

## Solution to Homework Set VI

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1. Assume  $x^* := \mathbb{E}[X] < \infty$ . Since  $U : \mathbb{R} \mapsto \mathbb{R}$  is concave, there exist  $m, b \in \mathbb{R}$  such that  $mx^* + b = U(x^*)$  and  $mx + b \geq U(x)$  for all  $x \in \mathbb{R}$ . It follows that

$$\mathbb{E}[U(X)] = \int_{\Omega} U(X) d\mathbb{P} \leq \int_{\Omega} (mX + b) d\mathbb{P} = m\mathbb{E}[X] + b = mx^* + b = U(x^*) = U(\mathbb{E}[X]).$$

2. As shown in class, the Bellman equation for  $H(v, t)$  is

$$\begin{aligned} \partial_t H - \frac{\mu^2}{2\sigma^2} \frac{H_v^2}{H_{vv}} + e^{-\rho t} g^*(-e^{\rho t} H_v) &= 0, \quad x > 0, t < T; \\ H(v, T) &= 0, \quad v > 0; \\ H(0, t) &= 0, \quad t < T, \end{aligned} \tag{1}$$

where  $g^*(\cdot)$  is the Legendre transform of  $-U(x) = -x^\gamma$  with  $0 < \gamma < 1$ , i.e.

$$g^*(x^*) := \sup_{x \in \mathbb{R}} \{x^*x + x^\gamma\} = \begin{cases} \infty & \text{if } x^* > 0, \\ (1 - \gamma)\gamma^{\frac{\gamma}{1-\gamma}} (-x^*)^{\frac{\gamma}{\gamma-1}} & \text{if } x^* \leq 0. \end{cases}$$

Take  $H(v, t) = u(t)v^\gamma$ . Then by direct calculations, (1) becomes the ODE

$$\begin{aligned} u_t - \frac{\mu^2}{2\sigma^2} \frac{\gamma}{\gamma-1} u + (1 - \gamma)e^{\frac{\rho t}{\gamma-1}} u^{\frac{\gamma}{\gamma-1}} &= 0, \quad t < T; \\ u(T) &= 0. \end{aligned} \tag{2}$$

Set  $w(t) = (u(t))^{\frac{1}{1-\gamma}}$ . Then by direct calculations, (2) becomes

$$\begin{aligned} w_t - \frac{\mu^2}{2\sigma^2} \frac{\gamma}{(\gamma-1)^2} w + e^{\frac{\rho t}{\gamma-1}} &= 0, \quad t < T; \\ w(T) &= 0. \end{aligned} \tag{3}$$

We can solve the ODE (3) explicitly and have

$$w(t) = \frac{2\sigma^2(\gamma-1)^2}{2\sigma^2(\gamma-1)\rho + \mu^2\gamma} \left( e^{\frac{\rho T}{\gamma-1}} e^{\frac{\mu^2\gamma}{2\sigma^2(\gamma-1)^2}(T-t)} - e^{\frac{\rho t}{\gamma-1}} \right), \quad t \leq T.$$

We can therefore conclude

$$\begin{aligned} H(v, t) &= u(t)v^\gamma = (w(t))^{1-\gamma} v^\gamma \\ &= \left[ \frac{2\sigma^2(\gamma-1)^2}{2\sigma^2(\gamma-1)\rho + \mu^2\gamma} \left( e^{\frac{\rho T}{\gamma-1}} e^{\frac{\mu^2\gamma}{2\sigma^2(\gamma-1)^2}(T-t)} - e^{\frac{\rho t}{\gamma-1}} \right) \right]^{1-\gamma} v^\gamma. \end{aligned}$$

