# Application of the Malliavin Calculus to the Black-Scholes Model

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11 April 2023

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1) Introduction

#### Introduction

#### Background:

- Named after Paul Malliavin (1925 2010).
- Also known as the **stochastic calculus of variations**.
- Originally introduced by Paul Malliavin in the 1970s in his proof of Hörmander's hypoellipticity theorem for partial differential equations.
- Notable mathematicians: Paul Malliavin, David Nualart and Eulalia Nualart.

#### Central Question:

• How can the Malliavin Calculus be applied to calculate and estimate the Greeks of certain option prices?

2) Elements of the Malliavin Calculus

#### In what follows, let:

- $T \in \mathbb{R}_{\geq 0}$ ;
- $(\Omega, \mathcal{F}, \mathbb{P})$  be a complete probability space;
- $(W_t)_{t\in[0,T]}$  be a  $\mathbb{R}$ -valued Brownian motion on  $(\Omega, \mathscr{F}, \mathbb{P})$ ;
- $\mathscr{F}$  be the  $\sigma$ -algebra generated by  $(W_t)_{t\in[0,T]}$ , and;
- $\mathscr{S}$  be the set of all random variables X of the form  $X = F(W_{t_1}, \ldots, W_{t_n})$ , for some  $n \in \mathbb{N}_{\geqslant 1}$ , some smooth function  $F \colon \mathbb{R}^n \to \mathbb{R}$  and some  $t_1, \ldots, t_n \in [0, T]$ .

### Definition (Malliavin Derivative) [2]:

• Let  $X \in \mathcal{S}$  and let  $t \in \mathbb{R}$ . Define the Malliavin derivative  $D_t(X)$  of X by:

$$D_t(X) = \sum_{i=1}^n \frac{\partial}{\partial x_i} F(W_{t_1}, \dots, W_{t_n}) \Big|_{x_i = W_{t_i}} \mathbf{1}_{[0, t_i]}(t)$$

• For  $j \in \mathbb{N}_{\geq 1}$ , define:

$$D_{t_1,\dots,t_j}^j X = \left(D_{t_1}\left(\dots\left(D_{t_j}X\right)\right)\right)$$

### Proposition [5, 7]:

Let  $X, Y \in \mathcal{S}$ , let  $t, \lambda \in \mathbb{R}$  and let  $f: \mathbb{R} \to \mathbb{R}$  be a smooth function. Then:

② 
$$D_t(\lambda X) = \lambda D_t(X)$$
 (Scalar Product Rule)  
③  $D_t(XY) = D_t(X)Y + XD_t(Y)$  (Product Rule Rule)

$$D_t(XY) = D_t(X)Y + XD_t(Y)$$
 (Product Rule Rule) 
$$D_t(f(X)) = f'(X)D_t(X)$$
 (Chain Rule)

$$D_t(f(X)) = f'(X)D_t(X)$$
 (Chain Rule)

#### Proof.

Omitted (refer to [6, Proposition 1.20, Page 28] or to [7, Proposition 2.1.2, Page 15]).

#### Definition [3]:

For  $k \in \mathbb{N}_{\geqslant 1}$  and  $p \in \mathbb{R}_{\geqslant 1}$ , denote by  $\mathbb{D}^{k,p}$  the closure of  $\mathscr{S}$  with respect to the norm:

$$||X||_{k,p} = \left( \mathbb{E}\left[ |X|^p + \left( \sum_{j=1}^k \int_{[0,T]^j} \left| D_{s_1,\dots,s_j}^j X \right|^2 ds_1 \dots ds_j \right)^{\frac{p}{2}} \right] \right)^{\frac{1}{p}}$$

and let:

$$||X||_{0,p} = (\mathbb{E}[|F|^p])^{\frac{1}{p}}$$

Define:

$$\mathbb{D}^{\infty} = \bigcap_{k \in \mathbb{N}_{\geq 1}} \bigcap_{p \in \mathbb{R}_{\geq 1}} \mathbb{D}^{k,p}$$

#### Examples

Let  $s, t \in [0, T]$  and let  $f: \mathbb{R} \to \mathbb{R}$  be a smooth function. Then:

- $D_sW_T=1$
- $D_sW_t = \mathbf{1}_{[0,t]}(s)$
- $D_s f(W_t) = f'(W_t) \mathbf{1}_{[0,t]}(s)$
- $D_s \left( \int_0^T f(W_u) dW_u \right) = \int_s^T f'(W_u) dW_u + f(W_s)$

2)b) The Skorokhod Integral

# The Skorokhod Integral

### Definition [2, 6]:

The **Skorokhod integral** operator is the adjoint operator of D., denoted by  $D^*$ .

• Remark [7, Proposition 2.2.1, Page 17]: If  $(u_t)_{t \in [0,T]}$  is stochastic process adapted to  $\mathscr{F}$ , then:

$$D^*(u) = \int_0^T u_t \, \mathrm{d}W_t$$

that is,  $D^*$  coincides with the Itô integral of  $(u_t)_{t \in [0,T]}$ .

