

Solution to Exercise 10.29

*10.29 Derive the loglikelihood function for the Box-Cox regression model (10.99). Then consider the following special case:

$$B(y_t, \lambda) = \beta_1 + \beta_2 B(x_t, \lambda) + u_t, \quad u_t \sim \text{NID}(0, \sigma^2).$$

Derive the OPG regression for this model and explain precisely how to use it to test the hypotheses that the DGP is linear ($\lambda = 1$) and loglinear ($\lambda = 0$).

As usual, we start with the density of u_t , which is

$$(2\pi)^{-1/2} \sigma^{-1} \exp\left(-\frac{1}{2} u_t^2 / \sigma^2\right).$$

We replace u_t by

$$B(y_t, \lambda) - \sum_{i=1}^{k_1} \beta_i z_{ti} - \sum_{i=k_1+1}^k \beta_i B(x_{ti}, \lambda)$$

and multiply by the Jacobian of the transformation, which is

$$\frac{\partial B(y_t, \lambda)}{\partial y_t} = y_t^{\lambda-1}. \quad (\text{S10.79})$$

Therefore, the contribution to the loglikelihood made by observation t is

$$\begin{aligned} \ell_t(\boldsymbol{\beta}, \lambda, \sigma) &= -\frac{1}{2} \log 2\pi - \frac{1}{2} \log \sigma^2 + (\lambda - 1) \log y_t \\ &\quad - \frac{1}{2\sigma^2} \left(B(y_t, \lambda) - \sum_{i=1}^{k_1} \beta_i z_{ti} - \sum_{i=k_1+1}^k \beta_i B(x_{ti}, \lambda) \right)^2. \end{aligned} \quad (\text{S10.80})$$

The third term here is the Jacobian term, which is the the logarithm of (S10.79) and vanishes when $\lambda = 1$. The loglikelihood function is the sum of the contributions given by expression (S10.80) over all t :

$$\begin{aligned} \ell(\boldsymbol{\beta}, \lambda, \sigma) &= -\frac{n}{2} \log 2\pi - \frac{n}{2} \log \sigma^2 + (\lambda - 1) \sum_{t=1}^n \log y_t \\ &\quad - \frac{1}{2\sigma^2} \sum_{t=1}^n \left(B(y_t, \lambda) - \sum_{i=1}^{k_1} \beta_i x_{ti} - \sum_{i=k_1+1}^k \beta_i B(x_{ti}, \lambda) \right)^2. \end{aligned} \quad (\text{S10.81})$$

In the special case given in the question, the contribution to the loglikelihood made by the t^{th} observation simplifies to

$$C - \frac{1}{2} \log \sigma^2 + (\lambda - 1) \log y_t - \frac{1}{2\sigma^2} \left(B(y_t, \lambda) - \beta_1 - \beta_2 B(x_t, \lambda) \right)^2, \quad (\text{S10.82})$$

where the constant $C \equiv -\frac{1}{2} \log 2\pi$ can be ignored for most purposes. The OPG regression has four regressors, each of which corresponds to one of the four parameters, β_1 , β_2 , λ , and σ . A typical element of each of these regressors is the derivative of (S10.82) with respect to the appropriate parameter. These derivatives are:

$$\begin{aligned}\beta_1: & \frac{1}{\sigma^2} (B(y_t, \lambda) - \beta_1 - \beta_2 B(x_t, \lambda)) \\ \beta_2: & \frac{1}{\sigma^2} (B(y_t, \lambda) - \beta_1 - \beta_2 B(x_t, \lambda)) B(x_t, \lambda) \\ \lambda: & \log y_t - \frac{1}{\sigma^2} (B(y_t, \lambda) - \beta_1 - \beta_2 B(x_t, \lambda)) (B'(y_t, \lambda) - \beta_2 B'(x_t, \lambda)) \\ \sigma: & -\frac{1}{\sigma} + \frac{1}{\sigma^3} (B(y_t, \lambda) - \beta_1 - \beta_2 B(x_t, \lambda))^2\end{aligned}$$

In the expression for the regressor that corresponds to λ , $B'(z, \lambda)$ denotes the derivative of $B(z, \lambda)$ with respect to λ , which is

$$\frac{\lambda z^\lambda \log z - z^\lambda + 1}{\lambda^2}. \quad (\text{S10.83})$$

For the OPG regression, the regressand is an n -vector of 1s, and the four regressors have the typical elements given above.

