Zachary Probst Page:1 denotes the t^{th} diagonal element of P_X . 1 Basics vector of (true) model params: θ Distributions Bias: $E(\hat{\theta}) - \theta_0$, $E((\mathbf{X}^{\top}\mathbf{X})^{-1}\mathbf{X}^{\top}\mathbf{u}) = 0$ Normal: $\phi(x) = (2\pi)^{-1/2} \exp(-\frac{1}{2}x^2)$ estimating eq: $g(\mathbf{y}, \theta) = 0$ unbiased iff Normal CDF: $\Phi(\mathbf{x}) = \int_{-\infty}^{x} \phi(y) dy$ $\forall \mu \in \mathbb{M}, E_{\mu}g(\mathbf{y}, \theta_{\mu}) = \mathbf{0} \text{ or } E(\mathbf{X}^{\top}\mathbf{u}) = \mathbf{0}$ $X \text{ exogenous } \Longrightarrow E(\mathbf{u} \mid \mathbf{X}) = \mathbf{0} \text{ and both } \hat{\beta}$ and estimating equations unbiased. Continuous: $m_k(X) \equiv \int_{-\infty}^{\infty} x^k f(x) dx$ Make exog assumpt in cross-sec not time. Central: regressors predetermined: $E(\mathbf{X}^{\top}\mathbf{u}) = \mathbf{0}$ $\mu_k \equiv E(X - E(X)^k) = \int_{-\infty}^{\infty} (x - \mu)^k f(x) dx$ **Stochastic Limits** Discrete Central: Converg in prob: $\lim Pr(|Y_n - Y_\infty| > \epsilon) =$ $\mu_k \equiv E(X - E(X)^k) = \sum_{i=1}^{m} p(x)(x_i - \mu)^k$ $0 \Rightarrow \text{p lim } Y_n = Y_\infty \implies \text{converg dist}$ Converg dist: $\lim F_n(x) = F(x) \equiv Y_n \to F$ Multivariate LLN: $\operatorname{plim} \overline{Y_n} = \operatorname{plim} \frac{1}{n} \sum_{t=1}^{n} Y_t = \mu_Y$, $Y_t \operatorname{IID}$ Joint Density Func: $f(x_1, x_2) = \frac{\partial^2 F(x_1, x_2)}{\partial x_1 \partial x_2}$ $\overline{Y_n}$ sample mean of Y_t , μ_T pop mean. Independence: LLN2: $\operatorname{plim} \frac{1}{n} \sum_{t=1}^{n} Y_{t} = \lim_{t \to \infty} \frac{1}{n} \sum_{t=1}^{n} E(Y_{t})$ $F(x_1, x_2) = F(x_1, \infty)F(\infty, x_2)$ $p\lim Y_n Z_n = p\lim Y_n p\lim Z_n$ if converg or $f(x_1, x_2) = f(x_1)f(x_2)$ $\mathbf{X}^{\top}\mathbf{X}$ may not have plim so mult by $1 \setminus n$. Marginal Density: consistent: $p\lim_{\mu} \beta = \beta_{\mu}$, may be bias $f(x_1) \equiv F_1(x_1, \infty) = \int_{-\infty}^{\infty} f(x_1, x_2) dx_2$ $E(\mu_t \mid \mathbf{X}_t) = 0 \implies \hat{\beta}$ consistent. Conditional Density: $f(x_1|x_2) = \frac{f(x_1,x_2)}{f(x_2)}$ **Covariance and Precision Matrices** Law Iterate Expec: $E(E(X_1|X_2)) = E(X_1)$ $Cov(b_i, b_i) \equiv E((b_i - E(b_i))(b_i - E(b_i)))$ Any Deterministic Func h: if i = j, $Cov(b_i, b_i) = Var(b_i)$ $E(X_1 h(X_2) | X_2) = h(X_2)E(X_1 | X_2)$ $Var(\mathbf{b}) \equiv E((\mathbf{b} - E(\mathbf{b}))(\mathbf{b} - E(\mathbf{b}))^{\top})$ when $E(\mathbf{b}) = \mathbf{0}$, $Var(\mathbf{b}) = E(\mathbf{b}\mathbf{b}^{\top}) b_i$, b_i Matrix Algebra indep: $Cov(b_i, b_i) = 0$, converse false Dot Product: $\mathbf{a}^{\top}\mathbf{b} = \sum_{i=1}^{n} a_i b_i$ correlation: $\rho(b_i, b_j) \equiv \frac{\text{Cov}(b_i, b_j)}{(\text{Var}(b_i)\text{Var}(b_j))^{1/2}}$ Matrix Multiplication: $C_{ij} = \sum_{k=1}^{m} A_{ik} B_{ki}$ Transpose: $(\mathbf{A}\mathbf{B})^{\top} = \mathbf{B}^{\top}\mathbf{A}^{\top}$ Var(b) positive semidefinite. cov and corr $\|\mathbf{x}\| = (\mathbf{x}^{\top}\mathbf{y})^{1/2} = (\sum_{i=1}^{n} x_i^2)^{1/2}$ matrix positive definite most of the time. $\langle \mathbf{x}, \mathbf{y} \rangle = ||\mathbf{x}|| ||\mathbf{y}|| \cos(\theta)$ positive definite: $\mathbf{x}^{\top} \mathbf{A} \mathbf{x} > 0$ for $\mathbf{x} \in k \times 1$. Cauchy-Schwartz: $\langle x, y \rangle \le ||x||||y||$ Linear dep: Xb = 0, $b \ne 0$ $\mathbf{x}^{\top} \mathbf{A} \mathbf{x} = \sum_{i=1}^{k} \sum_{j=1}^{k} x_{i} x_{j} A_{ij}$. If $\geq 0 \Rightarrow$ semidef. Any $\mathbf{B}^{\mathsf{T}}\mathbf{B}$ is pos semidef. If full col rank Singular: $\exists \mathbf{x} \neq 0 : \mathbf{A}\mathbf{x} = \mathbf{0}$ then pos def. pos def \Rightarrow diag > 0 & nonsingular. (pos def) $^{-1}$ \exists & is pos def. 2 Linear Regression Precision mtrx: invers of cov mtrx of estmatr. ∃ & pos def iff cov mtrx pos def. Estimator: $\hat{\beta} = (\mathbf{X}^{\top}\mathbf{X})^{-1}\mathbf{X}^{\top}\mathbf{y}$ $E(x_{ti}u_t) = 0 \implies \mathbf{X}^{\top}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) = \mathbf{0}$ $SSR(\beta) := \sum_{t=1}^{n} (y_i - \mathbf{X}_t \beta)^2$ Ω = err cov mtrx. If diag of Ω differ, heteroskedastic. Homoskedastic: all u $\mathbf{y}^{\top}\mathbf{y} = \hat{\beta}^{\top}\mathbf{X}^{\top}\mathbf{X}\hat{\beta} + (\mathbf{y} - \mathbf{X}\hat{\beta})^{\top}(\mathbf{y} - \mathbf{X}\hat{\beta})$ same Var. Autocorrelated: off-diag $\Omega \neq 0$. Projection: $P_{\mathbf{X}} = \mathbf{X}(\mathbf{X}^{\top}\mathbf{X})^{-1}\mathbf{X}^{\top}$ $\hat{\beta}$ unbiased & $\Omega = \sigma^2 \mathbf{I}$ so no hetero or $\mathbf{M}_{\mathbf{X}} = \mathbf{I} - \mathbf{P}_{\mathbf{X}} = \mathbf{I} - \mathbf{X}(\mathbf{X}^{\top}\mathbf{X})^{-1}\mathbf{X}^{\top}$ autocorr, then $Var(\hat{\beta}) = \sigma^2(\mathbf{X}^{\top}\mathbf{X})^{-1}$. $\mathbf{P}_{\mathbf{X}}\mathbf{y} = \mathbf{X}((\mathbf{X}^{\top}\mathbf{X})^{-1}\mathbf{X}^{\top}\mathbf{y}); \, \mathbf{P}_{\mathbf{X}}\mathbf{P}_{\mathbf{X}} = \mathbf{P}_{\mathbf{X}}$ $M_X y = \hat{\mathbf{u}}; M_X \dot{\mathbf{X}} = 0; \dot{M}_X M_X = M_X$ Precision affected by n, σ^2 , X. Collinearity: precision for β_1 dep on X_2 . $P_X + M_X = I; P_X M_X = 0; P_Y^{\perp} = P_X$ **Efficiency** $\|\mathbf{v}\|^2 = \|\mathbf{P}_{\mathbf{X}}\mathbf{v}\|^2 + \|\mathbf{M}_{\mathbf{X}}\mathbf{v}\|^2; \|\mathbf{P}_{\mathbf{X}}\mathbf{v}\| \le \|\mathbf{v}\|$ $\tilde{\beta}$ more efficient than $\hat{\beta}$ iff $Var(\tilde{\beta})^{-1}$ – Centering: $\mathbf{M}_{\iota}\mathbf{x} = \mathbf{z} = \mathbf{x} - \overline{x}\iota$; $\iota^{\mathsf{T}}\mathbf{z} = 0$ $P_1 \equiv P_{X_1}$; $P_1 P_X = P_X P_1 = P_1$ $Var(\hat{\beta})^{-1}$ is nonzero pos semidef mtrx. FWL: β_2 from $\mathbf{y} = \mathbf{X}_1 \beta_1 + \mathbf{X}_2 \beta_2 + \mathbf{u}$ and Gauss-Markov: If $E(\mathbf{u} \mid \mathbf{X}) = \mathbf{0}$ and $\mathbf{M_1y} = \mathbf{M_1X_2\beta_2} + \text{res are the same.} (+ \text{res})$ $E(\mathbf{u}\mathbf{u}^{\top} \mid \mathbf{X}) = \sigma^2 \mathbf{I}$ then OLS $\hat{\beta}$ is BLUE Seasonal w const: $s'_{i} = s_{i} - s_{4}$, i = 1, 2, 3. (best linear unbiased estimator). Not