• Notation [2, Page 2]: We shall write:

$$\int_0^T u_t \, \mathrm{d}W_t \coloneqq D^*(u)$$

even if  $(u_t)_{t\in[0,T]}$  is not adapted to  $\mathscr{F}$ .

# The Skorokhod Integral

#### Examples

Let  $s, t \in [0, T]$  and let  $f: \mathbb{R} \to \mathbb{R}$  be a smooth function. Then:

- $D^*(1) = W_T$
- $D^*(\mathbf{1}_{[0,t]}(s)) = W_t$
- $D^*(f'(W_t)\mathbf{1}_{[0,t]}(s)) = f(W_t)$
- $D^* \left( \int_s^T f'(W_u) dW_u + f(W_s) \right) = \int_0^T f(W_u) dW_u$

#### Proposition:

Let  $X, Y \in \mathcal{S}$  and let  $\lambda \in \mathbb{R}$ . Then:

 $D^*(X+Y) = D^*(X) + D^*(Y)$ 

(Sum Rule)

 $D^*(\lambda X) = \lambda D^*(X)$ 

(Scalar Product Rule)

# The Skorokhod Integral

#### Proof.

Omitted (the result is an immediate consequence of the definition of an adjoint operator).

### Theorem (Duality Principle) [2, 6, 7]:

Let  $X \in \mathbb{D}^{1,2}$  and let  $(u_t)_{t \in [0,T]}$  be a stochastic process. Then:

$$\mathbb{E}\left[\int_0^T (D_t(X))u_t \,dt\right] = \mathbb{E}\left[XD^*(u)\right]$$

#### Proof.

Ommitted (refer to [2, Appendix A, Page 18 for a heuristic derivation]).



#### Proposition [7]:

Let  $X, Y \in \mathbb{D}^{1,2}$  and let  $(u_t)_{t \in [0,T]}$  be a stochastic process. Then:

$$\mathbb{E}\left[YD^*(Xu)\right] = \mathbb{E}\left[Y\left(XD^*(u) - \int_0^T D_t(Xu) \,dt\right)\right]$$

#### Proof.

By the product rule and the duality principle, one has:

$$\mathbb{E}[YXD^*(u)] = \mathbb{E}\left[\int_0^T D_t(YX)u_t \,dt\right]$$

$$= \mathbb{E}\left[\int_0^T YD_t(X)u_t \,dt\right] + \mathbb{E}\left[\int_0^T D_t(Y)Xu_t \,dt\right]$$

$$= \mathbb{E}\left[\int_0^T YD_t(X)u_t \,dt\right] + \mathbb{E}[YD^*(Xu)]$$

#### Corollary [7]:

Let  $X \in \mathbb{D}^{1,2}$  and let  $(u_t)_{t \in [0,T]}$  be a stochastic process. Then:

$$\int_0^T X u_t \, \mathrm{d}W_t = X \int_0^T u_t \, \mathrm{d}W_t - \int_0^T D_t(X) u_t \, \mathrm{d}t$$

### Theorem (Integration By Parts) [1, 2, 6, 7]:

Let  $X, Y \in \mathbb{D}^{1,2}$ . Then, for any stochastic process  $(u_t)_{t \in [0,T]}$  such that

$$\int_0^T D_t(X) u_t \, \mathrm{d}t \stackrel{\mathbb{P}\text{-a.s.}}{\neq} 0$$

and for any smooth function  $f: \mathbb{R} \to \mathbb{R}$ , one has:

$$\mathbb{E}\left[f'(X)Y\right] = \mathbb{E}\left[f(X)H(X,Y)\right]$$

where:

$$H(X,Y) = D^* \left( \frac{Yu}{\int_0^T D_t(X)u_t dt} \right)$$

#### Proof:

By the chain rule, one has:

$$\int_0^T D_t(f(X))u_t dt = f'(X) \int_0^T D_t(X)u_t dt$$

#### Proof:

Thus, by the duality principle, one has:

$$\mathbb{E}\left[f'(X)Y\right] = \mathbb{E}\left[\frac{Y\int_0^T D_t(f(X))u_t \,dt}{\int_0^T D_t(X)u_t \,dt}\right]$$

$$= \mathbb{E}\left[\int_0^T \frac{D_t(f(X))Yu_t}{\int_0^T D_s(X)u_s \,ds} \,dt\right]$$

$$= \mathbb{E}\left[f(X)D^*\left(\frac{Yu}{\int_0^T D_t(X)u_t \,dt}\right)\right]$$

$$= \mathbb{E}\left[f(X)H(X,Y)\right]$$

#### Corollary [7]:

Let  $X, Y \in \mathbb{D}^{1,2}$ . If the function  $t \mapsto D_t(X)$  is differentiable on [0, T] and:

$$\int_0^T \frac{\partial D_t(X)}{\partial t} D_t(X) dt \overset{\mathbb{P}\text{-a.s.}}{\neq} 0$$

then, for any smooth function  $f: \mathbb{R} \to \mathbb{R}$ , one has:

$$\mathbb{E}\left[f'(X)Y\right] = \mathbb{E}\left[f(X)D^*\left(\frac{2Y\frac{\partial D_{\cdot}(X)}{\partial \cdot}}{D_T(X)^2 - D_0(X)^2}\right)\right]$$

