

The stochastic process followed by stock prices.

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# The stochastic process followed by stock prices

The price of a certain stock at a future time  $t$  is unknown at the present.

We think of it as being a random variable  $S_t$ .

**What sort of random variable are  $S_t$  for  $t \geq 0$ ?**

## Brownian motion

A *Brownian motion* is a family of random variables

$$\{B_t \mid t \geq 0\}$$

on some probability space  $(\Omega, \mathcal{F}, P)$  such that:

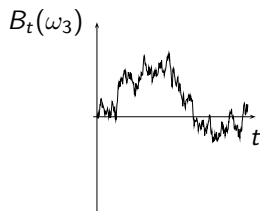
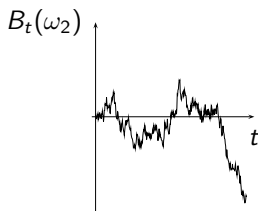
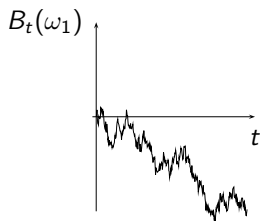
- (1)  $B_0 = 0$ ,
- (2) for  $0 \leq s < t$  the increment  $B_t - B_s$  is normally distributed with mean 0 and variance  $t - s$ ,
- (3) for any  $0 \leq t_1 < t_2 < \dots < t_n$  the increments

$$B_{t_1} - B_0, B_{t_2} - B_{t_1}, \dots, B_{t_n} - B_{t_{n-1}}$$

are independent random variables, and

- (4) For any  $\omega \in \Omega$  the function  $t \mapsto B_t(\omega)$  is continuous.

Three instances of Brownian Motion  
corresponding to  $\omega_1, \omega_2, \omega_3 \in \Omega$ .



Does Brownian motion exist?

Yes— by *Kolmogorov's Existence Theorem*.

Brownian motion has surprising properties; for example,

(1) The function  $t \mapsto B_t(\omega)$  is nowhere differentiable with probability 1,

(2) if  $B_t = x$  for some  $t$  then for any  $\epsilon > 0$  the set  $\{\tau : |\tau - t| < \epsilon \text{ and } B_\tau = x\}$  is infinite with probability one.

Brownian motion is useful for describing the jiggling of prices: buying and selling jiggle prices.

# The Ito integral

Brownian motion is an example of a *stochastic process* i.e., a family of random variables indexed by time  $t \geq 0$ .

We now construct a more general kind of stochastic processes whose definition is based on Brownian motion.

We want to construct a stochastic process  $\{X_t \mid t \geq 0\}$  on the same probability space  $(\Omega, \mathcal{F}, P)$  on which the Brownian motion  $\{B_t \mid t \geq 0\}$  is defined with the property that the change of  $X$  over an infinitesimal period of time  $dt$  is given by

$$dX = a(\omega, t)dt + b(\omega, t)dB$$

where  $a$  and  $b$  are themselves stochastic processes on  $(\Omega, \mathcal{F}, P)$  with continuous paths and where  $dB$  is the change in the Brownian motion over the infinitesimal period of time  $dt$ .

Fix any  $\omega \in \Omega$ ; for any partition  $\mathcal{P}$  of  $[0, t]$  into small intervals  $[s_0, s_1], [s_1, s_2], \dots, [s_{n-1}, s_n]$  where  $s_0 = 0$  and  $s_n = t$ , we compute the sum

$$\Sigma_{\mathcal{P}} = \sum_{i=0}^{n-1} b(\omega, s_i) (B(\omega)_{s_{i+1}} - B(\omega)_{s_i}) .$$

Define the *norm* of the partition  $\mathcal{P}$  to be

$$\|\mathcal{P}\| = \max \{s_1 - s_0, s_2 - s_1, \dots, s_n - s_{n-1}\} ;$$

If  $b$  satisfies some technical conditions, the limit as  $\|\mathcal{P}\| \rightarrow 0$  of  $\Sigma_{\mathcal{P}}$  exists.

This limit is known as an *Ito integral* and we denote it with

$$\int_0^t b(\omega, s) dB(\omega)_s .$$

We now define the process

$$X_t(\omega) = X_0(\omega) + \int_0^t a(\omega, s) ds + \int_0^t b(\omega, s) dB(\omega)_s$$

for all  $t \geq 0$ .



