

# Quantitative Finance and Derivatives

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# Chapter 1

## Models for asset pricing

### 1.1 Underlying processes

#### 1.1.1 Stochastic Processes

Stochastic processes are collections of random variables representing the evolution of some system over time. Stochastic processes can have discrete or continuous values, and can evolve over discrete or continuous time.

We have four different possible situations:

1.  $X(n, \omega) : \mathbb{N} \times (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow$  a subset of  $\mathbb{Z}$  : discrete time, discrete values. For example: a *random walk*.
2.  $X(n, \omega) : \mathbb{N} \times (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow$  a subset of  $\mathbb{R}$  : discrete time, continuous values.
3.  $X(n, \omega) : \mathbb{R}^+ \times (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow$  a subset of  $\mathbb{Z}$  : continuous time, discrete values. For example: a *Poisson process*.
4.  $X(n, \omega) : \mathbb{R}^+ \times (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow$  a subset of  $\mathbb{R}$  : continuous time, continuous values. For example: a *Brownian motion*.

#### From random walk to Brownian motion

Let

$$(X_n)_{n \geq 0}$$

be a stochastic process such that  $X_i$ , for any  $i$ , can take value 1 with probability  $\mathbb{P}(X_i = 1) = \frac{1}{2}$ , and  $-1$  with probability  $\mathbb{P}(X_i = -1) = \frac{1}{2}$ . Let then  $S_n = X_1 + X_2 + \dots + X_n$  be the position you are at on a line after  $n$  steps. Informally, each  $X_i$  "moves" you randomly one step to the right or one step to the left. We want to know expectation and variance of this process. Let's assume the  $(X_n)_{n \geq 0}$  to be *independent and identically distributed*. We can now assert the following:

$$E[X_i] = (+1) \cdot \frac{1}{2} + (-1) \cdot \frac{1}{2} = 0$$

$$E[X_i^2] = (+1)^2 \cdot \frac{1}{2} + (-1)^2 \cdot \frac{1}{2} = 1$$

Hence,

$$E[S_n] = \sum_{i=1}^n E[X_i] = 0$$

$$Var[S_n] = \sum_{i=1}^n E[X_i^2] = n$$

As  $n$  approaches infinity, the conditions for the *Central Limit Theorem* hold:  $X_i$ s are *i.i.d.*, so we can apply

$$\frac{S_n - n \cdot E[X_i]}{\sqrt{n \cdot Var[X_i]}} = \frac{S_n}{\sqrt{n}} \underset{n \rightarrow \infty}{\sim} \mathcal{N}(0, 1)$$

Consider now a non-unitary time. Suppose we move in time steps of  $\delta > 0$  and in space steps of  $\sqrt{\delta}$ , and let's consider the process in the interval  $[0, t]$ ,  $t \in \mathbb{R}^+$ . Then,

$$S_t = \sum_{i=0}^{\lfloor \frac{t}{\delta} \rfloor} X_i$$

where  $X_i$  moves by  $\pm\sqrt{\delta}$  with probability  $\mathbb{P} = \frac{1}{2}$ . Then,  $E[S_t] = 0$  and

$$Var[X_i] = E^2[X_i] - E[X_i^2] = E^2[X_i] = (+\sqrt{\delta})^2 \cdot \frac{1}{2} + (-\sqrt{\delta})^2 \cdot \frac{1}{2} = \delta$$

$$\text{Var}[S_t] = \frac{t}{\delta} \cdot \delta = t$$

Let's now apply *Central Limit Theorem*:

$$\frac{S_t - \frac{t}{\delta} E[X_i]}{\sqrt{\frac{t}{\delta} \text{Var}[X_i]}} = \frac{S_t}{\sqrt{t}} \underset{t \rightarrow \infty}{\sim} \mathcal{N}(0, 1).$$

So,  $S_t \sim \mathcal{N}(0, t)$ : this is the *Brownian motion*.