#### Proof:

Take  $(u_t)_{t\in[0,T]}$  in the previous theorem to be defined by:

$$\forall t \in [0, T], \ u_t = \frac{\partial D_t(X)}{\partial t}$$

and compute  $\int_0^T \frac{\partial D_t(X)}{\partial t} D_t(X) dt$  as follows:

$$\int_0^T \frac{\partial D_t(X)}{\partial t} D_t(X) dt = \int_0^T \frac{d}{dt} \left( \frac{1}{2} D_t(X)^2 \right) dt = \frac{D_T(X)^2 - D_0(X)^2}{2}$$

3) Application to the Black-Scholes Model

3)a) General Setting

# General Setting

#### Let:

- $T, K \in \mathbb{R}_{\geqslant 0}$ ;
- $S_0, r \in \mathbb{R}_{>0}$ ;
- $\sigma \in \mathbb{R}$ ;
- $M \in \mathbb{N}_{\geq 1}$ ;
- $(W_t)_{t \in [0,T]}$  be a  $\mathbb{R}$ -valued Brownian motion;
- $(S_t)_{t \in [0,T]}$  be a  $\mathbb{R}$ -valued geometric Brownian motion satisfying the following:

$$dS_t = rS_t dt + \sigma S_t dW_t, \quad S_t = S_0 e^{\left(r - \frac{\sigma^2}{2}\right)t + \sigma W_t}, \quad t \in [0, T]$$

and;

•  $(V_t)_{t \in [0,T]}$  be a stochastic process such that  $V_T = \Phi(S_T)$ , for some smooth function  $\Phi \colon \mathbb{R} \to \mathbb{R}$ .

# General Setting

Consider an options contract written on an asset whose price follows the dynamics of  $(S_t)_{t\in[0,T]}$ . In particular, let T be the contract's maturity date, K be the strike price,  $S_0$  be the initial asset price, r be the risk-free interest rate,  $\sigma$  be the volatility and  $V_T$  be option's payoff at maturity. Should the asset price be discretely monitored, suppose that it is monitored at M distinct and evenly separated points in time from the beginning of the options contract until its maturity date T. In what follows, the following sensitivities of the options contract's price also known as *Greeks* - will be calculated:

• 
$$\Delta := \frac{\partial V_0}{\partial S_0}$$
 (Delta)

• 
$$\mathcal{V} := \frac{\partial V_0}{\partial \sigma}$$
 (Vega)  
•  $\Gamma := \frac{\partial^2 V_0}{\partial S_0^2}$  (Gamma)

$$\bullet \ \Gamma := \frac{\partial^2 V_0}{\partial S^2} \tag{Gamma}$$

# General Setting

Under the no-arbitrage principle, we have  $V_0 = e^{-rT}\mathbb{E}[V_T]$ . Moreover, the following cases will be presented:

• 
$$V_T = (S_T - K)^+$$
 (European Call)

• 
$$V_T = (\frac{1}{T} \int_0^T S_t dt - K)^+$$
 (Asian Fixed Strike Call)

3)b) Calculating the Greeks of a European Call
Option

# Analytic Expression

# Theorem (Analytic Formula for the Greeks of a European Call Option) [2, 7]:

For a European call option on an asset whose price follows the dynamics of  $(S_t)_{t\in[0,T]}$ , one has:

$$\Gamma = \frac{e^{-\frac{d^2}{2}}}{S_0 \sigma \sqrt{2\pi T}}$$

where:

$$d = \frac{\ln\left(\frac{S_0}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

# Analytic Expression

#### Proof.

Omitted (refer to [2, Pages 10-12] for the proof).



# Computation via Malliavin Calculus

### Lemma [2, 7]:

In the Black-Scholes model, one has:

$$D^*(S_T) = S_T(W_T - \sigma T)$$

$$0 D^*(W_T) = W_T^2 - T$$

$$D^* \left( \frac{S_T}{\int_0^T D_u(S_T) du} \right) = \frac{W_T}{\sigma T}$$

# Computation via Malliavin Calculus

#### Proof.

One has:

$$\int_0^T D_u(S_T) du = \int_0^T D_u \left( S_0 e^{\left(r - \frac{\sigma^2}{2}\right)t + \sigma W_T} \right) du = \int_0^T \sigma S_T du = \sigma T S_T$$

$$D^*(S_T) = \int_0^T S_T \, dW_t = S_T \int_0^T dW_t - \int_0^T D_t(S_T) \, dt = S_T(W_T - \sigma T)$$

$$D^*(W_T) = W_T \int_0^T dW_T - \int_0^T D_t(W_T) dt = W_T^2 - T$$



# Computation via Malliavin Calculus

### Proposition ( $\Delta$ for a European Call Option) [7]:

For a European call option on an asset whose price follows the dynamics of  $(S_t)_{t\in[0,T]}$ , one has:

$$\Delta = \frac{e^{-rT}}{\sigma T S_0} \mathbb{E} \left[ \Phi(S_T) W_T \right]$$

where  $\Phi(x) = (x - K)^+$ .

