

Finan. Optimization

(1) Merton's Optimization:

- Consider a market with const. interest r .
and stock price $S_t = S_0 e^{\sigma W_t + (\mu - \frac{1}{2}\sigma^2)t}$.
- We want to maximize the expected term.
wealth $\mathbb{E}(V_T^{x,\theta})$. where $V_T^{x,\theta} = x + \int_0^T \theta_s dx_s$
 $X_t := e^{-rt} S_t$ discounted price. But:
 $\sup_{\theta} \mathbb{E}(V_T^{x,\theta}) = +\infty$.
and.

Pf: Let β is const. proportion strategy.

$$i.e. dV_t = \beta V_t dX_t$$

$$\Rightarrow V_t = X \exp(\beta \sigma W_T + (\beta(\mu - r) - \frac{1}{2}\beta^2 \sigma^2)T)$$

$$So: \mathbb{E}(V_T^{x,\theta}) = e^{\beta(\mu - r)T} \xrightarrow{\beta \rightarrow \infty} \infty$$

Where assume $\mu > r$ in engineer view

(We can make more profit than put it in bank as expected).

$\beta > 1$ means we can borrow money.

unless P is mart. measure. But $E(V_T^{x, \theta}) \equiv X$. which doesn't make sense!

Prob: Note $V_T^{x, \theta} \rightarrow 0$ as $|\beta| \rightarrow \infty$. which has contrary behavior to expect. (as kind of compensation!). It means high expected return is from taking high risk.

\therefore We need to take risk aversion into account! Merton introduces a method: to maximize expected "utility" (which penalize losses more than its reward gains.) i.e. maximize $E(u(V_T^{x, \theta}))$. $u(\cdot)$ is utility func.
eg. i) $u(x) = -e^{-\alpha x}$. $\alpha > 0$ ii) $u(x) = \log x$.

① Dynamic program Prin.:

Goal: Don't focus on optimal strategy. But

on $u(T, X) = \sup_{\theta} E(u(V_T^{x, \theta}))$ value func.

Def: Value process $U_t^\theta := u(T-t, V_t^{x, \theta})$

② Mart. Optimize Prin.:

Intuition: i) Suboptimal strategy lead to worse value $\Rightarrow U^\theta$ is supermart. for \forall admissible θ

ii) Optimal strategy preserve value $\Rightarrow U^{\theta^*}$ is mart for optimal θ^* .

Now suppose $U \in C^{1,2}$. Apply Itô's:

$$\begin{aligned} dU_t^\theta &= dU(T-t, V_t) \\ &= (-\partial_t U(T-t, V_t) + \partial_x U(T-t, V_t) \theta_t X_t (\mu - r) \\ &\quad + \frac{1}{2} \partial_x^2 U(T-t, V_t) \theta_t^2 X_t^2 \sigma^2) dt + \partial_x U(T-t, V_t) \\ &\quad \cdot \theta_t X_t \sigma dW_t \quad \text{where } V_t^{\theta, \theta} = X + \int_0^t \theta_s dX_s. \end{aligned}$$

With principle i). ii) above. We require:

$$\square \quad \dot{U}_t = 0 \quad \text{for } \forall \text{ ad } \theta; \quad \square \quad \dot{U}_t = 0, \forall \theta^*.$$

i.e. We suggest that:

$$\sup_{\theta \in \mathcal{K}} \left\{ -\partial_t U(t, x) + \partial_x U(t, x) \theta (\mu - r) + \frac{1}{2} \partial_x^2 U(t, x) \theta^2 \sigma^2 \right\} = 0$$

$U(0, x) = U(x)$. called HJB equation.

If \tilde{U} solve this HJB equation. Then:

$$\bar{E}(U(V_T^\theta)) = \bar{E}(\tilde{u}(0, V_T^\theta)) = \bar{E}(\tilde{u}_T^\theta)$$

$$\stackrel{\text{supremum}}{\leq} \bar{E}(\tilde{u}_0^\theta) = \tilde{u}(T, X).$$

So performance of $\bar{E}(U(V_T^\theta))$ for any strategy θ can't be better than $\tilde{u}(T, X)$

If we let $\theta = \theta^*$, $V_T = V_T^*$. we have:

$$\bar{E}(\tilde{u}_T^{\theta^*}) = \bar{E}(\tilde{u}_0^{\theta^*}) = \tilde{u}(T, X) \text{ by definition}$$

i.e. $\bar{E}(U(V_T^*)) = \tilde{u}(T, X)$. attain max.

② To derive HJB equation:

As we did in above:

i) identify state variables: maturity T & present wealth X in control system.

ii) Introduce value function $u(t, X)$ and value process $u_t^\theta := u(T-t, V_t^\theta)$.

iii) Compute the semimartingale dynamics of value process from Itô's formula

iv) identify drift component and find condns on $u(t, X)$ ensure it's $\begin{matrix} \leq 0 \\ \geq 0 \end{matrix}$ for $\begin{matrix} \max \\ \min \end{matrix}$ opt.

v) make sure the links on $u(t, x)$ are the weakest for optimum the drift. i.e.

$$\sup_{f \in K'} \left\{ -\partial_t u + f(\mu - r) \partial_x u + \frac{1}{2} f^2 \sigma^2 \partial_x^2 u \right\} = 0$$

Remark: i) The HJB equation is nonlinear PDE

since the existence of $\sup \{ \dots \}$.