Avg is const coeff. $M_S y$ is deseasonalized.

ECON 468 Cheat Sheet

necessary that *u* normally distributed.

 $\beta^{(t)} - \hat{\beta} = -1 \setminus 1 - h_t(\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}_t^\top \hat{u_t}$ where h_t

angle between **y** and P_X **y**. $0 \le R_y^2 \le 1$. R_c^2 : center all vars first. Invalid if $\iota \notin \mathcal{S}(\mathbf{X})$. $R_c^2 = 1 - \sum_t^n \hat{u}_t^2 \setminus \sum_t^n (y_t - \overline{y})^2.$ Adj R^2 : unbiased estimators. maybe < 0. $\overline{R}^2 \equiv 1 - \frac{\frac{1}{n-k} \sum_t^n \hat{u_t}^2}{\frac{1}{n-1} \sum_t^n (y_t - \overline{y})^2} = 1 - \frac{(n-1)\mathbf{y}^\top \mathbf{M_X y}}{(n-k)\mathbf{y}^\top \mathbf{M_t y}}$ \overline{R}^2 does not always \uparrow in regressors. **Hypothesis Testing** If u_t normal, and σ known, test $\beta = \beta_0$ w $z = \frac{\hat{\beta} - \beta_0}{(\operatorname{Var}(\hat{\beta}))^{1/2}} = \frac{n^{1/2}}{\sigma}(\hat{\beta} - \beta_0), z \sim N(0, 1)$ NCP: $\lambda = \frac{n^{1/2}}{\sigma} (\beta_1 - \beta_0), \, \beta_1 \neq \beta_0$ Reject null if z large enough. 2-tail: |z|. Type 1: reject true null, 2: accept false left-tail $\Phi(-c_{\alpha}) = \alpha \setminus 2$, $c_{\alpha} = \Phi^{-1}(\alpha \setminus 2)$. $\Phi^{-1}(.975) = 1.96$. Power: prob test rejects the null. Prob of Type 2 = 1 - P(power). Power \uparrow with $(\beta_1 - \beta_0) \uparrow$ or $\sigma \downarrow$ or $n \uparrow$. $p(z) = 2(1 - \Phi(|z|))$ $x \sim N(\mu, \sigma^2) \Rightarrow z = (x - \mu) \setminus \sigma, z \sim N(0, 1).$ Lin comb of rand vars that are jointly multivariate normal must be $\sim \dot{N}$. If $\dot{\mathbf{x}}$ of \mathbf{x} are mutually indep. χ^2 : $y = ||\mathbf{z}||^2 = \mathbf{z}^{\top}\mathbf{z} = \sum_{i=1}^{m} z_i^2$., $y \sim \chi^2(m)$ If u IID w Var σ^2 and cov of any pair with $\mathbf{z} \sim N(\mathbf{0}, \mathbf{I})$; E(y) = m. Var(y) = 2m. = 0: $Var(\mathbf{u}) = E(\mathbf{u}\mathbf{u}^{\top}) = \sigma^2 \mathbf{I}$. If false, $v_1 \sim \chi^2(m_1) \& v_2 \sim \chi^2(m_2)$ indep $\Rightarrow y_1 + y_2 \sim \chi^2(m_1 + m_2)$ $m \times 1 \mathbf{x} \sim N(\mathbf{0}, \mathbf{\Omega})$, then $\mathbf{x}^{\top} \mathbf{\Omega}^{-1} \mathbf{x} \sim \chi^{2}(m)$ If $P n \times n$ w rank r < n and $z \sim N(0, I)$ then $\mathbf{z}^{\top}\mathbf{P}\mathbf{z} \sim \chi^2(r)$. $z \sim N(0,1) \& y \sim \chi^{2}(m)$, z, y indep, then $t \equiv z \setminus (y \setminus m)^{1/2}$. Or $t \sim t(m)$. Only first m-1 moments exist. Cauchy: t(1). $Var(t) = m \setminus (m-2)$. t(m) tends to std y_1 , y_2 indep rand var $\sim \chi^2(m_1)$ & $\chi^{2}(m_{2})$, then $F \equiv \frac{y_{1} \setminus m_{1}}{y_{2} \setminus m_{2}}$. $F \sim F(m_{1}, m_{2})$. As $m_2 \to \infty$, $F \sim 1 \setminus m_1$ times $\chi^2(m_1)$. $t \sim t(m_2) \Rightarrow t^2 \sim F(1, m_2).$