#### Proof.

By the chain rule and the integration by parts formula, one has:

$$\begin{split} &\Delta = \frac{\partial V_0}{\partial S_0} = \frac{\partial}{\partial S_0} \left( e^{-rT} \mathbb{E}[V_T] \right) = e^{-rT} \mathbb{E} \left[ \frac{\partial \Phi(S_T)}{\partial S_0} \right] \\ &= e^{-rT} \mathbb{E} \left[ \Phi'(S_T) \frac{\partial S_T}{\partial S_0} \right] = e^{-rT} \mathbb{E} \left[ \Phi'(S_T) \frac{\partial}{\partial S_0} \left( r - \frac{\sigma^2}{2} \right) T + \sigma W_T \right) \right] \\ &= \frac{e^{-rT}}{S_0} \mathbb{E} \left[ \Phi(S_T) D^* \left( \frac{S_T}{\int_0^T D_u(S_T) \, \mathrm{d}u} \right) \right] = \frac{e^{-rT}}{S_0} \mathbb{E} \left[ \Phi(S_T) D^* \left( \frac{S_T}{\sigma T S_T} \right) \right] \\ &= \frac{e^{-rT}}{S_0} \mathbb{E} \left[ \Phi(S_T) D^* \left( \frac{1}{\sigma T} \right) \right] = \frac{e^{-rT}}{\sigma T S_0} \mathbb{E} \left[ \Phi(S_T) W_T \right] \end{split}$$

### Proposition ( $\mathcal{V}$ for a European Call Option) [7]:

For a European call option on an asset whose price follows the dynamics of  $(S_t)_{t \in [0,T]}$ , one has:

$$\mathcal{V} = e^{-rT} \mathbb{E} \left[ \Phi(S_T) \left( \frac{W_T^2 - T}{\sigma T} - W_T \right) \right]$$

where  $\Phi(x) = (x - K)^+$ .

#### Proof.

By the chain rule and the integration by parts formula, one has:

$$\begin{split} \mathcal{V} &= \frac{\partial V_0}{\partial \sigma} = \frac{\partial}{\partial \sigma} \left( e^{-rT} \mathbb{E}[V_T] \right) = e^{-rT} \mathbb{E} \left[ \frac{\partial \Phi(S_T)}{\partial \sigma} \right] \\ &= e^{-rT} \mathbb{E} \left[ \Phi'(S_T) \frac{\partial S_T}{\partial \sigma} \right] = e^{-rT} \mathbb{E} \left[ \Phi'(S_T) \frac{\partial \left( S_0 e^{\left( r - \frac{\sigma^2}{2} \right) T + \sigma W_T} \right)}{\partial \sigma} \right] \\ &= e^{-rT} \mathbb{E} \left[ \Phi'(S_T) S_T (W_T - \sigma T) \right] = e^{-rT} \mathbb{E} \left[ \Phi(S_T) D^* \left( \frac{S_T (W_T - \sigma T)}{\int_0^T D_u(S_T) \, \mathrm{d}u} \right) \right] \\ &= e^{-rT} \mathbb{E} \left[ \Phi(S_T) D^* \left( \frac{S_T (W_T - \sigma T)}{\sigma T S_T} \right) \right] \\ &= e^{-rT} \mathbb{E} \left[ \Phi(S_T) D^* \left( \frac{W_T}{\sigma T} - 1 \right) \right] = e^{-rT} \mathbb{E} \left[ \Phi(S_T) \left( \frac{W_T^2 - T}{\sigma T} - W_T \right) \right] \end{split}$$

### Proposition ( $\Gamma$ for a European Call Option) [7]:

For a European call option on an asset whose price follows the dynamics of  $(S_t)_{t\in[0,T]}$ , one has:

$$\Gamma = \frac{e^{-rT}}{\sigma T S_0^2} \mathbb{E} \left[ \Phi(S_T) \left( \frac{W_T^2 - T}{\sigma T} - W_T \right) \right] \left( = \frac{\mathcal{V}}{\sigma T S_0^2} \right)$$

where  $\Phi(x) = (x - K)^+$ .

#### Proof.

By the chain rule and the integration by parts formula, one has:

