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MORE ON THE GROUPED HETEROSKEDASTICITY MODEL *

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Abstract- Binkley (1989) presented Monte Carlo evidence on the relative efficiency of two estimators of the regression coefficients in the grouped heteroskedastic model. The alternative methods differ according to whether the disturbance variances are estimated using residuals from individual group regressions or one pooled regression. This note extends this discussion, placing particular emphasis on the question of computational convenience, and on testing hypotheses and imposing restrictions on variance parameters. The arguments presented here provide further information on which to base a choice between the alternative methods.

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I Introduction

The grouped heteroskedasticity model specifies a partitioning of the n observations in a regression model into M mutually exclusive groups. Disturbance variances are assumed to be constant within groups but are permitted to vary between groups. Recently in this REVIEW Binkley (1989) presented Monte Carlo evidence on the relative efficiency of two estimators of the regression coefficients in the grouped heteroskedasticity model. The alternative methods differ according to whether the disturbance variances are estimated using residuals from individual group regressions or one pooled regression. This note extends this discussion with particular emphasis on matters of computational convenience, and on testing hypotheses and imposing restrictions on variance parameters. The arguments presented here provide further information on which to base a choice between the alternative methods.

II The grouped heteroskedasticity model

The grouped heteroskedasticity model can be written as

(1) $$Y_i = X_i\beta + u_i, \quad i = 1, \ldots, M$$

where Y_i and u_i are n_i element vectors, X_i is an $n_i \times k$ matrix of explanatory variables, β is a $k \times 1$ vector of coefficients and var $(u_i) = \sigma_i^2 I_{n_i}$.

Binkley (1989) has compared two alternative methods of generating the estimated generalized least squares (EGLS) estimator of β. In the first method, a separate OLS regression is run for each group of observations and σ_i^2 is estimated by

(2) $$\hat{\sigma}_i^2 = \frac{(Y_i - X_i b_i)'(Y_i - X_i b_i)}{n_i - k}$$

where $b_i = (X_i'X_i)^{-1}X_i'Y_i$.

In the alternative method, the information that each b_i is an estimate of the same β is incorporated by obtaining a pooled estimate of β, namely $b = (X'X)^{-1}X'Y$ where X and Y contain the stacked X_i and Y_i. Estimates of the individual group variances are then obtained from

$$(3) \qquad \tilde{\sigma}_i^2 = \frac{(Y_i - X_i b)'(Y_i - X_i b)}{n_i - k}$$

Let us call the EGLS estimators of β based on (2) and (3) the unrestricted and restricted estimators. Binkley (1989) provides simulation results comparing these estimators. The evidence suggests that for extreme heteroskedasticity the unrestricted estimator is more efficient in finite samples, whereas for moderate and low degrees of heteroskedasticity the restricted estimator is more efficient. Asymptotically, both estimators are of course fully efficient.

For applied work, Binkley expresses a preference for the unrestricted estimator. This preference is reinforced by his view that this estimator is also computationally more convenient. With reference to the restricted estimator he comments that:

> "This is somewhat more troublesome to employ, since it requires the partitioning of a residual vector." Binkley (1989, p660),

and concludes that:

> "Since in general it is more troublesome to employ, we see little recommendation for this method when the sample size is adequate." Binkley (1989, p.664).

Unfortunately this particular criticism is misplaced. Computation of (3) can be carried out in an entirely simple and straightforward manner. The key is to recognize that this particular heteroskedastic model falls into the class of additive heteroskedasticity models where the disturbance variance is specified as a linear function of a set of exogenous variables. Importantly, this relationship is conveniently represented by a secondary equation which facilitates the computation of estimates of disturbance variances. Moreover we suggest that this framework has the added advantage of providing a ready framework for testing hypotheses and imposing restrictions on these variance parameters.

III Additive heteroskedasticity

The additive heteroskedasticity model postulates the following particular relationship

$$(4) \qquad \sigma_j^2 = z_j'\alpha \qquad j = 1, \ldots, n; \quad n = \Sigma n_i;$$

where z_j' is a $1 \times p$ vector of exogenous variables and α a conformable vector of unknown parameters. Notice that this represents a general situation where variances are allowed to vary over the individual observations. In order to obtain estimates of α and ultimately σ_j^2, one estimates a secondary equation of the form

$$(5) \qquad \hat{u}_j^2 = z_j'\alpha + \varepsilon_j$$

where $\hat{u}_j$ are the OLS residuals from the estimation of the primary equation given by (1). For extensive analysis of this model see Amemiya (1977, 1985).

For the special case of the grouped heteroskedasticity model, the secondary equation in matrix form is given by

$$(6) \qquad \begin{bmatrix} \hat{u}_1^2 \\ \hat{u}_2^2 \\ \vdots \\ \hat{u}_n^2 \end{bmatrix} = \begin{bmatrix} \iota_1 & 0 & 0 & \ldots & 0 \\ 0 & \iota_2 & 0 & \ldots & 0 \\ 0 & 0 & \iota_3 & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \ldots & \iota_M \end{bmatrix} \begin{bmatrix} \sigma_1^2 \\ \sigma_2^2 \\ \vdots \\ \sigma_M^2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

where ι_i is an $n_i \times 1$ vector of unit elements and $\alpha = (\sigma_1^2, \ldots, \sigma_M^2)'$. Calculation of (3) is simply a matter of running an OLS regression of the squared residuals from OLS estimation of (1) on a matrix of dummy variables.

