Econometric Computing with HC and HAC Covariance Matrix Estimators

Achim Zeileis

Wirtschaftsuniversität Wien

Abstract

sandwich

Keywords: covariance matrix estimator, heteroskedasticity, autocorrelation, estimating functions, econometric computing, R.

1. Introduction

R Development Core Team (2004) Cribari-Neto and Zarkos (2003)

stress econometric computing

reusable components

covariance matrices not only as options to certain test but as stand-alone functions which can be plugged into various inference procedures

2. The linear regression model

To fix notations, we consider the linear regression model

$$y_i = x_i^{\top} \beta + u_i \qquad (i = 1, \dots, n), \tag{1}$$

with dependent variable y_i , a k-dimensional regressor x_i with coefficient vector β and error term u_i . In the usual matrix notation comprising all n observations this can be formulated as $y = X\beta + u$. In the general linear model

zero mean and variance $VAR[u] = \Omega$.

$$\hat{\beta} = (X^{\top}X)^{-1}X^{\top}y \tag{2}$$

$$\hat{u} = (I_n - H) u = (I_n - X (X^{\top} X)^{-1} X^{\top}) u$$
(3)

H is called hat matrix

$$\Psi = \mathsf{VAR}[\hat{\beta}] = (X^{\top}X)^{-1} X^{\top} \Omega X (X^{\top}X)^{-1}$$

$$\tag{4}$$

$$= \frac{1}{n} \left(\frac{1}{n} X^{\top} X \right)^{-1} \Phi \left(\frac{1}{n} X^{\top} X \right)^{-1} \tag{5}$$

$$\Phi = n^{-1} X^\top \Omega X^\top$$

estimating functions $V_i(\beta) = x_i(y_i - x_i^{\top}\beta)$

squerical errors $\hat{\Psi}_{\text{const}} = \hat{\sigma}(X^{\top}X)^{-1}$

 $\hat{V}_i = V_i(\hat{\beta})$

3. Estimating covariance matrices

3.1. Dealing with heteroskedasticity

 $\hat{\Psi}_{HC}$ plugging in a $\hat{\Omega} = \operatorname{diag}(\omega_1, \dots, \omega_n)$

$$\begin{array}{rclcrcl} \operatorname{const}: & \omega_i & = & \hat{\sigma}^2 \\ \operatorname{HC0}: & \omega_i & = & \hat{u}_i^2 \\ \operatorname{HC1}: & \omega_i & = & \frac{n}{n-k} \hat{u}_i^2 \\ \operatorname{HC2}: & \omega_i & = & \frac{\hat{u}_i^2}{1-h_i} \\ \operatorname{HC3}: & \omega_i & = & \frac{\hat{u}_i^2}{(1-h_i)^2} \\ \operatorname{HC4}: & \omega_i & = & \frac{\hat{u}_i^2}{(1-h_i)^{\delta_i}} \end{array}$$

where $h_i = H_{ii}$ are the diagonal elements of the hat matrix and $\delta_i = \min\{4, h_i/\bar{h}\}.$

```
vcovHC(lmobject, omega = NULL, type = "HC3",
    order.by = NULL)
```

"HC3", "const", "HC", "HC0", "HC1", "HC2", "HC4" omega(residuals, diaghat, df)

White (1980) MacKinnon and White (1985) Long and Ervin (2000) Cribari-Neto (2004)

3.2. Dealing with autocorrelation

 $\hat{\Psi}_{\text{HAC}}$ plugging in a $\hat{\Phi}$ with

$$\hat{\Phi} = \frac{1}{n} \sum_{i,j=1}^{n} w_{|i-j|} \hat{V}_i \hat{V}_j^{\top}$$
 (6)

weights w_k $(k = 0, \ldots, n-1)$

finite sample correction n/(n-k)

Newey-West or Bartlett kernel

$$w_i = 1 - \frac{i}{L+1} \tag{7}$$

where L is the maximum lag, other weights are zero. In terms of a generic bandwidth B usually formulated as B = L + 1.

Quadratic spectral kernel

$$w_i = \frac{3}{x^2} \left(\frac{\sin(x)}{x} - \cos(x) \right) \tag{8}$$

where $x = 6/5\pi \cdot i/B$ and B is again a bandwidth parameter.

vcovHAC(lmobject, weights,
 order.by = NULL, prewhite = FALSE, adjust = TRUE)

```
weights(x, order.by, prewhite, ar.method, data)
Newey and West (1987) Andrews (1991) Andrews and Monahan (1992) Lumley and Heagerty
(1999)
```

