

# Selection Bias

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## 1.1 Heckman model

Consider a standard linear regression model

$$Y = \sum_{j=1}^K \beta_j X_j + \epsilon. \quad (1)$$

Given observed values  $\mathbf{Y}$  and design matrix  $X$ , we obtain the usual estimate  $\hat{\beta} = \hat{\Sigma}^{-1}X^T\mathbf{Y}$ . When fitting a regression model, the predictor values can be sampled in any way and it will not change our estimator of  $\hat{\beta}$ , it being defined by expectations conditioned on  $X$ . What concerns is situations where the response variable is filtered for censored in some way.

Heckman proposed a famous model for this. This idea is that there is an auxiliary variable  $W$  defined by

$$W = \sum_{j=1}^K \alpha_j X_j + \eta \quad (2)$$

We assume the covariance matrix of the noise terms is

$$\begin{bmatrix} \sigma_\epsilon^2 & \rho \\ \rho & \sigma_\eta^2 \end{bmatrix} \quad (3)$$

The observed  $Y$  are then selected based on the auxiliary process. We consider data points to be randomly selected based on  $W$  (in Heckman's formulation there is a sharp cutoff). We therefore introduce a new variable  $S$  which indicate whether data point  $i$  is selected and take

$$S \sim \text{Bernoulli}(h(W)) \quad (4)$$

for  $h : \mathbb{R} \rightarrow \mathbb{R}_{>0}$ . Combing everything,

$$Y|X \sim \text{Normal} \left( \sum_{j=1}^K \beta_j X_j, \sigma_\epsilon^2 \right) \quad (5)$$

$$W|X = \text{Normal} \left( \sum_{j=1}^K \alpha_j X_j, \sigma_\eta^2 \right) \quad (6)$$

$$S|W \sim \text{Bernoulli}(h(W)) \quad (7)$$

Also note that

$$\text{cov}(Y, W|X) = \rho \quad (8)$$

in fact the covariance matrix of  $Y|X$  and  $W|X$  are the same as  $\epsilon$  and  $\eta$ . We then define the selected sample as  $Y_s$ . What if we have observations of  $Y_s$ . Let's assume we have an estimate  $\hat{h}(W)$  of the conditional probability of

being selected conditioned on the auxiliary variable  $W$ . The idea is to define a regression model for  $Y$  among the selected samples. That is, for  $Y|X, W\{S = 1\}$ . We note that

$$Y = \sum_{j=1}^K \beta_j X_j + \epsilon = \sum_{j=1}^K \beta_j X_j \quad (9)$$

$$W = \sum_{j=1}^K \alpha_j \quad (10)$$