In the case of M = 2, both methods discussed by Binkley (1989) involve two OLS regressions to determine estimates of σ_i^2 and hence would seem to be computationally equally convenient. It is true that as M increases there is a difference in computational convenience. However it is the method preferred by Binkley that becomes somewhat troublesome, as it requires M OLS regressions while the alternative method still only requires two. While the weight of the simulation evidence in favour of either estimator depends on the degree of heteroskedasticity, the computational aspects surely favour the restricted estimator that utilizes the secondary equation.

IV Hypothesis testing

Notice that (6) does not contain an intercept. We can consider an alternative form of (6) where say the first group dummy is replaced by an intercept. In this reparameterization of the model, the coefficients on the remaining group dummies; say $\alpha_2^*, \ldots, \alpha_M^*$, represent deviations from the disturbance variance of the first group. This serves to highlight an additional advantage of using the secondary equation approach to estimate the σ_i^2. Namely it provides a ready framework for testing hypotheses and imposing restrictions on these variance parameters.

Estimation of the secondary equation would naturally provide "t-statistics" for use in the testing of hypotheses regarding individual α_i^* parameters. More importantly the null hypothesis of homoskedasticity is represented by the restriction $\alpha_2^* = \ldots = \alpha_M^* = 0$. The LM test of this hypothesis is based on a statistic given by the regression sums of squares from this regression divided by $2\hat{\sigma}^4$, where $\hat{\sigma}^2$ is the average of the squared residuals from the OLS regression of (1); see Breusch and Pagan (1979) for further details. Moreover, a simple alternative that is asymptotically equivalent to the Breusch-Pagan statistic but which is robust to nonnormality can be calculated as n times the R^2 from this regression; see Koenker (1981). See Buse (1984) for some Monte Carlo comparisons of alternative methods of testing for additive heteroskedasticity.

As an example of a framework that facilitates the imposition of restrictions on the form of the heteroskedasticity, suppose one has a priori information of the form $\sigma_1^2 < \sigma_2^2 < \ldots < \sigma_M^2$. The secondary equation then becomes

$$(7)\qquad \begin{bmatrix} \hat{u}_1^2 \\ \hat{u}_2^2 \\ \vdots \\ \hat{u}_n^2 \end{bmatrix} = \begin{bmatrix} \iota_1 & 0 & 0 & \ldots & 0 \\ \iota_2 & \iota_2 & 0 & \ldots & 0 \\ \iota_3 & \iota_3 & \iota_3 & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \iota_M & \iota_M & \iota_M & \ldots & \iota_M \end{bmatrix} \begin{bmatrix} \alpha_1^* \\ \alpha_2^* \\ \vdots \\ \alpha_M^* \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

where $\alpha_1^* = \sigma_1^2$ and $\alpha_i^* = \sigma_i^2 - \sigma_{i-1}^2 \geq 0$, $i = 2, \ldots, M$. A special case is the model proposed by Nerlove (1971) as an alternative reparametrization of an error components model with individual effects. Here $M = 2$ with $\sigma_1^2 = \sigma_\nu^2$ and $\sigma_2^2 = \sigma_\nu^2 + T\sigma_\mu^2$, where σ_μ^2 is the variance of the individual effect, σ_ν^2 is the variance of the disturbance and T is the number of time series observations available for each cross-section. The reparameterization leads to $\alpha_1^* = \sigma_\nu^2$ and $\alpha_2^* = T\sigma_\mu^2$.

As another example, suppose $M = 3$ and that the variance in one group is the sum of the other group variances. Here the secondary equation takes the form

$$(8)\qquad \begin{bmatrix} \hat{u}_1^2 \\ \vdots \\ \hat{u}_n^2 \end{bmatrix} = \begin{bmatrix} \iota_1 & 0 \\ 0 & \iota_2 \\ \iota_3 & \iota_3 \end{bmatrix} \begin{bmatrix} \alpha_1^* \\ \alpha_2^* \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

where $\alpha_1^* = \sigma_1^2$, $\alpha_2^* = \sigma_2^2$ and $\alpha_1^* + \alpha_2^* = \sigma_3^2$. Again the secondary equation framework proves to be very convenient.

V Comments

Before concluding, there are several points worth noting that relate to the additive heteroskedastic model and the special case of grouped heteroskedasticity. First, in (5), the condition that $E(\varepsilon_j | z_j) = 0$ is only satisfied asymptotically. Hence, even though the OLS estimates of α in (6) are identical to (3), inferential procedures in regard to α are asymptotic.

