Continuous Time Finance II: Part I

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Chapter 1

Stochastic Processes in Continuous Time

1.1 Stochastic Processes, Stopping Times and Martingales

1.1.1 Basic Notions

We work on a probability space $(\Omega, \mathcal{F}, P)$ with filtration $\{\mathcal{F}_t\}$. Recall that a filtration is a family of σ-fields $\{\mathcal{F}_t,\, t \geq 0\}$ such that $\mathcal{F}_t \subseteq \mathcal{F}_s$ for $s > t$. As usual $\mathcal{F}_t$ is interpreted as the set of events which are observable at time t such that the filtration represents information-flow over time.

A stochastic process $X = (X_t)_{t\geq 0}$ is a family of random variables on $(\Omega, \mathcal{F}, P)$. We introduce the following notions:

- The process X is called *adapted*, if for all $t > 0$ the random variable (rv) X_t is $\mathcal{F}_t$-measurable.
- The *marginal distribution* of the process at a given $t \geq 0$ is the distribution $\mu(t)$ of the rv X_t.
- Consider a finite set of time points $(t_1, ..., t_n)$ in $[0, \infty)$. Then $(X_{t_1}, ..., X_{t_n})$ is a random vector with values in $\mathbb{R}^n$ and distribution $\mu(t_1, ..., t_n)$, say. The class of all such distributions is called the set of finite-dimensional distributions of X. The finite-dimensional distributions satisfy a set of obvious consistency requirements, moreover, they determine the stochastic properties of a stochastic process; see for instance Chapter 2 of Karatzas & Shreve (1988).
- Fix some $\omega \in \Omega$. The mapping

$$X.(\omega)\colon [0, \infty) \to \mathbb{R}, \quad t \to X_t(\omega)$$

  is called *trajectory* or *sample path* of X; a stochastic process can be viewed as random draw of a sample-path. We are only interested in processes whose sample paths have certain regularity properties. Of particular interest will be processes with continuous sample paths like Brownian motion or right continuous with left limits (RCLL) such as the Poisson processes (see below).

Equality of stochastic processes. There are two nations of equality for stochastic processes.

Definition 1.1. Given two stochastic processes X and Y. Then X is called *modification of* Y if for all $t \geq 0$ we have

$$P\big(\{\omega \in \Omega \colon X_t(\omega) = Y_t(\omega)\}\big) = 1.$$

The processes are called *indistinguishable* if

$$P\big(\{\omega \in \Omega \colon X_t(\omega) = Y_t(\omega)\, \forall t > 0\}\big) = 1.$$

We obviously have that if X and Y are indistinguishable then X is a modification of Y. For the converse implication extra regular assumptions on the trajectories are needed.

Lemma 1.2. *Suppose that X and Y have right-continuous trajectories and that X is a modification of Y. Then X and Y are indistinguishable.*

Proof. Put $N_t := \{\omega \in \Omega \colon X_t(\omega \neq Y_t(\omega\}$ and let $N := \bigcup_{q \in \mathbb{Q} \cap [0,\infty)} N_q$. Since $\mathbb{Q}$ is countable and since X is a modification of Y we have $0 = P(N_q) = P(N)$. We want to show that for $\omega \in \Omega \backslash N$ we have $X_t(\omega) = Y_t(\omega)\ \forall t \geq 0$. This is clear for $t \in \mathbb{Q}$. For $t \in \mathbb{R} \backslash \mathbb{Q}$ there is a sequence $q_n \in \mathbb{Q}$ with $q_n \downarrow t$. By definition of N we have $X_{q_n}(\omega) = Y_{q_n}(\omega)$ for all $\omega \in \Omega \backslash N$. Since X and Y have right-continuous trajectories we moreover get

$$X_t(\omega) = \lim_{n \to \infty} X_{q_n}(\omega)) = \lim_{n \to \infty} Y_{q_n}(\omega) = Y_t(\omega),$$

which proves the claim. □

1.1.2 Classes of Processes

1. Martingales: An adapted stochastic process X with $E(|X_t|) < \infty$ for all $t > 0$ is

   - a submartingale if $\forall t, s$ with $t > s$ we have $E(X_t | \mathcal{F}_s) \geq X_s$.
   - a supermartingale if $\forall t, s$ with $t > s$ we have $E(X_t | \mathcal{F}_s) \leq X_s$.
   - a martingale if X is both a sub- and a supermartingale, i.e. if $E(X_t | \mathcal{F}_s) = X_s$ for all t, s.

Important examples for martingales are the Brownian motion and the compensated Poisson process. Both processes will be introduced below.

2. Semimartingales In financial modelling we often encounter processes which are the sum of a completely unpredictable part – modelled by a martingale – and a systematic predictable component such as the long-term growth rate of an asset. If the systematic component of such a process satisfies certain regularity properties these processes are called semimartingales. A formal definition of semimartingales is given in Definition 2.12 below.

3. Markov-Processes: An adapted stochastic process X is called Markov process, if for all $t, s > 0$ and all bounded functions $f \colon \mathbb{R} \to \mathbb{R}$

$$E(f(X_{t+s}) \mid \mathcal{F}_t) = E(f(X_{t+s}) \mid \sigma(X_t)). \tag{1.1}$$

Here $\sigma(X_t)$ denotes the σ-field generated by the rv X_t, a notation which we will use throughout these notes. Intuitively speaking a process is Markovian if the conditional distribution of future values X_{t+s}, $s \geq 0$, of the process is completely determined by the present value X_t of the process; in particular given the value of X_t, past values X_u, $u < t$ of the process do not contain any additional information which is useful for predicting X_{t+s}. There is an obvious link to the efficient market hypothesis: if X models the price fluctuations of some asset the assertion that X is Markovian is equivalent to saying that the market for the asset satisfies the weak form of the efficient market hypothesis; see for instance the survey Malkiel (1987).

Remark 1.3. A Markov process X is called a strong Markov-process, if (1.1) holds for all stopping-times τ and not only for deterministic times t.[1] All Markov-processes we will encounter are also strong Markov processes, but there are a few 'pathological' exceptions.

4. Diffusions: A diffusion is a strong Markov process with continuous trajectories such that for all (t, x) the limits:

$$\mu(t,x) = \lim_{h \to 0} \frac{1}{h} E(X(t+h) - X(t) | X(t) = x) \quad \text{and} \tag{1.2}$$

$$\sigma^2(t,x) = \lim_{h \to 0} \frac{1}{h} E((X(t+h) - X(t))^2 | X(t) = x) \tag{1.3}$$

exist. Then $\mu(t, x)$ is called the drift, $\sigma^2(t, x)$ the diffusion coefficient. The name diffusion stems from applications in physics; the most important mathematical examples are solutions to stochastic differential equations.

5. Point processes and the Poisson process: Assume that certain relevant 'events' – for instance claims in an insurance context or defaults of counterparties in a financial context – occur at random points in time $\tau_0 < \tau_1 < \ldots$. The corresponding point process N_t is then given by $N_t := \sup\{n, \tau_n \leq t\}$, i.e. N_t measures the number of events which have occurred up to time t.

The Poisson process is a special point process. To construct it we take a sequence Y_n of independent exponentially distributed random variables with $P(Y_n \leq x) = 1 - e^{-\lambda x}$ and define $\tau_n := \sum_{j=1}^{n} Y_j$, such that Y_n is the waiting time between event τ_{n-1} and τ_n. The process $N_t = \sup\{n \colon \tau_n \leq t\}$ is then a Poisson process with intensity λ. It has among others the following properties

- $P(N_t = k) = e^{-\lambda t} \frac{(\lambda t)^k}{k!}$, $k = 0, 1, \ldots,\ t \geq 0$.
- $N_{t+u} - N_t$ is independent of N_s for $s \leq t$ and Poisson-distributed with parameter (λu).
- The compensated Poisson process $M_t := N_t - \lambda t$ is a martingale; in particular $E(N_t) = \lambda t$.

1.2 Stopping Times and Martingales

Throughout this section we work on a probability space $(\Omega, \mathcal{F}, P)$ with filtration $\{\mathcal{F}_t\}$.

[1] As in discrete time a random variable τ with values in $[0, \infty]$ will be called a stopping time if for all $t \geq 0$ the set $\{\omega\,, \tau(\omega) \leq t\}$ belongs to the sigma-field $\mathcal{F}_t$; see Section 1.2 below.

1.2.1 Stopping Times

Definition 1.4. A rv $\tau\colon \Omega \to [0,\infty]$ is called *stopping time wrt.* $\{\mathcal{F}_t\}$ if $\forall t \geq 0$ holds that $\{\tau \leq t\} \in \mathcal{F}_t$.

Remark 1.5. τ can be interpreted as the time of the occurence of an observed event. $\{\tau = \infty\}$ means that the event never occurs.

Lemma 1.6. *Let $\{\mathcal{F}_t\}$ be right-continuous, i.e. $\mathcal{F}_t = \bigcap_{\varepsilon>0} \mathcal{F}_{t+\varepsilon}$, for all $t \geq 0$. Then $\tau\colon \Omega \to [0,\infty]$ is a stopping time if and only if $\{\tau < t\} \in \mathcal{F}_t$, $\forall t \geq 0$.*

Proof. It holds $\{\tau \leq t\} = \bigcap_{\varepsilon>0}\{\tau < t+\varepsilon\}$. Let $\{\tau < t\} \in \mathcal{F}_t$, $\forall t \geq 0$. Hence $\{\tau < t+\varepsilon\} \in \mathcal{F}_{t+\varepsilon}$ and $\{\tau \leq t\} \in \bigcap\limits_{\varepsilon>0} \mathcal{F}_{t+\varepsilon} = F_t$. For the converse statement note that

$$\{\tau < t\} = \bigcup_{\varepsilon\in\mathbb{Q}_+} \underbrace{\{\tau \leq t-\varepsilon\}}_{\in\mathcal{F}_{t-\varepsilon}\subseteq\mathcal{F}_t} \in \mathcal{F}_t\,.$$

□

The most important example for stopping times are first hitting times for Borel sets.

Definition 1.7. Given a stochastic process X and a Borel set A in $\mathbb{R}$. Define $\tau_A := \inf\{t \geq 0\colon X_t \in A\}$. Then the rv τ_A is called *first hitting time* into the set A.

Next we address the question when τ_A is a stopping time.

Lemma 1.8. *Let X be $\{\mathcal{F}_t\}$-adapted and right-continuous and let $A \subseteq \mathbb{R}^d$ be open. If the filtration $\{\mathcal{F}_t\}$ is right-continuous, then the hitting time τ_A is a stopping time.*

Proof. Suppose, that $\{\mathcal{F}_t\}$ is right-continuous. We only have to show $\{\tau_A < t\} \in \mathcal{F}_t\, \forall t > 0$. Since X is right-continuous and A is open, it holds that

$$\{\tau_A < t\} = \bigcup_{q\in[0,t)\cup\mathbb{Q}} \{X_q \in A\}\,.$$

As $\{X_q \in A\} \in \mathcal{F}_q \subseteq \mathcal{F}_t$ and as the union of countable sets from $\mathcal{F}_t$ also belongs to $\mathcal{F}_t$, the claim follows. □

Lemma 1.9. *Let X be continuous and $A \subseteq \mathbb{R}$ closed. Then τ_A is a stopping time.*

Proof. Define open sets $A_n \supseteq A$ by $A_n := \{x\colon d(x,A) < 1/n\}$. Since X is continuous and A is closed, it holds that

$$\{\omega\colon \tau_A(\omega) \leq t\} = \{\omega\colon \exists s \in [0,t],\, X_s(\omega) \in A\} = \{\omega\colon \forall n \in \mathbb{N}\ \exists s \in [0,t] \text{ with } X_s(\omega) \in A_n\}.$$

As all A_n are open, the last set equals

$$\{\omega\colon \forall n \in \mathbb{N} \exists q \in \mathbb{Q} \cap [0,t], X_q(\omega) \in A_n\} = \bigcap_{n\in\mathbb{N}} \bigcup_{q\in\mathbb{Q}\cap[0,t]} \underbrace{\{\omega\colon X_q(\omega) \in A_n\}}_{\in\mathcal{F}_q\subseteq\mathcal{F}_t}.$$

The right-hand side consists of countably many operations on sets from $\mathcal{F}_t$, hence it belongs to $\mathcal{F}_t$. □

The sigma-field $\mathcal{F}_\tau$. Next, we define the σ-field generated by all observable events up to a stopping time τ.

Definition 1.10. Given a stopping time τ. Then we call

$$\mathcal{F}_\tau := \big\{A \in \mathcal{F} \colon A \cap \{\tau \le t\} \in \mathcal{F}_t \, \forall t \ge 0\big\} \tag{1.4}$$

the σ-field of the events which are observable up to τ.

$\mathcal{F}_\tau$ is indeed a σ-field as is easily checked; a more intuitive characterization of $\mathcal{F}_\tau$ will be given in Lemma 1.16 below. It is easily seen that the rv $\omega \to \tau(\omega)$ is $\mathcal{F}_\tau$-measurable: For all $t_0 \ge 0$ we have

$$\{\tau \le t_0\} \cap \{\tau \le t\} = \{\tau \le (t_0 \wedge t)\} \in \mathcal{F}_{t_0 \wedge t} \subseteq \mathcal{F}_t \,.$$

Let S and T be stopping times, where $S \le T$. Intuitively, we can say, that if event A is observable up to time S, then event A is also observable up to T, so that one would expect the inclusion $\mathcal{F}_S \subseteq \mathcal{F}_T$. This is in true.

Lemma 1.11. *Given two stopping times S and T with $S \le T$. Then $\mathcal{F}_S \subseteq \mathcal{F}_T$.*

Proof. Since $S \le T$, it holds $\{T \le t\} \subseteq \{S \le t\}$. Using this we have for $A \in \mathcal{F}_S$:

$$A \cap \{T \le t\} = \underbrace{A \cap \{S \le t\}}_{\in \mathcal{F}_t, \text{ as } A \in \mathcal{F}_S} \;\cap\; \underbrace{\{T \le t\}}_{\substack{\in \mathcal{F}_t, \text{ as } T \\ \text{stopping time}}} \,,$$

and hence, $A \in \mathcal{F}_T$. □

Lemma 1.12. *Given two stopping times S and T. Then*

i) $S \wedge T := \min\{S, T\}$ *is a stopping time.*

ii) $S \vee T := \max\{S, T\}$ *is a stopping time.*

iii) $\mathcal{F}_{S \wedge T} = \mathcal{F}_S \cap \mathcal{F}_T$.

Proof. We have $\{S \wedge T \le t\} = \{S \le t\} \cup \{T \le t\}$, $\{S \vee T \le t\} = \{S \le t\} \cap \{T \le t\}$. As S and T stopping times, that means $\{S \le t\} \in \mathcal{F}_t$ and $\{T \le t\} \in \mathcal{F}_t$, claims i) and ii) are proved.
iii) is proved as follows. From Lemma 1.11 we see, that, $\mathcal{F}_{S \wedge T} \subseteq \mathcal{F}_S$ and $\mathcal{F}_{S \wedge T} \subseteq \mathcal{F}_T$, hence $\mathcal{F}_{S \wedge T} \subseteq \mathcal{F}_S \cap \mathcal{F}_t$. Now, let $A \in \mathcal{F}_S \cap \mathcal{F}_T$. As S and T stopping times we have $A \cap \{S \le t\} \in \mathcal{F}_t$ and $A \cap \{T \le t\} \in \mathcal{F}_t$. It holds

$$(A \cap \{S \le t\}) \cup (A \cap \{T \le t\}) = A \cap (\{S \le t\} \cup \{T \le t\}) = A \cap \{S \wedge T \le t\} \in \mathcal{F}_t,$$

and hence $A \in \mathcal{F}_{S \wedge T}$. □

Let $(X_t)_{t \ge 0}$ be a right-continuous stochastic process und let T be a stopping time. We define the stopped rv X_T by

$$X_T(\omega) := X_{T(\omega)}(\omega) \cdot 1_{\{T < \infty\}}(\omega), \quad \omega \in \Omega. \tag{1.5}$$

Lemma 1.13. *Let $(X_t)_{t\geq 0}$ be an $\{\mathcal{F}_t\}$-adapted and right-continuous stochastic process and let T be a stopping time. Then the rv X_T is $\mathcal{F}_T$-measurable.*

For a proof we refer to Protter (1992) or to Karatzas & Shreve (1988).

Definition 1.14. Given a right-continuous stochastic process $(X_t)_{t\geq 0}$ and a stopping time T. Then the *in T stopped process* $X^T = (X_t^T)_{t\geq 0}$ is defined by

$$X_t^T(\omega) := X_{t\wedge T(\omega)}(\omega) = \begin{cases} X_{T(\omega)}(\omega), & T(\omega) \leq t. \\ X_t(\omega), & T(\omega) > t. \end{cases} \tag{1.6}$$

Lemma 1.15. *If X is adapted and right-continuous, then the stopped process X^T is adapted.*

Proof. We have $X_t^T = X_t \cdot 1_{\{t<T\}} + X_T \cdot 1_{\{t\geq T\}}$. The first summand is $\mathcal{F}_t$-measurable, since it is a product consisting of two $\mathcal{F}_t$-measurable rvs. For the second summand we conclude as follows. $X_T \cdot 1_{\{t\geq T\}} = X_{T\wedge t} \cdot 1_{\{t\geq T\}}$. The rv $X_{T\wedge t}$ is $\mathcal{F}_{T\wedge t}$-measurable and $\mathcal{F}_{T\wedge t} \subseteq \mathcal{F}_t$. The rv $1_{\{t\geq T\}}$ is $\mathcal{F}_t$-measurable, as T is a stopping time. □

Finally we give a more intuitive interpretation of $\mathcal{F}_T$, which legitimates the description "σ-field of the observable events up to time T".

Lemma 1.16. *Let T be a stopping time. If $P(T < \infty) = 1$, then $\mathcal{F}_T = \sigma(X^T,\ X$ adapted and cadlag$)$.*

Proof. Let X be adapted and cadlag. Then the rv $X_t^T = X_{T\wedge t}$ is $\mathcal{F}_{T\wedge t}$-measurable. Since $\mathcal{F}_{T\wedge t} \subseteq \mathcal{F}_T$ the rv X_t^T is also $\mathcal{F}_T$-measurable, hence $\mathcal{F}_T \supseteq \sigma(X^T,\ X$ adapted and cadlag$)$. Now, let $A \in \mathcal{F}_T$ and define a stochastic process $X = (X_t)_{t\geq 0}$ by $X_t(\omega) = 1_A(\omega) \cdot 1_{\{T\leq t\}}(\omega)$. The process X is cadlag. It holds $\{X_t = 1\} = A \cap \{T \leq t\} \in \mathcal{F}_t$, hence X is adapted. Moreover we have $A = \bigcup_n \{X_n(\omega) = 1\}$, since T is finite. Hence, $A \in \sigma(X^T,\ X$ adapted and cadlag$)$. □

1.2.2 The optional sampling theorem

The following results gives a crucial link between stopping times and martingales.

Theorem 1.17 (Optional sampling theorem)**.** *Consider an adapted stochastic process $X = (X_t)_{t\geq 0}$ with $E(|X_t|) < \infty$, $t \geq 0$. Then the following statements are equivalent.*

(1) X is a martingale.

(2) For all bounded stopping times τ ($\tau(\omega) \leq C$ for some $C > 0$, all $\omega \in \Omega$) one has $E(X_\tau) = E(X_0)$.

(3) Given two stopping times S and T such that $S \leq T \leq C$ for some $C > 0$. Then $E(X_T \,|\, \mathcal{F}_S) = X_S$.

We omit the proof; see for instance Protter (1992), Section I.2.

Corollary 1.18. *Let X be a martingale with right-continuous trajectories and let τ be a stopping time. Then the stopped process X^τ with $X_t^\tau = X_{t\wedge\tau}$ is also a martingale.*

See again Protter (1992), Section I.2 for a proof.

Corollary 1.19 (Martingale inequality)**.** *Let X be a right-continuous martingale such that $X_t > 0$ a.s. Then we have for $C > 0$*

$$P\left(\sup_{t\geq 0} X_t > C\right) \leq \frac{1}{C}E(X_T).$$

Proof. Put $T_C := \inf\{t \geq 0 \colon X_t > C\}$. Since $X_t > 0$, we have for an arbitrary $n \in \mathbb{N}$

$$P\left(\sup_{0\leq t\leq n} X_t > C\right) \leq E\left(\frac{1}{C}X_{T_C\wedge n}\right) = \frac{1}{C}E(X_0),$$

where the last equality is due to Theorem 1.17, (2). For $n \to \infty$ we obtain the result by monotone convergence. □

1.3 Brownian Motion

Brownian motion is the most important building block for continuous-time asset pricing models. It has a long history in the modelling of random events in science.

Around 1830 R. Brown, a Scottish botanist, discovered that molecules of water in a suspension perform an erratic movement under the buffeting of other water molecules. While Brown's research had no relation to mathematics this observation gave Brownian motion its name. In 1900 Bachelier introduced Brownian motion as model for stock-prices; see Bachelier (1900). In 1905 Einstein proposed Brownian motion as a mathematical model to describe the movement of particles in suspension. The first rigorous theory of Brownian motion is due to N. Wiener (1923); therefore Brownian motion is often referred to as Wiener process.

1.3.1 Definition and Construction

Definition 1.20. A stochastic process $X = (X_t)_{t\geq 0}$ on $(\Omega, \mathcal{F}, P)$ is standard one-dimensional *Brownian motion*, if

(i) $X_0 = 0$ a.s.

(ii) X has independent increments: for all $t, u \geq 0$ the increment $X_{t+u} - X_t$ is independent of X_s for all $s \leq t$.

(iii) X has stationary, normally distributed increments: $X_{t+u} - X_t \sim N(0, u)$.

(iv) X has continuous sample paths.

In honor of Brown and Wiener Brownian motion is often denoted by $(B_t)_{t\geq 0}$ or by $(W_t)_{t\geq 0}$.

Definition 1.21. Standard Brownian motion in $\mathbb{R}^d$ is a d-dimensional process $W_t = (W_t^1, ..., W_t^d)$ where $W^1, ..., W^d$ are d independent standard Brownian motions in $\mathbb{R}^1$.

Definition 1.20 has some elementary consequences:

(i) $W_t = W_t - W_0$ is $N(0, t)$-distributed.

(ii) Let $t > s$. Then the covariance of W_t and W_s is given by $\text{cov}(W_t, W_s) = E[W_t W_s] = E[(W_t - W_s)W_s] + E[W_s^2] = E[W_t - W_s]E[W_s] + s = s$.