## Example: $\int_0^t s dB_s$

We compute the integral from definition

- (1) Take any partition  $\mathcal{P}$  of  $[0, t]$  into small intervals  $[s_0, s_1], [s_1, s_2], \dots, [s_{n-1}, s_n]$  where  $s_0 = 0$  and  $s_n = t$ .
- (2) The sum

$$\Sigma_{\mathcal{P}} = \sum_{i=0}^{n-1} s_i (B_{s_{i+1}} - B_{s_i})$$

is a sum of independent normally distributed random variables with mean 0 and variance  $s_0^2(s_1 - s_0), s_1^2(s_2 - s_1), \dots, s_{n-1}^2(s_n - s_{n-1})$ .

- (3)  $\Sigma_{\mathcal{P}}$  is normally distributed with mean 0 and variance  $s_0^2(s_1 - s_0) + s_1^2(s_2 - s_1) + \dots + s_{n-1}^2(s_n - s_{n-1})$ .
- (4) As  $\|\mathcal{P}\| \rightarrow 0$  this variance converges to  $\int_0^t s^2 ds = t^3/3$ .
- (5) We conclude that  $\int_0^t s dB_s$  is a normally distributed random variable with mean 0 and variance  $t^3/3$ .

Henceforth we write

$$dX = a(X, t) dt + b(X, t) dB$$

to denote that fact that  $X$  is a stochastic process defined by

$$X_t(\omega) = X_0(\omega) + \int_0^t a(X_s(\omega), s) ds + \int_0^t b(X_s(\omega), s) dB(\omega)_s.$$

We shall refer to stochastic processes of this form *Ito processes*.

## Back to stock prices

As a first approximation we model the proportional increase in stock prices as a Brownian motion.

We could then derive the following discrete time version

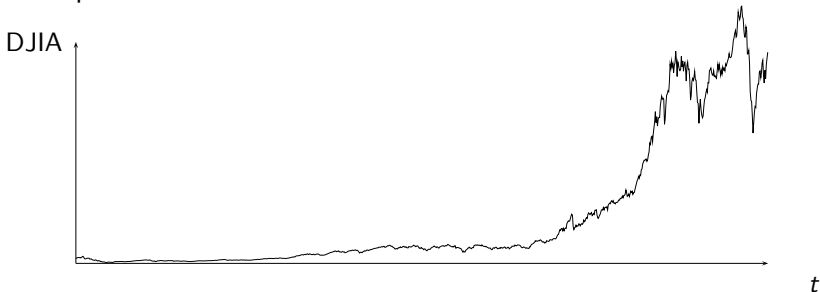
$$\frac{dS}{S} = \sigma dB$$

where  $dS$  is the change in the stock price over a short time from  $t$  to  $t + dt$ ,  $dB = B_{t+dt} - B_{dt}$  and  $B$  is a Brownian motion.

(In particular proportional increases in  $S$  are independent, e.g., today's increase in a stock price is independent of tomorrow's increase.)

model implies that the values of stocks vary without any long term trend, i.e.,  $E\left(\frac{dS}{S}\right) = 0$ .

A quick glance at historical data shows that this is not very plausible:



Despite the randomness of the value of the DJIA, its long term exponential growth is quite visible.

To take into account this upward trend in stock prices we introduce a *drift term*

$$\frac{dS}{S} = \sigma dB + \mu dt.$$

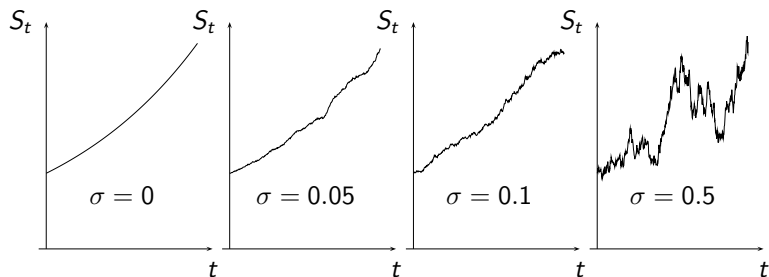
We refer to a process  $S$  defined above as a *geometric Brownian motion*.

Now

$$E\left(\frac{dS}{S}\right) = \mu dt.$$

We shall refer to  $\mu$  as the *expected return* of the stock and to  $\sigma$  as the *volatility* of the stock.

