## Suggested Solutions to the Exam

## 80 points, 80 minutes. Closed books, notes, calculators. Indicate your reasoning. Use BOTH clearly written words and math.

- 1. (30 pts) A firm produces output q from inputs  $z=(z_1,\ldots,z_n)$  using a strictly increasing  $C^2$  production function f. Let c(w,q) be the firm's cost function, z(w,q) be its conditional factor demand function, and  $D_w z(w,q) = [\partial z_i/\partial w_j]$  be the Jacobian matrix of z(w,q) with respect to w. For each property below, state further assumptions that imply it is true, and prove your answer.
  - (a) (10 pts) c(w, q) is convex in q.

**Soln:** True if f is concave.

**Proof.** Given  $q^0$ ,  $q^1$ , let  $z^0$  and  $z^1$  be the corresponding cost minimizing input bundles. Let  $\lambda \in [0,1]$ , and define

$$q^{\lambda} = \lambda q^{1} + (1 - \lambda)q^{1},$$
  

$$z^{\lambda} = \lambda z^{1} + (1 - \lambda)z^{1}.$$

The concavity of *f* implies

$$f(z^{\lambda}) \ge \lambda f(z^1) + (1 - \lambda)f(z^0)$$
  
 
$$\ge \lambda q^1 + (1 - \lambda)q^0 = q^{\lambda}.$$

Hence,  $z^{\lambda}$  is feasible for the cost minimization problem for producing output  $q^{\lambda}$ . It follows that c is convex in q since

$$c(w,q) \le w \cdot z^{\lambda}$$
  
=  $\lambda(w \cdot z^1) + (1 - \lambda)(w \cdot z^0)$   
=  $\lambda c(q^1) + (1 - \lambda)c(q^0)$ .

(b) (10 pts) c(w, q) is linear in q.

**Soln:** True if f is homogeneous of degree one (constant returns to scale).

**Proof.** (Drop the *w* here, as it is held constant). We have

$$c(tq) = \min_{z} w \cdot z \text{ such that } f(z) \ge tq$$

$$= t \min_{z} w \cdot \frac{z}{t} \text{ such that } f(z) \ge tq$$

$$= t \min_{z} w \cdot \frac{z}{t} \text{ such that } f(\frac{z}{t}) \ge q,$$

where the last equality holds because f is homogeneous of degree one. Letting  $\hat{z} = z/t$ , we reach our conclusion:

$$c(tq) = t \min_{\hat{z}} w \cdot \hat{z} \text{ such that } f(\hat{z}) \ge q$$
  
=  $tc(q)$ .

(c) (10 pts)  $D_w z(w,q) w = 0$ .

**Soln:** True at any (w, q) at which the derivatives  $D_w z(w, q)$  exist.

**Proof.** The conditional factor demands are homogeneous of degree zero in w. Hence, by Euler's formula, for any i we have

$$\sum_{j} \frac{\partial z_{i}(w,q)}{\partial w_{j}} w_{j} = 0.$$

In matrix form, these *n* equations are  $D_w z(w, q) w = 0$ .

2. (20 pts) Robinson Crusoe has an endowment  $e \in \mathbb{R}_{++}$  of bananas that he can consume or use to make clothing. If he uses  $x \in [0,e]$  bananas to make clothing, his utility will be u(e-x,f(x)), where  $u:\mathbb{R}^2_+\to\mathbb{R}$  and  $f:\mathbb{R}_+\to\mathbb{R}_+$  are strictly increasing functions. Let

$$x^*(e) := \arg\max_{0 \le x \le e} u(e - x, f(x)).$$

(a) (10 pts) Show that  $x^*$  (e) is convex if u is quasiconcave and f is concave.