(iii) The finite-dimensional distributions of W are multivariate normal distributions with mean 0 and covariance matrix given in (ii).

Theorem 1.22. *A stochastic process with the properties of Definition 1.20 exists.*

Remarks: 1) There are various methods to construct Brownian motion and hence to prove Theorem 1.22, which are also useful for simulating Brownian sample paths; see for instance Karatzas & Shreve (1988).

2) Theorem 1.22 is more than a mere exercise in mathematical rigour: if we replace the normal distribution in Definition 1.20 (iii) by a fat-tailed α-stable distribution, the corresponding process – referred to as α-stable motion – necessarily has discontinuous trajectories; see for instance Section 2.4 of Embrechts, Klüppelberg & Mikosch (1997) for details.

1.3.2 Some stochastic properties of Brownian motion:

Proposition 1.23. *Let W_t be standard Brownian motion and define $\mathcal{F}_t := \sigma(W_s, s \leq t)$. Then a) $(W_t)_{t\geq 0}$ b) $(W_t^2 - t)_{t\geq 0}$ and c) $\exp(\sigma W_t - 1/2\sigma^2 t)$ are martingales with respect to the filtration $\{\mathcal{F}_t\}$.*

Proof. We start with claim a). Let $t > s$; by point (ii) of Definition 1.20 the increment $W_t - W_s$ is independent of $\mathcal{F}_s$. Hence we get

$$E[W_t|\mathcal{F}_s] = E[W_t - W_s + W_s|\mathcal{F}_s] = E[W_t - W_s] + W_s = W_s\,.$$

To prove claim b) we first show that $E[W_t^2 - W_s^2|\mathcal{F}_s] = E[(W_t - W_s)^2|\mathcal{F}_s]$. We have

$$\begin{aligned} E[(W_t - W_s)^2|\mathcal{F}_s] &= E[W_t^2 - 2W_tW_s + W_s^2|\mathcal{F}_s] = E[W_t^2|\mathcal{F}_s] - 2W_sE[W_t|\mathcal{F}_s] + W_s^2 \\ &= E[W_t^2|\mathcal{F}_s] - 2W_s^2 + W_s^2 = E[W_t^2 - W_s^2|\mathcal{F}_s]. \end{aligned}$$

The claim is proved if we can show that $E[W_t^2 - W_s^2|\mathcal{F}_s] = (t - s)$. By the first step of the proof this is equivalent to $E\left[(W_t - W_s)^2|\mathcal{F}_s\right] = (t - s)$. Now $W_t - W_s$ is independent of $\mathcal{F}_s$; hence $E[(W_t - W_s)^2|\mathcal{F}_s] = E[(W_t - W_s)^2] = t - s$, as $W_t - W_s \sim N(0, t - s)$.

Sketch of c) (Bitte ausarbeiten !!!) $G_t = e^{(W_t - W_s - \frac{1}{2}(t-s))}$, then $E[G_t] = G_s E[e^{(W_t - W_s - \frac{1}{2}(t-s))}]$ and $E[G_t|\mathcal{F}_s] = G_s E[e^{(W_t - W_s - \frac{1}{2}(t-s))}|\mathcal{F}_s] = G_s E[e^{(W_t - W_s - \frac{1}{2}(t-s))}] = G_s$ (properties of t the lognormal distribution). □

1.3.3 Quadratic Variation

Fix some point in time $\overline{T}$, which represents the time-point where our model ends. To define first and quadratic variation we need the notion of a partition of the interval $[0, \overline{T}]$.

Definition 1.24. A *partition* τ of $[0, \overline{T}]$ is a set of time-points $t_0 = 0 < t_1 < \ldots < t_n = \overline{T}$. The *mesh* of this partition is given by $|\tau| := \sup_{1\leq i\leq n} |t_i - t_{i-1}|$.

Definition 1.25 (First Variation). Consider a function $X : [0, \overline{T}] \to \mathbb{R}$. The first variation of X on $[0, \overline{T}]$ is defined as

$$\mathrm{Var}(X) := \sup \left\{ \sum_{t_i \in \tau} |X(t_i) - X(t_{i-1})| \,,\ \tau \text{ a partition of } [0, \overline{T}] \right\} \in [0,\, \infty] \,. \tag{1.7}$$

If $\mathrm{Var}(X) < \infty$ X is said to be of finite variation.

Remarks on notation: 1) Following standard conventions we denote by $\mathrm{Var}(f)$ the first variation of a function f, whereas $\mathrm{var}(Y)$ stands for the variance of a random variable Y.

2) Whenever a summation formula such as (1.7) contains the index t_{-1} it is understood that the corresponding summand is equal to zero.

Definition 1.26 (Quadratic Variation). Consider again a function $X : [0, \overline{T}] \to \mathbb{R}$ and a sequence τ_n of partitions of $[0, \overline{T}]$ such that $|\tau_n| \to 0$ as $n \to \infty$. Define for $t \in [0, \overline{T}]$ the quadratic variation of X along the partition τ_n by

$$V_t^2(X; \tau_n) := \sum_{t_i \in \tau_n;\, t_i < t} (X(t_i) - X(t_{i-1}))^2 \,.$$

Assume that for all $t \in [0, \overline{T}]$ the limit $\langle X \rangle_t := \lim_{n\to\infty} V_t^2(X; \tau_n)$ exists and that the function $t \to \langle X \rangle_t$ is continuous. In that case X is said to admit the continuous quadratic variation $\langle X \rangle_t$.

In principle $\langle X \rangle_t$ might depend on the sequence τ_n. However, we are mainly interested in the case where X is a sample path of a continuous semimartingale such as Brownian motion. It can be shown that in this case $\langle X \rangle_t$ is independent of the sequence of partitions used in its definition. Obviously $\langle X \rangle_t$ is increasing in t and hence in particular of finite variation.

We now discuss the relation between first and quadratic variation.

Proposition 1.27. *If $X : [0, \overline{T}] \to \mathbb{R}$ is continuous and of finite variation its quadratic variation $\langle X \rangle_t$ is zero.*

By negating this result we have

Corollary 1.28. *If X is continuous and if the function $t \to \langle X \rangle_t$ is strictly increasing, X is of infinite first variation on every subinterval $[a, b]$ of $[0, \overline{T}]$.*

Proof. (of Proposition 1.27) Choose a sequence of partitions τ_n of $[0, \overline{T}]$ such that $\lim_{n\to\infty} |\tau_n| = 0$. Then

$$\begin{aligned} \sum_{t_i \in \tau_n;\, t_i \le t} (X(t_i) - X(t_{i-1}))^2 &\le \sup_{t_i \in \tau_n} |X(t_i) - X(t_{i-1})| \sum_{t_i \in \tau_n} |X(t_i) - X(t_{i-1})| \\ &\le \sup_{t_i \in \tau_n} |X(t_i) - X(t_{i-1})| \, \mathrm{Var}(X). \end{aligned} \tag{1.8}$$

Now note that $\mathrm{Var}(X) < \infty$ and that $\sup_{t_i \in \tau_n} |X(t_i) - X(t_{i-1})| \to 0$ for $n \to \infty$ as X is continuous and as $\lim_{n\to\infty} |\tau_n| = 0$. Hence the right side of (1.8) converges to zero which proves the proposition. □

The following result allows us to conclude that the quadratic variation of the sample paths of a continuous semimartingale is determined by the quadratic variation of its martingale part.

Proposition 1.29. *Assume that X is continuous with continuous quadratic variation $\langle X\rangle_t$ and consider a continuous function $A : [0,\overline{T}] \to \mathbb{R}$ which is of finite first variation. Then $Y(t) = X(t) + A(t)$ is of continuous quadratic variation and we have $\langle Y\rangle_t = \langle X\rangle_t$.*

Proof. We have

$$\begin{aligned}\sum_{t_i\in\tau_n;\, t_i\le t} (Y_{t_i} - Y_{t_{i-1}})^2 &= \sum_{t_i\in\tau_n;\, t_i\le t} (X_{t_i} - X_{t_{i-1}})^2 + \sum_{t_i\in\tau_n;\, t_i\le t} (A_{t_i} - A_{t_{i-1}})^2 \\ &+ 2\sum_{t_i\in\tau_n;\, t_i\le t} (X_{t_i} - X_{t_{i-1}})(A_{t_i} - A_{t_{i-1}})\end{aligned}$$

Now $\sum_{t_i\in\tau_n;\, t_i\le t}(X_{t_i} - X_{t_{i-1}})^2$ converges to $\langle X\rangle_t$ by assumption and $\sum_{t_i\in\tau_n}(A_{t_i} - A_{t_{i-1}})^2$ converges to zero as A is continuous and of finite variation. The last term can be estimated as follows:

$$\sum_{t_i\in\tau_n;\, t_i\le t} (X_{t_i} - X_{t_{i-1}})(A_{t_i} - A_{t_{i-1}}) \le \sup_{t_{i-1}\in\tau_n} |X_{t_i} - X_{t_{i-1}}|\mathrm{Var}(A),$$

which converges to zero as X is continuous. □

Now we deal with quadratic variation of the sample paths $B_\cdot(\omega)$ of Brownian motion. Roughly speaking, for (almost) all $\omega \in \Omega$ we have $\langle B_\cdot(\omega)\rangle_t = t$. The following theorem makes this relation precise.

Theorem 1.30. *Consider a sequence of partitions τ_n of $[0,\overline{T}]$ such that $\lim_{n\to\infty} |\tau_n| = 0$. Then we have for all $t \in [0,\overline{T}]$ that $E\left(V_t^2(B_\cdot(\omega);\tau_n) - t\right)^2 \to 0$ as $n \to \infty$.*

Proof. For a fixed partition τ_n we have

$$\begin{aligned}E\left(\sum_{t_i\in\tau_n, t_i<t} (B_{t_i} - B_{t_{i-1}})^2 - t\right)^2 &= E\left(\sum_{t_i\in\tau_n, t_i<t} (B_{t_i} - B_{t_{i-1}})^2 - (t_i - t_{i-1})\right)^2 \\ &= \sum_{t_i\in\tau_n, t_i<t} E\left((B_{t_i} - B_{t_{i-1}})^2 - (t_i - t_{i-1})\right)^2,\end{aligned}$$

as $(B_{t_i} - B_{t_{i-1}})$ and $(B_{t_j} - B_{t_{j-1}})$ are independent for $i \neq j$. Now note that

$$E\left((B_{t_i} - B_{t_{i-1}})^2 - (t_i - t_{i_1})\right)^2 = \mathrm{var}\left((B_{t_i} - B_{t_{i-1}})^2\right).$$

It is well known that for a $N(\mu,\sigma^2)$-distributed rv ζ we have $\mathrm{var}(\zeta^2) = 2\sigma^4$. Hence $\mathrm{var}(B_{t_i} - B_{t_{i-1}})^2 = 2(t_i - t_{i-1})^2$, and we get

$$E\left(\sum_{t_i\in\tau_n, t_i<t} (B_{t_i} - B_{t_{i-1}})^2 - t\right)^2 = 2\sum_{t_i\in\tau_n, t_i<t} (t_i - t_{i-1})^2 \le |\tau_n| t \to 0,$$

which proves the theorem. □

The type of convergence in Theorem 1.30 is known as $\mathcal{L}^2$-convergence. It implies in particular that $V_t^2(B_\cdot(\omega);\tau_n)$ converges to t in probability as $n \to \infty$. By exploiting the fact that every sequence of random variables which converges in probability has a subsequence which converges almost surely we obtain the following

Corollary 1.31. *There exists a sequence τ_n of partitions of $[0,\overline{T}]$ with $\lim_{n\to\infty}|\tau_n| = 0$ such that almost surely $V_t^2(B_\cdot(\omega);\tau_n) \to t$ for every $t \in [0,\overline{T}]$.*

This corollary is important as it shows that the pathwise Itô-calculus developed in Section 2 applies to sample paths of Brownian motion.

Combining Theorem 1.30 and Corollary 1.28 yields another surprising property of Brownian sample paths.

Corollary 1.32. *Sample paths of Brownian motion are of infinite first variation.*

Remark 1.33. The sample paths of Brownian motion have many surprising properties. We refer the reader to Karatzas & Shreve (1988) and in particular to Revuz & Yor (1994) for further information.

We have seen that Brownian motion is a martingale with continuous trajectories and quadratic variation $\langle B_\cdot(\omega)\rangle_t = t$. The following theorem, which is usually referred to as Levy's characterization of Brownian motion, establishes the converse:

Theorem 1.34. *If M is a martingale with continuous trajectories such that $M_0 = 0$ and $\langle M\rangle_t = t\ \forall t$ then M is Brownian motion.*

Chapter 2

Pathwise Itô-Calculus

Motivation. Consider a function $f : \mathbb{R} \to \mathbb{R}$ which is once continuously differentiable (abbreviated f is a $\mathcal{C}^1$-function) with derivative f' and a $\mathcal{C}^1$-function $X : \mathbb{R}^+ \to \mathbb{R}$ with derivative $\dot{X} := \frac{\partial}{\partial t} X(t)$. The fundamental theorem of calculus yields

$$f(X(t)) - f(X(0)) = \int_0^t f'(X(s))\dot{X}(s)ds =: \int_0^t f'(X_s)dX_s. \tag{2.1}$$

A similar expression for the difference $f(X_t) - f(X_0)$ can be given if X is not $\mathcal{C}^1$ but only continuous and of finite variation:

Proposition 2.1. *Consider a continuous function $X : [0, \overline{T}] \to \mathbb{R}$ which is of finite variation and a $\mathcal{C}^1$-function $f : \mathbb{R} \to \mathbb{R}$ with derivative f'. Let τ_n denote a sequence of partitions of $[0, \overline{T}]$ with $\lim_{n\to\infty} |\tau_n| = 0$. Then we have that*

$$\lim_{n\to\infty} \sum_{t_i \in \tau_n, t_i \leq t} f'(X_{t_{i-1}})(X_{t_i} - X_{t_{i-1}}) =: \int_0^t f'(X_s)dX_s \tag{2.2}$$

exists. Moreover, we have the change of variable rule

$$f(X_t) = f(X_0) + \int_0^t f'(X_s)dX_s. \tag{2.3}$$

Proposition 2.1 is a special case of Itô's formula (Theorem 2.2 below), hence we omit the proof.

2.1 Itô's formula

In this section we derive the Itô-formula – in financial texts often referred to as Itô's Lemma – which extends the chain-rule (2.3) to functions with infinite first but finite quadratic variation. Our exposition is based on the so-called pathwise Itô-calculus developed by Föllmer (1981); this approach allows us to give an elementary and relatively simple derivation of most results from stochastic calculus which are needed for the Black-Scholes option pricing model without having to develop the full theory of stochastic integration.

Throughout this section we consider a continuous function $X : [0, \overline{T}] \to \mathbb{R}$ which admits a continuous quadratic variation $\langle X \rangle_t$ in the sense of Definition 1.26. As shown in Corollary 1.31 this is true for paths of Brownian motion. More generally, it can be shown

that the sample paths of every continuous semimartingale admit a continuous quadratic variation.

As $\langle X\rangle_t$ is increasing in t, the integral $\int_0^t g(s)d\langle X\rangle_s$ is defined for every continuous function $g : [0,\overline{T}] \to \mathbb{R}$ in the ordinary 'Riemann-sense'; as $\langle X\rangle_t$ is continuous this integral is moreover a continuous function of the upper bound t. Now we can state

Theorem 2.2 (Itô's formula)**.** *Given a continuous function $X : [0,T] \to \mathbb{R}$ with continuous quadratic variation $\langle X\rangle_t$. Let $F : \mathbb{R} \to \mathbb{R}$ denote a twice continuously differentiable function. Then we have for $t \leq \overline{T}$*

$$F(X_t) = F(X_0) + \int_0^t F'(X_s)dX_s + \frac{1}{2}\int_0^t F''(X_s)d\langle X\rangle_s \tag{2.4}$$

where

$$\int_0^t F'(X_s)dX_s := \lim_{n\to\infty} \sum_{t_i\in\tau_n;\, t_i\leq t} F'(X_{t_{i-1}})(X_{t_i} - X_{t_{i-1}}). \tag{2.5}$$

Remarks: 1) The existence of the limit in (2.5) is shown in the proof of the theorem. The integral $\int_0^t F'(X_s)dX_s$ is called Itô-integral; it is a continuous function of the upper boundary t as is immediately apparent from (2.4).

2) The classical case of Proposition 2.1, where X is of finite variation is a special case of Theorem 2.2. If $\langle X\rangle_t$ is non-zero the additional 'correction-term' $\frac{1}{2}\int_0^t F''(X_s)d\langle X\rangle_s$ enters our formula for the differential $F(X_t) - F(X_0)$. We will see that this term is of crucial importance for most results in continuous-time finance.

3) Note that the sums used in defining the Itô-integral are non-anticipating, i.e. the integrand $F'(X_s)$ is evaluated at the left boundary of the interval $[t_{i-1}, t_i]$; we will see in Section 3.2 below that this makes the Itô-integral the right tool for the modeling of gains from trade.

4) Often formula (2.4) is expressed in the following short-hand notation: $dF(X_t) = F'(X_t)dX_t + \frac{1}{2}F''(X_t)d\langle X\rangle_t$.

5) It is possible to give extensions of this theorem to the case where X has discontinuous sample paths; see for instance Chapter II.7 of Protter (1992).

Proof. As a first step we establish the following

Lemma 2.3. *For every piecewise continuous function $g : [0,T] \to \mathbb{R}$ we have*

$$\lim_{n\to\infty} \sum_{t_i\in\tau_n;\, t_i\leq t} g(t_{i-1})(X_{t_i} - X_{t_{i-1}})^2 = \int_0^t g(s)d\langle X\rangle_s. \tag{2.6}$$

Proof of the Lemma. Recall the definition of $V_t^2(X;\tau_n)$ in Definition 1.26. For indicator functions of the form $g(t) = 1_{(a,b]}(t)$ the convergence in (2.6) translates as

$$\lim_{n\to\infty} \left(V_b^2(X;\tau_n) - V_a^2(X;\tau_n)\right) = \langle X\rangle_b - \langle X\rangle_a\,,$$

which is satisfied by definition, as X admits the continuous quadratic variation $\langle X\rangle_t$. For a general piecewise continuous function g the claim of the Lemma follows if we approximate g by piecewise constant functions.

Now we turn to the theorem itself. Consider $t_i, t_{i-1} \in \tau_n$, such that $t_i \leq t$ and denote by $(\Delta X)_{i,n}$ the increment $X_{t_i} - X_{t_{i-1}}$. We get from a Taylor-expansion of F

$$\begin{aligned} F(X_{t_i}) - F(X_{t_{i-1}}) &= F'(X_{t_{i-1}})(\Delta X)_{i,n} + \frac{1}{2}F''(X_{\tilde{t}})(\Delta X)^2_{i,n} \\ &= F'(X_{t_{i-1}})(\Delta X)_{i,n} + \frac{1}{2}F''(X_{t_{i-1}})(\Delta X)^2_{i,n} + R_{i,n}\,, \end{aligned}$$

where $\tilde{t}$ is some point in the interval (t_{i-1}, t_i), and where $R_{i,n} := \frac{1}{2}(F''(X_{\tilde{t}}) - F''(X_{t_{i-1}}))(\Delta X)^2_{i,n}$. Define $\delta_n := \max\{|X_t - X_{t_{i-1}}|\,, t \in [t_{i-1}, t_i], t_i \in \tau_n\}$. As X is continuous and as $|\tau_n| \to 0$ for $n \to \infty$ we have $\delta_n \to 0,\ n \to \infty$. Moreover,

$$|R_{i,n}| \leq \left(\frac{1}{2} \max_{|x-y|<\delta_n} |F''(x) - F''(y)|\right)(\Delta X)^2_{i,n} =: \varepsilon_n (\Delta X)^2_{i,n}\,.$$

Now $\varepsilon_n \to 0$, for $n \to \infty$ as F'' is uniformly continuous and as $\delta_n \to 0$. Hence

$$\left|\sum_{t_i \in \tau_n} R_{i,n}\right| \leq \sum_{t_i \in \tau_n} |R_{i,n}| \leq \varepsilon_n \sum (\Delta X)^2_{i,n} \to 0 \text{ as } n \to \infty\,,$$

as X admits the continuous quadratic variation $\langle X \rangle_t$. Now

$$\begin{aligned} F(X_t) - F(X_0) &= \lim_{n\to\infty} \sum_{t_i \in \tau_n;\, t_i \leq t} F(X_{t_i}) - F(X_{t_{i-1}}) \\ &= \lim_{n\to\infty} \sum_{t_i \in \tau_n;\, t_i \leq t} F'(X_{t_{i-1}})(\Delta X)_{i,n} + \frac{1}{2} \sum_{t_i \in \tau_n;\, t_i \leq t} F''(X_{t_{i-1}})(\Delta X)^2_{i,n} + \sum_{t_i \in \tau_n;\, t_i \leq t} R_{i,n}\,. \end{aligned}$$

We have just shown that the sum over the $R_{i,n}$ tends to zero. Moreover, by Lemma 2.3 $\sum_{t_i \in \tau_n;\, t_i \leq t} F''(X_{t_{i-1}})(\Delta X)^2_{i,n}$ converges to $\int_0^t F''(X_s) d\langle X \rangle_s$. Hence the limit

$$\int_0^t F'(X_s) dX_s := \lim_{n\to\infty} \sum_{t_i \in \tau_n;\, t_i \leq t} F'(X_{t_{i-1}})(X_{t_i} - X_{t_{i-1}})$$

exists, and we obtain the Itô-formula (2.4). □

Some Examples:

1) Take $F(x) = x^n$. Applying the Itô-formula yields

$$X_t^n = X_0^n + n \int_0^t X_s^{n-1} dX_s + \frac{n(n-1)}{2} \int_0^t X_s^{n-2} d\langle X \rangle_s\,.$$

In short notation this can be written as $dX_t^n = nX_t^{n-1} dX_t + \frac{n(n-1)}{2} X_t^{n-2} d\langle X \rangle_t$. In the special case where X is a sample path of a Brownian motion B with $B_0 = 0$ we obtain

$$B_t^2 = 2 \int_0^t B_s dB_s + \int_0^t d\langle B \rangle_s = 2 \int_0^t B_s dB_s + t$$

2) Take $F(x) = e^x$. We get $e^{X_t} = e^{X_0} + \int_0^t e^{X_s} dX_s + \frac{1}{2} \int_0^t e^{X_s} d\langle X \rangle_s$, or in short notation $de^{X_t} = e^{X_t} dX_t + \frac{1}{2} e^{X_t} d\langle X \rangle_t$.