If f^* opt. attained: $(\frac{1}{2} f^{*2} \sigma^2 \partial_x^2 u)$ both side)

$0 = (\mu - r) \partial_x u + \frac{1}{2} f^{*2} \sigma^2 \partial_x^2 u$, \therefore we solve

$$f^* = - \frac{\mu - r}{\sigma^2} \cdot \frac{\partial_x u}{\partial_x^2 u} \quad \text{We obtain:}$$

$$-\partial_t u - \frac{1}{2} \cdot \frac{\mu - r}{\sigma^2} \cdot \frac{(\partial_x u)^2}{\partial_x^2 u} = 0 \quad (\text{HJB})$$

ii) If $\partial_x^2 u > 0$, we find $f^* \rightarrow +\infty$

and $\sup \{ \dots \} \rightarrow +\infty$.

$\therefore f^*$ is maximizer $(\Rightarrow \partial_x^2 u < 0)$.

(If $\partial_x^2 u < 0$, same case happens: it depend sign of $\partial_x u$)

Verification Thm:

$$\text{Next, set } u(x) = \begin{cases} X^{1-q}/(1-q), & x > 0 \\ -\infty, & x < 0 \end{cases} \quad \begin{matrix} \text{power} \\ \text{utility} \end{matrix}$$

with $q > 0, q \neq 1$

Thm. The value function of Metron's problem for power utility is:

$$u(t, x) := \exp\left(\frac{1}{2}(1-\alpha) \frac{(\mu-r)^2}{\sigma^2} T\right) \frac{x^{1-\alpha}}{1-\alpha}, \quad x > 0$$

and $X_t \theta_t^* = Z^* V_t^*$, where $Z^* = (\mu-r)/\sigma^2$. i.e. optimal strategy is always to invest the same fraction Z^* of total wealth in stock.

pf: 1) Note value function satisfies:

$$\begin{aligned} u(t, \lambda x) &= \sup_{\theta} \mathbb{E} (U(V_T^{\theta, \lambda x})) \\ &= \lambda^{1-\alpha} \sup_{\theta} \mathbb{E} (U(V_T^{\theta/\lambda, x})) = \lambda^{1-\alpha} u(t, x) \end{aligned}$$

$$\begin{aligned} \text{So: } u(t, x) &= x^{1-\alpha} u(t, 1) \\ &\stackrel{\Delta}{=} \frac{x^{1-\alpha}}{1-\alpha} f(t) \end{aligned}$$

and $f(0) = 1$. Since $u(0, x) = U(x)$

We put it inside HJB' equation

$$\Rightarrow \text{Obtain } f(t) = \exp\left(\frac{1}{2} \frac{(\mu-r)^2}{\sigma^2} \frac{1-\alpha}{\alpha} T\right)$$

So we also get $u(t, x) = \square$

$$\text{And } \theta^* = - \frac{\mu-r}{\sigma^2} \frac{\partial_x u}{\partial_{xx} u} = \square.$$

$$B_j \text{ Arg: } \theta_t^* = \beta^* (V_t^*) / x_t = \frac{n-r}{\alpha \delta^2} V_t^* / x_t$$

2) Next, we want to prove the value func. candidate we get in 1) is the real value function. (denoted by \hat{u})

$$\text{First } \hat{u}(T, x) \geq E(U(V_T^{\theta, x})) \quad \forall \theta, \text{ and.}$$

WLOG, Set $V_t^{\theta, x} \geq 0, \forall t$. otherwise:

$$IP(\exists t > 0, \text{ s.t. } V_t^{\theta, x} < 0) > 0 \Rightarrow IP(V_T < 0) > 0$$

$$J_1: E(U(V_T^{\theta, x})) = -\infty, \text{ suboptimal.}$$

$$\text{And By Itô's: } \hat{u}(T-t, V_t^{\theta, x}) = \hat{u}(T, x)$$

$$+ \int_0^t (-\partial_t \hat{u}(T-s, V_s) + \theta_t x_t (n-r) \partial_x \hat{u}(T-s, V_s) + \frac{1}{2} (\theta_t x_t \delta)^2 \partial_x^2 \hat{u}(T-s, V_s)) ds \quad \textcircled{A}$$

$$+ \int_0^t \partial_x \hat{u}(T-s, V_s) \sigma \theta_t x_t dW_s \quad \textcircled{B}$$

Since \hat{u} solves HJB equation $\Rightarrow \textcircled{A}$

$$\text{part (i.e. Itô-part)} \leq 0$$

If $\alpha \in (0, 1)$. Then \textcircled{B} part has lower bound. So it's supermart.

$$\Rightarrow E(U(V_T)) = E(\hat{u}(0, V_T)) \stackrel{\textcircled{A} \leq 0}{\leq} E(\hat{u}(T, V_0)) \stackrel{\text{supermart}}{=} \hat{u}(T, x)$$

To remove $q \in (0, 1)$. We replace $\hat{u}(t, x)$ by $\hat{u}(t, x + \varepsilon)$ for some $\varepsilon > 0$ to avoid the explosion of $u(x)$ around $x = 0$. So $\mathbb{E}(u(V_T + \varepsilon)) \leq \hat{u}(T, x + \varepsilon)$. Let $\varepsilon \rightarrow 0$ and apply MCT.

