

# Stochastic Analysis

## Exercise Sheet 4

December 15

## Theorem

Consider a Brownian motion  $(B_t)_{t \in [0,1]}$  with continuous paths. Let  $\mu$  denote the distribution of  $(B_t)_{t \in [0,1]}$  on  $(C[0,1], \mathcal{F})$  (i.e.  $\mu$  is the Wiener measure) and let  $\mu_h$  denote the distribution of  $(B_t + h(t))_{t \in [0,1]}$  for some function  $h \in C[0,1]$ . Then we have:

- 1 If  $h \notin \mathcal{H}$ , then  $\mu_h \perp \mu$ .
- 2 If  $h \in \mathcal{H}$ , then  $\mu_h \approx \mu$ .

Thereby

$$\mathcal{H} := \left\{ h \in C[0,1] : \text{There is } f \in \mathcal{L}^2[0,1] \right. \\ \left. \text{such that } h(t) = \int_0^t f(s) ds, 0 \leq t \leq 1 \right\}$$

denotes the Cameron-Martin space.

Recall:

$$\mu_h \perp \mu,$$

i.e.  $\mu$  and  $\mu_h$  are singular, if there is at least one set  $A \in \mathcal{F}$  such that

$$\mu(A) = 1 \quad \text{and} \quad \mu_h(A^c) = 1.$$

## Remember

*In order to show  $\mu_h \perp \mu$ , it is enough to find **one set** with this total different behaviour under  $\mu_h$  and  $\mu$ .*

Therefore the total mass of the two probability measure lies on the disjoint sets  $A$  and  $A^c$ , i.e. the information of  $\mu$  cannot be used to characterize  $\mu_h$ .

Example: The distributions of  $(B_t)_{t \in [0,1]}$  and  $(B_t + x)_{t \in [0,1]}$  are singular for  $x \neq 0$ .

Recall:

$$\mu_h \approx \mu,$$

i.e.  $\mu$  and  $\mu_h$  are equivalent, if  $\mu \ll \mu_h$  and  $\mu_h \ll \mu$ . Here  $\mu \ll \mu_h$  means that  $\mu$  is absolute continuous with respect to  $\mu_h$ , i.e. we have for all  $A \in \mathcal{F}$

$$\begin{aligned}\mu_h(A) = 0 &\Rightarrow \mu(A) = 0 && \text{and} \\ \mu_h(A) = 1 &\Rightarrow \mu(A) = 1.\end{aligned}$$

## Remember

*$\mu_h \approx \mu$  has the consequence that all sets with probability 0 or 1 have this property under both probability measures  $\mu_h$  and  $\mu$ .*

## Theorem

We have  $\mu \ll \mu_h$  iff there exists a density  $f$  such that

$$\mu(A) = \int_A f(x) d\mu_h(x)$$

for all  $A \in \mathcal{F}$ . We denote this density  $f$  by  $\frac{d\mu}{d\mu_h}$ .

**Proof:** See Theorem 9.8 (Radon-Nikodym Theorem) of Probability Theory!

## For probabilists:

The Cameron-Martin Theorem helps us to characterize the paths of  $(B_t + h(t))_{t \in [0,1]}$  for  $h \in \mathcal{H}$ :

Differentiability:

$$P(B_t + h(t) \text{ is differentiable for some } t_0 \in [0, 1]) = 0$$

Quadratic variation:

$$P(\langle (B_t + h(t))_{t \in [0,1]} \rangle_T = T \text{ for all } T \in [0, 1]) = 1$$

(where  $\langle \cdot \rangle_T$  denotes the quadratic variation in  $T$ )

**(Remark:** This statement about the quadratic variation is a little stronger than Theorem 2.11 from the lecture. The missing part can be proven by using that  $\langle \cdot \rangle_T$  is monotone increasing in  $T$ .)

## **For financial mathematics:**

A short outlook on continuous models in financial mathematics

# Generalized Black-Scholes Model

In financial mathematics the models which are used are often determined by stochastic differential equations. For example in the generalized Black-Scholes Model the following equation appears

$$dX(t) = \alpha(t, \omega)X(t)dt + \beta(t, \omega)X(t)dB(t)$$

where  $(B(t))_{t \in [0,1]}$  is a Brownian motion.

We will see that the solution is given by

$$X(t) = X(0) \exp \left( \int_0^t \beta(s, \omega) dB(s) + \int_0^t (\alpha(s, \omega) - \frac{1}{2}\beta^2(s, \omega)) ds \right)$$

So there is a lot of similarity with our density in Exercise 4.2 (ii).  
Coincidence?



**Answer:** No!

In financial mathematics the search for equivalent (martingale) measures plays a key role. In the generalized Black-Scholes Model there exists a function

$$u(t, \omega)$$

which depends on the parameters  $\alpha(t, \omega), \beta(t, \omega)$  (and the interest rate) of the model. Under some conditions on  $u(t, \omega)$  there exists an equivalent martingale measure  $Q$  which is determined by the density

$$\frac{dQ}{dP}(\omega) = \exp \left( - \int_0^1 u(t, \omega) dB(s) - \frac{1}{2} \int_0^1 u^2(s, \omega) ds \right)$$

(where we consider the time interval  $[0, 1]$  here). Martingale measure means here that the process  $(X(t))_{t \in [0, 1]}$  from the last slide is a martingale with respect to the new measure  $Q$ .

