

# Measure Theory

## Exam

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E20

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# Conditional Expectation Strategy

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## Conditional Expectation

### Defintion of Conditional Expectation

**Definition 4.42.** Let  $\mathcal{A} \subset \mathcal{F}$  be a sub- $\sigma$ -algebra of  $\mathcal{F}$  and let  $f : \Omega \rightarrow \mathbb{R}$  be  $\mathbb{P}$ -integrable. Then a function  $g : \Omega \rightarrow \mathbb{R}$  is called a *representative of the conditional expectation of  $f$  under the hypothesis  $\mathcal{A}$* , iff it is  $\mathbb{P}$ -integrable,  $\mathcal{A}$ -measurable, and satisfies

$$\int_A f \, d\mathbb{P} = \int_A g \, d\mathbb{P}, \quad A \in \mathcal{A}. \quad (1.1)$$

**Remark 4.46.** Substituting  $A = \Omega$  in (1.1), we obtain

$$\int_{\Omega} f \, d\mathbb{P} = \int_{\Omega} g \, d\mathbb{P} \quad (1.2)$$

$$\mathbb{E}[f] = \mathbb{E}[g] \quad (1.3)$$

$$\mathbb{E}[f] = \mathbb{E}[\mathbb{E}^{\mathcal{A}}[f]] , \quad (1.4)$$

for all sub- $\sigma$ -algebras  $\mathcal{A} \subset \mathcal{F}$  and all  $\mathbb{P}$ -integrable  $f : \Omega \rightarrow \mathbb{C}$ .

## Conditional Expectation

### Exercise 4.47

**Exercise.** Recall that  $\{\emptyset, \Omega\}$  is a sub- $\sigma$ -algebra of  $\mathcal{F}$ . Convince yourself of the validity of the formula

$$\mathbb{E}^{\{\emptyset, \Omega\}}[f] = \mathbb{E}[f], \quad \mathbb{P} - \text{a.s.}, \quad (1.5)$$

for every  $\mathbb{P}$ -integrable  $f : \Omega \rightarrow \mathbb{R}$ .

**Solution.** We start by defining  $g := \mathbb{E}[f]$ , then we have by the definition of the conditional expectation that  $g$  is a representative iff it is

- ▶  $\mathbb{P}$ -integrable.
- ▶  $\mathcal{A}$ -measurable.
- ▶ It satisfies that

$$\int_A f \, d\mathbb{P} = \int_A g \, d\mathbb{P}, \quad A \in \{\emptyset, \Omega\}. \quad (1.6)$$

## Exercise 4.47

We verify that it is in fact the case for both  $\Omega$  and  $\emptyset$ ,

$$\int_{\Omega} f \, d\mathbb{P} = \mathbb{E}[f] = \int_{\Omega} \mathbb{E}[f] \, d\mathbb{P} = \int_{\Omega} g \, d\mathbb{P}. \quad (1.7)$$

$$\int_{\emptyset} f \, d\mathbb{P} = 0 = \int_{\emptyset} g \, d\mathbb{P}. \quad (1.8)$$

This shows that  $\mathbb{E}[f] = g = \mathbb{E}^{\{\emptyset, \Omega\}}[f]$   $\mathbb{P}$ -a.s.



## Conditional Expectation

### Exercise 4.48

**Exercise.** *Linearity.* Let  $\mathcal{A}$  be a sub- $\sigma$ -algebra of  $\mathcal{F}$ ,  $\alpha, \beta \in \mathbb{R}$ , and let  $f, g : \Omega \rightarrow \mathbb{R}$  be  $\mathbb{P}$ -integrable. Show that

$$\mathbb{E}^{\mathcal{A}}[\alpha f + \beta g] = \alpha \mathbb{E}^{\mathcal{A}}[f] + \beta \mathbb{E}^{\mathcal{A}}[g], \quad \mathbb{P} - \text{a.s.} \quad (1.9)$$

**Solution.**

$$\begin{aligned} \int_A \mathbb{E}^{\mathcal{A}}[\alpha f + \beta g] d\mathbb{P} &= \int_A \alpha f + \beta g d\mathbb{P} \\ &= \int_A \alpha f d\mathbb{P} + \int_A \beta g d\mathbb{P} = \alpha \int_A f d\mathbb{P} + \beta \int_A g d\mathbb{P} \\ &= \alpha \int_A \mathbb{E}^{\mathcal{A}}[f] d\mathbb{P} + \beta \int_A \mathbb{E}^{\mathcal{A}}[g] d\mathbb{P} = \int_A \alpha \mathbb{E}^{\mathcal{A}}[f] + \beta \mathbb{E}^{\mathcal{A}}[g] d\mathbb{P}. \end{aligned}$$

## Conditional Expectation

### Exercise 4.51

**Exercise.** Let  $m, n \in \mathbb{N}$ ,  $m < n$ , and  $X_1, \dots, X_n : \Omega \rightarrow \mathbb{R}$  be independent  $\mathbb{P}$ -integrable random variables. Let

$$\mathcal{F}_m := \sigma(X_1, \dots, X_m) \quad (1.10)$$

$$:= \sigma(\{X_i^{-1}(B) \mid B \in \mathcal{B}(\mathbb{R}), i \in \{1, \dots, m\}\}) \quad (1.11)$$

denote the  $\sigma$ -algebra induced by  $X_1, \dots, X_m$ . Show that

$$\mathbb{E}^{\mathcal{F}_m} \left[ \sum_{i=1}^n X_i \right] = \sum_{i=1}^m X_i + \sum_{j=m+1}^n \mathbb{E}[X_j], \quad (1.12)$$

$$\mathbb{E}^{\mathcal{F}_m} \left[ \prod_{i=1}^n X_i \right] = \left( \prod_{i=1}^m X_i \right) \left( \prod_{j=m+1}^n \mathbb{E}[X_j] \right). \quad (1.13)$$

