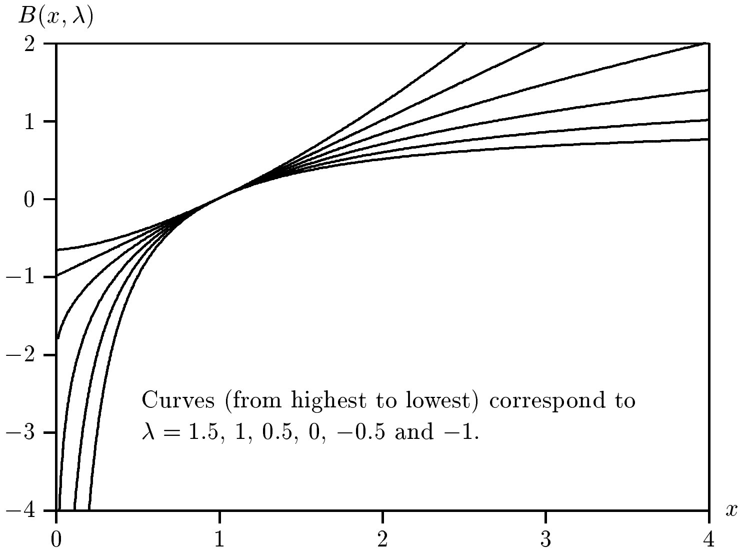

Figure 14.1 Box-Cox transformations for various values of λ

the regressors include a constant term, subjecting the dependent variable to a Box-Cox transformation with $\lambda = 1$ is equivalent to not transforming it at all. Subjecting it to a Box-Cox transformation with $\lambda = 0$ is equivalent to using $\log y_t$ as the regressand. Since these are both very plausible special cases, it is attractive to use a transformation that allows for both of them. Even when it is not considered plausible in its own right, the conventional Box-Cox model provides a convenient alternative against which to test the specification of linear and loglinear regression models; see Section 14.6.

The Box-Cox transformation is not without some serious disadvantages, however. Consider the simple Box-Cox model

$$B(y_t, \lambda) = x_t(\boldsymbol{\beta}) + u_t, \quad u_t \sim \mathrm{NID}(0, \sigma^2). \tag{14.07}$$

For most values of λ (but not for $\lambda = 0$ or $\lambda = 1$) the value of $B(y_t, \lambda)$ is bounded either from below or above; specifically, when $\lambda > 0$, $B(y_t, \lambda)$ cannot be less than $-1/\lambda$ and, when $\lambda < 0$, $B(y_t, \lambda)$ cannot be greater than $-1/\lambda$. However, if u_t is normally distributed, the right-hand side of (14.07) is not bounded and could, at least in principle, take on arbitrarily large positive or negative values. Thus, strictly speaking, (14.07) is logically impossible as a model for y_t. This remains true if we replace $x_t(\boldsymbol{\beta})$ by a regression function that depends on λ.

One way to deal with this problem is to assume that data on y_t are observed only when the bounds are not violated, as in Poirier (1978b) and Poirier and Ruud (1979). This leads to loglikelihood functions similar to