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Econometrics

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Binary dep. var., LPM, Logit Model, Odds Ratio, Marginal Effect, predicted probability, Pseudo- R^2 , Maximum Likelihood

Saturated Model: (Ex, $y = \alpha + \beta \text{single} + \delta \text{male} + \epsilon(\text{single} \text{male}) + \eta$)

We have a parameter for Difference-in-Difference

⊕ Parallel Trend Assumption (?)

Considering binary variables as dependent variables

$$\text{i.e. } \text{Vote}_i = \alpha_0 + \alpha_1 \text{Income}_i + \eta$$

LPM: Linear Probability Model

generating a dummy variable in STATA: `gen d = wage > 574`

Benefits of LPM: Simplicity (to run, estimate, interpret)

Coefficients are marginal effects

We get goodness-of-fit statistics (R^2)

Unbiased (By Gauss-Markov)

Disadvantage of LPM: $P > 1$ or $P < 0$

STATA: `wfplot` (Residuals are ^{not randomly distributed} totally linear)

$$\text{Var} = \beta(1-\beta) \text{ [Violates homoskedasticity]}$$

Logit Model

$$\Pr(y=1|x) = \beta_0 + \beta_1 x + \eta \quad (\text{or} = \beta_0 x)$$

$$\Lambda(z) = \frac{e^z}{1+e^z} \Rightarrow \Lambda(-\infty) = 0 \quad \Lambda(\infty) = 1$$

$$\Pr(y=1|x) = \Lambda(\beta_0 x) = \frac{e^{\beta_0 x}}{1+e^{\beta_0 x}}$$

$$p = \frac{e^z}{1+e^z} \Rightarrow e^z = \frac{p}{1-p}$$

Odd Ratio

$$z = \ln\left(\frac{p}{1-p}\right)$$

STATA: logit d educ exper

Ask about the difference

The coefficient is the effect on the odd ratio

Use logistic d educ exper

The co-efficient is the impact on odd ratio

STATA: use mfx for marginal probability
~~use eif to plot the mfx~~

Pseudo-R²

$$\text{Pseudo-R}^2 = 1 - \frac{d_1}{d_0} \quad (\text{Log(Likelihood)})$$

Log(Likelihood)

$$y = [1 \ 0 \ 0 \ 1 \ x] \quad (\text{ex.})$$

What are the values of β_0 and β_1 that maximize the likelihood (probability) of observing the data.

We have $\prod p(y_i) = e^{\sum \ln(p(y_i))}$

Probit Model

$$\Pr(y=1|x) = \Phi(\beta x)$$

STATA:

probit d educ exper

Near the averages :

Logit = 4 OLS

Probit = 2.5 OLS

Logit = 1.6 OLS

{ Rule of
Thumb }