**Solution.** For the first part we have that

$$\text{for } i \leq m : X_i \in \mathcal{M}(\mathcal{F}^m) \Rightarrow \mathbb{E}[X_i | \mathcal{F}^m] = X_i \quad (1.14)$$

$$\text{for } j > m : X_j \perp \mathcal{F}^m \Rightarrow \mathbb{E}[X_j | \mathcal{F}^m] = \mathbb{E}[X_j]. \quad (1.15)$$

Thus we have that

$$\mathbb{E}^{\mathcal{F}^m} \left[ \sum_{i=1}^n X_i \right] = \sum_{i=1}^m X_i + \sum_{j=m+1}^n \mathbb{E}[X_j]. \quad (1.16)$$

## Conditional Expectation

### Exercise 4.51

For the second part we have that, because  $X_1, \dots, X_m \in \mathcal{M}(\mathcal{F}^m)$  and by independence

$$\mathbb{E}^{\mathcal{F}^m} \left[ \prod_{i=1}^n X_i \right] = \left( \prod_{i=1}^m X_i \right) \mathbb{E}^{\mathcal{F}^m} \left[ \prod_{j=m+1}^n X_j \right] \quad (1.17)$$

$$= \left( \prod_{i=1}^m X_i \right) \mathbb{E} \left[ \prod_{j=m+1}^n X_j \right] \quad (1.18)$$

$$= \left( \prod_{i=1}^m X_i \right) \left( \prod_{j=m+1}^n \mathbb{E}[X_j] \right). \quad (1.19)$$

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# Brownian Motion

## Strategy

- ▶ Definition of Brownian motion
- ▶ Exercise 5.43
- ▶ Exercise 5.44

**Definition 5.38.** Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space and  $d \in \mathbb{N}$ . Then a stochastic process  $B = (B_t)_{t \geq 0}$  on  $(\Omega, \mathcal{F}, \mathbb{P})$  with target space  $(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$  and parameter set  $[0, \infty)$  is called a  $d$ -dimensional *standard Brownian motion* or, synonymously, *Wiener process* on  $(\Omega, \mathcal{F}, \mathbb{P})$ , iff it has the following four properties:

1. All its paths  $B_\bullet(\omega)$ ,  $\omega \in \Omega$ , are continuous.
2.  $\mathbb{P}(\{B_0 = 0\}) = 1$
3.  $B$  has independent and stationary increments.
4. For all  $t > s \geq 0$ , the distribution of  $B_t - B_s$  is a  $d$ -dimensional centered Gaussian distribution with covariance matrix  $(t - s)\mathbb{1}_d$ .

## Exercise 5.43

**Exercise.** Compute the probabilities  $\mathbb{P}(\{B_1 = 0\})$  and  $\mathbb{P}(\{B_\bullet = f\})$  for  $f \in C([0, \infty), \mathbb{R}^d)$ .

**Solution.** For the first part we have

$$\begin{aligned}\mathbb{P}(\{B_1 = 0\}) &= \mathbb{P}(\{B_1 - B_0 = 0\}) \\ &= \int_{\{0\}} \frac{e^{-\|x\|^2/2(1-0)}}{(2\pi(1-0))^{d/2}} dx = \int_{\{0\}} \frac{e^{-\|x\|^2/2}}{(2\pi)^{d/2}} dx = 0.\end{aligned}$$

For the second part let us first look at the event itself

$$\{B_\bullet = f\} = \{\omega \in \Omega \mid \forall t \geq 0 : B_t(\omega) = f(t)\}. \quad (2.1)$$



Further we observe that

$$\begin{aligned} \{B_{\bullet} = f\} &\subset \{B_1 = f(1)\} \\ \{\omega \in \Omega \mid \forall t \geq 0 : B_t(\omega) = f(t)\} &\subset \{\omega \in \Omega \mid B_1(\omega) = f(1)\}. \end{aligned}$$

Notice then that

$$\mathbb{P}(B_1 = f(1)) = 0 \quad \Rightarrow \quad \mathbb{P}(B_{\bullet} = f) = 0. \quad (2.2)$$

### Exercise 5.44

**Exercise.** Let  $B$  be a one-dimensional standard Brownian motion on the probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  and let  $\mathbb{E}[\cdot]$  denote the expectation with respect to  $\mathbb{P}$ . Show that  $\mathbb{E}[B_t] = 0$  and  $\mathbb{E}[B_s B_t] = s \wedge t$  for all  $s, t \geq 0$ .

