

## ECON 452\*: Stata 11 Tutorial 9

**TOPIC:** Estimating and Interpreting Probit Models with Stata: Extensions

**DATA:** `mroz.dta` (a *Stata*-format dataset you created in *Stata 11 Tutorial 8*)

**TASKS:** *Stata 11 Tutorial 9* is an extension of *Stata 11 Tutorial 8*, and therefore deals with the estimation, testing, and interpretation of *probit models* for binary dependent variables. In particular, it illustrates how to use a cross-sectional sample of married women in the United States to investigate *whether and how the probability of labour force participation differs between two distinct groups of married women, namely (1) married women who have one or more pre-school aged children and (2) married women who have no pre-school aged children.* It demonstrates how *Stata* can be used to conduct an econometric investigation into differences in the conditional probability of labour force participation between these two distinct groups of married women.

- The *Stata* **commands** that constitute the primary subject of this tutorial are:

<b>probit</b>	Used to compute ML estimates of <i>probit coefficients</i> in probit models of binary dependent variables.
<b>dprobit</b>	Used to compute ML estimates of the <b>marginal probability effects</b> of explanatory variables in probit models.
<b>test</b>	Used after probit estimation to compute <i>Wald tests</i> of linear coefficient equality restrictions on probit coefficients.
<b>lincom</b>	Used after probit estimation to compute and test the marginal effects of individual explanatory variables.

- The *Stata* statistical functions used in this tutorial are:

**normalden(z)** Computes *value of the standard normal density function (p.d.f.)* for a given value  $z$  of a standard normal random variable.

**normal(z)** Computes *value of the standard normal distribution function (c.d.f.)* for a given value  $z$  of a standard normal random variable.

**invnormal(p)** Computes *the inverse of the standard normal distribution function*; if  $\text{normal}(z) = p$ , then  $\text{invnormal}(p) = z$ .

**NOTE:** *Stata* commands are *case sensitive*. All *Stata* command names must be typed in the Command window in **lower case letters**.

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## □ Two Probit Models of Married Women's Participation: Specification of Models 2 and 3

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We consider two different models of married women's labour force participation.

- **Model 2** was introduced in *Stata 11 Tutorial 8*. The **binary indicator variable**  $dkidslt6_i$  enters only as an **additive regressor**.
- **Model 3** is a generalization of Model 2: it allows all probit coefficients to differ between (1) married women who currently have one or more pre-school aged children and (2) married women who currently have no pre-school aged children. The **binary explanatory variable**  $dkidslt6_i$  enters both **additively and multiplicatively**.

The **observed dependent variable** in both models is the binary variable  $inlf_i$  defined as follows:

$inlf_i = 1$  if the  $i$ -th married woman is in the employed labour force  
 $= 0$  if the  $i$ -th married woman is not in the employed labour force

The **explanatory variables** in Models 2 and 3 are:

$nwifeinc_i$  = non-wife family income of the  $i$ -th woman (in thousands of dollars per year);  
 $ed_i$  = years of formal education of the  $i$ -th woman (in years);  
 $exp_i$  = years of actual work experience of the  $i$ -th woman (in years);  
 $age_i$  = age of the  $i$ -th woman (in years);  
 $dkidslt6_i$  = 1 if the  $i$ -th woman has one or more children less than 6 years of age, = 0 otherwise.

Four of these explanatory variables --  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$  -- are **continuous** variables, whereas the fifth explanatory variable --  $dkidslt6_i$  -- is a **binary** indicator (dummy) variable.

**Model 2 – binary explanatory variable  $dkidslt6_i$  enters only additively**

The **probit index function for Model 2** is:

$$\mathbf{x}_i^T \boldsymbol{\beta} = \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i + \beta_6 \text{dkidslt6}_i$$

**Remarks:** In Model 2, the binary explanatory variable  $dkidslt6_i$  enters only additively; only the intercept coefficient in the index function differs between the two groups of married women, those who have pre-school aged children and those who do not.

- ◆ In Model 2, the probit index function for *married women who have no pre-school aged children*, for whom  $dkidslt6_i = 0$ , is obtained by setting  $dkidslt6_i = 0$  in the index function for Model 2:

$$\begin{aligned} (\mathbf{x}_i^T \boldsymbol{\beta} \mid \text{dkidslt6}_i = 0) &= \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i + \beta_6 0 \\ &= \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i \end{aligned}$$

- ◆ In Model 2, the probit index function for *married women who have one or more pre-school aged children*, for whom  $dkidslt6_i = 1$ , is obtained by setting  $dkidslt6_i = 1$  in the index function for Model 2:

$$\begin{aligned} (\mathbf{x}_i^T \boldsymbol{\beta} \mid \text{dkidslt6}_i = 1) &= \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i + \beta_6 1 \\ &= \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i + \beta_6 \end{aligned}$$

- ◆ In Model 2, the **marginal index effect** of the **binary indicator variable**  $dkidslt6_i$  is simply the difference between (1) the index function for *married women who currently have one or more pre-school aged children*,  $(x_i^T \beta | dkidslt6_i = 1)$  and (2) the index function for *married women who currently have no pre-school aged children*,  $(x_i^T \beta | dkidslt6_i = 0)$ :

$$\begin{aligned}
 & (x_i^T \beta | dkidslt6_i = 1) - (x_i^T \beta | dkidslt6_i = 0) \\
 &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \beta_6 \\
 &\quad - (\beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i) \\
 &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \beta_6 \\
 &\quad - \beta_0 - \beta_1 nwifeinc_i - \beta_2 ed_i - \beta_3 exp_i - \beta_4 exp_i^2 - \beta_5 age_i \\
 &= \beta_6
 \end{aligned}$$