2.2 Properties of the Itô-Integral

2.2.1 Quadratic Variation

Throughout this section we consider a continuous function $X(t)$ with continuous quadratic variation $\langle X\rangle_t$.

Proposition 2.4. *Let $F \in \mathcal{C}^1(\mathbb{R})$; then the function $t \to F(X_t)$ has quadratic variation $\int_0^t (F'(X_s))^2\, d\langle X\rangle_s$.*

Corollary 2.5. *For $f \in \mathcal{C}^1(\mathbb{R})$ the Itô-integral $I_t := \int_0^t f(X_s)dX_s$ is well-defined; its quadratic variation equals $\langle I\rangle_t = \int_0^t f^2(X_s)d\langle X\rangle_s$.*

Proof. Denote by τ_n a sequence of partitions of $[0,\overline{T}]$ with $|\tau_n| \to 0$. Then

$$\begin{aligned}\sum_{t_i\in\tau_n;\, t_i\le t} \big(F(X_{t_i}) - F(X_{t_{i-1}})\big)^2 &= \sum_{t_i\in\tau_n;\, t_i\le t} \big(F'(X_{\tilde{t}_i})(\Delta X)_{i,n}\big)^2,\ \tilde{t}_i \in (t_{i-1}, t_i)\\ &= \sum_{t_i\in\tau_n;\, t_i\le t} F'(X_{t_{i-1}})^2(\Delta X)_{i,n}^2 + \sum_{t_i\in\tau_n;\, t_i\le t} \underbrace{(F'(X_{\tilde{t}_i})^2 - (F'(X_{t_{i-1}}))^2}_{\to 0,\ n\to\infty}(\Delta X)_{i,n}^2 .\end{aligned}$$

The first sum converges to $\int_0^t (F'(X_s))^2\, d\langle X\rangle_s$ by Lemma 2.3; a similar argument as in the proof of Theorem 2.2 shows that the second sum converges to zero as $n \to \infty$.

To proof the Corollary we define $F(x) = \int_0^x f(y)dy$, such that $F' = f$. As F is a $\mathcal{C}^2$-function the existence of the integral $I_t = \int_0^t F'(X_s)dX_s$ follows from the previous theorem. Moreover, we get from Itô's formula that

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

As the function A is of finite variation we get $\langle I\rangle_t = \langle F(X)\rangle_t$. By Proposition (2.4), we know that $\langle F(X)\rangle_t = \int_0^t f^2(X_s)d\langle X\rangle_s$, which proves the corollary. □

Example: We compute the quadratic variation of the square of Brownian motion B. We have $B_t^2 = \int_0^t 2B_s dB_s + t$. Define $I_t := \int_0^t 2B_s dB_s$. We get $\langle B^2\rangle_t = \langle I\rangle_t = \int_0^t 4B_s^2 ds$.

2.2.2 Martingale-property of the Itô-integral

Up to now we have only used analytic properties of the function X such as the fact that X admits a continuous quadratic variation in our analysis of the Itô-integral. If $X(t)$ is the sample path of a stochastic process such as Brownian motion we may study probabilistic properties of the process $I_t(\omega) = \int_0^t f(X_s(\omega))dX_s(\omega)$. In particular we may consider the case that our integrator is a martingale.

If M is a martingale with trajectories of continuous quadratic variation and f a $\mathcal{C}^1$ function we expect the Itô-integral $I_t := \int_0^t f(M_s)dM_s$ to inherit the martingale property from M, as I_t is defined as limit of non-anticipating sums, $I_t = \lim_{n\to\infty} I_t^n$ with $I_t^n = \sum_{t_i\in\tau_n;\, t_i\le t} f(M_{t_{i-1}})(M_{t_i} - M_{t_{i-1}})$. The martingale property of the I_t^n is just a variation of the 'you can't gain by betting on a martingale' argument used already in our proof that the discounted gains from trade of an admissible selffinancing strategy are a martingale

under an equivalent martingale measure in Chapter **??** (Lemma **??**). Unfortunately some integrability problems arise when we pass from the approximating sums to the limit such that only a slightly weaker result is true. To state this result we need the notion of a local martingale.

Definition 2.6. A stochastic process M is called a local martingale, if there are stopping times $T_1 \leq \ldots \leq T_n \leq \ldots$ such that

(i) $\lim_{n\to\infty} T_n(\omega) = \infty$ a.s.

(ii) $(M_{T_n \wedge t})_{t\geq 0}$ is a martingale for all n.

Obviously every martingale in the sense of Section 1.1.2 (every true martingale) is a local martingale. The opposite assertion is not true; see for instance Remark 2.10 below.

Theorem 2.7. *Consider a local martingale M with continuous trajectories and continuous quadratic variation $\langle M\rangle_t$ and a function $f \in C^1(\mathbb{R})$. Then $I_t(\omega) = \int_0^t f(M_s(\omega))dM_s(\omega)$ is a local martingale.*

Partial proof. We restrict ourselves to the case where M is a bounded martingale and where f is bounded; the general case follows by localization (introduction of an increasing sequence of stopping time $(T_n)_{n\in\mathbb{N}}$). The proff goes in two steps.

a) Let τ_n be a sequence of partitions with $|\tau_n| \to 0$, and fix n. Then the discrete-time process $I_k^n := \sum_{t_i\in\tau_n,\, i\leq k} f(M_{t_{i-1}})(M_{t_i} - M_{t_{i-1}})$, $k \leq n$, is a martingale wrt the discrete filtration $\{\mathcal{F}_k^n\}_k$ with $\mathcal{F}_k^n := \mathcal{F}_{t_k}$, as can be seen from the following easy argument.

$$E(I_k^n - I_{k-1}^n|\mathcal{F}_{k-1}^n) = E(f(M_{t_{k-1}})(M_{t_k} - M_{t_{k-1}})|\mathcal{F}_{t_{k-1}}) = f(M_{t_{k-1}})E((M_{t_k} - M_{t_{k-1}})|\mathcal{F}_{t_{k-1}}),$$

and the last term is obviously equal to zero as M is a martingale. Note that here we have used the fact that the Itô-integral is non-anticipating.

b) Let $s < t$. We will show that $E(I_t; A) = E(I_s; A)$ for all $A \in \mathcal{F}_s$, as this implies that $E(I_t|\mathcal{F}_s) = I_s$. Choose $t_n, s_n \in \tau_n$ with $t_n \searrow t$, $s_n \searrow s$ and $t_n > s_n$. By Step a) we have

$$E(I_{t_n}; A) = E(I_{s_n}; A);$$

moreover $I_{t_n} \to I_t$, $I_{s_n} \to I_s$, as I has continuous paths. Moreover, one can show that $(I_{t_n})_n$ and $(I_{s_n})_n$ are uniformly integrable (using the boundedness of M and f), so that the claim follows from the theorem of Lebesgue. □

Remark 2.8. If f is defined only on a subset $G \subseteq \mathbb{R}$ the process $I_t = \int_0^t f(M_s)dM_s$ can be defined up to the stopping-time $\tau = \inf\{t > 0,\ M_t \notin G\}$ and it can be shown that I_t is a local martingale until τ.

In applications one often needs to decide if a local martingale M is in fact a true martingale. The following Proposition provides a useful criterion for this

Proposition 2.9. *Let M be a local martingale with continuous trajectories. Then the following two assertions are equivalent.*

(i) M is a true martingale and $E(M_t^2) < \infty$ $\forall t \geq 0$.

(ii) $E(\langle M\rangle_t) < \infty$ $\forall t$.

If either (i) or (ii) holds, we have $E(M_t^2) = E(\langle M \rangle_t)$.

For a proof and a generalization to discontinuous martingales see Chapter II.6 of Protter (1992).

Remark 2.10. The following process is an example of a local martingale which is not a true martingale. Consider a three-dimensional Brownian motion $W_t = (W_t^1, W_t^2, W_t^3)$ with $W_0 = (1, 1, 1)$ and define

$$M_t = \frac{1}{||W_t||} = \frac{1}{\sqrt{(W_t^1)^2 + (W_t^2)^2 + (W_t^3)^2}}\,.$$

Then M is a local martingale, as can be checked using the Itô-formula in higher dimensions, but it is not a full martingale; see again Chapter II.6 of Protter (1992) for details.

The following Proposition shows that interesting martingales with continuous trajectories are necessarily of infinite variation.

Proposition 2.11. *Consider a local martingale M with continuous trajectories of finite variation Then the paths of M are constant, i.e. $M_t = M_0$ almost surely.*

Note that there are martingales with discontinuous non-constant trajectories of finite variation; an example is provided by the compensated Poisson process; see Section 1.1.2.

Proof. By Itô's-formula we get for M_t^2

$$M_t^2 = M_0^2 + 2\int_0^t M_s dM_s + \langle M \rangle_t = M_0^2 + 2\int_0^t M_s dM_s\,,$$

as $\langle M \rangle_t = 0$ by Proposition 1.27. The martingale-property of the Itô-integral implies that M_t^2 is a local martingale. Assume that both M_t and M_t^2 are a real martingales.[1] Then we have

$$0 \leq E\left((M_t - M_0)^2\right) = E\left(M_t^2 - 2M_t M_0 + M_0^2\right) = M_0^2 - 2M_0^2 + M_0^2 = 0\,,$$

which shows that $E\left(M_t - M_0\right)^2 = 0$ so that $M_t = M_0$ a.s. □

We close this section with a formal definition of semimartingales.

Definition 2.12. A stochastic process X with RCLL paths is called a *semimartingale* if X has a decomposition of the form $X_t = X_0 + M_t + A_t$ where M is a local martingale and A is an adapted process with continuous trajectories of finite variation; M is called the martingale part of X, A the finite variation part.

Note that the decomposition of X into a martingale part and a finite variation part is unique by Proposition 2.11.

[1] For an argument how to deal with the case where M_t^2 is only a local martingale we refer the reader to Protter (1992).

2.3 Covariation and d-dimensional Itô-formula

2.3.1 Covariation

Fix a sequence τ_n of partitions of $[0,\overline{T}]$ with $\tau_n \to 0$ and continuous functions X, Y which admit a continuous quadratic variation $\langle X\rangle_t$ and$\langle Y\rangle_t$ along the sequence τ_n.

Definition 2.13. Assume that for all $t \in [0,T]$ the following limit exists:

$$\lim_{n\to\infty} \sum_{t_i\in\tau_n;\, t_i\le t} (X_{t_i} - X_{t_{i-1}})(Y_{t_i} - Y_{t_{i-1}}) =: \langle X, Y\rangle_t.$$

Then $\langle X, Y\rangle_t$ is called *covariation* of X and Y.

Theorem 2.14. *$\langle X, Y\rangle_t$ exists if and only if $\langle X + Y\rangle_t$ exists; in that case we have the following so-called polarization-identity*

$$\langle X, Y\rangle_t = \frac{1}{2}\left(\langle X + Y\rangle_t - \langle X\rangle_t - \langle Y\rangle_t\right). \tag{2.7}$$

Proof. Recall the notation $(\Delta X)_{i,n} = X_{t_i} - X_{t_{i-1}}$, for $t_i, t_{i-1} \in \tau_n$. We have

$$\begin{aligned}
\langle X + Y\rangle_t &= \lim_{n\to\infty} \sum_{t_i\in\tau_n;\, t_i\le t} ((\Delta X)_{i,n} + (\Delta Y)_{i,n})^2 \\
&= \lim_{n\to\infty} \left\{ \sum_{t_i\in\tau_n;\, t_i\le t} (\Delta X)^2_{i,n} + \sum_{t_i\in\tau_n;\, t_i\le t} (\Delta Y)^2_{i,n} + 2 \sum_{t_i\in\tau_n;\, t_i\le t} (\Delta X)_{i,n}(\Delta Y)_{i,n} \right\} \\
&= \langle X\rangle_t + \langle Y\rangle_t + 2 \lim_{n\to\infty} \sum_{t_i\in\tau_n;\, t_i\le t} (\Delta X)_{i,n}(\Delta Y)_{i,n}\,. \qquad (2.8)
\end{aligned}$$

Hence the last limit on the right hand side of (2.8) exists iff $\langle X + Y\rangle_t$ exists. Solving for this limit yields the polarization identity. □

Note that $\langle X, Y\rangle_t$ is of finite variation as it is the difference of monotone functions. We now use the polarization identity to compute the covariation for a few important examples.

1) If X is a continuous function with continuous quadratic variation $\langle X\rangle_t$ and A a continuous function of finite variation we have $\langle X + A\rangle_t = \langle X\rangle_t$ and hence $\langle X, A\rangle_t = 0$.

2) Consider two independent Brownian motions B^1, B^2 on our probability space $(\Omega, \mathcal{F}, P)$. Then $\langle B^1\cdot(\omega), B^2\cdot(\omega)\rangle_t = 0$. To prove this claim we have to compute $\langle B^1 + B^2\rangle_t$. Note that $(B^1_t + B^2_t)/\sqrt{2}$ is again a Brownian motion and has therefore quadratic variation equal to t. Hence

$$\frac{1}{2}(\langle B^1 + B^2\rangle_t - \langle B^1\rangle_t - \langle B^2\rangle_t) = \frac{1}{2}(2t - t - t) = 0\,.$$

3) Consider a continuous function X with continuous quadratic variation, and $\mathcal{C}^1$-functions f and g. Define $Y_t := \int_0^t f(X_s)dX_s$ and $Z_t := \int_0^t g(X_s)dX_s$. Then $\langle Y, Z\rangle_t = \int_0^t f(X_s)g(X_s)d\langle X\rangle_s$. This follows from the polarization identity and the following computation:

$$\langle Y + Z\rangle_t \;=\; \int_0^t (f+g)^2(X_s)d\langle X\rangle_s = \langle Y\rangle_t + \langle Z\rangle_t + 2\int_0^t f(X_s)g(X_s)d\langle X\rangle_s.$$

Example 3) is a special case of a more general rule for stochastic Itô-integrals.

2.3.2 The d-dimensional Itô-formula

Theorem 2.15 (d-dimensional Itô-formula)**.** *Given continuous functions $X = (X^1, \dots, X^d) : [0, \overline{T}] \to \mathbb{R}$ with continuous covariation*

$$\langle X^k, X^l \rangle_t = \begin{cases} \langle X^k \rangle_t, \ k{=}l, \\ 1/2 \left(\langle X^k + X^l \rangle_t - \langle X^k \rangle_t - \langle X^l \rangle_t \right), \ k \neq l \end{cases}$$

and a twice continuously differentiable function $F : \mathbb{R}^d \to \mathbb{R}$. Then

$$F(X_t) = F(X_0) + \sum_{i=1}^{d} \int_0^t \frac{\partial}{\partial x_i} F(X_s) dX_s^i + \frac{1}{2} \sum_{i,j=1}^{d} \int_0^t \frac{\partial^2}{\partial x_i \partial x_j} F(X_s) d\langle X^i, X^j \rangle_s \,.$$

Remark on notation: For $\frac{\partial}{\partial x_i} F$ we often write F_{x_i}, $\frac{\partial^2}{\partial x_i \partial x_j} F$ is denoted by F_{x_i, x_j}. In short-notation the d-dimensional Itô-formula hence writes as:

$$dF(X_t) = \sum_{i=1}^{d} F_{x_i}(X_t) dX_t^i + \frac{1}{2} \sum_{i,j=1}^{d} F_{x_i, x_j}(X_t) d\langle X^i, X^j \rangle_t \,.$$

EXAMPLE: Let $W = (W^1, \dots, W^d)$ be d-dimensional Brownian motion so that that $\langle W_t^k, W_t^l \rangle_t = \delta_{kl} t$ where $\delta_{kl} = 1$ if $k = l$ and $\delta_{kl} = 0$ otherwise. Hence we have

$$F(W_t) = F(W_0) + \sum_{i=0}^{d} \int_0^t F_{x_i}(W_s) dW_s^i + \frac{1}{2} \sum_{i=0}^{d} \int_0^t F_{x_i, x_i}(W_s) ds \,. \tag{2.9}$$

Corollary 2.16 (Itô's product formula)**.** *Given X, Y with continuous quadratic variation $\langle X \rangle_t$, $\langle Y \rangle_t$ and covariation $\langle X, Y \rangle_t$. Then*

$$X_t Y_t = X_0 Y_0 + \int_0^t X_s dY_s + \int_0^t Y_s dX_s + \langle X, Y \rangle_t.$$

Proof. Apply Theorem (2.15) to $F(x, y) = xy$. □

In short notation the product formula can be written as $d(XY)_t = X_t dY_t + Y_t dX_t + d\langle X, Y \rangle_t$.

Corollary 2.17 (Itô-formula for time-dependent functions)**.** *Given a continuous function X with continuous quadratic variation $\langle X \rangle_t$ and a function $F(t, x)$ which is once continuously differentiable in t and twice continuously differentiable in x. Then*

$$F(t, X_t) = F(0, X_0) + \int_0^t F_t(s, X_s) ds + \int_0^t F_x(s, X_s) dX_s + \frac{1}{2} \int_0^t F_{xx}(s, X_s) d\langle X \rangle_s.$$

We now consider several applications of the d-dimensional Itô-formula.

1) *Geometric Brownian motion:* Given a Brownian motion W, an initial value $S_0 > 0$ and constants μ, σ with $\sigma > 0$ we define geometric Brownian motion S by

$$S_t = S_0 \exp\left(\sigma W_t + (\mu - 1/2\sigma^2) t \right) \,.$$

Geometric Brownian motion will be our main model for the fluctuation of asset prices in Section 3. Using the Itô-formula we now derive a more intuitive expression for the dynamics of S. Define $X_t := \sigma B_t$ and $Y_t := (\mu - 1/2\sigma^2)t$ and note that $\langle X\rangle_t = \sigma^2 t$ and $\langle Y\rangle_t = \langle X, Y\rangle_t = 0$. Let $F(x, y) := S_0 \exp(x + y)$ such that $F_x = F_y = F_{xx} = F$. By definition $S_t = F(X_t, Y_t)$, and we get

$$\begin{aligned} S_t &= S_0 + \int_0^t F(X_s, Y_s)dX_s + \int_0^t F(X_s, Y_s)dY_s + \frac{1}{2}\int_0^t F(X_s, Y_s)d\langle X\rangle_s \\ &= S_0 + \int_0^t F(X_s, Y_s)\sigma dB_s + \int_0^t F(X_s, Y_s)(\mu - \frac{1}{2}\sigma^2)ds + \frac{1}{2}\int_0^t F(X_s, Y_s)\sigma^2 ds \\ &= S_0 + \int_0^t \sigma S_s dB_s + \int_0^t \mu S_s ds\,. \end{aligned} \tag{2.10}$$

In our short-notation the equation solved by S can be written as $dS_t = \mu S_t dt + \sigma S_t dB_t$. In the special case where $\mu = 0$ we get that $S_t = S_0 + \int_0^t \sigma S_s dB_s$ is a local martingale.[2]

2) Brownian motion and the reverse heat-equation. Consider a function $F(t, x)$ that solves the reverse heat-equation $F_t(t, x) + 1/2F_{xx}(t, X) = 0$ and a Brownian motion B. Then $F(t, B_t)$ is a local martingale. The proof is again based on Itô's formula. We get

$$\begin{aligned} F(t, B_t) &= F(0, B_0) + \int_0^t F_x(s, B_s)dB_s + \int_0^t F_t(s, B_s)ds + \frac{1}{2}\int_0^t F_{xx}(s, B_s)d\langle B\rangle_s \\ &= F(0, B_0) + \int_0^t F_x(s, B_s)dB_s + \int_0^t (F_t + \frac{1}{2}F_{xx})(s, B_s)ds \\ &= F(0, B_0) + \int_0^t F_x(s, B_s)dB_s\,. \end{aligned}$$

In case that $F_x(t, B_t)$ is sufficiently integrable $F(t, B_t)$ is even a real martingale. In that case one easily obtains a probabilistic representation of the solution of our reverse heat equation. For more on the interplay between solutions of partial differential equations and stochastic processes we refer to Chapter 4 and 5 of Karatzas & Shreve (1988).

[2]It can be shown that in that case S is even a full martingale.

Chapter 3

The Black-Scholes Model: a PDE-Approach

We now have all the mathematical tools at hand we need to study pricing and hedging of derivatives in the classical Black-Scholes model.

3.1 Asset Price Dynamics

As in the classical paper Black & Scholes (1973) we consider a market with two traded assets, a risky non-dividend-paying stock and a riskless money market account. The price of the stock at time t is denoted by S_t^1, the price of the money market account by S_t^0. For simplicity we work with a deterministic continuously compounded interest rate r such that $S_t^0 = \exp(rt)$. We now look for appropriate models for the dynamics of the stock-price. As usual we work on a filtered probability space $(\Omega, \mathcal{F}, P)$, $\{\mathcal{F}_t\}$ supporting a standard Brownian motion W_t representing the uncertainty in our market.

In his now famous PhD-thesis Bachelier (1900) proposed to model asset prices by an arithmetic Brownian motion, i.e. he suggested the model $S_t^1 = S_0 + \sigma W_t + \mu t$ for constants $\mu, \sigma > 0$. While this was a good first approximation to the dynamics of stock prices, arithmetic Brownian motion has one serious drawback: as S_t^1 is $N(S_0 + \mu t, \sigma^2 t)$ distributed, the asset price can become negative with positive probability, which is at odds with the fact that real-world stock-prices are always nonnegative because of limited liability of the shareholders.

Samuelson (1965) therefore suggested replacing arithmetic Brownian motion by geometric Brownian motion

$$S_t^1 = S_0^1 \exp\left(\sigma W_t + (\mu - \frac{1}{2}\sigma^2 t)\right). \tag{3.1}$$

We know from (2.10) that this model solves the linear stochastic differential equation (SDE)

$$dS_t^1 = \mu S_t^1 dt + \sigma S_t^1 dW_t\,.$$

Geometric Brownian motion - often referred to as Black-Scholes model - is nowadays widely used as reference model both in option pricing theory and in the theory of portfolio-optimization; we therefore adopt it as our model for the stock price dynamics in this

section. Model (3.1) implies that log-returns

$$\ln S^1_{t+h} - \ln S^1_t = \sigma(W_{t+h} - W_t) + (\mu - \frac{1}{2}\sigma^2)h$$

are $N((\mu - \frac{1}{2}\sigma^2)h, \sigma^2 h)$-distributed; in particular the volatility σ is the instantaneous variance of the log-returns. Moreover, under (3.1) log-returns over non-overlapping time periods are stochastically independent.

