

**Chapter II. PROBABILITY BACKGROUND.****1. Measure**

The language of option pricing involves that of probability, which in turn involves that of *measure theory*. This originated with Henri LEBESGUE (1875-1941), in his 1902 thesis, '*Intégrale, longueur, aire*'. We begin with the simplest case.

*Length.* The length  $\mu(I)$  of an interval  $I = (a, b), [a, b], [a, b)$  or  $(a, b]$  should be  $b - a$ :  $\mu(I) = b - a$ . The length of the disjoint union  $I = \bigcup_{r=1}^n I_r$  of intervals  $I_r$  should be the sum of their lengths:

$$\mu\left(\bigcup_{r=1}^n I_r\right) = \sum_{r=1}^n \mu(I_r) \quad (\text{finite additivity, fa}).$$

Consider now an infinite sequence  $I_1, I_2, \dots$  (*ad infinitum*) of disjoint intervals. Letting  $n \rightarrow \infty$  suggests that length should again be additive over disjoint intervals:

$$\mu\left(\bigcup_{r=1}^{\infty} I_r\right) = \sum_{r=1}^{\infty} \mu(I_r) \quad (\text{countable additivity, ca}).$$

For  $I$  an interval,  $A$  a subset of length  $\mu(A)$ , the length of the complement  $I \setminus A := I \cap A^c$  of  $A$  in  $I$  should be

$$\mu(I \setminus A) = \mu(I) - \mu(A) \quad (\text{complementation}).$$

If  $A \subseteq B$  and  $B$  has length  $\mu(B) = 0$ , then  $A$  should have length 0 also:

$$A \subseteq B \ \& \ \mu(B) = 0 \ \Rightarrow \ \mu(A) = 0 \quad (\text{completeness}).$$

Let  $\mathcal{F}$  be the smallest class of sets  $A \subset \mathbb{R}$  containing the intervals, closed under countable disjoint unions and complements, and complete (containing all subsets of sets of length 0 as sets of length 0). The above suggests – what Lebesgue showed – that length can be sensibly defined on the sets  $\mathcal{F}$  on the line, but on no others. There are others – but they are hard to construct (in technical language: the Axiom of Choice (AC), or some variant of it such as Zorn's Lemma, is needed to demonstrate the existence of non-measurable

sets – but all such proofs are highly non-constructive). So: some but not all subsets of the line have a length. These are called the *Lebesgue-measurable sets*, and form the class  $\mathcal{F}$  described above; length, defined on  $\mathcal{F}$  is called *Lebesgue measure*  $\mu$  (on the real line,  $\mathbb{R}$ ).

*Area.* The area of a rectangle  $R = (a_1, b_1) \times (a_2, b_2)$  – with or without any of its perimeter included – should be  $\mu(R) = (b_1 - a_1) \times (b_2 - a_2)$ . The area of a finite or countably infinite union of disjoint rectangles should be the sum of their areas:

$$\mu\left(\bigcup_{n=1}^{\infty} R_n\right) = \sum_{n=1}^{\infty} \mu(R_n) \quad (\text{countable additivity, ca}).$$

If  $R$  is a rectangle and  $A \subseteq R$  with area  $\mu(A)$ , the area of the complement  $R \setminus A$  should be

$$\mu(R \setminus A) = \mu(R) - \mu(A) \quad (\text{complementation}).$$

If  $B \subseteq A$  and  $A$  has area 0,  $B$  should have area 0:

$$A \subseteq B \ \& \ \mu(B) = 0 \ \Rightarrow \ \mu(A) = 0 \quad (\text{completeness}).$$

Let  $\mathcal{F}$  be the smallest class of sets, containing the rectangles, closed under finite or countably infinite unions, closed under complements, and complete (containing all subsets of sets of area 0 as sets of area 0). Lebesgue showed that area can be sensibly defined on the sets in  $\mathcal{F}$  and no others. The sets  $A \in \mathcal{F}$  are called the *Lebesgue-measurable sets* in the plane  $\mathbb{R}^2$ ; area, defined on  $\mathcal{F}$ , is called *Lebesgue measure* in the plane. So: some but not all sets in the plane have an area.