Second, prove: $\exists \theta^*$ s.t. $\hat{u}(T, x) \leq \mathbb{E}(u(V_T^*))$

Consider candidate optimal strategy with dynamics $V_0^* = x$. $dV_t^* = z^* V_t^* dX_t / X_t$

i.e. $V_t^* = \exp((z^*(\mu - r) - \frac{1}{2} z^{*2} \sigma^2)t + \sigma z^* W_t)$

Next, we prove $\hat{u}(T-t, V_t^*)$ is true mart.

Then $\mathbb{E}(u(V_T^*)) = \mathbb{E}(\hat{u}(0, V_T)) = \hat{u}(T, x)$

With calculation above, we

have ① - part = 0 after replace V_t^* .

So we only need to show ⑤ - part is true mart. : By Zai's isometry,

Since $\mathbb{E}(\int_0^T (dx \hat{u}(T-s, V_s^*, X_s \theta, \sigma))^2 ds)$

$= \int_0^T \mathbb{E}(\text{"Some LBM"}) ds \Rightarrow$ Zai's is

$= \int_0^T (c_2 s^2 + c_1 s + c_0) ds < \infty$. L^2 -mart.

(2) Maximization via convex anal:

consider financial model with 2 assets:

i) predictable interest $r_t, r_t^e, \int_0^t |r_s| dt < \infty$

ii) conti. stock price S_t allowing NA.

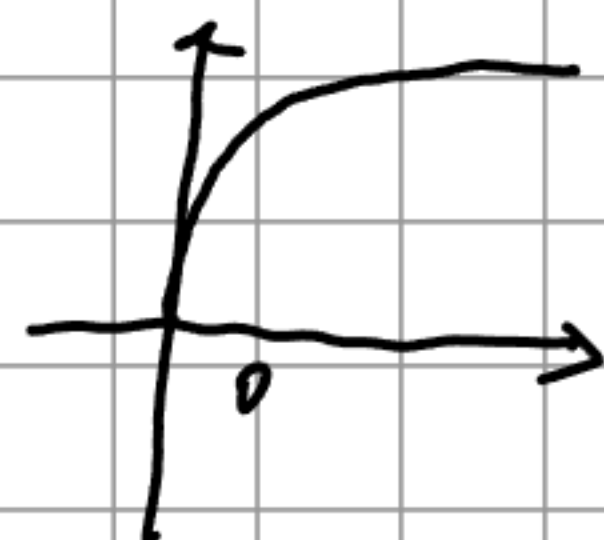
and with initial capital $x > 0$. Fix (λ, p)

Assume utility function $U(x)$ satisfies:

$U \in C^1, \uparrow$ strictly concave on $\mathbb{R}_{\geq 0}$ and

$U(x) = -\infty$ for $x < 0$. $U(0) = 0$ with

$U'(0+) = +\infty$. $U'(+\infty) = 0$ (Inada cond.)



Prop: Recall in argument of HJB' eqn.:

$\partial_x u < 0 \Rightarrow$ maximizer exists. So intro. concave.

① Complete case:

We assume the market is complete, i.e.

\exists unique EMM. \mathbb{P}^* in the following.

Lemma. $H \geq 0 \in \mathcal{F}_T$ is dominated by $V_T^{x, \theta}$

discounted final wealth for some θ

and with $x > 0 \Leftrightarrow \overline{\mathbb{H}}^*(H) \leq x$.

Proof: So next, instead of opt. θ ,
we can maximize over $H > 0$.

Lemma. Assume $V(X) := \sup_{\bar{E}^*(H) \leq X} \bar{E}(U(H)) < \infty$. Then

$H^* \geq 0 \in \mathcal{Z}_T$ is the terminal wealth of
an optimal strategy with initial capital

$X > 0 \iff \bar{E}^*(H^*) = X$ and that:

$\bar{E}(U'(H^*), H) \leq \bar{E}(U'(H^*), H^*) < \infty$ for

$\forall H \geq 0$ and $\bar{E}^*(H) \leq X$.

Proof: It turns out H^* is also a
optimizer for linear optimization.

Pf: (\Leftarrow) By concave:

$$U(H) - U(H^*) \leq U'(H^*)(H - H^*)$$

$$\Rightarrow \bar{E}(U(H)) - \bar{E}(U(H^*)) \stackrel{\text{and}}{\leq} 0.$$

(\Rightarrow) For opt. H^* and $H \geq 0$. $\bar{E}^*(H) \leq X$.

