does not arise, because, if the model is correctly specified, the transformed explanatory variables are predetermined with respect to the transformed error terms, as in (7.17). When the OLS estimator is inconsistent, we must obtain a consistent estimator of $\boldsymbol{\gamma}$ in some other way.

Whether or not feasible GLS is a desirable estimation method in practice depends on how good an estimate of $\boldsymbol{\Omega}$ can be obtained. If $\boldsymbol{\Omega}(\hat{\boldsymbol{\gamma}})$ is a very good estimate, then feasible GLS has essentially the same properties as GLS itself, and inferences based on the GLS covariance matrix (7.05), with $\boldsymbol{\Omega}(\hat{\boldsymbol{\gamma}})$ replacing $\boldsymbol{\Omega}$, should be reasonably reliable, even though they are not exact in finite samples. Note that condition (7.22), in addition to being necessary for the validity of feasible GLS, guarantees that the feasible GLS covariance matrix estimator converges as $n \to \infty$ to the true GLS covariance matrix. On the other hand, if $\boldsymbol{\Omega}(\hat{\boldsymbol{\gamma}})$ is a poor estimate, feasible GLS estimates may have quite different properties from real GLS estimates, and inferences may be quite misleading.

It is entirely possible to iterate a feasible GLS procedure. The estimator $\hat{\boldsymbol{\beta}}_{\mathrm{F}}$ can be used to compute a new set of residuals, which can be used to obtain a second-round estimate of $\boldsymbol{\gamma}$, which can be used to calculate second-round feasible GLS estimates, and so on. This procedure can either be stopped after a predetermined number of rounds or continued until convergence is achieved (if it ever is achieved). Iteration does not change the asymptotic distribution of the feasible GLS estimator, but it does change its finite-sample distribution.

Another way to estimate models in which the covariance matrix of the error terms depends on one or more unknown parameters is to use the method of maximum likelihood. This estimation method, in which $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are estimated jointly, will be discussed in Chapter 10. In many cases, an iterated feasible GLS estimator is the same as a maximum likelihood estimator based on the assumption of normally distributed errors.

7.5 Heteroskedasticity

There are two situations in which the error terms are heteroskedastic but serially uncorrelated. In the first, the form of the heteroskedasticity is completely unknown, while, in the second, the skedastic function is known except for the values of some parameters that can be estimated consistently. Concerning the case of heteroskedasticity of unknown form, we saw in Sections 5.5 and 6.5 how to compute asymptotically valid covariance matrix estimates for OLS and NLS parameter estimates. The fact that these HCCMEs are sandwich covariance matrices makes it clear that, although they are consistent under standard regularity conditions, neither OLS nor NLS is efficient when the error terms are heteroskedastic.

If the variances of all the error terms are known, at least up to a scalar factor, then efficient estimates can be obtained by weighted least squares, which we