**Solution.** To show the first part observe that from 2. we have that

$$B_t = B_t - B_0. \quad (2.3)$$

It then follows from 4. that

$$B_t - B_0 \sim N(0, t). \quad (2.4)$$

## Brownian Motion

### Exercise 5.44

For the second part observe that from 3.  $B$  has independent increments. Without loss of generality assume that  $s \leq t$ . Then we can rewrite in the following way

$$\mathbb{E}[B_s B_t] = \mathbb{E}[B_s((B_t - B_s) + B_s)] \quad (2.5)$$

$$= \mathbb{E}[B_s(B_t - B_s)] + \mathbb{E}[B_s^2]. \quad (2.6)$$

Because  $B_s = B_s - B_0$  from 2., we have that

$$\mathbb{E}[B_s(B_t - B_s)] = \mathbb{E}[(B_s - B_0)(B_t - B_s)] \quad (2.7)$$

$$= \mathbb{E}[(B_s - B_0)]\mathbb{E}[(B_t - B_s)] = 0. \quad (2.8)$$

Where the second equality follows from the two increments being independent. Finally we have

$$\mathbb{E}[B_s B_t] = \mathbb{E}[B_s^2] = s. \quad (2.9)$$

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# Martingales & Quadratic Variation

## Strategy

- ▶ Introduce the martingale definition
- ▶ Show that one-dimensional Brownian motion is a martingale
- ▶ Definition of Quadratic Variation
- ▶ Find the Quadratic Variation of Brownian motion

## Martingales & Quadratic Variation

### Martingale definition

Let  $(M_t)_{t \in I}$  be an adapted  $\mathbb{R}$ -valued stochastic process such that  $M_t : \Omega \rightarrow \mathbb{R}$  is  $\mathbb{P}$ -integrable for every  $t \in I$ .

►  $M$  is called a  $(\mathcal{F}_t)_{t \in I}$ -martingale iff

$$\mathbb{E}^{\mathcal{F}_s}[M_t] = M_s, \quad \mathbb{P} - \text{a.s. for all } s, t \in I \text{ with } s \leq t. \quad (3.1)$$

## Martingales & Quadratic Variation

### Martingale definition

Let  $(M_t)_{t \in I}$  be an adapted  $\mathbb{R}$ -valued stochastic process such that  $M_t : \Omega \rightarrow \mathbb{R}$  is  $\mathbb{P}$ -integrable for every  $t \in I$ .

►  $M$  is called a  $(\mathcal{F}_t)_{t \in I}$ -submartingale iff

$$\mathbb{E}^{\mathcal{F}_s}[M_t] \geq M_s, \quad \mathbb{P} - \text{a.s. for all } s, t \in I \text{ with } s \leq t. \quad (3.2)$$

## Martingales & Quadratic Variation

### Martingale definition

Let  $(M_t)_{t \in I}$  be an adapted  $\mathbb{R}$ -valued stochastic process such that  $M_t : \Omega \rightarrow \mathbb{R}$  is  $\mathbb{P}$ -integrable for every  $t \in I$ .

- ▶  $M$  is called a  $(\mathcal{F}_t)_{t \in I}$ -submartingale iff

$$\mathbb{E}^{\mathcal{F}_s}[M_t] \geq M_s, \quad \mathbb{P} - \text{a.s. for all } s, t \in I \text{ with } s \leq t. \quad (3.2)$$

- ▶ Analogously for supermartingale.



## Martingales & Quadratic Variation

### One-dimensional Brownian Motion

If  $B$  is a one-dimensional  $(\mathcal{F}_t)_{t \geq 0}$ -Brownian motion, then  $B$  is a  $(\mathcal{F}_t)_{t \geq 0}$ -martingale.

In particular, every one-dimensional standard Brownian motion  $B$  is a martingale with respect to its natural filtration  $(\mathcal{B}_t^B)_{t \geq 0}$ .

## Martingales & Quadratic Variation

### One-dimensional Brownian Motion

► Let us first recall that

$$\int_{\Omega} |B_t| d\mathbb{P} = \frac{1}{(2\pi t)^{1/2}} \int_{\mathbb{R}} |x| e^{-x^2/2t} dx < \infty, \quad (3.3)$$

$$\mathbb{E}[B_t] = \frac{1}{(2\pi t)^{1/2}} \int_{\mathbb{R}} x e^{-x^2/2t} dx = 0, \quad (3.4)$$

for every  $t > 0$ .

## Martingales & Quadratic Variation

### One-dimensional Brownian Motion

- ▶ Since  $B_0 = 0$ ,  $\mathbb{P}$ -a.s., it follows in particular that  $B_t$  is  $\mathbb{P}$ -integrable with  $\mathbb{E}[B_t] = 0$  for all  $t \geq 0$ .
- ▶ For all  $0 \leq s \leq t < \infty$ , we further observe that,  $\mathbb{P}$ -a.s.,

$$\mathbb{E}^{\mathcal{F}_s}[B_t] = \mathbb{E}^{\mathcal{F}_s}[B_t - B_s] + \mathbb{E}^{\mathcal{F}_s}[B_s] \quad (3.5)$$

$$= \mathbb{E}[B_t - B_s] + B_s \quad (3.6)$$

$$= \mathbb{E}[B_t] - \mathbb{E}[B_s] + B_s \quad (3.7)$$

$$= B_s, \quad (3.8)$$

since the increment  $B_t - B_s$  is  $\mathcal{F}_s$ -independent and  $B_s$  is  $\mathcal{F}_s$ -measurable.

