# **Problem Set 3**

# 1. (Walrasian Demand Function)

1(a)

$$egin{aligned} p \cdot x &= w \ p \cdot x(p,w) &= w \ x(p,w) &= (p^{-1} \cdot w)^T \ x(p,w) &= w \cdot (p^{-1})^T \ \end{pmatrix} \ x(p,w) &= \left( egin{aligned} x_1(p,w) \ x_2(p,w) \ dots \ x_L(p,w) \ \end{matrix} 
ight) \ D_w x(p,w) &= 
abla_w x(p,w) &= p \cdot p^{-1} \ D_w x(p,w) &= rac{\partial x(p,w)}{\partial w} \end{aligned}$$

Walras' Law:

$$p \cdot x(p, w) = w$$

Differentiate both sides with respect to  $\boldsymbol{w}$  :

$$p \cdot D_w x(p, w) = 1$$

2(b)

At least one good must be a normal good

$$\exists \ l: rac{orall x_l(p,w)}{\partial w} \geq 0$$

$$\begin{array}{l} \text{negation:} \quad \forall \ l: \frac{\partial x_l(p,w)}{\partial w} < 0 \\ \\ \neg \ \exists \ l: \frac{\partial x_l(p,w)}{\partial w} \geq 0 \equiv \forall \ l: \frac{\partial x_l(p,w)}{\partial w} < 0 \end{array}$$

Assume that there is no such good  $~\forall~l: rac{\partial x_l(p,w)}{\partial w} < 0$  .

$$p \cdot D_w x(p,w) = \sum_{l=1}^L p_l \cdot \underbrace{rac{\partial x_l(p,w)}{\partial w}}_{ ext{negative}} \leq 0$$

In **2(a)** , we derived  $p \cdot D_w x(p,w) = 1$  . We have a contradiction.

Therefore, there must be at least one normal good.

# 2. (UMP and strictly convex preferences)

 $\succeq$  are strictly convex  $\updownarrow$   $u(\cdot)$  is strictly quasi-concave  $\Downarrow$  x(p,w) is single-valued

Prove by contradiction

Assume  $\exists~p,w:x_1,x_2\in x(p,w), x_1\neq x_2 ext{ but } u(x_1)=u(x_2)$ 

$$u(\lambda x_1 + (1-\lambda)x_2) > \min\{u(x_1), u(x_2)\}$$
 (by strict quasi-concavity)

Check if  $\lambda x_1 + (1-\lambda)x_2$  is affordable under p,w

$$p \cdot [\lambda x_1 + (1-\lambda)x_2] = \lambda \underbrace{p \cdot x_1}_{\leq w} + (1-\lambda) \cdot \underbrace{p \cdot x_2}_{\leq w} \leq w$$

I can always find a linear combination of  $x_1$  and  $x_2$  within the budget constraint such that this linear combination yields a higher utility.

Therefore,  $x_1, x_2$  could never have been optimal (contradiction).

$$\forall p, w : x(p, w) \text{ is single-valued}$$

#### 3. (Kuhn-Tucker)

**Constant Elasticity of Substitution (CES)** 

$$u(x) = \left(\sum_{l=1}^L x_l^\sigma
ight)^{rac{1}{\sigma}}$$

3(a)

Convexity

$$\frac{\partial u(x)}{\partial x_l} = \frac{1}{\sigma} \left( \sum_{l=1}^L x_l^{\sigma} \right)^{\frac{1}{\sigma}-1} \sigma \cdot x_l^{\sigma-1} = \left( \sum_{l=1}^L x_l^{\sigma} \right)^{\frac{1}{\sigma}-1} x_l^{\sigma-1}$$

$$\frac{\partial^2 u(x)}{\partial x_l^2} = \left( \frac{1}{\sigma} - 1 \right) \left( \sum_{l=1}^L x_l^{\sigma} \right)^{\frac{1}{\sigma}-2} (\sigma - 1) x_l^{\sigma-2} = -\frac{(1-\sigma)^2}{\sigma} \left( \sum_{l=1}^L x_l^{\sigma} \right)^{\frac{1}{\sigma}-2} x_l^{\sigma-2} < 0$$

