

Clustering in the Linear Model

1 Introduction

This handout extends the handout on “The Multiple Linear Regression model” and refers to its definitions and assumptions in section 2. It relaxes the homoscedasticity assumption (*OLS4a*) and allows the error terms to be heteroscedastic and correlated within groups or so-called clusters. It shows in what situations the parameters of the linear model can be consistently estimated by OLS and how the standard errors need to be corrected.

The canonical example (Moulton 1986, 1990) for clustering is a regression of individual outcomes (e.g. wages) on explanatory variables of which some are observed on a more aggregate level (e.g. employment growth on the state level).

Clustering also arises when the sampling mechanism first draws a random sample of groups (e.g. schools, households, towns) and then surveys all (or a random sample of) observations within that group. Stratified sampling, where some observations are intentionally under- or oversampled asks for more sophisticated techniques.

2 The Econometric Model

Consider the multiple linear regression model

$$y_{gi} = x'_{gi}\beta + u_{gi}$$

where observations belong to a cluster $g = 1, \dots, G$ and observations are indexed by $i = 1, \dots, M$ within their cluster. G is the number of clusters, M is the number of observations per cluster, and $N = \sum_g M = GM$ is the total number of observations. For notational simplicity, M is assumed

constant in this handout. It is easily generalized to a cluster specific number M_g . y_{gi} is the dependent variable, x'_{gi} is a $(K + 1)$ -dimensional row vector of K explanatory variables plus a constant, β is a $(K + 1)$ -dimensional column vector of parameters, and u_{gi} is the error term.

Stacking observations within a cluster, we can write

$$y_g = X_g\beta + u_g$$

where y_g is a $M \times 1$ vector, X_g is a $M \times (K + 1)$ matrix and u_g is a $M \times 1$ vector. Stacking observations cluster by cluster, we can write

$$y = X\beta + u$$

where $y = [y_1' \dots y_G']'$ is $N \times 1$, X is $N \times (K + 1)$ and u is $N \times 1$.

The data generation process (dgp) is fully described by:

CL1: Linearity

$$y_{gi} = x'_{gi}\beta + u_{gi} \text{ and } E(u_{gi}) = 0$$

CL2: Independence

$$(X_g, y_g)_{g=1}^G \text{ i.i.d. (independent and identically distributed)}$$

CL2 assumes that the observations in one cluster are independent from the observations in all other clusters. It does *not* assume independence of the observations *within* clusters.

CL3: Strict Exogeneity

- a) $u_{gi}|X_g \sim N(0, \sigma_{gi}^2)$
- b) $u_{gi} \perp X_g$ (independent)
- c) $E(u_{gi}|X_g) = 0$ (mean independent)
- d) $cov(X_g, u_{gi}) = 0$ (uncorrelated)

CL3 assumes that the error term u_{gi} is unrelated to all explanatory variables of all observations within its cluster.

CL4: Clustered Errors

$V(u_g|X_g) = \sigma^2\Omega_g = \sigma^2\Omega(X_g)$ is p.d. and finite

CL4 means that the error terms are allowed to have different variances and to be correlated within clusters conditional on all explanatory variables of all observations within the cluster.

Under *CL2*, *CL3c* and *CL4*, the conditional variance-covariance matrix of the vector of error terms in the whole sample is

$$V(u|X) = E(uu'|X) = \sigma^2\Omega$$

$$= \begin{pmatrix} \sigma^2\Omega_1 & 0 & \cdots & 0 \\ 0 & \sigma^2\Omega_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma^2\Omega_G \end{pmatrix}$$

where the typical diagonal element

$$\sigma^2\Omega_g = V(u_g|X) = V(u_g|X_g) = E(u_g u_g' | X_g) = \sigma^2\Omega(X_g)$$

$$= \begin{pmatrix} \sigma_{g1}^2 & \rho_{12}\sigma_{1g}\sigma_{g2} & \cdots & \rho_{g1M}\sigma_{g1}\sigma_{gM} \\ \rho_{g21}\sigma_{g2}\sigma_{g1} & \sigma_{g2}^2 & \cdots & \rho_{g2M}\sigma_{g2}\sigma_{gM} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{gM1}\sigma_{gM}\sigma_{g1} & \rho_{gM2}\sigma_{gM}\sigma_{g2} & \cdots & \sigma_{gM}^2 \end{pmatrix}$$

is the variance covariance matrix of the error terms within cluster g and all its elements are a function of X_g . The decomposition into σ^2 and Ω_g is arbitrary but useful.