## Martingales & Quadratic Variation

### Definition of Quadratic Variation

**Theorem (and definition) 6.50.** Assume that  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$  satisfies the usual hypotheses and let  $M$  be a continuous local martingale. Then there exists an up to indistinguishability unique finite variation process  $\langle M \rangle = (\langle M \rangle_t)_{t \geq 0}$  such that  $\langle M \rangle_0 = 0$ ,  $\mathbb{P}$ -a.s., and

$$M^2 - \langle M \rangle = (M_t^2 - \langle M \rangle_t)_{t \geq 0} \text{ is a local martingale.} \quad (3.9)$$

This process is called quadratic variation of  $M$ . The quadratic variation  $\langle M \rangle$  can be chosen such that it is a non-decreasing process. Furthermore,

$$\langle M^\tau \rangle = \langle M \rangle^\tau, \quad (3.10)$$

up to indistinguishability for every stopping time  $\tau : \Omega \rightarrow [0, \infty]$ . Finally, again up to indistinguishability,

$$\langle M \rangle = \langle M - M_0 \rangle. \quad (3.11)$$

**Exercise 6.51.** Let  $B = (B_t)_{t \geq 0}$  be a 1-dimensional standard Brownian motion. Show that

$$\langle B \rangle_t = t, \quad t \geq 0. \quad (3.12)$$

**Solution.** Define the continuous finite variation process  $(t)_{t \geq 0}$ . Note that, obviously,  $\langle B \rangle_0 = 0$ . Thus what is left to show is that  $(B_t^2 - t)_{t \geq 0}$  is a local martingale.

## Martingales & Quadratic Variation

### Quadratic Variation of 1-dimensional standard Brownian motion

First of all note that  $B_t^2 - t$  is  $\mathbb{P}$ -integrable and adapted. For  $t > s$  we have that

$$\begin{aligned}\mathbb{E}^{\mathcal{F}_s} [B_t^2 - t] &= \mathbb{E}^{\mathcal{F}_s} [(B_s + [B_t - B_s])^2] - t \\&= \mathbb{E}^{\mathcal{F}_s} [B_s^2] + 2\mathbb{E}^{\mathcal{F}_s} [B_s(B_t - B_s)] + \mathbb{E} [(B_t - B_s)^2] - t \\&= B_s^2 + 2B_s\mathbb{E}^{\mathcal{F}_s} [B_t - B_s] + \mathbb{E} [(B_t - B_s)^2] - t \\&= B_s^2 + 2B_s\mathbb{E} [B_t - B_s] + \mathbb{E} [B_{t-s}^2] - t \\&= B_s^2 + t - s - t \\&= B_s^2 - s,\end{aligned}$$

showing that  $B_t^2 - t$  is in fact a martingale.

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# Stochastic Integrals

## Strategy

- ▶ Definition 6.34 (Elementary stochastic integral)
- ▶ Theorem 7.4 (Approximation by bounded simple processes)
- ▶ 7.2.2 Extension of the stochastic integral by isometry



## Stochastic Integrals

### Definition 6.34 (Elementary stochastic integral)

**Definition 6.34.** Let  $Y = (Y_t)_{t \geq 0}$  be some progressively measurable process with target space  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  and let  $X$  be a predictable step process having the representation

$$X_t = \sum_{k=1}^{\infty} \xi_k \chi_{\{\tau_{k-1} < t \leq \tau_k\}}, \quad t \geq 0. \quad (4.1)$$

for a non decreasing series of stopping times and some  $\mathcal{F}_{\tau_{k-1}}$ -measurable  $\xi_k : \Omega \rightarrow \mathbb{R}$ . Then the stochastic integral with integrand  $X$  with respect to the integrator  $Y$  is the stochastic process

$$\int X dY := \left( \int_0^t X_s dY_s \right)_{t \geq 0} \quad (4.2)$$

defined by

$$\int_0^t X_s dY_s := \sum_{k=1}^{\infty} \xi_k (Y_{\tau_k \wedge t} - Y_{\tau_{k-1} \wedge t}). \quad (4.3)$$

## Theorem 7.4

**Theorem 7.4.** Let  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$  be a filtered probability space satisfying the usual hypotheses and  $M$  a continuous square-integrable martingale. Let  $X$  be a progressively measurable stochastic process satisfying

$$\mathbb{E} \left[ \int_0^t X_s^2 d\langle M \rangle_s \right] < \infty, \quad t \geq 0. \quad (4.4)$$

Then there exists a sequence  $(X^{[n]})_{n \in \mathbb{N}}$  of bounded simple processes such that

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[ \int_0^t (X_s^{[n]} - X_s)^2 d\langle M \rangle_s \right] = 0. \quad (4.5)$$

## Stochastic Integrals

### Extension of the stochastic integral

Let  $M$  be a continuous square integrable martingale and  $X$  a progressively measurable process satisfying

$$\mathbb{E} \left[ \int_0^t X_s^2 d\langle M \rangle_s \right] < \infty, \quad t \geq 0.$$

Theorem 7.4 then gives a sequence  $(X^{[n]})_{n \in \mathbb{N}}$  of bounded predictable step processes satisfying

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[ \int_0^t (X_s^{[n]} - X_s)^2 d\langle M \rangle_s \right] = 0.$$

