

## Appendix C: Properties of the Squared, EWLS and MMRR Means Model Residuals

### Appendix C.1: Distribution of $e_i^{2(\text{mmrr})}$

Recall that we write the robust means model fit as:

$$\hat{\mathbf{y}}^{(\text{mmrr})} = \mathbf{H}^{(\text{mmrr})} \mathbf{y}$$

where

$$\mathbf{H}^{(\text{mmrr})} = \mathbf{H}^{(\text{ewls})} + \lambda_\mu \mathbf{H}_{b_\mu}^{(\text{llr})} (\mathbf{I} - \mathbf{H}^{(\text{ewls})}).$$

Notice from above that if there is no means model misspecification,  $\lambda_\mu = 0$ , and thus,  $\mathbf{H}^{(\text{mmrr})} = \mathbf{H}^{(\text{ewls})}$ . The properties of the squared, MMRR means model residuals which are discussed in this Appendix can therefore be applied to the EWLS squared residuals simply by replacing  $\mathbf{H}^{(\text{mmrr})}$  with  $\mathbf{H}^{(\text{ewls})}$  (since  $\mathbf{H}^{(\text{mmrr})} = \mathbf{H}^{(\text{ewls})}$  when  $\lambda_\mu$  is zero).

We have that  $\mathbf{e}^{(\text{mmrr})} = (\mathbf{I} - \mathbf{H}^{(\text{mmrr})}) \mathbf{y}$  where  $\mathbf{y} \sim N[\mathbf{X}\boldsymbol{\beta} + \mathbf{f}, \mathbf{V}]$ . Thus,  $\mathbf{e}^{(\text{mmrr})}$  has a Normal distribution with mean  $(\mathbf{I} - \mathbf{H}^{(\text{mmrr})}) \mathbf{f}$  and variance  $(\mathbf{I} - \mathbf{H}^{(\text{mmrr})}) \mathbf{V} (\mathbf{I} - \mathbf{H}^{(\text{mmrr})})'$ . It follows that the distribution of the  $i^{\text{th}}$  means model residual is given by:

$$e_i^{(\text{mmrr})} \sim N[\mu_{e_i}, \sigma_{e_i}^2]$$

where

$$\mu_{e_i} = \left(1 - h_{ii}^{(\text{mmrr})}\right) f_i - \sum_{j \neq i}^n h_{ij}^{(\text{mmrr})} f_j$$

and

$$\sigma_{e_i}^2 = \left(1 - h_{ii}^{(\text{mmrr})}\right)^2 \sigma_i^2 + \sum_{i \neq j}^n h_{ij}^{2(\text{mmrr})} \sigma_j^2.$$

Rescaling  $e_i^{(\text{mmrr})}$  we have:

$$\frac{e_i^{(\text{mmrr})}}{\sigma_{e_i}} \sim N \left[ \frac{\mu_{e_i}}{\sigma_{e_i}}, 1 \right].$$

Squaring both sides results in:

$$\frac{e_i^{2(\text{mmrr})}}{\sigma_{e_i}^2} \sim \chi_{(1), \delta_i}^{\prime 2}$$

where

$$\delta_i = \frac{\mu_{e_i}^2}{\sigma_{e_i}^2}.$$

Thus, it follows that  $e_i^{2(\text{mmrr})}$  has a distribution which is a multiple of a non-central Chi-Square distribution:

$$e_i^{2(\text{mmrr})} \sim \sigma_{e_i}^2 \chi_{(1), \delta_i}^{\prime 2}.$$

### Appendix C.2: Expected Value of $e_i^{2(\text{mmrr})}$

Since  $e_i^{2(\text{mmrr})}$  has a distribution which is a multiple of a non-central Chi-Square distribution, we can write

$$\begin{aligned} E\left(e_i^{2(\text{mmrr})}\right) &= \sigma_{e_i}^2 E\left(\chi_{(1), \delta_i}^{\prime 2}\right) \\ &= \sigma_{e_i}^2 (1 + \delta_i). \end{aligned}$$

Substituting for  $\delta_i$  we have:

$$E\left(e_i^{2(\text{mmrr})}\right) = \sigma_{e_i}^2 \left(1 + \frac{\mu_{e_i}^2}{\sigma_{e_i}^2}\right)$$

$$= \sigma_{e_i}^2 + \mu_{e_i}^2$$

### Appendix C.3: Variance of $e_i^{2(\text{mmrr})}$

In a similar fashion to the derivation of the  $E(e_i^{2(\text{mmrr})})$ , the variance of  $e_i^{2(\text{mmrr})}$  proceeds as follows:

$$\begin{aligned} \text{Var}[e_i^{2(\text{mmrr})}] &= \text{Var}(\sigma_{e_i}^2 \chi_{(1), \delta_i}^2) \\ &= [\sigma_{e_i}^2]^2 [2(1 + 2\delta_i)] \\ &= 2[\sigma_{e_i}^2]^2 \left\{ 1 + 2 \left\{ \frac{\mu_{e_i}^2}{\sigma_{e_i}^2} \right\} \right\} \end{aligned}$$

$$\text{Var}(e_i^{2(\text{mmrr})}) = 2[\sigma_{e_i}^2]^2 + 4[(\sigma_{e_i}^2)(\mu_{e_i}^2)].$$