

# Mathematical Finance

## Exercise sheet 12

**Exercise 12.1** Let  $U$  be a utility function satisfying the Inada conditions, i.e.  $U \in C^1(\mathbb{R}_+; \mathbb{R})$  is strictly increasing, strictly concave and

$$U'(0) := \lim_{x \searrow 0} U'(x) = +\infty$$
$$U'(+\infty) := \lim_{x \rightarrow +\infty} U'(x) = 0.$$

Let  $J$  be the Legendre transform of  $-U(-\cdot)$ ,

$$J(y) := \sup_{x > 0} (U(x) - xy),$$

and denote by  $I := (U')^{-1}$  the inverse of the derivative of  $U$ .

Show the following properties:

1.  $J$  is strictly decreasing and strictly convex.
2.  $J'(0) = -\infty$ ,  $J'(+\infty) = 0$ ,  $J(0) = U(+\infty)$  and  $J(+\infty) = U(0)$ .
3. For any  $x > 0$ ,

$$U(x) = \inf_{y > 0} (J(y) + xy).$$

4. For any  $y > 0$ ,

$$J(y) = U(I(y)) - yI(y).$$

5.  $J' = -I$ .

### Solution 12.1

First we show that the supremum defining  $J$  is a maximum, i.e. for any  $y > 0$ , we have

$$J(y) = \sup_{x > 0} (U(x) - xy) = U(x_y) - x_y y$$

for some  $x_y > 0$ .

Note that, letting  $g_y(x) = U(x) - xy$ , we have that  $g_y$  is differentiable and

$$g'_y(x) = U'(x) - y.$$

Since  $U$  is  $C^1$  (i.e.  $U'$  is continuous), strictly concave (i.e.  $U'$  is strictly decreasing), with  $U'(0) = +\infty$  and  $U'(+\infty) = 0$  by the Inada conditions, we obtain exactly one solution to  $U'(x_y) = y$ . Moreover,  $g'_y$  is negative for  $x > x_y$  and positive for  $x < x_y$ . Thus the maximum is obtained exactly at  $x_y = (U')^{-1}(y)$ , which is a continuous, decreasing function of  $y$  (since  $U'$  is). We keep using the notation  $x_y$ .

On the other hand, we can see that for  $y \leq 0$ , the maximum is obtained as  $x \rightarrow +\infty$  (since  $g_y$  is increasing in  $x$ ), which gives that  $J(0) = U(+\infty)$  (possibly  $= +\infty$ ) and  $J(y) = +\infty$  for  $y < 0$ .

We show first that  $J$  is differentiable on  $(0, +\infty)$ . Note that the equation  $U'(x_y) = y$  implies that  $x_y$  is increasing in  $y$ . Thus, we have the following: picking some arbitrary  $\bar{y}$ , and letting  $\bar{x} = x_{\bar{y}}$ ,

$$\begin{aligned}
J(y) &= U(x_y) - x_y y \\
&= U(\bar{x}) - \bar{x}\bar{y} + \int_{\bar{x}}^{x_y} U'(w)dw - \int_{\bar{y}}^y (sdx_s + x_s ds) \\
&= U(\bar{x}) - \bar{x}\bar{y} + \int_{\bar{y}}^y U'(x_s)dx_s - \int_{\bar{y}}^y (sdx_s + x_s ds)
\end{aligned}$$

(using a Riemann-Stieltjes integral, chain rule and integration by parts).

Since  $U'(x_s) = s$ , this simplifies as

$$J(y) = J(\bar{y}) - \int_{\bar{y}}^y x_s ds.$$

But since  $x_s = (U')^{-1}(s)$  is a continuous function of  $s$ , this shows that  $J$  is differentiable with  $J'(y) = -x_y$ .

1.  $J$  is strictly decreasing and strictly convex since  $J'(y) = -(U')^{-1}(y)$  is a strictly negative and strictly increasing function of  $y$ .
2. We have  $J'(0) = -(U')^{-1}(0) = -\infty$  and  $J'(+\infty) = -(U')^{-1}(+\infty) = 0$ , by the Inada conditions. We already saw earlier that  $J(0) = U(+\infty)$ .

Note that  $J(y) = \sup_{x>0}(U(x) - xy) \geq U(0)$  for any  $y > 0$ , by taking  $x \rightarrow 0$ . Moreover,  $J(y) \leq U(\epsilon)$  for small enough  $y > 0$ , since for  $y \geq U'(\epsilon)$ , we have

$$U(x) - xy \leq U(x) \leq U(\epsilon)$$

if  $x \leq \epsilon$ , and we know that the maximiser  $x_y$  must be in  $[0, \epsilon]$  (since  $U'$  is decreasing). Thus, taking  $\epsilon \rightarrow 0$  we get  $J(+\infty) = U(0)$ .