**Definition 1. (Brownian motion).** The stochastic process

$$(W_t)_{t \in \mathbb{R}^+} : \mathbb{R}^+ \times (\Omega, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P}) \rightarrow \mathbb{R}$$

is a Brownian motion if and only if

- (I)  $W_0 = 0$ ,
- (II) it is continuous,
- (III) has stationary increments: the distribution doesn't depend on initial time, only on waiting time.

$$\forall t > s, W_t - W_s \sim \mathcal{N}(0, t - s)$$

- (IV) has independent increments over disjoint intervals:

$$\forall q < r < s < t, (W_r - W_q) \perp (W_t - W_s).$$

**Definition 2. (Classes of Brownian motions.)**

- (I) *Standard Brownian motion*, or *Wiener Process*.
- (II) *Arithmetic Brownian motion*, or *Bachelier Model*.

$$dp_t = p_{t+h} - p_t = \mu dt + \sigma dW_t$$

Where  $\mu$  is called *drift*, and  $\sigma$  the *volatility*. This is a *stochastic differential equation*, *SDE* for short: while the  $\mu dt$  part is *deterministic*, the  $\sigma dW_t$  contains a *stochastic* component, which is a standard Brownian

motion. This kind of equations provides a model for the change of the price  $p_t$  over the infinitesimal time increment from  $t$  to  $t + h$ . The price variation could be equivalently modeled this way:

$$p_t - p_0 = \mu(t - 0) + \sigma(W_t - W_0) = \mu t + \sigma W_t$$

Noting that

$$E[W_t] = 0 \quad \text{and} \quad \text{Var}[\sigma W_t] = E[(\sigma W_t)^2] = \sigma^2 E[W_t^2] = \sigma^2 t,$$

we have that, in Bachelier's model, the price  $p_t = \mu t + \sigma W_t + p_0$  is a *random variable* distributed like

$$p_t \sim \mathcal{N}(p_0 + \mu t + E[W_t], \sigma^2 t) \equiv \mathcal{N}(p_0 + \mu t, \sigma^2 t).$$

(III) *Geometric Brownian motion, or Black-Scholes model.*

$$dp_t = \mu p_t dt + \sigma p_t dW_t$$

This model is similar to Bachelier's, but acts on a multiplicative instead of additive principle. For this model, we will need to find a solution and its distribution.

### 1.1.2 Itô Formula

Suppose a model for an underlying asset price dynamics is given: we know the form of  $dp_t$ ; we'll assume Black-Scholes. It is now natural to assume that the price of a derivative on this asset is a *function*, let it be  $f(p_t)$ , of the asset price. How can we get a *stochastic differential equation* that models the derivative price variation?

Let's evaluate the *Taylor expansion* for  $f(p_t)$  like in a deterministic setting.

$$f(x) \approx f(x_0) + f'(x_0)(x - x_0) + \frac{1}{2}f''(x_0)(x - x_0)^2 + \varepsilon$$

where  $\varepsilon$  is a remainder that goes quickly to zero. We will now discard all terms in the approximation that go to 0 faster than  $dt$  does, thus truncating the approximation to the first order. Let now  $x = p_{t+dt}$ ,  $x_0 = p_t$  and  $dp_t = p_{t+dt} - p_t$

$$f(p_{t+dt}) \approx f(p_t) + f'(p_t)(dp_t) + \frac{1}{2}f''(p_t)(dp_t)^2 + \varepsilon$$

and substitute the increment  $dp_t$  with the Black-Scholes model:

$$\begin{aligned} f(p_{t+dt}) = & f(p_t) + f'(p_t)(\mu p_t dt + \sigma p_t dW_t) + \\ & \frac{1}{2}f''(p_t)(\mu^2 p_t^2 (dt)^2 + \sigma^2 p_t^2 (dW_t)^2 + 2\mu\sigma p_t^2 dt dW_t) \end{aligned}$$

Since  $E[(dW_t)^2] = dt$ , we can assume  $dW_t = \sqrt{dt} = (dt)^{\frac{1}{2}}$  to have order  $\frac{1}{2}$ . Let's analyze the orders of all the terms in the approximation:

- $\mu p_t dt$ : First order: keep it.
- $\sigma p_t dW_t$ : Order  $\frac{1}{2}$ : keep it.
- $\mu^2 p_t^2 (dt)^2$ : Second order: discard it.
- $\sigma^2 p_t^2 (dW_t)^2$ : First order, because  $(dW_t)^2 = dt$ : keep it.
- $2\mu\sigma p_t^2 dt dW_t$ : Order  $\frac{3}{2}$  because of  $dt dW_t$ : discard it.