CL5: Identifiability

$\text{rank}(X) = K + 1 < N$ and $E(X_g'X_g) = Q$ is p.d. and finite

CL5 assumes that the regressors have identifying variation (non-zero variance) and are not perfectly collinear.

3 A Special Case: Random Cluster-specific Effects

Suppose as Moulton(1986) that the error term u_{gi} consists of a cluster specific random effect c_g and an individual effect v_{gi}

$$u_{gi} = c_g + v_{gi}$$

Assume that the individual error term is strictly exogenous, homoscedastic and independent across all observations

$$E(v_{gi}|X_g) = 0$$

$$V(v_{gi}|X_g) = \sigma_v^2$$

$$\text{Cov}(v_{gi}, v_{gj}|X_g) = 0, i \neq j$$

and that the cluster specific effect is exogenous, homoscedastic and uncorrelated with the individual effect

$$E(c_g|X_g) = 0$$

$$V(c_g|X_g) = \sigma_c^2$$

$$\text{Cov}(c_g, v_{gi}|X_g) = 0$$

The resulting variance-covariance structure within each cluster g is then

$$V(u_g|X_g) = \sigma_u^2\Omega_g = \sigma_u^2[\rho_u\iota\iota' + (1 - \rho)I] = \sigma_u^2 \begin{pmatrix} 1 & \rho_u & \cdots & \rho_u \\ \rho_u & 1 & \cdots & \rho_u \\ \vdots & \vdots & \ddots & \vdots \\ \rho_u & \rho_u & \cdots & 1 \end{pmatrix}$$

where $\sigma_u^2 = \sigma_c^2 + \sigma_v^2$, $\rho_u = \sigma_c^2/(\sigma_c^2 + \sigma_v^2)$ and ι is a $(M \times 1)$ column vector of ones. This structure is called *equicorrelated* errors. In a less restrictive version, σ_u^2 and ρ_u are allowed to be cluster specific as a function of X_g .

Note: this structure is formally identical to a random effects model for panel data with many “individuals” g observed over few “time periods” i . The cluster specific random effect is also called an *unrelated effect*.

4 Estimation with OLS

The parameter β can be estimated with OLS as

$$\hat{\beta}_{OLS} = (X'X)^{-1} X'y$$

The OLS estimator of β remains unbiased in small samples under *CL1*, *CL2*, *CL3c*, *CL4*, and *CL5* and normally distributed additionally assuming *CL3a*. It is consistent and approximately normally distributed under *CL1*, *CL2*, *CL3d*, *CL4*, and *CL5* in samples with a large number of clusters. However, the OLS estimator is not efficient any more. More importantly, the usual standard errors of the OLS estimator and tests (*t*-, *F*-, *z*-, Wald-) based on them are not valid any more.

5 Estimating Correct Standard Errors

The small sample covariance matrix of $\hat{\beta}_{OLS}$ is under *CL3c* and *CL4*

$$V(\hat{\beta}_{OLS}|X) = \sigma^2 (X'X)^{-1} [X'\Omega X] (X'X)^{-1}$$

and differs from usual OLS where $V(\hat{\beta}_{OLS}|X) = \sigma^2(X'X)^{-1}$. Consequently, the usual estimator $\hat{V}(\hat{\beta}_{OLS}|X) = \hat{\sigma}^2(X'X)^{-1}$ is incorrect. Usual small sample test procedures, such as the *F*- or *t*-Test, based on the usual estimator are therefore not valid.

