

CHAPTER II
 CONDITIONAL EXPECTATION III :
 PROPERTIES.

- Goals:
- presentation of the properties of conditional expectation
 - specific properties: "effect" of the σ -algebra
 - properties of an expectation.

Setup: (Ω, \mathcal{F}, P) probability space.

$L^1 = \{X: \Omega \rightarrow \mathbb{R} \text{ (n.v.) } E(|X|) < \infty\}$.

I BASIC PROPERTIES

Prop: Let $\mathcal{G} \subset \mathcal{F}$ σ -algebra. $X \in L^1$.

- ① If X is \mathcal{G} -measurable, then

$$E(X | \mathcal{G}) = X \text{ a.s.}$$
- ② If X is independent of \mathcal{G} , then

$$E(X | \mathcal{G}) = E(X) \text{ a.s.}$$
- ③ $E(E(X | \mathcal{G})) = E(X)$.

Proof. ① Since we trivially have $E(1_A X) = E(1_A X)$ for every $A \in \mathcal{G}$, if X is \mathcal{G} -measurable, it is a version of $E(X | \mathcal{G})$.

② $E(X)$ is constant, hence it is \mathcal{G} -measurable.

$$\begin{aligned} \text{Furthermore } \forall A \in \mathcal{G}, E(X 1_A) &\stackrel{\text{indep.}}{=} E(X) E(1_A) \\ &= E(E(X) 1_A). \end{aligned}$$

③ By applying ② with $A = \Omega \in \mathcal{G}$, we get

$$E(X \cdot 1) = E(E(X | \mathcal{G}) \cdot 1). \quad \square$$

Application: • If $X \in L^1$, we have

$$E(X | X) = X \text{ a.s. by } \textcircled{1}$$

$$E(X | \{\Omega, \emptyset\}) = E(X) \text{ a.s. by } \textcircled{2}$$

$$\bullet \text{ If } X, Y \text{ indep. } E(X | Y) = E(X) \text{ a.s.}$$

2 LINEARITY

Prop. Let $X, Y \in L^1$ $a, b \in \mathbb{R}$, or $X, Y \geq 0$ $a, b \geq 0$
 $E(aX + bY | \mathcal{G}) = aE(X | \mathcal{G}) + bE(Y | \mathcal{G})$ a.s.

Proof. L^1 case

Let Z \mathcal{G} -measurable bounded.

$$\begin{aligned} E(Z(aX + bY)) &= a E(ZX) + b E(ZY) \\ &= a E(ZE(X | \mathcal{G})) + b E(ZE(Y | \mathcal{G})) \\ &= E(Z(aE(X | \mathcal{G}) + bE(Y | \mathcal{G}))). \end{aligned}$$

Since $aE(X | \mathcal{G}) + bE(Y | \mathcal{G})$ is \mathcal{G} -meas., this concludes the proof.

≥ 0 case: same proof with $Z \geq 0$.

3 MONOTONICITY.

Rk: positivity of the integral. If $X \geq 0$ and $X \in L^1$ we gave two definitions of $E(X | \mathcal{G})$. These two definitions coincide by uniqueness. We always have

$$X \geq 0 \text{ a.s.} \Rightarrow E(X | \mathcal{G}) \geq 0 \text{ a.s.}$$

Prop. Let $X, Y \in L^1$ and $X, Y \geq 0$

$$X \leq Y \text{ a.s.} \implies E(X|G) \leq E(Y|G) \text{ a.s.}$$

pp. $Y = X + \underbrace{Y-X}_{\geq 0 \text{ a.s.}}$. By linearity, we have

$$E(Y|G) = E(X|G) + \underbrace{E(Y-X|G)}_{\geq 0} \text{ a.s.} \quad \blacksquare$$

4 TOWER PROPERTY.

Prop. Let $G, \mathcal{H} \subset \mathcal{F}$ σ -algebras s.t. $\mathcal{H} \subset G$.

$$\bullet E(E(X|\mathcal{H})|G) = E(X|\mathcal{H}) \text{ a.s.}$$

$$\bullet E(E(X|G)|\mathcal{H}) = E(X|\mathcal{H}) \text{ a.s.}$$

Proof. • For the first equality, notice that $E(X|\mathcal{H})$ is G -measurable.

• For the second equality, let $X' = E(X|G)$.