**Soln:** Let  $x^0, x^1 \in x^*(e)$ , and  $\bar{u} = u(e - x^0, f(x^0)) = u(e - x^1, f(x^1))$ . Let  $x^{\lambda} = \lambda x^1 + (1 - \lambda)x^1$  for some  $\lambda \in [0, 1]$ . Since f is concave, we have

$$f(x^{\lambda}) \ge \lambda f(x^1) + (1 - \lambda)f(x^0).$$

Thus, as u is increasing in its second argument and is quasiconcave, we have

$$u(e - x^{\lambda}, f(x^{\lambda})) \ge u(e - x^{\lambda}, \lambda f(x^{1}) + (1 - \lambda)f(x^{0}))$$

$$= u(\lambda(e - x^{1}) + (1 - \lambda)(e - x^{0}), \lambda f(x^{1}) + (1 - \lambda)f(x^{0}))$$

$$\ge \min\{u(e - x^{1}, f(x^{1})), u(e - x^{0}, f(x^{0}))\}$$

$$= \bar{u}.$$

Since  $\bar{u}$  is the maximal utility Robinson can obtain,  $x^{\lambda}$  must be a maximizer:  $x^{\lambda} \in x^*(e)$ . This proves  $x^*(e)$  is a convex set.

(b) (10 pts) Assume now that  $x^*(e)$  is a singleton for any e > 0, u and f are  $C^2$  functions, f and u are concave, and  $u_{12} \ge 0$ . Prove that  $x^*(e)$  is a nondecreasing function, stating any further (minor) assumptions you need.

**Soln: Proof 1.** To simplify notation, let v(e, x) := u(e - x, f(x)). Note that

$$v_{12} = -u_{11} + u_{12}f' \ge 0,$$

since the concavity of u implies  $u_{11} \leq 0$ , f increasing implies  $f' \geq 0$ , and we've been told that  $u_{12} \geq 0$ . Now, for some  $\bar{e}$  and  $\hat{e} > \bar{e}$ , let  $\bar{x} = x^*(\bar{e})$  and  $\hat{x} = x^*(\hat{e})$ . We must show that  $\hat{x} \geq \bar{x}$ . This is obvious if the two are equal, so we can assume  $\bar{x} \neq \hat{x}$ . Then

$$\int_{\hat{x}}^{\bar{x}} \int_{\bar{e}}^{\hat{e}} v_{12}(e,x) de \, dx = [v(\hat{e},\bar{x}) - v(\hat{e},\hat{x})] - [v(\bar{e},\bar{x}) - v(\bar{e},\hat{x})] < 0,$$

since  $\hat{x}$  is the unique maximizer of  $v(\hat{e},\cdot)$  and  $\bar{x}$  is the unique maximizer of  $v(\bar{e},\cdot)$ . Since  $v_{12} \geq 0$  and  $\hat{e} > \bar{e}$ , the double integral would be nonnegative if  $\hat{x} < \bar{x}$ . Hence,  $\hat{x} > \bar{x}$ .

**Proof 2.** This time we use the implicit function theorem to find  $x^{*\prime}(e)$  at some e, making stronger derivative assumptions to make sure the troublesome denominator is not zero.

First additional assumption:

(A1) 
$$0 < x^*(e) < e$$
.

The FOC thus holds with equality at  $x^*(e) : -u_{11} + u_2 f' = 0$ . Differentiate it with respect to e and solve for  $x^{*'}(e)$ :

$$x^{*'}(e) = \frac{u_{11} - u_{12}f'}{D},\tag{1}$$

where

$$D = (1, -f') \begin{bmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \end{bmatrix} \begin{pmatrix} 1 \\ -f' \end{pmatrix} + u_2 f''$$

and all functions are evaluated at  $x = x^*(e)$ . The concavity of u implies its Hessian is negative semidefinite, so the quadratic form term is nonpositive. The last term is nonpositive because  $u_2 \ge 0$  and  $f'' \le 0$ . To make sure D is not zero, we make a second additional assumption:

(A2)  $[u_{ij}]$  is a negative definite matrix, or  $u_2 > 0$  and f'' < 0.