## Stochastic Integrals

### Extension of the stochastic integral

By the Minkowski inequalities we get that

$$\begin{aligned} & \mathbb{E} \left[ \int_0^t (X_s^{[m]} - X_s^{[n]})^2 d\langle M \rangle_s \right]^{1/2} \\ & \leq \mathbb{E} \left[ \int_0^t (X_s^{[m]} - X_s)^2 d\langle M \rangle_s \right]^{1/2} + \mathbb{E} \left[ \int_0^t (X_s - X_s^{[n]})^2 d\langle M \rangle_s \right]^{1/2}. \end{aligned}$$

Taking limits entails that

$$\mathbb{E} \left[ \int_0^t (X_s^{[m]} - X_s^{[n]})^2 d\langle M \rangle_s \right] \xrightarrow{m,n \rightarrow \infty} 0. \quad (4.6)$$

## Stochastic Integrals

### Extension of the stochastic integral

**Lemma 7.3.** Let  $X$  be a bounded step process and  $M = (M_t)_{t \geq 0}$  a continuous square-integrable martingale. Then we have the isometry

$$\mathbb{E} \left[ \left( \int_0^t X_s dM_s \right)^2 \right] = \mathbb{E} \left[ \int_0^t X_s^2 d\langle M \rangle_s \right], \quad t \geq 0. \quad (4.7)$$

## Stochastic Integrals

### Extension of the stochastic integral

By linearity and isometry (Lemma 7.3) of the elementary stochastic integral we can rewrite

$$\begin{aligned} & \mathbb{E} \left[ \int_0^t (X_s^{[m]} - X_s^{[n]})^2 d\langle M \rangle_s \right] \\ &= \mathbb{E} \left[ \left( \int_0^t X_s^{[m]} - X_s^{[n]} dM_s \right)^2 \right] \\ &= \mathbb{E} \left[ \left( \int_0^t X_s^{[m]} dM_s - \int_0^t X_s^{[n]} dM_s \right)^2 \right]. \end{aligned}$$

Thus

$$\mathbb{E} \left[ \left( \int_0^t X_s^{[m]} dM_s - \int_0^t X_s^{[n]} dM_s \right)^2 \right] \xrightarrow{m,n \rightarrow \infty} 0 \quad (4.8)$$

# Stochastic Integrals

## Extension of the stochastic integral

**Theorem 6.32.** Consider the case  $I = [0, \infty)$  and assume that  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$  satisfies the usual hypotheses. Let  $M^{[n]} = (M_t^{[n]})_{t \geq 0}$  be a right-continuous, square-integrable martingale for every  $n \in \mathbb{N}$ . Assume that

$$\mathbb{E} \left[ (M_t^{[p]} - M_t^{[n]})^2 \right] \xrightarrow{n,p \rightarrow \infty} 0, \quad t \geq 0. \quad (4.9)$$

Then there exists a càdlàg square-integrable martingale  $M = (M_t)_{t \geq 0}$  such that

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[ (M_t^{[n]} - M_t)^2 \right] = 0, \quad t \geq 0. \quad (4.10)$$

Every other martingale  $M'$  having these properties is indistinguishable from  $M$ .

Furthermore, there exists integers  $1 \leq n_1 < n_2 < \dots$  and some  $\mathbb{P}$ -zero set  $N \in \mathcal{F}$  such that

$$\sup_{s \in [0, t]} \left\| M_s^{[n_j]}(\omega) - M_s(\omega) \right\| \xrightarrow{j \rightarrow \infty} 0, \quad \omega \in \Omega \setminus N, \quad t \geq 0. \quad (4.11)$$

In particular, if all  $M^{[n]}$  with  $n \in \mathbb{N}$  are continuous, then  $M$  can be chosen continuous as well.

## Stochastic Integrals

### Extension of the stochastic integral

Theorem 6.32 thus gives a continuous square integrable martingale  $(I_t)_{t \geq 0}$  such that

$$\mathbb{E} \left[ \left( \int_0^t X_s^{[m]} dM_s - I_t \right)^2 \right] \xrightarrow{m \rightarrow \infty} 0, \quad (4.12)$$

and every martingale  $I'$  having these properties are indistinguishable from  $I$ .



## Stochastic Integrals

### Extension of the stochastic integral

Next we can verify that  $I$ , does not depend on the choice of approximating sequence.

Let  $(Y^{[n]})_{n \in \mathbb{N}}$  be another bounded predictable step process such that

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[ \int_0^t \left( Y_s^{[n]} - X_s \right)^2 d\langle M \rangle_s \right] = 0. \quad (4.13)$$

Let  $(J_t)_{t \geq 0}$  be a corresponding continuous square-integrable martingale satisfying

$$\mathbb{E} \left[ \left( \int_0^t Y_s^{[n]} dM_s - J_t \right)^2 \right] \xrightarrow{n \rightarrow \infty} 0 \quad (4.14)$$