Set $H^\varepsilon := \varepsilon H + (1-\varepsilon)H^*$ still satis-
fies $\bar{E}^*(H^\varepsilon) \leq X$ and $H^\varepsilon \geq 0$

$0 \geq \bar{E}(U(H^\varepsilon)) - \bar{E}(U(H^*)) / \varepsilon$ by Def.

$$\text{And } RHS = \frac{U(H^L) - U(H^*)}{H^L - H^*} \cdot \frac{H^L - H^*}{\varepsilon} I_{\{H^L \neq H^*\}}.$$

is monotone w.r.t $\varepsilon > 0$.

Let $\varepsilon \downarrow 0$. By MCT, we get that

$$0 \geq \mathbb{E}(U'(H^*), (H - H^*)).$$

with $U(0) - U(H^*) \leq U'(H^*)(-H^*)$,

we have $\mathbb{E}(U'(H^*)H^*) < \infty$.

If $\mathbb{E}^*(H^*) < x$, we set $\tilde{H}^* = xH^*$

$/ \mathbb{E}^*(H^*) > H^*$. then by min of U .

$$\mathbb{E}(U(\tilde{H}^*)) > \mathbb{E}(U(H^*)) \text{ Contradict!}$$

Cor. $H^* \geq 0$. $\mathbb{E}^*(H^*) = x$. satisfies 1st

order and: $\mathbb{E}(U'(H^*)H) \leq \mathbb{E}(U'(H^*))$

H^* for $\forall H \geq 0$. $\mathbb{E}^*(H) \leq x \Leftrightarrow$

$\exists \eta > 0$, s.t. $H^* = (u')^{-1}(\eta \frac{K(P^*)}{K(P)})$ is

the unique opt. where $\eta > 0$ is

uniquely chosen to let $\mathbb{E}^*(H^*) = x$.

Pf: 1) Unique: if H^*, \tilde{H}^* both opt.

Let $H = (H^* + \tilde{H}^*)/2$. then

$\mathbb{E}^*(H) = x$ and by strictly

concave of $U(x)$. we have:

$$\mathbb{E}(U(\eta)) > \frac{1}{2}(U(x) + U(x)) = U(x)$$

which's a contradiction!

2) Next, we prove: $\exists \gamma > 0$, s.t. $\eta^\gamma = (u')^{-1}(\gamma \lambda p^* / \lambda p)$ has $\mathbb{E}(\eta^\gamma) = x$.

Note $\lambda p^* / \lambda p > 0$. $\gamma \mapsto \mathbb{E}^*(\eta^\gamma)$

will be concave (by Mono. Convergence Thm)

and monotone. $\mathbb{E}^*(\eta^\gamma) \rightarrow \infty$ if

$\gamma \downarrow 0$ and $\mathbb{E}^*(\eta^\gamma) \rightarrow 0$ if $\gamma \rightarrow \infty$

So it's bijection from $\mathbb{R}^{>0}$ to $\mathbb{R}^{>0}$.

3) Next, we show η^γ is optimal.

$$\mathbb{E}(U(\eta^*) | \mathcal{H}) = \mathbb{E}(\gamma \mathcal{H} \frac{\lambda p^*}{\lambda p}) = \gamma \mathbb{E}^*(\eta)$$

$$= x \gamma = \mathbb{E}^*(\gamma \eta^*) = \mathbb{E}(U(\eta^*) | \mathcal{H}^*).$$

Ex 7: (Application in Black-Scholes market)

Consider $r > 0$. $dX_t / X_t = (r - r)dt + \sigma dW_t$

Stock price dynamics. This is a comp

lete market as we saw before, with

$$\lambda p^* / \lambda p = \mathbb{E}(-\theta dW_t), \quad \theta = (r - r) / \sigma.$$

Let $V(x) = x^{1-p}/(1-p)$ power utility.

$$\Rightarrow M^* = \eta^{-\frac{1}{p}} (X_T^* / X_T)^{-\frac{1}{p}}$$

$$= \eta^{-\frac{1}{p}} X_T^{\theta/\sigma} / E(X_T^{\theta/\sigma})^{-\frac{1}{p}}$$

$$= \text{const.} \cdot X_T^p \quad p = \theta/\sigma.$$

i.e. the optimal strategy is to "all in" power option with $p = \theta/\sigma$ at time T . ($E^X(M^*) = x$ is initial capital)

Proof: There is two ways to get the optimal above. One is "all in" i.e. apply strategy θ continuously on stock for $\forall t \leq T$.

Another is to apply derivative investment at time T as above! Push all money on derivative is more practical!

How to replicate the power option.

$$E^X(e^{-rT} X_T^p | \mathcal{F}_t) = X_t^p \exp((p-1)(\frac{1}{2}p\sigma^2(T-t) + rT))$$

is the discounted price.