Since (A2) implies D < 0, the IFT tells us  $x^*$  is differentiable at e and its derivative there is as shown in (1). Since  $u_{11} \le 0$ ,  $u_{12} \ge 0$ , and  $f' \ge 0$ , we conclude that  $x^{*'}(e) \ge 0$ .

3. (30 pts) Let  $\tilde{x} = a + \tilde{\epsilon}$  be a gamble, where  $a \in \mathbb{R}$  and  $\tilde{\epsilon}$  is a random variable with mean zero. A consumer has a  $C^2$  Bernoulli utility function,  $u : \mathbb{R} \to \mathbb{R}$ , satisfying u' > 0 and  $u'' \le 0$ . Her sale price for the gamble is the minimum amount she would sell the gamble for: it is the number s(a) satisfying

$$u(s(a)) = \mathbb{E}u(a + \tilde{\varepsilon}).$$

(a) (10 pts) If u exhibits constant absolute risk aversion, what can you say about the derivative s'(a)? Prove your answer.

**Soln:** s'(a) = 1, i.e., s(a) = a + constant.

**Proof.** Let A be the constant coefficient of absolute risk aversion. If A = 0, then we can normalize so  $u(x) \equiv x$ , and the definition of s(a) implies  $s(a) = a + \mathbb{E}(\tilde{\epsilon}) = a$ . So we can assume A > 0 (if A < 0, u would not be concave). We can now normalize u so that

$$u(x) = -e^{-Ax},$$

and so the definition of s(a) implies

$$e^{-As(a)} = e^{-Aa} \mathbb{E} e^{-A\tilde{\varepsilon}} \implies e^{-A(s(a)-a)} = \mathbb{E} e^{-A\tilde{\varepsilon}}.$$

This implies that s(a) - a does not depend on a, and so again s'(a) = 1.

(b) (20 pts) If u exhibits decreasing absolute risk aversion (DARA), what can you say about the derivative s'(a)? Prove your answer.

**Soln:**  $s'(a) \ge 1$ .

**Proof 1.** For any a, define a utility function  $u_a$  by  $u_a(z) := u(a+z)$ . DARA implies  $u_a$  is more risk averse than  $u_{\hat{a}}$  if  $a < \hat{a}$ . The definition of s(a) implies

$$u_a(s(a) - a) = u(s(a)) = \mathbb{E}u(a + \tilde{\varepsilon}) = \mathbb{E}u_a(\tilde{\varepsilon}).$$

Thus, s(a) - a is the certainty equivalent of the risk  $\tilde{\epsilon}$  for the utility function  $u_a$ . Since  $u_a$  becomes less risk averse as a increases, this certainty equivalent increases in a. Hence,  $s'(a) - 1 \ge 0$ .

**Proof 2.** Differentiate the identity defining s(a) to obtain.

$$s'(a) = \frac{\mathbb{E}u'(a+\tilde{\varepsilon})}{u'(s(a))}.$$

Now we observe that DARA implies u' is a convex function of u: letting  $g := u' \circ u^{-1}$ , we have u'(z) = g(u(z)) for any z, and at any  $\bar{u}$ ,

$$g'(\bar{u}) = \frac{u''(u^{-1}(\bar{u}))}{u'(u^{-1}(\bar{u}))}$$

is increasing in  $\bar{u}$  by DARA. Rewrite the expression for s'(a) in terms of g:

$$s'(a) = \frac{\mathbb{E}g(u(a+\tilde{\varepsilon}))}{g(u(s(a)))}.$$

Since g is convex, Jensen's theorem and the definition of s(a) yield

$$\mathbb{E}g(u(a+\tilde{\epsilon})) \geq g(\mathbb{E}u(a+\tilde{\epsilon})) = g(\mathbb{E}u(s(a))),$$

and so  $s'(a) \ge 1$ .