Robust Standard Errors in Small Samples

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Description[1]

This package implements small-sample degrees of freedom adjustments to robust and cluster-robust standard errors in linear regression, as discussed in Imbens and Kolesár [2016]. The implementation can handle models with fixed effects, and cases with a large number of observations or clusters

```
library(dfadjust)
```

To give some examples, let us construct an artificial dataset with 11 clusters

```
set.seed(7)
d1 <- data.frame(y = rnorm(1000), x1 = c(rep(1, 3), rep(0,
    997)), x2 = c(rep(1, 150), rep(0, 850)), x3 = rnorm(1000),
    cl = as.factor(c(rep(1:10, each = 50), rep(11, 500))))
```

Let us first run a regression of `y` on `x1`. This is a case in which, in spite of moderate data size, the effective number of observations is small since there are only three treated units:

```
r1 <- lm(y ~ x1, data = d1)
## No clustering
dfadjustSE(r1)
#>
#> Coefficients:
#>             Estimate HC1 se HC2 se Adj. se     df p-value
#> (Intercept)  0.00266 0.0311  0.031  0.0311 996.00   0.932
#> x1           0.12940 0.8892  1.088  2.3743   2.01   0.916
```

[1]We thank Bruce Hansen for comments and Ulrich Müller for suggesting to us a version of Lemma 2 below.

We can see that the usual robust standard errors (`HC1 se`) are much smaller than the effective standard errors (`Adj. se`), which are computed by taking the `HC2` standard errors and applying a degrees of freedom adjustment.

Now consider a cluster-robust regression of `y` on `x2`. There are only 3 treated clusters, so the effective number of observations is again small:

```
r1 <- lm(y ~ x2, data = d1)
# Default Imbens-Kolesár method
dfadjustSE(r1, clustervar = d1$cl)
#>
#> Coefficients:
#>             Estimate HC1 se HC2 se Adj. se   df p-value
#> (Intercept)  -0.0236 0.0135 0.0169  0.0222 4.94  0.2215
#> x2            0.1778 0.0530 0.0621  0.1157 2.43  0.0826
# Bell-McCaffrey method
dfadjustSE(r1, clustervar = d1$cl, IK = FALSE)
#>
#> Coefficients:
#>             Estimate HC1 se HC2 se Adj. se   df p-value
#> (Intercept)  -0.0236 0.0135 0.0169  0.0316 2.42  0.2766
#> x2            0.1778 0.0530 0.0621  0.1076 2.70  0.0731
```

Now, let us run a regression of `y` on `x3`, with fixed effects. Since we're only interested in `x3`, we specify that we only want inference on the second element (the first one being the intercept):

```
r1 <- lm(y ~ x3 + cl, data = d1)
dfadjustSE(r1, clustervar = d1$cl, ell = 2)
#>
#> Coefficients:
#>    Estimate HC1 se HC2 se Adj. se   df p-value
#> x3   0.0261 0.0463 0.0595  0.0928 3.23   0.688
dfadjustSE(r1, clustervar = d1$cl, ell = 2, IK = FALSE)
#>
#> Coefficients:
#>    Estimate HC1 se HC2 se Adj. se   df p-value
#> x3   0.0261 0.0463 0.0595  0.0928 3.23   0.688
```

Finally, an example in which the clusters are large. We have 500,000 observations:

```
d2 <- do.call("rbind", replicate(500, d1, simplify = FALSE))
d2$y <- rnorm(length(d2$y))
r2 <- lm(y ~ x2, data = d2)
summary(r2)
#>
#> Call:
#> lm(formula = y ~ x2, data = d2)
#>
#> Residuals:
#>    Min     1Q Median     3Q    Max
```

```
#> -5.073 -0.675  0.000  0.675  4.789
#>
#> Coefficients:
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -0.000991   0.001535   -0.65     0.52
#> x2          -0.003590   0.003963   -0.91     0.37
#>
#> Residual standard error: 1 on 499998 degrees of freedom
#> Multiple R-squared:  1.64e-06,   Adjusted R-squared:  -3.59e-07
#> F-statistic: 0.821 on 1 and 5e+05 DF,  p-value: 0.365
# Default Imbens-Kolesár method
dfadjustSE(r2, clustervar = d2$cl)
#>
#> Coefficients:
#>              Estimate  HC1 se  HC2 se Adj. se   df p-value
#> (Intercept) -0.000991 0.00133 0.00168 0.00294 2.66   0.603
#> x2          -0.003590 0.00483 0.00568 0.00997 2.65   0.578
# Bell-McCaffrey method
dfadjustSE(r2, clustervar = d2$cl, IK = FALSE)
#>
#> Coefficients:
#>              Estimate  HC1 se  HC2 se Adj. se   df p-value
#> (Intercept) -0.000991 0.00133 0.00168 0.00315 2.42   0.607
#> x2          -0.003590 0.00483 0.00568 0.00984 2.70   0.577
```

Methods

This section describes the implementation of the Imbens and Kolesár [2016] and Bell and McCaffrey [2002] degrees of freedom adjustments.