$$\begin{split} &\Gamma = \frac{\partial^2 V_0}{\partial S_0^2} = \frac{\partial^2}{\partial S_0^2} \left( e^{-rT} \mathbb{E} \left[ V_T \right] \right) = e^{-rT} \mathbb{E} \left[ \frac{\partial^2 \Phi(S_T)}{\partial S_0^2} \right] = e^{-rT} \mathbb{E} \left[ \frac{\partial}{\partial S_0} \left( \Phi'(S_T) e^{\left(r - \frac{\sigma^2}{2}\right)T + \sigma W_T} \right) \right] \right] \\ &= e^{-rT} \mathbb{E} \left[ \Phi''(S_T) \left( e^{\left(r - \frac{\sigma^2}{2}\right)T + \sigma W_T} \right)^2 \right] = \frac{e^{-rT}}{S_0^2} \mathbb{E} \left[ \Phi''(S_T) S_T^2 \right] \\ &= \frac{e^{-rT}}{S_0^2} \mathbb{E} \left[ \Phi'(S_T) D^* \left( \frac{S_T^2}{\int_0^T D_u(S_T) du} \right) \right] = \frac{e^{-rT}}{\sigma T S_0^2} \mathbb{E} \left[ \Phi'(S_T) D^* \left( S_T \right) \right] \\ &= \frac{e^{-rT}}{\sigma T S_0^2} \mathbb{E} \left[ \Phi'(S_T) S_T (W_T - \sigma T) \right] = \frac{e^{-rT}}{\sigma T S_0^2} \mathbb{E} \left[ \Phi(S_T) D^* \left( \frac{S_T (W_T - \sigma T)}{\int_0^T D_u(S_T) du} \right) \right] \\ &= \frac{e^{-rT}}{\sigma T S_0^2} \mathbb{E} \left[ \Phi(S_T) D^* \left( \frac{W_T}{\sigma T} - 1 \right) \right] = \frac{e^{-rT}}{\sigma T S_0^2} \mathbb{E} \left[ \Phi(S_T) \left( \frac{W_T^2 - T}{\sigma T} - W_T \right) \right] \end{split}$$

### Lemma [7]:

Let  $\overline{S}_T = \int_0^T S_t dt$  and let  $t \in [0, T]$ . Then, in the Black-Scholes model, one has:

- $D^*(S_{\cdot}) = \frac{S_T S_0 r\overline{S}_T}{\sigma}$

#### Proof.

Omitted (refer to [7, Pages 30-34]) for the proof.

### Proposition ( $\Delta$ for an Asian Fixed Strike Call Option) [7]:

Let  $\overline{S}_T = \int_0^T S_t dt$ . Then, for an Asian fixed strike call option on an asset whose price follows the dynamics of  $(S_t)_{t \in [0,T]}$ , one has:

$$\Delta = \frac{e^{-rT}}{S_0 \sigma^2} \mathbb{E} \left[ \Phi \left( \overline{S}_T \right) \left( \frac{2(S_T - S_0)}{\overline{S}_T} + \sigma^2 - 2r \right) \right]$$

where  $\Phi(x) = (\frac{1}{T}x - K)^+$ .

#### Proof.

By the chain rule and integration by parts formula, one has:

$$\begin{split} &\Delta = \frac{\partial V_0}{\partial S_0} = \frac{\partial}{\partial S_0} \left( e^{-rT} \mathbb{E} \left[ V_T \right] \right) = e^{-rT} \mathbb{E} \left[ \frac{\partial \Phi(\overline{S}_T)}{\partial S_0} \right] = e^{-rT} \mathbb{E} \left[ \Phi'(\overline{S}_T) \frac{\partial \overline{S}_T}{\partial S_0} \right] \\ &= e^{-rT} \mathbb{E} \left[ \Phi'(\overline{S}_T) \int_0^T \frac{\partial \overline{S}_T}{\partial S_0} \, \mathrm{d}t \right] = \frac{e^{-rT}}{S_0} \mathbb{E} \left[ \Phi'(\overline{S}_T) \overline{S}_T \right] \\ &= \frac{e^{-rT}}{S_0} \mathbb{E} \left[ \Phi(\overline{S}_T) D^* \left( \frac{2\overline{S}_T \frac{\partial}{\partial S} D \cdot (\overline{S}_T)}{D_T(\overline{S}_T)^2 - D_0(\overline{S}_T)^2} \right) \right] = \frac{e^{-rT}}{S_0} \mathbb{E} \left[ \Phi(\overline{S}_T) D^* \left( \frac{2\overline{S}_T(-\sigma S.)}{-(\sigma \overline{S}_T)^2} \right) \right] \\ &= \frac{e^{-rT}}{S_0} \mathbb{E} \left[ \Phi(\overline{S}_T) D^* \left( \frac{2S.}{\sigma \overline{S}_T} \right) \right] = \frac{2e^{-rT}}{\sigma S_0} \mathbb{E} \left[ \Phi(\overline{S}_T) \left( \frac{D^*(S.)}{\overline{S}_T} - \int_0^T S_t D_t \left( \frac{1}{\overline{S}_T} \right) \mathrm{d}t \right) \right] \\ &= \frac{2e^{-rT}}{\sigma S_0} \mathbb{E} \left[ \Phi(\overline{S}_T) \left( \frac{S_T - S_0 - r\overline{S}_T}{\sigma \overline{S}_T} + \frac{1}{\overline{S}_T^2} \int_0^T S_t D_t(\overline{S}_T) \, \mathrm{d}t \right) \right] \\ &= \frac{e^{-rT}}{S_0 \sigma^2} \mathbb{E} \left[ \Phi\left(\overline{S}_T\right) \left( \frac{2(S_T - S_0)}{\overline{S}_T} + \sigma^2 - 2r \right) \right] \end{split}$$

