The fundamental result that makes the DLR possible is that, for this class of models, the information matrix $\mathfrak{I}(\boldsymbol{\theta})$ satisfies the equality

$$\mathfrak{I}(\boldsymbol{\theta}) = \operatorname*{plim}_{n\to\infty}\Big(\frac{1}{n}\big(\boldsymbol{F}^{\top}(\boldsymbol{y},\boldsymbol{\theta})\boldsymbol{F}(\boldsymbol{y},\boldsymbol{\theta}) + \boldsymbol{K}^{\top}(\boldsymbol{y},\boldsymbol{\theta})\boldsymbol{K}(\boldsymbol{y},\boldsymbol{\theta})\big)\Big) \tag{14.20}$$

and so can be consistently estimated by

$$\frac{1}{n}\big(\boldsymbol{F}^{\top}(\boldsymbol{y},\ddot{\boldsymbol{\theta}})\boldsymbol{F}(\boldsymbol{y},\ddot{\boldsymbol{\theta}}) + \boldsymbol{K}^{\top}(\boldsymbol{y},\ddot{\boldsymbol{\theta}})\boldsymbol{K}(\boldsymbol{y},\ddot{\boldsymbol{\theta}})\big), \tag{14.21}$$

where $\ddot{\boldsymbol{\theta}}$ is any consistent estimator of $\boldsymbol{\theta}$. We are interested in the implications of (14.20) rather than how it is derived. The derivation makes use of some rather special properties of the normal distribution and may be found in Davidson and MacKinnon (1984a).

The principal implication of (14.20) is that a certain artificial regression, which we call the DLR, has all the properties that we expect an artificial regression to have. The DLR may be written as

$$\begin{bmatrix} \boldsymbol{f}(\boldsymbol{y},\boldsymbol{\theta}) \\ \boldsymbol{\iota} \end{bmatrix} = \begin{bmatrix} -\boldsymbol{F}(\boldsymbol{y},\boldsymbol{\theta}) \\ \boldsymbol{K}(\boldsymbol{y},\boldsymbol{\theta}) \end{bmatrix} \boldsymbol{b} + \text{residuals}. \tag{14.22}$$

This artificial regression has $2n$ **artificial observations**. The regressand is $f_t(y_t,\boldsymbol{\theta})$ for observation $t$ and unity for observation $t+n$, and the regressors corresponding to $\boldsymbol{\theta}$ are $-\boldsymbol{F}_t(\boldsymbol{y},\boldsymbol{\theta})$ for observation $t$ and $\boldsymbol{K}_t(\boldsymbol{y},\boldsymbol{\theta})$ for observation $t+n$, where $\boldsymbol{F}_t$ and $\boldsymbol{K}_t$ denote, respectively, the $t^{\text{th}}$ rows of $\boldsymbol{F}$ and $\boldsymbol{K}$. Intuitively, the reason we need a double-length regression here is that each genuine observation makes two contributions to the loglikelihood function: a sum-of-squares term $-\frac{1}{2}f_t^2$ and a Jacobian term $k_t$. As a result, the gradient and the information matrix each involve two parts as well, and the way to take both of these into account is to incorporate two artificial observations into the artificial regression for each genuine one.

Why is (14.22) a valid artificial regression? As we noted when we discussed the OPG regression in Section 13.7, there are two principal conditions that an artificial regression must satisfy. It is worth stating these conditions somewhat more formally here.[4] Let $\boldsymbol{r}(\boldsymbol{y},\boldsymbol{\theta})$ denote the regressand for some artificial regression and let $\boldsymbol{R}(\boldsymbol{y},\boldsymbol{\theta})$ denote the matrix of regressors. Let the number of rows of both $\boldsymbol{r}(\boldsymbol{y},\boldsymbol{\theta})$ and $\boldsymbol{R}(\boldsymbol{y},\boldsymbol{\theta})$ be $n^*$, which will generally be either $n$ or an integer multiple of $n$. The regression of $\boldsymbol{r}(\boldsymbol{y},\boldsymbol{\theta})$ on $\boldsymbol{R}(\boldsymbol{y},\boldsymbol{\theta})$ will have the properties of an artificial regression if

$$\boldsymbol{R}^{\top}(\boldsymbol{y},\boldsymbol{\theta})\boldsymbol{r}(\boldsymbol{y},\boldsymbol{\theta}) = \rho(\boldsymbol{\theta})\boldsymbol{g}(\boldsymbol{y},\boldsymbol{\theta}) \quad \text{and} \tag{14.23}$$

$$\operatorname*{plim}_{n\to\infty}{}_{\boldsymbol{\theta}}\Big(\frac{1}{n}\boldsymbol{R}^{\top}(\boldsymbol{y},\ddot{\boldsymbol{\theta}})\boldsymbol{R}(\boldsymbol{y},\ddot{\boldsymbol{\theta}})\Big) = \rho(\boldsymbol{\theta})\,\mathfrak{I}(\boldsymbol{\theta}), \tag{14.24}$$