Interesting consequence of the change of measure:

The change of measure eliminates the drift! More precisely, we have for a Brownian motion  $(B_t)_{t \in [0,1]}$  and some function  $h \in \mathcal{H}$  that the Brownian motion  $(\tilde{B}_t)_{t \in [0,1]}$  with drift defined by

$$\tilde{B}_t := B_t + h(t)$$

is a standard Brownian motion (without drift!) with respect to the measure  $P_{-h}$  which is determined by the density

$$\frac{dP_{-h}}{dP} = \exp \left( - \int_0^1 h' dB(s) - \frac{1}{2} \int_0^1 h'(s)^2 ds \right).$$

Remark: We hope to prove this statement at the end of the lecture in the broader setting of the Girsanov Theorem.

**Exercise 4.2:** The mathematical construction behind it!

For any Brownian motion which is constructed on some probability space  $(\Omega, \mathcal{A}, P)$  there exists a set  $A \in \mathcal{A}$  with  $P(A) = 1$  and

$$t \mapsto B_t(\omega)$$

is continuous (in  $t$ ) for  $\omega \in A$ . In particular the mapping  $(\tilde{B}_t)_{t \in [0,1]}$

$$(\tilde{B}_t)_{t \in [0,1]} : (\Omega, \mathcal{A}) \rightarrow (C[0,1], \mathcal{F})$$

$$\omega \mapsto \begin{cases} (B_t(\omega))_{t \in [0,1]} & \text{for } \omega \in A \\ (0)_{t \in [0,1]} & \text{for } \omega \in A^c \end{cases}$$

is well defined and measurable. Note that  $(\tilde{B}_t)_{t \in [0,1]}$  and  $(B_t)_{t \in [0,1]}$  only differ on a set of probability 0!

# The Wiener measure $\mu$ and the measure $\mu_h$

To avoid this technical problem we will assume for the rest of the slides that the mapping

$$t \mapsto B_t(\omega)$$

is continuous for all  $\omega$ ! Then  $(B_t)_{t \in [0,1]}$  really is a random variable with values in  $(C[0,1], \mathcal{F})$  and therefore it induces a probability measure  $\mu$  on  $(C[0,1], \mathcal{F})$  - which is the image measure under  $P$  (cf. Lemma 2.8 in Probability Theory). This measure is called Wiener measure and has the property

$$\mu(A) = P^{(B_t)_{t \in [0,1]}}(A) = P\left(\left(B_t\right)_{t \in [0,1]} \in A\right) \quad \text{for } A \in \mathcal{F}.$$

We can use the same construction to get the distribution  $\mu_h$  of the Brownian motion with drift for  $h \in C[0,1]$ :

$$\mu_h(A) = P^{(B_t+h(t))_{t \in [0,1]}}(A) = P\left(\left(B_t + h(t)\right)_{t \in [0,1]} \in A\right) \quad \text{for } A \in \mathcal{F}.$$

## The measures $\mu_n$ and $\mu_{h,n}$

Recall that  $\mu$  and  $\mu_h$  are measures on  $(C[0, 1], \mathcal{F})$ . We can now consider the following sub- $\sigma$ -fields  $\mathcal{F}_n$  of  $\mathcal{F}$

$$\mathcal{F}_n := \sigma(\{g_t : t \in \mathcal{D}_n\}) \quad \text{where } \mathcal{D}_n := \{j2^{-n} : j = 0, 1, \dots, 2^n\}$$

where by definition

$$\mathcal{F} := \sigma(\{g_t : 0 \leq t \leq 1\}).$$

Then

$$\mu_n := \mu \Big|_{\mathcal{F}_n} \quad \text{and} \quad \mu_{h,n} := \mu_h \Big|_{\mathcal{F}_n}$$

are the restriction of  $\mu_n$  and  $\mu_{h,n}$  to  $\mathcal{F}_n$  in which the sets only depend on finitely many time points  $t \in \{j2^{-n} : j = 0, 1, \dots, 2^n\}$ . More precisely for every  $A \in \mathcal{F}_n$  there exists  $C \in \mathcal{B}(\mathbb{R}^{2^n})$  with

$$A = \left( (g_t)_{t \in \mathcal{D}_n} \right)^{-1} (C).$$

In order to work with  $\mu$  and  $\mu_h$  the following picture might help:

$$\begin{array}{ccc}
 (\Omega, \mathcal{A}) & \longrightarrow & (C[0, 1], \mathcal{F}) \\
 \mathbb{P} & \xrightarrow{(B_t)_{t \in [0,1]}} & \mu \\
 \mathbb{P} & \xrightarrow{(B_t+h(t))_{t \in [0,1]}} & \mu_h
 \end{array}$$

Further we have the following connection of  $\mu_n$  and  $\mu_{h,n}$  with the finite-dimensional marginal distributions:

$$\begin{array}{ccc}
 (C[0, 1], \mathcal{F}_n) & \longrightarrow & (\mathbb{R}^{2^n}, \mathcal{B}(\mathbb{R}^{2^n})) \\
 \mu_n & \xrightarrow{(g_t)_{t \in \mathcal{D}_n}} & \mathbb{P}(B_t)_{t \in \mathcal{D}_n} \\
 \mu_{h,n} & \xrightarrow{(g_t)_{t \in \mathcal{D}_n}} & \mathbb{P}(B_t+h(t))_{t \in \mathcal{D}_n}
 \end{array}$$

Thereby  $\mathcal{F}_n = \left( (g_t)_{t \in \mathcal{D}_n} \right)^{-1} (\mathcal{B}(\mathbb{R}^{2^n}))$ . Further  $\mu$  and  $\mu_h$  are uniquely determined by  $(\mu_n)_{n \in \mathbb{N}}$  and  $(\mu_{h,n})_{n \in \mathbb{N}}$  respectively!