PLSC 503 – Spring 2017 "Variances"

February 28, 2017

Variances: Why We Care

2016 ANES pilot study "feeling thermometer" toward gays and lesbians (N = 1200):

> summary(ANES\$ftgay)

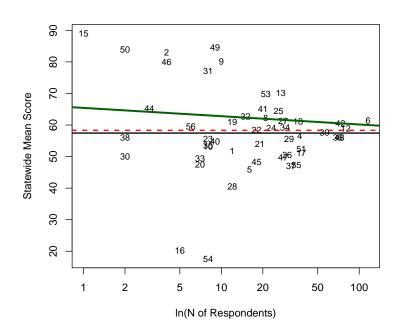
```
Min. 1st Qu. Median Mean 3rd Qu. Max. NA's 0.00 40.50 54.00 57.45 88.50 100.00 1
```

Suppose we wanted to create aggregate measures, by state (N = 51). We would get:

> summary(StateFT)

state	Nresp	meantherm
Min. : 1.00	Min. : 1.00	Min. :17.62
1st Qu.:17.25	1st Qu.: 8.00	1st Qu.:51.33
Median :29.50	Median : 18.00	Median :57.11
Mean :29.32	Mean : 24.00	Mean :58.33
3rd Qu.:41.75	3rd Qu.: 30.75	3rd Qu.:62.55
Max. :56.00	Max ·116 00	Max .89 00

Variances: Why We Care



Variances: A Generalization

Start with:

$$Y_i = \mathbf{X}_i \boldsymbol{\beta} + u_i$$

with:

$$Var(u_i) = \sigma^2/w_i$$

with w_{iu} known.

Weighted Least Squares

WLS now minimizes:

$$\mathsf{RSS} = \sum_{i=1}^N w_i (Y_i - \mathbf{X}_i \boldsymbol{\beta}).$$

which gives:

$$\hat{\boldsymbol{\beta}}_{WLS} = [\mathbf{X}'(\sigma^2\Omega)^{-1}\mathbf{X}]^{-1}\mathbf{X}'(\sigma^2\Omega)^{-1}\mathbf{Y}$$
$$= [\mathbf{X}'\mathbf{W}^{-1}\mathbf{X}]^{-1}\mathbf{X}'\mathbf{W}^{-1}\mathbf{Y}$$

where:

$$\mathbf{W} = egin{bmatrix} rac{\sigma^2}{w_1} & 0 & \cdots & 0 \\ 0 & rac{\sigma^2}{w_2} & \cdots & dots \\ dots & 0 & \ddots & 0 \\ 0 & \cdots & 0 & rac{\sigma^2}{w_N} \end{bmatrix}$$

Getting to Know WLS

The variance-covariance matrix is:

$$\mathsf{Var}(\hat{eta}_{\mathit{WLS}}) = \sigma^2(\mathbf{X}'\Omega^{-1}\mathbf{X})^{-1} \\ \equiv (\mathbf{X}'\mathbf{W}^{-1}\mathbf{X})^{-1}$$

A common case is:

$$\mathsf{Var}(u_i) = \sigma^2 \frac{1}{N_i}$$

where N_i is the number of observations upon which (aggregate) observation i is based.

"Robust" Variance Estimators

Recall that, if $\sigma_i^2 \neq \sigma_i^2 \forall i \neq j$,

$$\begin{array}{rcl} \mathsf{Var}(\beta_{\mathsf{Het.}}) & = & (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}'\mathbf{W}^{-1}\mathbf{X})(\mathbf{X}'\mathbf{X})^{-1} \\ & = & (\mathbf{X}'\mathbf{X})^{-1}\,\mathbf{Q}\,(\mathbf{X}'\mathbf{X})^{-1} \end{array}$$

where $\mathbf{Q} = (\mathbf{X}'\mathbf{W}^{-1}\mathbf{X})$ and $\mathbf{W} = \sigma^2\Omega$.

We can rewrite **Q** as

$$\mathbf{Q} = \sigma^{2}(\mathbf{X}'\Omega^{-1}\mathbf{X})$$
$$= \sum_{i=1}^{N} \sigma_{i}^{2}\mathbf{X}_{i}\mathbf{X}'_{i}$$

Huber's Insight

Estimate **Q** as:

$$\widehat{\mathbf{Q}} = \sum_{i=1}^{N} \widehat{u}_i^2 \mathbf{X}_i \mathbf{X}_i'$$

Yields:

$$\widehat{\mathsf{Var}(\boldsymbol{\beta})}_{\mathsf{Robust}} = (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}'\widehat{\mathbf{Q}}^{-1}\mathbf{X})(\mathbf{X}'\mathbf{X})^{-1} \\
= (\mathbf{X}'\mathbf{X})^{-1} \left[\mathbf{X}' \left(\sum_{i=1}^{N} \widehat{u}_{i}^{2}\mathbf{X}_{i}\mathbf{X}_{i}' \right)^{-1} \mathbf{X} \right] (\mathbf{X}'\mathbf{X})^{-1}$$

Practical Things

"Robust" VCV estimates:

- are heteroscedasticity-consistent, but
- are biased in small samples, and
- are less efficient than "naive" estimates when $Var(u) = \sigma^2 \mathbf{I}$.