For every Z \mathcal{H} -measurable bounded, we have

$$E(Z E(X'|\mathcal{H})) = E(Z X')$$

$$= E(Z E(X|G)) \underset{\substack{\uparrow \\ \text{because } Z \text{ is } G\text{-meas.}}}{=} E(Z X)$$

Since $E(X'|\mathcal{H})$ is \mathcal{H} -measurable, we have

$$E(X'|\mathcal{H}) = E(X|\mathcal{H}) \text{ a.s.} \quad \blacksquare$$

⚠ In general if \mathcal{G} and \mathcal{H} are not ordered, we do not have

$$E(E(X|\mathcal{G})|\mathcal{H}) = E(X|\mathcal{G} \cap \mathcal{H}) \text{ a.s.}$$

(see exercises)

5 \mathcal{G} -MEASURABLE RVS. BEHAVE LIKE CONSTANTS.

$\mathcal{G} \subset \mathcal{F}$ fixed σ -algebra.

Prop. Let X, Y r.v.s s.t. $X, Y \geq 0$ or $X, XY \in L^1$.
If Y is \mathcal{G} -measurable, then
$$E(XY|\mathcal{G}) = Y E(X|\mathcal{G}) \text{ a.s.}$$

Proof. Case $X, Y \geq 0$

- $Y E(X|\mathcal{G})$ is \mathcal{G} -measurable
- Let $Z \geq 0$ \mathcal{G} -measurable

Since $YZ \geq 0$ \mathcal{G} -measurable, we have

$$\begin{aligned}
 E(Z \cdot XY) &= E(ZY \cdot X) \\
 &= E(ZY E(X|\mathcal{G}))
 \end{aligned}$$

Hence $E(XY|\mathcal{G}) = Y E(X|\mathcal{G})$ a.s.

Case $X, XY \in L^1$

$$\text{let } X = X_+ - X_- \quad Y = Y_+ - Y_-$$

$$\begin{aligned} E(XY | \mathcal{G}) &= E(X_+Y_+ + X_-Y_- - X_+Y_- - X_-Y_+ | \mathcal{G}) \\ &\stackrel{\text{lin}}{=} (Y_+ - Y_-) E(X_+ | \mathcal{G}) - (Y_+ - Y_-) E(X_- | \mathcal{G}) \\ &= Y E(X | \mathcal{G}) \end{aligned}$$

Application X, Y iid $\text{Ber}(\frac{1}{2})$ $E(XY | Y) = \frac{1}{2} Y$ a.s.

6 INDEPENDENT INFORMATION DOES NOT HELP.

Prop. Let $X \in L^1$, $\mathcal{G}, \mathcal{H} \subset \mathcal{F}$ σ -algebras.
 $n \geq 0$
 If \mathcal{H} is independent of $\sigma(\sigma(X) \cup \mathcal{G})$,
 then

$$E(X | \sigma(\mathcal{G} \cup \mathcal{H})) = E(X | \mathcal{G}).$$

Rk: This generalizes the basic property $E(X | \mathcal{H}) = E(X)$ if X independent of \mathcal{H} .

Proof. $\{A \cap B, A \in \mathcal{G}, B \in \mathcal{H}\}$ is a π -system generating $\sigma(\mathcal{G} \cup \mathcal{H})$.

Let $A \in \mathcal{G}, B \in \mathcal{H}$.

$$\begin{aligned}
 \text{We have } E(1_{A \cap B} X) &= E(1_A 1_B X) \\
 &= E(1_A) E(1_B X) \\
 &= E(1_A) E(1_B E(X | \mathcal{G})) \\
 &= E(1_{A \cap B} E(X | \mathcal{G}))
 \end{aligned}$$

Since $E(X | \mathcal{G})$ is $\sigma(\mathcal{G} \cup \mathcal{F})$ -measurable, this concludes the proof.

7 MONOTONE CONVERGENCE

Thm. Let $X_n, n \geq 1$ be an increasing sequence of r.v. in $[0, \infty]$ with $X = \lim_{n \rightarrow \infty} \uparrow X_n$.
Let $\mathcal{G} \subset \mathcal{F}$ σ -algebra.

$$E(X | \mathcal{G}) = \lim_{n \rightarrow \infty} \uparrow E(X_n | \mathcal{G}) \text{ a.s.}$$

Proof. By monotonicity $(E(X_n | \mathcal{G}))_{n \geq 1}$ is an increasing sequence.

$$\text{Let } X' = \lim_{n \rightarrow \infty} \uparrow E(X_n | \mathcal{G})$$

• X' is \mathcal{G} -measurable (as a limit of \mathcal{G} -measurable random variables)

• Let $Z \geq 0$ \mathcal{G} -measurable.