Instances of the process  $dS = 0.1Sdt + \sigma SdB$



One can raise several objections to this model. Consider the following list of all trades in Vodafone shares between 16:22:08 and 16:23:08 on August 16th, 2002:

Trade time	Trade price	Bid	Ask	Volume	Block price	Buy/Sell
16:23:08	100.75p	100.75p	101p	180,614	£181,969	SELL
16:23:08	100.75p	100.75p	101p	1,185	£1,194	SELL
16:23:08	100.75p	100.5p	100.75p	250,000	£251,875	BUY
16:23:01	100.5p	100.25p	100.75p	2,500	£2,512	
16:22:55	100.75p	100.5p	100.75p	28,383	£28,596	BUY
16:22:55	100.75p	100.5p	100.75p	3,000	£3,022	BUY
16:22:55	100.75p	100.5p	100.75p	248,815	£250,681	BUY
16:22:55	100.75p	100.5p	100.75p	179,802	£181,151	BUY
16:22:55	100.75p	100.5p	100.75p	40,000	£40,300	BUY
16:22:42	100.5p	100.5p	100.75p	1,500	£1,508	SELL
16:22:41	100.75p	100.5p	100.75p	23,117	£23,290	BUY
16:22:39	100.527p	100.5p	100.75p	10,000	£10,053	SELL
16:22:38	100.75p	100.5p	100.75p	48,500	£48,864	BUY
16:22:38	100.75p	100.5p	100.75p	150,000	£151,125	BUY
16:22:38	100.75p	100.5p	100.75p	25,000	£25,188	BUY
16:22:38	100.75p	100.5p	100.75p	26,500	£26,699	BUY
16:22:29	100.688p	100.5p	100.75p	25,000	£25,172	BUY
16:22:18	100.75p	100.5p	100.75p	25,000	£25,188	BUY
16:22:08	100.75p	100.5p	100.75p	11,000	£11,082	BUY



(1) The model allows any real number to be a value for  $S$ , but in real life there is a smallest unit.

(2) We assume that prices are changing continuously but trades occur at discrete times.

(3) Shares are often traded through market makers.

They buy at the *bid* price and sell at the *ask* price. So there are two prices! Sometimes it is crucial to model both.

(4) Sometimes, e.g., during market crashes, changes seem to have a “memory”.

We should regard our model as an approximation to real life prices and trades, not as an accurate description.

## Ito's Lemma.

Consider a stochastic process  $X_t$  whose change over a small interval of time from  $t$  to  $t + dt$  is given by

$$dX = a(X, t)dt + b(X, t)dB$$

where  $a(x, t)$  and  $b(x, t)$  are functions of  $x$  and  $t$ .

Consider a new stochastic process  $Y = G(X, t)$  where  $G(x, t)$  is a function of  $x$  and  $t$ .

What sort of process is  $Y$ ?

### **Theorem: (Ito's Lemma)**

Assume that  $G(x, t)$  is twice continuously differentiable with respect to  $x$  and continuously differentiable with respect to  $t$ .

The process  $Y$  is also an Ito process.

In fact,

$$dY = \left( \frac{\partial G}{\partial x} a + \frac{\partial G}{\partial t} + \frac{1}{2} \frac{\partial^2 G}{\partial x^2} b^2 \right) dt + \frac{\partial G}{\partial x} b dB.$$

" $dB^2 = dt$ "

Write  $dB = B_{t+\Delta t} - B_t$  as  $\sqrt{\Delta t}Z$  for some standard normal  $Z$ .

Note:  $1 = \text{Var}(Z) = E(Z^2) - E(Z)^2 = E(Z^2)$ .

So,  $E(dB^2) = E(\Delta t Z^2) = \Delta t E(Z^2) = \Delta t$ , and

$\text{Var}(dB^2) = \Delta t^2 \text{Var}(Z^2)$  is of order  $\Delta t^2$ .

As  $\Delta t \rightarrow 0$ ,  $\text{Var}(dB^2) \ll \Delta t = E(dB^2)$ , so  $dB^2$  "converges to"  $\Delta t$ .

## (Very) informal proof of Ito's Lemma:

Using the Taylor series for  $G$  we can write

$$dY = \frac{\partial G}{\partial x} \Delta X + \frac{\partial G}{\partial t} \Delta t + \frac{1}{2} \frac{\partial^2 G}{\partial x^2} \Delta X^2 + \frac{\partial^2 G}{\partial x \partial t} \Delta X \Delta t +$$
$$\frac{1}{2} \frac{\partial^2 G}{\partial t^2} \Delta t^2 + \text{higher order terms.}$$

Now

$$(\Delta X)^2 = (a \Delta t + b dB)^2 = b^2 \Delta t + \text{higher terms in } \Delta t$$

