

## Nonlinear Least Squares (NLS)

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## Nonlinear Least Squares

- ▶ So far we considered regression models that are linear in parameters.
- ▶ We are able to handle certain types of nonlinearity by transforming regressors and dependent variable in the linear regression model framework.
- ▶ However, there many other types of nonlinearity that cannot be handles within this framework. In this case we need to estimate nonlinear regression models.
- ▶ In nonlinear regression models conditional expectation of  $y_i$  with respect to the information set  $\Omega_i$  is a nonlinear function of the parameters.
- ▶ We assume that no transformation exists to make the model linear in parameters (e.g., natural log transformation).

## Nonlinear Least Squares

- ▶ A nonlinear regression can be written as

$$y_i = f(\mathbf{x}_i, \boldsymbol{\beta}) + u_i, \quad E(u_i) = 0, \quad E(u_i^2) = \sigma^2, \quad \forall i. \quad (1)$$

where

$$\mathbf{x}_i = [x_{1i}, x_{2i}, \dots, x_{ki}]^T, \quad i = 1, \dots, n$$

- ▶ Under the assumption that the functional form is correctly specified

$$E[y_i | \mathbf{x}_i] = f(\mathbf{x}_i, \boldsymbol{\beta}), \quad i = 1, 2, \dots, n.$$

where  $f(\cdot)$  is a twice differentiable function.

- ▶ The nonlinear function  $f(\mathbf{x}_i, \boldsymbol{\beta})$  determines the value of  $y_i$  conditional on the information set  $\Omega_i$  which usually consists of some set of explanatory variables.
- ▶ These explanatory variables may include lagged values of the dependent variable (if we have a time series or panel data) and exogenous variables.

## Nonlinear Least Squares

- ▶ The NLS objective function is

$$Q(\boldsymbol{\beta}) = \frac{1}{2} \sum_{i=1}^n (y_i - f(\mathbf{x}_i, \boldsymbol{\beta}))^2 \quad (2)$$

- ▶ and the NLS estimator is

$$\hat{\boldsymbol{\beta}} = \arg \min_{\boldsymbol{\beta}} Q(\boldsymbol{\beta}) \quad (3)$$

- ▶ FOC:

$$\frac{\partial Q(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}} = - \sum_{i=1}^n (y_i - f(\mathbf{x}_i, \boldsymbol{\beta})) \frac{\partial f(\mathbf{x}_i, \boldsymbol{\beta})}{\partial \boldsymbol{\beta}} = \mathbf{0} \quad (4)$$

## Nonlinear Least Squares

Let the  $n \times k$  matrix  $\mathbf{G}$  be the first derivatives of the nonlinear function whose typical element is

$$g_{ij} = \frac{\partial f(\mathbf{x}_i, \boldsymbol{\beta})}{\partial \beta_j}, \quad i = 1, \dots, n, \quad j = 1, \dots, k$$

Using this we can write:

$$-\mathbf{G}^\top (\mathbf{y} - f(\mathbf{X}, \boldsymbol{\beta})) = \mathbf{0}. \quad (5)$$

Under certain assumptions the NLS estimator has an asymptotic normal distribution:

$$\sqrt{n}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}) \rightarrow N \left( 0, \sigma^2 \text{plim}_{n \rightarrow \infty} \left( \frac{1}{n} \mathbf{G}^\top \mathbf{G} \right)^{-1} \right) \quad (6)$$

where  $\boldsymbol{\beta}$  is the unknown true parameter vector,  $\sigma^2$  is the unknown true variance of the error term and  $\mathbf{G}$  is the first derivative matrix evaluated at the true parameter vector.

## Nonlinear Least Squares

In practice the covariance matrix can be estimated using

$$V(\hat{\boldsymbol{\beta}}) = s^2 (\hat{\mathbf{G}}^\top \hat{\mathbf{G}})^{-1} \quad (7)$$

where  $s^2$  is an unbiased estimator of the error variance:

$$s^2 = \frac{1}{n - k} \sum_{t=1}^n \left( y_i - f(\mathbf{x}_i, \hat{\boldsymbol{\beta}}) \right)^2.$$

$\hat{\mathbf{G}}$  is the first derivative matrix evaluated at the NLS solution  $\hat{\boldsymbol{\beta}}$ .