3. In deriving the Bellman equation (1) in problem 2., we used the formula for optimal control

$$u_1^* = -\frac{\mu H_v}{\sigma^2 v H_{vv}} > 0.$$

Now suppose  $u_1^*(t, v) \leq 1$  on some region  $F \subseteq [0, T] \times [0, \infty)$ . Then the Bellman equation (1) is satisfied on  $F$ . As shown in problem 2., the solution is of the form  $H(v, t) = u(t)v^\gamma$  on  $F$ . However, this implies that for any  $(t, v) \in F$ ,

$$u_1^*(t, v) = -\frac{\mu H_v(v, t)}{\sigma^2 v H_{vv}(v, t)} = -\frac{\mu \gamma u(t) v^{\gamma-1}}{\sigma^2 v \gamma (\gamma-1) u(t) v^{\gamma-2}} = \frac{\mu}{\sigma^2 (1-\gamma)} > 1,$$

under the assumption that  $\sigma^2(1-\gamma) < \mu$ . This contradicts  $u^* \leq 1$  on  $F$ . Thus, we conclude that in the case where  $\sigma^2(1-\gamma) < \mu$ , the optimal control  $u_1^*$  should be taken as  $u_1^* \equiv 1$ . Then, the corresponding Bellman equation becomes

$$\begin{aligned} 0 &= H_t + \max_{u_1 \in [0, 1]} \left\{ u_1 \mu v H_v + \frac{(u_1 \sigma v)^2}{2} H_{vv} \right\} + \max_{u_2 > 0} \{ e^{-\rho t} U(u_2) - u_2 H_v \} \\ &= H_t + \frac{\sigma^2}{2} v^2 H_{vv} + e^{-\rho t} g^*(-e^{\rho t} H_v), \end{aligned} \quad (4)$$

where  $g^*$  is given as in problem 2.. Taking  $H(v, t) = u(t)v^\gamma$  and  $w(t) = (u(t))^{\frac{1}{1-\gamma}}$ , we may proceed as what we did in problem 2. and derive from (4) the following ODE

$$0 = w_t + \gamma \left( \frac{-\sigma^2}{2} - \frac{\mu}{\gamma-1} \right) w + e^{\frac{\rho t}{\gamma-1}}. \quad (5)$$

Note that  $H(v, T) = 0$  implies  $w(T) = 0$ . We can then solve (5) explicitly and obtain

$$w(t) = \frac{2(\gamma-1)}{-\gamma\sigma^2(\gamma-1) - 2\gamma\mu + 2\rho} \left[ \exp \left\{ \frac{\rho}{\gamma-1} T + \gamma \left( \frac{-\sigma^2}{2} - \frac{\mu}{\gamma-1} \right) (T-t) \right\} - e^{\frac{\rho}{\gamma-1} t} \right].$$

Thus,

$$\begin{aligned} H(v, t) &= u(t)v^\gamma = (w(t))^{1-\gamma} v^\gamma \\ &= \left( \frac{2(\gamma-1)}{-\gamma\sigma^2(\gamma-1) - 2\gamma\mu + 2\rho} \left[ \exp \left\{ \frac{\rho}{\gamma-1} T + \gamma \left( \frac{-\sigma^2}{2} - \frac{\mu}{\gamma-1} \right) (T-t) \right\} - e^{\frac{\rho}{\gamma-1} t} \right] \right)^{1-\gamma} v^\gamma. \end{aligned}$$

Now, we intend to verify that  $H(v, t) = M(v, t)$ , where

$$M(v, t) := \max_{u_1 \in [0, 1], u_2 > 0} \mathbb{E} \left[ \int_t^T e^{-\rho s} U(u_2(s)) ds \mid V(t) = v \right].$$

Note that  $H(v, t)$  is the maximum expected utility when we set  $u_1 \equiv 1$ . It follows that  $H(v, t) \leq M(v, t)$ . Thus, we only need to show the opposite inequality. Take arbitrary controls  $u_1(\cdot)$  and  $u_2(\cdot)$  such that

$$0 \leq u_1(s) \leq 1 \text{ and } u_2(s) > 0, \text{ a.s.}$$

Then the corresponding wealth process  $V(\cdot)$  satisfies

$$dV(t) = u_1(t)V(t)[\mu dt + \sigma dB(t)] - u_2(t)dt,$$

where  $B(\cdot)$  is a Brownian motion. Now, applying Itô's rule to the process  $H(V, \cdot)$ , we get

