

13.2

Suppose the risk measure is convex. (Choose  $X, Y \in L^\infty$ )

$\lambda \in [0, 1]$  then:

$$g(\lambda X + (1-\lambda)Y) \leq \lambda \underbrace{g(X)}_{\leq g(X) \vee g(Y)} + (1-\lambda) \underbrace{g(Y)}_{\leq g(X) \vee g(Y)} \leq g(X) \vee g(Y)$$

" $\Rightarrow$ "

Suppose the risk measure is quasi-convex: (choose  $X, Y \in L^\infty, \lambda \in [0, 1]$ )

We need to show:  $g(\lambda X + (1-\lambda)Y) \leq \lambda g(X) + (1-\lambda)g(Y)$

By cash additivity this is equivalent to:

$$g(\lambda(X + g(X)) + (1-\lambda)(Y + g(Y))) \leq 0 \quad (*)$$

By quasi convexity we have:

$$g(\lambda(X + g(X)) + (1-\lambda)(Y + g(Y))) \leq \max(\underbrace{\lambda g(X + g(X))}_{=0}, \underbrace{(1-\lambda)g(Y + g(Y))}_{=0}) = 0$$

Hence (\*) is true.

13.3

$$g(\lambda X + (1-\lambda) \cdot 0) \stackrel{\substack{\lambda \in [0, 1] \\ \text{convexity}}}{\leq} \lambda g(X) + (1-\lambda)g(0) \stackrel{\substack{\text{normalized} \\ g(0) = 0}}{=} \lambda g(X)$$

choose  $\lambda \in [1, \infty)$ , then:  $0 < \frac{1}{\lambda} \leq 1$ .

By the first part:

$$\Rightarrow g\left(\frac{1}{\lambda} \lambda X\right) \leq \frac{1}{\lambda} g(\lambda X) \\ \Rightarrow \lambda g(X) \leq g(\lambda X)$$

13.4

(a)  $g(X) + g(-X) \geq \sup_{Q \in \mathcal{Q}} (\mathbb{E}_Q[-X] + \mathbb{E}_Q[X]) = 0$

(b)

1.  $\Rightarrow$  2.

$$g(X) + g(-X) = g(0) = 0$$

2.  $\Rightarrow$  3.

for  $X \in L^p(\Omega, \mathcal{F})$  we have:  $\longrightarrow$

$$\sup_{Q \in \mathcal{Q}} \mathbb{E}_Q[-X] = -\sup_{Q \in \mathcal{Q}} (-\mathbb{E}_Q[-X]) = \inf_{Q \in \mathcal{Q}} \mathbb{E}_Q[-X]$$

This implies for any  $\tilde{Q} \in \mathcal{Q}$ :

$$f(X) = \sup_{Q \in \mathcal{Q}} \mathbb{E}_Q[-X] = \mathbb{E}_{\tilde{Q}}[-X]$$

$$3. \Rightarrow 1. \quad f(X+Y) = \mathbb{E}_{\tilde{Q}}[-(X+Y)] = f(X) + f(Y)$$