RISK NEUTRAL VALUATION

## EXAMPLE: BLACK SCHOLES MODEL

## Example: Black-Scholes Model

### Black-Scholes Model:

$$dS = \mu S dt + \sigma S dW \Leftrightarrow \frac{dS}{S} = \frac{\mu dt}{S} + \sigma dW$$

**Interpretation:** Consider discrete times  $t_0, t_1, t_2, t_3, \dots$ . Then:

$$\frac{\Delta S(t_i)}{S} = \mu \cdot \Delta t_i + \sigma \cdot \Delta W(t_i)$$

where

$$\Delta t_i = t_{i+1} - t_i$$

A time period.

$$\frac{\Delta S(t_i)}{S(t_i)} = \frac{S(t_{i+1}) - S(t_i)}{S(t_i)}$$

Relative change of the stock over the period  $\Delta t_i = t_{i+1} - t_i$ .

$$\mu \cdot \Delta t_i = \mu \cdot (t_{i+1} - t_i)$$

Risk less part: A deterministic drift.  
 $\mu$  = annualized risk less rate of return.

$$\sigma \cdot \Delta W(t_i) = \sigma \cdot \underbrace{(W(t_{i+1}) - W(t_i))}_{\text{Normal distributed with variance } \Delta t_i}$$

Risky part: A normal distributed random variable.  $\sigma$  = annualized standard deviation of the return.

## Example: Black-Scholes Model

### Black-Scholes Model:

$$dS = \mu S dt + \sigma S dW \Leftrightarrow \frac{dS}{S} = \frac{\mu dt}{S} + \sigma dW$$

**Interpretation:** Consider discrete times  $t_0, t_1, t_2, t_3, \dots$ . Then:

$$\frac{\Delta S(t_i)}{S} = \mu \cdot \Delta t_i + \sigma \cdot \Delta W(t_i)$$

where

$$\Delta t_i = t_{i+1} - t_i \quad \text{A time period.}$$

$$\frac{\Delta S(t_i)}{S(t_i)} = \frac{S(t_{i+1}) - S(t_i)}{S(t_i)} \quad \text{Relative change of the stock over the period } \Delta t_i = t_{i+1} - t_i.$$

$$\mu \cdot \Delta t_i = \mu \cdot (t_{i+1} - t_i)$$

**Risk less part:** A deterministic drift.  
 $\mu$  = annualized risk less rate of return.

$$\sigma \cdot \Delta W(t_i) = \sigma \cdot \underbrace{(W(t_{i+1}) - W(t_i))}_{\text{Normal distributed with variance } \Delta t_i}$$

**Risky part:** A normal distributed random variable.  $\sigma$  = annualized standard deviation of the return.

## Example: Black-Scholes Model

### Monte-Carlo Implementation

**Implementation: (Monte-Carlo) Simulation:** Consider time-discrete version of Black-Scholes Model

$$\frac{\Delta S(t_i)}{S} = \mu \cdot \Delta t_i + \sigma \cdot \Delta W(t_i)$$

i.e.

$$S(t_{i+1}) = S(t_i) + \mu \cdot S(t_i) \cdot \Delta t_i + \sigma \cdot S(t_i) \cdot \Delta W(t_i).$$

For a single path (scenario) we have

$$S(t_{i+1}, \omega) = S(t_i, \omega) + \mu \cdot S(t_i, \omega) \cdot \Delta t_i + \sigma \cdot S(t_i, \omega) \cdot \Delta W(t_i, \omega) \quad (\text{Euler Sch})$$

Remark: Much more accurate numerical simulation is given by

$$S(t_{i+1}, \omega) = S(t_i, \omega) \cdot \exp \left( \left( \mu - \frac{1}{2} \sigma^2 \right) \cdot \Delta t_i + \sigma \cdot \Delta W(t_i, \omega) \right) \quad (\text{Log-Euler})$$

## Example: Black-Scholes Model

### Binomial Tree Implementation

**Implementation: (Binomial) Tree:** Consider time-discrete version of Black-Scholes Model

$$S(t_{i+1}) = S(t_i) + \mu \cdot S(t_i) \cdot \Delta t_i + \sigma \cdot S(t_i) \cdot \Delta W(t_i).$$

Approximate the normal distributed  $\Delta W(t_i)$  by a binomial distributed random variable  $\Delta B(t_i)$

$$S(t_{i+1}) \approx S(t_i) + \mu \cdot S(t_i) \cdot \Delta t_i + \sigma \cdot S(t_i) \cdot \Delta B(t_i).$$

where

$$\Delta B(t_i) = \begin{cases} +\sqrt{\Delta t_i} & \text{with probability } \frac{1}{2} \\ -\sqrt{\Delta t_i} & \text{with probability } \frac{1}{2} \end{cases}$$

*Justification:* Repetitive binomial experiments converge to a normal distribution.

$$\sum_{i=0}^n \Delta B(t_i) \approx \sum_{i=0}^n \Delta W(t_i) \quad \text{for } n \text{ large.}$$

## Example: Black-Scholes Model

Under Martingale Measure

### Black-Scholes Model:

Evolution of Money Market Account:  $dB = r \cdot B dt$

Evolution of Stock ..... :  $dS = \mu \cdot S dt + \sigma \cdot S dW(t)$

### Choose Numéraire and consider Martingale Measure:

$B$  chosen as Numéraire  $\Rightarrow \frac{S}{B}$  is  $\mathbb{Q}$ -martingale