$$\begin{aligned} H(V_{T \wedge \tau_n}, T \wedge \tau_n) = H(v, t) &+ \int_t^{T \wedge \tau_n} \left( H_t + (u_1 \mu V - u_2)H_v + \frac{1}{2}(u_1 \sigma V)^2 H_{vv} \right) (V_s, s) ds \\ &+ \int_t^{T \wedge \tau_n} (u_1 \sigma V H_v) (V_s, s) dB(s), \end{aligned}$$

where  $\tau_n := \inf\{s \geq t : |V_s| > n\}$ ,  $n \in \mathbb{N}$ . It follows that for each  $n \in \mathbb{N}$

$$\mathbb{E}[H(V_{T \wedge \tau_n}, T \wedge \tau_n)] = H(v, t) + \mathbb{E} \left[ \int_t^{T \wedge \tau_n} \left( H_t + (u_1 \mu V - u_2)H_v + \frac{1}{2}(u_1 \sigma V)^2 H_{vv} \right) (V_s, s) ds \right]. \quad (6)$$

Under the condition  $\sigma^2(1 - \gamma) < \mu$ , we know that  $H(v, t)$  solves (4). Then we see from (4) that we must have

$$0 \geq H_t + u_1 \mu V H_v + \frac{1}{2}(u_1 \sigma V)^2 H_{vv} + e^{-\rho t} U(u_2) - u_2 H_v.$$

This, together with (6), implies that for each  $n \in \mathbb{N}$

$$H(v, t) \geq \mathbb{E}[H(V_{T \wedge \tau_n}, T \wedge \tau_n)] + \mathbb{E} \left[ \int_t^{T \wedge \tau_n} e^{-\rho t} U(u_2(s)) ds \right].$$

Now we let  $n \rightarrow \infty$ . For the first expectation, we use the dominated convergence theorem and get

$$\lim_{n \rightarrow \infty} \mathbb{E}[H(V_{T \wedge \tau_n}, T \wedge \tau_n)] = \mathbb{E}[H(V_T, T)] = 0.$$

Note that we may apply the dominated convergence theorem here because

$$H(v, t) \leq Cv, \text{ for some constant } C > 0,$$

which can be seen from the formula for  $H(v, t)$  we derived above and  $0 < \gamma < 1$ . For the second expectation, we apply the monotone convergence theorem. Finally, we obtain

$$H(v, t) \geq \mathbb{E} \left[ \int_t^T e^{-\rho t} U(u_2(s)) ds \right]$$

Now by the arbitrariness of  $u_1$  and  $u_2$ ,

$$H(v, t) \geq \max_{u_1 \in [0, 1], u_2 > 0} \mathbb{E} \left[ \int_t^T e^{-\rho t} U(u_2(s)) ds \right] = M(v, t).$$

4. (a) As mentioned in class,  $g_\beta$  is the solution to

$$\frac{\partial g_\beta}{\partial t} = \mu \frac{\partial g_\beta}{\partial x} + \frac{1}{2} \sigma^2 \frac{\partial^2 g_\beta}{\partial x^2}, \quad x, t > 0, \quad (7)$$

with  $\lim_{t \rightarrow 0} g_\beta(x, t) = \beta + x$  for  $x > 0$  and  $\lim_{x \rightarrow 0} g_\beta(x, t) = 0$  for  $t > 0$ . Now that we know  $p(x, t) := \mathbb{P}_x(\tau < t)$  is the solution to (7) with  $\lim_{t \rightarrow 0} p(x, t) = 0$  for  $x > 0$  and  $\lim_{x \rightarrow 0} p(x, t) = 1$  for  $t > 0$ , we conclude that

$$w(x, t) := \mathbb{E}[x + \mu t + \sigma B(t) \mid \tau > t] = g_\beta(x, t) - \beta \mathbb{P}_x(\tau > t) = g_\beta(x, t) - \beta + \beta p(x, t)$$

is the solution to (7) with

$$\lim_{t \rightarrow 0} w(x, t) = x \text{ for } x > 0; \quad \lim_{x \rightarrow 0} w(x, t) = 0 \text{ for } t > 0. \quad (8)$$