*Volume.* Similarly in three-dimensional space  $\mathbb{R}^3$ , starting with the volume of a cuboid  $C = (a_1, b_1) \times (a_2, b_2) \times (a_3, b_3)$  as

$$\mu(C) = (b_1 - a_1) \cdot (b_2 - a_2) \cdot (b_3 - a_3).$$

*Euclidean space.* Similarly in  $k$ -dimensional Euclidean space  $\mathbb{R}^k$ . We start with

$$\mu\left(\prod_{i=1}^k (a_i, b_i)\right) = \prod_{i=1}^k (b_i - a_i),$$

and obtain the class  $\mathcal{F}$  of *Lebesgue-measurable* sets in  $\mathbb{R}^k$ , and *Lebesgue measure*  $\mu$  in  $\mathbb{R}^k$ .

*Probability.*

The unit cube  $[0, 1]^k$  in  $\mathbb{R}^k$  has Lebesgue measure 1. It can be used to model the *uniform distribution* (density  $f(x) = 1$  if  $\mathbf{x} \in [0, 1]^k$ , 0 otherwise), with probability = length/area/volume if  $k = 1/2/3$ .

*Note.* If a property holds everywhere except on a set of measure zero, we say it holds *almost everywhere* (a.e.) [French: *presque partout*, p.p.; German: *fast überall*, f.u.]. If it holds everywhere except on a set of probability zero, we say it holds *almost surely* (a.s.) [or, with probability one].

## 2 Integral.

1. *Indicators.* We start in dimension  $k = 1$  for simplicity, and consider the simplest calculus formula  $\int_a^b 1 \, dx = b - a$ . We rewrite this as

$$I(f) := \int_{-\infty}^{\infty} f(x) \, dx = b - a \quad \text{if } f(x) = I_{[a,b]}(x),$$

the *indicator* function of  $[a, b]$  (1 in  $[a, b]$ , 0 outside it), and similarly for the other three choices about end-points.

2. *Simple functions.* A function  $f$  is called *simple* if it is a finite linear combination of indicators:  $f = \sum_{i=1}^n c_i f_i$  for constants  $c_i$  and indicator functions  $f_i$  of intervals  $I_i$ . One then extends the definition of the integral from indicator functions to simple functions by linearity:

$$I\left(\sum_{i=1}^n c_i f_i\right) := \sum_{i=1}^n c_i I(f_i)$$

for constants  $c_i$  and indicators  $f_i$  of intervals  $I_i$ .

3. *Non-negative measurable functions.* Call  $f$  a (*Lebesgue-*) *measurable function* if, for all  $c$ , the sets  $\{x : f(x) \leq c\}$  is a Lebesgue-measurable set (§1). If  $f$  is a non-negative measurable function, we quote that it is possible to construct  $f$  as the increasing limit of a sequence of simple functions  $f_n$ :

$$f_n(x) \uparrow f(x) \quad \text{for all } x \in \mathbb{R} \quad (n \rightarrow \infty), \quad f_n \text{ simple.}$$

We then define the integral of  $f$  as

$$I(f) := \lim_{n \rightarrow \infty} I(f_n) \quad (\leq \infty).$$

We quote that this does indeed define  $I(f)$ : the value does not depend on *which* approximating sequence  $(f_n)$  we use. Since  $f_n$  increases in  $n$ , so does

$I(f_n)$  (the integral is *order-preserving*), so either  $I(f_n)$  increases to a finite limit, or diverges to  $\infty$ . In the first case, we say  $f$  is (*Lebesgue-*) *integrable* with (*Lebesgue-*) *integral*  $I(f) = \lim I(f_n)$ , or  $\int f(x) \, dx = \lim \int f_n(x) \, dx$ , or simply  $\int f = \lim \int f_n$ .

4. *Measurable functions.* If  $f$  is a measurable function that may change sign, we split it into its positive and negative parts,  $f_{\pm}$  (I.7; Problems 2 Q1):

$$\begin{aligned} f_+(x) &:= \max(f(x), 0), & f_-(x) &:= -\min(f(x), 0), \\ f(x) &= f_+(x) - f_-(x), & |f(x)| &= f_+(x) + f_-(x) \end{aligned}$$