The truncated approximation now states that

$$f(p_{t+dt}) = f(p_t) + f'(p_t)(\mu p_t dt + \sigma p_t dW_t) + \frac{1}{2}f''(p_t)(\sigma^2 p_t^2 dt).$$

The second derivative term of this equation is called *Itô correction term*. The derivative of the function with respect to time can then be computed this way:

$$df(p_t) = f(p_{t+dt}) - f(p_t) = f'(p_t)(\mu p_t dt + \sigma p_t dW_t) + \frac{1}{2}f''(p_t)(\sigma^2 p_t^2 dt)$$

Let's now separate the deterministic terms from the stochastic terms, so we can identify a *drift* and a *volatility* for the model.

$$df(p_t) = \left[ f'(p_t)\mu p_t + \frac{1}{2}f''(p_t)\sigma^2 p_t^2 \right] dt + f'(p_t)\sigma p_t dW_t$$

**Example 1.** Let  $f(p_t) = \ln(p_t)$  be the price of a derivative instrument with underlying price  $p_t$ ; the dynamic for the underlying follows the Black-Scholes model. Apply Itô's formula to this derivative:

$$\begin{aligned} d \ln(p_t) &= \left[ \frac{1}{p_t} \mu p_t + \frac{1}{2} \left( -\frac{1}{p_t^2} \sigma^2 p_t^2 \right) \right] dt + \frac{1}{p_t} \sigma p_t dW_t = \\ &= \left[ \mu - \frac{1}{2} \sigma^2 \right] dt + \sigma dW_t \end{aligned}$$

Considering the time interval  $[0, t]$ , we observe that

$$d \ln(p_t) = \ln(p_t) - \ln(p_0) = \left( \mu - \frac{1}{2} \sigma^2 \right) (t - 0) + \sigma (W_t - W_0)$$

and then

$$\ln \left( \frac{p_t}{p_0} \right) = \left( \mu - \frac{1}{2} \sigma^2 \right) t + \sigma W_t \iff \frac{p_t}{p_0} = e^{(\mu - \frac{1}{2} \sigma^2)t + \sigma W_t}$$

which yields the solution

$$p_t = p_0 e^{(\mu - \frac{1}{2} \sigma^2)t + \sigma W_t}.$$

**Example 2.** Black-Scholes model assumes the *spot risk-free interest rate*  $r$  to be constant and independent of maturity. Consider *discounting* as a function of time and asset price:

$$f(t; p_t) = e^{-rt} p_t$$

The general Itô formula for a function of such a form is

$$\begin{aligned} d[f(t; p_t)] &= \frac{\partial f}{\partial p_t} dp_t + \frac{\partial f}{\partial t} dt + \frac{1}{2} \frac{\partial^2 f}{\partial p_t^2} (dp_t)^2 + \underbrace{\frac{1}{2} \frac{\partial^2 f}{\partial t^2} (dt)^2}_{\text{order 2}} + \underbrace{\frac{1}{2} \frac{\partial^2 f}{\partial p_t \partial t} 2dt dp_t}_{\text{order 3/2}} \\ &= \frac{\partial f}{\partial p_t} dp_t + \frac{\partial f}{\partial t} dt + \frac{1}{2} \frac{\partial^2 f}{\partial p_t^2} \sigma^2 p_t^2 dt \end{aligned}$$