Since it's a martingale. Σ :

$$f_t dX_t = \lambda X_t^p = p X_t^{p-1} \langle X, p \rangle \lambda X_t$$

i.e. $f_t = p X_t^{p-1} \langle X, p \rangle$ is repli.

$$\begin{aligned} C f_t &= p \mathbb{E}^* [C e^{-rT} X_T^p | \mathcal{F}_t] / X_t \\ &= p V_t^* / X_t. \end{aligned}$$

V_t^* is NA price for C many power option

$$\Rightarrow C f_t X_t / V_t^* = p = \sigma / \sigma^2 = \frac{\mu - r}{\sigma^2}.$$

Which coincides with the result of
HJB equation in Merton's prob. before.

② Incomplete case:

Set $\mathcal{P} := \{ \text{equi. local Mart. p.m. for } X \}.$ $|\mathcal{P}| > 1$.

Then (Optimal decomposition)

right-anti. process $U \geq 0$ is \mathcal{P} -super-
mart. (i.e. $\forall P \in \mathcal{P}$, U is P -supermart.)

$$\Leftrightarrow U_t = U_0 + \int_0^t \theta_s dX_s - A_t. \text{ where}$$

θ is predictable and λX -integrable and

$A \geq 0$ \uparrow . right-anti and adapted.

Prop: 1) It's variant of Doob-Meyer's decomposition. But note that we require A_t to be adapted & right conti. (i.e. optional). rather predictable. So this is why we call it optional theorem.

ii) The decomposition isn't unique.

Thm (Doob-Meyer's decomposition)

\forall local submart X can be uniquely decomposed as $X = M + A$, where $M \in \mathcal{M}^{loc}$. $A \uparrow$, predictable, right-anti.

Prop: i) e.g., For $M \in \mathcal{M}_c^{loc} \Rightarrow M^2$ is submart. then $A = \langle M \rangle$

ii) X can be only ind (or modif.)

Cor. \forall local submart is semimart.

Pf: For simplicity \forall Mart follows are conti.

(\Leftarrow) is trivial $E(X_T) \leq E(X_0)$. $\forall T$

For (\Rightarrow): Fix $\mathbb{P}^0 \in \mathcal{P}$. Apply Doob-Meyer

Decomposition: $U_t = U_0 + M_t^0 - A_t^0$.

$M^0 \in \mathcal{P}^0 - \mathcal{M}^{0,c}$. $A^0 \geq 0$. \mathcal{I} predictable.

Next, we show: $M_t^0 = \int_0^t \theta_s dX_s$ for some $\theta \in L(X)$.

(\Rightarrow) M^0 is a \mathcal{G} -local martingale.

(*) $Z_n = \inf \{t \geq 0 \mid |M_t^0| \geq n\} \rightarrow \infty$ since M^0 is a local mart. \Rightarrow local mart.
 (Since $\mathbb{E}^{P^*}(M^0) = 0$ doesn't depend on $P^* \in \mathcal{G}$. $\xrightarrow{\text{localiz}^{(*)}}$ it's attainable!)

(\Rightarrow) $\langle M^0, L \rangle = 0$ for $\forall P^* \in \mathcal{G}$ where $\Sigma(L)$ is density of $\frac{LP^*}{LP^0}$.

If \exists some such L s.t. $\langle M^0, L \rangle \neq 0$.

Set $Z_n = \inf \{t \geq 0 \mid \Sigma(L) \leq \frac{1}{n} \text{ or } \Sigma(L) \geq n\}$

Let $LP_{q,n}^* / LP^0 = \Sigma(qL) \tau_{n,Z_n}$

1) $LP_{q,n}^* \in \mathcal{G}$ for $\forall |q| \geq 1$.

$\Sigma(qL) = \Sigma(L)^q \cdot \frac{1}{2}(1+q^2)\Sigma(L)$ is held.

$\Rightarrow \Sigma(qL)$ is a.i. P^0 -mart.

And $\langle X, qL^{Z_n} \rangle = q \langle X, L \rangle^{Z_n} = 0$.

So: $LP_{q,n}^* \in \mathcal{G}$.

2) $U_t = U_0 + (M_t^0 - \langle M^0, qL^{Z_n} \rangle_t) - (A_t^0 - \langle M^0, \tau L^{Z_n} \rangle_t)$

Since U_t is $\mathbb{P}_{\alpha,n}^*$ -supermart. So:

$$A_t^0 - \alpha < M^0 \cdot L^{z_n} \geq 0 \cdot \uparrow \cdot \forall |\alpha| \geq 1, \forall n.$$

Note $z_n \uparrow \infty, n \rightarrow \infty$,

$$\mathbb{P}^0(A_t^0 - \alpha < M^0 \cdot L^{z_n} \geq 0) = 1 \leq \mathbb{P}^0(z_n \leq t)$$

$$+ \mathbb{P}^0(z_n > t, \square) \text{, set } n \rightarrow \infty, T \rightarrow \infty$$

and $n \rightarrow \infty, \alpha \rightarrow -\infty$. We have:

$$\mathbb{P}^0(\langle M^0, L \rangle < 0) = \mathbb{P}^0(\langle M^0, L \rangle > 0) = 1.$$

Which's a contradiction!