If both  $f_+$  and  $f_-$  are integrable, we say that  $f$  is too, and define

$$\int f := \int f_+ - \int f_-.$$

Then, in particular,  $|f|$  is also integrable, and

$$\int |f| = \int f_+ + \int f_-.$$

*Note.* The Lebesgue integral is thus, by construction, an *absolute integral*:  $f$  is integrable iff  $|f|$  is integrable. Thus, for instance, the well-known formula

$$\int_0^\infty \frac{\sin x}{x} \, dx = \frac{\pi}{2}$$

has no meaning for Lebesgue integrals, since  $\int_1^\infty \frac{|\sin x|}{x} \, dx$  diverges to  $+\infty$  like  $\int_1^\infty \frac{1}{x} \, dx$ . It has to be replaced by the limit relation

$$\int_0^X \frac{\sin x}{x} \, dx \rightarrow \frac{\pi}{2} \quad (X \rightarrow \infty).$$

The class of (*Lebesgue-*) integrable functions  $f$  on  $\mathbb{R}$  is written  $L(\mathbb{R})$  or (for reasons explained below)  $L_1(\mathbb{R})$  – abbreviated to  $L_1$  or  $L$ .

*Higher dimensions.* In  $\mathbb{R}^k$ , we start instead from  $k$ -dimensional boxes. If  $f$  is the indicator of a box  $B = [a_1, b_1] \times [a_2, b_2] \times \cdots \times [a_k, b_k]$ ,  $\int f := \prod_{i=1}^k (b_i - a_i)$ . We then extend to simple functions by linearity, to non-negative measurable functions by taking increasing limits, and to measurable functions by splitting into positive and negative parts.

*L<sub>p</sub> spaces.*

For  $p \geq 1$ , the  $L_p$  spaces  $L_p(\mathbb{R}^k)$  on  $\mathbb{R}^k$  are the spaces of measurable functions  $f$  with  $L_p$ -norm

$$\|f\|_p := \left( \int |f|^p \right)^{\frac{1}{p}} < \infty.$$

*Riemann integrals.*

Our first exposure to integration is the ‘Sixth-Form integral’, taught non-rigorously at school. Mathematics undergraduates are taught a rigorous integral (in their first or second years), the *Riemann integral* [G.B. RIEMANN (1826-1866)] – essentially this is just a rigourization of the school integral. It is much easier to set up than the Lebesgue integral, but much harder to manipulate.

For finite intervals  $[a, b]$ , we quote:

- (i) for any function  $f$  Riemann-integrable on  $[a, b]$ , it is Lebesgue-integrable to the same value (but many more functions are Lebesgue integrable);
- (ii)  $f$  is Riemann-integrable on  $[a, b]$  iff it is continuous a.e. on  $[a, b]$ .

Thus the question, “Which functions are Riemann-integrable?” cannot be answered without the language of measure theory – which then gives one the technically superior Lebesgue integral anyway.

*Note.* Integration is like summation (which is why Leibniz gave us the integral sign  $\int$ , as an elongated S). Lebesgue was a very practical man – his father was a tradesman – and used to think about integration in the following way. Think of a shopkeeper totalling up his day’s takings. The Riemann integral is like adding up the takings – notes and coins – *in the order in which they arrived*. By contrast, the Lebesgue integral is like totalling up the takings *in order of size* – from the smallest coins up to the largest notes. This is obviously better! In mathematical effect, it exchanges ‘integrating by  $x$ -values’ (abscissae) with ‘integrating by  $y$ -values’ (ordinates). See e.g. the picture on the cover of

René L. SCHILLING, *Measures, integrals and martingales*, CUP, 2005.

*Lebesgue-Stieltjes integral.*

Suppose that  $F(x)$  is a *non-decreasing* function on  $\mathbb{R}$ :

$$F(x) \leq F(y) \quad \text{if } x \leq y$$

(prime example:  $F$  a probability distribution function). Such functions can have at most countably many discontinuities, which are at worst jumps. We

may without loss re-define  $F$  at jumps so as to be *right-continuous*.

We now generalise the starting points above:

(i) *Measure*. We take  $\mu((a, b]) := F(b) - F(a)$ .

(ii) *Integral*. We take  $\int_a^b 1 := F(b) - F(a)$ .

We may now follow through the successive extension procedures used above. We obtain:

(i) *Lebesgue-Stieltjes measure*  $\mu$ , or  $\mu_F$ ,

(ii) *Lebesgue-Stieltjes integral*  $\int f d\mu$ , or  $\int f d\mu_F$ , or even  $\int f dF$ .