- ◆ In Model 2, the **marginal probability effect** of the **binary indicator variable**  $dkidslt6_i$  is the difference between (1) the conditional probability that  $\mathbf{inlf}_i = 1$  for *married women with one or more pre-school aged children* and (2) the conditional probability that  $\mathbf{inlf}_i = 1$  for *married women with no pre-school aged children*:

$$\Pr(\mathbf{inlf}_i = 1 | dkidslt6_i = 1) - \Pr(\mathbf{inlf}_i = 1 | dkidslt6_i = 0) = \Phi(\mathbf{x}_{1i}^T \boldsymbol{\beta}) - \Phi(\mathbf{x}_{0i}^T \boldsymbol{\beta})$$

where  $\Phi(*)$  is the cumulative distribution function (cdf) of the standard normal distribution and

$$\mathbf{x}_{1i}^T = (1 \text{ nwifeinc}_i \text{ ed}_i \text{ exp}_i \text{ exp}_i^2 \text{ age}_i \ 1)$$

$$\mathbf{x}_{0i}^T = (1 \text{ nwifeinc}_i \text{ ed}_i \text{ exp}_i \text{ exp}_i^2 \text{ age}_i \ 0)$$

$$\boldsymbol{\beta} = (\beta_0 \ \beta_1 \ \beta_2 \ \beta_3 \ \beta_4 \ \beta_5 \ \beta_6)^T$$

$$\mathbf{x}_{1i}^T \boldsymbol{\beta} = \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i + \beta_6$$

$$\mathbf{x}_{0i}^T \boldsymbol{\beta} = \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i$$

$$\Pr(\mathbf{inlf}_i = 1 | dkidslt6_i = 1) = \Phi(\mathbf{x}_{1i}^T \boldsymbol{\beta}) = \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i + \beta_6)$$

$$\begin{aligned} \Pr(\mathbf{inlf}_i = 1 | dkidslt6_i = 0) &= \Phi(\mathbf{x}_{0i}^T \boldsymbol{\beta}) = \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i + \beta_6 \cdot 0) \\ &= \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i) \end{aligned}$$

Thus, the **marginal probability effect of the indicator variable  $dkidslt6_i$  in Model 2** is

$$\begin{aligned} \Pr(\text{inlf}_i = 1 \mid dkidslt6_i = 1) - \Pr(\text{inlf}_i = 1 \mid dkidslt6_i = 0) &= \Phi(\mathbf{x}_{1i}^\top \boldsymbol{\beta}) - \Phi(\mathbf{x}_{0i}^\top \boldsymbol{\beta}) \\ &= \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i + \beta_6) \\ &\quad - \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i) \end{aligned}$$



**Model 3** – a full interaction model in the binary variable  $dkidslt6_i$ 

The **probit index function**, or regression function, for **Model 3** is:

$$\begin{aligned} x_i^T \beta &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \beta_6 dkidslt6_i \\ &\quad + \beta_7 dkidslt6_i nwifeinc_i + \beta_8 dkidslt6_i ed_i + \beta_9 dkidslt6_i exp_i + \beta_{10} dkidslt6_i exp_i^2 + \beta_{11} dkidslt6_i age_i \end{aligned}$$

**Remarks:** Model 3 is the *full-interaction* generalization of Model 2: it interacts the  $dkidslt6_i$  indicator variable with all the other regressors in Model 2, and thereby permits all index function coefficients to differ between the two groups of married women distinguished by  $dkidslt6_i$ .

- ◆ In Model 3, the **probit index function** for *married women who currently have no pre-school aged children*, for whom  $dkidslt6_i = 0$ , is obtained by setting  $dkidslt6_i = 0$  in the index function for Model 3:

$$(x_i^T \beta | dkidslt6_i = 0) = \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i$$

- ◆ In Model 3, the **probit index function** for *married women who currently have one or more pre-school aged children*, for whom  $dkidslt6_i = 1$ , is obtained by setting  $dkidslt6_i = 1$  in the index function for Model 3:

$$\begin{aligned} (x_i^T \beta | dkidslt6_i = 1) &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i \\ &\quad + \beta_6 1 + \beta_7 1 \cdot nwifeinc_i + \beta_8 1 \cdot ed_i + \beta_9 1 \cdot exp_i + \beta_{10} 1 \cdot exp_i^2 + \beta_{11} 1 \cdot age_i \\ &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \beta_6 + \beta_7 nwifeinc_i + \beta_8 ed_i + \beta_9 exp_i + \beta_{10} exp_i^2 + \beta_{11} age_i \\ &= \beta_0 + \beta_6 + (\beta_1 + \beta_7) nwifeinc_i + (\beta_2 + \beta_8) ed_i + (\beta_3 + \beta_9) exp_i + (\beta_4 + \beta_{10}) exp_i^2 + (\beta_5 + \beta_{11}) age_i \end{aligned}$$

- ◆ In Model 3, the **marginal index effect** of the **binary indicator variable**  $dkidslt6_i$  is simply the difference between (1) the index function for *married women who currently have one or more pre-school aged children*,  $(x_i^T \beta | dkidslt6_i = 1)$  and (2) the index function for *married women who currently have no pre-school aged children*,  $(x_i^T \beta | dkidslt6_i = 0)$ :

$$\begin{aligned}
 & (x_i^T \beta | dkidslt6_i = 1) - (x_i^T \beta | dkidslt6_i = 0) \\
 &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \beta_6 + \beta_7 nwifeinc_i + \beta_8 ed_i + \beta_9 exp_i + \beta_{10} exp_i^2 + \beta_{11} age_i \\
 &\quad - (\beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i) \\
 &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \beta_6 + \beta_7 nwifeinc_i + \beta_8 ed_i + \beta_9 exp_i + \beta_{10} exp_i^2 + \beta_{11} age_i \\
 &\quad - \beta_0 - \beta_1 nwifeinc_i - \beta_2 ed_i - \beta_3 exp_i - \beta_4 exp_i^2 - \beta_5 age_i \\
 &= \beta_6 + \beta_7 nwifeinc_i + \beta_8 ed_i + \beta_9 exp_i + \beta_{10} exp_i^2 + \beta_{11} age_i
 \end{aligned}$$

- ◆ In Model 3, the **marginal probability effect** of the **binary indicator variable**  $dkidslt6_i$  is the difference between (1) the conditional probability that  $\mathbf{inlf}_i = 1$  for *married women with one or more pre-school aged children* and (2) the conditional probability that  $\mathbf{inlf}_i = 1$  for *married women with no pre-school aged children*:

$$\Pr(\mathbf{inlf}_i = 1 | dkidslt6_i = 1) - \Pr(\mathbf{inlf}_i = 1 | dkidslt6_i = 0) = \Phi(\mathbf{x}_{1i}^T \boldsymbol{\beta}) - \Phi(\mathbf{x}_{0i}^T \boldsymbol{\beta})$$

where  $\Phi(*)$  is the cumulative distribution function (cdf) of the standard normal distribution and

$$\mathbf{x}_{1i}^T = (1 \text{ nwifeinc}_i \text{ ed}_i \text{ exp}_i \text{ exp}_i^2 \text{ age}_i \text{ 1 nwifeinc}_i \text{ ed}_i \text{ exp}_i \text{ exp}_i^2 \text{ age}_i)$$