There are a number of practical and theoretical considerations which make geometric Brownian motion attractive as a model for stock price dynamics.

- Geometric Brownian motion fits asset prices data reasonably well, even if the fit is far from perfect. For an overview the empirical deficiencies of the Black-Scholes model we refer to Chapter I of **?** or Section 4.1 of McNeil, Frey & Embrechts (2005).
- Geometric Brownian motion allows for explicit pricing formulae for a relatively large class of derivatives. Moreover, there are a number of good discrete-time approximations to the Black-Scholes model such as the CRR model presented in Section **??**.
- The Black-Scholes model is quite robust as a model for hedging of derivatives: if real asset-price dynamics are 'not too different from geometric Brownian motion' hedging strategies computed using the Black-Scholes model perform reasonably well. There is now a large literature on *model risk* in derivative pricing; see for instance the collection of papers in Gibson (2000) or Cont (2006); we present a brief discussion of the model-risk related to volatility-misspecification in Subsection **??** below.

There are also a number of theoretical considerations in favour of the Black-Scholes model.

- The model is in line with the efficient markets hypothesis. Moreover, there are a number of economic models which show that the Black-Scholes model can be sustained as a model for economic equilibrium; see for instance He & Leland (1993) for a rational expectations model and Föllmer & Schweizer (1993) for a model based on the temporary equilibrium concept.
- The Black-Scholes model is an arbitrage-free and complete model, making derivative pricing straightforward from a conceptual point of view.

3.2 Pricing and Hedging of Terminal Value Claims

Consider now a contingent claim with maturity date T and payoff H. As in the discrete-time setup of Chapter **??** we want to find a dynamic trading strategy replicating the claim; such a strategy can be used for pricing and hedging purposes. It can be shown that in the framework of the Black-Scholes model such a strategy exists for every claim whose payoff is measurable with respect to the information generated by the asset price. However, such a result requires the notion of the stochastic Itô-integral $\int_0^t \xi_s dS^1_s$ for general predictable processes ξ which we do not have at our disposal. We therefore restrict our analysis to so-called terminal value claims whose payoff is of the form $H = h(S^1_T)$. For these claims one can find Markov hedging strategies which are functions of time and the current stock-price. This includes most examples which are relevant from a practical viewpoint; as

shown in Section **??** extensions to path-dependent derivatives are also possible. For the general theory we refer the reader to Bingham & Kiesel (1998) or to the advanced text Karatzas & Shreve (1998).

3.2.1 Basic Notions

TRADING STRATEGY: A *Markov trading strategy* is given by a pair of smooth functions $(\phi(t,S),\ \eta(t,S))$, where $\phi(t,S_t^1)$ and $\eta(t,S_t^1)$ give the number of stocks respectively of units of the money market account in the portfolio at time t. The value at time t of this strategy is given by $V(t,S_t^1) = S_t^1\phi(t,S_t^1) + \eta(t,S_t^1)S^0(t)$. Note that the strategy can alternatively be described by specifying the functions $\phi(t,S)$ and $V(t,S)$; the position in the money market account is then given by the function $\eta(t,S) := (V(t,S) - S\phi(t,S))/S^0(t)$.

GAINS FROM TRADE: To motivate the subsequent definitions we introduce piecewise constant approximations to our trading strategies. Consider a sequence τ_n of partitions with $|\tau_n| \to 0$ and define

$$\phi_t^n(\omega) = \sum_{t_i \in \tau_n} \phi(t_{i-1}, S_{t_{i-1}}^1(\omega))\, 1_{(t_{i-1},t_i]}(t) \tag{3.2}$$

$$\eta_t^n(\omega) = \sum_{t_i \in \tau_n} \eta(t_{i-1}, S_{t_{i-1}}^1(\omega))\, 1_{(t_{i-1},t_i]}(t) \tag{3.3}$$

and $V_t^n = \phi_t^n S_t^1 + \eta_t^n S_t^0$. A similar argument as the one used in the proof of Lemma **??** now yields that this piecewise constant strategy is selffinancing if and only if we have for all $t_i \in \tau_n$

$$V_{t_i}^n = V_0 + G_t^n,\ \text{where } G_t^n = \sum_{j=1}^{i} \left(\phi_{t_j}^n (S_{t_j}^1 - S_{t_{j-1}}^1) + \eta_{t_j}^n (S_{t_j}^0 - S_{t_{j-1}}^0) \right).$$

Now recall that by definition of the Itô-integral G_t^n converges to $\int_0^t \phi(s,S_s^1)dS_s^1 + \int_0^t \eta(s,S_s^1)dS_s^0$. Hence the following definition is natural.

Definition 3.1. Given a Markov trading strategy $(\phi(t,S_t^1),\eta(t,S_t^1))$ induced by smooth functions $\phi,\ \eta:\ [0,T]\times\mathbb{R}^+ \to \mathbb{R}$.

(i) The *gains from trade* of this strategy are given by

$$G_t = \int_0^t \phi(s,S_s^1)dS_s^1 + \int_0^t \eta(s,S_s^1)dS_s^0\,.$$

(ii) The strategy is *selffinancing*, if $V(t,S_t^1) = V(0,S_0) + G_t$ for all $t \le T$.

(iii) Consider a terminal value claim with payoff $h(S_T^1)$. A selffinancing strategy is a *replicating strategy* for the claim if $V(T,S) = h(S)$ for all $S > 0$; in that case $V(t,S_t^1)$ is the fair price of the claim at time t.

3.2.2 The pricing-equation for terminal-value-claims

We now derive a partial differential equation (PDE) for the value of the replicating strategy. We have the following

Theorem 3.2. *Let $V : [0,T] \times \mathbb{R}^+ \to \mathbb{R}$ be a continuous function which solves the PDE*

$$V_t(t,S) + \frac{1}{2}\sigma^2 S^2 V_{SS}(t,S) + rSV_S(t,S) = rV(t,S)\,, \quad (t,S) \in [0,T) \times \mathbb{R}^+\,. \tag{3.4}$$

Then the hedging strategy with stock-position $\phi(t,S) = V_S(t,S)$ and value $V(t,S)$ is self-financing. If V satisfies moreover the terminal condition $V(T,S) = h(S)$, the strategy replicates the terminal value claim with payoff $h(S_T^1)$ and the fair price at time t of the claim equals $V(t,S_t^1)$.

Proof. As a first step we compute the quadratic variation of geometric Brownian motion. Recall that

$$S_t^1 = S_0 + \int_0^t \sigma S_s^1 dW_s + \int_0^t \mu S_s^1 ds =: M_t + A_t\,.$$

As A is of finite variation we get $\langle S^1\rangle_t = \langle M\rangle_t = \int_0^t \sigma^2 (S_s^1)^2 ds$.

Now we turn to the first claim. We get from Itô's formula

$$\begin{aligned} V(t,S_t^1) &= V(0,S_0^1) + \int_0^t V_S(s,S_s^1)dS_s^1 + \int_0^t V_t(s,S_s^1)ds + \frac{1}{2}\int_0^t V_{SS}(s,S_s^1)d\langle S^1\rangle_s \\ &= V(0,S_0^1) + \int_0^t V_S(s,S_s^1)dS_s^1 + \int_0^t \left(V_t(s,S_s^1) + \frac{1}{2}\sigma^2 (S_s^1)^2 V_{SS}(s,S_s^1)\right) ds\,. \end{aligned}$$

Using the PDE (3.4) and the definition of ϕ this equals

$$\begin{aligned} &= V(0,S_0^1) + \int_0^t \phi(s,S_s^1)dS_s^1 + \int_0^t r(V(s,S_s^1) - \phi(s,S_s^1)S_s^1)ds \\ &= V(0,S_0^1) + \int_0^t \phi(s,S_s^1)dS_s^1 + \int_0^t \eta(s,S_s^1)dS_s^0, \end{aligned}$$

where $\eta(t,S_t^1) = (V(t,S_t^1) - \phi(t,S_t^1)S_t^1)/S^0(t)$ is the position in the money-market account which corresponds to our strategy. Hence our strategy is selffinancing. The remaining claims are obvious. □

3.3 The Black-Scholes formula

3.3.1 The formula

To price a European call option we have to solve the PDE (3.4) with terminal condition $h(S) = (S-K)^+$. To solve this problem analytically one usually reduces the PDE (3.4) to the heat equation by a proper change of variables. This technique is useful also for the implementation of numerical schemes to solve the pricing PDE; see for instance Wilmott, Dewynne & Howison (1993). Details are given in the following Lemma.

Lemma 3.3. *Define $\tau(t) = \sigma^2(T-t)$ and $z(t,S) = \ln S - (r + \frac{1}{2}\sigma^2)(T-t)$. Denote by $u(t,z) : [0,T] \times \mathbb{R} \to \mathbb{R}$ the solution of the heat-equation $u_t = \frac{1}{2}u_{zz}$ with initial condition $u(0,z) = (e^z - K)^+$. Then $C(t,S) := e^{-r(T-t)}u(\tau(t), z(t,S))$ solves the terminal value problem for the price of a European call.*

Proof. We have $C(T,S) = u(\tau(T), z(T,S)) = u(0, \ln S) = (S-K)^+$, so that the function C has the right value at maturity. Moreover,

$$\frac{\partial C}{\partial t} = e^{-r(T-t)}\left(ru - \sigma^2 u_\tau + (1/2\sigma^2 + r)u_z\right)$$
$$\frac{\partial C}{\partial S} = e^{-r(T-t)}u_z 1/S\,,\ \frac{\partial^2 C}{\partial S^2} = e^{-r(T-t)}\left(u_{zz}(1/S)^2 - u_z(1/S)^2\right)$$

Plugging these expressions into the PDE (3.4) yields the result. □

It is well-known that the solution u of the heat-equation with initial condition $u(0,z) = u_0(z)$ equals

$$u(\tau, z) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty} u_0(z + x\sqrt{\tau})e^{-x^2/2}dx.$$

From this follows after tedious but straightforward computations (see for instance Sandmann (1999) or Wilmott et al. (1993))

Theorem 3.4. *Denote by $N(\cdot)$ the standard normal distribution function. The no-arbitrage price of a European call with strike K and time to maturity T in the Black-Scholes model with volatility σ and interest rate r is given by*

$$C_{BS}(t,S;\sigma,r,K,T) := SN(d_1) - e^{-r(T-t)}KN(d_2)\,, \tag{3.5}$$

with

$$d_1 = \frac{\ln S/K + (r + \frac{1}{2}\sigma^2)(T-t)}{\sigma\sqrt{T-t}} \text{ and } d_2 = d_1 - \sigma\sqrt{T-t}\,.$$

The corresponding hedge-portfolio consists of $\frac{\partial}{\partial S}C_{BS} = N(d_1)$ units of the risky asset and $(C_{BS}(t,S) - N(d_1)S)/e^{rt} = -e^{-rT}KN(d_2)$ units of the money market account.

A probabilistic derivation of the Black-Scholes formula is given in Section 5.2 below.

3.3.2 Application of the formula: volatility estimation

For an extensive discussion how the Black-Scholes formula can be applied in practice we refer to Cox & Rubinstein (1985) and Hull (1997). Here we content ourselves with a few remarks about possible approaches to determine the volatility σ. As volatility is not directly observable – in contrast to the other parameters in the Black-Scholes formula – finding a 'good' value for σ is by for the most problematic part in applying the Black-Scholes formula. The fact that in real markets volatility is rarely constant but tends to fluctuate in a rather unpredictable manner makes matters even worse.[1] There are two common approaches to determining σ.

1) Historical volatility: This approach is based on statistical considerations. Recall that under (2.10) log-returns over non-overlapping periods of length Δ are independent and $N((\mu - \frac{1}{2}\sigma^2)\Delta, \sigma^2\Delta)$ distributed. Given asset price data at times t_i, $i = 1,\ldots,N$ with $t_i - t_{i-1} = \Delta$ (e.g. daily returns) define $Y_i = \ln S_{t_i} - \ln S_{t_{i-1}}$. The standard estimator

[1] The stochastic nature of volatility has given rise to the development of the stochastic volatility models; see for instance Frey (1997) for an overview.

from elementary statistics for σ_Δ, the volatility of the log-returns over the time-period Δ is given by

$$\hat{\sigma}_\Delta = \left(\frac{1}{N-1} \sum_{i=1}^{N} \left(Y_i - \overline{Y} \right)^2 \right)^{\frac{1}{2}}, \quad \text{where } \overline{Y} = \frac{1}{N} \sum_{i=1}^{N} Y_i.$$

Estimated historical volatility is then given by $\hat{\sigma}_{hist} = \hat{\sigma}_\Delta / \sqrt{\Delta}$.

2) Implied volatility The idea underlying the implied volatility concept is the use of observed prices of traded derivatives to find the 'prediction of the market' for the volatility of the stock. To explain the concept we consider the following example:

Assume that a call option with strike K and maturity T is traded at time t and at a given stock-price $(S_t^1)^*$ for a price of C_t^*. The implied volatility $\hat{\sigma}_{impl}$ is then given by the solution to the equation

$$C_{BS}(t, (S_t^1)^*; \hat{\sigma}_{impl}, K, T) = C_t^* \, .$$

As C_{BS} is strictly increasing in σ a unique solution to this equation exists; it is usually determined by numerical procedures.

In practice traders tend to use a combination of both approaches, implied volatility being the slightly more popular concept.

Chapter 4

Further Tools from Stochastic Calculus

4.1 Stochastic Integration for Continuous Martingales

In this section we want to define the stochastic integral $\int_0^t H_s dX_s$ for semimartingales of the form $X = X_0 + M + A$, where M is a continuous martingale and A is a continuous FV-process, and where H is a suitable limit of integrands of the form

$$H_t^n = \sum_{i=0}^{n-1} h_{t_i}(\omega) 1_{(t_i, t_{i+1}]}(t), \quad t_i \in \tau_n,$$

where τ_n is a fixed partition of $(0, T]$, and where each of the h_{t_i} is $\mathcal{F}_{t_i}$-measurable. This extends the pathwise Itô calculus to a larger class of integrands. This is reasonable from a financial viewpoint, as we want to work with a larger class of trading strategies than just Markov strategies of the form $\Phi(t, S_t)$. The key point is to define the integral $\int_0^t H_s dM_s$, as M will typically have paths of infinite first variation, so that standard Stieltjes integration does not apply. To overcome these problems we use special properties of the space $\mathcal{M}^2$ of square integrable martingales.

4.1.1 The Spaces $\mathcal{M}^2$ and $\mathcal{M}^{2,c}$

Throughout we work on a given a filtered probability space $(\Omega, \mathcal{F}, P)$, $\{\mathcal{F}_t\}$ with fixed horizon T.

Definition 4.1. The space of all martingales $M = (M_t)_{0 \le t \le T}$ with $M_0 = 0$ and $E[M_T^2] < \infty$ is denoted $\mathcal{M}^2$; $\mathcal{M}^{2,c} \subseteq \mathcal{M}^2$ denotes the subspace of all martingales with continuous trajectories.

Note that the Jensen inequality gives for $M \in \mathcal{M}^2$, $t \le T$ that

$$E[M_t^2] = E\left[(E[M_T|\mathcal{F}_t])^2\right] \le E\left[E[M_T^2|\mathcal{F}_t]\right] = E[M_T^2],$$

so that M_t is square integrable for all $0 \le t \le T$.

Lemma 4.2. *$\mathcal{M}^2$ is a Hilbert-space with scalar product*

$$\langle M, N \rangle_{\mathcal{M}^2} = E[M_T N_T] = \langle M_T, N_T \rangle_{\mathcal{L}^2}.$$

Proof. $\langle M, N\rangle_{\mathcal{M}^2}$ is a scalar product. In particular, if $\langle M, M\rangle_{\mathcal{M}^2} = 0$, we have $M_T = 0$ a.s. which yields $M_t = E[M_T|\mathcal{F}_t] = 0$ for all t. The Hilbert-space property is obvious, as $\mathcal{M}^2$ can be identified with $\mathcal{L}^2(\Omega, \mathcal{F}_T, P)$ by identifying a martingale $(M_t)_t$ with its terminal value M_T via $M_t = E[M_T|\mathcal{F}_t]$. □

The following result establishes a link between the pathwise supremum the and the terminal value of a martingale.

Theorem 4.3 (Doob inequality)**.** *Let $p > 1$ and $(M_t)_{0\le t\le T}$ be a martingale. Define q by $\frac{1}{p} + \frac{1}{q} = 1$. Then we have for $t \le T$*

$$\|\sup_{s\le t} |M_s|\|_{\mathcal{L}^p} \le q\|M_t\|_{\mathcal{L}^p}. \tag{4.1}$$

In particular we get with $M_T^* := \sup_{t\le T} |M_t|$ that

$$E\left[(M_T^*)^2\right] \le 4E\left[M_T^2\right]. \tag{4.2}$$

We omit the proof.

Lemma 4.4. *$\mathcal{M}^{2,c}$ is a closed subspace of $\mathcal{M}^2$ and hence a Hilbert-space.*

Proof. Consider a sequence $M^n \in \mathcal{M}^{2,c}$ with $M^n \to M$, i.e. with $\lim_{n\to\infty} E\left[(M_T^n - M_T)^2\right] = 0$. We want to show that the limit $(M_t)_{t\ge 0}$ with $M_t = E\left[M_T|\mathcal{F}_t\right]$ has continuous sample paths. By Doobs inequality we get

$$E\left[((M^n - M)_T^*)^2\right] \le 4E\left[(M_T^n - M_T)^2\right] \to 0,$$

i.e. $(M^n - M)_T^* = \sup_{t\le T} |M_t^n - M_t| \to 0$ in $\mathcal{L}^2(\Omega, \mathcal{F}_T, P)$. It follows that $(M^{n'} - M)_T^*$ converges to zero a.s. for a subsequence n', which implies the result, as the limit of continuous functions in the supremum-norm is continuous. □

Quadratic variation. Recall the definition

$$V_t^2(M; \tau_n) := \sum_{t_i\in\tau_n;\, t_i<t} (M_{t_i} - M_{t_{i-1}})^2 = \sum_{t_i\in\tau_n;\, t_i<t} (\Delta M_{i,n})^2, \tag{4.3}$$

for the quadratic variation of M along a partition τ_n of $[0, T]$.

Theorem 4.5. *Consider a sequence $(\tau_n)_n$ of partitions of $[0, T]$ such that $|\tau_n| \to 0$ and let $M \in \mathcal{M}^{2,c}$. Then*

1. *$V_t^2(M, \tau_n)$ converges in probability to an increasing and continuous process $\langle M\rangle_t$ with $\langle M\rangle_0 = 0$.*
2. *$M_t^2 - \langle M\rangle_t$ is a martingale, in particular we have $E\left[M_t^2\right] = E\left[\langle M\rangle_t\right]$, $t \le T$.*
3. *$\langle M\rangle_t$ is uniquely defined by the requirements*
   - *(i) $\langle M\rangle_t$ is increasing and continuous, $\langle M\rangle_0 = 0$.*
   - *(ii) $M_t^2 - \langle M\rangle_t$ is a martingale.*

Remark 4.6. 1. The hard parts of the theorem are 1 and 2; the uniqueness of $\langle M\rangle_t$ follows immediately from the fact that a continuous martingale with trajectories of finite variation is a.s. constant. 2. The convergence of $V_t^2(M,\tau_n) \to \langle M\rangle_t$ in probability implies that $V_t^2(M,\tau_{n'}) \to \langle M\rangle_t$ almost surely for a subsequence n'; hence the pathwise Itô-calculus of Chapter 1 applies to martingales from $\mathcal{M}^{2,c}$

Recall that for two functions $X, Y : (0,T] \to \mathbb{R}$ such that $\langle X\rangle_t$ and $\langle Y\rangle_t$ exist, the quadratic covariation

$$\langle X,Y\rangle_t = \lim_{n\to\infty} \sum_{t_i\in\tau_n;\, t_i\le t} \Delta X_{i,n}\Delta Y_{i,n}$$

exists if and only if $\langle X+Y\rangle_t$ exists and that $\langle X,Y\rangle_t = \frac{1}{2}\left(\langle X+Y\rangle_t - \langle X\rangle_t - \langle Y\rangle_t\right)$, the so-called polarization identity. Now for $M,N \in \mathcal{M}^{2,c}$, $M+N \in \mathcal{M}^{2,c}$ and $\langle M+N\rangle_t$ exists by Theorem 4.5. Hence we get

Corollary 4.7. *For $M,N \in \mathcal{M}^{2,c}$ the covariation*

$$\langle M,N\rangle_t = \lim_{n\to\infty} \sum_{t_i\in\tau_n;\, t_i\le t} \Delta M_{i,n}\Delta N_{i,n}$$

exists. $\langle M,N\rangle$ is characterized by the following properties

(i) $\langle M,N\rangle_t$ is a continuous FV-process with $\langle M,N\rangle_0 = 0$.

(ii) $M_tN_t - \langle M,N\rangle_t$ is a martingale.

The result follows from Theorem 4.5 and the polarization identity.

Note that $\langle\cdot,\cdot\rangle$ is bilinear and symmetric on $\mathcal{M}^{2,c}$, i.e. $\langle \alpha M_1 + \beta M_2, N\rangle = \alpha\langle M_1,N\rangle + \beta\langle M_2,N\rangle$. Note that for $M,N \in \mathcal{M}^{2,c}$, $\langle M,N\rangle$ gives the conditional covariance of the increments of M and N, i.e. we have for $t \le s \le 0$

$$E\left[(M_t - M_s)\left(N_t - N_s\right)|\mathcal{F}_s\right] = E\left[\langle M,N\rangle_t - \langle M,N\rangle_s|\mathcal{F}_s\right]. \tag{4.4}$$

The proof of (4.4) is easy. We have

$$\begin{aligned} E\left[(M_t-M_s)(N_t-N_s)|\mathcal{F}_s\right] &= E\left[M_tN_t - M_tN_s - M_sN_t + M_sN_s|\mathcal{F}_s\right] \\ &= E\left[M_tN_t|\mathcal{F}_s\right] - \underbrace{2E\left[M_tN_s|\mathcal{F}_s\right]}_{=2M_sN_s} + \underbrace{E\left[M_sN_s|\mathcal{F}_s\right]}_{=M_sN_s} \\ &= E\left[M_tN_t|\mathcal{F}_s\right] - M_sN_s \\ &= E\left[\langle M,N\rangle_t - \langle M,N\rangle_s|\mathcal{F}_s\right], \end{aligned}$$

where we have used the fact that $M_tN_t - \langle M,N\rangle_t$ is a martingale.