[4] For a fuller treatment of this topic, see Davidson and MacKinnon (1990).

where $\ddot{\boldsymbol{\theta}}$ denotes any consistent estimator of $\boldsymbol{\theta}$. The notation $\operatorname{plim}_{\boldsymbol{\theta}}$ indicates, as usual, that the probability limit is being taken under the DGP characterized by the parameter vector $\boldsymbol{\theta}$, and $\rho(\boldsymbol{\theta})$ is a scalar defined as

$$\rho(\boldsymbol{\theta}) \equiv \operatorname*{plim}_{n\to\infty}{}_{\boldsymbol{\theta}}\Bigl(\frac{1}{n^*}\boldsymbol{r}^{\top}(\boldsymbol{y},\boldsymbol{\theta})\boldsymbol{r}(\boldsymbol{y},\boldsymbol{\theta})\Bigr).$$

Because $\rho(\boldsymbol{\theta})$ is equal to unity for both the OPG regression and the DLR, those two artificial regressions satisfy the simpler conditions

$$\boldsymbol{R}^{\top}(\boldsymbol{y},\boldsymbol{\theta})\boldsymbol{r}(\boldsymbol{y},\boldsymbol{\theta}) = \boldsymbol{g}(\boldsymbol{y},\boldsymbol{\theta}) \quad \text{and} \tag{14.25}$$

$$\operatorname*{plim}_{n\to\infty}{}_{\boldsymbol{\theta}}\Bigl(\tfrac{1}{n}\boldsymbol{R}^{\top}(\boldsymbol{y},\ddot{\boldsymbol{\theta}})\boldsymbol{R}(\boldsymbol{y},\ddot{\boldsymbol{\theta}})\Bigr) = \mathfrak{I}(\boldsymbol{\theta}), \tag{14.26}$$

as well as the original conditions (14.23) and (14.24). However, these simpler conditions are not satisfied by the GNR and are thus evidently too simple in general.

It is now easy to see that the DLR (14.21) satisfies conditions (14.25) and (14.26). For the first of these, simple calculation shows that

$$\begin{bmatrix} -\boldsymbol{F}(\boldsymbol{y},\boldsymbol{\theta}) \\ \boldsymbol{K}(\boldsymbol{y},\boldsymbol{\theta}) \end{bmatrix}^{\top} \begin{bmatrix} \boldsymbol{f}(\boldsymbol{y},\boldsymbol{\theta}) \\ \boldsymbol{\iota} \end{bmatrix} = -\boldsymbol{F}^{\top}(\boldsymbol{y},\boldsymbol{\theta})\boldsymbol{f}(\boldsymbol{y},\boldsymbol{\theta}) + \boldsymbol{K}^{\top}(\boldsymbol{y},\boldsymbol{\theta})\boldsymbol{\iota},$$

which by (14.19) is equal to the gradient $\boldsymbol{g}(\boldsymbol{y},\boldsymbol{\theta})$. For the second, we see that

$$\begin{bmatrix} -\boldsymbol{F}(\boldsymbol{y},\boldsymbol{\theta}) \\ \boldsymbol{K}(\boldsymbol{y},\boldsymbol{\theta}) \end{bmatrix}^{\top} \begin{bmatrix} -\boldsymbol{F}(\boldsymbol{y},\boldsymbol{\theta}) \\ \boldsymbol{K}(\boldsymbol{y},\boldsymbol{\theta}) \end{bmatrix} = \boldsymbol{F}^{\top}(\boldsymbol{y},\boldsymbol{\theta})\boldsymbol{F}(\boldsymbol{y},\boldsymbol{\theta}) + \boldsymbol{K}^{\top}(\boldsymbol{y},\boldsymbol{\theta})\boldsymbol{K}(\boldsymbol{y},\boldsymbol{\theta}).$$

The right-hand side here is just the expression that appears in the fundamental result (14.20). Hence it is clear that the DLR must satisfy (14.26). All this discussion assumes, of course, that the matrices $\boldsymbol{F}(\boldsymbol{y},\boldsymbol{\theta})$ and $\boldsymbol{K}(\boldsymbol{y},\boldsymbol{\theta})$ satisfy appropriate regularity conditions, which may not always be easy to verify in practice; see Davidson and MacKinnon (1984a).

The DLR can be used in all the same ways that the GNR and the OPG regression can be used. In particular, it can be used

(i) to verify that the first-order conditions for a maximum of the loglikelihood function are satisfied sufficiently accurately,

(ii) to calculate estimated covariance matrices,

(iii) to calculate test statistics,

(iv) to calculate one-step efficient estimates, and

(v) as a key part of procedures for finding ML estimates.