$$\mathbf{x}_{0i}^T = (1 \text{ nwifeinc}_i \text{ ed}_i \text{ exp}_i \text{ exp}_i^2 \text{ age}_i \text{ 0 0 0 0 0 0})$$

$$\boldsymbol{\beta} = (\beta_0 \beta_1 \beta_2 \beta_3 \beta_4 \beta_5 \beta_6 \beta_7 \beta_8 \beta_9 \beta_{10} \beta_{11})^T$$

$$\begin{aligned} \mathbf{x}_{1i}^T \boldsymbol{\beta} &= \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i \\ &\quad + \beta_6 + \beta_7 \text{nwifeinc}_i + \beta_8 \text{ed}_i + \beta_9 \text{exp}_i + \beta_{10} \text{exp}_i^2 + \beta_{11} \text{age}_i \end{aligned}$$

$$\mathbf{x}_{0i}^T \boldsymbol{\beta} = \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i$$

$$\begin{aligned} \Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 1) &= \Phi \left( \begin{array}{l} \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i \\ + \beta_6 + \beta_7 \text{nwifeinc}_i + \beta_8 \text{ed}_i + \beta_9 \text{exp}_i + \beta_{10} \text{exp}_i^2 + \beta_{11} \text{age}_i \end{array} \right) \\ &= \Phi \left( \begin{array}{l} (\beta_0 + \beta_6) + (\beta_1 + \beta_7) \text{nwifeinc}_i + (\beta_2 + \beta_8) \text{ed}_i \\ + (\beta_3 + \beta_9) \text{exp}_i + (\beta_4 + \beta_{10}) \text{exp}_i^2 + (\beta_5 + \beta_{11}) \text{age}_i \end{array} \right) \end{aligned}$$

$$\begin{aligned} \Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 0) &= \Phi \left( \begin{array}{l} \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i \\ + \beta_6 0 + \beta_7 0 + \beta_8 0 + \beta_9 0 + \beta_{10} 0 + \beta_{11} 0 \end{array} \right) \\ &= \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i) \end{aligned}$$

Thus, the **marginal probability effect of the indicator variable  $\text{dkidslt6}_i$**  in Model 3 is

$$\begin{aligned} &\Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 1) - \Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 0) = \\ &\Phi \left( \begin{array}{l} \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i \\ + \beta_6 + \beta_7 \text{nwifeinc}_i + \beta_8 \text{ed}_i + \beta_9 \text{exp}_i + \beta_{10} \text{exp}_i^2 + \beta_{11} \text{age}_i \end{array} \right) \\ &- \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i) \end{aligned}$$

We are concerned with **three aspects** of the **marginal probability effect of the indicator variable  $\text{dkidslt6}_i$** :

1. the **existence** of the **marginal probability effect of the indicator variable  $\text{dkidslt6}_i$** ;
2. the **direction** (**sign**) of the **marginal probability effect of the indicator variable  $\text{dkidslt6}_i$** ;
3. the **magnitude** (**size**) of the **marginal probability effect of the indicator variable  $\text{dkidslt6}_i$** .

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□ **Testing the marginal *probability* effect of the binary explanatory variable  $dkidslt6_i$  -- *test* and *lincom***

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**Proposition to be Tested**

- ♦ Does the ***conditional probability of labour force participation*** for married women depend on the presence in the family of one or more dependent children under 6 years of age?
- ♦ Is the probability of labour force participation for married women with given values of  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$  who currently have one or more pre-school aged children equal to the probability of labour force participation for married women with the same values of  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$  who currently have no pre-school aged children?
- ♦ Is it true that

$$\begin{aligned} & \Pr(\text{inlf}_i = 1 \mid dkidslt6_i = 1, nwifeinc_i, ed_i, exp_i, age_i) \\ &= \Pr(\text{inlf}_i = 1 \mid dkidslt6_i = 0, nwifeinc_i, ed_i, exp_i, age_i)? \end{aligned}$$

**Null and Alternative Hypotheses: General Formulation**

The ***null hypothesis*** in general is:

$$H_0: \Pr(\text{inlf}_i = 1 \mid dkidslt6_i = 1, \dots) = \Pr(\text{inlf}_i = 1 \mid dkidslt6_i = 0, \dots)$$

The ***alternative hypothesis*** in general is:

$$H_1: \Pr(\text{inlf}_i = 1 \mid dkidslt6_i = 1, \dots) \neq \Pr(\text{inlf}_i = 1 \mid dkidslt6_i = 0, \dots)$$

### Testing the Existence of the Marginal Probability Effect of the Indicator Variable $dkidslt6_i$

For testing the *existence of a relationship* between any explanatory variable and the probability that the observed dependent variable equals 1, use either of the two *Stata* commands for probit estimation: use *either* the **probit** command *or* the **dprobit** command.

#### Null and Alternative Hypotheses: Model 2

The null hypothesis in general is:

$$H_0: \Pr(\text{inlf}_i = 1 | \text{dkidslt6}_i = 1, \dots) = \Pr(\text{inlf}_i = 1 | \text{dkidslt6}_i = 0, \dots)$$

For Model 2,

$$\begin{aligned} \Pr(\text{inlf}_i = 1 | \text{dkidslt6}_i = 1, \dots) &= \Phi(\mathbf{x}_i^T \boldsymbol{\beta} | \text{dkidslt6}_i = 1) \\ &= \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i + \beta_6) \end{aligned}$$

$$\begin{aligned} \Pr(\text{inlf}_i = 1 | \text{dkidslt6}_i = 0, \dots) &= \Phi(\mathbf{x}_i^T \boldsymbol{\beta} | \text{dkidslt6}_i = 0) \\ &= \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i) \end{aligned}$$

These two probabilities are equal if the exclusion restriction  $\beta_6 = 0$  is true. In other words, a *sufficient condition* for these two probabilities to be equal is the exclusion restriction  $\boldsymbol{\beta}_6 = \mathbf{0}$ .

The *null and alternative hypotheses for Model 2* are therefore:

$$H_0: \beta_6 = 0$$

$$H_1: \beta_6 \neq 0$$

**Important Point:** A test of the null hypothesis that the **marginal probability effect** of pre-school aged children is zero **is equivalent to** a test of the null hypothesis that the **marginal index effect** of pre-school aged children is zero.

