

# Mathematical Foundations for Finance

## Exercise sheet 1

**Exercise 1.1** Let  $\Omega = \{\omega_1, \omega_2, \dots, \omega_N\}$  be a finite set and  $X : \Omega \rightarrow \mathbb{R}$  a mapping which takes the values  $+5, 0$  and  $-5$ . You can think of  $X$  as a stock price change over one time period.

- (a) What is the  $\sigma$ -field  $\sigma(X)$  generated by  $X$ ?
- (b) Show that  $|X|$  is measurable with respect to  $\sigma(X^2)$ .
- (c) Let  $Y : \Omega \rightarrow \mathbb{R}$  be another function. If  $\sigma(Y) = 2^\Omega$ , what can you say about  $Y$ ?

### Solution 1.1

- (a) We have

$$\begin{aligned}\sigma(X) &= \sigma(\{X = 5\}, \{X = 0\}, \{X = -5\}) \\ &= \{\emptyset, \Omega, \{X = 5\}, \{X = 0\}, \{X = -5\}, \\ &\quad \{X = 5\} \cup \{X = 0\}, \{X = -5\} \cup \{X = 0\}, \{X = -5\} \cup \{X = 5\}\}.\end{aligned}$$

The second equality follows from the fact that the last system of sets is a  $\sigma$ -field and contains a generator of  $\sigma(X)$ . Thus by definition, they have to be equal.

- (b) Since  $|X| = \sqrt{X^2}$ ,  $|X|$  is a continuous function of  $X^2$ , hence  $\sigma(X^2)$ -measurable. One could also argue by explicitly writing out the  $\sigma$ -field  $\sigma(X^2)$  as in a). One gets

$$\begin{aligned}\sigma(X^2) &= \{\emptyset, \Omega, \{X^2 = 25\}, \{X^2 = 0\}, \{X^2 = 0\} \cup \{X^2 = 25\}\} \\ &= \{\emptyset, \Omega, \{|X| = 5\}, \{|X| = 0\}\}.\end{aligned}$$

It follows immediately that  $|X|$  is  $\sigma(X^2)$ -measurable.

- (c) Because  $\Omega$  is finite,  $Y$  can take at most  $N$  different values. Therefore  $\sigma(Y)$  is finite and generated by the sets of the form  $\{Y = y_i\}$  for a finite collection of numbers  $y_1, y_2, \dots, y_n \in \mathbb{R}$ ,  $n \leq N$ . The  $\sigma$ -field generated by these sets has exactly  $2^n$  elements. The power set  $2^\Omega$  of  $\Omega$  has  $2^N$  elements. Hence  $Y$  must take a different value on each one of the  $\omega_1, \omega_2, \dots, \omega_n$ , and so  $N = n$ . In summary, then, we can say that  $Y$  takes a different value on each  $\omega_i$ ,  $i = 1, \dots, N$ .

**Exercise 1.2** Consider a probability space  $(\Omega, \mathcal{F}, P)$ . A  $\sigma$ -algebra  $\mathcal{F}_0 \subseteq \mathcal{F}$  is said to be *P-trivial* if  $P[A] \in \{0, 1\}$  for all  $A \in \mathcal{F}_0$ . Prove that  $\mathcal{F}_0$  is *P-trivial* if and only if every  $\mathcal{F}_0$ -measurable random variable  $X : \Omega \rightarrow \mathbb{R}$  is *P*-a.s. constant.

**Solution 1.2** Suppose that  $\mathcal{F}_0$  is *P*-trivial, and consider an  $\mathcal{F}_0$ -measurable random variable  $X : \Omega \rightarrow \mathbb{R}$ . By definition we have that  $\{X \leq a\} \in \mathcal{F}_0$  for all  $a \in \mathbb{R}$ , and thus  $P[X \leq a] \in \{0, 1\}$ . Define

$$c := \inf\{a \in \mathbb{R} : P[X \leq a] = 1\}.$$

We first prove that  $c \in \mathbb{R}$ . Since  $\{X \leq n\} \uparrow \{X \in \mathbb{R}\}$ , then  $P[X \leq n] \uparrow P[X \in \mathbb{R}] = 1$ , and so the above infimum is over a nonempty set (i.e.  $c \neq \infty$ ). Then, if  $c = -\infty$ , we have