Similarly in higher dimensions; we omit further details.

*Finite variation*.

If instead of being monotone non-decreasing,  $F$  is the *difference* of two such functions,  $F = F_1 - F_2$ , we can define the integrals  $\int f dF_1$ ,  $\int f dF_2$  as above, and then define

$$\int f dF = \int f d(F_1 - F_2) := \int f dF_1 - \int f dF_2.$$

If  $[a, b]$  is a finite interval and  $F$  is defined on  $[a, b]$ , a finite collection of points,  $x_0, x_1, \dots, x_n$  with  $a = x_0 < x_1 < \dots < x_n = b$ , is called a *partition* of  $[a, b]$ ,  $\mathcal{P}$  say. The sum  $\sum_{i=1}^n |F(x_i) - F(x_{i-1})|$  is called the *variation* of  $F$  over the partition. The least upper bound of this over all partitions  $\mathcal{P}$  is called the *variation* of  $F$  over the interval  $[a, b]$ ,  $V_a^b(F)$ :

$$V_a^b(F) := \sup_{\mathcal{P}} \sum |F(x_i) - F(x_{i-1})|.$$

This may be  $+\infty$ ; but if  $V_a^b(F) < \infty$ ,  $F$  is said to be of *finite variation* on  $[a, b]$ ,  $F \in FV_a^b$  (*bounded variation*, BV, is also used). If  $F$  is of finite variation on all finite intervals,  $F$  is said to be *locally of finite variation*,  $F \in FV_{loc}$ ; if  $F$  is of finite variation on the real line,  $F$  is of *finite variation*,  $F \in FV$ .

We quote (*Jordan's theorem*: Camille JORDAN (1838-1922) in 1881)) that the following are equivalent:

(i)  $F$  is locally of finite variation,

(ii)  $F$  can be written as the difference  $F = F_1 - F_2$  of two monotone functions.

So the above procedure defines the integral  $\int f dF$  when the *integrator*  $F$  is of *finite variation* (FV).

*Note*. We have just introduced one new kind of integral – the Lebesgue-Stieltjes (LS) integral. Later (Ch. V) we shall meet another, the *Itô integral*

(or *stochastic integral*). This is different, harder, and even more important for mathematical finance (as we shall see in Ch. VI). There, we use as integrator (a stochastic process called) *Brownian motion (BM)*, which is *not* FV! So the Itô and LS integrals are fundamentally different.

### 3 Probability.

#### *Probability spaces.*

The mathematical theory of probability can be traced to 1654, to correspondence between PASCAL (1623-1662) and FERMAT (1601-1665). However, the theory remained both incomplete and non-rigorous till the 20th century. It turns out that the Lebesgue theory of measure and integral sketched above is exactly the machinery needed to construct a rigorous theory of probability adequate for modelling reality (option pricing, etc. for us). This was realised by the great Russian mathematician and probabilist A.N.KOLMOGOROV (1903-1987), whose classic book of 1933, *Grundbegriffe der Wahrscheinlichkeitsrechnung* [Foundations of probability theory] inaugurated the modern era in probability.

Recall from your first course on probability that, to describe a random experiment mathematically, we begin with the *sample space*  $\Omega$ , the set of all possible outcomes. Each point  $\omega$  of  $\Omega$ , or *sample point*, represents a possible – random – outcome of performing the random experiment. For a set  $A \subseteq \Omega$  of points  $\omega$  we want to know the probability  $P(A)$  (or  $\Pr(A)$ ,  $\text{pr}(A)$ ). We clearly want

1.  $P(\emptyset) = 0$ ,  $P(\Omega) = 1$ ,
2.  $P(A) \geq 0$  for all  $A$ ,
3. If  $A_1, A_2, \dots, A_n$  are disjoint,  $P(\bigcup_{i=1}^n A_i) = \sum_{i=1}^n P(A_i)$  (finite additivity, fa), which, as above we will strengthen to
- 3\*. If  $A_1, A_2 \dots$  (*ad inf.*) are disjoint,

$$P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i) \quad (\text{countable additivity, ca}).$$