## Nonlinear Least Squares

### Example (DM,p.212)

Consider the following model:

$$y_i = \beta_1 + \beta_2 x_{i1} + \frac{1}{\beta_2} x_{i2} + u_i$$

Here the nonlinear part is

$$f(\mathbf{x}_i, \boldsymbol{\beta}) = \beta_1 + \beta_2 x_{i1} + \frac{1}{\beta_2} x_{i2}$$

### Example (The Linear Regression Model with AR(1) Errors (Davidson and MacKinnon, p.212))

Consider the following linear regression model for time series data:

$$y_t = \mathbf{X}_t \boldsymbol{\beta} + u_t$$

where  $u_t$  follows a first order autoregressive process:

$$u_t = \rho u_{t-1} + \epsilon_t, \quad \epsilon_t \sim iid(0, \sigma_\epsilon^2)$$

Substituting  $\rho u_{t-1} + \epsilon_t$  for  $u_t$  and then replacing  $u_{t-1}$  by  $y_{t-1} - \mathbf{X}_{t-1} \boldsymbol{\beta}$  we obtain

$$y_t = \rho y_{t-1} + \mathbf{X}_t \boldsymbol{\beta} - \rho \mathbf{X}_{t-1} \boldsymbol{\beta} + \epsilon_t, \quad \epsilon_t \sim iid(0, \sigma_\epsilon^2)$$

which is nonlinear in parameters. The model cannot be estimated by OLS. Instead we need to use NLS.

### Example (CES Production Function)

A flexible form for the production function is the constant elasticity of substitution (CES):

$$y = \alpha (\delta L^{-\gamma} + (1 - \delta)K^{-\gamma})^{-\lambda/\gamma}$$

where  $y$  is output,  $K$  is capital and  $L$  is labor, and  $\alpha > 0$ ,  $0 < \delta < 1$ ,  $\gamma \geq -1$ . Elasticity of substitution is given by

$$s = \frac{d \log(K/L)}{d \log(MP_L/MP_K)} = \frac{1}{1 + \gamma} \geq 0$$

where  $MP_j$  is the marginal product of inputs,  $j = K, L$ . Taking natural logs and adding an error term we obtain a nonlinear model:

$$\log(y) = \log(\alpha) - \frac{\lambda}{\gamma} \log(\delta L^{-\gamma} + (1 - \delta)K^{-\gamma}) + u$$

An alternative to this model is translog production function which can be estimated by OLS.

### NLS Application 1: Consumption Function

- ▶ This example is from Greene (p.191)
- ▶ Consider the following nonlinear consumption function:

$$C = \alpha + \beta Y^\gamma + u$$

- ▶ If we assume that  $\gamma$  the model becomes linear in parameters.
- ▶ We will use income and consumption data for the US economy 1950Q1-2000Q4
- ▶ STATA: TableF5-2.dta

### NLS Application 1: Consumption Function

```
. nl (realcons = {alpha=400} + {beta=1}*realdpi^{gamma=1} )
(obs = 204)
```

Source	SS	df	MS
Model	432036555	2	216018277
Residual	504403.222	201	2509.46877
Total	432540958	203	2130743.64

Number of obs =	204
R-squared =	0.9988
Adj R-squared =	0.9988
Root MSE =	50.0946
Res. dev. =	2172.781

  

realcons	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
/alpha	458.7991	22.50139	20.39	0.000	414.4301 503.1682
/beta	.100852	.0109104	9.24	0.000	.0793386 .1223655
/gamma	1.244828	.0120548	103.26	0.000	1.221057 1.268598

Parameter alpha taken as constant term in model & ANOVA table

```
. matrix list e(V)
```

```
symmetric e(V) [3,3]
```

	alpha: _cons	beta: _cons	gamma: _cons
alpha:_cons	506.31259		
beta:_cons	-.2345446	.00011904	
gamma:_cons	.25756744	-.00013149	.00014532

### NLS Application 2: CES Production Function

- ▶ CES production function

$$\log(y) = \log(\alpha) - \frac{\lambda}{\gamma} \log(\delta L^{-\gamma} + (1 - \delta)K^{-\gamma}) + u$$

- ▶ Elasticity of substitution

$$s = \frac{1}{1 + \gamma} \geq 0$$

- ▶ STATA: production.dta

## Example: CES Production Function

```
nl (logQ = log({alpha=1}) - ({lambda=1}/{gamma=1})*
    log( {delta=0.5}*L^(-1*{gamma}) + (1-{delta})*K^(-1*{gamma}) ) )
```

Source	SS	df	MS	
Model	91.1542478	3	30.3847493	Number of obs = 100
Residual	29.3565583	96	.305797482	R-squared = 0.7564
Total	120.510806	99	1.21728087	Adj R-squared = 0.7488
				Root MSE = .5529896
				Res. dev. = 161.2223

logQ	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
/alpha	44.32413	4.51106	9.83	0.000	35.36975 53.27851
/lambda	.9888227	.0632858	15.62	0.000	.8632014 1.114444
/gamma	1.432666	.5570501	2.57	0.012	.3269304 2.538402
/delta	.5193183	.0552948	9.39	0.000	.4095589 .6290776

Parameter alpha taken as constant term in model & ANOVA table

## Example: CES Production Function

```
. // Elasticity of substitution
. nlcom (1 / (1+_b[/gamma]))
```

```
_nl_1: 1 / (1+_b[/gamma])
```

logQ	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
_nl_1	.4110716	.0941303	4.37	0.000	.2242246