Example 4.8 (Constructing correlated Brownian motions.)**.** Let W_1 and W_2 be independent Brownian motions and recall from Section 2.3.1 that $\langle W_1,W_2\rangle_t = 0$. Put $B_1 = W_1$, $B_2 = \rho W_1 + \sqrt{1-\rho^2}W_2$. Then B_1 and B_2 are standard one-dimensional Brownian motions, and $\langle B_1,B_2\rangle_t = \rho\langle W_1,W_1\rangle_t + \sqrt{1-\rho^2}\langle W_2,W_1\rangle_t = \rho t$.

4.1.2 Stochastic Integrals for elementary processes

We begin the construction of $\int_0^t H_s dM_s$ by taking H from the class of elementary processes, defined as follows:

$$\xi \;:=\; \Big\{H : H_t(\omega) = \sum_{i=0}^{n-1} h_{t_i}(\omega) 1_{(t_i, t_{i+1}]}(t)\Big\}, \tag{4.5}$$

for deterministic $0 \le t_0 < t_1 < ... < t_n < T = t_{n+1},\ n \in \mathbb{N}$, and bounded, $\mathcal{F}_{t_i}$-measurable random variables $h_{t_i},\ 1 \le i \le n$. Note that the elements of ξ are bounded and left-continuous. From a financial point of view, elements of ξ correspond to simple, piecewise constant trading strategies.

Definition 4.9. For $H \in \xi$ and $M \in \mathcal{M}^{2,c}$ we define the stochastic integral $(H.M)$ by

$$(H.M)_t := \int_0^t H_s dM_s := \sum_{0 \le i \le n} h_{t_i} \left(M_{t_{i+1}\wedge t} - M_{t_i \wedge t}\right),\ t \le T,$$

H is called integrand, M integrator.

Lemma 4.10 (Properties of $(H.M)$ for $H \in \xi$)**.** *We have $(H.M) \in \mathcal{M}^{2,c}$ and the quadratic variation is given by $\langle\,(H.M)\,\rangle_t = \int_0^t H_s^2\, d\langle M\rangle_s$.*

Corollary 4.11 (Itô-isometry)**.** *We have*

$$E\left[(H.M)_t^2\right] = E\left[(\int_0^t H_s dM_s)^2\right] = E\left[\int_0^t H_s^2 d\langle M\rangle_s\right]. \tag{4.6}$$

Proof. (of Lemma 4.10) The continuity of $(H.M)$ is obvious, as M is continuous. In order to show that $(H.M)$ is a martingale, by the optional sampling theorem we have to show that for all bounded stopping times τ with $\tau \le T$ a.s. we have $E\left[(H.M)_\tau\right] = (H.M)_0$. Now $(H.M)_0$ is obviously equal to zero. Moreover,

$$\begin{aligned} E\left[(H.M)_\tau\right] &= E\left[\sum_{0 \le i \le n} h_{t_i}(M_{t_{i+1}\wedge\tau} - M_{t_i\wedge\tau})\right] \\ &= \sum_{0 \le i \le n} E\left[h_{t_i} E\left[M_{t_{i+1}\wedge\tau} - M_{t_i\wedge\tau} | \mathcal{F}_{t_i}\right]\right]. \end{aligned}$$

By the optional sampling theorem $E\left[M_{t_{i+1}\wedge\tau} - M_{t_i\wedge\tau}|\mathcal{F}_{t_i}\right] = 0$, and the martingale property of $(H.M)$ follows. In order to show that $\langle (H.M)\rangle_t = \int_0^t H_s^2 d\langle M\rangle_s$, we show that $(H.M)_t^2 - \int_0^t H_s^2 d\langle M\rangle_s$ is a martingale, which gives the result by Statement 3 of Theorem 4.5. Again we use the optional sampling theorem. Consider a stopping time $\tau \le T$. We have

$$E\left[(H.M)_\tau^2\right] = \sum_{i,j=1}^{n+1} E\left[h_{t_{i-1}} h_{t_{j-1}} \Delta M_i^\tau \Delta M_j^\tau\right], \tag{4.7}$$

where $\Delta M_i^\tau = M_{t_i\wedge\tau} - M_{t_{i-1}\wedge\tau}$. Suppose that $i < j$. By conditioning on $\mathcal{F}_{t_{j-1}}$ we see that $E\left[h_{t_{i-1}} h_{t_{j-1}} \Delta M_i^\tau \Delta M_j^\tau\right] = 0$. Hence (4.7) equals

$$\sum_{i=1}^{n+1} E\left[h_{t_{i-1}}^2 (\Delta M_i^\tau)^2\right] = \sum_{i=1}^{n+1} E\left[h_{t_{i-1}}^2 \left(\langle M^\tau\rangle_{t_i} - \langle M^\tau\rangle_{t_{i-1}}\right)\right],$$

using (4.4). Now we obviously have $\langle M^\tau\rangle_t = \langle M\rangle_{\tau\wedge t}$, so that

$$\begin{aligned}\sum_{i=1}^{n+1} E\left[h^2_{t_{i-1}}\left(\langle M^\tau\rangle_{t_i} - \langle M^\tau\rangle_{t_{i-1}}\right)\right] &= \sum_{i=1}^{n+1} E\left[h^2_{t_{i-1}}\left(\langle M\rangle_{t_i\wedge\tau} - \langle M\rangle_{t_{i-1}\wedge\tau}\right)\right] \\ &= E\left[\int_0^\tau H_t^2 d\langle M\rangle_t\right].\end{aligned}$$

The relation $E\left[(H.M)_T^2\right] = E\left[\int_0^T H_s^2\, d\langle M\rangle_s\right]$, which we obtain by putting $\tau \equiv T$, shows that $(H.M)_T \in \mathcal{L}^2(\Omega, \mathcal{F}_T, P)$, as H is bounded and as $E[\langle M\rangle_T] = E\left[M_T^2\right] < \infty$ since $M \in \mathcal{M}^2$. □

4.1.3 Extension to General Integrands

We use the Itô-isometry to extend the integral $(H.M)$ from ξ to a larger class of integrands. We begin with an abstract interpretation of $E\left[\int_0^T H_s^2\, d\langle M\rangle_s\right]$ for $M \in \mathcal{M}^{2,c}$ fixed.

Put $\bar\Omega = \Omega \times [0,T]$, $\bar{\mathcal{F}} = \mathcal{F}_T \otimes \mathcal{B}([0,T])$ and define a measure $\bar P_M$ on $\bar\Omega$, $\bar{\mathcal{F}}$ by

$$\bar P_M(A) = E\left[\int_0^T 1_A(\omega,t)\, d\langle M\rangle_t\right], \quad A \in \bar{\mathcal{F}}. \tag{4.8}$$

With this definition we have for $H \in \xi$

$$\|H\|_{\mathcal{L}^2(\bar\Omega,\bar{\mathcal{F}},\bar P_M)} = \bar E_M\left[H^2\right] = E\left[\int_0^T H_s^2\, d\langle M\rangle_s\right]$$

i.e. $E\left[\int_0^T H_s^2\, d\langle M\rangle_s\right]$ is the $\mathcal{L}^2$-norm of H (regarded as a random variable on $\bar\Omega$, $\bar{\mathcal{F}}$) with respect to the measure $\bar P_M$. By Corollary 4.7 the mapping

$$I : \xi \to \mathcal{M}^{2,c}, \quad H \mapsto (H.M)$$

is therefore an isometry from $(\xi, \|\cdot\|_{\mathcal{L}^2(\bar\Omega,\bar{\mathcal{F}},\bar P_M)})$ to $(\mathcal{M}^{2,c}, \|\cdot\|_{\mathcal{M}^2})$. Denote by $\overline{\xi}$ the closure of ξ in $\|\cdot\|_{\mathcal{L}^2(\bar\Omega,\bar{\mathcal{F}},\bar P_M)}$, and let $H \in \overline{\xi}$. By definition there exists a sequence $H^n \in \xi$ with $H^n \to H$ in $\mathcal{L}^2(\bar\Omega, \bar{\mathcal{F}}, \bar P_M)$; in particular the sequence H^n is Cauchy. By the Itô-isometry the sequence $I(H^n) = (H^n.M)$ is therefore Cauchy in $\mathcal{M}^2$ respectively $\mathcal{M}^{2,c}$. Since $\mathcal{M}^{2,c}$ is a Hilbert space (Lemma 4.2), the limit $\lim_{n\to\infty}(H^n.M)$ exists in $\mathcal{M}^{2,c}$, and the following definition makes sense.

Definition 4.12. For $H \in \overline{\xi} \subset \mathcal{L}^2(\bar\Omega, \bar{\mathcal{F}}, \bar P_M)$ the stochastic integral $(H.M)$ is the uniquely defined element of $\mathcal{M}^{2,c}$ such that

$$\lim_{n\to\infty} \|(H^n.M) - (H.M)\|_{\mathcal{M}^2} = 0 \quad \text{for all } H^n \in \xi \text{ with } \|H^n - H\|_{\mathcal{L}^2(\bar\Omega,\bar{\mathcal{F}},\bar P_M)} \to 0.$$

Corollary 4.13. *Let $M \in \mathcal{M}^{2,c}$, $H_1, H_2 \in \overline{\xi}$ and $\alpha_1, \alpha_2 \in \mathbb{R}$. Then we have*

- *Linearity of $(H.M)$: $(\alpha_1 H_1 + \alpha_2 H_2 \,.\, M) = \alpha_1(H_1 \,.\, M) + \alpha_2(H_2 \,.\, M)$ and*
- *Itô-isometry: $E\left[(H.M)_t^2\right] = E\left[\int_0^t H_s^2\, d\langle M\rangle_s\right]$, for $t \le T$.*

In the next theorem we give a partial characterization of the abstract set $\overline{\xi}$.

Theorem 4.14. *Let $M \in \mathcal{M}^{2,c}$. Then $\overline{\xi}$ contains all adapted, left-continuous processes H such that $E\left[\int_0^T H_s^2\, d\langle M\rangle_s\right] < \infty$.*

We omit the proof.

Extensions. The definition of the stochastic integral $(H.M)$ can be extended in a number of ways.

a) Localisation. If H is adapted, leftcontinuous and M is a continuous local martingale with $\int_0^T H_s^2\, d\langle M\rangle_s < \infty$ P-a.s. we may find an increasing sequence of stopping times $\tau_n \nearrow T$ such that $M^{\tau_n} \in \mathcal{M}^{2,c}$, $E\left[\int_0^T H_s^2\, d\langle M^{\tau_n}\rangle_s\right] < \infty$. Then, for $t < \tau_n$ we put

$$(H.M)_t = (H.M^{\tau_n})_t, \tag{4.9}$$

where the right hand side is defined by Definition 4.12. It is easily shown that (4.9) gives a consistent definition of $(H.M)_t$, and that $(H.M)_t$ is a continuous local martingale.

b) Semimartingales as integrands. Let $X = X_0 + M + A$, where M is a continuous local martingale and A a continuous FV-process. Then one defines for H adapted and left continuous such that $\int_0^T H_s^2\, d\langle M\rangle_s + \int_0^T |H_s|\, d|A|s < \infty$,

$$\int_0^t H_s\, dX_s = \int_0^t H_s\, dM_s + \int_0^t H_s\, dA_s,$$

where the integral with respect to M is constructed as before and $\int_0^t H_s\, dA_s$ is an ordinary Stieltjes integral.

4.1.4 Kunita-Watanabe characterization

Theorem 4.15 (Kunita-Watanabe characterization)**.** *Let $H \in \overline{\xi}$, $M \in \mathcal{M}^{2,c}$. Then we have for all $N \in \mathcal{M}^{2,c}$*

$$\langle (H.M), N\rangle_t = \int_0^t H_s\, d\langle M, N\rangle_s. \tag{4.10}$$

Conversely if $L \in \mathcal{M}^{2,c}$ satisfies $\langle L, N\rangle_t = \int_0^t H_s\, d\langle M, N\rangle_s$, $t \le T$ for all $N \in \mathcal{M}^{2,c}$, we have $L = (H.M)$.

Partial proof. Establishing (4.10) for $H \in \overline{\xi}$ is a technical approximation argument and will be omitted. Uniqueness of a process L that satisfies (4.10) is easy to show. (4.10) implies that

$$E\left[L_T N_T\right] = E\left[\langle L, N\rangle_T\right] = E\left[\int_0^T H_s\, d\langle M, N\rangle_s\right] \quad \text{for all } N \in \mathcal{M}^{2,c},$$

i.e. the scalar product $\langle L, N\rangle_{\mathcal{M}^2}$ is determined from (4.10) for all $N \in \mathcal{M}^{2,c}$, , so that L is uniquely determined. □

Further Properties of $(H.M)$. Theorem 4.15 allows us to establish a number of very useful properties of the stochastic integral $(H.M)$.

Quadratic covariation. If we put $N = M$ we get

$$\langle (H.M), M\rangle_t = \int_0^t H_s\, d\langle M, M\rangle_s = \int_0^t H_s\, d\langle M\rangle_s,$$

and hence

$$\begin{aligned}\langle (H.M)\rangle_t &= \langle (H.M),(H.M)\rangle_t = \int_0^t H_s\, d\langle H.M, M\rangle \\ &= \int_0^t H_s\, d\Big(\int_0^s H_u\, d\langle M\rangle_u\Big) \qquad (4.11)\\ &= \int_0^t H_s^2\, d\langle M\rangle_s,\end{aligned}$$

by the chain-rule of Stieltjes-calculus, i.e. we have shown that $\langle (H.M)\rangle_t = \int_0^t H_s^2\, d\langle M\rangle_s$ for $H \in \overline{\xi}$ (and not just in ξ).

Chain rule of stochastic integration. Consider two integrands $H_1, H_2 \in \overline{\xi}$ such that $E\left[\int_0^T (H_{1,s}H_{2,s})^2\, d\langle M\rangle_s\right] < \infty$. Then we have $(H_1\,.\,(H_2\,.\,M)) = (H_1H_2\,.\,M)$ or, in the long version,

$$\int_0^t H_{1,s}\, d(H_2\,.\,M)_s = \int_0^t H_{1,s}H_{2,s}\, dM_s. \qquad (4.12)$$

Relation (4.12) is the *chain rule* of stochastic integration.

Proof. Let $L = H_1\,.\,(H_2\,.\,M)$. By Theorem 4.15 we get

$$\begin{aligned}\langle L, N\rangle_t &= \int_0^t H_{1,s}\, d\langle (H_2\,.\,M), N\rangle_s = \int_0^t H_{1,s}\, d\int_0^s H_{2,u}\, d\langle M, N\rangle_u \\ &= \int_0^t H_{1,s}\, H_{2,s}\, d\langle M, N\rangle_s = \langle (H_1H_2\,.\,M), N\rangle_t.\end{aligned}$$

Hence $L_t = \int_0^t H_{1,s}\, H_{2,s}\, dM_s$ as claimed. □

The next result is important in the context of incomplete markets.

Theorem 4.16 (Kunita Watanabe decomposition)**.** *Consider martingales $N, M_1, \ldots, M_n \in \mathcal{M}^{2,c}$. Then there is a unique decomposition of the form*

$$N_t = N_0 + \sum_{i=1}^n \int_0^t H_{s,i} dM_{s,i} + L_t, \quad t \le T,$$

with $H_1, \ldots, H_n \in \overline{\xi}$ and $L \in \mathcal{M}^{2,c}$ strongly orthogonal to $M_1, \ldots, M_n$, that is with $\langle L, M_i\rangle \equiv 0$ for all $1 \le i \le n$.

Note that L is also weakly orthogonal to $M_1, \ldots, M_n$, that is $E(L_T M_{T,i}) = L_0 M_{0,i} = 0$ as LM_i is a martingale.

Sketch of the proof. We let $n = 1$. By the Itô-isometry, the space of stochastic integrals $\mathcal{M}^H = \{(H.M)\colon H \in \overline{\xi}\}$ is a closed subspace of $\mathcal{M}^{2,c}$. Hence we can project the rv $N_T - N_0$ on that space, that is there is a representation

$$N_T = N_0 + \int_0^T H_s dM_s + L_T$$

and $E(L\int_0^T H_s dM_s) = 0$ for all $H \in \overline{\xi}$. Define the martingale L via $L_t = E(L_T \mid \mathcal{F}_t)$. Then L is the desired martingale. It remains to show that $\langle L, M\rangle \equiv 0$. Here one uses that $\mathcal{M}^H$ is *stable under stopping*, i.e. $\tilde{M} \in \mathcal{M}^H$ implies that also the stopped martingale $\tilde{M}^\tau \in \mathcal{M}^H$ for an arbitrary stopping time τ; we omit the details.

□

4.2 Itô Processes and the Feynman-Kac formula

Itô processes. Itô processes are solutions of stochastic differential equations driven by Brownian motion; they will be our basic model for asset price dynamics.

Definition 4.17. Given a d-dimensional Brownian motion $W = (W_{t,1}, ..., W_{t,d})_{t\geq 0}$, a time point $t_0 \geq 0$, some vector $x \in \mathbb{R}^n$ and functions $\mu : \mathbb{R}^+ \times \mathbb{R}^n \to \mathbb{R}^n$ and $\sigma : \mathbb{R}^+ \times \mathbb{R}^n \to \mathbb{R}^{n\times d}$. Then the n-dimensional process $X = (X_{t,1}, ..., X_{t,n})_{t\geq 0}$ is called an *Itô process* with initial value t_0, x, drift μ and dispersion matrix σ if X satisfies the SDE

$$X_{t,i} = x_i + \int_{t_0}^{t} \mu_i(s, X_s)\, ds + \sum_{j=1}^{d} \int_{t_0}^{t} \sigma_{ij}(s, X_s)\, dW_{sj}\,, \quad t \geq t_0\,. \tag{4.13}$$

In short notation (4.13) is often written in the form $dX_t = \mu(t, X_t)\, dt + \sigma(t, X_t)\, dW_t$. Moreover, one frequently takes $t_0 = 0$.

An intuitive way to understand the SDE (4.13) is the *Euler approximation*. For a small time step Δt one has with $t_n = n\Delta t$

$$X_{t_{n+1}} = X_{t_n} + \mu(t_n, X_{t_n})\delta t + \sum_{j=1}^{d} \sigma_j(t_n, X_{t_n})\epsilon_{n,j} \tag{4.14}$$

where $\epsilon_{n,j}$ are iid $\sim N(0, \Delta_t)$. (4.14) can be used to generate (approximations of) the trajectories of X on a computer.

Define the $n \times n$ matrix $C(t, X) = \sigma(t, X)\sigma'(t, X)$. Then we have

$$\begin{aligned}
\langle X_i, X_j\rangle_t &= \langle \sum_{k=1}^{d} \int_0^{\cdot} \sigma_{ik}\, dW_{s,k}\,, \sum_{l=1}^{d} \int_0^{\cdot} \sigma_{jl}\, dW_{s,l}\,\rangle_t \\
&= \sum_{k,l=1}^{d} \int_0^t \sigma_{ik}\sigma_{jl}\, d\underbrace{\langle W_k, W_l\rangle_s}_{=\delta_{kl}\, s} \\
&= \sum_{k=1}^{d} \int_0^t \sigma_{ik}\sigma_{jk}\, ds \\
&= \int_0^t C_{ij}(s, X_s)\, ds.
\end{aligned}$$

Hence C is sometimes called instantaneous covariance matrix of X.

Let $f : \mathbb{R}^n \to \mathbb{R}$ be a smooth function and define the differential operator A by

$$Af(t, x) = \sum_{i=1}^{n} \mu_i(t, x)\frac{\partial f}{\partial x_i}(x) + \frac{1}{2}\sum_{i,j=1}^{n} C_{ij}(t, x)\frac{\partial^2 f}{\partial x_i \partial x_j}(t, x). \tag{4.15}$$

Then we have

Lemma 4.18. *For $f : \mathbb{R}^n \to \mathbb{R}$ smooth such that f and its first two derivatives are bounded the process $M_t^f = f(X_t) - \int_0^t \frac{\partial f}{\partial t}(s, X_s) Af(s, X_s)\, ds$ is a martingale.*

Proof. We consider only the time-independent case. Applying Itô's formula in n dimensions we get

$$\begin{aligned} f(X_t) &= f(X_0) + \sum_{i=1}^{n} \int_0^t \frac{\partial f}{\partial x_i}(X_s)\, dX_{s,i} + \frac{1}{2} \sum_{i,j=1}^{n} \int_0^t \frac{\partial^2 f}{\partial x_i x_j}(X_s)\, d\langle X_i, X_j \rangle_s \\ &= f(X_0) + \sum_{i=1}^{n} \int_0^t \frac{\partial f}{\partial x_i}(X_s)\mu_i(s, X_s)\, ds + \sum_{i=1}^{n}\sum_{j=1}^{d} \int_0^t \frac{\partial f}{\partial x_i}(X_s)\sigma_i(s, X_s)\, dW_{s,j} \\ &\quad + \frac{1}{2} \sum_{i,j=1}^{n} \int_0^t \frac{\partial^2 f}{\partial x_i \partial x_j} C_{ij}(s, X_s)\, ds \\ &= f(X_0) + \sum_{i=1}^{n}\sum_{j=1}^{d} \int_0^t \frac{\partial f}{\partial x_i}(X_s)\sigma_i(s, X_s)\, dW_{s,j} + \int_0^t Af(s, X_s) ds. \end{aligned}$$

Hence $f(X_t) - \int_0^t Af(s, X_s)\, ds$ can be represented as a sum of stochastic integrals wrt Brownian assumed motion, and is therefore a local martingale. Since f and its derivatives are bounded by assumption, this expression is a true martingale and the claim follows. □

In the following theorem we give conditions ensuring that a solution to the SDE (4.13) exists.

Theorem 4.19. *Suppose that μ, σ satisfy Lipschitz and growth conditions of the form*

$$\begin{aligned} \|\mu(t, X) - \mu(t, Y)\| &\leq K\|X - Y\|, \quad t \geq 0, \\ \|\sigma(t, X) - \sigma(t, Y)\| &\leq K\|X - Y\|, \quad t \geq 0, \\ \|\mu(t, X) + \sigma(t, X)\| &\leq K(1 + \|X\|), \quad t \geq 0. \end{aligned}$$

Then for all initial values $(t_0, x) \in [0, \infty) \times \mathbb{R}^n$ a unique solution to (4.13) exists. Moreover, this solution is $(\mathcal{F}_t^W)$-adapted, where $\mathcal{F}_t^W = \sigma(W_{s,i} : 1 \leq i \leq d,\, s \leq t)$.