### Proposition ( $\Gamma$ for an Asian Fixed Strike Call Option) [7]:

Let  $\overline{S}_T = \int_0^T S_t dt$ . Then, for an Asian fixed strike call option on an asset whose price follows the dynamics of  $(S_t)_{t \in [0,T]}$ , one has:

$$\Gamma = \frac{4e^{-rT}}{S_0^2 \sigma^3} \mathbb{E} \left[ \Phi \left( \overline{S}_T \right) \left( \frac{(S_T - S_0)^2 - (S_T - S_0)r\overline{S}_T}{\sigma \overline{S}_T^2} - \frac{\sigma S_0}{\overline{S}_T} \right) \right] - \frac{2r}{S_0 \sigma^2} \Delta$$

#### Proof.

By the chain rule and integration by parts formula, one has:

$$\begin{split} &\Gamma = \frac{\partial^2 V_0}{\partial S_0^2} = \frac{\partial^2}{\partial S_0^2} \left( e^{-rT} \mathbb{E} \left[ V_T \right] \right) = e^{-rT} \mathbb{E} \left[ \frac{\partial^2 \Phi(\overline{S}_T)}{\partial S_0^2} \right] = \frac{e^{-rT}}{S_0^2} \mathbb{E} \left[ \Phi''(\overline{S}_T) \overline{S}_T^2 \right] \\ &= \frac{e^{-rT}}{S_0^2} \mathbb{E} \left[ \Phi'(\overline{S}_T) D^* \left( \frac{2 \overline{S}_T^2}{D_T} \frac{\partial}{\partial \cdot} D \cdot (\overline{S}_T)}{D_T(\overline{S}_T)^2 - D_0(\overline{S}_T)^2} \right) \right] = \frac{e^{-rT}}{S_0^2} \mathbb{E} \left[ \Phi'(\overline{S}_T) D^* \left( \frac{2 \overline{S}_T^2 (-\sigma S.)}{-(\sigma \overline{S}_T)^2} \right) \right] \\ &= \frac{2 e^{-rT}}{\sigma S_0^2} \mathbb{E} \left[ \Phi'(\overline{S}_T) D^* \left( S. \right) \right] = \frac{2 e^{-rT}}{\sigma^2 S_0^2} \mathbb{E} \left[ \Phi'(\overline{S}_T) \left( S_T - S_0 \right) \right] - \frac{2 e^{-rT}}{\sigma^2 S_0^2} \mathbb{E} \left[ \Phi'(\overline{S}_T) \left( r \overline{S}_T \right) \right] \\ &= \frac{2 e^{-rT}}{\sigma^2 S_0^2} \mathbb{E} \left[ \Phi(\overline{S}_T) D^* \left( \frac{2 (S_T - S_0) (-\sigma S.)}{-(\sigma \overline{S}_T)^2} \right) \right] - \frac{2 r}{\sigma^2 S_0} \Delta \\ &= \frac{4 e^{-rT}}{\sigma^3 S_0^2} \mathbb{E} \left[ \Phi(\overline{S}_T) \left( \frac{S_T - S_0}{\sigma \overline{S}_T^2} \left( S_T - S_0 - r \overline{S}_T \right) - \frac{\sigma S_0}{\overline{S}_T} \right) \right] - \frac{2 r}{\sigma^2 S_0} \Delta \\ &= \frac{4 e^{-rT}}{S_0^2 \sigma^3} \mathbb{E} \left[ \Phi\left(\overline{S}_T\right) \left( \frac{(S_T - S_0)^2 - (S_T - S_0) r \overline{S}_T}{\sigma \overline{S}_T^2} - \frac{\sigma S_0}{\overline{S}_T} \right) \right] - \frac{2 r}{S_0 \sigma^2} \Delta \end{split}$$

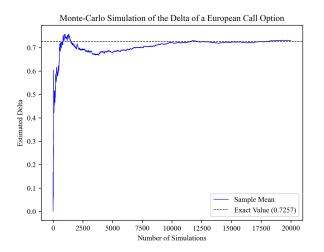


Figure 1: Monte-Carlo simulation of the Delta for a European call option with  $(r, \sigma, S_0, K, T) = (0.1, 0.2, 100, 100, 1)$  in 20000 simulations

```
1 import numpy as np
 2 import pandas as pd
3 import matplotlib.pyplot as plt
4 from scipy.stats import norm
6 def MonteCarloEuropeanCallDelta(r, sigma, SO, K, T, N):
       d = (np.log((S0) / (K)) + (r + (sigma**2 / 2)) * T) / (sigma * np.sqrt(T))
8
       SAMPLE = []
       PATH = []
       for i in range(N):
           W = np.random.normal(0, np.sgrt(T))
           S = S0*np.exp((r - (sigma**2) / 2)*T + sigma*W)
           V = \max(\hat{S} - \hat{K}, 0)
           SAMPLE.append(np.exp(-r*T)*V*W / (SO*T*sigma))
           PATH.append(sum(SAMPLE) / len(SAMPLE))
       plt.rcParams["font.family"] = "Times New Roman"
       pd.Series(PATH).plot(linewidth = 0.75, color = "b")
18
       plt.axhline(norm.cdf(d), color = "black", linestyle = "--", linewidth = 0.75)
       plt.xlabel("Number of Simulations")
       plt.vlabel("Estimated Delta")
20
       plt.legend(["Sample Mean", "Exact Value (" + str(round(norm.cdf(d),4)) + ")"])
       plt.title("Monte-Carlo Simulation of the Delta of a European Call Option")
       plt.rcParams['figure.dpi'] = 300
       plt.rcParams['savefig.dpi'] = 300
26 MonteCarloEuropeanCallDelta(0.1,0.2,100,100,1,20000)
```