There are S clusters, and we observe n_s observations in cluster s, for a total of $n = \sum_{s=1}^{S} n_s$ observations. We handle the case with independent observations by letting each observation be in its own cluster, with $S = n$. Consider the linear regression of a scalar outcome Y_i onto a p-vector of regressors X_i,

$$Y_i = X_i'\beta + u_i, \qquad E[u_i \mid X_i] = 0.$$

We're interested in inference on $\ell'\beta$ for some fixed vector $\ell \in \mathbb{R}^p$. Let X, u, and Y denote the design matrix, and error and outcome vectors, respectively. For any $n \times k$ matrix M, let M_s denote the $n_s \times k$ block corresponding to cluster s, so that, for instance, Y_s corresponds to the outcome vector in cluster s. For a positive semi-definite matrix M, let $M^{1/2}$ be a matrix satisfying $M^{1/2'}M^{1/2} = M$, such as its symmetric square root or its Cholesky decomposition.

Assume that

$$E[u_s u_s' \mid X] = \Omega_s, \quad \text{and} \quad E[u_s u_t' \mid X] = 0 \quad \text{if } s \neq t.$$

Denote the conditional variance matrix of u by Ω, so that Ω_s is the block of Ω corresponding to cluster s. We estimate $\ell'\beta$ using OLS. In R, the OLS estimator is computed via a QR decomposition,

$X = QR$, where $Q'Q = I$ and R is upper-triangular, so we can write the estimator as

$$\ell'\hat{\beta} = \ell' \left(\sum_s X_s' X_s \right)^{-1} \sum_s X_s Y_s = \tilde{\ell}' \sum_s Q_s' Y_s, \qquad \tilde{\ell} = R^{-1'} \ell.$$

It has variance

$$V := \text{var}(\ell'\hat{\beta} \mid X) = \ell' \left(X'X\right)^{-1} \sum_s X_s' \Omega_s X_s \left(X'X\right)^{-1} \ell = \tilde{\ell}' \sum_s Q_s' \Omega_s Q_s \tilde{\ell}.$$

Variance estimate

We estimate V using a variance estimator that generalizes the HC2 variance estimator to clustering. Relative to the LZ2 estimator described in Imbens and Kolesár [2016], we use a slight modification that allows for fixed effects:

$$\hat{V} = \ell'(X'X)^{-1} \sum_s X_s' A_s \hat{u}_s \hat{u}_s' A_s' X_s (X'X)^{-1} \ell = \ell' R^{-1} \sum_s Q_s' A_s \hat{u}_s \hat{u}_s' A_s' Q_s R'^{-1} \ell = \sum_{s=1}^{S} (\hat{u}_s' a_s)^2,$$

where

$$\hat{u}_s := Y_s - X_s \hat{\beta} = u_s - Q_s Q' u, \qquad a_s = A_s' Q_s \tilde{\ell},$$

and A_s is a generalized inverse of the symmetric square root of $I - Q_s Q_s'$, the block of the hat matrix corresponding to cluster s. In presence of cluster-specific fixed effects, $I - Q_s Q_s'$ is not generally invertible, which necessitates taking a generalized inverse. So long as the vector ℓ doesn't load on these fixed effects, $\hat{V}$ will be unbiased under homoskedasticity, as the next result, which slightly generalizes the Theorem 1 in Pustejovsky and Tipton [2018], shows.