that  $P[X \leq -n] = 1$  for all  $n \in \mathbb{N}$ , and from the fact that  $\{X \leq -n\} \downarrow \emptyset$ , it follows that  $1 = \lim_{n \rightarrow \infty} P[X \leq -n] = P[\emptyset] = 0$ . We get the desired contradiction. By the definition of the infimum, we have that  $P[X \leq c + \frac{1}{n}] = 1$  and  $P[X \leq c - \frac{1}{n}] = 0$  for all  $n \in \mathbb{N}$ . Since  $\{X \leq c + \frac{1}{n}\} \downarrow \{X \leq c\}$  and  $\{X \leq c - \frac{1}{n}\} \uparrow \{X < c\}$ , we get that

$$P[X \leq c] = \lim_{n \rightarrow \infty} P\left[X \leq c + \frac{1}{n}\right] = 1, \text{ and } P[X < c] = \lim_{n \rightarrow \infty} P\left[X \leq c - \frac{1}{n}\right] = 0.$$

Hence, we conclude that  $X = c$   $P$ -a.s. because

$$P[X = c] = P[X \leq c] - P[X < c] = 1.$$

Conversely, suppose that every  $\mathcal{F}_0$ -measurable random variable is  $P$ -a.s. constant, and take  $A \in \mathcal{F}_0$ . Then,

$$\mathbb{1}_A = \begin{cases} 1 & \text{if } \omega \in A \\ 0 & \text{if } \omega \in A^c \end{cases}$$

is an  $\mathcal{F}_0$ -measurable random variable, and hence must be  $P$ -a.s. constant. It follows immediately that either  $P[\mathbb{1}_A = 1] = P[A] = 1$  or  $P[\mathbb{1}_A = 0] = P[A^c] = 1$ , so that  $P[A] \in \{0, 1\}$ . This completes the proof.

**Exercise 1.3** Let  $(\Omega, \mathcal{F}, P)$  be a probability space,  $X$  an integrable random variable and  $\mathcal{G} \subseteq \mathcal{F}$  a  $\sigma$ -algebra. Then, the  $P$ -a.s. unique random variable  $Z$  such that

- $Z$  is  $\mathcal{G}$ -measurable and integrable,
- $E[X\mathbb{1}_A] = E[Z\mathbb{1}_A]$  for all  $A \in \mathcal{G}$ ,

is called the *conditional expectation of  $X$  given  $\mathcal{G}$*  and is denoted by  $E[X | \mathcal{G}]$ .

[This is the formal definition of the conditional expectation of  $X$  given  $\mathcal{G}$ ; see Section 8.2 in the lecture notes.]

- (a) Show that if  $X$  is  $\mathcal{G}$ -measurable, then  $E[X | \mathcal{G}] = X$   $P$ -a.s.
- (b) Show that  $E[E[X | \mathcal{G}]] = E[X]$ .
- (c) Show that if  $P[A] \in \{0, 1\}$  for all  $A \in \mathcal{G}$  (that is, if  $\mathcal{G}$  is  $P$ -trivial), then  $E[X | \mathcal{G}] = E[X]$   $P$ -a.s.
- (d) Consider an integrable random variable  $Y$  on  $(\Omega, \mathcal{F}, P)$ , and some constants  $a, b \in \mathbb{R}$ . Show that  $E[aX + bY | \mathcal{G}] = aE[X | \mathcal{G}] + bE[Y | \mathcal{G}]$   $P$ -a.s.
- (e) Suppose that  $\mathcal{G}$  is generated by a finite partition of  $\Omega$ , i.e., there exists a collection  $(A_i)_{i=1, \dots, n}$  of sets  $A_i \in \mathcal{F}$  such that  $\bigcup_{i=1}^n A_i = \Omega$ ,  $A_i \cap A_j = \emptyset$  for  $i \neq j$  and  $\mathcal{G} = \sigma(A_1, \dots, A_n)$ . Additionally, assume that  $P[A_i] > 0$  for all  $i = 1, \dots, n$ . Show that

$$E[X | \mathcal{G}] = \sum_{i=1}^n E[X | A_i] \mathbb{1}_{A_i} \text{ } P\text{-a.s.}$$

This says that the conditional expectation of a random variable given a finitely generated  $\sigma$ -algebra is a *piecewise constant* function with the constants given by the elementary conditional expectations given the sets of the generating partition.

[This is a very useful property when one conditions on a finitely generated  $\sigma$ -algebra, as for instance in the multinomial model.]

*Hint 1:* Recall that  $E[X | A_i] = E[X\mathbb{1}_{A_i}] / P[A_i]$  and try to write  $X$  as a sum of random variables each of which only takes non-zero values on a single  $A_i$ .