Homotheticity

$$u(\lambda x) = \left(\sum_{l=1}^L (\lambda x_l)^\sigma
ight)^{rac{1}{\sigma}} = \left(\lambda^\sigma \sum_{l=1}^L x_l^\sigma
ight)^{rac{1}{\sigma}} = \lambda \left(\sum_{l=1}^L x_l^\sigma
ight)^{rac{1}{\sigma}} = \lambda u(x)$$

Solution:

We need to show that  $u(\cdot)$  is strictly quasiconcave.

Let us do a monotonic transformation

$$f(x) = x^{\sigma}$$
  $v(x) = f(u(x)) = (u(x))^{\sigma} = \sum_{l=1}^{L} x_l^{\sigma}$ 

v(x) represents the same preferences as u(x)

We therefore need to show that  $v(\cdot)$  is strictly quasiconcave.

$$x^{\sigma}$$
 is strictly concave  $(\sigma \in (0,1))$ 
 $\downarrow$ 
the sum of  $x^{\sigma}$  is also strictly concave
 $\downarrow$ 
 $v(x)$  is strictly concave
 $\downarrow$ 
 $v(x)$  is strictly quasiconcave
 $\downarrow$ 
 $u(x)$  is strictly quasiconcave
 $\downarrow$ 
 $u(x)$  is strictly convex

3(b)

$$egin{aligned} \max & u(x) \ ext{s.t.} & p \cdot x \leq w, x_l \geq 0 \quad orall l = 1, 2, \cdots, L \ L = \left(\sum_{l=1}^L x_l^\sigma
ight)^{rac{1}{\sigma}} - \lambda(p \cdot x - w) + \eta_1 \cdot x_1 + \cdots \eta_L \cdot x_L \end{aligned}$$

FOC:

$$egin{aligned} \left(\sum_{l=1}^L x_l^\sigma
ight)^{rac{1}{\sigma}-1} x_l^{\sigma-1} & \leq \lambda p_l \ & x_l \left[\left(\sum_{l=1}^L x_l^\sigma
ight)^{rac{1}{\sigma}-1} x_l^{\sigma-1} - \lambda p_l
ight] = 0 \ & \lambda(p\cdot x - w) = 0 \end{aligned}$$

At the interior optimum:  $x_l > 0: \nabla u(x) = \lambda p$ 

$$\left(\sum_{l=1}^L x_l^\sigma
ight)^{rac{1}{\sigma}-1} x_l^{\sigma-1} = \lambda p_l \ p\cdot x = w$$

$$\max\left(\sum_{l=1}^L x_l^\sigma
ight)^{rac{1}{\sigma}} \quad ext{s.t.} \quad p\cdot x \leq w$$

Monotonic transformation:

$$egin{align} u(x) &= \left(\sum_{l=1}^L x_l^\sigma
ight)^{rac{1}{\sigma}} \ f(x) &= rac{x^\sigma}{\sigma} \ v(x) &= f(u(x)) &= rac{\sum_{l=1}^L x_l^\sigma}{\sigma} &= \sum_{l=1}^L rac{x_l^\sigma}{\sigma} \ \end{cases}$$

u(x) is strictly increasing in each argument



Walras' Law holds  $p \cdot x = w$ 

Lagrangian function:

$$L(x,\lambda) = \sum_{l=1}^L rac{x_l^\sigma}{\sigma} - \lambda (\sum_{l=1}^L p_l \cdot x_l - w)$$