## Stochastic Integrals

### Extension of the stochastic integral

For every  $t \geq 0$ , we then obtain

$$\begin{aligned}\mathbb{E} [(I_t - J_t)^2] &= \lim_{n \rightarrow \infty} \mathbb{E} \left[ \left( \int_0^t X_s^{[n]} dM_s - \int_0^t Y_s^{[n]} dM_s \right)^2 \right] \\ &= \lim_{n \rightarrow \infty} \mathbb{E} \left[ \left( \int_0^t X_s^{[n]} - Y_s^{[n]} dM_s \right)^2 \right] \\ &= \lim_{n \rightarrow \infty} \mathbb{E} \left[ \int_0^t \left( X_s^{[n]} - Y_s^{[n]} \right)^2 d\langle M \rangle_s \right] = 0,\end{aligned}$$

where we used isometry and

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[ \int_0^t (X_s^{[n]} - X_s)^2 d\langle M \rangle_s \right] = 0, \quad \lim_{n \rightarrow \infty} \mathbb{E} \left[ \int_0^t (Y_s^{[n]} - X_s)^2 d\langle M \rangle_s \right] = 0.$$

The processes  $(I_t)_{t \geq 0}$  and  $(J_t)_{t \geq 0}$  are thus modification of each other and therefore indistinguishable as they are both continuous.

### Definition 7.8

**Definition 7.8.** Any choice of the up to indistinguishability well-defined and unique continuous square-integrable martingale  $(I_t)_{t \geq 0}$  introduced in the preceding argumentation is called the stochastic integral of  $X$  with respect to  $M$  and we write

$$\int_0^t X_s dM_s := I_t, \quad t \geq 0, \quad \int X dM := \left( \int_0^t X_s dM_s \right)_{t \geq 0}.$$

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# Itô's Formula

## Strategy

- ▶ Definition of semi martingales
- ▶ Itô's formula for semi martingales
- ▶ Exercise 8 (Part of Example 4)

## Itô's Formula

### Semi Martingales

Denote by  $\mathcal{M}_{c,loc}$  the linear space of  $(\mathcal{F}_t)_{t \geq 0}$ -continuous local martingales.

Denote by  $\mathcal{A}_{loc}$  the space of adapted processes whose paths are continuous and locally of bounded variation.

Let  $X = (X_t)_{t \geq 0}$  be a stochastic process defined on  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$ . We say that  $X$  is a continuous semimartingale if  $X$  can be decomposed as

$$X_t = X_0 + M_t + A_t, \quad t \geq 0, \quad (5.1)$$

where  $M \in \mathcal{M}_{c,loc}$ ,  $A \in \mathcal{A}_{loc}$ . We will denote by  $\mathcal{SM}^c$  the linear space of continuous semimartingales.

## Itô's Formula

### Itô's formula for semi martingales

**Theorem 7.** Let  $X = (X^{(1)}, \dots, X^{(d)})$ , where  $X^{(i)} \in \mathcal{SM}^c$ , for all  $i = 1, \dots, d$ . If  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  is twice continuously differentiable and  $X = (X^{(1)}, \dots, X^{(d)})$ , then

$$\begin{aligned} f(X_t) = f(X_0) &+ \sum_{i=1}^d \int_0^t \partial_{x_i} f(X_s) dX_s^{(i)} \\ &+ \frac{1}{2} \sum_{i,j=1}^d \int_0^t \partial_{x_i} \partial_{x_j} f(X_s) d\langle X^{(i)}, X^{(j)} \rangle_s. \end{aligned}$$

In the case  $d = 1$  we have

$$f(X_t) = f(X_0) + \int_0^t f'(X_s) dX_s + \frac{1}{2} \int_0^t f''(X_s) d\langle X \rangle_s.$$

**Example 4 (Complex Exponential Process).** Let  $M \in \mathcal{M}_{c,loc}$  starting at 0 and define for  $t \geq 0$

$$N_t^{(1)} := \cos(M_t)e^{\frac{1}{2}\langle M \rangle_t}, \quad N_t^{(2)} := \sin(M_t)e^{\frac{1}{2}\langle M \rangle_t}. \quad (5.2)$$

Verify that

$$N_t^{(2)} = \int_0^t N_s^{(1)} dM_s, \quad t \geq 0. \quad (5.3)$$



## Itô's Formula

### Exercise 8

We will start by observing that Itô's formula applied to the function  $f(x, y) = xy$  results in the following integration by parts formula

$$X_t Y_t = X_0 Y_0 + \int_0^t X_s dY_s + \int_0^t Y_s dX_s + \langle X, Y \rangle_t, \quad \forall X, Y \in \mathcal{SM}^c,$$

$$\text{as } \frac{1}{2} \left( \int_0^t 1 d\langle X, Y \rangle_s + \int_0^t 1 d\langle X, Y \rangle_s \right) = \langle X, Y \rangle_t.$$

Thus we get that

$$N_t^{(2)} = \sin(M_t) e^{\frac{1}{2} \langle M \rangle_t} \quad (5.4)$$

$$= \int_0^t \sin(M_s) d \left( e^{\frac{1}{2} \langle M \rangle_s} \right) + \int_0^t e^{\frac{1}{2} \langle M \rangle_s} d(\sin(M_s)). \quad (5.5)$$

since  $\sin(M_0) = \sin(0) = 0$ , and the fact that  $e^{\frac{1}{2} \langle M \rangle_s}$  have no martingale part.

