# **APPENDIX**

## **Taylor Series Expansion**

In this appendix, we review the Taylor Series expansion formula from ordinary analysis. This expansion is commonly used to relate sensitivities (risk, PV01, convexity) to profit and loss (P&L) for financial instruments (bonds, swaps,...), as shown in Chapters 1 and 6. The much-dreaded Ito's Lemma used in Chapters 10 and 11 is basically Taylor Series expansion in a stochastic setting, and can be easily used in practice via a *multiplication table*.

#### **FUNCTION OF ONE VARIABLE**

For a function of one variable, f(x), the Taylor Series formula is:

$$f(x + \Delta x) = f(x) + f'(x)\Delta x + 1/2 f''(x)(\Delta x)^{2} + \ldots + 1/n! f^{(n)}(x)(\Delta x)^{n} + \ldots$$

where f'(x) is the first derivative, f''(x) the second derivative,  $f^{(n)}(x)$  the *n*-th derivative, and so on. In practice, we usually just use the first two derivatives, and ignore the effect of the remaining *higher-order* terms:

$$f(x + \Delta x) - f(x) = f'(x)\Delta x + 1/2 f''(x)(\Delta x)^2 + \text{Higher Order Terms}$$

For example, considering the Price-Yield formula for bonds, we have:

$$P(y + \Delta y) - P(y) \approx P'(y)\Delta y + 1/2P''(y)(\Delta y)^{2}$$

$$= PV01 \times \frac{\Delta y}{0.0001} + 1/2 \times \text{Convexity} \times (\Delta y)^{2}$$

#### **FUNCTION OF SEVERAL VARIABLES**

A similar formula holds for functions of several variables  $f(x_1, ..., x_n)$ . This is usually written as

$$f(x_1 + \Delta x_1, \dots, x_n + \Delta x_n) = f(x_1, \dots, x_n)$$

$$+ \sum_{i=1}^n \frac{\partial f}{\partial x_i}(x_1, \dots, x_n) \Delta x_i$$

$$+ 1/2 \sum_{i=1}^n \sum_{j=1}^n \frac{\partial f}{\partial x_i}(x_1, \dots, x_n) \frac{\partial f}{\partial x_j}(x_1, \dots, x_n) \Delta x_i \Delta x_j$$
+ Higher Order Terms

For example, using Black's Formula, the expected P&L of an option is usually computed by considering the first-order terms and only one second-order term (gamma), ignoring all others:

$$C(F + \Delta F, \sigma + \Delta \sigma, t + \Delta t) - C(F, \sigma, t) \approx \frac{\partial C}{\partial F} \Delta F + \frac{\partial C}{\partial \sigma} \Delta \sigma + \frac{\partial C}{\partial t} \Delta t + 1/2 \frac{\partial^2 C}{\partial F^2} (\Delta F)^2$$

$$= \text{Delta} \times \Delta F + 1/2 \times \text{Gamma} \times (\Delta F)^2$$

$$+ \text{Vega} \times \Delta \sigma + \text{Theta} \times \Delta t$$

### ITO'S LEMMA: TAYLOR SERIES FOR DIFFUSIONS

Ito's Lemma is basically Taylor series expansions for stochastic diffusions. For a given diffusion  $X(t, \omega)$  driven by

$$dX(t,\omega) = \mu(t,\omega)dt + \sigma(t,\omega)dB(t,\omega)$$

consider a function  $f(t, X(t, \omega))$ . Ito's Lemma allows one to compute the diffusion for f(t, X) by following Taylor series expansion for two variables, and employing the following simple *multiplication rule*:<sup>1</sup>

$$\begin{array}{c|cc} \times & dt \ dB(t, \omega) \\ \hline dt & 0 & 0 \\ dB(t, \omega) & 0 & dt \end{array}$$

In particular, it means that we only need to keep first-order terms and only one second-order term ( $dB \times dB = dt$ ), ignoring all other terms.