In order to test the hypothesis that the model is linear, that is, that $\lambda = 1$, we first regress y_t on a constant and x_t , obtaining parameter estimates under the null which we denote $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\sigma}$. We then evaluate the components of the OPG regression at these estimates and $\lambda = 1$. A typical observation of the OPG regression is

$$\begin{aligned}1 = & \frac{1}{\hat{\sigma}^2} (y_t - 1 - \hat{\beta}_1 - \hat{\beta}_2(x_t - 1)) c_1 \\ & + \frac{1}{\hat{\sigma}^2} (y_t - 1 - \hat{\beta}_1 - \hat{\beta}_2(x_t - 1)) (x_t - 1) c_2 \\ & + \left(\log y_t - \frac{1}{\hat{\sigma}^2} (y_t - 1 - \hat{\beta}_1 - \hat{\beta}_2(x_t - 1)) (B'(y_t, 1) - \hat{\beta}_2 B'(x_t, 1)) \right) c_3 \\ & + \left(\frac{1}{\hat{\sigma}^3} (y_t - 1 - \hat{\beta}_1 - \hat{\beta}_2(x_t - 1))^2 - \frac{1}{\hat{\sigma}} \right) c_4 + \text{residual},\end{aligned}$$

where, from (S10.83), we see that $B'(z, 1) = z \log z - z + 1$. To test the null hypothesis that $\lambda = 1$, we can use $n - \text{SSR}$ from this regression as a test statistic. It is asymptotically distributed as $\chi^2(1)$.

In order to test the hypothesis that the model is loglinear, that is, that $\lambda = 0$, we first regress $\log y_t$ on a constant and $\log x_t$, obtaining parameter estimates under the null which we denote $\tilde{\beta}_1$, $\tilde{\beta}_2$, and $\tilde{\sigma}$. We then evaluate the components of the OPG regression at these estimates and $\lambda = 0$. A typical

observation of the OPG regression is

$$\begin{aligned}
 1 &= \frac{1}{\tilde{\sigma}^2}(\log y_t - \tilde{\beta}_1 - \tilde{\beta}_2 \log x_t)c_1 \\
 &+ \frac{1}{\tilde{\sigma}^2}(\log y_t - \tilde{\beta}_1 - \tilde{\beta}_2 \log x_t) \log x_t c_2 \\
 &+ \left(\log y_t - \frac{1}{\tilde{\sigma}^2}(\log y_t - \tilde{\beta}_1 - \tilde{\beta}_2 \log x_t)(B'(y_t, 0) - \tilde{\beta}_2 B'(x_t, 0)) \right) c_3 \\
 &+ \left(\frac{1}{\tilde{\sigma}^3}(\log y_t - \tilde{\beta}_1 - \tilde{\beta}_2 \log x_t)^2 - \frac{1}{\tilde{\sigma}} \right) c_4 + \text{residual}.
 \end{aligned}$$

In the above regression, we need an expression for $B'(z, 1)$. If we attempt to evaluate expression (S10.83) at $\lambda = 0$, we find that both the numerator and the denominator equal 0. The first derivatives of both the numerator and the denominator are also equal to 0 when they are evaluated at $\lambda = 0$. However, the second derivatives at $\lambda = 0$ are equal to $(\log z)^2$ and 2, respectively. Thus l'Hôpital's Rule gives us the result that $B'(z, 0) = \frac{1}{2}(\log z)^2$.

To test the hypothesis that $\lambda = 0$, we once again use $n - \text{SSR}$ from the OPG regression. This test statistic is asymptotically distributed as $\chi^2(1)$ under the null hypothesis.