Cor. $|\mathcal{D}| > 1 \Rightarrow |\mathcal{D}| = +\infty$ (By i))

Thm (Superreplication)

The super-replication price process for

$$H \text{ is } U_t := \operatorname{ess\,sup}_{\mathbb{P}^* \in \mathcal{Q}} \mathbb{E}^*(H | \mathcal{F}_t) = \operatorname{sup}_{\mathbb{P}^* \in \mathcal{Q}} \mathbb{E}^*(H)$$

$$+ \int_0^t \theta \Delta X - A_t, \forall t \in [0, T], \text{ for some ad.}$$

$\theta, A_t \uparrow \geq 0$. optimal process.

Pf: U_t is $\sim \mathcal{Q}$ -supermart. \Rightarrow Apply opt. _{decomp}

Cor. $H \in \mathcal{G}_T \geq 0$. satisfies $H \leq X + \int_0^T \theta \Delta X$

for some ad. $\theta \Leftrightarrow \sup_{\mathbb{P}^* \in \mathcal{Q}} \mathbb{E}^*(H) \leq X.$

Lemma. (Komlos's)

Seq of r.v.'s (X^n) . s.t. $X_n \geq 0$ on

$(\Omega, \mathcal{F}, P) \Rightarrow \exists \tilde{X}^\infty \in \text{conv}\{X^n, X^{n+1}, \dots\}$

s.t. $\tilde{X}^n \xrightarrow{a.s.} X$ r.v. takes value $\in \mathbb{R}^+$.

Pf: Let $U(x) = 1 - e^{-x}$. and consider

$$U_n := \sup_{\tilde{X} \in \text{conv}\{X^n, \dots\}} E[U(\tilde{X})] \downarrow$$

$$S_0: U_n \rightarrow \inf U_n =: U_\infty$$

Let $\tilde{X}^n \in \text{conv}\{X^n, \dots\}$. s.t. $E[U(\tilde{X}^n)] \rightarrow U_\infty$.

prove: (\tilde{X}^n) converges in pr.

By strictly concave & C^1 of $U(x)$

$$\exists \beta > 0. \text{ s.t. } U(\frac{1}{2}(x+y)) \geq \frac{1}{2}U(x) + \frac{1}{2}U(y) + \beta I_{\{x, y \in N, |x-y| \geq \varepsilon\}}.$$

$(f(x, y) = U(\frac{1}{2}(x+y)) - \beta I_{\{x, y \in N, |x-y| \geq \varepsilon\}})$ can't attain

0 on compact set $\{|x| \leq N, |y| \leq N\}$.

Let $x = \tilde{X}^n, y = \tilde{X}^m$. take $E(\cdot)$.

LHS $\leq U_{m \wedge n}$. Let $m, n \rightarrow \infty$. S_0 :

$$\beta \lim_{m, n} P(|\tilde{X}^n - \tilde{X}^m| \geq \varepsilon, \square \leq k) \leq 0$$

$$S := \{p \in \mathbb{R}^n : |\tilde{x}_n - \tilde{x}_m| \geq \varepsilon\} \rightarrow \emptyset$$

$$\Rightarrow \tilde{x}_n \rightarrow x \text{ in pr.}$$

$$S_0 := \exists \tilde{x}_{n_k} \in \text{conv}\{x_k, \dots\} \xrightarrow{\text{a.s.}} x.$$

Thm. (Existence of optimizer)

$$\text{Assume } K(x) = \sup_{E^*(\eta) \leq x, \forall p^* \in \mathcal{P}} E(U(\eta)) < \infty.$$

$$\lim_{\eta \rightarrow \infty} K(\eta)/\eta = 0. \text{ (sublinear growth)} \Rightarrow$$

$$\forall x > 0. \exists M^x > 0 \text{ } \mathbb{P}\text{-a.s. unique. s.t. } M^x =$$

$$\arg \max_{\eta \geq 0, E^*(\eta) \leq x, \forall p^* \in \mathcal{P}} E(U(\eta)).$$

Prop. If U is bad from above. then:

\exists unique optimizer to the ump .

Pf. 1) Unique: as before, by strictly concave

2) Take $M^x > 0$. s.t. $E^*(M^x) \leq x$. for

$$\forall p^* \in \mathcal{P}. \& E(U(M^x)) \rightarrow K(x).$$

By Komlos's Lemma: $\exists \tilde{M}^n \in \text{conv}$

$$\{M^x, \dots\}. \text{ s.t. } \tilde{M}^n \xrightarrow{\text{a.s.}} M^x.$$

First, we note $E^*(\tilde{M}^n) \leq x, \forall n$.

$$u(x) \geq \mathbb{E}(U(\tilde{H}^n))$$

$$\stackrel{\text{concave}}{>} \sum_{m \geq n} \lambda_m^n \mathbb{E}(U(H_m))$$

$$\geq \sum \lambda_m^n (u(x) - \varepsilon) = u(x) - \varepsilon$$

for some $\varepsilon > 0$ and n large enough.

$$J_n: \mathbb{E}(U(\tilde{H}^n)) \rightarrow u(x) \text{ as well.}$$

As for H^* : we check it's opt.:

$$\mathbb{E}(H^*) \stackrel{\text{Fatou's}}{\leq} \liminf \mathbb{E}(\tilde{H}^n) = x \text{ by } H^* \geq 0$$

$$\text{And } \mathbb{E}(U(H^*)) \stackrel{\text{u.i.}}{=} \lim \mathbb{E}(U(\tilde{H}^n)) \\ = u(x)$$

u.i. follows from $u(x)/x \rightarrow 0, x \rightarrow \infty$:

Pf: (Wrong proof).