Second, Amemiya (1977, 1985) notes that the ε_j in (5) are themselves heteroskedastic with an asymptotic variance (under normality) equal to $2(z_j'\alpha)^2$ and hence recommends a second step in the estimation of (5) in which the equation is reestimated using weights derived from the OLS estimates of α to obtain EGLS estimates.

Interestingly, a special feature of the grouped heteroskedastic model is that this additional step is unnecessary because GLS produces estimates of α that are identical to OLS. (See the Appendix for a proof of this proposition.) Hence there is no efficiency gain in carrying out Amemiya's second step. It is true that the standard errors of the α's produced by OLS will be biased, so that the full 2-step procedure should be carried out for making (asymptotically) correct inferences about α.

A pervasive problem in the estimation of secondary equations is that of ensuring nonnegative estimates of the variances, σ_j^2 . Again it is interesting to note that the special case of the grouped heteroskedastic model is one situation where this problem does not appear. The estimates of the σ_j^2 generated by the secondary equation are nonnegative with probability one. This is easily seen from the form of the estimates given in (3). On the other hand OLS (or EGLS) estimates generated from the secondary equations of other models such as (7) and (8) are not necessarily guaranteed to satisfy the appropriate nonnegativity constraints. Notice here the distinction between nonnegativity of estimates of α^* and of σ_j^2; the former is not necessary for the latter. In fact unconstrained estimation of (7) will guarantee nonnegative estimates of σ_j^2, but not of α^* as required by the specification. Fortunately an easily computed constrained version of the Amemiya 2-step method, has recently been suggested by Bartels and Fiebig (1990). This method has good small sample properties and has been successfully implemented in the empirical work of Fiebig, Bartels and Aigner (1988).

Ronning (1985) provides a more detailed analysis of the violation of nonnegativity constraints. In the case where the dependent variable is nonnegative with probability one, as it is in the secondary equation, Ronning provides easy to check conditions for predictions of the dependent variable, here estimates of σ_j^2, to be nonnegative with probability one.

For the secondary equation in (5), let Z be the n×p full-rank matrix of regressors and suppose it has $r \le n$ nonproportional rows. If B is the r×p matrix containing these rows then we can write Z = AB with A having exactly one nonzero element in each row. A necessary and sufficient condition for the nonnegativity of the σ_i^2 estimates is that p = r and that each column of A is either nonnegative or nonpositive. Immediately we see the potential pervasive nature of the nonnegativity problem. A typical situation would have r > p; i.e. there would be many distinct nonproportional rows of Z. However, for the grouped heteroskedastic model of (6) Z = A and B is an M×M identity matrix; the conditions of Ronning are satisfied. On the other hand the model in (8) yields

$$A = \begin{bmatrix} \iota_1 & 0 & 0 \\ 0 & \iota_2 & 0 \\ 0 & 0 & \iota_3 \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 1 \end{bmatrix}$$

where rank (B) = 2 < r = 3. Hence variance predictions from the secondary equation of this model are not guaranteed to be nonnegative.

VI Conclusion

The paper of Binkley (1989) is important because it alerts practitioners to differences in the efficiencies of EGLS estimators of β that may be attributable to the use of different estimators of the group disturbance variances. We have nothing to add to his Monte Carlo results and we agree with his conclusion that the choice of alternatives is somewhat problematic. Our purpose has been to provide extra information that may aid the practitioner in making the choice between methods. In particular we show that the method that restricts β to be equal over groups in the first stage OLS regression can be put into a framework which involves estimation of a secondary equation for the variance parameters.

Having made this connection, it is clear that, despite Binkley's contention, the restricted estimator which takes advantage of the secondary equation representation is computationally convenient and its comparative advantage over the alternative method of estimating M separate first stage regressions increases with the number of groups. Moreover, the secondary equation also provides a framework that is extremely convenient and flexible for the purpose of testing hypotheses and imposing restrictions on the variance parameters.

While with hindsight the relationship between grouped heteroskedasticity and the model of additive heteroskedasticity that utilizes a secondary equation may seem obvious, it appears as though Binkley is not alone in missing the connection. The econometrics texts of Amemiya (1985), Fomby, Hill and Johnson (1984) and Johnston (1984) all refer to the two models of heteroskedasticity without indicating the relationship that has been described here.

Appendix

Proof of the equivalence of OLS and GLS estimation of (6)

Let the design matrix in (6) be given by Z and let var $(\varepsilon) = 2\Omega$. The equivalence of the OLS and GLS estimators of α requires Kruskal's (1968) condition to hold, namely there exists a nonsingular G such that $\Omega Z = ZG$. Here

$$Z = \begin{bmatrix} \iota_1 & & 0 \\ & \ddots & \\ 0 & & \iota_M \end{bmatrix}, \quad \Omega = \begin{bmatrix} \sigma_1^4 I_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_M^4 I_M \end{bmatrix}$$

and the required G is given by

$$G = \begin{bmatrix} \sigma_1^4 & & 0 \\ & \ddots & \\ 0 & & \sigma_M^4 \end{bmatrix} \quad \blacksquare$$

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