3. By definition,  $J(y) = \sup_{x>0}(U(x) - xy)$ , from which we see that

$$J(y) - U(x) \geq -xy$$

for any  $y, x \geq 0$ . We can also write it as

$$U(x) \leq J(y) + xy.$$

On the other hand, for any  $x > 0$  we know that this inequality is attained at  $y = U'(x)$ , and therefore

$$U(x) = \inf_{y>0} J(y) + xy.$$

In the case of  $x = 0$ , we saw before that  $U(0) = J(+\infty)$ , and we can show that this is equal to the infimum.

4. We already showed this above.
5. Likewise.

**Exercise 12.2** Let the financial market  $S = (S_k)_{k=0,\dots,N}$  be defined over the *finite* filtered probability space  $(\Omega, \mathcal{F}, (\mathcal{F}_k)_{k=0,\dots,N}, P)$  and satisfy  $\mathcal{M}^a(S) \neq \emptyset$ , and let  $U$  be a utility function satisfying the Inada conditions. Consider the value functions

$$u(x) = \sup_{X_T \in C(x)} E[U(X_T)] \text{ and } v(y) = \inf_{Q \in \mathcal{M}^a(S)} E \left[ V \left( y \frac{dQ}{dP} \right) \right],$$

where  $V$  is the convex conjugate of  $U$  and

$$C(x) = \{X_T \in L^0(\Omega, \mathcal{F}_T, P) \mid \forall Q \in \mathcal{M}^a(S) : E_Q[X_T] \leq x\}.$$

Show that the optimisers  $\hat{X}_T(x)$ ,  $\hat{Q}(x)$  and  $\hat{y}(x)$  satisfy  $U'(\hat{X}_T(x)) = \hat{y}(x) \frac{d\hat{Q}(x)}{dP}$  for each  $x \in \text{dom}(U)$ .

**Solution 12.2** From minimax considerations, and writing the Lagrangian  $L(X_T, y, Q) = E \left[ U(X_T) - y \left( \frac{dQ}{dP} X_T - x \right) \right]$  for  $X_T \in L^0(\Omega)$ ,  $y > 0$  and  $Q \in \mathcal{M}^a(S)$ , we have

$$\begin{aligned} \sup_{X_T \in C(x)} E[U(X_T)] &= \sup_{X_T} \inf_{y>0, Q \in \mathcal{M}^a(S)} L(X_T, y, Q) \\ &= \sup_{X_T} \inf_{y>0, Q \in \mathcal{M}^a(S)} E \left[ U(X_T) - y \left( \frac{dQ}{dP} X_T - x \right) \right] \\ &= \inf_{y>0, Q \in \mathcal{M}^a(S)} \sup_{X_T} E \left[ U(X_T) - y \left( \frac{dQ}{dP} X_T - x \right) \right] \\ &= \inf_{y>0, Q \in \mathcal{M}^a(S)} E \left[ V \left( y \frac{dQ}{dP} \right) \right] - xy \\ &= \inf_{y>0} v(y) - xy. \end{aligned}$$

Note that we obtain the third line by maximising for each fixed  $\omega$ , since we no longer have any constraint on  $X_T$  (other than measurability). From question 1 we know that this supremum is attained exactly when  $U'(X_T) = y \frac{dQ}{dP}$ . Furthermore, the last infimum is attained exactly when  $y = \hat{y}(x)$ , and the infimum over the martingale measure is obtained exactly when  $\frac{dQ}{dP} = \frac{d\hat{Q}(x)}{dP}$ . Likewise, the supremum over  $X_T$  is attained exactly when  $\hat{X}_T(x)$ . Therefore, the unique saddle point of the Lagrangian satisfies  $U'(\hat{X}_T(x)) = \hat{y}(x) \frac{d\hat{Q}(x)}{dP}$ , as we wanted.

**Exercise 12.3** (optional) Consider the utility function  $u_\gamma(x) = \frac{x^\gamma}{\gamma}$ , for  $x > 0$  and  $\gamma \in (-\infty, 1) \setminus \{0\}$ . Show that  $u_\gamma(x) - \frac{1}{\gamma} \rightarrow \log x$  as  $\gamma \rightarrow 0$ . Compute the conjugate functions of  $u_\gamma$  and  $\log$ .

**Solution 12.3** Fixing  $x$ , we can easily see that

$$\begin{aligned} u_\gamma(x) - \frac{1}{\gamma} &= \frac{x^\gamma - 1}{\gamma} \\ &= \frac{e^{\gamma \log x} - 1}{\gamma} \\ &= \frac{1 + \gamma \log x + o(\gamma) - 1}{\gamma} \\ &= \log x + o(1) \rightarrow \log x \end{aligned}$$

as  $\gamma \rightarrow 0$ . This shows the desired convergence.