Now consider  $h_1(x, t) := x + \mu t$  and  $h_2(x, t) := \int_0^t p(x, s) ds$ . It can be easily checked that  $h_1$  is the solution to (7) with  $\lim_{t \rightarrow 0} h_1(x, t) = x$  for  $x > 0$  and  $\lim_{x \rightarrow 0} h_1(x, t) = \mu t$  for  $t > 0$ . Moreover, observe that

$$\begin{aligned} \frac{\partial h_2}{\partial t}(x, t) &= p(x, t) = \int_0^t \frac{\partial p}{\partial t}(x, s) ds = \int_0^t \mu \frac{\partial p}{\partial x} + \frac{1}{2} \sigma^2 \frac{\partial^2 p}{\partial x^2} ds \\ &= \mu \frac{\partial}{\partial x} \int_0^t p(x, s) ds + \frac{1}{2} \sigma^2 \frac{\partial^2}{\partial x^2} \int_0^t p(x, s) ds \\ &= \mu \frac{\partial h_2}{\partial x}(x, t) + \frac{1}{2} \sigma^2 \frac{\partial^2 h_2}{\partial x^2}(x, t). \end{aligned}$$

Thus,  $h_2$  is the solution to (7) with  $\lim_{t \rightarrow 0} h_2(x, t) = 0$  for  $x > 0$  and  $\lim_{x \rightarrow 0} h_2(x, t) = t$  for  $t > 0$ . We can therefore conclude that  $h(x, t) := h_1(x, t) - \mu h_2(x, t)$  is the solution to (7) with  $\lim_{t \rightarrow 0} h(x, t) = x$  for  $x > 0$  and  $\lim_{x \rightarrow 0} h(x, t) = 0$  for  $t > 0$ . Then by (8), we have  $w(x, t) = h(x, t)$ . It follows that

$$g_\beta(x, t) = \beta[1 - p(x, t)] + h(x, t) = \beta[1 - p(x, t)] + x + \mu t - \mu \int_0^t p(x, s) ds.$$

(b) From the result in (a), for any  $t, x > 0$ , we have

$$\begin{aligned} \frac{\partial g_\beta}{\partial x}(x, t) &= -\beta \frac{\partial p}{\partial x}(x, t) + 1 - \mu \int_0^t \frac{\partial p}{\partial x}(x, s) ds, \\ \frac{\partial^2 g_\beta}{\partial x^2}(x, t) &= -\beta \frac{\partial^2 p}{\partial x^2}(x, t) - \mu \int_0^t \frac{\partial^2 p}{\partial x^2}(x, s) ds. \end{aligned} \quad (9)$$

Note that  $p(x, t)$  is by definition decreasing in  $x$  and increasing in  $t$ . This implies  $\frac{\partial p}{\partial x} \leq 0$ ,  $\frac{\partial p}{\partial t} \geq 0$ , and thus  $\frac{\partial^2 p}{\partial x^2} = \frac{2}{\sigma^2} (\frac{\partial p}{\partial t} - \mu \frac{\partial p}{\partial x}) \geq 0$ . Now, we can see from (9) that

$$\frac{\partial g_\beta}{\partial x} > 0, \quad \text{and} \quad \frac{\partial g_\beta}{\partial x^2} \leq 0, \quad \text{as } \beta > 0.$$

We therefore conclude that  $g_\beta(x, t)$  is a concave increasing function of  $x > 0$ , provided  $\beta > 0$ .

5. For any  $u_2 \leq \mu/\rho$  and  $\beta \leq \mu/\rho - u_2$ , consider the two functions  $g_{\mu/\rho - u_2}(x, t)$  and  $h(x, t) := e^{\rho t} \left[ \frac{\mu}{\rho} + x - u_2 \right]$ . Fix  $x \geq u_2$ . Observe that at  $t = 0$ ,

$$g_{\mu/\rho - u_2}(x, 0) = \frac{\mu}{\rho} - u_2 + x = h(x, 0).$$

From the formula of  $g_\beta(x, t)$  and the properties of  $p(x, t)$  in problem 4., we have

$$\frac{\partial}{\partial t} g_{\mu/\rho - u_2}(x, t) = - \left( \frac{\mu}{\rho} - u_2 \right) \frac{\partial p}{\partial t}(x, t) + \mu - \mu p(x, t) \leq \mu, \text{ for all } t \geq 0.$$