4. If  $B \subseteq A$  and  $P(A) = 0$ , then  $P(B) = 0$  (completeness).
- Then by 1 and 3 (with  $A = A_1$ ,  $\Omega \setminus A = A_2$ ),

$$P(A^c) = P(\Omega \setminus A) = 1 - P(A).$$

So the class  $\mathcal{F}$  of subsets of  $\Omega$  whose probabilities  $P(A)$  are defined should be closed under countable, disjoint unions and complements, and contain the

empty set  $\emptyset$  and the whole space  $\Omega$ . Such a class is called a  $\sigma$ -field of subsets of  $\Omega$  [or sometimes a  $\sigma$ -algebra, which one would write  $\mathcal{A}$ ]. For each  $A \in \mathcal{F}$ ,  $P(A)$  should be defined (and satisfy 1, 2, 3\*, 4 above). So,  $P : \mathcal{F} \rightarrow [0, 1]$  is a set-function,

$$P : A \mapsto P(A) \in [0, 1] \quad (A \in \mathcal{F}).$$

The sets  $A \in \mathcal{F}$  are called *events*. Finally, 4 says that all subsets of null-sets (events) with probability zero (we will call the empty set  $\emptyset$  empty, not null) should be null-sets (completeness). A *probability space*, or *Kolmogorov triple*, is a triple  $(\Omega, \mathcal{F}, P)$  satisfying these *Kolmogorov axioms* 1,2,3\*,4 above. A probability space is a mathematical model of a random experiment.

*Random variables.*

Next, recall random variables  $X$  from your first probability course. Given a random outcome  $\omega$ , you can calculate the value  $X(\omega)$  of  $X$  (a scalar – a real number, say; similarly for vector-valued random variables, or random vectors). So,  $X$  is a function from  $\Omega$  to  $\mathbb{R}$ ,  $X : \Omega \rightarrow \mathbb{R}$ ,

$$X : \omega \mapsto X(\omega) \quad (\omega \in \Omega).$$

Recall also that the *distribution function* of  $X$  is defined by

$$F(x), \quad \text{or} \quad F_X(x), \quad := P\left(\{\omega : X(\omega) \leq x\}\right), \quad \text{or} \quad P(X \leq x), \quad (x \in \mathbb{R}).$$

We can only deal with functions  $X$  for which all these probabilities are defined. So, for each  $x$ , we need  $\{\omega : X(\omega) \leq x\} \in \mathcal{F}$ . We summarize this by saying that  $X$  is *measurable* with respect to the  $\sigma$ -field  $\mathcal{F}$  (of events), briefly,  $X$  is  $\mathcal{F}$ -*measurable*. Then,  $X$  is called a *random variable* [non- $\mathcal{F}$ -measurable  $X$  cannot be handled, and so are left out]. So,

- (i) a random variable  $X$  is an  $\mathcal{F}$ -measurable function on  $\Omega$ ,
- (ii) a function on  $\Omega$  is a random variable (is measurable) iff its distribution function is defined.

*Generated  $\sigma$ -fields.*

The smallest  $\sigma$ -field containing all the sets  $\{\omega : X(\omega) \leq x\}$  for all real  $x$  [equivalently,  $\{X < x\}$ ,  $\{X \geq x\}$ ,  $\{X > x\}$ ] is called the  $\sigma$ -field *generated* by  $X$ , written  $\sigma(X)$ . Thus,

$$X \text{ is } \mathcal{F}\text{-measurable [is a random variable] iff } \sigma(X) \subseteq \mathcal{F}.$$

When the (random) value  $X(\omega)$  is *known*, we know *which* of the events in the  $\sigma$ -field generated by  $X$  have happened: these are the events  $\{\omega : X(\omega) \in B\}$ ,



where  $B$  runs through the Borel  $\sigma$ -field [the  $\sigma$ -field generated by the intervals] on the line.

*Interpretation.*

Think of  $\sigma(X)$  as representing *what we know when we know  $X$* , or in other words *the information contained in  $X$*  (or in knowledge of  $X$ ). This is from the following result, due to J. L. DOOB (1910-2004), which we quote:

$$\sigma(X) \subseteq \sigma(Y) \quad \text{iff} \quad X = g(Y)$$

for some measurable function  $g$ . For, knowing  $Y$  means we know  $X := g(Y)$  – but not vice-versa, unless the function  $g$  is one-to-one [injective], when the inverse function  $g^{-1}$  exists, and we can go back via  $Y = g^{-1}(X)$ .

