

I - Let us assume that a consumer has an utility  $u(Q, \theta) - Q\varepsilon$  for a quantity  $Q$  of some good. The function  $u$  is known up to some parameters  $\theta$  and  $\varepsilon$  is an heterogeneity component distributed with some probability measure. The consumer is faced to a non linear pricing rule  $P(Q)$  assumed to be differentiable and known by the agents and by the econometrician. Then the optimal decision for the consumer is obtained by the resolution of

$$V(Q, \theta) - p(Q) = \varepsilon$$

where  $V(Q, \theta) = \frac{\partial}{\partial Q}u(Q, \theta)$  and  $p(Q) = \frac{\partial}{\partial Q}P(Q)$

- i) For iid sample of consumer the  $\varepsilon_i (i = 1, \dots, n)$  are non observable but we assume that there are  $(N(0, \sigma^2))$ . We observe the sample  $Q_i (i = 1, \dots, n)$ . Write the likelihood of the sample given the parameters  $\theta$  and  $\sigma^2$ . What are the properties of the MLE of  $\theta$  and  $\sigma^2$  and give the asymptotic variance of these estimators.
- ii) Assume that  $\theta$  is given and that the interest is focused on the  $\sigma$  parameter which describes the heterogeneity of the consumer. What is a natural conjugate prior on  $\sigma$  (you may parametrize the model by  $\sigma^2$  or by  $\frac{1}{\sigma^2}$ ) and what in the posterior distribution? Let us denote the prior density by  $\nu(\sigma)$ . If now  $\theta$  and  $\sigma$  are unknown and provided by a prior density  $\mu(\theta)\nu(\sigma)$  how do you compute the posterior distribution on  $\theta$ ?
- iii) We keep the assumption that the  $\varepsilon_i$  are iid but we ignore their distribution. The distributional assumption is now replaced by the introduction of some instruments. Let  $Z \in \mathbb{R}^p$  a vector of observed variables (possibly including the constant 1) and we assume that  $E(\varepsilon|Z) = 0$ . Explain how to estimate  $\theta$  by GMM under the assumption  $Var(\varepsilon|Z) = \sigma^2 \quad \forall Z$ . Consider the case where the optimal weighting matrix is used and explain how you estimate this matrix. Discuss also the choice of the optimal instruments.  
As the optional instruments involve  $E(\frac{\partial}{\partial \theta}V(Q, \theta)|Z)$  we propose a non parametric estimation of this conditional expectation.  
Explain how you may construct this estimator by a kernel smoothing method and how this estimator may be used in the GMM approach.
- iv) We now assume that the distribution of  $\varepsilon$  is known and we want to relax the parametric specification of  $u$ .

Let us write the model :

$$\varphi(Q) = \varepsilon \text{ where } \varphi(Q) = V(Q) - p(Q)$$

We first want to estimate  $\varphi(Q)$  using the iid sample  $(Q_i | i = 1, \dots, n)$ . Assuming  $\varphi$  strictly monotone and decreasing how can we estimate  $\varphi$  from the relation between the c.d.f. of  $Q$  and the c.d.f. of  $\varepsilon$ . (We assume that  $\varepsilon$  has a continuous distribution such that its c.d.f. is invertible).

- v) We now consider a continuous variable  $X$  such that  $V$  becomes a function  $V(Q, X)$  and  $V$  is treated non parametrically. Assume that we observe two prices regimes  $p^1(Q)$  and  $p^2(Q)$ . We want to show that in that case  $V$  is non parametrically identifiable. Let  $G(q|x) = Prob(Q \leq q | X = x)$ . Show that  $\frac{\partial G}{\partial q} / \frac{\partial G}{\partial x}$  does not depend on the distribution of  $\varepsilon$  and deduce from this equality the identification result.

**II** - Let  $X$  an univariate random variable with a density  $f$  and  $x_1, \dots, x_n$  an iid sample. We estimate  $f$  by  $\hat{f}$  the kernel estimate. Show that the bootstrap distribution of  $\hat{f}$  has a mean equal to  $\hat{f}$ .