



**Figure 14.1** Box-Cox transformations for various values of  $\lambda$

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

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

For most values of  $\lambda$  (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  $x_t(\beta)$  by a regression function that depends on  $\lambda$ .

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