- ♦ **Marginal probability effect of pre-school aged children equals zero** in Model 2 if

$$\Phi(x_i^T \beta | dkidslt6_i = 1) = \Phi(x_i^T \beta | dkidslt6_i = 0).$$

**In Model 2,**

$$\Phi(x_i^T \beta | dkidslt6_i = 1) = \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i + \beta_6)$$

$$\Phi(x_i^T \beta | dkidslt6_i = 0) = \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i)$$

**Question:** What coefficient restriction(s) are sufficient to make these two probabilities equal for any given values of  $\text{nwifeinc}_i$ ,  $\text{ed}_i$ ,  $\text{exp}_i$ , and  $\text{age}_i$ ?

**Answer:** By inspection – i.e., by comparing the function  $\Phi(x_i^T \beta | dkidslt6_i = 1)$  and the function  $\Phi(x_i^T \beta | dkidslt6_i = 0)$  – we can see that a sufficient condition for  $\Phi(x_i^T \beta | dkidslt6_i = 1) = \Phi(x_i^T \beta | dkidslt6_i = 0)$  in Model 2 is the single coefficient exclusion restriction  $\beta_6 = 0$ .

- ♦ **Marginal *index* effect of pre-school aged children equals zero** if

$$\left( x_i^T \beta \mid dkidslt6_i = 1 \right) = \left( x_i^T \beta \mid dkidslt6_i = 0 \right).$$

**In Model 2,**

$$\left( x_i^T \beta \mid dkidslt6_i = 1 \right) = \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \beta_6$$

$$\left( x_i^T \beta \mid dkidslt6_i = 0 \right) = \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i$$

**Question:** What coefficient restriction(s) are sufficient to make these two index functions equal for any given values of  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$ ?

**Answer:** By inspection – i.e., by comparing the index function  $\left( x_i^T \beta \mid dkidslt6_i = 1 \right)$  and the index function  $\left( x_i^T \beta \mid dkidslt6_i = 0 \right)$  – we can see that a sufficient condition for  $\left( x_i^T \beta \mid dkidslt6_i = 1 \right) = \left( x_i^T \beta \mid dkidslt6_i = 0 \right)$  in Model 2 is the single coefficient exclusion restriction  $\beta_6 = 0$ .

- **Result:** The single coefficient exclusion restriction  $\beta_6 = 0$  is sufficient to make the **both the marginal probability effect and the marginal index effect** of pre-school aged children equal to zero in Model 2.



---

□ **How to Perform this Test for Model 2 in Stata**

- First, compute ML estimates of probit Model 2 and display the full set of saved results. Enter the following commands:

```
probit inlf nwifeinc ed exp expsq age dkidslt6
ereturn list
```

- To calculate a **Wald test** of  $H_0$  against  $H_1$  and the p-value for the calculated W-statistic, enter the following **test**, **return list** and **display** commands:

```
test dkidslt6      or      test dkidslt6 = 0
return list
display sqrt(r(chi2))
```

- To calculate a **two-tail asymptotic t-test** of  $H_0$  against  $H_1$ , enter the following **lincom**, **return list** and **display** commands:

```
lincom _b[dkidslt6]
return list
display r(estimate)/r(se)
```

The results of this two-tail t-test are identical with those of the previous Wald test.

Note that this **lincom** command merely replicates the test statistic and p-value that are displayed in the output of the **probit** command for the regressor *dkidslt6*.

**Null and Alternative Hypotheses: Model 3**

The null hypothesis in general is:

$$H_0: \Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 1, \dots) = \Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 0, \dots)$$

**For Model 3,**

$$\begin{aligned} \Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 1) &= \Phi(\mathbf{x}_i^T \boldsymbol{\beta} \mid \text{dkidslt6}_i = 1) \\ &= \Phi \left( \begin{array}{l} \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i \\ + \beta_6 + \beta_7 \text{nwifeinc}_i + \beta_8 \text{ed}_i + \beta_9 \text{exp}_i + \beta_{10} \text{exp}_i^2 + \beta_{11} \text{age}_i \end{array} \right) \end{aligned}$$

$$\begin{aligned} \Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 0) &= \Phi(\mathbf{x}_i^T \boldsymbol{\beta} \mid \text{dkidslt6}_i = 0) \\ &= \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i) \end{aligned}$$

These two probabilities are equal if the six exclusion restrictions  $\beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = 0$  are true. In other words, a *sufficient condition* for **these two probabilities to be equal** is the set of six coefficient exclusion restrictions  $\beta_j = 0$  for all  $j = 6, \dots, 11$ .

The *null and alternative hypotheses for Model 3* are therefore:

$$H_0: \beta_j = 0 \quad \forall j = 6, 7, 8, 9, 10, 11$$

$$\Rightarrow \beta_6 = 0 \text{ and } \beta_7 = 0 \text{ and } \beta_8 = 0 \text{ and } \beta_9 = 0 \text{ and } \beta_{10} = 0 \text{ and } \beta_{11} = 0$$

$$H_1: \beta_j \neq 0 \quad j = 6, 7, 8, 9, 10, 11$$

$$\Rightarrow \beta_6 \neq 0 \text{ and/or } \beta_7 \neq 0 \text{ and/or } \beta_8 \neq 0 \text{ and/or } \beta_9 \neq 0 \text{ and/or } \beta_{10} \neq 0 \text{ and/or } \beta_{11} \neq 0$$

**Important Point:** A test of the null hypothesis that the **marginal probability effect** of pre-school aged children is zero **is equivalent to** a test of the null hypothesis that the **marginal index effect** of pre-school aged children is zero.

- ♦ **Marginal probability effect of pre-school aged children equals zero** in Model 3 if

$$\Phi(x_i^T \beta | dkidslt6_i = 1) = \Phi(x_i^T \beta | dkidslt6_i = 0).$$

**In Model 3,**

$$\Phi(x_i^T \beta | dkidslt6_i = 1) = \Phi \left( \begin{array}{l} \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i \\ + \beta_6 + \beta_7 \text{nwifeinc}_i + \beta_8 \text{ed}_i + \beta_9 \text{exp}_i + \beta_{10} \text{exp}_i^2 + \beta_{11} \text{age}_i \end{array} \right)$$

$$\Phi(x_i^T \beta | dkidslt6_i = 0) = \Phi(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i)$$

**Question:** What coefficient restriction(s) are sufficient to make these two probabilities equal for any given values of  $\text{nwifeinc}_i$ ,  $\text{ed}_i$ ,  $\text{exp}_i$ , and  $\text{age}_i$ ?

**Answer:** By inspection – i.e., by comparing the function  $\Phi(x_i^T \beta | dkidslt6_i = 1)$  and the function  $\Phi(x_i^T \beta | dkidslt6_i = 0)$  – we can see that a sufficient condition for  $\Phi(x_i^T \beta | dkidslt6_i = 1) = \Phi(x_i^T \beta | dkidslt6_i = 0)$  in Model 3 is the set of **six coefficient exclusion restrictions**  
 $\beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \mathbf{0}$ .