For the discounting function, this means



$$\begin{aligned}
d[e^{-rt} p_t] &= e^{-rt} \cdot 1 \cdot dp_t + -re^{-rt} p_t dt + \cancel{\frac{1}{2} \cdot 0 \cdot \sigma^2 p_t^2 dt} \xrightarrow{0} \\
&= e^{-rt} (\mu p_t dt + \sigma p_t dW_t - r p_t dt) \\
&= (\mu - r) e^{-rt} p_t dt + e^{-rt} p_t \sigma dW_t \\
d\tilde{p}_t &= (\mu - r) \tilde{p}_t dt + \sigma \tilde{p}_t dW_t
\end{aligned}$$

Hence, the distribution for a discounted asset price follows Black-Scholes model:

$$\tilde{p}_t = \tilde{p}_0 e^{(\mu - r - \frac{\sigma^2}{2})t + \sigma W_t}$$

Note that the deterministic and stochastic parts were grouped together, to underline the *risk factor*.

### 1.1.3 Black-Scholes PDE for option pricing

In the context of option pricing, Black-Scholes model assumes the following:

- $p_t$  is the underlying asset price at time  $t$ ,
- $r$  is a constant, risk-free interest rate,
- There are no transaction costs, no taxes, and no arbitrage opportunity,
- The market is liquid, and so all the instruments,
- $f(t; p_t)$  is the option price.

By Itô's lemma, we get that the option price is

$$df(t; p_t) = \left[ \frac{\partial f}{\partial t} + \frac{\partial f}{\partial p_t} \mu p_t + \frac{1}{2} \frac{\partial^2 f}{\partial p_t^2} \sigma^2 p_t^2 \right] dt + \frac{\partial f}{\partial p_t} \sigma p_t dW_t$$

Construct a *locally* risk-free portfolio,  $\Pi_t$ , such that

$$\Pi_t = \begin{cases} -1 & \text{positions in options (short)} \\ \Delta_t \equiv \frac{\partial f}{\partial p_t} & \text{positions in underlying (long)} \end{cases}$$

and study the dynamics of the portfolio value by multiplying the number of positions by the dynamics for each kind of instrument (option and asset).

$$\begin{aligned} d\Pi_t &= -1 \cdot df(t; p_t) + \frac{\partial f}{\partial p_t} dp_t \\ &= - \underbrace{\left[ \frac{\partial f}{\partial t} + \frac{\partial f}{\partial p_t} \mu p_t + \frac{1}{2} \frac{\partial^2 f}{\partial p_t^2} \sigma^2 p_t^2 \right] dt}_{\text{option}} - \underbrace{\frac{\partial f}{\partial p_t} \sigma p_t dW_t + \frac{\partial f}{\partial p_t} (\mu p_t dt + \sigma p_t dW_t)}_{\text{asset}} \\ &= - \left[ \frac{\partial f}{\partial t} + \frac{1}{2} \frac{\partial^2 f}{\partial p_t^2} \sigma^2 p_t^2 \right] dt - \cancel{\frac{\partial f}{\partial p_t} \mu p_t dt} - \cancel{\frac{\partial f}{\partial p_t} \sigma p_t dW_t} + \cancel{\frac{\partial f}{\partial p_t} \mu p_t dt} + \cancel{\frac{\partial f}{\partial p_t} \sigma p_t dW_t} \\ &= - \left( \frac{\partial f}{\partial t} + \frac{1}{2} \frac{\partial^2 f}{\partial p_t^2} \sigma^2 p_t^2 \right) dt \end{aligned}$$

Having removed the Brownian motion, we are left without any risky term. We impose now the *no arbitrage assumption*, stating that a portfolio is risk-free if and only if its dynamics is the same of a bond, that is, it accrues interest at a constant (by assumption) rate over time.

$$\begin{aligned} d\Pi_t &\equiv - \left( \frac{\partial f}{\partial t} + \frac{1}{2} \frac{\partial^2 f}{\partial p_t^2} \sigma^2 p_t^2 \right) dt \stackrel{\text{NAA}}{=} r \Pi_t dt \\ - \frac{\partial f}{\partial t} - \frac{1}{2} \frac{\partial^2 f}{\partial p_t^2} \sigma^2 p_t^2 &= -r f(t; p_t) + \frac{\partial f}{\partial p_t} r p_t \end{aligned}$$