On the other hand,

$$\frac{\partial}{\partial t} h(x, t) = \rho e^{\rho t} \left[ \frac{\mu}{\rho} + x - u_2 \right] = e^{\rho t} [\mu + \rho(x - u_2)] \geq \mu, \text{ for all } t \geq 0.$$

Since  $g_{\mu/\rho - u_2}(x, 0) = h(x, 0)$  and  $\frac{\partial}{\partial t} g_{\mu/\rho - u_2}(x, t) \leq \mu \leq \frac{\partial}{\partial t} h(x, t)$  for all  $t \geq 0$ , we conclude that

$$g_\beta(x, t) \leq g_{\mu/\rho - u_2}(x, t) \leq h(x, t) = e^{\rho t} \left[ \frac{\mu}{\rho} + x - u_2 \right], \text{ for all } t \geq 0.$$

We therefore have  $e^{-\rho t} g_\beta(x, t) \leq \mu/\rho + (x - u_2)$ , as  $x \geq u_2$ .

6. Set  $y = -z > 0$ . Define  $h(y, t) := H^*(-y, t)$  for  $y > 0$ ,  $0 \leq t \leq T$ . Then the PDE for  $H^*$

$$H_t^* + z^2 H_{zz}^* + f^*(t, z) = 0 \text{ for } z < 0, \quad 0 \leq t \leq T, \text{ with } H^*(z, T) = 0$$

becomes the PDE for  $h$

$$h_t + y^2 h_{yy} + g(t, y) = 0 \text{ for } y > 0, \quad 0 \leq t \leq T, \text{ with } h(y, T) = 0, \quad (10)$$

where  $g(t, y) := f^*(t, -y)$ . Note that the convexity of  $f^*$  in  $z$  implies the convexity of  $g$  in  $y$ . Indeed, for any  $y_1, y_2 > 0$  and  $\lambda \in [0, 1]$ ,

$$\begin{aligned} g(t, \lambda y_1 + (1 - \lambda)y_2) &= f^*(t, \lambda(-y_1) + (1 - \lambda)(-y_2)) \leq \lambda f^*(t, -y_1) + (1 - \lambda)f^*(t, -y_2) \\ &= \lambda g(t, y_1) + (1 - \lambda)g(t, y_2). \end{aligned} \quad (11)$$

By using the Feynmann-Kac representation theorem, the solution of (10) can be expressed as

$$h(y, t) = \mathbb{E} \left[ \int_t^T g(s, Y_s) ds \right],$$

where the process  $Y_s$  satisfies  $dY_s = \sqrt{2}Y_s dB_s$  for  $s \geq t$  and  $Y_t = y$ , which can be solved explicitly as

$$Y_s = y \exp\{(t - s) + \sqrt{2}(B_s - B_t)\} =: y\mathcal{E}(s).$$

Now, for any  $y_1, y_2 > 0$  and  $\lambda \in [0, 1]$ , we have, thanks to the convexity of  $g$  in  $y$ , that

$$\begin{aligned} h(\lambda y_1 + (1 - \lambda)y_2, t) &= \mathbb{E} \left[ \int_t^T g(s, (\lambda y_1 + (1 - \lambda)y_2) \mathcal{E}(s)) ds \right] \\ &\leq \lambda \mathbb{E} \left[ \int_t^T g(s, y_1 \mathcal{E}(s)) ds \right] + (1 - \lambda) \mathbb{E} \left[ \int_t^T g(s, y_2 \mathcal{E}(s)) ds \right] \\ &= \lambda h(y_1, t) + (1 - \lambda)h(y_2, t). \end{aligned}$$

This shows the convexity of  $h$  in  $y$ . Finally, since  $H^*(z, t) = h(-z, t)$ , the convexity of  $h$  in  $y$  implies the convexity of  $H^*$  in  $z$ , by the same calculation as (11).