Residuals & Disturbances

 $\hat{\mathbf{u}} = \mathbf{M}_{\mathbf{X}}\mathbf{u}$ (hat resid, u dist).

 $\operatorname{Var}(\hat{u_t}) < \sigma^2$; $\hat{\sigma}^2 \equiv \frac{1}{n} \sum_{t=1}^{n} \hat{u_t}^2$

 s^2 unbiased and consistent.

 $MSE(\tilde{\beta}) \equiv E((\tilde{\beta} - \beta_0)(\tilde{\beta} - \beta_0)^{\top})$

I β unbiased MSE(β) = Var(β).

Measures of Goodness of Fit

 $E(\hat{\sigma}^2) = \frac{n-k}{n} \sigma^2$

If $E(\mathbf{u} \mid \mathbf{X}) = \mathbf{0} \Rightarrow E(||\hat{\mathbf{u}}||^2) \le E(||\mathbf{u}||^2)$

 $E(\mathbf{u}^{\top}\mathbf{M}_{\mathbf{X}}\mathbf{u}) = E(SSR(\hat{\beta})) = (n-k)\sigma^{2}$

unbiased: $s^2 \equiv \frac{1}{n-k} \sum_{t=0}^{n} u_t^2$; s = std err.

unbias est of $Var(\hat{\beta})$: $\widehat{Var}(\hat{\beta}) = s^2(\mathbf{X}^{\top}\mathbf{X})^{-1}$

 $R_u^2 = \frac{\text{ESS}}{\text{TSS}} = \frac{\|\mathbf{P}_{\mathbf{X}}\mathbf{y}\|^2}{\|\mathbf{y}\|^2} = \cos^2\theta$, where θ

If $\mathbf{u} \sim IID(\mathbf{0}, \sigma^2 \mathbf{I})$, $E(u_t \mid \mathbf{X}_t) = 0$, $E(u_t^2 \mid \mathbf{X_t} = \sigma^2)$, $p\lim_{n \to \infty} \mathbf{X}^{\top} \mathbf{X} = S_{X^{\top} X}$ where S finite, deterministic, pos def

mtrx, then $n^{1/2}(\hat{\beta} - \beta_0) \xrightarrow{d} N(\mathbf{0}, \sigma^2 \mathbf{S}_{\mathbf{X}^{\top} \mathbf{Y}}^{-1})$ and plim $s^2(n^{-1}\mathbf{X}^{\top}\mathbf{X})^{-1} = \sigma^2\mathbf{S}_{\mathbf{X}^{\top}\mathbf{X}}^{-1}$.