With the number of clusters $G \rightarrow \infty$ and fixed cluster size $M = N/G$, the OLS estimator is asymptotically normally distributed under *CL1*, *CL2*, *CL3d*, *CL4*, and *CL5*

$$\sqrt{G}(\hat{\beta} - \beta) \xrightarrow{d} N(0, \Sigma)$$

where $\Sigma = Q_{XX}^{-1} E(X'_g u_g u'_g X_g) Q_{XX}^{-1}$ and $Q_{XX} = E(X'_g X_g)$. The OLS estimator is therefore approximately normally distributed in samples with a large number of clusters

$$\hat{\beta} \overset{A}{\sim} N(\beta, Avar(\hat{\beta}))$$

where $Avar(\hat{\beta}) = G^{-1}\Sigma$ can be estimated as

$$\widehat{Avar}(\hat{\beta}) = (X'X)^{-1} \left[\sum_{g=1}^G X'_g \hat{u}_g \hat{u}'_g X_g \right] (X'X)^{-1}$$

with $\hat{u}_g = y_g - X_g \hat{\beta}_{OLS}$ under some additional assumptions on higher order moments of X_g .

This so-called *cluster-robust* covariance matrix estimator is a generalization of Huber(1967) and White(1980).¹ It does not impose any restrictions on the form of both heteroscedasticity and correlation within clusters (though we assumed independence of the error terms across clusters). We can perform the usual *z*- and Wald-test for large samples using the cluster-robust covariance estimator.

Note: the cluster-robust covariance matrix is consistent when the number of clusters $G \rightarrow \infty$. In practice we should have at least 50 clusters.

Bootstrapping is an alternative method to estimate a cluster-robust covariance matrix under the same assumptions. See the handout on “The Bootstrap”. Clustering is addressed in the bootstrap by randomly drawing clusters g (rather than individual observations gi) and taking all M observations for each drawn cluster. This so-called *block bootstrap* preserves all within cluster correlation.

6 Efficient Estimation with GLS

In some cases, for example with cluster specific random effects, we can estimate β efficiently using feasible GLS (see the handout on “Heteroscedasticity in the Linear Model” and the handout on “Panel Data”). In practice, we can rarely rule out additional serial correlation beyond the one induced by the random effect. It is therefore advisable to always use cluster-robust standard errors in combination with FGLS estimation of the random effects model.

¹Note: the cluster-robust estimator is not clearly attributed to a specific author.

7 Special Case: Estimating Correct Standard Errors with Random Cluster-specific Effects

Moulton (1986, 1990) studies the bias of the usual OLS standard errors for the special case with random cluster-specific effects. Assume cluster-specific random effects in a bivariate regression:

$$y_{gi} = \beta_0 + \beta_1 x_{gi} + u_{gi}$$

where $u_{gi} = c_g + v_{gi}$ with $\sigma_u^2 = \sigma_c^2 + \sigma_v^2$, $\rho_u = \sigma_c^2 / (\sigma_c^2 + \sigma_v^2)$. Then the (cluster-robust) asymptotic variance can be estimated as

$$\widehat{Avar}_{cluster}(\widehat{\beta}_1) = \frac{\widehat{\sigma}_u^2}{\sum_{g=1}^G \sum_{i=1}^M (x_{gi} - \bar{x})^2} [1 + (M-1)\widehat{\rho}_x \widehat{\rho}_u]$$

where $\widehat{\sigma}_u^2$ is the usual OLS estimator, ρ_x is the within cluster correlation of x and $[1 + (M-1)\rho_x \rho_u] > 1$ is called the *Moulton factor*. $\widehat{\sigma}^2$, $\widehat{\rho}_u$ and $\widehat{\rho}_x$ are consistent estimators of σ^2 , ρ_u and ρ_x , respectively. The robust standard error for the slope coefficient is accordingly

$$\widehat{se}_{cluster}(\widehat{\beta}_1) = \widehat{se}_{ols}(\widehat{\beta}_1) \sqrt{1 + (M-1)\widehat{\rho}_x \widehat{\rho}_u}$$

where $\widehat{se}_{ols}(\widehat{\beta}_1)$ is the usual OLS standard error.

The square root of the Moulton factor measures how much the usual OLS standard errors understate the correct standard errors. For example, with cluster size $M = 500$ and intraclass correlations $\rho_u = 0.1$ and $\rho_x = 0.1$, the correct standard errors are 2.45 times the usual OLS ones.