## Itô's Formula

### Exercise 8

Applying Itô's formula again ( $d = 1$ ) we get

$$\begin{aligned} e^{\frac{1}{2}\langle M \rangle_t} &= 1 + \int_0^t \partial_{\langle M \rangle} e^{\frac{1}{2}\langle M \rangle_s} d\langle M \rangle_s + \frac{1}{2} \int_0^t \partial_{\langle M \rangle}^2 e^{\frac{1}{2}\langle M \rangle_s} d\langle \langle M \rangle \rangle_s \\ &= 1 + \frac{1}{2} \int_0^t e^{\frac{1}{2}\langle M \rangle_s} d\langle M \rangle_s \end{aligned} \quad (5.6)$$

$$\sin(M_t) = \int_0^t \partial_M \sin(M_s) dM_s + \frac{1}{2} \int_0^t \partial_M^2 \sin(M_s) d\langle M \rangle_s \quad (5.7)$$

$$= \int_0^t \cos(M_s) dM_s - \frac{1}{2} \int_0^t \sin(M_s) d\langle M \rangle_s. \quad (5.8)$$

## Itô's Formula

### Exercise 8

Using now that

$$X_t = X_0 + \int_0^t H_s dY_s$$

$$dX_s = H_s dY_s,$$

which gives that

$$\int_0^t G_s dX_s = \int_0^t G_s H_s dY_s.$$

We are able to “rewrite”

$$d\left(e^{\frac{1}{2}\langle M \rangle_s}\right) = \frac{1}{2}e^{\frac{1}{2}\langle M \rangle_s} d\langle M \rangle_s,$$

$$d(\sin(M_s)) = \cos(M_s) dM_s - \frac{1}{2}\sin(M_s) d\langle M \rangle_s.$$

# Itô's Formula

## Exercise 8

Now inserting what we just found

$$\begin{aligned}N_t^{(2)} &= \sin(M_t) e^{\frac{1}{2} \langle M \rangle_t} \\&= \int_0^t \sin(M_s) d \left( e^{\frac{1}{2} \langle M \rangle_s} \right) + \int_0^t e^{\frac{1}{2} \langle M \rangle_s} d (\sin(M_s)) \\&= \frac{1}{2} \int_0^t \sin(M_s) e^{\frac{1}{2} \langle M \rangle_s} d \langle M \rangle_s + \int_0^t \cos(M_s) e^{\frac{1}{2} \langle M \rangle_s} dM_s \\&\quad - \frac{1}{2} \int_0^t \sin(M_s) e^{\frac{1}{2} \langle M \rangle_s} d \langle M \rangle_s \\&= \int_0^t \cos(M_s) e^{\frac{1}{2} \langle M \rangle_s} dM_s \\&= \int_0^t N_t^{(1)} dM_s.\end{aligned}$$

which concludes the exercise.

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# Girsanov-Transformation

## Strategy

- ▶ Definition of the exponential martingale
- ▶ Novikov Theorem
- ▶ Girsanov Theorem
- ▶ Black & Scholes example

### Definition of the exponential martingale

**Definition 6.** The process

$$\mathcal{E}(X)_t := \exp \left\{ X_t - X_0 - \frac{1}{2} \langle X \rangle_t \right\}, \quad t \geq 0,$$

is called the exponential semimartingale, when  $X \in \mathcal{SM}^c$ , and the exponential local martingale, when  $X \in \mathcal{M}_{c,loc}$ .

**Theorem 12 (Novikov).** Let  $M \in \mathcal{M}_{C,loc}$ . If for every  $t \geq 0$

$$\mathbb{E}(e^{\frac{1}{2}\langle M \rangle_t}) < \infty,$$

then  $\mathcal{E}(M)_t$  is a true martingale with  $\mathbb{E}(\mathcal{E}(M)_t) = 1$ , for all  $t \geq 0$ .



## Girsanov-Transformation

### Introduction to Girsanov

Fix  $0 < T < +\infty$  and consider  $(\Omega, \mathcal{F}_T, (\mathcal{F}_t)_{0 \leq t \leq T}, \mathbb{P})$ . Let  $\xi$  be a non-negative r.v. on  $(\Omega, \mathcal{F}_T)$  with  $\mathbb{E}(\xi) = 1$ . Then the measure

$$\mathbb{Q}(A) := \mathbb{E}_{\mathbb{P}}(\chi_A \xi), \quad A \in \mathcal{F}_T,$$

is a probability measure which is absolutely continuous w.r.t.  $\mathbb{P}$ . We will write

$$\frac{d\mathbb{Q}}{d\mathbb{P}} = \xi, \quad \text{on } \mathcal{F}_T.$$

With  $\mathbb{Q}$  as above we have

$$\mathbb{E}_{\mathbb{Q}}[X] = \mathbb{E}_{\mathbb{P}}[X\xi] = \int_{\Omega} X(\omega)\xi(\omega) d\mathbb{P}(\omega),$$

for an arbitrary stochastic process  $X \in \mathcal{F}_T$ .

## Girsanov-Transformation

### Girsanov's Theorem

**Theorem 14 (Girsanov).** Let  $(B_t)_{t \geq 0}$  be a Brownian motion on  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$ , and  $H$  a progressively measurable process such that

$$\mathbb{E}_{\mathbb{P}}(e^{\frac{1}{2}\langle H \cdot B \rangle_T}) = \mathbb{E}_{\mathbb{P}}(e^{\frac{1}{2} \int_0^T H_s^2 ds}) < \infty.$$

Then the process defined as

$$\tilde{B}_t := B_t - \int_0^t H_s ds, \quad 0 \leq t \leq T,$$

is a Brownian motion on  $(\Omega, \mathcal{F}_T, (\mathcal{F}_t)_{0 \leq t \leq T}, \mathbb{Q})$ , where

$$d\mathbb{Q} = \mathcal{E}(H \cdot B)_T d\mathbb{P} = \exp \left\{ \int_0^T H_s dB_s - \frac{1}{2} \int_0^T H_s^2 ds \right\} d\mathbb{P}.$$

Furthermore  $\mathbb{Q} \sim \mathbb{P}$ .