An estimator for cov mtrx is consistent if $plim(nVar(\hat{\theta})) = V(\theta)$, where $V(\theta)$ is limiting cov mtrx of $n^{1/2}(\hat{\theta} - \theta_0)$ If u IID and testing $\beta_2 = \beta_2^0$ multivar norm with 0 cov, componenets $t_{\beta_2} = \frac{\beta_2 - \beta_2^0}{\sqrt{s^2(\mathbf{X}^T\mathbf{X})_{72}^{-1}}}$ and $t_{\beta_2} \stackrel{a}{\sim} N(0,1) \Rightarrow$ of \mathbf{x} are mutually indep. $t_{\beta_2} = O_p(1)$. Under null $\beta_2 = 0$, w predetermined regressors $rF_{\beta_2} \stackrel{a}{\sim} \chi^2(r)$ where $r = k_2$ is dim of β_2 . $W(\hat{\beta}) = (\mathbf{R}\hat{\beta} - r)^{\top} (\mathbf{R}\widehat{\mathrm{Var}}(\hat{\beta})\mathbf{R}^{\top})^{-1} (\mathbf{R}\hat{\beta} - r)$ is Wald where cov mtrx consistent. $W(\hat{\beta}) \stackrel{a}{\sim} \chi^2(r)$ under null where r is r-vector. **Multiple Testing** FWER: $\alpha_m = 1 - (1 - \alpha)^m$. Bonferroni: $Pr(\bigcup_{i=1}^{m} P_i \leq \alpha/m) \leq \alpha$. Simes: $P_{(i)} \leq j\alpha/m$ for increasing P. Bonf more conservative than Simes. If $\mathbf{z} \sim N(\mu, \mathbf{I})$ then $\mathbf{z}^{\top}\mathbf{z} \sim \text{non-central}$ $\hat{p}^*(\hat{\tau}) = \frac{1}{B} \sum_{h}^{B} \mathbb{I}(\tau_h^* > \hat{\tau})$ $\chi^2(m, \Lambda = \mu^\top \mu)$ If $\mathbf{z} \sim N(\mu, \mathbf{I})$ then $\mathbf{z}^\top \mathbf{z} \sim \hat{p}_{et}^*(\hat{\tau}) = 2 \min\left(\frac{1}{B} \sum_h^B \mathbb{I}(\tau_h^* \leq \hat{\tau}), \frac{1}{B} \sum_h^B \mathbb{I}(\tau_h^* > \hat{\tau})\right)$ non-central $\chi^2(m, \Lambda = \mu^T \mu)$. Under null when biased param est and 2-tailed. $\beta_2 = \mathbf{0} \Rightarrow \Lambda = 0.$

 θ_0 true then prob is $1-\alpha$. Asymp tstat: $(\hat{\theta} - \theta)/s_{\theta}$. Pivot: same distribution \forall DGP. CI exact only if τ pivot. If no stat with known finite sample dist, use Wald with k_2 vector $\hat{\theta}_2$ asym normal: $(\hat{\theta}_2 - \theta_{20})^{\top} (\widehat{\text{Var}}(\hat{\theta}_2))^{-1} (\hat{\theta}_2 - \theta_{20}) \leq c_{\alpha}.$ $\operatorname{Var}(\hat{\beta}) = (\mathbf{X}^{\top} \mathbf{X})^{-1} \mathbf{X}^{\top} \mathbf{\Omega} \mathbf{X} (\mathbf{X}^{\top} \mathbf{X})^{-1}$ $\hat{\Omega}$: $\frac{1}{n} \sum_{t=1}^{n} \hat{u}_{t}^{2} x_{ti} x_{ti}$ $\widehat{\operatorname{Var}}(\hat{\beta}) = (\mathbf{X}^{\top}\mathbf{X})^{-1}\mathbf{X}^{\top}\widehat{\mathbf{\Omega}}\mathbf{X}(\mathbf{X}^{\top}\mathbf{X})^{-1}$

 $t(n-k,\lambda) \sim \frac{N(\lambda,1)}{(\chi^2(n-k)/(n-k))^{1/2}}, \ \lambda^2 = \Lambda.$

Pretest estimator: $\hat{\beta} = \mathbb{I}(F_{\nu=0} > c_{\alpha})\hat{\beta} +$

 $\mathbb{I}(F_{\nu=0} \le c_{\alpha})\tilde{\beta}$ where c_{α} is critical value

for F test with r and n - k - r df at α .

 $\hat{\beta} = \hat{\beta}$ when pretest rejects and $\hat{\beta} = \hat{\beta}$

Confidence & Sandwich Cov Matrices

 HC_0 : Use \hat{u}_t^2 in diag of $\hat{\Omega}$ and 0 else.