Python implementation of the Monte-Carlo simulation in Figure 1

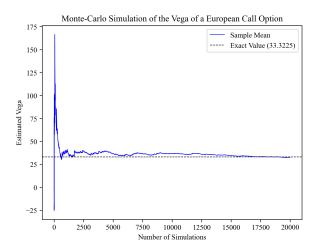


Figure 2: Monte-Carlo simulation of the Vega for a European call option with  $(r, \sigma, S_0, K, T) = (0.1, 0.2, 100, 100, 1)$  in 20000 simulations.

```
1 import numpy as np
 2 import pandas as pd
3 import matplotlib.pyplot as plt
4 from scipy.stats import norm
6
   def MonteCarloEuropeanCallVega(r, sigma, SO, K, T, N):
       d = (np.log((S0) / (K)) + (r + (sigma**2 / 2)) * T) / (sigma * np.sqrt(T))
       SAMPLE = []
       PATH = []
       for i in range(N):
           W = np.random.normal(0, np.sqrt(T))
           S = S0*np.exp((r - (sigma**2) / 2)*T + sigma*W)
           V = \max(S - K.0)
           SAMPLE.append(np.exp(-r*T) * V * (((W**2 - T) / (sigma * T)) - T))
           PATH.append(sum(SAMPLE) / len(SAMPLE))
       plt.rcParams["font.family"] = "Times New Roman"
       pd.Series(PATH).plot(linewidth = 0.75, color = "b")
18
       plt.axhline(S0*np.exp(-(d**2) / 2)*np.sqrt((T) / (2*np.pi)), color = "black",
        linestyle = "--", linewidth = 0.75)
       plt.xlabel("Number of Simulations")
       plt.ylabel("Estimated Vega")
       plt.legend(["Sample Mean", "Exact Value (" + str(round(S0*np,exp(-(d**2) / 2)*np,sgrt
        ((T) / (2*np.pi)),4)) + ")"])
       plt.title("Monte-Carlo Simulation of the Vega of a European Call Option")
       plt.rcParams['figure.dpi'] = 300
       plt.rcParams['savefig.dpi'] = 300
26 MonteCarloEuropeanCallVega(0.1,0.2,100,100,1,20000)
```

Python implementation of the Monte-Carlo simulation in Figure 2

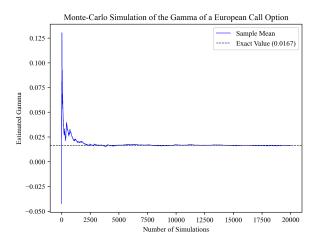


Figure 3: Monte-Carlo Simulation of the Gamma for a European call option with  $(r,\sigma,S_0,K,T)=(0.1,0.2,100,100,1)$  in 20000 simulations.

```
1 import numpy as np
 2 import pandas as pd
3 import matplotlib.pyplot as plt
4 from scipv.stats import norm
6 def MonteCarloEuropeanCallGamma(r, sigma, SO, K, T, N):
       d = (np.log((S0) / (K)) + (r + (sigma**2 / 2)) * T) / (sigma * np.sqrt(T))
8
       SAMPLE = []
9
       PATH = []
       for i in range(N):
           W = np.random.normal(0, np.sqrt(T))
           S = S0*np.exp((r - (sigma**2) / 2)*T + sigma*W)
           V = \max(S - K.0)
           SAMPLE.append(((np.exp(-r*T)) / (sigma * T * S0**2)) * V * (((W**2 - T) / (sigma
        * T)) - T))
           PATH.append(sum(SAMPLE) / len(SAMPLE))
       end = time.time()
       plt.rcParams["font.family"] = "Times New Roman"
       pd.Series(PATH).plot(linewidth = 0.75, color = "b")
       plt.axhline((np.exp(-(d**2) / 2)) / (S0*sigma*np.sqrt(2*np.pi*T)), color = "black",
        linestyle = "--", linewidth = 0.75)
       plt.xlabel("Number of Simulations")
       plt.ylabel("Estimated Gamma")
       plt.legend(["Sample Mean", "Exact Value (" + str(round((np.exp(-(d**2) / 2)) / (S0*
        sigma*np.sqrt(2*np.pi*T)),4)) + ")"])
       plt.title("Monte-Carlo Simulation of the Gamma of a European Call Option")
24
       plt.rcParams['figure.dpi'] = 300
       plt.rcParams['savefig.dpi'] = 300
27 MonteCarloEuropeanCallGamma(0.1,0.2,100,100,1,20000)
```