Starting with

$$dX(t, \omega) = \mu(t, \omega)dt + \sigma(t, \omega)dB(t, \omega)$$

we proceed formally with Taylor Series for a function of two variables f(t, X), and ignore all terms with order higher than 2, or any term with  $(dt)^2$  or  $dt \times dB$ :

$$\begin{split} df(t,X(t,\omega)) &= \frac{\partial f}{\partial t}dt + \frac{\partial f}{\partial X}dX(t,\omega) + 1/2\frac{\partial^2 f}{\partial X^2}(dX(t,\omega))^2 \\ &= \frac{\partial f}{\partial t}dt + \frac{\partial f}{\partial X}[\mu(t,\omega)dt + \sigma(t,\omega)dB(t,\omega)] + 1/2\frac{\partial^2 f}{\partial X^2}\sigma^2(t,\omega)dt \\ &= \left[\frac{\partial f}{\partial t} + \frac{\partial f}{\partial X}\mu(t,\omega) + 1/2\frac{\partial^2 f}{\partial X^2}\sigma^2(t,\omega)\right]dt + \frac{\partial f}{\partial X}\sigma(t,\omega)dB(t,\omega) \end{split}$$

The most common application of Ito's Lemma in finance is to start with the following dynamics for proportional (percent changes) of an asset:

$$\frac{dA(t,\omega)}{A(t,\omega)} = \mu dt + \sigma dB(t,\omega)$$

where the drift  $\mu$  and volatility  $\sigma$  are constant numbers. Therefore,

$$dA(t, \omega) = \mu(t, \omega)dt + \sigma(t, \omega)dB(t, \omega)$$

where

$$\mu(t, \omega) = \mu \times A(t, \omega)$$
  
$$\sigma(t, \omega) = \sigma \times A(t, \omega)$$

Considering  $f(t, A(t, \omega)) = \ln A(t, \omega)$ , we notice  $\frac{\partial}{\partial t} f = 0$  since f is not a direct function of t, and recalling

$$\frac{d}{dx}\ln(x) = 1/x, \qquad \frac{d^2}{dx^2}\ln(x) = -1/x^2$$

from ordinary calculus, Ito's Lemma gives us:

$$\begin{split} d\ln(A(t,\omega)) &= df(t,\omega) \\ &= \left[ \frac{1}{A(t,\omega)} \times \mu \times A(t,\omega) - 1/2 \frac{1}{A^2(t,\omega)} \times \sigma^2 \times A^2(t,\omega) \right] dt \\ &+ \left[ \frac{1}{A(t,\omega)} \times \sigma \times A(t,\omega) \right] dB(t,\omega) \\ &= (\mu - \sigma^2/2) dt + \sigma dB(t,\omega) \end{split}$$

Integrating both sides, we have

$$\ln A(t,\omega) - \ln A(0,\omega) = (\mu - \sigma^2/2)t + \sigma \int_0^t dB(t,\omega)$$
$$= (\mu - \sigma^2/2)t + \sigma(B(t,\omega) - B(0,\omega))$$
$$= (\mu - \sigma^2/2)t + \sigma B(t,\omega)$$

since a Brownian motion is started at 0,  $B(0, \omega) = 0$ . Recalling that a standard Brownian motion is Normally distributed,  $B(t, \omega) \sim N(0, t)$ , we get:

$$A(t, \omega) = A(0, \omega)e^{(\mu - 1/2\sigma^2)t + \sigma N(0,t)}$$

that is,  $A(t, \omega)/A(0)$  is Log-Normal:  $A(t, \omega)/A(0) \sim LN((\mu - \sigma^2/2)t, \sigma^2 t)$ ,  $EA(t, \omega) = A(0)e^{\mu t}$ . Note that if the process for A is drift less, that is,  $\mu = 0$ , then  $dA(t, \omega) = \sigma A(t, \omega)dB(t, \omega)$ , and  $EA(t, \omega) = A(0)$ . In this case, A(t) has zero expected change and is a martingale.