*Hint 2:* Check that any set  $A \in \mathcal{G}$  has the form  $\bigcup_{j \in J} A_j$  for some  $J \subseteq \{1, \dots, n\}$ .

**Solution 1.3**

- (a)  $X$  is  $\mathcal{G}$ -measurable and integrable by assumption, so the first requirement in the definition of conditional expectation is satisfied for  $Z = X$ . Moreover, we clearly have that  $E[X\mathbb{1}_A] = E[X\mathbb{1}_A]$  for all  $A \in \mathcal{G}$ , hence  $E[X|\mathcal{G}] = X$   $P$ -a.s.
- (b) In the definition of the conditional expectation, set  $A = \Omega$ . Then, we obtain that  $E[E[X|\mathcal{G}]] = E[E[X|\mathcal{G}]\mathbb{1}_\Omega] = E[X\mathbb{1}_\Omega] = E[X]$ .
- (c) Since  $|E[X]| \leq E[|X|]$  by Jensen's inequality and  $E[|X|] < \infty$  by the assumption that  $X$  is integrable, we have that  $E[X]$  is integrable as well.  $E[X]$  is also trivially  $\mathcal{G}$ -measurable since it is a constant random variable. Moreover, in this setting,  $A \in \mathcal{G}$  only if  $P[A] = 0$  or  $P[A] = 1$ . Noting that

$$\begin{aligned} E[X\mathbb{1}_A] &= 0 = E[E[X]\mathbb{1}_A], & \forall A \in \mathcal{G} \text{ such that } P[A] = 0, \\ E[X\mathbb{1}_A] &= E[X] = E[E[X]\mathbb{1}_A], & \forall A \in \mathcal{G} \text{ such that } P[A] = 1, \end{aligned}$$

we obtain  $E[X|\mathcal{G}] = E[X]$   $P$ -a.s.

- (d) By the definition of the conditional expectation, we have that  $E[X|\mathcal{G}]$  and  $E[Y|\mathcal{G}]$  are  $\mathcal{G}$ -measurable and integrable; hence, the same holds for  $aE[X|\mathcal{G}] + bE[Y|\mathcal{G}]$ . Choosing some  $A \in \mathcal{G}$ , we can compute that

$$\begin{aligned} E[(aE[X|\mathcal{G}] + bE[Y|\mathcal{G}])\mathbb{1}_A] &= aE[E[X|\mathcal{G}]\mathbb{1}_A] + bE[E[Y|\mathcal{G}]\mathbb{1}_A] \\ &= aE[X\mathbb{1}_A] + bE[Y\mathbb{1}_A] = E[(aX + bY)\mathbb{1}_A], \end{aligned}$$

where the first equality uses the linearity of the (classical) expectation and the second uses the definition of  $E[X|\mathcal{G}]$  and  $E[Y|\mathcal{G}]$ . By the arbitrariness of  $A \in \mathcal{G}$ , we can conclude that  $E[aX + bY|\mathcal{G}] = aE[X|\mathcal{G}] + bE[Y|\mathcal{G}]$   $P$ -a.s.

- (e) First recall that  $E[X|A_i] = E[X\mathbb{1}_{A_i}]/P[A_i]$ . Using that

$$X = X\mathbb{1}_\Omega = X\mathbb{1}_{\cup_{i=1}^n A_i} = X \sum_{i=1}^n \mathbb{1}_{A_i} = \sum_{i=1}^n X\mathbb{1}_{A_i},$$

where the third equality holds because  $A_i$  are pairwise disjoint, we get by part (d) that

$$E[X|\mathcal{G}] = \sum_{i=1}^n E[X\mathbb{1}_{A_i}|\mathcal{G}] \quad P\text{-a.s.},$$

and hence we only have to show that  $E[X\mathbb{1}_{A_i}|\mathcal{G}] = \frac{E[X\mathbb{1}_{A_i}]}{P[A_i]}\mathbb{1}_{A_i}$   $P$ -a.s. for each  $i \in \{1, \dots, n\}$ .