Finally, we obtain the Black-Scholes PDE by rearranging.

$$r f(t; p_t) = \frac{\partial f}{\partial t} + \frac{\partial f}{\partial p_t} r p_t + \frac{1}{2} \frac{\partial^2 f}{\partial p_t^2} \sigma^2 p_t^2$$

The objective is to establish the *fair* (or *no arbitrage*) price of an option today, that is,  $f(0; p_0)$ . A *final condition* can be imposed:  $f(T, p_T)$ , which is the *option price at maturity* or, equivalently, the *payoff*, which is known.

$$f(T; p_T) \stackrel{\text{e.g.}}{=} \begin{cases} (P_T - K)^+ = \max\{P_T - K, 0\} & \text{European call option} \\ (K - P_T)^+ = \max\{K - P_T, 0\} & \text{European put option} \end{cases}$$

European options satisfy Black-Scholes assumptions: the payoff depends *only* on the price of the underlying at time  $T$ , and it is not *path dependent*. The drift term  $\mu$  does not appear in Black-Scholes PDE, and neither does in the payoff function  $f(t; p_t)$ ; this means that the Black-Scholes option price doesn't depend on it. The drift term is strongly linked to investor's *risk aversion*: this means the option can be priced *as if* the investor is *risk neutral*.

A *risk neutral* valuation intuitively means that we are pricing in a world where every investor behaves as if he himself is risk neutral; the real world is not risk neutral, though, and investors' risk aversion is embedded in the *historical* data.

A *risk neutral* valuation of current option price, given payoff  $f(T, p_T)$ , is

$$f(0; p_0) = \tilde{\mathbb{E}} [e^{-rT} f(T; p_T)]$$

Where  $\tilde{\mathbb{E}}$  is the expectation according to the *risk neutral probability*  $\tilde{\mathbb{P}}$ . We now have, in fact, two probability spaces: the first is the *historical probability space*  $(\Omega, \mathcal{F}, \mathbb{P})$ , the second is the *risk neutral probability space*  $(\Omega, \mathcal{F}, \tilde{\mathbb{P}}) \supseteq (\Omega, \mathcal{F}, \mathbb{P})$ . To calculate the option price at any given time  $t : 0 < t < T$  the information in the filtration up to time  $t$  can be used:

$$f(t; p_t) = \tilde{\mathbb{E}} [e^{-r(T-t)} f(T; p_T) | \mathcal{F}_t]$$

**Theorem 1.** If, in time  $t : 0 \leq t \leq T$  the payoff is  $(P_T - K)^+$ , the price of an option at time  $t$  is

$$C(\tau = T - t, p_t, K, r, \sigma) = f(t; p_t) = p_t \mathcal{N}(d_1) - K e^{-r\tau} \mathcal{N}(d_2)$$

where

$$d_1 = \frac{\ln\left(\frac{p_t}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)(T - t)}{\sigma\sqrt{T - t}}$$

$$d_2 = \frac{\ln\left(\frac{p_t}{K}\right) + \left(r - \frac{\sigma^2}{2}\right)(T - t)}{\sigma\sqrt{T - t}} = d_1 - \sigma\sqrt{T - t}$$

*Proof.* Suppose we are in a Black-Scholes world: we have one risky asset with dynamics such that  $dp_t = \mu p_t dt + \sigma p_t d\tilde{W}_t$ , a riskless asset with

dynamics such that  $dB_t = rB_t dt$ , and no arbitrage opportunities. Define  $\tilde{W}_t = W_t + \frac{\mu-r}{\sigma}t$  where  $\mu - r$  is the *risk premium* and  $\frac{\mu-r}{\sigma}$  is the *market price of risk*. Hence,

$$\begin{aligned} dp_t &= rp_t dt + \sigma p_t \left[ dW_t + \frac{\mu-r}{\sigma} dt \right] \\ &= \cancel{rp_t dt} + \sigma p_t dW_t + \mu p_t dt - \cancel{rp_t dt} \\ &= \mu p_t dt + \sigma p_t dW_t \end{aligned}$$