- ♦ **Marginal index effect of pre-school aged children equals zero** in Model 3 if

$$\left( x_i^T \beta \mid dkidslt6_i = 1 \right) = \left( x_i^T \beta \mid dkidslt6_i = 0 \right).$$

**In Model 3,**

$$\begin{aligned} \left( x_i^T \beta \mid dkidslt6_i = 1 \right) &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i \\ &\quad + \beta_6 + \beta_7 nwifeinc_i + \beta_8 ed_i + \beta_9 exp_i + \beta_{10} exp_i^2 + \beta_{11} age_i \end{aligned}$$

$$\left( x_i^T \beta \mid dkidslt6_i = 0 \right) = \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i$$

**Question:** What coefficient restriction(s) are sufficient to make these two index functions equal for any given values of  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$ ?

**Answer:** By inspection – i.e., by comparing the index function  $\left( x_i^T \beta \mid dkidslt6_i = 1 \right)$  and the index function  $\left( x_i^T \beta \mid dkidslt6_i = 0 \right)$  – we can see that a sufficient condition for  $\left( x_i^T \beta \mid dkidslt6_i = 1 \right) = \left( x_i^T \beta \mid dkidslt6_i = 0 \right)$  in Model 3 is the set of **six coefficient exclusion restrictions**  $\beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = 0$ .

- **Result:** The six coefficient exclusion restrictions  $\beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = 0$  are sufficient to make the **both the marginal probability effect and the marginal index effect** of pre-school aged children **equal to zero** in Model 3.

---

□ **How to Perform this Test for Model 3 in *Stata***

$$H_0: \beta_j = 0 \quad \forall j = 6, 7, 8, 9, 10, 11$$

$$H_1: \beta_j \neq 0 \quad j = 6, 7, 8, 9, 10, 11$$

- Before estimating Model 3, it is necessary to create the *dkidslt6*; **interaction variables**. Enter the following **generate** commands:

```
generate d6nwinc = dkidslt6*nwifeinc
generate d6ed = dkidslt6*ed
generate d6exp = dkidslt6*exp
generate d6expsq = dkidslt6*expsq
generate d6age = dkidslt6*age
```

- Next, compute ML estimates of probit Model 3 and display the full set of saved results. Enter the following commands:

```
probit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age
ereturn list
```

- To calculate a **Wald test** of  $H_0$  against  $H_1$  and the p-value for the calculated W-statistic, enter the following **test** and **return list** commands:

```
test dkidslt6 d6nwinc d6ed d6exp d6expsq d6age
return list
```

- A second hypothesis test you should perform on Model 3 is a test of the null hypothesis that ***all slope coefficient differences*** between married women who have one or more pre-school aged children and married women who have no pre-school aged children **equal zero**. The null and alternative hypotheses are:

$$H_0: \beta_j = 0 \quad \forall j = 7, 8, 9, 10, 11$$

$$\Rightarrow \beta_7 = 0 \text{ and } \beta_8 = 0 \text{ and } \beta_9 = 0 \text{ and } \beta_{10} = 0 \text{ and } \beta_{11} = 0$$

$$H_1: \beta_j \neq 0 \quad j = 7, 8, 9, 10, 11$$

$$\Rightarrow \beta_7 \neq 0 \text{ and/or } \beta_8 \neq 0 \text{ and/or } \beta_9 \neq 0 \text{ and/or } \beta_{10} \neq 0 \text{ and/or } \beta_{11} \neq 0$$

Note that the null hypothesis  $H_0$  implies Model 2, whereas the alternative hypothesis  $H_1$  implies Model 3. Enter the **test** command:

```
test d6nwinc d6ed d6exp d6expsq d6age
```

```
. probit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age
```

```
Iteration 0: log likelihood = -514.8732
Iteration 1: log likelihood = -406.48086
Iteration 2: log likelihood = -402.63328
Iteration 3: log likelihood = -402.61111
Iteration 4: log likelihood = -402.61111
```

Probit estimates

```
Number of obs = 753
LR chi2(11) = 224.52
Prob > chi2 = 0.0000
Pseudo R2 = 0.2180
```

Log likelihood = -402.61111

inlf	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
nwifeinc	-.0109103	.0056007	-1.95	0.051	-.0218874	.0000668
ed	.1215786	.0280427	4.34	0.000	.0666159	.1765413
exp	.137317	.0208939	6.57	0.000	.0963657	.1782682
expsq	-.0022349	.0006495	-3.44	0.001	-.003508	-.0009619
age	-.0593504	.0085496	-6.94	0.000	-.0761072	-.0425935
dkidslt6	-2.527031	1.267708	-1.99	0.046	-5.011694	-.0423684
d6nwinc	-.0059201	.0109624	-0.54	0.589	-.0274059	.0155658
d6ed	.0327202	.0623143	0.53	0.600	-.0894135	.154854
d6exp	-.1128835	.0663563	-1.70	0.089	-.2429394	.0171724
d6expsq	.0030026	.0033465	0.90	0.370	-.0035564	.0095616
d6age	.0503914	.0260813	1.93	0.053	-.0007271	.1015099
_cons	.6084091	.4961565	1.23	0.220	-.3640398	1.580858



---

```
. ereturn list
```

```
scalars:
```

```
      e(N) = 753  
      e(ll_0) = -514.8732045671461  
      e(ll) = -402.6111063731551  
      e(df_m) = 11  
      e(chi2) = 224.5241963879821  
      e(r2_p) = .2180383387563736
```

```
macros:
```

```
      e(depvar) : "inlf"  
      e(cmd) : "probit"  
      e(crittype) : "log likelihood"  
      e(predict) : "probit_p"  
      e(chi2type) : "LR"
```

```
matrices:
```

```
      e(b) : 1 x 12  
      e(V) : 12 x 12
```

```
functions:
```

```
      e(sample)
```

```
. * Test 1:
. test dkidslt6 d6nwinc d6ed d6exp d6expsq d6age

( 1) dkidslt6 = 0
( 2) d6nwinc = 0
( 3) d6ed = 0
( 4) d6exp = 0
( 5) d6expsq = 0
( 6) d6age = 0

      chi2( 6) =    58.11
Prob > chi2 =    0.0000

. return list

scalars:
      r(drop) = 0
      r(chi2) = 58.11036668348744
      r(df) = 6
      r(p) = 1.08838734793e-10
```