WLOG. $U(x) \rightarrow \infty$ as $x \rightarrow \infty$. Or $U(\tilde{H}^n)$ are u.i. \checkmark

$u(x) \geq U(x)$ by Set $H = x$.

$$\Rightarrow U(x)/x \rightarrow 0 \text{ as } x \rightarrow \infty$$

$$\text{Set } \varepsilon_m = \sup_{U(x) \geq m} U(x)/x \rightarrow 0 \text{ as } m \rightarrow \infty$$

$$\mathbb{E}(U(\tilde{H}^n) I_{\{U(\tilde{H}^n) \geq m\}}) \leq$$

$$\mathbb{E}(\varepsilon_m \tilde{H}^n I_{\{U(\tilde{H}^n) \geq m\}}) \leq \varepsilon_m x \xrightarrow{m \rightarrow \infty} 0.$$

Rmk: It's wrong because $\mathbb{E}(H)$

may not $\in X$ except $p = p^*$.

Then, in this case:

$$\overline{E}^*(U(N)) \stackrel{\text{Jensen}}{\leq} U(\overline{E}^*(N)) \stackrel{\text{mono}}{\leq} U(x),$$

i.e. $U(x) = U(x)$, trivial case!

Lemma. $(X_i)_i$ is a.i. (\Rightarrow) (X_i) is L' -bdd

and \forall decomposition $\lambda = \sum A_k$, we

$$\text{have: } \lim_{n \rightarrow \infty} \sup_i \overline{E}(X_i | I_{A_n}) = 0.$$

Note $\overline{E}(U(\tilde{H}_n)) \rightarrow U(x)$. So it's L' -bdd

By contradiction: $\exists (A_n)$ s.t. $\lambda = \sum A_n$.

$$\text{and } \overline{E}(U(\tilde{H}^n) | I_{A_n}) \geq \varepsilon$$

$$\text{Set } R_n := \sum_{i=1}^n \tilde{H}^n | I_{A_n} \geq 0.$$

$$X_n \stackrel{\Delta}{=} \sup_{\varphi^* \in \mathcal{P}} \overline{E}^*(R_n) \leq \sup_i \sum_{i=1}^n \overline{E}^*(\tilde{H}^n) \leq nX$$

$$U(X_n) \geq \overline{E}(U(R_n)) \stackrel{\text{Jensen}}{\geq} \sum_{i=1}^n \overline{E}(U(\tilde{H}^n) | I_{A_n})$$

$$\geq n\varepsilon \quad \text{So: } U(X_n)/X_n \geq \varepsilon.$$

But $X_n \geq n\varepsilon \rightarrow \infty$ if $X \rightarrow \infty$.

Contradiction with sub-linear growth.

Thm. (First order condition in incomplete).

$U^* \geq 0$ is terminal wealth of optimal strategy with initial $X \Leftrightarrow \sup_{\mathcal{D}} E^*(U^*) = X$
 and $E(u'(U^*), U) \leq E(u'(U^*), U^*) < \infty$
 for $\forall U \geq 0$ and $\sup_{\mathcal{D}} E^*(U) \leq X$.

Convex duality:

$\forall U \geq 0$. $U \leq X + \int_0^T \phi dX$ for some admissible ϕ and $\forall \theta^* \in \mathcal{D}$. we have:

$$\begin{aligned}
 E(U) &\stackrel{a)}{\leq} E(U) - \eta (E^*(U) - X) \stackrel{b)}{\leq} 0 \\
 &= E(U) - \eta \frac{\lambda \theta^*}{\lambda \theta} U + X\eta.
 \end{aligned}$$

$$\text{So } V(\eta) = \sup_{X \geq 0} \{ E(U) - X\eta \}$$

$$\text{So: } LHS \stackrel{b)}{\leq} E\left(V\left(\eta \frac{\lambda \theta^*}{\lambda \theta}\right)\right) + X\eta.$$

$$\begin{aligned}
 \Rightarrow \sup_{\substack{U \geq 0, E^*(U) \leq X \\ \text{for } \forall \theta^* \in \mathcal{D}}} E(U) &\stackrel{c)}{\leq} \inf_{\eta > 0} \inf_{\theta^* \in \mathcal{D}} \{ E\left(V\left(\eta \frac{\lambda \theta^*}{\lambda \theta}\right)\right) + X\eta \}. \\
 &= \inf_{\eta > 0} \{ V(\eta) + X\eta \}.
 \end{aligned}$$

