

function in (37). When the two quantities are different, we have the important case generalizing Tobit where the censoring is determined by different factors than determine the magnitude of the dependent variable when it is not censored. This would be the correct model (for example) for the demand for fertilizer if what determines whether a fanner uses fertilizer at all — perhaps the existence of a local extension agent — is different from what determines how much is used conditional on use perhaps the price of fertilizer, land quality, or the anticipated price of output.

For this generalized Tobit model, (36) and (37) imply that, if we condition on y being positive, the regression function is

$$z_i, Y_i > 0) = x_i\beta + A(z_i; 1) \quad (39)$$

where I have suppressed the zero suffix and where

$$A(z_i; 1) = E(u_{0i} | u_{2i} > z_i; y) \quad (40)$$

Equation (40) can also be applied to the case of truncation. In contrast to censoring, where we see zeros when the observation is censored, with truncation, the observation does not appear in the sample. In this case, although (40) holds, and although the switching equation (37) still explains the truncation, we cannot use it to estimate the switching parameters in the absence of the information that would have been contained in the truncated observations. We have only (40) to work with, and it is clear from inspection that identification, if it is to be achieved at all, will require strong supplementary assumptions. In cases where truncation cannot be avoided, it will rarely be possible to make a convincing separation between the truncation variables and the variables in the structural equation. With censoring, we have both (37) and (40) and, as we shall see below, identification is easier.

Heckman's general formulation can also be used to analyze the "policy evaluation" or "treatment" case that was discussed in the context of heterogeneity. In (36), set $u_1 = u_2$ and $\beta_0 = \beta$, except for the constant term. Equation (38) then becomes

$$y_i = \beta_0 + \beta x_i + u_i + \theta D_i + v_i \quad (41)$$

where the parameter θ is the difference between the two constant terms and captures the effect of the policy on the outcome. Given the structure of the model, and the determination of D_i by (37), the policy indicator will generally be correlated with the error term in (41) so that the policy effect cannot be consistently estimated by least squares. This is simply another way of looking at the same problem discussed above, that when we want to estimate the