- ▶ Consider the Black and Scholes model

$$dA_t = rA_t dt, \quad A_0 = 1, \quad \frac{dS_t}{S_t} = \mu dt + \sigma dB_t, \quad S_0 = s_0 > 0.$$

- ▶ We have seen that

$$A_t = e^{rt},$$
$$S_t = s_0 e^{(\mu - \frac{\sigma^2}{2})t + \sigma B_t} \quad t \geq 0.$$

## Girsanov-Transformation

### Black & Scholes Example

- ▶ Itô's formula can be simplified to

$$\begin{aligned}\tilde{S}_t &= e^{-rt} S_t \\ &= s_0 + \int_0^t \partial_t \tilde{S}_s \, ds + \int_0^t \partial_{B_t} \tilde{S}_s \, dB_s + \frac{1}{2} \int_0^t \partial_{B_t}^2 \tilde{S}_s \, ds\end{aligned}$$

because the remaining terms have integrator  $\langle B_s, s \rangle$  and  $\langle s, s \rangle$  which both equal zero.

- ▶ We can then find the derivatives

$$\begin{aligned}\tilde{S}_t &= e^{-rt} s_0 e^{(\mu - \frac{\sigma^2}{2})t + \sigma B_t} \\ \partial_t \tilde{S}_t &= \left\{ \mu - r - \frac{\sigma^2}{2} \right\} \tilde{S}_t \\ \partial_{B_t} \tilde{S}_t &= \sigma \tilde{S}_t \\ \partial_{B_t}^2 \tilde{S}_t &= \sigma^2 \tilde{S}_t\end{aligned}$$

## Girsanov-Transformation

### Black & Scholes Example

Now rewriting

$$\tilde{S}_t = s_0 + \int_0^t \sigma \tilde{S}_s dB_s - \int_0^t (r - \mu) \tilde{S}_s ds \quad (6.1)$$

$$= s_0 + \int_0^t \sigma \tilde{S}_s d\tilde{B}_s, \quad (6.2)$$

where

$$\tilde{B}_t := B_t - \frac{(r - \mu)}{\sigma} t, \quad t \geq 0. \quad (6.3)$$

Which follows from

$$\tilde{S}_t = s_0 + \int_0^t \sigma \tilde{S}_s d\left(B_s - \frac{r - \mu}{\sigma} s\right) \quad (6.4)$$

$$= s_0 + \int_0^t \sigma \tilde{S}_s dB_s - \int_0^t (r - \mu) \tilde{S}_s ds. \quad (6.5)$$

## Girsanov-Transformation

### Black & Scholes Example

Applying Girsanov's Theorem to

$$\tilde{B}_t := B_t - \int_0^t H_s ds, \quad (6.6)$$

where  $H_t := \frac{r-\mu}{\sigma}$  denotes the market price of risk.

## Girsanov-Transformation

### Black & Scholes Example

Note first that, for all  $t \geq 0$

$$\mathbb{E} \left[ \exp \left( \frac{1}{2} \int_0^t H_s^2 ds \right) \right] = \mathbb{E} \left[ \exp \left( \frac{1}{2} \int_0^t \frac{(r - \mu)^2}{\sigma^2} ds \right) \right] < \infty.$$

Novikov's Condition and Girsanov's Theorem imply that the process  $\tilde{B}$  is a Brownian motion w.r.t. to the measure

$$d\mathbb{Q} = \exp \left( \int_0^T \frac{r - \mu}{\sigma} dB_s - \frac{1}{2} \int_0^T \left( \frac{r - \mu}{\sigma} \right)^2 ds \right) d\mathbb{P}. \quad (6.7)$$

This further gives that  $\mathbb{Q}$  is a local martingale measure as the discounted price process is a local martingale w.r.t.  $\mathbb{Q}$

$$\tilde{S}_t = s_0 + \int_0^t \sigma \tilde{S}_s d\tilde{B}_s, \quad (6.8)$$

because the stochastic integral w.r.t. to a Brownian motion are in general local martingales.

### Definition

A probability measure  $\mathbb{Q}$  on  $(\Omega, \mathcal{F}_T)$  is said to be a local martingale measure if the discounted price process  $(\tilde{P}_t)_{0 \leq t \leq T}$  is a  $\mathbb{Q}$  local martingale.

In our case the discounted price process is

$$\tilde{P}_t = \frac{1}{A_t} (A_t, S_t) = (1, \tilde{S}_t).$$

We only need to check that  $\tilde{S}_t$  is a martingale, as 1 is clearly a martingale w.r.t. any probability measure.

### The First Fundamental Theorem of Asset Pricing

The market  $M$  is arbitrage free, if there exists a local martingale measure  $\mathbb{Q}$  that is equivalent to  $\mathbb{P}$ .

Thus we have shown that the Black & Scholes model is arbitrage free.