

Econometric Methods

PC-tutorial: M-Estimation

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Example 1: the impact of education on woman's fertility. The dependent variable, *children*: number of living children, is non-negative value

$$E(\text{children}|x) = \exp(x\beta)$$

Example 2¹: y is the probability of owning home ($0 \leq y \leq 1$) and x is income

$$E(y|x) = \frac{\exp(x\beta)}{1+\exp(x\beta)}$$

¹Basic Econometrics, Gujarati and Porter

M-Estimation

the nonlinear conditional expectation model (θ_0 is true parameters)

$$E(y|x) = m(x, \theta_0) \quad (1)$$

The M estimators $\hat{\theta}$ minimizes the certain sample functions

$$\min_{\theta \in \Theta} N^{-1} \sum_{i=1}^N q(w_i, \theta) \quad (2a)$$

$q(w_i, \theta)$ is objective function, where $w_i = (y_i, x_i)$

Non-linear least squares (NLS)

$$\min_{\theta \in \Theta} N^{-1} \sum_{i=1}^N q(w_i, \theta) = N^{-1} \sum_{i=1}^N [y_i - m(x_i, \theta)]^2 \quad (3a)$$

Stata command for NSL `nls`

Interpretation: Marginal effects at mean(MEM) and Average marginal effects (AME)

Example: we are interest in the effects of education on woman's fertility

Linear regression

$$children = \beta_0 + \beta_1 educ + z\gamma + u = x\beta + u \quad (4)$$

$$\frac{\partial E(children|x)}{\partial educ} = \beta_1 = const$$

Non-linear regression

$$children = \exp(\beta_0 + \beta_1 educ + z\gamma) + u = \exp(x\beta) + u \quad (5)$$

$\frac{\partial E(children|x)}{\partial educ} = \beta_1 \exp(x\beta)$, depends on the value of educ, and others control variables. This is also called the **marginal effect**

Marginal effects at means (MEM): the marginal effects evaluated at the average values of the regressors.

$$MEM = \frac{\partial children}{\partial educ} | (x = \bar{x}) = \hat{\beta}_1 \exp(\bar{x} \hat{\beta}) \quad (6)$$

Example: MEM of education is -0.04 means keeping other variables at their average values, one additional year of education from its average value of 5 to 6 years has negative impact on the woman's fertility .

Average marginal effects (AME): the marginal effects averaged across all observations in the data:

$$AME = \frac{1}{N} \sum_i^N \left(\frac{\partial children}{\partial educ} | x = x_i \right) = \frac{1}{N} \sum_i^N \hat{\beta}_i \exp(x_i \hat{\beta}) \quad (7)$$

Example: AME of education is -0.043 means one additional year of education leads to an decrease in the number of living children by 0.043 on average while keeping other variables constant.

Consider the Stata dataset `fertil2.dta`. The aim is to estimate the effects of education on women's fertility in Botswana. Estimate the model

$$children = \exp(x\beta) + u \quad (8)$$

the response variable, *children*, is the number of living children. The explanatory variables x are years of schooling (*educ*), age of the woman (*age*), age squared (*agesq*), and binary indicators for ever married (*evermarr*), living in an urban area (*urban*), having electricity (*electric*), and owning a television (*tv*).

- a) Estimate the model by apply the nonlinear least squares with initial values of zero. Why may this model be more appropriate than linear OLS?

$$E(y|x) = \exp(x\beta)$$

M-estimator $\hat{\theta}$ minimizes

$$\min \sum_i^N (y_i - \exp(x_i\beta))^2$$

Stata command for nls : `nls` Stata solves the minimization problem by running iterative method, which requires **initial values for parameters**.

- b) Re-estimate with different initial values. Discuss.

- c) Compute the average partial effects of education and age
- d) Compute the partial effects of education and age at the sample average. Interpret. What may be “problematic” with using a sample average?
- e) Compute the partial effects of education and age at $\text{educ} = 5$, $\text{evermarr} = 0$, $\text{urban} = 0$, $\text{electric} = 0$, $\text{tv} = 0$ for different ages of 15, 20, . . . , 45 years. Interpret your results.

Consider the crime data set of Agresti and Finlay (1997) for the US states. Suppose the violent crime rate $crime_i$ (number of violent crimes per 100,000 people) can be explained by the covariates $poverty_i$ (percent of population living under poverty line), $single_i$ (percent of population that are single parents), and a constant. Assume there are no endogeneity problems like reverse causality.

- a) Load the data set into Stata and perform a robust regression using the command `rreg crime poverty single`.

Stata then applies a robust regression technique that partially relies on the Huber estimator. Interpret the estimated parameter values. Are they statistically and economically significant?

Model:

$$crime = \beta_0 + \beta_1 poverty + \beta_2 single + u \quad (9)$$

Robust regression (`rreg`), Stata doesn't provide robust standard errors for `rreg`

- b) Compare the results to an OLS regression. Is the difference in estimated effects relevant?
- c) To understand why there are differences, regress $crime_i$ on $poverty_i$ using (i) robust estimation, (ii) OLS estimation, and (iii) OLS estimation excluding the last observation (... if $state \neq "dc"$). Predict $crime_i$ in each case. Then scatter $crime_i$ against $poverty_i$ and add the three regression lines to this scatter graph. Discuss your findings.