"Clustering"

Huber / White

????????

WLS / GLS

I know very little about my error variances... I know a great deal about my error variances...

"Clustering"

A common case:

$$Y_{ij} = \mathbf{X}_{ij}\boldsymbol{\beta} + u_{ij}$$

with

$$\sigma_{ij}^2 = \sigma_{ik}^2$$
.

"Robust, clustered" estimator:

$$\widehat{\mathsf{Var}(\boldsymbol{\beta})}_{\mathsf{Clustered}} = (\mathbf{X}'\mathbf{X})^{-1} \left\{ \mathbf{X}' \left[\sum_{i=1}^{N} \left(\sum_{j=1}^{n_j} \hat{u}_{ij}^2 \mathbf{X}_{ij} \mathbf{X}_{ij}' \right) \right]^{-1} \mathbf{X} \right\} (\mathbf{X}'\mathbf{X})^{-1}$$

"Real-Data" Example

- > Justices<-read.csv("Justices.csv")
- > attach(Justices)
- > summary(Justices)

J (• •		
name	score	civrts	econs
Length:31	Min. :-1.0000	Min. :19.80	Min. :34.60
Class : character	1st Qu.:-0.4700	1st Qu.:35.90	1st Qu.:43.85
Mode :character	Median : 0.3300	Median :43.70	Median :50.20
	Mean : 0.1210	Mean :51.42	Mean :55.75
	3rd Qu.: 0.6250	3rd Qu.:75.55	3rd Qu.:66.65
	Max. : 1.0000	Max. :88.90	Max. :81.70
Neditorials	eratio	scoresq	lnNedit
Min. : 2.000	Min. : 0.5000	Min. :0.0000	Min. :0.6931
1st Qu.: 4.000	1st Qu.: 0.7083	1st Qu.:0.1936	1st Qu.:1.3863
Median : 6.000	Median : 1.0000	Median :0.2500	Median :1.7918
Mean : 8.742	Mean : 2.0242	Mean :0.4599	Mean :1.8442
3rd Qu.:11.500	3rd Qu.: 2.5000	3rd Qu.:0.8281	3rd Qu.:2.4414
Max. :47.000	Max. :11.7500	Max. :1.0000	Max. :3.8501

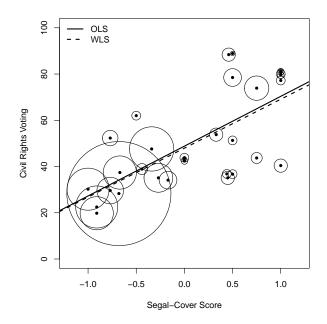
OLS...

```
> OLSfit<-with(Justices, lm(civrts~score))
> summary(OLSfit)
Call:
lm(formula = civrts ~ score)
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 48.810 2.852 17.113 < 2e-16 ***
             21.544 4.206 5.122 1.81e-05 ***
score
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
Residual standard error: 15.63 on 29 degrees of freedom
Multiple R-squared: 0.475, Adjusted R-squared: 0.4569
F-statistic: 26.24 on 1 and 29 DF, p-value: 1.806e-05
```

WLS, Weighting by ln(N of Editorials)

```
> WLSfit<-with(Justices, lm(civrts~score,weights=lnNedit))
> summarv(WLSfit)
Call:
lm(formula = civrts ~ score, weights = lnNedit)
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 47.936 2.600 18.439 < 2e-16 ***
             21.158 3.797 5.572 5.18e-06 ***
score
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
Residual standard error: 19.59 on 29 degrees of freedom
Multiple R-squared: 0.5171, Adjusted R-squared: 0.5004
F-statistic: 31.05 on 1 and 29 DF, p-value: 5.179e-06
```

Figure: Plot of civrts Against score, Weighted by Neditorials



"Robust" Standard Errors

```
> library(car)
> hccm(OLSfit, type="hc1")
          (Intercept)
                         score
(Intercept) 6.963921 2.929622
score
             2 929622 13 931212
> library(rms)
> OLSfit2<-ols(civrts~score, x=TRUE, v=TRUE)
> RobSEs<-robcov(OLSfit2)
> RobSEs
Linear Regression Model
ols(formula = civrts ~ score, x = TRUE, y = TRUE)
       n Model L.R. d.f. R2
                                            Sigma
                         1 0.475
       31 19.97
                                           15.63
Residuals:
   Min
          1Q Median
                                Max
-29 954 -8 088 -2 120 9 396 29 680
Coefficients:
        Value Std. Error t Pr(>|t|)
Intercept 48.81
                  2.552 19.123 0.000e+00
score 21.54
                  3.610 5.968 1.739e-06
Residual standard error: 15.63 on 29 degrees of freedom
Adjusted R-Squared: 0.4569
```