**Appendix 3**. The principle of Ordered Probit Regression

Due to our dependent variable is a discrete variable in order, and its distribution does not meet the requirements of the OLS model. Therefore, we use ordered probit regression to estimate the coefficient β1 and thus the total effect.

Assuming $y^* = \mathbf{x}'\boldsymbol{\beta} + \varepsilon$ ( $y^*$ is an unobservable variable), the selection rule is given by:

$$y = \begin{cases} 0, & y^* \le r_0 \\ 1, & r_0 \le y^* \le r_1 \\ 2, & r_1 \le y^* \le r_2 \\ \cdots\cdots\cdots\cdots & \\ J, & r_{J-1} \le y^*{}_2 \end{cases}$$

where $r_0 < r_1 < r_2 < \cdots < r_{J-1}$ are the parameters to be estimated, and are called "cutoff points .

Assuming $\varepsilon \sim N(0,1)$ (normalize the variance of the perturbation term $\varepsilon$ to 1), we have:

$$\begin{aligned}
\mathrm{P}(y=0 \mid x) &= \mathrm{P}(y^* \le r_0 \mid x) = \mathrm{P}(\mathbf{x}'\boldsymbol{\beta} + \varepsilon \le r_0 \mid x) \\
&= \mathrm{P}(\varepsilon \le r_0 - \mathbf{x}'\boldsymbol{\beta} \mid x) = \Phi(r_0 - \mathbf{x}'\boldsymbol{\beta}) \\
\mathrm{P}(y=1 \mid x) &= \mathrm{P}(r_0 \le y^* \le r_1 \mid x) = \mathrm{P}(y^* \le r_1 \mid x) - \mathrm{P}(y^* < r_0 \mid x) \\
&= \mathrm{P}(\mathbf{x}'\boldsymbol{\beta} + \varepsilon \le r_1 \mid x) - \Phi(r_0 - \mathbf{x}'\boldsymbol{\beta}) \\
&= \mathrm{P}(\varepsilon \le r_1 - \mathbf{x}'\boldsymbol{\beta} \mid x) - \Phi(r_0 - \mathbf{x}'\boldsymbol{\beta}) \\
&= \Phi(r_1 - \mathbf{x}'\boldsymbol{\beta}) - \Phi(r_0 - \mathbf{x}'\boldsymbol{\beta}) \\
\mathrm{P}(y=2 \mid x) &= \Phi(r_2 - \mathbf{x}'\boldsymbol{\beta}) - \Phi(r_1 - \mathbf{x}'\boldsymbol{\beta}) \\
&\cdots\cdots\cdots\cdots \\
\mathrm{P}(y=J \mid x) &= 1 - \Phi(r_{J-1} - \mathbf{x}'\boldsymbol{\beta})
\end{aligned}$$

In this way, the sample likelihood function is obtained to further obtain the MLE estimator, i.e. the ordered probit model.