The Feynman Kac formula. Lemma 4.18 forms the basis for a close interplay between stochastic processes and solution of parabolic PDEs, which is extremely fruitful in financial mathematics. The basic result is the celebrated Feynman Kac formula.

We start with the one dimensional case, which is notationally easier. Consider scalar functions $\mu(t, x)$, $\sigma(t, x)$, and $r(t, x)$ and some function ϕ on $\mathbb{R}$. Suppose that $F(t, x)$ is a solution to the terminal value problem

$$\frac{\partial F}{\partial t}(t, x) + \mu(t, x)\frac{\partial F}{\partial x}(t, x) + \frac{1}{2}\sigma^2(t, x)\frac{\partial^2 F}{\partial x^2}(t, x) = r(t, x)F(t, x), \tag{4.16}$$

$$F(T, x) = \phi(x). \tag{4.17}$$

We want to represent F in terms of some Itô process X. Consider the SDE

$$dX_t = \mu(t, X_t)dt + \sigma(t, X_t)dW_t, \quad X_{t_0} = x \tag{4.18}$$

and recall that the infinitesimal generator of X equals

$$\mathcal{A}f(t, x) = \mu(t, x)\frac{\partial f}{\partial x} + \frac{1}{2}\sigma^2(t, x)\frac{\partial^2 f}{\partial x^2}, \quad f \in C^{1,2},$$

so that (4.16) can be written as $\frac{\partial F}{\partial t} + \mathcal{A}F = rF$. Consider now the process $Z_t = \exp(-\int_{t_0}^t r(s, X_s)ds)F(t, X_t)$. Application of Itô 's Lemma Yields with $D_t = \exp(-\int_{t_0}^t r(s, X_s)ds)$

$$dZ_t = d(D_t F(t, X_t)) = F(t, X_t)dD_t + D_t dF(t, X_t) + d\langle D, F(t, X)\rangle_t.$$

Now D is an FV-process which solves the ODE $dD_t = -r(t, X_t)D_t dt$, so that $\langle D, F(t, X)\rangle_t \equiv 0$. Moreover, the Itô formula gives $dF(t, X_t) = (\frac{\partial F}{\partial t} + \mathcal{A}F)(t, X_t)dt + \frac{\partial F}{\partial x}\sigma(t, X_t)dW_t$. Hence we get, using the chain rule for stochastic integration

$$\begin{aligned} dZ_t = &- r(t, X_t)F(t, X_t)D_t dt + \{(\frac{\partial f}{\partial t} + \mathcal{A}F)(t, X_t)D_t\}dt \\ &+ D_t \frac{\partial F}{\partial x}(t, X_t)dW_t. \end{aligned}$$

Using the PDE (4.16) for F we see that the dt terms vanish, i.e.

$$Z_t = Z_{t_0} + \int_{t_0}^t \frac{\partial F}{\partial x}(s, X_s)D_s\sigma(s, X_s)dW_s$$

is a (local) martingale and a true martingale given sufficient integrality, which we assume form now on. Moreover, by definition $D_{t_0} = 1$ so that $Z_{t_0} = F(t_0, X_{t_0}) = f(t_0, x)$. The martingality of Z now gives, as $Z_T = \exp\big(-\int_{t_0}^T r(s, X_s)ds\big)\phi(X_T)$ because of (4.17),

$$F(t_0, X_{t_0}) = Z_{t_0} = E_{t_0,x}(Z_T) = E_{t_0,x}\Big(\exp(-\int_{t_0}^T r(s, X_s))\phi(X_T)\Big). \tag{4.19}$$

Formula (4.19) is called Feynman Kac formula. It can be used in two ways:

- We can use probabilistic techniques or Monte-Carlo simulation to compute the expectation on the rhs of (4.19) in order to solve numerically the PDE (4.16), (4.17).
- We can try to solve the PDE (4.16), (4.17), perhaps numerically, in order to compute the expectation on the rhs of (4.19).

Both approaches are frequently used in financial mathematics. For a generalization of (4.19) to multi-dimensional processes and for a precise statement of the necessary integrality conditions we refer to Section 5.7 of Karatzas & Shreve (1988).

Example 4.20 (The Black-Scholes PDE)**.** In Theorem 3.2 we showed that the fair price $V_t = \mu(t, S_t)$ of a terminal-value claim with payoff $h(S_T)$ in the Black-Scholes Model solves the terminal value problem

$$u_t + rS\mu_S + \frac{1}{2}\sigma^2 S^2 u_{SS} = ru, \quad u(T, S) = h(S).$$

In order to give a probabilistic interpretation we consider the SDE

$$dS_t = rS_t dt + \sigma S_t dW_t$$

with generator $\mathcal{A} = rS\frac{\partial}{\partial S} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2}{\partial S^2}$, and we obtain from (4.19)

$$u(t_0, S) = E_{t_0,S}\big(e^{-r(T-t_0)}h(S_T)\big), \quad t_0 \le T. \tag{4.20}$$

This can be viewed as risk-neutral pricing formula in continuous time. In the next Chapter we give a derivation of (4.20) using only probabilistic techniques.

4.3 Change of Measure and Girsanov Theorem for Brownian motion

4.3.1 Motivation

In discrete-time models, it was shown that the price in $t < T$ of any attainable claim with $\mathcal{F}_T$-measurable payoff H is given by the risk-neutral pricing formula

$$H_t = S_{t,0}\, E^Q \left[\frac{H}{S_{T,0}} | \mathcal{F}_t \right], \quad t \leq T. \tag{4.21}$$

Here $S_{t,0} > 0$ represents the numeraire at time t (often $S_{t,0} = \exp(rt)$), and Q satisfies the following properties:

(i) $Q \sim P$, i.e. $Q(A) > 0 \Leftrightarrow P(A) > 0, \quad A \in \mathcal{F}_T$.

(ii) The discounted price processes $\tilde{S}_{t,i} = S_{t,i}/S_{t,0}$, $1 \leq i \leq n$, are Q-martingales, i.e. $E^Q \left[\tilde{S}_{t,i} | \mathcal{F}_s \right] = \tilde{S}_{s,i}\,,\ 0 \leq s \leq t \leq T$.

In this section we provide the mathematical tools for extending (4.21) to continuous-time models 'driven' by Brownian motion.

By the Radon-Nikodym theorem, the equivalence of P and Q implies the existence of an $\mathcal{F}_T$-measurable rv Z with $P(Z > 0) = 1$ such that for all $A \in \mathcal{F}_T$

$$Q(A) = E^P \left[Z 1_A \right] = E^P \left[Z; A \right]. \tag{4.22}$$

In particular, we get $E^P[Z] = Q(\Omega) = 1$. Conversely, any $\mathcal{F}_T$-measurable rv Z with $E[Z] = 1$ and $P(Z > 0) = 1$ can be used to define a measure Q on $\mathcal{F}_T$ via (4.22); P and Q are obviously equivalent. Z is called the (Radon-Nikodym) density of Q wrt P, denoted by $Z = \frac{dQ}{dP}$. Note that (4.22) implies that for every $\mathcal{F}_T$-measurable $X \geq 0$ we have $E^Q[X] = E^P[ZX]$ (by measure theoretic induction).

Example 4.21. For finite $\Omega = \{\omega_1, ..., \omega_k\}$ two measures P and Q are equivalent if for $1 \leq i \leq k$: $P(\{\omega_i\}) > 0 \Leftrightarrow Q(\{\omega_i\}) > 0$; it is immediate from (4.22) that $\frac{dQ}{dP}(\omega) = Q(\{\omega\})/P(\{\omega\})$ in that case.

In the next Example we show how a change-of-measure can be used to alter the mean of a normally distributed random variable.

Example 4.22. Let $X \sim N(0, \sigma^2)$ on some $(\Omega, \mathcal{F}, P)$. Define a random variable Z by $Z = \exp\left(\frac{\mu}{\sigma^2} X - \frac{1}{2} \frac{\mu^2}{\sigma^2} \right)$. Then we get, using standard rules for the mean of lognormal random variables

$$\begin{aligned} E[Z] &= \exp\left(-\frac{1}{2} \frac{\mu^2}{\sigma^2} \right) \exp\left(E\left[\frac{\mu}{\sigma^2} X \right] + \frac{1}{2} \mathrm{var}\left(\frac{\mu}{\sigma^2} X \right) \right) \\ &= \exp\left(-\frac{1}{2} \frac{\mu^2}{\sigma^2} \right) \exp\left(\frac{1}{2} \frac{\mu^2}{\sigma^2} \right) = 1, \end{aligned}$$

so that we can define a measure Q by putting $\frac{dQ}{dP} = Z$. Note that we have for any bounded $g : \mathbb{R} \to \mathbb{R}$:

$$\begin{aligned} E^Q \left[g(X) \right] &= E^P \left[Z g(x) \right] = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} g(x) \exp\left(\frac{\mu}{\sigma^2} x - \frac{1}{2} \frac{\mu^2}{\sigma^2} \right) e^{-\frac{x^2}{2\sigma^2}}\, dx \\ &= \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} g(x) \exp\left(-\frac{(x-\mu)^2}{2\sigma^2} \right) dx, \end{aligned}$$

which shows that $X \sim N(\mu, \sigma^2)$ under Q.

The main result of this section, Girsanov's theorem for Brownian motion, can be thought of as the infinite-dimensional analogue of this example: by a proper change of measure it is possible to alter the drift of an Itô process. In particular, by choosing $Q \sim P$ properly, it is usually possible to turn an asset price into a martingale.

4.3.2 Density martingales

Now we return to the change of measure for stochastic processes. Suppose that we have a filtered probability space $(\Omega, \mathcal{F}, P)$, $(\mathcal{F}_t)_{0\le t\le T}$, and a strictly positive, $\mathcal{F}_T$-measurable random variable Z with $E[Z] = 1$, and define the measure Q by $E^Q[X] = E^P[XZ]$, X bounded, $\mathcal{F}_T$-measurable. Define the associated density martingale by

$$Z_t = E^P[Z|\mathcal{F}_t], \quad 0 \le t \le T. \tag{4.23}$$

Lemma 4.23. *$(Z_t)_{0\le t\le T}$ is a martingale, and for every $\mathcal{F}_t$-measurable random variable Y we have $E^Q[Y] = E^P[YZ_t]$, $t \le T$.*

Proof. The martingale property of $(Z_t)_{t\ge 0}$ is obvious. For the second claim note that by iterated conditioning

$$E^Q[Y] = E^P[YZ] = E^P\left[E^P[YZ|\mathcal{F}_t]\right] = E^P\left[YE^P[Z|\mathcal{F}_t]\right] = E^P[YZ_t].$$

□

The next lemma extends this result to conditional expectations.

Lemma 4.24 (abstract Bayes formula)**.** *Given $0 \le s \le t \le T$ and let Y be some $\mathcal{F}_t$-measurable integrable random variable. Then*

$$E^Q[Y|\mathcal{F}_s] = \frac{1}{Z_s}E^P[YZ_t|\mathcal{F}_s] \tag{4.24}$$

Proof. We have to check that the right hand side of (4.24) satisfies the characterizing equation of conditional expectations, i.e.

$$E^Q\left[\frac{1}{Z_s}E^P[YZ_t|\mathcal{F}_s]\,1_A\right] = E^Q[Y1_A], \quad A \in \mathcal{F}_s.$$

Using Lemma 4.23, the left hand side equals, as $A \in \mathcal{F}_s$,

$$E^P\left[Z_s\frac{1}{Z_s}E^P[YZ_t|\mathcal{F}_s]\,1_A\right] = E^P\left[E^P[YZ_t1_A|\mathcal{F}_s]\right] = E^P[YZ_t1_A],$$

which is equal to $E^Q[Y1_A]$ by Lemma 4.23. □

Lemma 4.25. *Let $Q \sim P$ with $\frac{dQ}{dP} = Z$. An adapted process $(M_t)_{0\le t\le T}$ is a Q-martingale if and only if the process $(M_tZ_t)_{0\le t\le T}$ is a P-martingale.*

Proof. By the Bayes formula (4.24) we have for $t \le T$ with $Z_T := Z$

$$E^Q[M_T|\mathcal{F}_t] = \frac{1}{Z_t}E^P[M_TZ_T|\mathcal{F}_t]. \tag{4.25}$$

If $(M_tZ_t)_{0\le t\le T}$ is a P-martingale the right hand side equals $\frac{1}{Z_t}M_tZ_t = M_t$ and M is a Q-martingale. Conversely, if M is a Q-martingale the left hand side equals M_t and multiplying (4.25) with Z_t gives $M_tZ_t = E^P[M_TZ_T|\mathcal{F}_t]$. □

4.3.3 The Girsanov Theorem

We begin with the one-dimensional version. Let $(W_t)_{0\le t\le T}$ be a one-dimensional Brownian motion on the filtered probability space $(\Omega, \mathcal{F}, P)$, $(\mathcal{F}_t)_{0\le t\le T}$. Let $(\theta_t)_{0\le t\le T}$ be an adapted process, and define

$$Z_t = \exp\left(\int_0^t \theta_s\, dW_s - \frac{1}{2}\int_0^t \theta_s^2\, ds\right), \quad 0 \le s \le T. \tag{4.26}$$

We show that Z_t can be written as a stochastic integral with respect to W. Define $X_t = \int_0^t \theta_s\, dW_s - \frac{1}{2}\int_0^t \theta_s^2\, ds$. Then

$$\langle X\rangle_t = \langle \int_0^{\cdot} \theta_s\, dW_s\rangle_t = \int_0^t \theta_s^2\, ds,$$

and since $Z_t = \exp(X_t)$, Itô's formula gives with $f(x) = e^x$:

$$\begin{aligned} dZ_t &= f'(X_t)\, dX_t + \frac{1}{2}f''(X_t)\, d\langle X\rangle_t \\ &= e^{X_t}\, dX_t + \frac{1}{2}e^{X_t}\theta_t^2\, dt \\ &= Z_t\, dX_t + \frac{1}{2}\theta_t^2 Z_t\, dt \\ &= \theta_t Z_t\, dW_t - \frac{1}{2}\theta_t^2 Z_t\, dt + \frac{1}{2}\theta_t^2 Z_t\, dt, \end{aligned}$$

so that $Z_t = Z_0 + \int_0^t \theta_s Z_s\, dW_s$. It follows that Z is a nonnegative local martingale and hence a supermartingale. Z is a true martingale if and only if $E[Z_T] = Z_0 = 1$. In that case Z can be used as a Radon-Nikodym density.

Theorem 4.26 (Girsanov)**.** *Suppose that $(Z_t)_{0\le t\le T}$ defined in (4.26) is a martingale. Define a probability measure Q on $\mathcal{F}_T$ by putting $\frac{dQ}{dP} = Z_T$. Then the process $\tilde{W}$ defined by*

$$\tilde{W}_t = W_t - \int_0^t \theta_s\, ds, \quad 0 \le t \le T \tag{4.27}$$

is a Brownian motion under Q.

Remark 4.27. The process $W_t = \tilde{W}_t + \int_0^t \theta_s\, ds$ is under Q a Brownian motion with drift $(\theta_t)_{0\le t\le T}$; in that sense Theorem 4.26 generalises Example 4.22.

Proof. The proof is based on the Levy-characterization of Brownian motion:

Theorem 4.28 (Levy)**.** *Given a filtered probability space $(\Omega, \mathcal{F}, P)$, $(\mathcal{F}_t)_{t\ge 0}$. An adapted process $M = (M_t)_{t\ge 0}$ with continuous trajectories is a one-dimensional Brownian motion if and only if the following conditions hold:*

1. *M is a local martingale.*
2. *$\langle M\rangle_t = t$, where $\langle M\rangle$ is the pathwise quadratic variation defined for instance in (4.3).*

Condition 2 is easily verified: Since $\int_0^t \theta_s\,ds$ is FV, we have $\langle W\rangle_t = \langle \tilde{W}\rangle_t$, and since W is a P-Brownian motion, we have $\langle W\rangle_t = t$ P-a.s. and hence also Q-a.s. (as $P \sim Q$). The theorem is proven if we can show that $\tilde{W}$ is a Q-local martingale. By Lemma 4.25 this is equivalent to showing that $(\tilde{W}_t Z_t)_{0\le t\le T}$ ia a P-local martingale. Recall that Z has the representation $Z_t = Z_0 + \int_0^t \theta_s Z_s\,dW_s$. Hence we get, using Itô's product formula

$$d\tilde{W}_t Z_t = \tilde{W}_t\,dZ_t + Z_t\,d\tilde{W}_t + d\langle \tilde{W}, Z\rangle_t.$$

Now we have

$$\begin{aligned}\langle \tilde{W}, Z\rangle_t &\overset{(i)}{=} \langle W, Z\rangle_t = \langle W, \int_0^{\cdot} \theta_s Z_s\,dW_s\rangle_t \\ &\overset{(ii)}{=} \int_0^t \theta_s Z_s\,d\langle W, W\rangle_s \\ &= \int_0^t \theta_s Z_s\,ds, \end{aligned} \tag{4.28}$$

using (i) that W and $\tilde{W}$ differ only by a continuous FV process and (ii) the Kunita-Watanabe characterization (Theorem 4.15). Hence we get, using (4.28) and the chain-rule for stochastic integrals (4.13),

$$\begin{aligned} d\tilde{W}_t Z_t &= \tilde{W}_t\theta_t Z_t\,dW_t + Z_t\,dW_t - Z_t\theta_t\,dt + Z_t\theta_t\,dt \\ &= (\tilde{W}_t\theta_t Z_t + Z_t)\,dW_t. \end{aligned}$$

This shows that the product $\tilde{W}_t Z_t$ has a representation as an integral with respect to the P-Brownian motion $(W_t)_{0\le t\le T}$ and is therefore a P-local martingale, proving the result. □

d-dimensional version

Remark 4.29. The following conditions are sufficient to ensure that $(Z_t)_{0\le t\le T}$ is a martingale, so that Theorem 4.26 applies.

(a) $E\left[\int_0^T \theta_s^2 Z_s^2\,ds\right] < \infty$ (integrable quadratic variation).

(b) $E[Z_T] = 1$. (This is necessary and sufficient.)

(c) Novikov-criterion: $E\left[\exp\left(\frac{1}{2}\int_0^T |\theta_s|^2\,ds\right)\right] < \infty$.

We discuss two mathematical applications of Theorem 4.26.

1. Solution of SDEs via change of measure. Given some function $b(s, X) : \mathbb{R}^+ \to \mathbb{R}$, bounded (but not Lipschitz). We want to construct a solution X of the SDE

$$dX_t = b(t, X_t)\,dt + dW_t, \quad 0 \le t \le T, \tag{4.29}$$

with W some Brownian motion. Start with some probability space $(\Omega, \mathcal{F}, P)$, $(\mathcal{F}_t)_{0\le t\le T}$, supporting a Brownian motion $(X_t)_{0\le t\le T}$. Define a measure Q via

$$\left.\frac{dQ}{dP}\right|_{\mathcal{F}_T} = Z_T := \exp\left(\int_0^T \theta(s, X_s)\,dX_s - \frac{1}{2}\int_0^T \theta^2(s, X_s)\,ds\right).$$

By Theorem 4.26, $W_t := X_t - \int_0^t \theta(s, X_s)\,ds$ is a Q-Brownian motion; hence

$$X_t = W_t + \int_0^t \theta(s, X_s)\,ds$$

solves equation (4.29) for a Q-Brownian motion W.

2. Maximum-likelihood estimation for a Brownian motion with drift. We observe a process $X_t = W_t + \mu t$, $\mu \in \mathbb{R}$ a constant and W a Brownian motion and want to estimate the unknown parameter μ. A possible approach is maximum-likelihood estimation (MLE):

Consider some 'random variable' X with values in the space $(\tilde{\Omega}, \tilde{\mathcal{F}})$ whose distribution P^μ on $(\tilde{\Omega}, \tilde{\mathcal{F}})$ depends on an unknown parameter $\mu \in A^\mu$. Suppose moreover, that there is a common reference measure $\tilde{P}$ on $(\tilde{\Omega}, \tilde{\mathcal{F}})$ such that $P^\mu \sim \tilde{P}$ and

$$\frac{dP^\mu}{d\tilde{P}} = L(X;\mu), \quad \mu \in A^\mu.$$

Given some observation $\hat{X}$ of X, the (abstract) ML-estimator $\hat{\mu}$ for μ is given by

$$\hat{\mu} = \arg\max_{\mu \in A^\mu} L(\hat{X}, \mu), \tag{4.30}$$

i.e. $\hat{\mu}$ is the value of μ that makes the observation $\hat{X}$ most likely. ML-estimators typically have desirable properties such as asymptotic normality and consistency.

Let us apply the approach to the Brownian motion with drift X. In that case we choose $\tilde{\Omega} = C([0,T], \mathbb{R})$, $\tilde{P}$ equal to the Wiener measure, and we let $X_t(\tilde{\omega}) = \tilde{\omega}(t)$ (the so-called coordinate process on $C([0,T], \mathbb{R})$). Moreover, we define P^μ by

$$\frac{dP^\mu}{dP} = \exp\left(\mu X_T - \frac{1}{2}\mu^2 T\right), \quad \mu \in \mathbb{R}, \tag{4.31}$$

By definition of the Wiener measure, X is a $\tilde{P}$ Brownian motion. Moreover, as in the previous application, $X_t - \mu t$ is a $\tilde{P}^\mu$-Brownian motion, so that under P^μ $X_t = (X_t - \mu t) + \mu t$ is a Brownian motion with drift μ. Given an observed trajectory $(\hat{X}_t)_{0 \le t \le T}$ of X, the ML-estimator is hence given by

$$\begin{aligned} \hat{\mu} &= \arg\max_{\mu \in \mathbb{R}} \exp\left(\mu \hat{X}_T - \frac{1}{2}\mu^2 T\right) \\ &= \arg\max_{\mu \in \mathbb{R}} \mu \hat{X}_T - \frac{1}{2}\mu^2 T. \end{aligned} \tag{4.32}$$

Differentiating (4.32) with respect to μ gives $\hat{X}_T - \hat{\mu} T = 0$ and hence the ML-estimator $\hat{\mu} = \frac{\hat{X}_T}{T}$.