4. Applications and illustrations

4.1. Testing coefficients in cross-sectional data

```
Greene (1993) Cribari-Neto (2004) Zeileis and Hothorn (2002) Fox (2002)
R> data(PublicSchools)
R> ps <- na.omit(PublicSchools)</pre>
R> ps$Income <- ps$Income * 1e-04
R> fm.ps <- lm(Expenditure ~ Income + I(Income^2), data = ps)</pre>
R> coeftest(fm.ps, df = Inf, vcov = vcovHC(fm.ps, type = "HCO"))
z test of coefficients of "lm" object 'fm.ps':
           Estimate Std. Error z value Pr(>|z|)
(Intercept) 832.91 460.89 1.8072 0.07073.
           -1834.20
                       1243.04 -1.4756 0.14006
I(Income^2) 1587.04
                        829.99 1.9121 0.05586 .
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
R> coeftest(fm.ps, df = Inf, vcov = vcovHC(fm.ps, type = "HC4"))
z test of coefficients of "lm" object 'fm.ps':
           Estimate Std. Error z value Pr(>|z|)
(Intercept)
            832.91
                       3008.01 0.2769 0.7819
                                        0.8226
Income
           -1834.20
                       8183.19 -0.2241
I(Income^2) 1587.04
                       5488.93 0.2891 0.7725
vcovHC(fm.ps, type = "HCO")
4.2. Testing coefficients in time-series data
Greene (1993)
R> data(Investment)
R> fm.inv <- lm(RealInv ~ RealGNP + RealInt, data = Investment)</pre>
R> coeftest(fm.inv, df = Inf, vcov = NeweyWest(fm.inv, lag = 4))
z test of coefficients of "lm" object 'fm.inv':
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -12.533601 18.958298 -0.6611
                                           <2e-16 ***
RealGNP
             0.169136 0.016751 10.0972
RealInt
            -1.001438 3.342375 -0.2996
                                          0.7645
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
```

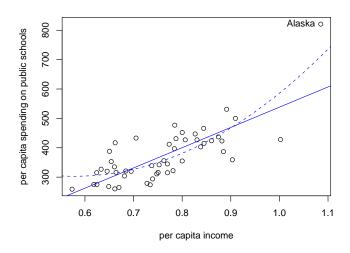


Figure 1: Expenditure on public schools and income with fitted models

4.3. Testing and dating structural changes in the presence of heteroskedasticity and autocorrelation

```
Zeileis, Leisch, Hornik, and Kleiber (2002) Zeileis (2004)
R> data(RealInt)
R> ocus <- gefp(RealInt ~ 1, fit = lm, vcov = kernHAC)</pre>
plot(ocus), sctest(ocus)
R> fs <- Fstats(RealInt ~ 1, vcov = kernHAC)
sctest(fs), plot(fs)
R> bp <- breakpoints(RealInt ~ 1)</pre>
R> confint(bp, vcov = kernHAC)
         Confidence intervals for breakpoints
         of optimal 3-segment partition:
Call:
confint.breakpointsfull(object = bp, vcov = kernHAC)
Breakpoints at observation number:
  2.5 % breakpoints 97.5 %
     37
                  47
                         48
1
     77
                  79
                         81
Corresponding to breakdates:
 2.5 %
          breakpoints 97.5 %
1 1970(1) 1972(3)
                       1972(4)
2 1980(1) 1980(3)
                       1981(1)
```

Bai and Perron (2003) Andrews (1993) Ploberger and Krämer (1992)

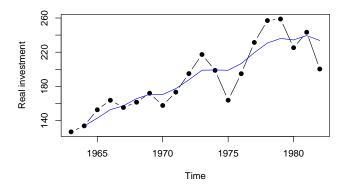


Figure 2: Investment equation data with fitted model

5. Summary

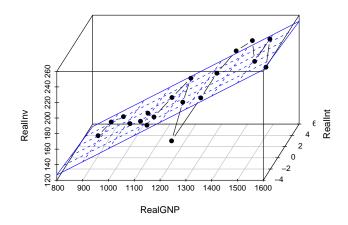


Figure 3: Investment equation data with fitted model (3D)

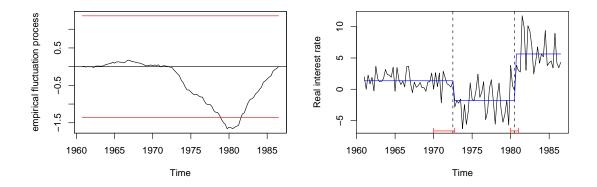


Figure 4: OLS-based CUSUM test (left) and fitted model (right) for real interest data

A. R code

A.1. Testing coefficients in cross-sectional data

```
Load public schools data, omit NA in Wisconsin and scale income:
```

```
data(PublicSchools)
ps <- na.omit(PublicSchools)</pre>
ps$Income <- ps$Income * 0.0001
Fit quadratic regression model:
fm.ps <- lm(Expenditure ~ Income + I(Income^2), data = ps)</pre>
Compare standard errors:
sqrt(diag(vcov(fm.ps)))
sqrt(diag(vcovHC(fm.ps, type = "const")))
sqrt(diag(vcovHC(fm.ps, type = "HCO")))
sqrt(diag(vcovHC(fm.ps, type = "HC3")))
sqrt(diag(vcovHC(fm.ps, type = "HC4")))
Test coefficient of quadratic term:
coeftest(fm.ps, df = Inf, vcov = vcovHC(fm.ps, type = "HCO"))
coeftest(fm.ps, df = Inf, vcov = vcovHC(fm.ps, type = "HC4"))
Visualization:
plot(Expenditure ~ Income, data = ps,
 xlab = "per capita income",
 ylab = "per capita spending on public schools")
inc \leftarrow seq(0.5, 1.2, by = 0.001)
lines(inc, predict(fm.ps, data.frame(Income = inc)), col = 4, lty = 2)
fm.ps2 <- lm(Expenditure ~ Income, data = ps)</pre>
abline(fm.ps2, col = 4)
text(ps[2,2], ps[2,1], rownames(ps)[2], pos = 2)
A.2. Testing coefficients in time-series data
Load investment equation data:
data(Investment)
Fit regression model:
fm.inv <- lm(RealInv ~ RealGNP + RealInt, data = Investment)</pre>
Test coefficients using Newey-West HAC estimator:
coeftest(fm.inv, df = Inf, vcov = NeweyWest(fm.inv, lag = 4))
Visualization:
plot(Investment[, "RealInv"], type = "b", pch = 19, ylab = "Real investment")
lines(ts(fitted(fm.inv), start = 1964), col = 4)
```

