GMM, Indirect Inference and Bootstrap

The three classical tests

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- Wald test, Lagrange multiplier test and likelihood ratio test (W, LM, LR)
- Hypotheses

$$H_0: r(\theta) = 0$$
 vs $H_1: r(\theta) \neq 0$

- Often, r is a scalar-valued function and θ is a scalar
- The function *r* may be non-linear!

Basic test ideas:

- Wald test: If $r(\theta) = 0$ is true, then $r(\hat{\theta}_{ML})$ will be close to 0
- Likelihood ratio test: If $r(\theta)=0$ is true, then $\ln L(\hat{\theta}_R)$ will not be far below $\ln L(\hat{\theta}_{ML})$
- Lagrange multiplier test: If $r(\theta) = 0$ is true, the score function $g(\hat{\theta}_R) = \partial \ln L(\hat{\theta}_R)/\partial \theta$ will be close to 0

Example:

- Let X_1, \ldots, X_n be a random sample from $X \sim Exp(\lambda)$
- Test $H_0: \lambda = 4$ against $H_1: \lambda \neq 4$
- Different notation:

$$H_0: r(\lambda) = 0$$

where
$$r(\lambda) = \lambda - 4$$

See threetests.R

Wald test

Wald test

Hypotheses

$$H_0$$
: $r(\theta) = 0$
 H_1 : $r(\theta) \neq 0$

with functions
$$r = (r_1, \ldots, r_m)$$

- m is the number of restrictions
- Wald test: If $r(\theta) = 0$ is true, then $r(\hat{\theta}_{ML})$ will be close to 0

Wald test

Asymptotically, under H₀ (by delta method!)

$$r(\hat{\theta}_{ML}) \sim N\left(0, Cov(r(\hat{\theta}_{ML}))\right)$$

with

$$Cov(r(\hat{\theta}_{ML})) = \frac{\partial r(\hat{\theta}_{ML})}{\partial \theta'} \cdot Cov(\hat{\theta}_{ML}) \cdot \frac{\partial r(\hat{\theta}_{ML})}{\partial \theta}$$

- Remember: If $extit{X} \sim extit{N}(\mu, \Sigma)$, then $\left(extit{X} \mu
 ight)' \Sigma^{-1} \left(extit{X} \mu
 ight) \sim \chi_{ extit{m}}^2$
- Wald test statistic

$$W = r(\hat{\theta}_{ML})' \left[Cov(r(\hat{\theta}_{ML})) \right]^{-1} r(\hat{\theta}_{ML}) \stackrel{\mathsf{asy}}{\sim} \chi_m^2$$

Wald test

Remarks:

- Reject H_0 if W is larger than the (1α) -quantile of the χ^2_m -distribution
- Usually, $Cov(r(\hat{\theta}_{ML}))$ must be replaced by $\widehat{Cov}(r(\hat{\theta}_{ML}))$
- The Wald test is not invariant with respect to re-parametrizations
- The Wald test only requires the unrestricted ML estimator
- ullet Ideal, if $\hat{ heta}_{ML}$ is much easier to calculate than $\hat{ heta}_R$

Likelihood ratio test

Likelihood ratio test

- Is $\ln L(\hat{\theta}_{ML})$ significantly larger than $\ln L(\hat{\theta}_{R})$?
- LR test statistic

$$LR = -2 \ln \left(\frac{L(\hat{\theta}_R)}{L(\hat{\theta}_{ML})} \right)$$
$$= -2 \left(\ln L(\hat{\theta}_R) - \ln L(\hat{\theta}_{ML}) \right)$$

• Asymptotic distribution: $LR \stackrel{\textit{asy}}{\sim} \chi_m^2$

Likelihood ratio test

Remarks:

- Reject H_0 if LR is larger than the (1α) -quantile of the χ^2_m -distribution
- To compute LR, one requires both the unrestricted estimator $\hat{\theta}_{ML}$ and the restricted estimator $\hat{\theta}_R$
- ullet Ideal, if both $\hat{ heta}_{ML}$ and $\hat{ heta}_R$ are easy to calculate
- The LR test is often used to compare different models to each other

Lagrange multiplier test

Lagrange multiplier test

- Is $g(\hat{\theta}_R)$ significantly different from 0?
- ullet The test is based on the restricted estimator $\hat{ heta}_R$
- Lagrange approach: $\max_{\theta} \ln L(\theta)$ s.t. $r(\theta) = 0$
- LM test statistic

$$LM = g(\hat{\theta}_R)' \cdot \left[\mathcal{I}(\hat{\theta}_R) \right]^{-1} \cdot g(\hat{\theta}_R) \overset{\mathsf{asy}}{\sim} \chi_m^2$$

with

$$\mathcal{I}(\hat{\theta}_R) = -E\left(\frac{\partial^2 \ln L(\hat{\theta}_R)}{\partial \theta \partial \theta'}\right)$$

Lagrange multiplier test

Remarks:

- Reject H_0 if LM is larger than the $(1-\alpha)$ -quantile of the χ^2_m -distribution
- The LM test only requires the restricted estimator
- ullet Ideal, if $\hat{ heta}_R$ is much easier to calculate than $\hat{ heta}_{ML}$
- The LM test is often used to test misspecifications (heteroskedasticity, autocorrelation, omitted variables etc.)
- Asymptotically, the three tests are equivalent

Multivariate case

• Example: Production function

$$Y_i = X_{i1}^{a_1} \cdot X_{i2}^{a_2} + u_i$$

where $u_i \sim N(0, 0.05^2)$

- Log-likelihood function $\ln L(a_1, a_2)$
- ML estimators \hat{a}_1 and \hat{a}_2
- Hypothesis test of $a_1 + a_2 = 1$ or $a_1 + a_2 1 = 0$
- See classtest.R