---

```
. * Test 2:
. test d6nwinc d6ed d6exp d6expsq d6age

( 1) d6nwinc = 0
( 2) d6ed = 0
( 3) d6exp = 0
( 4) d6expsq = 0
( 5) d6age = 0

           chi2( 5) =      9.03
       Prob > chi2 =      0.1078

. return list

scalars:
       r(drop) = 0
       r(chi2) = 9.031191992371875
       r(df) = 5
       r(p) = .1078264635420236
```

```
. dprobit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age
```

```
Iteration 0: log likelihood = -514.8732
Iteration 1: log likelihood = -406.48086
Iteration 2: log likelihood = -402.63328
Iteration 3: log likelihood = -402.61111
Iteration 4: log likelihood = -402.61111
```

Probit estimates

```
Number of obs = 753
LR chi2(11) = 224.52
Prob > chi2 = 0.0000
Pseudo R2 = 0.2180
```

Log likelihood = -402.61111

inlf	dF/dx	Std. Err.	z	P> z	x-bar	[	95% C.I.	]
nwifeinc	-.0042484	.0021794	-1.95	0.051	20.129	-.00852	.000023	
ed	.0473425	.0108958	4.34	0.000	12.2869	.025987	.068698	
exp	.053471	.0081365	6.57	0.000	10.6308	.037524	.069418	
expsq	-.0008703	.0002531	-3.44	0.001	178.039	-.001366	-.000374	
age	-.0231109	.0033213	-6.94	0.000	42.5378	-.029621	-.016601	
dkidslt6*	-.7273305	.1555487	-1.99	0.046	.195219	-1.0322	-.422461	
d6nwinc	-.0023053	.00427	-0.54	0.589	4.04408	-.010674	.006064	
d6ed	.0127412	.0242742	0.53	0.600	2.47809	-.034835	.060318	
d6exp	-.0439567	.0258347	-1.70	0.089	1.37317	-.094592	.006678	
d6expsq	.0011692	.0013032	0.90	0.370	15.012	-.001385	.003723	
d6age	.0196223	.0101508	1.93	0.053	6.87251	-.000273	.039518	
obs. P	.5683931							
pred. P	.5870885	(at x-bar)						

(\*) dF/dx is for discrete change of dummy variable from 0 to 1  
z and P>|z| are the test of the underlying coefficient being 0

```
. ereturn list
```

```
scalars:
```

```
      e(N) = 753  
      e(ll_0) = -514.8732045671461  
      e(ll) = -402.6111063731551  
      e(df_m) = 11  
      e(chi2) = 224.5241963879821  
      e(r2_p) = .2180383387563736  
      e(pbar) = .5683930942895087  
      e(xbar) = .220061785738521  
      e(offbar) = 0
```

```
macros:
```

```
      e(cmd) : "dprobit"  
      e(dummy) : " 0 0 0 0 0 1 0 0 0 0 0 0"  
      e(depvar) : "inlf"  
      e(crittype) : "log likelihood"  
      e(predict) : "probit_p"  
      e(chi2type) : "LR"
```

```
matrices:
```

```
      e(b) : 1 x 12  
      e(V) : 12 x 12  
      e(se_dfdx) : 1 x 11  
      e(dfdx) : 1 x 11
```

```
functions:
```

```
      e(sample)
```

```
. * Test 1:
. test dkidslt6 d6nwinc d6ed d6exp d6expsq d6age

( 1) dkidslt6 = 0
( 2) d6nwinc = 0
( 3) d6ed = 0
( 4) d6exp = 0
( 5) d6expsq = 0
( 6) d6age = 0

      chi2( 6) =    58.11
    Prob > chi2 =    0.0000

. return list

scalars:
      r(drop) = 0
      r(chi2) = 58.11036668348744
      r(df) = 6
      r(p) = 1.08838734793e-10
```

---

```
. * Test 2:
. test d6nwinc d6ed d6exp d6expsq d6age

( 1) d6nwinc = 0
( 2) d6ed = 0
( 3) d6exp = 0
( 4) d6expsq = 0
( 5) d6age = 0

           chi2( 5) =      9.03
       Prob > chi2 =      0.1078

. return list

scalars:
       r(drop) = 0
       r(chi2) = 9.031191992371875
       r(df) = 5
       r(p) = .1078264635420236
```

---

### □ Interpreting the coefficient estimates in full-interaction Model 3

---

Full-interaction Model 3 estimates *two distinct sets of probit coefficients*: (1) the probit coefficients for married women who have no pre-school aged children (for whom  $dkidslt6_i = 0$ ); and (2) the probit coefficients for married women who have one or more pre-school aged children (for whom  $dkidslt6_i = 1$ ).

- ◆ Recall that the **probit index function for Model 3** is:

$$\begin{aligned} x_i^T \beta &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i \\ &\quad + \beta_6 dkidslt6_i + \beta_7 dkidslt6_i nwifeinc_i + \beta_8 dkidslt6_i ed_i \\ &\quad + \beta_9 dkidslt6_i exp_i + \beta_{10} dkidslt6_i exp_i^2 + \beta_{11} dkidslt6_i age_i \end{aligned}$$

- ◆ The **probit index function for married women who have no pre-school aged children** (for whom  $dkidslt6_i = 0$ ) is obtained by **setting the indicator variable  $dkidslt6_i = 0$**  in the probit index function for Model 3:

$$\left( x_i^T \beta \mid dkidslt6_i = 0 \right) = \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i$$

**Implication:** The probit coefficient estimates for married women who have no pre-school aged children (for whom  $dkidslt6_i = 0$ ) are given directly by the coefficient estimates of the first six terms in the above index function. In particular, **for married women who currently have no pre-school aged children:**



The probit coefficient estimates for married women who have no pre-school aged children are:

$\beta_0$  = the intercept coefficient for women for whom  $dkidslt6_i = 0$

$\beta_1$  = the slope coefficient of  $nwifeinc_i$  for women for whom  $dkidslt6_i = 0$

$\beta_2$  = the slope coefficient of  $ed_i$  for women for whom  $dkidslt6_i = 0$

$\beta_3$  = the slope coefficient of  $exp_i$  for women for whom  $dkidslt6_i = 0$

$\beta_4$  = the slope coefficient of  $exp_i^2$  for women for whom  $dkidslt6_i = 0$

$\beta_5$  = the slope coefficient of  $age_i$  for women for whom  $dkidslt6_i = 0$ .