Note that  $\tilde{W}_t \sim \mathcal{N}\left(\frac{\mu-r}{\sigma}\Delta t; \Delta t\right)$  is no longer a standard Brownian motion. We want to know the option price at time  $t = 0$ , considering, for example, the payoff  $f(T; p_T) = (p_T - K)^+$ :

$$\begin{aligned} C_0 &= f(0; p_0) = \tilde{\mathbb{E}} \left[ e^{-rT} (p_T - K)^+ \right] \\ &\stackrel{\text{Markov}}{=} \tilde{\mathbb{E}} \left[ e^{-rT} \left( p_0 e^{\left(r - \frac{\sigma^2}{2}\right)T + \sigma \tilde{W}_T} - K \right)^+ \right] = (*)_1 \end{aligned}$$

Consider now that, if  $X \sim \mathcal{N}(0, T)$  and  $Y \sim \mathcal{N}(0, 1)$  then  $X = \sqrt{T}Y$ :

$$\begin{aligned} (*)_1 &= \tilde{\mathbb{E}} \left[ e^{-rT} \left( p_0 e^{\left(r - \frac{\sigma^2}{2}\right)T + \sigma \sqrt{T}Y} - K \right)^+ \right] \\ &= \int_{-\infty}^{+\infty} e^{-rt} \left( p_0 e^{\left(r - \frac{\sigma^2}{2}\right)T + \sigma \sqrt{T}y} - K \right)^+ \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy = (*)_2 \end{aligned}$$

We compute the integral only where the payoff is positive, that is, where

$$\begin{aligned} p_0 e^{\left(r - \frac{\sigma^2}{2}\right)T + \sigma \sqrt{T}y} &\geq K \iff e^{\left(r - \frac{\sigma^2}{2}\right)T + \sigma \sqrt{T}y} \geq \frac{K}{p_0} \\ &\iff \left(r - \frac{\sigma^2}{2}\right)T + \sigma \sqrt{T}y \geq \ln \frac{K}{p_0} \\ &\iff y \geq \frac{-\ln \frac{p_0}{K} - \left(r - \frac{\sigma^2}{2}\right)T}{\sigma \sqrt{T}} = -d_2 \end{aligned}$$

$$\begin{aligned}
(*)_2 &= \int_{-d_2}^{+\infty} e^{-rt} \left( p_0 e^{\left(r - \frac{\sigma^2}{2}\right)T + \sigma y \sqrt{T}} - K \right) \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy \\
&= \int_{-d_2}^{+\infty} \frac{p_0 e^{-\frac{\sigma^2}{2}T + \sigma y \sqrt{T} - \frac{y^2}{2}}}{\sqrt{2\pi}} dy - \int_{-d_2}^{+\infty} \frac{K e^{-rt - \frac{y^2}{2}}}{\sqrt{2\pi}} dy \\
&= p_0 \int_{-\infty}^{d_2} \frac{1}{\sqrt{2\pi}} e^{-\frac{(\sigma \sqrt{T} + y)^2}{2}} dy - K e^{-rt} \int_{-d_2}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy \\
&\quad \left( \text{Let } z = y + \sigma \sqrt{T} \text{ s.t. } -\infty \leq z \leq d_2 + \sigma \sqrt{T} \right) \\
&= p_0 \int_{-\infty}^{d_2 + \sigma \sqrt{T}} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz - K e^{-rt} \int_{-\infty}^{d_2} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy \\
&= p_0 \mathcal{N}(d_2 + \sigma \sqrt{T}) - K e^{-rt} \mathcal{N}(d_2) \\
&= p_0 \mathcal{N}(d_1) - K e^{-rt} \mathcal{N}(d_2).
\end{aligned}$$