*Expectation.*

A measure (II.1) determines an integral (II.2). A probability measure  $P$ , being a special kind of measure [a measure of total mass one] determines a special kind of integral, called an *expectation*.

**Definition.** The *expectation*  $E$  of a random variable  $X$  on  $(\Omega, \mathcal{F}, P)$  is defined by

$$E[X] := \int_{\Omega} X \, dP, \text{ or } \int_{\Omega} X(\omega) \, dP(\omega).$$

If  $X$  is real-valued, say, with distribution function  $F$ , recall that  $E[X]$  is defined in your first course on probability by

$$E[X] := \int x f(x) \, dx \text{ if } X \text{ has a density } f$$

or if  $X$  is discrete, taking values  $X_n$ , ( $n = 1, 2, \dots$ ) with probability function  $f(x_n) (\geq 0)$ , ( $\sum x_n f(x_n) = 1$ ),

$$E[X] := \sum x_n f(x_n).$$

These two formulae are the special cases (for the density and discrete cases) of the general formula

$$E[X] := \int_{-\infty}^{\infty} x \, dF(x)$$

where the integral on the right is a Lebesgue-Stieltjes (LS) integral. This in turn agrees with the definition above, since if  $F$  is the distribution function of  $X$ ,

$$\int_{\Omega} X \, dP = \int_{-\infty}^{\infty} x \, dF(x)$$

follows by the *change-of-variable formula* for the measure-theoretic integral, on applying the map  $X : \Omega \rightarrow \mathbb{R}$  (we quote this: see any book on measure theory).

*Glossary.* We now have two parallel languages, measure-theoretic and probabilistic:

Measure	Probability
Integral	Expectation
Measurable set	Event
Measurable function	Random variable
almost-everywhere (a.e.)	almost-surely (a.s.)

#### §4. Equivalent Measures and Radon-Nikodym derivatives.

Given two measures  $P$  and  $Q$  defined on the same  $\sigma$ -field  $\mathcal{F}$ , we say that  $P$  is *absolutely continuous* with respect to  $Q$ , written

$$P \ll Q,$$

if  $P(A) = 0$  whenever  $Q(A) = 0$ ,  $A \in \mathcal{F}$ . We quote from measure theory the vitally important *Radon-Nikodym theorem*:  $P \ll Q$  iff there exists a ( $\mathcal{F}$ -) measurable function  $f$  such that

$$P(A) = \int_A f \, dQ \quad \forall A \in \mathcal{F}$$

(note that since the integral of anything over a null set is zero, any  $P$  so representable is certainly absolutely continuous with respect to  $Q$  – the point is that the converse holds). Since  $P(A) = \int_A dP$ , this says that  $\int_A dP = \int_A f \, dQ$  for all  $A \in \mathcal{F}$ . By analogy with the chain rule of ordinary calculus, we write  $dP/dQ$  for  $f$ ; then

$$\int_A dP = \int_A \frac{dP}{dQ} dQ \quad \forall A \in \mathcal{F}.$$

Symbolically,

$$\text{if } P \ll Q, \quad dP = \frac{dP}{dQ} dQ.$$

The measurable function (= random variable)  $dP/dQ$  is called the *Radon-Nikodym derivative* (RN-derivative) of  $P$  with respect to  $Q$ .

If  $P \ll Q$  and also  $Q \ll P$ , we call  $P$  and  $Q$  *equivalent* measures, written  $P \sim Q$ . Then  $dP/dQ$  and  $dQ/dP$  both exist, and

$$\frac{dP}{dQ} = 1 / \frac{dQ}{dP}.$$

For  $P \sim Q$ ,  $P(A) = 0$  iff  $Q(A) = 0$ :  $P$  and  $Q$  have the same null sets. Taking negations:  $P \sim Q$  iff  $P, Q$  have the same sets of positive measure. Taking complements:  $P \sim Q$  iff  $P, Q$  have the same sets of probability one [the same a.s. sets]. Thus the following are equivalent:  $P \sim Q$  iff  $P, Q$  have the same null sets/the same a.s. sets/the same sets of positive measure.