- ♦ The **probit index function for married women who currently have one or more pre-school aged children** (for whom  $dkidslt6_i = 1$ ) is obtained by setting the indicator variable  $dkidslt6_i = 1$  in the probit index function for Model 3:

$$\begin{aligned} (x_i^T \beta \mid dkidslt6_i = 1) &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i \\ &\quad + \beta_6 + \beta_7 nwifeinc_i + \beta_8 ed_i + \beta_9 exp_i + \beta_{10} exp_i^2 + \beta_{11} age_i \end{aligned}$$

**Implication:** The probit coefficient estimates for married women who have one or more pre-school aged children (for whom  $dkidslt6_i = 1$ ) are obtained from Model 3 by summing pairs of coefficient estimates. In particular, **for married women who have one or more pre-school aged children:**

- $\beta_0 + \beta_6 =$  the intercept coefficient for women for whom  $dkidslt6_i = 1$
- $\beta_1 + \beta_7 =$  the slope coefficient of  $nwifeinc_i$  for women for whom  $dkidslt6_i = 1$
- $\beta_2 + \beta_8 =$  the slope coefficient of  $ed_i$  for women for whom  $dkidslt6_i = 1$
- $\beta_3 + \beta_9 =$  the slope coefficient of  $exp_i$  for women for whom  $dkidslt6_i = 1$
- $\beta_4 + \beta_{10} =$  the slope coefficient of  $exp_i^2$  for women for whom  $dkidslt6_i = 1$
- $\beta_5 + \beta_{11} =$  the slope coefficient of  $age_i$  for women for whom  $dkidslt6_i = 1$ .

- Compute from Model 3 the probit coefficient estimates, t-ratios and p-values for those married women who have one or more pre-school aged children (for whom  $dkidslt6_i = 1$ ). Enter the following **lincom** commands:

```
lincom _b[_cons] + _b[dkidslt6]
lincom _b[nwifeinc] + _b[d6nwinc]
lincom _b[ed] + _b[d6ed]
lincom _b[exp] + _b[d6exp]
lincom _b[expsq] + _b[d6expsq]
lincom _b[age] + _b[d6age]
```

```
. * Model 3 probit coefficients for women for whom dkidslt6 = 1
. lincom _b[_cons] + _b[dkidslt6]
```

```
( 1) dkidslt6 + _cons = 0
```

```
-----
      inlf |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      (1) |   -1.918622    1.166582   -1.64   0.100   -4.205081    .3678365
-----
```

```
. lincom _b[nwifeinc] + _b[d6nwinc]
```

```
( 1) nwifeinc + d6nwinc = 0
```

```
-----
      inlf |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      (1) |   -.0168304   .0094237   -1.79   0.074   -.0353004   .0016397
-----
```

```
. lincom _b[ed] + _b[d6ed]
```

```
( 1) ed + d6ed = 0
```

```
-----
      inlf |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      (1) |    .1542988   .0556478    2.77   0.006    .0452311    .2633665
-----
```

```
. lincom _b[exp] + _b[d6exp]
```

```
( 1)  exp + d6exp = 0
```

```
-----+-----
      inlf |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      (1) |   .0244335   .062981    0.39   0.698    - .0990069   .1478739
-----+-----
```

```
. lincom _b[expsq] + _b[d6expsq]
```

```
( 1)  expsq + d6expsq = 0
```

```
-----+-----
      inlf |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      (1) |   .0007676   .0032829    0.23   0.815    - .0056666   .0072019
-----+-----
```

```
. lincom _b[age] + _b[d6age]
```

```
( 1)  age + d6age = 0
```

```
-----+-----
      inlf |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      (1) |  -.0089589   .0246402   -0.36   0.716    - .0572529   .039335
-----+-----
```

---

□ **Computing the marginal *probability* effect of the binary explanatory variable *dkidslt6<sub>i</sub>* in Model 3 – *dprobit* with *at(vecname)* option**

---

This section demonstrates how to use the **dprobit** command with the **at(*vecname*)** option to compute the **marginal probability effect of the dummy variable *dkidslt6<sub>i</sub>* in Model 3** for married women who have the sample median values of the explanatory variables  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$ .

Here we are concerned with obtaining an estimate of the **direction and magnitude** of the **marginal probability effect of the dummy variable *dkidslt6<sub>i</sub>* in Model 3**.

The **marginal probability effect of the dummy variable *dkidslt6<sub>i</sub>* in Model 3** is:

$$\begin{aligned} \Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 1) - \Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 0) &= \Phi(\mathbf{x}_{1i}^T \boldsymbol{\beta}) - \Phi(\mathbf{x}_{0i}^T \boldsymbol{\beta}) \\ &= \Phi \left( \begin{array}{l} \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i \\ + \beta_6 + \beta_7 nwifeinc_i + \beta_8 ed_i + \beta_9 exp_i + \beta_{10} exp_i^2 + \beta_{11} age_i \end{array} \right) \\ &\quad - \Phi(\beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i) \end{aligned}$$

The procedure for this computation consists of three steps.

### Three-step procedure for computing the marginal *probability* effect of the dummy variable $dkidslt6_i$ in Model 3

**Step 1:** Estimate the probability of labour force participation for married women with the specified characteristics who currently have *one or more dependent children under 6 years of age*, for whom  $dkidslt6_i = 1$ : i.e., compute an estimate of

$$\Phi(x_{li}^T \beta) = \Phi \left( \begin{array}{l} \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i \\ + \beta_6 + \beta_7 nwifeinc_i + \beta_8 ed_i + \beta_9 exp_i + \beta_{10} exp_i^2 + \beta_{11} age_i \end{array} \right)$$

**Step 2:** Estimate the probability of labour force participation for married women with the specified characteristics who currently have *no dependent children under 6 years of age*, for whom  $dkidslt6_i = 0$ : i.e., compute an estimate of

$$\Phi(x_{oi}^T \beta) = \Phi(\beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i)$$

**Step 3:** Compute an estimate of the difference  $\Phi(x_{li}^T \beta) - \Phi(x_{oi}^T \beta)$ , which is the **marginal *probability* effect of having one or more pre-school aged children** for married women who have the specified characteristics.

- Compute (or select) the values of the explanatory variables at which you wish to compute the marginal probability effect of the binary variable  $dkidslt6_i$ .