Since  $A_i \in \mathcal{G}$  and  $E[X|A_i] = E[X\mathbb{1}_{A_i}]/P[A_i] \in \mathbb{R}$ , we already know that  $E[X|A_i]\mathbb{1}_{A_i}$  is  $\mathcal{G}$ -measurable and integrable. One can verify that the family of sets  $A = \bigcup_{j \in J} A_j$  for  $J \in 2^{\{1, \dots, n\}}$  (the power set of  $\{1, \dots, n\}$ ) forms a  $\sigma$ -field. Let us denote this  $\sigma$ -field by  $\tilde{\mathcal{G}}$ . Since we clearly have  $A_i \in \tilde{\mathcal{G}}$  for all  $i \in \{1, \dots, n\}$ , we get that  $\tilde{\mathcal{G}} \supseteq \mathcal{G}$ , which for any  $A \in \mathcal{G}$  implies that  $A = \bigcup_{j \in J} A_j$  for some  $J \subseteq \{1, \dots, n\}$ . For any such  $A \in \mathcal{G}$ , we have that

$$\mathbb{1}_{A_i}\mathbb{1}_A = \begin{cases} \mathbb{1}_{A_i} & \text{if } i \in J, \\ 0 & \text{else.} \end{cases}$$

Hence, we can then compute

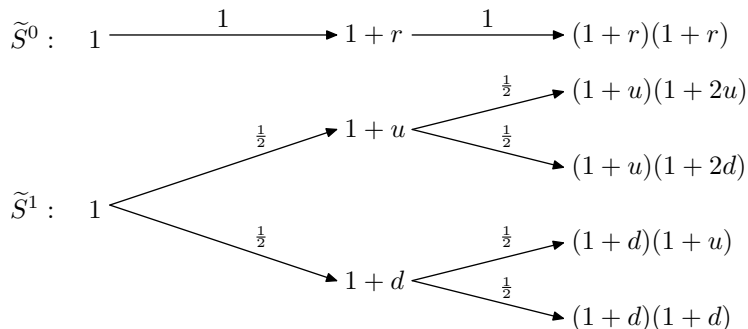
$$E\left[\left(\frac{E[X\mathbb{1}_{A_i}]}{P[A_i]}\mathbb{1}_{A_i}\right)\mathbb{1}_A\right] = \begin{cases} E[X\mathbb{1}_{A_i}]\frac{P[A_i]}{P[A_i]} = E[X\mathbb{1}_{A_i}] & \text{if } i \in J, \\ 0 & \text{else.} \end{cases}$$

On the other hand, we have that

$$E[X\mathbb{1}_{A_i}\mathbb{1}_A] = \begin{cases} E[X\mathbb{1}_{A_i}] & \text{if } i \in J, \\ 0 & \text{else.} \end{cases}$$

This shows that  $E[X\mathbb{1}_{A_i} | \mathcal{G}] = \frac{E[X\mathbb{1}_{A_i}]}{P[A_i]}\mathbb{1}_{A_i}$   $P$ -a.s. and concludes the proof.

**Exercise 1.4** Consider a financial market  $(\tilde{S}^0, \tilde{S}^1)$  given by the following trees, where the numbers beside the branches denote transition probabilities:



Intuitively, this means that the volatility of  $\tilde{S}^1$  increases after a stock price increase in the first period. Assume that  $u, r \geq 0$  and  $-0.5 < d \leq 0$ .

- (a) Construct for this setup a multiplicative model consisting of a probability space  $(\Omega, \mathcal{F}, P)$ , a filtration  $\mathbb{F} = (\mathcal{F}_k)_{k=0,1,2}$ , two random variables  $Y_1$  and  $Y_2$  and two adapted stochastic processes  $\tilde{S}^0$  and  $\tilde{S}^1$  such that  $\tilde{S}_k^1 = \prod_{j=1}^k Y_j$  for  $k = 0, 1, 2$ .
- (b) For which values of  $u$  and  $d$  are  $Y_1$  and  $Y_2$  *uncorrelated*?
- (c) For which values of  $u$  and  $d$  are  $Y_1$  and  $Y_2$  *independent*?
- (d) For which values of  $u, r$  and  $d$  is the discounted stock process  $S^1$  a  $P$ -martingale?

**Solution 1.4**

- (a) We construct the canonical model for this setup, a path space. Let  $\Omega := \{-1, 1\}^2$ , take  $\mathcal{F} := 2^\Omega$  and define  $P$  by