For every $n \geq 1$, we have

$$E(Z X_n) = E(Z E(X_n | \mathcal{G}))$$

Hence, by monotone convergence,

$$E(Z X) = E(Z X') .$$



Thm (Conditional Fatou).

Let $X_n, n \geq 1$ be a sequence of n.v. in $[0, \infty]$

Let $\mathcal{G} \subset \mathcal{F}$ σ -algebra.

$$\liminf E(X_n | \mathcal{G}) \geq E(\liminf X_n | \mathcal{G}) \text{ a.s.}$$

Proof. For $i \geq n \geq 1$

$$E(\inf_{k \geq n} X_k | \mathcal{G}) \leq E(X_i | \mathcal{G}) \text{ a.s.}$$

Hence

$$E(\inf_{k \geq n} X_k | \mathcal{G}) \leq \inf_{k \geq n} E(X_k | \mathcal{G}) \text{ a.s.}$$

The result follows from (conditional) monotone cv. \square

8 DOMINATED CONVERGENCE.

Thm. Let $X, X_n, n \geq 1$ real random variables satisfying

• $X_n \xrightarrow[n \rightarrow \infty]{a.s.} X$

• $\exists Z \geq 0$ in L^1 s.t $\forall n \quad |X_n| \leq Z$.

Then $E(X_n | \mathcal{G}) \rightarrow E(X | \mathcal{G})$ a.s. and in L^1 .

Proof. By applying Fatou's Lemma to $Z + X_n \geq 0$, we get

$$E(Z + X | \mathcal{G}) = E(\liminf (Z + X_n) | \mathcal{G}) \quad a.s. \\ \leq E(Z | \mathcal{G}) + \liminf E(X_n | \mathcal{G}) \quad a.s.$$

Thus $E(X | \mathcal{G}) \leq \liminf E(X_n | \mathcal{G}) \quad a.s.$

Equivalently, by applying Fatou's Lemma to $Z - X_n \geq 0$ we get $E(X | \mathcal{G}) \geq \limsup E(X_n | \mathcal{G}) \quad a.s.$

The L^1 -convergence follows from the domination

$$|E(X_n | \mathcal{G})| \leq E(Z | \mathcal{G}) \quad a.s.$$

(because $X_n \leq Z$ a.s and $-X_n \leq Z$ a.s).

which implies that $(E(X_n | \mathcal{G}))_{n \geq 1}$ is UI.

9 CONDITIONAL JENSEN.

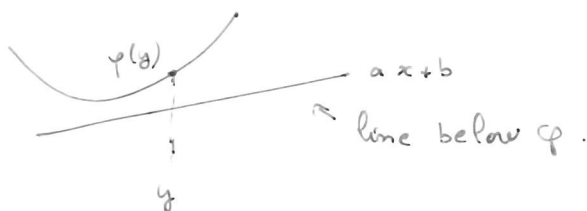
Thm: Let $\mathcal{G} \subset \mathcal{F}$ σ -algebra.

Let $X \in L^1$. Let $\varphi: \mathbb{R} \rightarrow \mathbb{R}_+$ convex

$$\varphi(E(X|\mathcal{G})) \leq E(\varphi(X)|\mathcal{G}) \text{ a.s.}$$

Proof. We use that for every $y \in \mathbb{R}$

$$\varphi(y) = \sup \{ ay + b : a, b \in \mathbb{Q}, \forall x \in \mathbb{R} \ ax + b \leq \varphi(x) \}.$$



(exercise)

Let $a, b \in \mathbb{Q}$ s.t. $\forall x \in \mathbb{R} \ ax + b \leq \varphi(x)$.

$$E(\varphi(X)|\mathcal{G}) \geq \overset{\text{(linearity)}}{a E(X|\mathcal{G}) + b} \text{ a.s.}$$

By taking the supremum over all $a, b \in \mathbb{Q}$ as above, we get the desired result.