FOC:

$$egin{dcases} rac{\partial L}{\partial x_i} = x_i^{\sigma-1} - \lambda p_i = 0 \ rac{\partial L}{\partial x_j} = x_j^{\sigma-1} - \lambda p_j = 0 \end{cases} \implies egin{dcases} x_i^{\sigma-1} = \lambda p_i \ x_j^{\sigma-1} = \lambda p_j \end{cases} \implies x_i = \left(rac{p_i}{p_j}
ight)^{rac{1}{\sigma-1}} x_j$$

Use budget constraint to pin down the demand function

$$egin{aligned} p \cdot x &= w \ \sum_{i=1}^L p_i \cdot x_i &= w \ \sum_{i=1}^L p_i \cdot \left(rac{p_i}{p_j}
ight)^{rac{1}{\sigma-1}} x_j &= w \ \sum_{i=1}^L p_i^{rac{\sigma}{\sigma-1}} \cdot rac{x_j}{p_j^{rac{1}{\sigma-1}}} &= w \ \end{aligned}$$
 demand function:  $x_j = rac{w \cdot p_j^{rac{1}{\sigma-1}}}{\sum_{i=1}^L p_i^{rac{\sigma}{\sigma-1}}}$ 

As  $\sigma 
ightarrow 1$ 

$$\lim_{\sigma o 1} \left( \sum_{l=1}^L x_l^\sigma 
ight)^{rac{1}{\sigma}} = \sum_{l=1}^L x_l^\sigma$$

As  $\sigma \to 0$  , goods become perfect substitutes

$$f(x) = \ln x$$
  $v(x) = f(u(x)) = \ln \left(\sum_{l=1}^L x_l^\sigma
ight)^{rac{1}{\sigma}} = rac{1}{\sigma} \ln \left(\sum_{l=1}^L x_l^\sigma
ight)$ 

$$egin{aligned} \lim_{\sigma o 0} v(x) &= \lim_{\sigma o 0} rac{1}{\sigma} \mathrm{ln} \left( \sum_{l=1}^L x_l^\sigma 
ight) \ &= \lim_{\sigma o 0} rac{\sum_{l=1}^L x_l^\sigma \ln x_l}{\sum_{l=1}^L x_l^\sigma} \ &= rac{1}{L} \sum_{l=1}^L \ln x_l \end{aligned}$$

 $\lim_{\sigma o -\infty} u(x) = \min_x \{x_i\} \quad ext{(leontief utility function)}$ 

3(c)

$$u(x_1,x_2) = (x_1^{\sigma} + x_2^{\sigma})^{1/\sigma} \quad x_1,x_2 \geq 0$$

The Kuhn-Tucker conditions:

$$egin{cases} \left( x_1^{\sigma} + x_2^{\sigma})^{rac{1}{\sigma}-1} x_1^{\sigma-1} \leq \lambda p_1 \ (x_1^{\sigma} + x_2^{\sigma})^{rac{1}{\sigma}-1} x_2^{\sigma-1} \leq \lambda p_2 \ x_1 [(x_1^{\sigma} + x_2^{\sigma})^{rac{1}{\sigma}-1} x_1^{\sigma-1} - \lambda p_1] = 0 \ x_2 [(x_1^{\sigma} + x_2^{\sigma})^{rac{1}{\sigma}-1} x_2^{\sigma-1} - \lambda p_2] = 0 \ \lambda (p_1 x_1 + p_2 x_2 - w) = 0 \end{cases}$$

 $x_1, x_2 > 0$ :

$$egin{cases} \left\{ (x_1^{\sigma} + x_2^{\sigma})^{rac{1}{\sigma} - 1} x_1^{\sigma - 1} - \lambda p_1 = 0 \ (x_1^{\sigma} + x_2^{\sigma})^{rac{1}{\sigma} - 1} x_2^{\sigma - 1} - \lambda p_2 = 0 \end{cases} \implies rac{\lambda p_1}{x_1^{\sigma - 1}} = rac{\lambda p_2}{x_2^{\sigma - 1}}$$