$$P[\{(x_1, x_2)\}] := p_{x_1}p_{x_1, x_2},$$

where  $p_1 = p_{-1} := 1/2$  and  $p_{1,1} = p_{1,-1} = p_{-1,1} = p_{-1,-1} := 1/2$ . Next, define  $Y_1$  and  $Y_2$  by  $Y_1((1, 1)) = Y_1((1, -1)) := 1 + u$ ,  $Y_1((-1, 1)) = Y_1((-1, -1)) := 1 + d$  and  $Y_2((1, 1)) := 1 + 2u$ ,  $Y_2((1, -1)) := 1 + 2d$ ,  $Y_2((-1, 1)) := 1 + u$ ,  $Y_2((-1, -1)) := 1 + d$ . Finally, define  $\tilde{S}^0$  and  $\tilde{S}^1$  by  $\tilde{S}_k^0 := (1 + r)^k$  and  $\tilde{S}_k^1 := \prod_{j=1}^k Y_j$  for  $k = 0, 1, 2$  and set  $\mathcal{F}_0 := \{\emptyset, \Omega\}$ ,  $\mathcal{F}_1 := \sigma(Y_1) = \{\emptyset, \{(1, 1), (1, -1)\}, \{(-1, 1), (-1, -1)\}, \Omega\}$  and  $\mathcal{F}_2 := \sigma(Y_1, Y_2) = 2^\Omega = \mathcal{F}$ .

- (b)  $Y_1$  and  $Y_2$  are uncorrelated if and only if  $E[Y_1Y_2] = E[Y_1]E[Y_2]$ . Set  $c := (u + d)/2$  to simplify the notation. Then we have

$$E[Y_1] = 1 + c \quad \text{and} \quad E[Y_2] = 1 + \frac{3}{2}c,$$

$$E[Y_1Y_2] = \frac{1 + u}{2}(1 + 2c) + \frac{1 + d}{2}(1 + c) = (1 + c)^2 + \frac{1 + u}{2}c.$$

Hence, we have

$$\begin{aligned} E[Y_1 Y_2] - E[Y_1] E[Y_2] &= (1+c)^2 + \frac{1+u}{2}c - \left( (1+c)^2 + (1+c)\frac{c}{2} \right) \\ &= (u-c)\frac{c}{2}. \end{aligned}$$

Since  $d \leq 0 \leq u$ , we have

$$(u-c)\frac{c}{2} = 0 \quad \Leftrightarrow \quad c = 0 \quad \text{or} \quad u-c = 0 \quad \Leftrightarrow \quad d = -u.$$

In conclusion,  $Y_1$  and  $Y_2$  are uncorrelated if and only if  $d = -u$ .

- (c) Since independent random variables are a fortiori uncorrelated, we only have to consider the case that  $u = -d$ . If  $u = d = 0$ ,  $Y_1$  and  $Y_2$  are both constant and hence independent. Otherwise, if  $u > 0$  we have on the one hand

$$P[Y_1 = 1+u, Y_2 = 1+u] = 0$$

and on the other hand

$$P[Y_1 = 1+u] P[Y_2 = 1+u] = 1/2 \cdot 1/4 = 1/8 \neq 0,$$

showing that in this case  $Y_1$  and  $Y_2$  are not independent. In conclusion,  $Y_1$  and  $Y_2$  are independent if and only if  $u = d = 0$ .

Note: If  $d = -u$  and  $u \neq 0$ , then  $Y_1$  and  $Y_2$  are uncorrelated but **not** independent.

- (d)  $S^1$  is a  $P$ -martingale if and only if

$$E[S_1^1 | \mathcal{F}_0] = S_0^1 \quad P\text{-a.s.} \quad \text{and} \quad E[S_2^1 | \mathcal{F}_1] = S_1^1 \quad P\text{-a.s.} \quad (1)$$

If  $u = d = 0$ , it is straightforward to check that  $S^1$  is a  $P$ -martingale if and only if  $r = 0$ . Next, assume that  $u > d$ . Since  $\mathcal{F}_0$  is trivial,  $\mathcal{F}_1 = \sigma(Y_1)$  and  $Y_1 > 0$ , (1) is equivalent to

$$E[Y_1] = 1+r \quad \text{and} \quad E[Y_2 | Y_1] = 1+r \quad P\text{-a.s.}$$

Since  $Y_1$  only takes two values, this is equivalent to

$$E[Y_1] = 1+r \quad \text{and} \quad E[Y_2 | Y_1 = 1+u] = 1+r \quad \text{and} \quad E[Y_2 | Y_1 = 1+d] = 1+r.$$

This is equivalent to

$$\begin{aligned} 1 + (u+d)/2 &= 1+r, \\ 1+u+d &= 1+r, \\ 1 + (u+d)/2 &= 1+r. \end{aligned}$$

Subtracting the first from the second equation yields  $(u+d)/2 = 0$ , which in turn implies  $r = 0$ . In conclusion,  $S^1$  is a  $P$ -martingale if and only if  $r = 0$  and  $d = -u$ .