Lemma 1. *Suppose that $X = (W, L)$ is full rank, and suppose that the vector ℓ loads only on elements of W. Let $\ddot{W}$ denote the residual from projecting W onto L, and suppose that for each cluster s, (i) $L_s' \ddot{W}_s = 0$ and that (ii) $\sum_{k=1}^{S} I(k \neq s) \ddot{W}_k' \ddot{W}_k$ is full rank. Then $\hat{V}$ is unbiased under homoskedasticity.*

The proof is given in the last section. By definition of projection, L and $\ddot{W}$ are orthogonal. Condition (i) of the lemma strengthens this requirement to orthogonality within each cluster. It holds if L corresponds to a vector of cluster fixed effects, or more generally if L contains cluster-specific variables. Condition (ii) ensures that after partialling out L, it is feasible to run leave-one-cluster-out regressions. Without clustering, the condition is equivalent to the requirement that the partial leverages associated with $\ddot{W}$ are smaller than one.[2]

If the observations are independent, the vector of leverages $(Q_1'Q_1, \ldots, Q_n'Q_n)$ can be computed directly using the `stats::hatvalues` function. In this case, we use this function to compute $A_i = 1/\sqrt{1 - Q_i'Q_i}$ directly, and we then compute $a_i = A_i Q_i' \tilde{\ell}$ using vector operations. For the case with clustering, computing an inverse of $I - Q_s Q_s'$ can be expensive or even infeasible if the cluster size n_s is large. We therefore use the following result, which allows us to compute a_s by computing a spectral decomposition of a $p \times p$ matrix.

[2]To see this, let $H = \ddot{W}(\ddot{W}'\ddot{W})^{-1}\ddot{W}'$ denote the partial projection matrix. Since $H = H^2$,

$$H_{ii} - H_{ii}^2 = \sum_{j \neq i} H_{ij} H_{ji} = \ddot{W}_i' (\ddot{W}'\ddot{W})^{-1} [\sum_{j \neq i} \ddot{W}_j \ddot{W}_j'] (\ddot{W}'\ddot{W})^{-1} \ddot{W}_i.$$

so that $H_{ii} = 1$ iff $\sum_{j \neq i} \ddot{W}_j \ddot{W}_j'$ is reduced rank.

Lemma 2. *Let $Q_s'Q_s = \sum_{i=1}^{p} \lambda_{is} r_{is} r_{is}'$ be the spectral decomposition of $Q_s'Q_s$. Then $a_s = Q_s D_s \tilde{\ell}$, where $D_s = \sum_{i:\, \lambda_i \neq 1} (1-\lambda_i)^{-1/2} r_{is} r_{is}'$.*

The lemma follows from the fact that $I - Q_s Q_s'$ has eigenvalues $1 - \lambda_{is}$ and eigenvectors $Q_s r_{is}$. More precisely, let $Q_s = \sum_i \lambda_{is}^{1/2} u_{is} r_{is}'$ denote the singular value decomposition of Q_s, so that $I - Q_s Q_s' = \sum_i (1-\lambda_{is}) u_{is} u_{is}'$, and we can take $A_s = \sum_{i:\, \lambda_{is} \neq 1} (1-\lambda_{is})^{-1/2} u_{is} u_{is}'$. Then,

$$A_s' Q_s = \sum_{i:\, \lambda_i \neq 1} (1-\lambda_{is})^{-1/2} \lambda_{is}^{1/2} u_{is} r_{is}' = Q_s \sum_{i:\, \lambda_i \neq 1} (1-\lambda_{is})^{-1/2} r_{is} r_{is}',$$

where the second equality uses $Q_s r_{is} = \lambda_{is}^{1/2} u_{is}$.

Degrees of freedom correction

Let G be an $n \times S$ matrix with columns $(I - QQ')_s' a_s$. Then the Bell and McCaffrey [2002] adjustment sets the degrees of freedom to

$$f_{\text{BM}} = \frac{\text{tr}(G'G)^2}{\text{tr}((G'G)^2)}.$$

Since $(G'G)_{st} = a_s'(I - QQ')_s (I - QQ)_t' a_t = a_s (\mathbb{1}\{s = t\} - Q_s Q_t') a_t$, the matrix $G'G$ can be efficiently computed as

$$G'G = \text{diag}(a_s' a_s) - BB' \qquad B_{sk} = a_s' Q_{sk}.$$

Note that B is an $S \times p$ matrix, so that computing the degrees of freedom adjustment only involves $p \times p$ matrices:

$$f_{\text{BM}} = \frac{(\sum_s a_s' a_s - \sum_{s,k} B_{sk}^2)^2}{\sum_s (a_s' a_s)^2 - 2\sum_{s,k} (a_s' a_s) B_{sk}^2 + \sum_{s,t} (B_s' B_t)^2}.$$