Lessons from the Moulton factor

1. If either the within cluster correlation of the combined error term u is zero ($\rho_u = 0$) or the within cluster correlation of x is zero ($\rho_x = 0$), then the Moulton factor is 1 and the usual OLS standard errors are correct. Both situations generalize to K explanatory variables.

2. If the variable of interest is an *aggregate variable* on the level of the cluster (hence $\rho_x = 1$), the Moulton factor is maximal. This case generalizes to K aggregate explanatory variables:

$$\widehat{Avar}_{cluster}(\widehat{\beta}) = \widehat{\sigma}^2 (X'X)^{-1} [1 + (M-1)\widehat{\rho}]$$

In this situation, we need to correct the standard errors. Alternatively, we could aggregate (average) all variables and run the regression on the collapsed data.

3. If only control variables are aggregated, we better include cluster fixed effects (i.e. dummy variables for the groups) which will take care of the cluster-specific effect. See also the handout on “Panel Data: Fixed and Random Effects”.
4. If the variable of interest is not aggregated but has an important cluster specific component (large ρ_x), then including cluster fixed effects may destroy valuable information and we better don't include cluster fixed effects. However, we need to correct the standard errors.
5. If only control variables have an important cluster-specific component, it is better to include cluster fixed effects.
6. If the variable of interest has only a small cluster specific component (i.e. a lot of within-cluster variation and very little between-cluster variation), it is better to include cluster fixed effects.

Standard errors are in practice most easily corrected using the Eicker-White cluster-robust covariance from section 5 and not via the Moulton factor. Note that we should have at least $G = 50$ clusters to justify the asymptotic approximation.

In the context of panel and time series data, serial correlation beyond the ones from a random effect becomes very important. See the handout on “Panel Data: Fixed and Random Effects”. In this case standard errors need to be corrected even when including fixed effects.

8 Implementation in Stata 11.0

Load example data

```
webuse auto7.dta
```

Stata reports the cluster-robust covariance estimator with the `vce(cluster)` option, e.g.²

```
regress price weight, vce(cluster manufacturer)
matrix list e(V)
```

Note: Stata multiplies \hat{V} with $(N - 1)/(N - K) \cdot G/(G - 1)$ to “correct” for degrees of freedom in small samples. This practice is ad-hoc and not based on asymptotic theory; it is practically irrelevant with large G . Stata reports t - and F -statistics with $G - 1$ degrees of freedom.

We can also estimate a cluster robust covariance using a nonparametric block bootstrap. For example with either of the following,

```
regress price weight, vce(bootstrap, reps(100) cluster(manufacturer))
bootstrap, reps(100) cluster(manufacturer): regress price weight
```

The cluster specific random effects model is efficiently estimated by FGLS. For example,

```
xtset manufacturer_grp
xtreg price weight, re
```

In addition, cluster-robust standard errors are reported with

```
xtreg price weight, re vce(cluster manufacturer)
```

²There are only 23 clusters in this example dataset used by the Stata manual. This is not enough to justify using large sample approximations.

9 Implementation in R 2.13

Load example data

```
library(foreign)
auto <- read.dta("http://www.stata-press.com/data/r11/auto7.dta")
```

The cluster-robust covariance estimator can be estimated in R with the package `rms`. First, we use an alternative regression command (`ols`) which stores the covariance matrix

```
library(rms)
fm <- ols(price~weight, data=auto, x=TRUE, y=TRUE)
print(fm)
```

Second, the cluster-robust covariance is called by³

```
cov <- robcov(fm, cluster=auto$manufacturer)
print(cov)
print(cov$var)
```

Note: R reports t -statistics with $N - K - 1$ degrees of freedom.

We can also estimate a cluster robust covariance using a nonparametric block bootstrap

```
cov <- bootcov(fm, cluster=auto$manufacturer, B=100)
print(cov)
```

³There are only 23 clusters in this example dataset used by the Stata manual. This is not enough to justify using large sample approximations.

References

Advanced textbooks

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