Chapter 5

Financial Mathematics in Continuous-Time

5.1 Basic Concepts

5.1.1 The Model

We start with a general model for a frictionless security market with continuous trading. Fix some horizon date T and consider some probability space $(\Omega, \mathcal{F}, P)$ with a filtration $\{\mathcal{F}_t\}_{0\le t\le T}$. There are $d+1$ traded assets with price process $S = (S^0, \dots, S^d)$. We assume throughout that $S^0, \dots, S^d$ follow semimartingales with continuous trajectories. We assume that $S^0(t) > 0$ P a.s. for all t and use S^0 as numeraire; often $S^0(t) = \exp\int_0^t r_s ds$ for some adapted process r with $r_s \ge 0$. In that case S^0 represents the so-called *savings account* and r is the *short rate* of interest.

Selffinancing trading strategies: A $\mathbb{R}^{d+1}$-valued adapted and left-continuous process $\phi(t) = \left(\phi_t^0, \dots, \phi_t^d\right)$ is called a trading strategy; ϕ_t^i represents the number of units of security i in the portfolio at time t. We assume that ϕ^i is sufficiently integrable so that the stochastic integral $\int_0^t \phi_s^i dS_s^i$ is well defined.

Definition 5.1. (i) The *value* of the portfolio at time t equals $V_t = V_t^\phi = \sum_{i=0}^d \phi_t^i S_t^i$; $V^\phi = (V_t^\phi)_{0\le t\le T}$ is called *value process* of the strategy.

(ii) The *gains process* of the strategy is given by

$$G_t^\phi = \int_0^t \phi_u dS_u := \sum_{i=0}^d \int_0^t \phi_u^i dS_u^i$$

(iii) The strategy is called *selffinancing*, if for all $t \in [0,T]$ $V_t^\phi = V_0^\phi + G_t^\phi$.

The economic justification of (ii) and (iii) is the same as in the case of the Markov strategies discussed in Chapter 3.

Numeraire invariance: We choose S^0 as our numeraire and introduce the discounted price process

$$\tilde{S}_t = (1, S_t^1/S_t^0, \dots, S_t^d/S_t^0), \tag{5.1}$$

and the discounted value process $\tilde{V}_t^\phi = V_t^\phi/S_t^0 = \sum_{i=0}^d \phi_t^i \tilde{S}_t^i$. Intuitively, one would expect that a change of numeraire has no substantial economic implications. The next result confirms this fact.

Proposition 5.2 (Numerare Invariance)**.** *Selffinancing strategies remain selffinancing after a change of numeraire.*

Proof. Let $X_t = \left(S_t^0\right)^{-1}$. We have, using Itô 's product formula, that

$$d\tilde{S}_t^k = dS_t^k X_t = S_t^k dX_t + X_t dS_t^k + d\langle S^k, X\rangle_t, \tag{5.2}$$

and similarly $d\tilde{V}_t^\phi = V_t^\phi dX_t + X_t dV_t^\phi + d\langle X, V^\phi\rangle_t$. Now we have $V_t^\phi = \sum_{k=0}^d \phi_t^k S_t^k$ by definition and, as ϕ is selffinancing, $dV_t^\phi = \sum_{k=0}^d \phi_t^k dS_t^k$. This gives the following dynamics of the discounted wealth process $\tilde{V}$:

$$\begin{aligned} d\tilde{V}_t^\phi &= \sum_{k=0}^d \phi_t^k S_t^k dX_t + \sum_{k=0}^d X_t \phi_t^k dS_t^k + \sum_{k=0}^d \phi_t^k d\langle S^k, X\rangle_t \\ &= \sum_{k=0}^d \phi_t^k \{S_t^k dX_t + X_t dS_t^k + d\langle S^k, X\rangle_t\} \qquad (5.3) \\ &= \sum_{k=0}^d \phi_t^k d\tilde{S}_t^k, \end{aligned}$$

as follows by comparing (5.3) and (5.1). Hence we have shown that $d\tilde{V}_t^\phi = \sum_{k=0}^d \phi_t^k d\tilde{S}_t^k$ so that the discounted value process can be represented as sum of the discounted initial value and of the gains process wrt the discounted securities prices. □

Corollary 5.3. *(i) A trading strategy ϕ is selffinancing if and only if*

$$\tilde{V}^\phi = \tilde{V}_0^\phi + \tilde{G}_t^\phi \quad \textit{with} \quad \tilde{G}_t^\phi = \sum_{k=1}^d \phi_t^k d\tilde{S}_t^k. \tag{5.4}$$

(ii) A selffinancing strategy is is completely determined by the initial investment V_0 and the position $\phi^1, \ldots, \phi^d$ in the assets $S^1, \ldots, S^d$.

Proof. Statement (i) follows immediately from the numeraire invariance (note that $\tilde{S}_t^0 \equiv 1$, so that $\int_0^t \phi_t^0 d\tilde{S}_t^0 \equiv 0$).

For the second statement note that V_0 and $\phi^1, \ldots, \phi^d$ uniquely determine the discounted wealth process $\tilde{V}_t^\phi$ by (5.4) and hence the undiscounted valued process V_t^ϕ; the position ϕ_t^0 is then given by

$$\phi_t^0 = (S_t^0)^{-1}\{V_t^\phi - \sum_{k=1}^d \phi_t^k S_t^k\}.$$

□

5.1.2 Martingale Measures and Arbitrage Opportunities

Definition 5.4 (Arbitrage). A selffinancing portfolio such that $P(V_t^\phi \geq 0 \quad \text{for all} \quad 0 \leq t \leq T) = 1$, $V_0^\phi = 0$ and $P(V_T^\phi > 0) > 0$ is an arbitrage opportunity.

Arbitrage opportunities represent a chance to create risk free profits and should not exist in a well-functioning market.

Definition 5.5 (Martingale measure). A probability measure Q is called an *equivalent martingale measure* if

(i) $Q \sim P$ on $\mathcal{F}_T$, i.e. for every $A \in \mathcal{F}_T$, $Q(A) = 0 \Leftrightarrow P(A) = 0$.

(ii) The discounted price processes $\tilde{S}^k$, $1 \leq k \leq d$ are Q-martingales.

Note that a martingale measure is always related to a given numeraire (due to the discounting in (ii)). If the numeraire is of the form $S_t^0 = \exp(\int_0^t r_s ds)$, r the spot rate of interest, Q is also called *spot martingale measure.*

Lemma 5.6. *Q is a spot martingale measure, if and only if every price process S^i has Q-dynamics of the form*

$$dS_t^i = r_t S_t^i dt + dM_t^i, \quad 0 \leq i \leq d, \tag{5.5}$$

where $M^0, \ldots, M^d$ are Q-martingales.

Proof. We get, as $(S_t^0)^{-1} = \exp(-\int_0^t r_s ds)$, that $d(S_t^0)^{-1} = -r_t (S_t^0)^{-1} dt$. Itô's product formula gives, as $(S_t^0)^{-1}$ is of finite variation, that

$$d\tilde{S}_t^i = -r_t \tilde{S}_t^i dt + (S_t^0)^{-1} dS_t^i,$$

which is a martingale if and only if S^i has dynamics (5.5). □

The next result shows that the existence of an equivalent martingale measure excludes arbitrage opportunities.

Theorem 5.7. *If the model $S^0, \ldots, S^d$ admits an equivalent martingale measure Q, there are no arbitrage opportunities.*

Proof. Step 1: For any selffinancing strategy ϕ such that $V_t^\phi \geq 0$, the discounted wealth process $\tilde{V}_t^\phi$ is a Q-supermartingale. We have $\tilde{V}_t^\phi = \tilde{V}_0^\phi + \sum_{k=1}^d \int_0^t \phi_s^k d\tilde{S}_s^k$. The discounted price processes are Q-martingales by assumption, hence $\tilde{V}_t^\phi$ is a local Q-martingale, as it is a sum of stochastic integral wrt martingales. Since $\tilde{V}_t^\phi \geq 0$, it follows that $\tilde{V}^\phi$ is a Q-supermartingale, using that every nonnegative local martingale is a supermartingale by the Fatou-Lemma for conditional expectations.

Step 2: Suppose now that $P(V_T^\phi > 0) > 0$. It follows that $Q(\tilde{V}_T^\phi > 0) > 0$, as $Q \sim P$. Since $\tilde{V}^\phi$ is a Q-supermartingale we get $\tilde{V}_0^\phi \geq E^Q(\tilde{V}_T^\phi)$, and this is strictly positive as $Q(V_T^\phi > 0) > 0$. Hence also $V_0^\phi > 0$, so that an arbitrage opportunity cannot exist. □

Remark 5.8. The converse statement (the fact that absence of arbitrage implies the existence of equivalent martingale measures) is 'in principle' correct as well. This is the famous first fundamental theorem of arbitrage, established in full generality by Delbaen & Schachermayer (1994), see for instance [ ]. A good discussion of the more technical aspects surrounding this result is also given in Chapter 10 of Björk (2004).

5.1.3 Hedging and risk-neutral pricing of contingent claims

A contingent claim X is an $\mathcal{F}_T$-measurable random variable, to be interpreted as payoff of some financial claims. In this section we introduce basic concepts related to hedging and pricing of contingent claim. We assume throughout that the model admits some martingale measure related to the numeraire S^0, and denote a fixed such measure by Q.

Definition 5.9. A selffinancing trading strategy is called Q-admissible, if the discounted gains process $\tilde{G}^\phi$ is a Q-martingale; $\Phi(Q)$ denotes the linear space of all Q-admissible strategies.

From now on we restrict our attention to contingent claims X such that $E^Q(|X|/S_T^0) < \infty$ (i.e. $\tilde{X} := X/S_T^0 \in \mathcal{L}^1(\Omega, \mathcal{F}_T, Q)$).

Definition 5.10. (i) A contingent claim X such that $\tilde{X} \in \mathcal{L}^1(\Omega, \mathcal{F}_T, Q)$ is called *attainable*, if there is at least one admissible strategy $\phi \in \Phi(Q)$ such that $V_T^\phi = X$, Q a.s.; any such strategy is called replicating strategy for X.

(ii) The financial market model is called *complete*, if any contingent claim X with $\tilde{X}S_T^0 \in \mathcal{L}^1(\Omega, \mathcal{F}_T, Q)$ is attainable.

The financial motivation for the definition is of course the fact that by initially investing V_0^ϕ and then following the trading strategy ϕ the claim can be replicated without any further cost or risk. Note that in reality the performance of the trading strategy ϕ may be sub-optimal due to market frictions or model errors, and perfect replication of the claim may be impossible.

The next result links attainability to martingale representation.

Lemma 5.11. *Consider a contingent claim X such that $\tilde{X} = X/S_T^0 \in \mathcal{L}^1(\Omega, \mathcal{F}_T, Q)$. Then X is attainable if and only if the Q-martingale M with $M_t = E^Q(\tilde{X}|\mathcal{F}_t)$ admits a representation as stochastic integral of the form*

$$M_t = x + \sum_{i=1}^{d} \int_0^t \phi_u^i d\tilde{S}_u^i, \quad 0 \le t \le T, \tag{5.6}$$

for some constant x and some Q-admissible strategy $\phi^1, \ldots, \phi^d$.

Proof. Suppose that (5.6) holds. We define the replicating strategy by putting $V_0 = xS^0(0)$, and by using $\phi_t^1, \ldots, \phi_t^d$ as position in $S^1, \ldots, S^d$. The discounted wealth process of the strategy satisfies (by Corollary 5.3 (ii))

$$\tilde{V}_T^\phi = x + \sum_{i=1}^{d} \int_0^T \phi_s^i d\tilde{S}_s^i = \frac{X}{S_T^0},$$

where the last equality follows from (5.6). Again by Corollary 5.3, we thus have $X = V_0 + G_T^\phi$, and the 'if' part follows. The converse statement is true by Corollary 5.3. □

Market completeness can be characterized by the uniqueness of an equivalent martingale measure.

Theorem 5.12 (Second fundamental theorem of asset pricing)**.** *Consider a market that admits (at least) one martingale measure Q. Then the market is complete if and only if the measure Q is unique.*

The 'if' part will be proven below; for the more difficult 'only if' part we refer to the literature.

Now we turn to the risk-neutral pricing of contingent claims. Consider an arbitrage-free market and a contingent claim X. Denote by $\Pi(t;X)$, $0 \leq t \leq T$ a candidate price process for X.

Proposition 5.13. *1. If the extended model with price processes $\big(S^0, S^1, \dots S^d, \Pi(\cdot, X)\big)$ admits an equivalent martingale measure and is thus arbitrage-free, we must have $X/S^0_T \in \mathcal{L}^1(\Omega, \mathcal{F}_T, Q)$ and*

$$\Pi(t,X) = S^0_t E^Q\Big(\frac{X}{S^0_T}|\mathcal{F}_t\Big) \tag{5.7}$$

for some martingale measure Q for the original market $(S^0, \dots, S^d)$.

2. Two different martingale measure Q_1, Q_2 will in general lead to two different price processes $\Pi_1(t,X)$, $\Pi_2(t,X)$ which are both consistent with absence of arbitrage.

3. If X is attainable, we have for any martingale measure Q with $X/S^0_T \in \mathcal{L}^1(\Omega, \mathcal{F}_T, Q)$ the relation

$$S^0_t E^Q\Big(\frac{X}{S^0_T}|\mathcal{F}_t\Big) = V^\phi_t,$$

where ϕ is a Q-admissible replicating strategy for X. In particular, the fair arbitrage-free price of an attainable claim is uniquely defined.

Proof. 1) (5.7) is necessary to ensure that there is some martingale measure for the extended market.

2) We have seen examples for this in the discrete-time setup.

3) If X is attainable we have the representation $X/S^0_T = x + \tilde{G}^\phi_T$ for some Q-admissible strategy ϕ. Taking conditional expectation gives, as $\tilde{G}^\phi$ is a martingale

$$E(\frac{X}{S^0_T}|\mathcal{F}_t) = x + \tilde{G}^\phi_t = \tilde{V}^\phi_t, \tag{5.8}$$

where the last equality follows form Corollary 5.3. Multiplying both side of (5.8) with S^0_t proves the claim. □

Remark 5.14. If the market is complete, we must have for any two martingales Q_1 and Q_2 and any bounded random variable X that

$$E^{Q_1}(X) = V^\phi(0) = E^{Q_2}(X),$$

where ϕ is a replicating strategy for $\tilde{X} = XS^0_T$ (which exists by market completeness). Hence we must have $Q_1 = Q_2$, which is the 'if ' part of Theorem 5.12.

5.1.4 Change of numeraire

We now discuss the technique of change of numeraire, which will be very useful for the valuation of claim under stochastic interest rates in the next section. We consider a model

with $d+1$ assets $S^0, S^1, \ldots, S^d$ and assume that there a martingale measure Q such that the discounted asset prices $\tilde{S}^i_t = S^i_t/S^0_t, 1 \leq i \leq d$ are Q-martingales. Consider now a new asset $X_t > 0$. The following theorem shows which martingale measure we have to use in order to work with X as new numeraire.

Theorem 5.15 (Change of numeraire)**.** *Consider a non-dividend-paying numeraire X_t such that X_t/S^0_t is a true Q-martingale. Define a measure Q^X by putting*

$$\frac{dQ^X}{dQ}|\mathcal{F}_t = \eta_t := \frac{X_t}{S^0_t} \cdot \frac{S^0_0}{X_0}. \tag{5.9}$$

Then the processes S^i_t/X_t, $1 \leq i \leq d$ (the basic security process discounted using X) are Q^X-martingales. Moreover, we have for every contingent claim H such that $H/S^0_T \in \mathcal{L}^1(\Omega, \mathcal{F}_T, Q)$ the change-of-numeraire formula

$$S^0_t E^Q(H/S^0_T|\mathcal{F}_t) = X_t E^{Q^X}(H/X_T|\mathcal{F}_t). \tag{5.10}$$

We mention that the theorem remains true for a general change of numeraire where one starts with an arbitrary numeraire X and goes to a new numeraire $\tilde{X}$.

Proof. First we note that η_t is in fact a martingale with mean one: we have

$$E^Q(\eta_T|\mathcal{F}_t) = \frac{S^0_0}{X_0} E^Q\Big(\frac{X_T}{S^0_T}|\mathcal{F}_t\Big) = \frac{S^0_0}{X_0} \cdot \frac{X_t}{S^0_t} = \eta_t;$$

moreover, $E^Q(\eta_T) = \eta_0 = 1$. Hence the measure Q^X is well-defined. Consider now an arbitrary stochastic process $(H_t)_{0\leq t\leq T}$ such that $\tilde{H}_t := H_t/S^0_t$ is a Q-martingale; H_t could for instance be the price process of one of the traded securities. We get from the Bayes formula (Lemma 4.24) that

$$\begin{aligned} E^{Q^X}\Big(\frac{H_T}{X_T}|\mathcal{F}_t\Big) =& \frac{1}{\eta_t} E^Q\Big(\frac{H_T}{X_T}\eta_T|\mathcal{F}_t\Big) \overset{i}{=} \frac{X_0 S^0_t}{S^0_0 X_t} E^Q\Big(\frac{H_T S^0_0 X_T}{X_T X_0 S^0_T}|\mathcal{F}_t\Big) \\ =& \frac{S^0_t}{X_t} E^Q\Big(\frac{H_T}{S^0_T}|\mathcal{F}_t\Big) \\ \overset{ii}{=}& \frac{H_t}{X_t}, \end{aligned}$$

where we have used i the definition of η in (5.9) and ii the fact that $\tilde{H}_t$ is a Q-martingale. The above computation shows that H_t/X_t is a Q^X-martingale and thus proves the first part of the theorem. Moreover, we have

$$S^0_t E^Q\Big(\frac{H}{S^0_T}|\mathcal{F}_t\Big) = S^0_t \frac{H_t}{S^0_t} = H_t = X_t \frac{H_t}{X_t} = X_t E^{Q^X}\Big(\frac{H_T}{X_T}|\mathcal{F}_t\Big),$$

which proves (5.10). □

5.2 The Black-Scholes Model Revisited

Setup. As in the previous section we consider a model with two traded assets, stock and money market account, with dynamics given by

$$dS^0_t = rS^0_t dt, \quad S^0_0 = 1 \tag{5.11}$$

$$dS^1_t = \mu S^1_t dt + \sigma S^1_t dW_t\,, \quad S^1_0 = S_0 > 0. \tag{5.12}$$

Note that (5.11) implies that $S_t^0 = \exp(rt)$. We define the discount factor by $D_t = (S_t^0)^{-1} = \exp(-rt)$. The discounted stock price is given by $\tilde{S}_t := D_t S_t^1$; the discounted price of S^0 is by definition equal to 1. In economic terms discounting corresponds to taking the money market account S^0 as new numeraire. We now use Itô's-formula to compute the dynamics of the discounted stock price. Since $dD_t = -r(D_t)dt$, the Itô'-product-formula yields

$$\begin{aligned} d\tilde{S}_t^1 &= S_t^1 dD_t + D_t dS_t^1 + d\langle S_t^1, D_t\rangle_t = -r\tilde{S}_t^1 dt + \mu\tilde{S}_t^1 dt + \sigma\tilde{S}_t^1 dW_t \\ &= (\mu - r)\tilde{S}_t^1 dt + \sigma\tilde{S}_t^1 dW_t, \end{aligned}$$

where we have used that $\langle S^1, D\rangle_t \equiv 0$ as (D_t) is of finite variation.

Equivalent Martingale Measures in the Black-Scholes Model. Recall from Lemma 5.6 that the discounted price process $\tilde{S}^1$ is a Q-martingale if and only if S^1 itself has dynamics of the form $S_t^1 = S_0 + \int_0^t rS_s^1 ds + M_t^Q$, where M^Q is a Q-local martingale. Comparison with the Black-Scholes SDE shows that we need to define Q in such a way that by going from P to Q the drift is changed from μ to r .

Remark: If $\{\mathcal{F}_t\}$ is generated by the Brownian motion W and if $Q \sim P$ it can be shown that the density $\frac{\partial Q}{\partial P}$ is necessarily of the form

$$\frac{dQ}{dP} = \exp\left(\int_0^T \tilde{\gamma}_s dW_s - 1/2\int_0^T \tilde{\gamma}_s^2 ds\right)$$

for some adapted process $\tilde{\gamma}$. This means that in a model based on Brownian motion like the Black-Scholes model changing the measure is equivalent to changing the drift.

Now we apply Girsanov's theorem to determine the equivalent martingale measure in the Black-Scholes model. We have

$$\begin{aligned} S_t^1 &= S_0 + \int_0^t \mu S_s^1 ds + \int_0^t \sigma S_s^1 dW_s \\ &= S_0 + \int_0^t rS_s^1 ds + \int_0^t \left(\frac{\mu - r}{\sigma}\right)\sigma S_s^1 ds + \int_0^t \sigma S_s^1 dW_s \\ &= S_0 + \int_0^t rS_s^1 ds + \int_0^t \sigma S_s^1 d\tilde{W}_s \end{aligned}$$

where $\tilde{W}_t = W_t + \int_0^t \frac{\mu - r}{\sigma} ds$. Define $\lambda := \frac{\mu - r}{\sigma}$; λ is often referred to as *market price of risk* of the stock. In order for S to be of the form $S_t^1 = S_0 + \int_0^t rS_s^1 ds + \tilde{M}_t$ we need to turn $\tilde{W}_t = W_t + \int_0^t \lambda ds$ into a martingale by a change of measure. Girsanov's theorem tells us that under Q with

$$\frac{dQ}{dP} = \exp(-\lambda W_T - 1/2\lambda^2 T)$$

the process $\tilde{W}$ is a Q-Brownian motion, hence the Itô-integral $\tilde{M}_t = \int_0^t \sigma S_s^1 d\tilde{W}_s$ is a Q-local martingale. Summing up we have

Proposition 5.16. *Consider a Black-Scholes model with stock-price dynamics of the form $dS_t^1 = \sigma S_t^1 dW_t + \mu S_t^1 dt$ for constants μ, σ. Then the equivalent martingale measure Q is given by the density $\frac{dQ}{dP} = G_T := \exp(-\lambda W_T - 1/2\lambda^2 T)$, where $\lambda = \frac{\mu - r}{\sigma}$ is the market price of risk of the stock. Under Q the stock-price process solves the SDE*

$$dS_t^1 = rS_t^1 dt + \sigma S_t^1 d\tilde{W}_t \tag{5.13}$$

Remark: It can be shown that Q is unique.

