

Which Moments To Match?

Gallant and Tauchen

Econometric Theory, 1996

Sargent Reading Group Presentation

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Introduction

Q: How to choose moment conditions when using GMM to estimate parameters of a structural model?

A: Use expectation, under structural model, of the score from an auxiliary model, as the vector of moment conditions.

Auxiliary Model:

1. fits the data well
2. likelihood can be computed

Notation

- Data: y , observed sample: $\{\tilde{y}_i\}_{i=1}^n$
- Model: $p(y|\rho)$, data generated by $p(y|\rho^0)$
- Auxiliary Model: $f(y|\theta)$

$$\begin{aligned}\sqrt{n}X_n &\approx N(0, V_v) \\ &\Leftrightarrow \\ \sqrt{n}X_n V_v^{-\frac{1}{2}} &\xrightarrow{d} N(0, I)\end{aligned}$$

Moment Conditions

- Auxiliary model parameter estimates:

$$\tilde{\theta}_n = \arg \max_{\theta \in \Theta} \frac{1}{n} \sum_{i=1}^n \log f(\tilde{y}_i | \theta)$$

- Exact:

$$m_n(\rho, \tilde{\theta}_n) = E \left[\frac{\partial}{\partial \theta} \log f(y | \tilde{\theta}_n) | \rho \right]$$

- By Simulation:

$$m_n(\rho, \tilde{\theta}_n) = \frac{1}{S} \sum_{s=1}^S \frac{\partial}{\partial \theta} \log f(y_s | \tilde{\theta}_n)$$

with y_s drawn from $p(y | \rho)$

- Estimator:

$$\hat{\rho}_n = \arg \min_{\rho \in R} m_n(\rho, \tilde{\theta}_n)' W m_n(\rho, \tilde{\theta}_n)'$$

Efficient Weighting Matrix

- From definition of $\tilde{\theta}_n$:

$$\frac{1}{n} \sum_{i=1}^n \frac{\partial}{\partial \theta} \log f(\tilde{y}_i | \tilde{\theta}_n) = 0$$

- Define the "psuedo-true value", θ_n^0 as

$$\begin{aligned} m_n(\rho^0, \theta_n^0) &\equiv E \left[\frac{\partial}{\partial \theta} \log f(y | \theta_n^0) | \rho^0 \right] = 0 \\ &\implies \lim_{n \rightarrow \infty} (\tilde{\theta}_n - \theta_n^0) = 0 \end{aligned}$$

- Expand $\frac{1}{n} \sum_{i=1}^n \frac{\partial}{\partial \theta} \log f(y_i | \tilde{\theta}_n)$ around θ_n^0 :

$$\begin{aligned} \sqrt{n} (\tilde{\theta}_n - \theta_n^0) &\approx N \left(0, (Q_n^0)^{-1} \Omega_n^0 (Q_n^0)^{-1} \right) \\ Q_n^0 &= \frac{\partial}{\partial \theta} m_n(\rho^0, \theta_n^0) \\ \Omega_n^0 &= \text{Var} \left[\frac{1}{\sqrt{n}} \sum_{i=1}^n \frac{\partial}{\partial \theta} \log f(\tilde{y}_i | \theta_n^0) \right] \end{aligned}$$

- Expand $m_n(\rho^0, \tilde{\theta}_n)$ around $m_n(\rho^0, \theta_n^0) = 0$:

$$\begin{aligned} \sqrt{n} m_n(\rho^0, \tilde{\theta}_n) &= \sqrt{n} Q_n^0 (\tilde{\theta}_n - \theta_n^0) + o_p(1) \\ &\implies \sqrt{n} m_n(\rho^0, \tilde{\theta}_n) \approx N(0, \Omega_n^0) \end{aligned}$$

- Efficient weighting matrix is $W = (\Omega_n^0)^{-1}$:

$$\hat{\rho}_n = \arg \min_{\rho \in R} m_n(\rho, \tilde{\theta}_n) \left(\tilde{\Omega}_n \right)^{-1} m_n(\rho, \tilde{\theta}_n)'$$

Consistency and Asymptotic Normality

Identification condition: $\exists n_0$ such that $\forall n \geq n_0$

$$\begin{aligned} m_n(\rho, \theta_n^0) &= 0 \\ &\implies \\ \rho &= \rho^0 \end{aligned}$$

Then:

1. $\hat{\rho}_n \xrightarrow{a.s.} \rho^0$
2. $\sqrt{n}(\hat{\rho}_n - \rho^0) \approx N\left(0, (M_n^0)^{-1} \Omega_n^0 (M_n^0)^{-1}\right)$
3. $\hat{M}_n \xrightarrow{a.s.} M_n^0$

where

$$\begin{aligned} M_n^0 &= \frac{\partial}{\partial \rho'} m_n(\rho^0, \theta_n^0) \\ \hat{M}_n &= \frac{\partial}{\partial \rho'} m_n(\hat{\rho}, \tilde{\theta}_n) \end{aligned}$$

Smooth-Embeddedness

\exists an open neighborhood, R^0 , of ρ^0 and twice continuously differentiable mapping, $g : R^0 \rightarrow \Theta$ s.t:

$$p(y|\rho) = f(y|g(\rho)) \quad \forall \rho \in R^0$$

Define:

$$1. \hat{\rho}_{mcs} = \arg \min_{\rho \in R} [\tilde{\theta} - g(\rho)]' \hat{\Omega}_n [\tilde{\theta} - g(\rho)]$$

$$2. \hat{\rho}_{mle} = \arg \max_{\rho \in R} \frac{1}{n} \sum_{i=1}^n \log f(\tilde{y}_i | g(\rho))$$

$\implies \hat{\rho}_n, \hat{\rho}_{mcs}, \hat{\rho}_{mle}$ all have same asymptotic distribution

Final Thoughts

- Choosing an auxiliary model? Semi-non parametric model with linear basis functions
- All results extend to non-stationary time series models of the form

$$\{p_1(x_1|\rho)\}, \{p_t(y_t|x_t, \rho)\}_{t=1}^{\infty}$$