Remark: $V(\eta)$ is Legendre-Fenchel transf.
 of $U(X)$. $\Rightarrow V(\eta)$ is convex.

ii) If the "=" above can be attained for $\forall x, \eta, p^* \in \text{fix}$, then:

$$\begin{cases} E^*(\eta) = x & \text{by a).} \\ U(\eta) = \eta \frac{L(p^*)}{L(p)} & \text{by b).} \end{cases} \quad \text{and from}$$

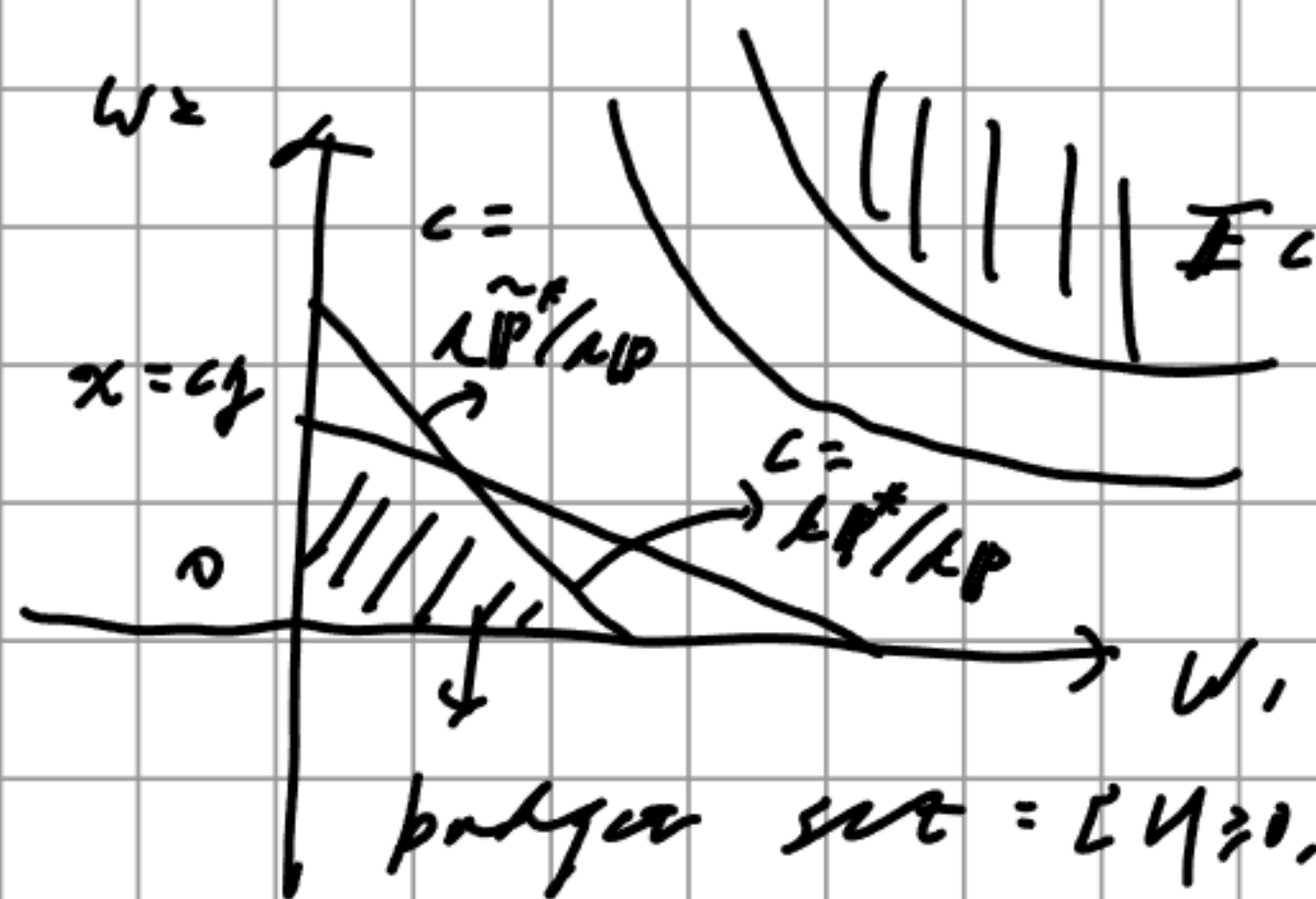
$$c): u(x) = \inf_{\eta > 0} [U(\eta) + x\eta]. \quad \text{So that}$$

$u(x)$ and $U(\eta)$ are in equality

$$\text{with } U(\eta) = \inf_{x > 0} [u(x) - x\eta].$$

iii) The problem in ii) is that which $p^* \in \mathcal{P}$. We should choose?

Visualization:



\Rightarrow when $E(u(\eta))$ tangent to the budget if budget set \Rightarrow optimal. i.e. $c = u(x)$

$$\Rightarrow U(\eta^*) = \eta \frac{L(p^*)}{L(p)}$$