Black-Scholes via risk-neutral valuation. We now derive the Black-Scholes formula from the risk-neutral valuation principle; this is the easiest approach from a computational perspective. We know that S_t^1 solves equation (5.13) and is thus of the form $S_t^1 = S_0 \exp(\sigma\tilde{W}_t + (r - 1/2\sigma^2)t)$. From the risk-neutral pricing-rule – which applies as we already know from Chapter 3 that the call can be replicated – we get for C_0, the call price at time zero

$$C_0 \quad = \quad E^Q(e^{-rT}(S_T^1 - K)^+) = \underbrace{E^Q(e^{-rT}S_T^1 1_{(S_T^1>K)})}_{(I)} - e^{-rT}K\underbrace{Q(S_T^1 > K)}_{(II)}.$$

We start with the second term. One has

$$Q(S_T^1 > K) = Q(\ln S_T^1 > \ln K) = Q\left(\frac{\sigma\tilde{W}_T}{\sqrt{\sigma T}} > \frac{\ln K - \ln S_0 - (r - 1/2\sigma^2)T}{\sqrt{\sigma T}}\right).$$

Now note that $Z = \frac{\sigma\tilde{W}_T}{\sigma\sqrt{T}} \sim N(0,1)$. By the symmetry of centered normal distributions we have for $M \in \mathbb{R}$ that $Q(Z > M) = Q(Z < -M)$. Hence

$$Q(S_T^1 > K) = Q\left(Z < \frac{\ln S_0/K + (r - 1/2\sigma^2)T}{\sigma\sqrt{T}}\right) = N(d_2).$$

To deal with term (I) we need to apply Girsanov's theorem once more. Note that $e^{-rT}S_T^1 = S_0 Y_T$ where $Y_T := \exp(\sigma\tilde{W}_T - 1/2\sigma^2 T)$ has the form of a Girsanov-density. Define a new measure Q^S by $dQ^S/dQ = Y_T$. Then we have

$$E^Q\left(e^{-rT}S_T^1 1_{\{S_T^1>K\}}\right) = S_0 E^Q\left(Y_T 1_{\{S_T^1>K\}}\right) = S_0 E^{Q^S}(1_{\{S_T^1>K\}}) = S_0 Q^S(\ln S_T^1 > \ln K).$$

Girsanov's theorem implies that $W_t^S := \tilde{W}_t - \sigma t$ is a Q^S-Brownian motion. Hence $\sigma\tilde{W}_T = \sigma W_T^S + \sigma^2 T$ and

$$Q^S(\ln S_t^1 > \ln K) = Q^S(\ln S_0 + (r - 1/2\sigma^2)T + \sigma W_T^S + \sigma^2 T > \ln K).$$

The right hand side is now evaluated in exactly the same way as before, yielding

$$E^Q\left(e^{-rT}S_T^1 1_{(S_T^1>K)}\right) = S_0 N(d_1). \quad \square$$

5.3 Fundamental Theorems of Asset Pricing in a Generalized Black-Scholes Model

5.3.1 A multidimensional Black-Scholes model

The traded assets consist of one money-market account S^0 and d stocks $S^1, \ldots, S^d$. Given a filtrated probability space $(\Omega, \mathcal{F}, P)$, $\{\mathcal{F}_t\}$, $0 \le t \le T$, we assume that the stock-price is an Itô-process of the form

$$dS_t^i = \alpha_t^i S_t^i dt + S_t^i \sum_{j=1}^n \sigma_{ij}(t) dW_t^j, \quad 1 \le i \le d, \tag{5.14}$$

for an n-dimensional standard Brownian motion $W_t = (W_t^1, \ldots, W_t^n)$ and adapted process α_t^i, $1 \leq i \leq d$ and $\sigma_{ij}(t)$, $1 \leq i \leq d$, $1 \leq j \leq n$. The initial values are given by $S_0 = (S_0^1, \ldots, S_0^d)$. The money-market account satisfies

$$S_t^0 = \exp(\int_0^t r_s ds)$$

for some adapted process $(r_s)_{0 \leq s \leq t}$ modelling the (random) short-rate of the interest. We now give a more intuitive description of the model (5.14). Define

$$\sigma_i(t) = \big(\sum_{j=1}^n \sigma_{ij}(t)^2\big)^{\frac{1}{2}} \tag{5.15}$$

and assume that $\sigma_i(t) > 0$ a.s.. Define processes B_t^i, $1 \leq i \leq d$, via

$$B_t^i = \sum_{j=1}^n \int_0^t \frac{\sigma_{ij}(s)}{\sigma_i(s)} dW_s^j. \tag{5.16}$$

It is easy seen that $\langle B^i \rangle_t = t$ (exercise!), so that $B^1, \ldots B^d$ are one-dimensional Brownian motion by the Lévy-characterization of Brownian motion. Moreover, one has for $i \neq j$ that

$$\langle B^i, B^j \rangle_t = \int_0^t \rho_{ij}(s) ds \quad \text{with} \quad \rho_{ij}(s) = \frac{\sum_{l=1}^n \sigma_{il}(t)\sigma_{jl}(t)}{\sigma_i(t)\sigma_j(t)}.$$

Note that $\rho_{ij}(t) \in [-1, 1]$; it is termed instantaneous correlation of B^i and B^j. In terms of the B^i the asset price dynamics can be written in the form

$$dS_t^i = \alpha_t^i S_t^i dt + \sigma_i(t) S_t^i dB_t^i, \quad 1 \leq i \leq d, \tag{5.17}$$

so that $\sigma_i(t)$ is the volatility of S^i at time t. Moreover, we get from Itô's formula

$$d \ln S_t^i = (\alpha_t^i - \frac{1}{2}\sigma_i^2(t))dt + \sigma_i(t) dB_t^i,$$

so that

$$\langle \ln S^i, \ln S^j \rangle_t = \int_0^t \sigma_i(s)\sigma_j(s) d\langle B^i, B^j \rangle_s = \int_0^t \sigma_i(s)\sigma_j(s)\rho_{ij}(s) ds.$$

The quantity ρ_{ij} therefore models the instantaneous correlation of the logarithmic return processes: for h small we have

$$E\big((\ln S_{t+h}^i - \ln S_t^i)(\ln S_{t+h}^j - \ln S_t^j)|\mathcal{F}_t\big) \approx (\sigma_i \cdot \sigma_j \cdot \rho_{ij})h.$$

As in the case of the one-dimensional Black-Scholes model the dynamics of the discounted stock prices $\tilde{S}_t^i = S_t^i / S_t^0$ are given by

$$d\tilde{S}_t^i = (\alpha_t^i - r_t)\tilde{S}_t^i dt + \sigma_i(t)\tilde{S}_t^i dB_t^i = (\alpha_t^i - r_t)\tilde{S}_t^i dt + \tilde{S}_t^i d(\sum_{j=1}^d \sigma_{ij}(t) dW_t^j). \tag{5.18}$$

5.3.2 Existence of equivalent martingale measure

The following Proposition gives sufficient conditions for the existence of an equivalent martingale measure, and hence for the absence of arbitrage in the model (5.14).

Proposition 5.17. *Suppose that for all $0 \leq t \leq T$ there is a solution $\theta_t = (\theta_t^1, \dots, \theta_t^n)$ of the so-called* market-price-of-risk equations

$$\alpha_t^i - r_t = \sum_{j=1}^n \sigma_{ij}(t)\theta_t^j, \quad 1 \leq i \leq d, \tag{5.19}$$

and that $E\big(\exp(\frac{1}{2}\int_0^T \|\theta_s\|^2 ds)\big) < \infty$. Then the model (5.14) admits an equivalent martingale measure.

Proof. Using the process θ_t from (5.19) we can write the SDE (5.18) for the discounted stock price $\tilde{S}^1, \dots \tilde{S}^d$ in the form in the form

$$d\tilde{S}_t^i = (\alpha_t^i - r_t)\tilde{S}_t^i dt + \tilde{S}_t^i \sum_{j=1}^n \sigma_{ij}(t) dW_t^j = \tilde{S}_t^i \sum_{j=1}^n \sigma_{ij}(t) dW_t^j + \int_0^t \theta_s^j ds \tag{5.20}$$

Define $\tilde{W}_t^j = W_t^j + \int_0^t \theta_s^j ds$, $1 \leq j \leq n$. We now use the Girsanov theorem to turn $\tilde{W}$ into a new Brownian motion. Define

$$Z_T := \exp(-\sum_{j=1}^n \int_0^T \theta_s^j dW_s^j - \int_0^T \|\theta_s\|^2 ds). \tag{5.21}$$

The integrability condition on θ ensures $E(Z_T) = 1$. Define a new measure Q by $\frac{dQ}{dP}|_{\mathcal{F}_T} = Z_T$. The multidimensional Girsanov-theorem shows that under Q the process $\tilde{W}$ with is Q-Brownian motion, and the result follow from Lemma 5.6. □

Denote by $\sigma(t)$ the matrix $(\sigma_{ij}(t))_{1\leq i\leq d, 1\leq j\leq n}$ and by $\mathbf{1}$ the vector $(1, \dots, 1)' \in \mathbb{R}^d$. Suppose that the market price of risk equation does not admit a solution. This implies that the vector $(\alpha_t - r_t\mathbf{1})$ does not belong to $\mathrm{Im}\sigma(t)$ (the range of the matrix $\sigma(t)$) and hence we get for $\ker\sigma'(t) = \{x \in \mathbb{R}^d : \sigma'(t)x = 0\}$

$$\ker\sigma'(t) = \big(\mathrm{Im}\sigma(t)\big)^\perp \neq \{0\}.$$

Hence we can find $\xi_t \in \mathbb{R}^d$ such that

$$\sum_{i=1}^d \xi_t^i(\alpha_t^i - r_t) \neq 0, \quad \text{and} \quad \sigma'(t)\xi_t = 0,$$

otherwise $(\alpha_t - r_t\mathbf{1}) \in \ker\sigma'(t) = \mathrm{Im}\sigma(t)$, which contradicts the fact that the market-price-of-risk equation has no solution. Define a trading-strategy ϕ by $\phi_t^i = \xi_t^i/\tilde{S}_t^i$. The corresponding discounted wealth process $\tilde{V}^\phi$ satisfies

$$d\tilde{V}_t^\phi = \sum_{i=1}^d \xi_t^i(\alpha_t^i - r_t)dt + \sum_{j=1}^n (\sum_{i=1}^d \sigma_{ij}(t)\xi_t^i) dW_t^j = \sum_{i=1}^d \xi_t^i(\alpha_t^i - r_t)dt,$$

where we have used that $\sum_{i=1}^d \sigma_{ij}(t)\xi_t^i = \big(\sigma'(t)\xi_t\big)_j = 0$ as $\xi_t \in \ker\sigma'(t)$. Hence we have constructed a locally riskless selffinancing trading strategy whose discounted wealth-process is non-constant, and it is easy to construct arbitrage-opportunities from this. Hence we have shown the following result:

Theorem 5.18. *Modulo integrability conditions, the model* (5.14) *is arbitrage-free if and only if the market-price of risk equation* (5.19) *admits a solution.*

5.3.3 Market completeness in the generalized Black-Scholes model

As before, we consider a model with $d+1$ traded assets and dynamics of the form $dS_t^0 = r_t S_t^0 dt$, and

$$dS_t^i = \alpha_t^i S_t^i dt + \sum_{j=1}^{n} \sigma_{ij}(t) S_t^i dW_t^j, \quad , 1 \leq i \leq d, \tag{5.22}$$

for an n-dimensional Brownian motion $W_t = (W_t^1, \ldots, W_t^n)$. Moreover, we assume that our filtration is generated by the Brownian motion, that is $\mathcal{F}_t = \sigma(W_s^i : s \leq t, 1 \leq i \leq n)$; this assumption restricts the contingent claims we may consider and is thus crucial for establishing completeness of the market.

Proposition 5.19. *Suppose that the model* (5.22) *is free of arbitrage, and that the underlying filtration is generated by the Brownian motion W. Then the market is complete if and only if P.a.s.* $\mathrm{Im}\sigma'(t) = \mathbb{R}^n$, $0 \leq t \leq T$, *where $\sigma(t)$ represents the matrix* $\big(\sigma_{ij}(t)\big)_{1 \leq i \leq d, 1 \leq j \leq n}$.

Since $\sigma(t)$ is a $d \times n$-matrix and since $\mathrm{rg}\sigma = \mathrm{rg}\sigma'$, a necessary condition for completeness is thus the inequality $d \geq n$.

Proof. Denote by Q some equivalent martingale measure, which exists as the market is assumed to be arbitrage-free. As shown before, under Q the discounted state prices have dynamics

$$d\tilde{S}_t^i = \tilde{S}_t^i \sum_{j=1}^{n} \sigma_{ij}(t) d\tilde{W}_t^j, \tag{5.23}$$

for $\tilde{W}^j$ is a Q-Brownian motion. By Lemma 5.11, the statement of the proposition in equivalent to the following statement:

$$\text{Every } Q\text{-martingale } M \text{ has a representation} M_t = M_0 + \sum_{i=1}^{d} \int_0^t \phi_s^i d\tilde{S}_s^i, \Leftrightarrow \mathrm{rg}\sigma(t) = d. \tag{5.24}$$

Using Itô's representation theorem and the assumption $\{\mathcal{F}_t\} = \{\mathcal{F}_t^W\}$ it can be shown that M has a unique representation of the form

$$M_t = M_0 + \sum_{j=1}^{n} \int_0^t h_s^j d\tilde{W}_s^j. \tag{5.25}$$

writing (5.24) in short-hand notation and using (5.23) we get that (5.24) is equivalent to

$$dM_t = \sum_{i=1}^{d} \tilde{S}_t^i \phi_t^i \sum_{j=1}^{n} \sigma_{ij}(t) d\tilde{W}_t^j = \sum_{j=1}^{n} \sum_{i=1}^{d} \tilde{S}_t^i \sigma_{ij}(t) \phi_t^i d\tilde{W}_t^j. \tag{5.26}$$

Comparing (5.25) and (5.26) we see that we must have

$$h_t^j = \sum_{i=1}^{d} \sigma_{ij}(t)\tilde{S}_t^i\phi_t^i = \sum_{i=1}^{d} \sigma_{ij}(t)\tilde{\phi}_t^i, \tag{5.27}$$

where $\tilde{\phi}_t^i = \phi_t^i\tilde{S}_t^i$. This equation is solvable for all h if and only if $\mathrm{Im}\sigma'(t) = \mathbb{R}^n$. □

Appendix A

Mathematical Background

A.1 Conditional Expectation

Given a probability space $(\Omega, \mathcal{F}, P)$ and a random variable X. A priori, the best prediction for X is $E(X)$. If we have additional information about the outcome of the experiment modelled by $(\Omega, \mathcal{F}, P)$, we can give a better prediction of X. The best-possible prediction – in an L^2-sense – is the conditional expectation. We first study this idea in an elementary setting where information is modelled by a (finite) partition of Ω, which leads us to an explicit formula for the conditional expectation. In a second step we will use the properties of this elementary conditional expectation to extend the notion to general probability spaces.

A.1.1 The elementary case

Definition A.1. A set $\mathcal{A} = \{A_1, \ldots, A_n\}$ of measurable subsets of Ω with $P(A_i) > 0$ for all i is called a partition of Ω if $A_i \cap A_j = \emptyset$ for $i \neq j$ and if moreover $\Omega = A_1 \cup \cdots \cup A_n$.

Now consider a partition $\mathcal{A}$ of Ω. Suppose that we have the additional information that the result ω of our random experiment belongs to a particular subset $A_{i_0} \in \mathcal{A}$. Our best prediction for the rv X is now

$$E(X|A_{i_0}) := \frac{1}{P(A_{i_0})} E(X 1_{A_{i_0}})$$

The 'prediction-mechanism' which gives the prediction of X if we are given the additional information which set from the partition $\mathcal{A}$ actually occurs is therefore given by the random variable

$$\sum_{i=1}^{n} 1_{A_i}(\omega) E(X|A_i) = \sum_{i=1}^{n} 1_{A_i}(\omega) \frac{E(X 1_{A_{i_0}})}{P(A_i)}.$$

Example: Consider a 2-period binomial model with $P(\text{'up'}) = P(\text{'down'}) = \frac{1}{2}$. Then $E(S_2) = S_0(\frac{1}{4}u^2 + \frac{1}{2}ud + \frac{1}{4}d^2) = S_0(\frac{1}{2}u + \frac{1}{2}d)^2$. Define the partition $\mathcal{A} = \{A_1, A_2\}$ with $A_1 = \{S_1 = uS_0\}$ and $A_2 = \{S_1 = dS_0\}$, i.e. the partition is formed by the value of the stock-price at $t = 1$. Then the forecast of S_2 given the information contained in $\mathcal{A}$ is given by

$$1_{A_1}(\omega) E(S_2|A_1) + 1_{A_2}(\omega) E(S_2|A_2) = 1_{A_1}(\omega) S_0 \left(\frac{1}{2}u^2 + \frac{1}{2}ud\right) + 1_{A_2}(\omega) S_0 \left(\frac{1}{2}ud + \frac{1}{2}d^2\right).$$

Obviously, this forecast differs depending on whether A_1 or A_2 actually occurs in $t = 1$.

Formally, the additional information is described by the σ-field $\mathcal{F}^A$ generated by the partition $\mathcal{A}$.

Definition A.2. Given a partition $\mathcal{A} = \{A_1, \ldots, A_n\}$ of Ω. The σ-field $\mathcal{F}^A$ generated by $\mathcal{A}$ is the set of all unifications $\bigcup_{j=1}^k A_j$, $A_j \in \mathcal{A}$, $k \in \mathbb{N}$.

Remark: Usually the σ-field $\mathcal{F}^{\mathcal{A}}$ is defined as the smallest σ-field containing all the sets $A_1, \ldots, A_n$. It is easily seen that the two definitions are equivalent.

Definition A.3. Given a partition $\mathcal{A} = \{A_1, ..., A_n\}$ of Ω with *sigma*-field $\mathcal{F}^{\mathcal{A}}$ and a random variable X. The conditional expectation of X given $\mathcal{F}^{\mathcal{A}}$ is the random variable

$$E(X|\mathcal{F}^{\mathcal{A}})(\omega) = \sum_{i=1}^n 1_{A_i}(\omega) E(X|A_i) = \sum_{i=1}^n 1_{A_i}(\omega) \frac{E(X1_{A_i})}{P(A_i)}\,.$$

Proposition A.4. *Given a partition $\mathcal{A}$ of Ω and a rv X. The conditional expectation $E(X|\mathcal{F}^{\mathcal{A}})$ has the following properties*

(i) $E(X|\mathcal{F}^{\mathcal{A}})$ is $\mathcal{F}^{\mathcal{A}}$-measurable.

(ii) For every random variable Y which is $\mathcal{F}^{\mathcal{A}}$-measurable (i.e. Y is constant on the sets A_i, $i = 1, ..., n$) we have $E(XY) = E(E(X|\mathcal{F}^{\mathcal{A}})Y)$.

Proof. The property (i) is clear, as $E(X|\mathcal{F}^{\mathcal{A}})$is constant on each A_j. As Y is $\mathcal{F}^{\mathcal{A}}$-measurable it is of the form $Y = \sum_{i=1}^n c_j 1_{A_j}$ for constants c_j. Hence

$$\begin{aligned} E(XY) &= \sum_{i=1}^n c_j E(X1_{A_j}) = \sum_{i=1}^n c_j P(A_j) \frac{E(X1_{A_j})}{P(A_j)} \\ &= E\left(\sum_{i=1}^n c_j \frac{E(X1_{A_j})}{P(A_j)} 1_{A_j}\right) = E(Y E(X|\mathcal{F}^{\mathcal{A}}))\,. \quad \square \end{aligned}$$

□

A.1.2 Conditional Expectation - General Case

The explicit definition of the conditional expectation works only if $P(A_i) \geq 0$ for all sets in our partition. However, in continuous models this is usually not the case. We therefore use the properties of the conditional expectation obtained in Proposition A.4 to define the conditional expectation in more general situations.

Definition A.5. Given an integrable rv X on $(\Omega, \mathcal{F}, P)$ and a sigma-field $\mathcal{G} \subset \mathcal{F}$. A random variable Z is called conditional expectation of X given $\mathcal{G}$, $Z = E(X|\mathcal{G})$, if

(i) Z is $\mathcal{G}$-measurable.

(ii) $E(YX) = E(YZ)$ for all rvs Y which are $\mathcal{G}$-measurable.

Theorem A.6. *There is exactly one random variable Z which satisfies (i), (ii).*

The proof can be found in any standard textbook on probability theory.

Examples:

(1) If $\mathcal{G} = \{\emptyset, \Omega\}$ we have $E(X|\mathcal{G}) = E(X)$.

(2) If X is $\mathcal{G}$-measurable we have $E(X|\mathcal{G}) = X$

(3) If X_1, X_2 are independent and $\mathcal{G} := \sigma(X_2)$ we get for any bounded measurable function f that $E(f(X_1)|\mathcal{G}) = E(f(X_1))$.

Proposition A.7. *The conditional expectation has the following properties:*

(1) Linearity: $E(c_1X_1 + c_2X_2|\mathcal{G}) = c_1E(X_1|\mathcal{G}) + c_2E(X_2|\mathcal{G})$.

(2) If Y *is* $\mathcal{G}$*-measurable we have* $E(YX|\mathcal{G}) = YE(X|\mathcal{G})$.

(3) Projectivity of the conditional expectation: Consider sigma-fields $\mathcal{G}_0 \subseteq \mathcal{G}_1 \subseteq \mathcal{F}$. *Then we have* $E(X|\mathcal{G}_0) = E(E(X|\mathcal{G}_1)|\mathcal{G}_0)$, *in particular* $E(X) = E(X|\mathcal{G})$ *for every sub-*σ*-field* $\mathcal{G}$.

Property (3) is often referred to as law of iterated expectations.

Proof. ad 2) We have to check the property (ii) of the definition of the conditional expectation. Let Z be $\mathcal{G}$-measurable. Then

$$E(YXZ) = E((YZ)X) = E(YZE(X|\mathcal{G})) = E(Y(ZE(X|\mathcal{G}))\,,$$

as the product (YZ) is $\mathcal{G}$-measurable.

ad 3) $E(X|\mathcal{G}_0)$ is obviously $\mathcal{G}_0$-measurable. Consider a $\mathcal{G}_0$-measurable random variable Y. As Y is also $\mathcal{G}_1$-measurable, we have $E(Y(E(X|\mathcal{G}_1)) = E(XY)$. On the other hand we get from the definition of $E(X|\mathcal{G}_0)$ that $E(XY) = E(YE(X|\mathcal{G}_0))$. This shows that $E((X|\mathcal{G}_1)Y) = E(YE(X|\mathcal{G}_0))$ so that Definition (A.5)(ii) holds. □

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