

## Qualifying Exam: CAS MA 575

Boston University, Spring 2013

1. Consider the model

$$Y_i = \beta + \epsilon_i ,$$

$i = 1, \dots, n$ , where  $\beta$  is a scalar and

$$\epsilon_i = \epsilon_1^* + \dots + \epsilon_i^* ,$$

for  $\epsilon_1^*, \dots, \epsilon_n^*$  a sequence of uncorrelated random variables with mean zero and unit variance<sup>1</sup>

- Provide a simplified expression for the ordinary least squares estimator  $\hat{\beta}_{OLS}$  of  $\beta$ .
- Similarly, provide a simplified expression for the generalized least squares estimator  $\hat{\beta}_{GLS}$  of  $\beta$ .
- Calculate the variances  $\text{Var}(\hat{\beta}_{OLS})$  and  $\text{Var}(\hat{\beta}_{GLS})$  of the two estimators in parts (a) and (b) and compare them.
- A colleague of yours, observing the structure of the model assumed here, suggests that it would be natural to instead consider estimating  $\beta$  using the differences  $D_i = Y_i - Y_{i-1}$ ,  $i = 1, \dots, n$ , where  $Y_0 \equiv 0$ . Comment on this idea and compare/contrast what you might get in this case with what you obtained using OLS and GLS.

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<sup>1</sup>Hint: For this problem you may wish to use the fact that the inverse of an  $m \times m$  matrix of the form

$$M = \begin{pmatrix} 1 & 1 & 1 & \dots & 1 & 1 \\ 1 & 2 & 2 & \dots & 2 & 2 \\ 1 & 2 & 3 & \dots & 3 & 3 \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots \\ 1 & 2 & 3 & \dots & m-1 & m-1 \\ 1 & 2 & 3 & \dots & m-1 & m \end{pmatrix}$$

can be expressed as

$$M^{-1} = \begin{pmatrix} 2 & -1 & 0 & \dots & 0 & 0 \\ -1 & 2 & -1 & \dots & 0 & 0 \\ 0 & -1 & 2 & \dots & 0 & 0 \\ 0 & 0 & -1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & -1 & 0 \\ 0 & 0 & 0 & \dots & 2 & -1 \\ 0 & 0 & 0 & \dots & -1 & 1 \end{pmatrix} .$$

2. Consider the multiple regression model

$$\mathbf{Y} = \mathbf{X}\beta + \mathbf{e} ,$$

where  $\mathbf{Y}$  is  $n \times 1$ ,  $\mathbf{X}$  is  $n \times p$ ,  $\beta$  is  $p \times 1$ , and  $\mathbf{e}$  is  $n \times 1$ . The errors  $\mathbf{e}$  are assumed to be uncorrelated with mean zero and variance  $\sigma^2$ .

Suppose that it is known that the entries of  $\beta$  should satisfy a set of  $j$  linear constraints, which can be encoded in the equations  $R\beta = r$ , for  $R$  a  $j \times p$  matrix of linear independent rows, and  $r$  a  $j \times 1$  vector.

The *restricted ordinary least squares* problem entails estimating  $\beta$  by optimizing the ordinary least squares error, subject to the additional constraints  $R\beta = r$ . Using the method of Lagrange multipliers, this means solving for that value, say  $\hat{\beta}^*$ , that minimizes

$$(\mathbf{Y} - \mathbf{X}\beta)^T(\mathbf{Y} - \mathbf{X}\beta) + 2\lambda^T(R\beta - r) ,$$

where  $\lambda$  is a  $j \times 1$  vector of weights (i.e., the so-called Lagrange multipliers) which form an additional set of parameters to be inferred.

(a) Show that, for fixed  $\lambda$ , the restricted OLS estimator  $\hat{\beta}^*$  takes the form

$$\hat{\beta}^* = \hat{\beta} - (\mathbf{X}^T\mathbf{X})^{-1}R^T\lambda ,$$

where  $\hat{\beta}$  is the standard ordinary least squares estimate. [That is, show that  $\hat{\beta}^*$  optimizes the restricted OLS criterion when the latter is treated as a function of  $\beta$  only, keeping  $\lambda$  fixed.]

(b) Using the result in part (a), as well as the fact that we must have  $R\hat{\beta}^* = r$ , show that

$$\lambda = [R(\mathbf{X}^T\mathbf{X})^{-1}R^T]^{-1} (R\hat{\beta} - r) .$$

Substituting appropriately, provide a final formula for  $\hat{\beta}^*$  in terms of  $\mathbf{X}$ ,  $R$ ,  $\hat{\beta}$ , and  $r$  only.

(c) Using the fact that  $\hat{\beta}$  is, in general, an unbiased estimate of  $\beta$ , show that under the restricted model assumed here (i.e., that  $R\beta = r$ ), the estimate  $\hat{\beta}^*$  is unbiased as well.

(d) Suppose that we only suspect that  $R\beta = r$  holds, but are not certain. Define an appropriate  $F$  statistic for testing  $H_0 : R\beta = r$  versus  $H_1 : R\beta \neq r$ , specifying the appropriate degrees of freedom of the corresponding  $F$  distribution.

(e) Consider the following special case of the general framework analyzed above. Let

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + e_i ,$$

and suppose that we restrict  $\beta = (\beta_0, \beta_1, \beta_2)^T$  such that  $2\beta_1 + 3\beta_2 = 5$ . Explain how, without using Lagrange multipliers, you would go about finding the restricted OLS estimate  $\hat{\beta}^*$ .