

GMM & Standard Errors for Business Cycle Statistics

Wouter J. Den Haan
London School of Economics

© 2011 by Wouter J. Den Haan

June 25, 2011

Overview

- Formulation of GMM estimation problem
 - large class of problems
- Formula for standard errors
- Calculating HAC estimator (correcting for heteroskedasticity and autocorrelation)

GMM problem

Underlying true model:

$$\mathbb{E}[h(x_t; \theta)] = 0_p$$

- $\theta : m \times 1$ vector with parameters
- $x : n \times 1$ vector of observables
- $h(\cdot) : p \times 1$ vector-valued function with $p \geq m$
- $0_p : p \times 1$ vector with zeros

Examples

OLS:

$$y_t = a + bx_t + u_t$$

$$\mathbb{E} \begin{bmatrix} u_t \\ u_t x_t \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

- IV:

$$y_t = a + bx_t + u_t$$

$$\mathbb{E} \begin{bmatrix} u_t \\ u_t z_t \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Examples

DSGE:

$$u_{t+1} = \beta (1 + r_{t+1}) c_{t+1}^{-\gamma} - c_t^{-\gamma}$$

$$\mathbb{E}[u_{t+1} z_t] = 0_p$$

where z_t is a vector with variables in information set in period t

GMM estimation

$$\hat{\theta}_T = \arg \min_{\theta \in \Theta} g(\theta; Y_T)' W_T g(\theta; Y_T)$$

where

$$g(\theta; Y_T) = \sum_{t=1}^T h(x_t; \theta) / T$$

W_T : $p \times p$ weighting matrix

Y_T : data

No weighting matrix needed if $p = m$

Asymptotic standard errors

$$\begin{aligned} W &= \underset{T \rightarrow \infty}{\text{plim}} W_T \\ D &= \underset{T \rightarrow \infty}{\text{plim}} \left. \frac{\partial g(\theta; Y_T)}{\partial \theta'} \right|_{\theta=\theta_0} \\ \theta_0 &: \text{ true } \theta \end{aligned}$$

Asymptotic standard errors

$$T^{\frac{1}{2}} (\widehat{\theta}_T - \theta_0) \longrightarrow N(0, V)$$

$$V = (DWD')^{-1} DW\Sigma_0 W'D' (DWD')^{-1}$$

Can be made easier

- ① $p = m$ (no overidentifying restrictions)

$$T^{\frac{1}{2}} (\widehat{\theta}_T - \theta_0) \longrightarrow N(0, V)$$
$$V = (D\Sigma_0^{-1}D')^{-1}$$

- ② using optimal weighting matrix $W = \Sigma_0$

$$T^{\frac{1}{2}} (\widehat{\theta}_T - \theta_0) \longrightarrow N(0, V)$$
$$V = (D\Sigma_0^{-1}D')^{-1}$$

What is left to figure out?

- "only" one thing left: estimate Σ_0
- Σ_0 is the variance-covariance matrix of
$$g(\theta; Y_T) = \sum_{t=1}^T h(x_t; \theta) / T$$

Estimate variance of a mean

- $g(\theta; Y_T)$ is the mean of $h(x_t; \theta)$
- variance of $g(\theta; Y_T)$ is easy to calculate if $h(x_t; \theta)$ is serially uncorrelated

Estimate variance of a mean

General formula

$$\Sigma_0 = \sum_{j=-\infty}^{\infty} \mathbb{E} \left[h(x_t; \theta_0) h(x_{t-j}; \theta_0)' \right]$$

How to estimate this?

$$\hat{\Sigma}_0 = \sum_{j=-J}^J \kappa(j) \frac{\sum_{t=\max\{1, j+1\}}^{\min\{T, T+j\}} \left[h(x_t; \theta_0) h(x_{t-j}; \theta_0)' \right]}{T}$$

Choice of kernel

- Truncated

$$\kappa(j) = \begin{cases} 1 & \text{if } |j| \leq J \\ 0 & \text{o.w.} \end{cases}$$

- disadvantage: answer not necessarily psd

- Newey-West

$$\kappa(j) = 1 - j/J + 1$$

- disadvantage: adds bias ($\kappa(j)$ should be = 1 for all j)

What to do in practice

- ➊ Find $\hat{\theta}_T$ (analytically or with minimization routine)
 - if $p > m$ first use non-optimal choice for W
- ➋ Calculate $h(x_t; \hat{\theta}_T)$ and estimate Σ_0
- ➌ Estimate D (using $\hat{\theta}_T$ for θ_0)
- ➍ Calculate variance of $\hat{\theta}_T$ using $\left(D\Sigma_0^{-1}D'\right)^{-1}$

Business cycles statistics

1

$$\psi = \frac{\text{standard deviation } (c_t)}{\text{standard deviation } (y_t)}$$

2

$$\rho = \text{correlation } (c_t, y_t)$$

Statistics easy to estimate, but what is the standard error?

Business cycles statistics

GMM problem for ψ

$$0 = E[c_t - \mu_c]$$

$$0 = E[y_t - \mu_y]$$

$$0 = E\left[\left(y_t - \mu_y\right)^2 \psi^2 - (c_t - \mu_c)^2\right]$$

$$\begin{aligned}
 D' &= \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 2E[(y_t - \mu_y)] & 2E[(y_t - \mu_y)\psi^2] & 2E[(y_t - \mu_y)^2\psi] \end{bmatrix} \\
 &= \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1E[(y_t - \mu_y)^2\psi] \end{bmatrix}
 \end{aligned}$$

Business cycles statistics

GMM problem for ρ

$$0 = E[c_t - \mu_c]$$

$$0 = E[y_t - \mu_y]$$

$$0 = E\left[\left(y_t - \mu_y\right)^2 \psi^2 - (c_t - \mu_c)^2\right]$$

$$0 = E\left[\left(y_t - \mu_y\right)^2 \psi \rho^2 - (c_t - \mu_c) \left(y_t - \mu_y\right)\right]$$

$$D' = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & 2E\left[\left(y_t - \mu_y\right)^2 \psi\right] & 0 \\ 0 & 0 & E\left[\left(y_t - \mu_y\right)^2 \rho^2\right] & 2E\left[\left(y_t - \mu_y\right)^2 \psi \rho\right] \end{bmatrix}$$

References

- Den Haan, W.J., and A. Levin, 1997, A practitioner's guide to robust covariance matrix estimation
 - a detailed survey of all the ways to estimate Σ_0 . There are a lot more ways than those discussed here