Solution

$$x_j = rac{w \cdot p_j^{rac{1}{\sigma - 1}}}{\sum_{i=1}^L p_i^{rac{\sigma}{\sigma - 1}}} \ x_1 = rac{w \cdot p_1^{rac{1}{\sigma - 1}}}{p_1^{rac{\sigma}{\sigma - 1}}} \ rac{\partial x_1(p,w)}{p_2} = (-1) \cdot w \cdot p_1^{rac{1}{\sigma - 1}} \cdot rac{1}{(p_1^{rac{\sigma}{\sigma - 1}} + p_2^{rac{\sigma}{\sigma - 1}})^2} \cdot rac{\sigma}{\sigma - 1} \cdot p_2^{rac{\sigma}{\sigma - 1} - 1} > 0$$

 $x_1, x_2$  are gross substitutes.

### 3(d)

 $x_1(p,w), x_2(p,w)$  are linear in w

$$\frac{x_1(p,w)}{x_2(p,w)}$$
 does not depend on  $w$ 

# 4. (Multiple Optima)

$$u(x) = egin{cases} x, & x \in [0,1) \ 1, & x \geq 1 \end{cases}$$

Continuity

$$\begin{cases} f(x) = x \text{ is continuous} \\ f(x) = 1 \text{ is continuous} \end{cases}$$

$$\begin{cases} \lim_{x\to 1-} u(x) = \lim_{x\to 1-} x = 1\\ \lim_{x\to 1+} u(x) = \lim_{x\to 1+} 1 = 1 \end{cases} \implies \lim_{x\to 1} u(x) = 1 \quad u(x) \text{ is continuous at } x = 1$$

Convexity (Quasiconcavity)

$$f(x) = x$$
 is convex  $f(x) = 1$  is convex

Check y < 1 < x

$$u(\lambda x + (1 - \lambda)y) \ge u(\lambda y + (1 - \lambda)y) = u(y) \implies \text{quasicavity} \implies \text{convex}$$

LNS

$$x>1, 
extstyle arepsilon>0, x'\in [x-arepsilon,x+arepsilon] ext{ such that } u(x')>u(x)=1$$

 $\succeq$  is not locally non-satiated.

4(b)

$$\max u(x) \quad ext{s.t.} \quad p \cdot x \leq w \implies x(p,w) = egin{cases} rac{w}{p}, & rac{w}{p} < 1 \ [1,rac{w}{p}], & rac{w}{p} \geq 1 \end{cases}$$

Zero-homothetic

$$x(p,w) = egin{cases} rac{\lambda w}{\lambda p}, & rac{\lambda w}{\lambda p} < 1 \ [1, rac{\lambda w}{\lambda p}], & rac{\lambda w}{\lambda p} \geq 1 \end{cases}$$

## 5. (Homothetic Preferences)

5(a)

$$x_1p_1+x_2p_2=w$$
  $MRS(x_1,x_2)=rac{p_1}{p_2}$   $MRS(x_1,x_2)=MRS(\lambda x_1,\lambda x_2)$ 

#### 5(b)

Prove

$$x(p, \lambda w) = \lambda x(p, w)$$

Prove by contradiction

Assume  $x 
eq \lambda x'$  and  $x \succ \lambda x^*$  ,  $x^*$  is optimal

$$x \succ \lambda x^* \implies u(x) > u(\lambda x^*)$$
  $u(x) > \lambda u(x^*)$   $\dfrac{1}{\lambda} u(x) > u(x^*)$   $u(\dfrac{x}{\lambda}) > u(x^*)$   $\dfrac{x}{\lambda} \succeq x^*$   $p \cdot \dfrac{x}{\lambda} = p \cdot \lambda x^* \cdot \dfrac{1}{\lambda} = w \quad \dfrac{x^*}{\lambda} \text{ is feasible under } p, w$ 

We find a bundle  $\frac{x^*}{\lambda}$  that yields higher utility within the budget constraint. Therefore,  $x^*$  could not have been optimal.