If the observations are independent, we compute B directly as `B <- a*Q`, and since a_i is a scalar, we have

$$f_{\text{BM}} = \frac{(\sum_i a_i^2 - \sum_{sk} B_{sk}^2)^2}{\sum_i a_i^4 - 2\sum_i a_i^2 B_i' B_i + \sum_{i,j} (B_i' B_j)^2}.$$

The Imbens and Kolesár [2016] degrees of freedom adjustment instead sets

$$f_{IK} = \frac{\text{tr}(G'\hat{\Omega}G)^2}{\text{tr}((G'\hat{\Omega}G)^2)},$$

where $\hat{\Omega}$ is an estimate of the Moulton [1986] model of the covariance matrix, under which $\Omega_s = \sigma_\epsilon^2 I_{n_s} + \rho \iota_{n_s} \iota_{n_s}'$. Using simple algebra, one can show that in this case,

$$G'\Omega G = \sigma_\epsilon^2 \,\text{diag}(a_s' a_s) - \sigma_\epsilon^2 BB' + \rho (D - BF')(D - BF')',$$

where

$$F_{sk} = \iota_{n_s}' Q_{sk}, \qquad D = \text{diag}(a_s' \iota_{n_s})$$

which can again be computed even if the clusters are large. The estimate $\hat{\Omega}$ replaces σ_ϵ^2 and ρ with analog estimates.

Proof of Lemma 1

The estimator of the block of V associated with W implied by $\hat{V}$ is given by

$$(\ddot{W}'\ddot{W})^{-1}\sum_s \ddot{W}_s' A_s (I - QQ')_s uu' (I - QQ')_s' A_s' \ddot{W}_s (\ddot{W}'\ddot{W})^{-1},$$

which is unbiased under homoskedasticity if for each s,

$$\ddot{W}_s' A_s (I - Q_s Q_s') A_s' \ddot{W}_s = \ddot{W}_s' \ddot{W}_s. \tag{1}$$

We will show that (1) holds. To this end, we first claim that under conditions (i) and (ii), $\ddot{W}_s$ is in the column space of $I - Q_s Q_s'$ (a claim that's trivial if this matrix is full rank). Decompose $I - QQ' = I - H_{\ddot{W}} - H_L$, where $H_{\ddot{W}}$ and H_L are hat matrices associated with $\ddot{W}$ and L. The block associated with cluster s can thus be written as $I - Q_s Q_s' = I - L_s(L'L)^{-1}L_s' - \ddot{W}_s(\ddot{W}'\ddot{W})^{-1}\ddot{W}_s'$. Let $B_s = \ddot{W}_s(\ddot{W}'\ddot{W} - \ddot{W}_s'\ddot{W}_s)^{-1}\ddot{W}'\ddot{W}$, which is well-defined under condition (ii). Then, using condition (i), we get

$$\begin{aligned}(I - Q_s Q_s')B_s &= (I - \ddot{W}_s(\ddot{W}'\ddot{W})^{-1}\ddot{W}_s')B_s \\ &= \ddot{W}_s(I - (\ddot{W}'\ddot{W})^{-1}\ddot{W}_s'\ddot{W}_s)(\ddot{W}'\ddot{W} - \ddot{W}_s'\ddot{W}_s)^{-1}\ddot{W}'\ddot{W} = \ddot{W}_s,\end{aligned}$$

proving the claim. Letting C denote the symmetric square root of $I - Q_s Q_s'$, the left-hand side of (1) can therefore be written as

$$\ddot{W}_s' A_s (I - Q_s Q_s') A_s' \ddot{W}_s = B_s' C C A_s C C A_s' C C B_s = \ddot{W}_s' \ddot{W}_s,$$

where the second equality follows by the definition of a generalized inverse.

References

Robert M. Bell and Daniel F. McCaffrey. Bias reduction in standard errors for linear regression with multi-stage samples. *Survey Methodology*, 28(2):169–181, December 2002.

Guido W. Imbens and Michal Kolesár. Robust standard errors in small samples: Some practical advice. *Review of Economics and Statistics*, 98(4):701–712, October 2016. doi: 10.1162/REST_a_00552.

Brent R. Moulton. Random group effects and the precision of regression estimates. *Journal of Econometrics*, 32(3):385–397, August 1986. doi: 10.1016/0304-4076(86)90021-7.

James E. Pustejovsky and Elizabeth Tipton. Small-sample methods for cluster-robust variance estimation and hypothesis testing in fixed effects models. *Journal of Business & Economic Statistics*, 36(4):672–683, October 2018. doi: 10.1080/07350015.2016.1247004.