So for small  $\Delta t$  we approximate

$$dY \approx$$

$$\frac{\partial G}{\partial x} \Delta X + \frac{\partial G}{\partial t} \Delta t + \frac{1}{2} \frac{\partial^2 G}{\partial x^2} b^2 \Delta t +$$

higher degree terms in  $\Delta X, \Delta t =$

$$\frac{\partial G}{\partial x} (a\Delta t + b\Delta B) + \frac{\partial G}{\partial t} \Delta t + \frac{1}{2} \frac{\partial^2 G}{\partial x^2} b^2 \Delta t +$$

higher degree terms in  $\Delta B, \Delta t.$

## An Example:

Use Ito's Lemma to show that

$$d(B_t^2) = dt + 2B_t(dB_t).$$

Deduce that

$$\int_0^t B_s dB_s = \frac{1}{2} B_t^2 - \frac{t}{2}.$$

Let  $X_t$  be the process with  $dX = 0 \times dt + 1 \times dB_t$  and consider the process  $Y_t = G(X_t, t)$  where  $G(x, t) = x^2$ . We have

$$\frac{\partial G}{\partial x} = 2x, \quad \frac{\partial^2 G}{\partial x^2} = 2, \quad \frac{\partial G}{\partial t} = 0$$

so Ito's Lemma implies that  $d(B_t^2) = dY =$

$$\left( 2X \times 0 + 0 + \frac{1}{2} 2 \times 1^2 \right) dt + 2X \times 1 dB = dt + 2B_t dB.$$

Integrating both sides of the equation above gives

$$\int_0^t d(B_s^2) = t + 2 \int_0^t B_s dB_s \Rightarrow \int_0^t B_s dB_s = \frac{1}{2} B_t^2 - \frac{t}{2}.$$

## The stochastic process followed by forward stock prices

Consider a forward contract on stock paying no dividends maturing at time  $T$ ; let  $F(t)$  be its forward price at time  $t \geq 0$ :

$$F(t) = S(t)e^{r(T-t)},$$

where  $S(t)$  is the spot price of the stock at time  $t$ .

Regard  $F$  as a function of  $s$  and  $t$ , i.e.,  $F = F(s, t) = se^{r(T-t)}$ :

$$\frac{\partial F}{\partial s} = e^{r(T-t)}, \quad \frac{\partial^2 F}{\partial s^2} = 0 \quad \text{and} \quad \frac{\partial F}{\partial t} = -rse^{r(T-t)}.$$

Our model assumes that

$$dS = \mu S dt + \sigma S dB$$

so Ito's Lemma implies that

$$dF = \left( e^{r(T-t)} \mu S - r S e^{r(T-t)} \right) dt + e^{r(T-t)} \sigma S dB =$$

$$(\mu - r) F dt + \sigma F dB,$$

i.e.,  $F$  follows a geometric Brownian motion with drift  $\mu - r$ .

## The stochastic process followed by the logarithm of stock prices

Let  $S$  be the spot price of a certain stock at time  $t$  and let  $G = G(s, t) = \log s$ . Since

$$\frac{\partial G}{\partial s} = \frac{1}{s}, \quad \frac{\partial^2 G}{\partial s^2} = \frac{-1}{s^2} \quad \text{and} \quad \frac{\partial G}{\partial t} = 0$$

and since  $dS = \mu S dt + \sigma S dB$  Ito's Lemma implies that

$$dG = \left( \frac{1}{S} \mu S - \frac{\sigma^2 S^2}{2S^2} \right) dt + \frac{\sigma S}{S} dB =$$
$$\left( \mu - \frac{\sigma^2}{2} \right) dt + \sigma dB.$$



Consider a fixed time  $T$  in the future and the spot price  $S_T$  at that time: we see that the logarithm of the proportional price change of the stock,

$$\log \frac{S_T}{S} = \log S_T - \log S,$$

is normally distributed

with expected value  $\left(\mu - \frac{\sigma^2}{2}\right) T$

and variance  $\sigma^2 T$ .

## Example:

Consider the price  $S$  of a stock with current price  $S_0 = \$10$ , expected annual return of  $\mu = 15\%$  and annual price volatility (i.e., standard deviation) of  $\sigma = 20\%$ .

The stock price follows a geometric Brownian motion

$$dS = \mu S dt + \sigma S dB = 0.15S dt + 0.2S dB$$

and for any time  $T$  in the future the price of the stock at time  $T$  satisfies  $\log S_T \sim N\left(\log S_0 + \left(\mu - \frac{\sigma^2}{2}\right) T, \sigma^2 T\right) = N\left(\log 10 + 0.13T, 0.2^2 T\right)$ . So for example, one can say that with 90% confidence in 6 months

$$\log 10 + 0.065 - \frac{0.2}{\sqrt{2}} \times 1.645 < \log S_{1/2} < \log 10 + 0.065 + \frac{0.2}{\sqrt{2}} \times 1.645$$

i.e., with 90% confidence the logarithm of stock price in 6 months will be between approximately 2.135 and 2.6 and so the stock price itself will be between approximately \$8.46 and \$13.47 with 90% confidence

The End