

(11)

QMLEENDOGEN. VAR: Y EXOGEN. VAR: X

THE MODEL SPECIFIES THE CONDITIONAL DENSITY OF

 Y_1, \dots, Y_T GIVEN X_1, \dots, X_T IT IS PARAMETRIZED BY $\theta \in \Theta$, OPEN IN \mathbb{R}^p :

$$l(y_1, \dots, y_T | x_1, \dots, x_T; \theta) = \prod_{i=1}^T f(y_i | x_i; \theta), \quad \theta \in \Theta$$

 Y_1, \dots, Y_T are independent conditional on the exogen.THE TRUE DENSITY OF Y :

$$l_0(y_1, \dots, y_T | x_1, \dots, x_T) = \prod_{i=1}^T f_0(y_i | x_i)$$

DOES NOT BELONG TO THE SELECTED FAMILY

$$f_0(y|x) \notin \{f(y|x; \theta), \theta \in \Theta\}$$

 \Rightarrow MISSPECIFICATIONMEASURE THE "DISTANCE" BTW THE TRUE f_0 AND THE MODEL $\{f(y|x; \theta), \theta \in \Theta\}$ USING KULLBACK CRITERION.

(2)

DEFINING THE PSEUDO-TRUE VALUE θ_0^* : THE VALUE OF CORRESPONDING TO THE MODEL CLOSEST POSSIBLE TO f_0 .

$$\theta_0^* = \text{Arg max}_{\theta \in \Theta} E_x E_0 \log f(Y|X; \theta)$$

E_0 : CONDITIONAL EXPECTATION OF Y GIVEN X UNDER f_0
SUPPOSE θ_0^* IS UNIQUE.

THE PSEUDO (QUASI) MAX LIKELIHOOD ESTIMATOR OF IS THE SOLUTION $\hat{\theta}_T$ OF

$$\text{MAX}_{\theta \in \Theta} \sum_{i=1}^T \log f(Y_i | X_i; \theta)$$

INTUITION

MLE COMPUTED FOR A MISSPECIFIED MODEL.

UNDER THE REGULARITY CONDITIONS QMLE CONVERGES TO THE PSEUDO-TRUE VALUE θ_0^*

THE MAXIMIZATION OF THE LIMITING PROBLEM IS:

$$\text{MAX}_{\theta \in \Theta} E_x E_0 \log f(Y|X; \theta)$$

AND IT HAS A UNIQUE SOLUTION θ_0^* .

(3)

REGULARITY COND:

- i) $Y_i | X_i$ are independent, with identical distribution,
- ii) Θ is OPEN
- iii) $\log f$ is CONTINUOUS IN Θ AND INTEGRABLE W.R TO THE TRUE DENSITY f_0 , $\forall \theta$.
- iv) $\frac{1}{T} \sum_{i=1}^T \log f(Y_i | X_i; \theta)$ CONVERGE A.S. UNIFORMLY ON Θ TO $E_X E_Y \log f(Y | X; \theta)$

E_X : expectation w.r to the true marginal density of X

E_Y : expectation w.r to the true conditional density of $Y | X$

- v) THE LIMITING PROBLEM ADMITS A UNIQUE SOLUTION = PSEUDO TRUE VALUE

ASYMPTOTIC NORMALITY

A DEVELOP IN THE NEIGHBORHOOD OF THE LIMITING PSEUDO-TRUE VALUE:

$$\sum_{i=1}^T \frac{d \log f(Y_i | X_i; \tilde{\theta}_T)}{d\theta} = 0$$

$$\Rightarrow \frac{1}{T} \sum_{i=1}^T \frac{d \log f(Y_i | X_i; \tilde{\theta}_0^*)}{d\theta} + \frac{1}{T} \sum_{i=1}^T \frac{d^2 \log f}{d\theta d\theta'} [\tilde{\theta}_T - \tilde{\theta}_0^*] \neq 0$$

(4)

$$\sqrt{T} [\hat{\theta}_T - \tilde{\theta}_0^*] \neq \left[-\frac{1}{T} \sum_{i=1}^T \frac{d^2 \log f}{d\theta d\theta'} \right]^{-1} \frac{1}{\sqrt{T}} \sum_{i=1}^T \frac{d \log f}{d\theta}$$

$$\neq \left[\mathbb{E}_{X_0} \mathbb{E}_0 - \frac{d^2 \log f}{d\theta d\theta'} \right]^{-1} \frac{1}{\sqrt{T}} \sum_{i=1}^T \frac{d \log f}{d\theta}$$

law of large No for the empirical mean of 2nd derivatives

: difference $\rightarrow 0$ in probability

$$\mathbb{E}_{X_0} \mathbb{E}_0 \frac{d \log f [Y_i | X_i; \tilde{\theta}_0^*]}{d\theta} = \frac{d}{d\theta} \mathbb{E}_{X_0} \mathbb{E}_0 \log f (Y_i | X_i; \theta_0^*) = 0$$

since θ_0^* is the solution of the limiting problem

THE VECTORS $\frac{d \log f [Y_i | X_i; \tilde{\theta}_0^*]}{d\theta}$ are iid of mean 0

and var-covar:

$$I = \mathbb{E}_{X_0} \mathbb{E}_0 \left[\frac{d \log f (Y | X; \theta_0^*)}{d\theta} \frac{d \log f (Y | X; \theta_0^*)}{d\theta} \right]$$

THE CENTRAL LIMIT THEOREM \Rightarrow

$$\frac{1}{\sqrt{T}} \sum_{i=1}^T \frac{d \log f (Y_i | X_i; \tilde{\theta}_0^*)}{d\theta} \underset{ASY}{\sim} N[0, I]$$

THE VECTOR $\sqrt{T} [\hat{\theta}_T - \theta_0^*]$ IS A LINEAR TRANSFORM OF IT;

FOLLOWS A $N(0, J^{-1} I J^{-1})$

$$J = E_X E_\theta \left[- \frac{\partial^2 \log f(Y|X; \theta_0^*)}{\partial \theta \partial \theta'} \right]$$

UNDER MISSPECIFICATION $I \neq J$

$$\hat{J} = - \frac{1}{T} \sum_{i=1}^T \frac{\partial^2 \log f(Y_i | X_i; \hat{\theta}_T)}{\partial \theta \partial \theta'}$$

$$\hat{I} = \frac{1}{T} \sum_{i=1}^T \left[\frac{\partial \log f(Y_i | X_i; \hat{\theta}_T)}{\partial \theta} \frac{\partial \log f(Y_i | X_i; \hat{\theta}_T)}{\partial \theta'} \right]$$