 $\theta_0 \in \text{confidence set iff } \tau(\mathbf{y}, \theta_0) \leq c_\alpha$, if

testing $\beta_1 = \beta_2$, let $\gamma = \beta_2 - \beta_1$ then $F_{\gamma} = \frac{(RSSR - SSR_1 - SSR_2)/k}{(SSR_1 + SSR_2)/(n-2k)}$ **Asymptotic Theory** EDF: $\hat{F}(x) \equiv \frac{1}{n} \sum_{t=1}^{n} \mathbb{I}(x_t \leq x)$. FTS: $p\lim \hat{F}(x) = F(x)$. CLT: $z_n \equiv \frac{1}{\sqrt{n}} \sum_{t=0}^{n} \frac{x_t - \mu}{\sigma}$

Exact Tests ($\mathbf{u} \sim N(\mathbf{0}, \sigma^2 \mathbf{I})$)

 $\frac{\mathbf{x}_{2}^{\top}\mathbf{M}_{1}\mathbf{y}}{s(\mathbf{x}_{2}^{\top}\mathbf{M}_{1}\mathbf{x}_{2})^{1/2}} = \left(\frac{\mathbf{y}^{\top}\mathbf{M}_{X}\mathbf{y}}{n-k}\right)^{-\frac{1}{2}} \frac{\mathbf{x}_{2}^{\top}\mathbf{M}_{1}\mathbf{y}}{(\mathbf{x}_{2}^{\top}\mathbf{M}_{1}\mathbf{x}_{2})^{1/2}}$

is t-stat $t_{\beta_2} \sim t(n-k)$ for testing $\beta_2 = 0$.

 $\beta_2 \in \mathbb{R} \Rightarrow \text{test for } \beta_2 = \beta_{20} : (\hat{\beta_2} - \beta_{20})/s_2.$

 $F_{\beta_2} \equiv \frac{(\text{RSSR - USSR})/r}{\text{USSR}/(n-k)} = \frac{\mathbf{y}^{\top} \mathbf{P}_{\mathbf{M}_1 \mathbf{X}_2} \mathbf{y}/r}{\mathbf{y}^{\top} \mathbf{M}_{\mathbf{X}} \mathbf{y}/(n-k)}$

is F-stat $\sim F(r, n - k)$, used for multiple hyp on β_2 . Under null,

 $\mathbf{M_1 y} = \mathbf{M_1 u} \Rightarrow F_{\beta_2} = \frac{e^{\top} \mathbf{P_{M_1 X_2}} e^{r/r}}{e^{\top} \mathbf{M_X} e^{r/(n-k)}}$, where

 $\epsilon \equiv \mathbf{u}/\sigma$, $\mathbf{P}_{\mathbf{M}_1\mathbf{X}_2} = \mathbf{P}_{\mathbf{x}} - \mathbf{P}_1$. P-value for F is

 $1 - F_{r,n-k}(F_{\beta_2})$. When only 1 restriction,

F and 2-tailed t test are the same. If

testing all $\beta = 0$, $F = \frac{n-k}{k-1} \times \frac{R_c^2}{1-R^2}$. If

when reject.

Uncorrelated x_t with $E(x_t) = 0 \Rightarrow$

 $n^{-1/2} \sum_{t=1}^{n} x_t$ goes to $N(0, \lim_{t=1}^{n} \sum_{t=1}^{n} \operatorname{Var}(x_t))$.

asymptotically $\sim N(0,1)$ if x_t IID.

 HC_1 : Use \hat{u}_t^2 in $\hat{\Omega}$ then mult by n/(n-k) HC_2 : $\hat{u}_t^2/(1-h_t)$ with $h_t \equiv \mathbf{X_t}(\mathbf{X}^\top \mathbf{X})^{-1}\mathbf{X_t}^\top$. HC_3 : $\hat{u}_t^2/(1-h_t)$ jackknife, for big

Ignore hetero for std err of sample mean. HAC for when u_t hetero and/or autocorr. $\hat{\Sigma} = (1/n)\mathbf{X}^{\top}\hat{\mathbf{\Omega}}\mathbf{X}$ (Newey-West/H. White)

 $f(a+h) = f(a) + hf'(a+\lambda h), h = b-a,$

Bootstrap

 $\hat{p}^*(\hat{\tau}) \to p(\hat{\tau})$ as $B \to \infty$. τ pivotal.