### Change of Drift Trick:

$$d\frac{S}{B} = (\mu - r) \frac{S}{B} dt + \sigma \frac{S}{B} dW(t)$$

drift has to be zero

$$\mu = r$$

RISK NEUTRAL VALUATION  
EXAMPLE: BLACK-SCHOLES MODEL  
MONTE-CARLO OPTION PRICER

## **Example: Black-Scholes Model**

## **Example: Monte-Carlo European Option Pricing**

**Example: European option value:** European option value is a known function of the underlying process(es) at some future time  $T_n$ :

$$V(T_n) = \max(S(T_n) - K, 0).$$

**Choose a Model for Underlyings:** e.g. Black-Scholes

Evolution of Money Market Account:  $dB = r \cdot B dt$

Evolution of Stock .....:  $dS = \mu \cdot S dt + \sigma \cdot S dW(t)$

**Choose Numéraire and consider Martingale Measure:**

$$B \text{ Numéraire} \Rightarrow \frac{S}{B} \text{ } \mathbb{Q}\text{-martingale} \Rightarrow \mu = r$$

**Monte-Carlo Simulation (of the  $\mathbb{Q}$  dynamics):**

$$B(t_{i+1}, \omega) = B(t_0) \cdot \exp(r \cdot t_{i+1})$$

$$S(t_{i+1}, \omega) = S(t_i) + r \cdot S(t_i) + \sigma \cdot S(t_i) \cdot \Delta W(t_i, \omega)$$

for  $\omega = \omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6, \dots, \omega_N$  (some 1000's samples).

## **Example: Black-Scholes Model**

## **Example: Monte-Carlo European Option Pricing**

**Example: European option value:** European option value is a known function of the underlying process(es) at some future time  $T_n$ :

$$V(T_n) = \max(S(T_n) - K, 0).$$

**Choose a Model for Underlyings:** e.g. Black-Scholes

Evolution of Money Market Account:  $dB = r \cdot B \, dt$

Evolution of Stock .....:  $dS = \mu \cdot S \, dt + \sigma \cdot S \, dW(t)$

Choose Numéraire and consider Martingale Measure:

$$B \text{ Numéraire} \Rightarrow \frac{S}{B} \text{ Q-martingale} \Rightarrow \mu = r$$

Monte-Carlo Simulation (of the  $\mathbb{Q}$  dynamics):

$$B(t_{i+1}, \omega) = B(t_0) \cdot \exp(r \cdot t_{i+1})$$

$$S(t_{i+1}, \omega) = S(t_i) + r \cdot S(t_i) + \sigma \cdot S(t_i) \cdot \Delta W(t_i, \omega)$$

for  $\omega = \omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6, \dots, \omega_N$  (some 1000's samples).

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Evolution of Stock .....:  $dS = \mu \cdot S \, dt + \sigma \cdot S \, dW(t)$

**Choose Numéraire and consider Martingale Measure:**

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for  $\omega = \omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6, \dots, \omega_N$  (some 1000's samples).

## Example: Black-Scholes Model

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$$S(t_{i+1}, \omega) = S(t_i) + r \cdot S(t_i) + \sigma \cdot S(t_i) \cdot \Delta W(t_i, \omega)$$

for  $\omega = \omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6, \dots, \omega_N$  (some 1000's samples).

## **Example: Black-Scholes Model**

## **Example: Monte-Carlo European Option Pricing**

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**Calculate Payoff for each Sample Path:**

$$V(T_n, \omega_j) = \max(S(T_n, \omega_j) - K, 0)$$

**Calculate Price:**

$$\begin{aligned} V(0) &= B(0) \cdot E^{\mathbb{Q}} \left( \frac{V(T_n)}{B(T_n)} \right) \approx \frac{1}{N} \sum_{j=1}^N \frac{V(T_n, \omega_j)}{B(T_n, \omega_j)} \\ &= \frac{1}{N} \sum_{j=1}^N \frac{\max(S(T_n, \omega_j) - K, 0)}{B(T_n, \omega_j)} \end{aligned}$$

## Example: Black-Scholes Model

## Example: Monte-Carlo European Option Pricing

## Exercise: Excel Sheet: Monte-Carlo Simulation with Option Pricing

Monte Carlo Simulation with Option Pricing.xlsx

Auf dem Blatt suchen

**Model Specification**

S(0) 100
r 5%
sigma 10%
delta t 0.01

**Product Specification**

Maturity: 1.00
Strike: 102

**Used in Black Scholes Formula**

d+ 0.4639983
d- 36%

**Pricing**

Option Value: 5.43
Analytic: 5.57

**Monte Carlo Paths of Underlying**

The chart displays 100 Monte Carlo paths of the underlying asset price over a period of 1.20 units of time. The paths start at a value of 100.00 at time 0.00 and follow a random walk pattern, with some paths reaching higher values and others lower values by time 1.20.

## Further Reading I

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-  FRIES, CHRISTIAN P.: Mathematical Finance. Theory, Modeling, Implementation. John Wiley & Sons, 2007. ISBN 0-470-04722-4.  
<http://www.christian-fries.de/finmath/book>.