*Note.* Far from being an abstract theoretical result, the Radon-Nikodym theorem is of key practical importance, in two ways:

- (a) It is the key to the concept of *conditioning* – using what is known (§5, §6 below), which is of central importance throughout;
- (b) The concept of equivalent measures is central to the key idea of mathematical finance, *risk-neutrality*, and hence to its main results, the *Black-Scholes formula*, the *Fundamental Theorem of Asset Pricing (FTAP)*, etc. The key to all this is that prices should be the *discounted expected values under the equivalent martingale measure* (EMM). Thus equivalent measures, and the operation of *change of measure*, are of central economic and financial importance. We shall return to this later in connection with the main mathematical result on change of measure, *Girsanov's theorem* (VI.4).

Recall that we first met the phrase ‘equivalent martingale measure’ in I.5 above. We now know what a measure is, and what equivalent measures are; we will learn about martingales in III.3 below.

### §5. Conditional Expectations.

Suppose that  $X$  is a random variable, whose expectation exists (i.e.  $E[|X|] < \infty$ , or  $X \in L_1$ ). Then  $E[X]$ , the expectation of  $X$ , is a scalar (a number) – non-random. The expectation operator  $E$  averages out all the randomness in  $X$ , to give its mean (a weighted average of the possible value of  $X$ , weighted according to their probability, in the discrete case).

It often happens that we have *partial information* about  $X$  – for instance, we may know the value of a random variable  $Y$  which is associated with  $X$ , i.e. carries information about  $X$ . We may want to average out *over the remaining randomness*. This is an expectation conditional on our partial information, or more briefly a *conditional expectation*.

This idea will be familiar already from elementary courses, in two cases (see e.g. [BF]):

1. *Discrete case*, based on the formula

$$P(A|B) := P(A \cap B)/P(B) \text{ if } P(B) > 0.$$

If  $X$  takes values  $x_1, \dots, x_m$  with probabilities  $f_1(x_i) > 0$ ,  $Y$  takes values  $y_1, \dots, y_n$  with probabilities  $f_2(y_j) > 0$ ,  $(X, Y)$  takes values  $(x_i, y_j)$  with

probabilities  $f(x_i, y_j) > 0$ , then

$$\begin{aligned} \text{(i)} \quad & f_1(x_i) = \sum_j f(x_i, y_j), \quad f_2(y_j) = \sum_i f(x_i, y_j), \\ \text{(ii)} \quad & P(Y = y_j | X = x_i) = P(X = x_i, Y = y_j) / P(X = x_i) = f(x_i, y_j) / f_1(x_i) \\ & = f(x_i, y_j) / \sum_j f(x_i, y_j). \end{aligned}$$

This is the *conditional distribution* of  $Y$  given  $X = x_i$ , written

$$f_{Y|X}(y_j | x_i) = f(x_i, y_j) / f_1(x_i) = f(x_i, y_j) / \sum_j f(x_i, y_j).$$

Its expectation is

$$\begin{aligned} E[Y | X = x_i] &= \sum_j y_j f_{Y|X}(y_j | x_i) \\ &= \sum_j y_j f(x_i, y_j) / \sum_j f(x_i, y_j). \end{aligned}$$

But this approach only works when the events on which we condition have *positive* probability, which only happens in the *discrete* case.

2. *Density case.* If  $(X, Y)$  has density  $f(x, y)$ ,

$$X \text{ has density } f_1(x) := \int_{-\infty}^{\infty} f(x, y) dy, \quad Y \text{ has density } f_2(y) := \int_{-\infty}^{\infty} f(x, y) dx.$$

We *define* the *conditional density* of  $Y$  given  $X = x$  by the continuous analogue of the discrete formula above:

$$f_{Y|X}(y | x) := f(x, y) / f_1(x) = f(x, y) / \int_{-\infty}^{\infty} f(x, y) dy.$$

Its expectation is

$$E[Y | X = x] = \int_{-\infty}^{\infty} y f_{Y|X}(y | x) dy = \int_{-\infty}^{\infty} y f(x, y) dy / \int_{-\infty}^{\infty} f(x, y) dy.$$

*Example:* Bivariate normal distribution,  $N(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho)$ .

$$E[Y | X = x] = \mu_2 + \rho \frac{\sigma_2}{\sigma_1} (x - \mu_1),$$

the familiar *regression line* of statistics (linear model: [BF, Ch. 1]).