To compute the conjugate functions, we have that

$$\begin{aligned} v_\gamma(u'_\gamma(x)) &= -xu'_\gamma(x) + u_\gamma(x) \\ \Rightarrow v_\gamma(x^{\gamma-1}) &= -x^\gamma + \frac{x^\gamma}{\gamma} \\ \Rightarrow v_\gamma(x^{\gamma-1}) &= \frac{1-\gamma}{\gamma}x^\gamma \\ \Rightarrow v_\gamma(y) &= \frac{\gamma-1}{\gamma}y^{\frac{\gamma}{\gamma-1}}. \end{aligned}$$

For the logarithm,

$$\begin{aligned} v(\log'(x)) &= -x \log'(x) + \log(x) \\ \Rightarrow v\left(\frac{1}{x}\right) &= -1 + \log(x) \\ \Rightarrow v(y) &= -1 - \log(y). \end{aligned}$$

**Exercise 12.4** Assume that the interest rate is 0, i.e. there exists a riskless asset with constant value 1, and consider the Bachelier model

$$dS_t = \mu dt + \sigma dB_t, \quad S_0 \in \mathbb{R},$$

with  $\mu \in \mathbb{R}$  and  $\sigma > 0$ .

Compute the optimal utility and optimal strategy associated with the problem

$$J_0 = \sup_{\vartheta \in \Theta_{\text{adm}}^x} E \left[ u \left( x + \int_0^T \vartheta_s dS_s \right) \right],$$

for the cases of power utility  $u_\gamma(x)$  and log-utility  $u(x) = \log(x)$ .

**Hint.** To find a good ansatz for the log-utility case, try (heuristically) taking a limit of the power utility case as  $\gamma \rightarrow 0$ .

**Solution 12.4** We compute the Hamilton-Jacobi-Bellman equation. Assuming that we have

$$J_t(\vartheta) = \text{ess sup}_{\psi \in \Theta(t, \vartheta)} E[U(X_T^\psi) | \mathcal{F}_t] = k(t, X_t^\vartheta),$$

where  $X^\vartheta = x + \vartheta \bullet S$ , we can use Itô's formula to obtain

$$dJ_t(\vartheta) = k_t(t, X_t^\vartheta)dt + k_x(t, X_t^\vartheta)\vartheta_t(\mu dt + \sigma dB_t) + \frac{1}{2}k_{xx}(t, X_t^\vartheta)\vartheta_t^2\sigma^2 dt.$$

With the martingale optimality principle in mind, we maximise over  $p$  the expression

$$k_t(t, X_t^\vartheta) + \mu k_x(t, X_t^\vartheta)p + \frac{\sigma^2}{2}k_{xx}(t, X_t^\vartheta)p^2,$$

which has a maximum at

$$\hat{p} = -\frac{\mu k_x(t, X_t^\vartheta)}{\sigma^2 k_{xx}(t, X_t^\vartheta)}.$$

Setting  $p = \hat{p}$ , the (heuristic) drift term for the optimal strategy  $\hat{\vartheta}$  becomes

$$k_t(t, X_t^{\hat{\vartheta}}) - \frac{\mu^2 k_x^2(t, X_t^{\hat{\vartheta}})}{2\sigma^2 k_{xx}(t, X_t^{\hat{\vartheta}})} = 0,$$

by the martingale optimality principle. We then obtain the HJB equation for  $k$ :

$$k_t - \frac{\mu^2 k_x^2}{2\sigma^2 k_{xx}} = 0.$$

Now, for power utility  $u_\gamma$ , we try a solution of the form

$$k(t, x) = f(t) \frac{x^\gamma}{\gamma},$$

where  $f(T) = 1$  to satisfy the terminal condition. With this ansatz, we obtain

$$\begin{aligned} f'(t) \frac{x^\gamma}{\gamma} &= \frac{\mu^2 f(t)^2 x^{2\gamma-2}}{2\sigma^2(\gamma-1)f(t)x^{\gamma-2}} \\ \Rightarrow f'(t) &= \frac{\mu^2 \gamma}{2\sigma^2(\gamma-1)} f(t) \\ \Rightarrow f(t) &= e^{\kappa(T-t)}, \end{aligned}$$

where  $\kappa_\gamma = -\frac{\mu^2 \gamma}{2\sigma^2(\gamma-1)}$ .

The optimal strategy is then given by the feedback control

$$\hat{\vartheta}_t = \hat{p} = -\frac{\mu X_t^{\hat{\vartheta}}}{\sigma^2(\gamma - 1)}.$$

In the case of logarithmic utility, we can find the following ansatz by taking a limit (or otherwise):

$$k(t, x) = g(t) + \log(x)$$

where  $g(T) = 0$ . With this ansatz, we obtain

$$\begin{aligned} g'(t) &= \frac{\mu^2 \frac{1}{x^2}}{-2\sigma^2 \frac{1}{x^2}} \\ \Rightarrow g'(t) &= -\frac{\mu^2}{2\sigma^2} \\ \Rightarrow g(t) &= \kappa(T - t), \end{aligned}$$

where  $\kappa = \frac{\mu^2}{2\sigma^2}$ .

The optimal strategy is then given by the feedback control

$$\hat{\vartheta}_t = \hat{p} = \frac{\mu X_t^{\hat{\vartheta}}}{\sigma^2}.$$