Python implementation of the Monte Carlo simulation in Figure 3

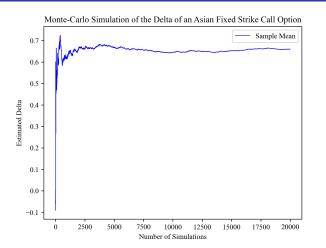


Figure 4: Monte-Carlo Simulation of the Delta for an Asian fixed strike call option with  $(r, \sigma, S_0, K, T, M) = (0.1, 0.2, 100, 100, 1, 252)$  in 20000 simulations.

```
1 import numpy as np
 2 import pandas as pd
 3 import matplotlib.pvplot as plt
4 from scipy.stats import norm
6 def MonteCarloAsianFixedStrikeCallDelta(r, sigma, SO, K, T, M, N):
       dt = T / M
8
       SAMPLE = []
       PATH = []
       S = np.zeros(M + 1)
       S[0] = S0
       for i in range(N):
           for j in range (1,M+1):
               S[j] = S[j-1]*np.exp((r - (sigma**2)/2)*dt + sigma*np.sqrt(dt)*np.random.
        normal(0,1))
           STBar = np.mean(S[1:])
           VT = max(STBar - K. 0)
           SAMPLE.append(((np.exp(-r*T)) / (S0*sigma**2)) * (VT*(((2*(S[-1]-S0)))/(STBar)+
        sigma**2-2*r)))
           PATH.append(sum(SAMPLE) / len(SAMPLE))
       end = time.time()
20
       plt.rcParams["font.family"] = "Times New Roman"
       pd.Series(PATH).plot(linewidth = 0.75, color = "b")
       plt.xlabel("Number of Simulations")
       plt.ylabel("Estimated Delta")
24
       plt.legend(["Sample Mean"])
       plt.title("Monte-Carlo Simulation of the Delta of an Asian Fixed Strike Call Option")
26
       plt.rcParams['figure.dpi'] = 300
       plt.rcParams['savefig.dpi'] = 300
28
29 MonteCarloAsianFixedStrikeCallDelta(0.1.0.2.100.100.1.252.20000)
```

Python implementation of the Monte Carlo simulation in Figure 4

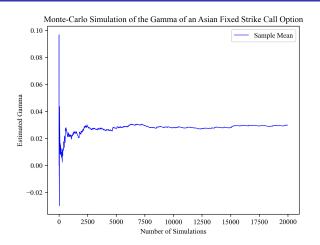


Figure 5: Monte-Carlo Simulation of the Gamma for an Asian fixed strike call option with  $(r, \sigma, S_0, K, T, M) = (0.1, 0.2, 100, 100, 1, 252)$  in 20000 simulations.

```
1 import numpy as np
 2 import pandas as pd
 3 import matplotlib.pyplot as plt
   from scipy.stats import norm
6 def MonteCarloAsianFixedStrikeCallGamma(r.sigma.SO.K.T.M.N);
       dt = T / M
8
       SAMPLE = []
       PATH = []
       S = np.zeros(M + 1)
       S[0] = S0
       for i in range(N):
           for j in range(1,M+1):
               S[j] = S[j-1]*np.exp((r - (sigma**2)/2)*dt + sigma*np.sqrt(dt)*np.random.
        normal(0,1))
           STBar = np.mean(S[1:])
           VT = max(STBar - K. 0)
           Delta = ((np.exp(-r*T)) / (S0*sigma**2)) * (VT*(((2*(S[-1]-S0))))/(STBar)+sigma
        **2-2*r))
           SAMPLE.append(((4*np.exp(-r*T)) / ((S0**2) * (sigma**3)))*(VT*((((S[-1] - S0)**2
        - (S[-1]-S0)*r*STBar) / (sigma*(STBar**2))) - ((sigma*S0) / (STBar)))) - ((2*r) / (
        S0* sigma**2))*Delta)
           PATH.append(sum(SAMPLE) / len(SAMPLE))
20
       plt.rcParams["font.family"] = "Times New Roman"
       pd.Series(PATH).plot(linewidth = 0.75, color = "b")
       plt.xlabel("Number of Simulations")
       plt.ylabel("Estimated Gamma")
24
       plt.legend(["Sample Mean"])
       plt.title("Monte-Carlo Simulation of the Gamma of an Asian Fixed Strike Call Option")
       plt.rcParams['figure.dpi'] = 300
26
       plt.rcParams['savefig.dpi'] = 300
28
29 MonteCarloAsianFixedStrikeCallGamma (0.1.0.2.100.100.1.252.20000)
```

Python implementation of the Monte Carlo simulation in Figure 5

4) Conclusion

#### Conclusion

#### In conclusion:

• The Malliavin Calculus can be applied to calculate the Greeks of certain options by way of the Duality Principle and the Integration by Parts formula. The quantities can then be estimated using the Monte-Carlo simulations.

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