3-d visualization:

```
library(scatterplot3d)
s3d <- scatterplot3d(Investment[,c(5,7,6)],
  type = "b", angle = 65, scale.y = 1, pch = 16)
s3d$plane3d(fm.inv, lty.box = "solid", col = 4)</pre>
```

A.3. Testing and dating structural changes in the presence of heteroskedasticity and autocorrelation

Load real interest series:

```
data(RealInt)
```

OLS-based CUSUM test with quadratic spectral kernel HAC estimate:

```
ocus <- gefp(RealInt ~ 1, fit = lm, vcov = kernHAC)
plot(ocus, aggregate = FALSE)
sctest(ocus)</pre>
```

 $\sup \! F$ test with quadratic spectral kernel HAC estimate:

```
fs <- Fstats(RealInt ~ 1, vcov = kernHAC)
plot(fs)
sctest(fs)</pre>
```

Breakpoint estimation and confidence intervals with quadratic spectral kernel HAC estimate: $\frac{1}{2}$

```
bp <- breakpoints(RealInt ~ 1)
confint(bp, vcov = kernHAC)</pre>
```

Visualization:

```
plot(RealInt, ylab = "Real interest rate")
lines(ts(fitted(bp), start = start(RealInt), freq = 4), col = 4)
lines(confint(bp, vcov = kernHAC))
```

References

- Andrews DWK (1991). "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation." *Econometrica*, **59**, 817–858.
- Andrews DWK (1993). "Tests for Parameter Instability and Structural Change With Unknown Change Point." *Econometrica*, **61**, 821–856.
- Andrews DWK, Monahan JC (1992). "An Improved Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator." *Econometrica*, **60**(4), 953–966.
- Bai J, Perron P (2003). "Computation and Analysis of Multiple Structural Change Models." Journal of Applied Econometrics, 18, 1–22.
- Cribari-Neto F (2004). "Asymptotic Inference Under Heteroskedasticity of Unknown Form." Computational Statistics & Data Analysis, 45, 215–233.
- Cribari-Neto F, Zarkos SG (2003). "Econometric and Statistical Computing Using Ox." Computational Economics, 21, 277–295.
- Fox J (2002). An R and S-PLUS Companion to Applied Regression. Sage Publications, Thousand Oaks, CA.
- Greene WH (1993). Econometric Analysis. Macmillan Publishing Company, New York, 2nd edition.
- Long JS, Ervin LH (2000). "Using Heteroscedasticity Consistent Standard Errors in the Linear Regression Model." *The American Statistician*, **54**, 217–224.
- Lumley T, Heagerty P (1999). "Weighted Empirical Adaptive Variance Estimators for Correlated Data Regression." *Journal of the Royal Statistical Society B*, **61**, 459–477.
- MacKinnon JG, White H (1985). "Some Heteroskedasticity-consistent Covariance Matrix Estimators with Improved Finite Sample Properties." *Journal of Econometrics*, **29**, 305–325.
- Newey WK, West KD (1987). "A Simple, Positive-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, **55**, 703–708.
- Ploberger W, Krämer W (1992). "The CUSUM Test With OLS Residuals." Econometrica, 60, 271-285.
- R Development Core Team (2004). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-00-3, URL http://www.R-project.org/.
- White H (1980). "A Heteroskedasticity-consistent Covariance Matrix and a Direct Test for Heteroskedasticity." *Econometrica*, **48**, 817–838.
- Zeileis A (2004). "Implementing a Class of Structural Change Tests: An Econometric Computing Approach." Report 7, Department of Statistics and Mathematics, Wirtschaftsuniversität Wien, Research Report Series. URL http://epub.wu-wien.ac.at/.
- Zeileis A, Hothorn T (2002). "Diagnostic Checking in Regression Relationships." R News, 2(3), 7-10. URL http://CRAN.R-project.org/doc/Rnews/.
- Zeileis A, Leisch F, Hornik K, Kleiber C (2002). "strucchange: An R Package for Testing for Structural Change in Linear Regression Models." *Journal of Statistical Software*, **7**(2), 1–38. URL http://www.jstatsoft.org/v07/i02/.