Use the **pooled sample medians** of the explanatory variables  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$ . Enter the following commands:

```
summarize nwifeinc, detail
return list
scalar nwinc50p = r(p50)
summarize ed, detail
scalar ed50p = r(p50)
summarize exp, detail
scalar exp50p = r(p50)
scalar expsq50p = exp50p^2
summarize age, detail
scalar age50p = r(p50)
scalar list nwinc50p ed50p exp50p expsq50p age50p
```

The sample median values of the explanatory variables computed by these commands are as follows:

```
nwinc50p = 17.700001
ed50p = 12
exp50p = 9
expsq50p = 81
age50p = 43
```

- **Step 1:** Use the **dprobit** command *with* the **at(vecname)** option to compute the marginal probability effects in Model 3 for median married women whose non-wife family income is \$17,700 per year (`nwifeinc = 17.700`), who have 12 years of formal education (`ed = 12`) and 9 years of actual work experience (`exp = 9`, `expsq = 81`), who are 43 years of age (`age = 43`), and **who have one or more dependent children under 6 years of age (`dkidslt6 = 1`)**.

First create the vector  $x_{ii}^T$  containing the median values of the regressors in Model 3 when `dkidslt6i = 1`. The coefficient vector  $\beta$  for Model 3 in *Stata* format is:

$$\beta = (\beta_1 \ \beta_2 \ \beta_3 \ \beta_4 \ \beta_5 \ \beta_6 \ \beta_7 \ \beta_8 \ \beta_9 \ \beta_{10} \ \beta_{11} \ \beta_0)^T$$

In *Stata* format, the vector  $x_{ii}^T$  for Model 3 thus takes the form:

$$\begin{aligned} x_{ii}^T &= (\text{nwifeinc}_i \ \text{ed}_i \ \text{exp}_i \ \text{exp}_i^2 \ \text{age}_i \ 1 \ \text{nwifeinc}_i \ \text{ed}_i \ \text{exp}_i \ \text{exp}_i^2 \ \text{age}_i \ 1) \\ &= \begin{pmatrix} \text{nwinc50p} \ \text{ed50p} \ \text{exp50p} \ \text{expsq50p} \ \text{age50p} \ 1 \\ \text{nwinc50p} \ \text{ed50p} \ \text{exp50p} \ \text{expsq50p} \ \text{age50p} \ 1 \end{pmatrix} \end{aligned}$$



**Step 1 Stata commands** are:

```
matrix xlmedian = (nwinc50p, ed50p, exp50p, expsq50p, age50p, 1, nwinc50p, ed50p,
exp50p, expsq50p, age50p, 1)
matrix list xlmedian
dprobit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age,
at(xlmedian)
ereturn list
```

Display and save the value of  $\Phi(\mathbf{x}_{li}^T \hat{\beta})$ , an estimate of  $\Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 1)$ . The value of  $\Phi(\mathbf{x}_{li}^T \hat{\beta})$  is temporarily stored as the scalar **e(at)** following the above **dprobit** command. Enter the commands:

```
display e(at)
scalar PHIx1med = e(at)
scalar list PHIx1med
```

These commands save the value of  $\Phi(\mathbf{x}_{li}^T \hat{\beta})$  as the scalar **PHIx1med**.

- **Step 2:** Now use the **dprobit** command *with* the **at(*vecname*)** option to compute the marginal probability effects in Model 3 for median married women whose non-wife family income is \$17,700 per year ( $\text{nwifeinc} = 17.700$ ), who have 12 years of formal education ( $\text{ed} = 12$ ) and 9 years of actual work experience ( $\text{exp} = 9$ ,  $\text{expsq} = 81$ ), who are 43 years of age ( $\text{age} = 43$ ), and **who have no dependent children under 6 years of age** ( $\text{dkidslt6} = 0$ ). Again, you will first have to create the vector  $\mathbf{x}_{0i}^T$  containing the median values of the regressors in Model 3 when  $\text{dkidslt6}_i = 0$ .

In *Stata* format, the vector  $\mathbf{x}_{0i}^T$  for Model 3 takes the form:

$$\begin{aligned} \mathbf{x}_{0i}^T &= (\text{nwifeinc}_i \ \text{ed}_i \ \text{exp}_i \ \text{exp}_i^2 \ \text{age}_i \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1) \\ &= (\text{nwinc50p} \ \text{ed50p} \ \text{exp50p} \ \text{expsq50p} \ \text{age50p} \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1) \end{aligned}$$

**Step 2 Stata commands** are:

```
matrix x0median = (nwinc50p, ed50p, exp50p, expsq50p, age50p, 0, 0, 0, 0, 0, 0, 1)
matrix list x0median
dprobit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age,
at(x0median)
ereturn list
```

Display and save the value of  $\Phi\left(x_{0i}^T \hat{\beta}\right)$ , an estimate of  $\Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 0)$ . The value of  $\Phi\left(x_{0i}^T \hat{\beta}\right)$  is temporarily stored as the scalar **e(at)** following the above **dprobit** command. Enter the commands:

```
display e(at)
scalar PHIx0med = e(at)
scalar list PHIx0med
```

These commands save the value of  $\Phi\left(x_{0i}^T \hat{\beta}\right)$  as the scalar **PHIx0med**.

- **Step 3:** Finally, compute the estimate of the difference  $\Phi(\mathbf{x}_{1i}^T\beta) - \Phi(\mathbf{x}_{0i}^T\beta)$ , which is the marginal probability effect having one or more dependent children under 6 years of age for married women who have the specified characteristics. **Step 3 Stata commands** are:

```
scalar diffPHImed = PHIx1med - PHIx0med
scalar list PHIx1med PHIx0med diffPHImed
```

The value of the scalar **diffPHImed** is the estimate for **Model 3** of

$$\Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 1) - \Pr(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 0) = \Phi(\mathbf{x}_{1i}^T\beta) - \Phi(\mathbf{x}_{0i}^T\beta)$$

i.e., of the **marginal probability effect of having one or more dependent children under 6 years of age** for married women who have the median characteristics of women in the full sample.

$$\mathbf{diffPHImed} = \hat{\Pr}(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 1) - \hat{\Pr}(\text{inlf}_i = 1 \mid \text{dkidslt6}_i = 0) = \Phi(\mathbf{x}_{1i}^T\hat{\beta}) - \Phi(\mathbf{x}_{0i}^T\hat{\beta})$$

**Output of Step 1 *Stata* Commands**

```
. dprobit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age, at(xlmedian)
```

```
Iteration 0: log likelihood = -514.8732
Iteration 1: log likelihood = -406.48086
Iteration 2: log likelihood = -402.63328
Iteration 3: log likelihood = -402.61111
Iteration 4: log likelihood = -402.61111
```

Probit estimates

```
Number of obs = 753
LR chi2(11) = 224.52
Prob > chi2 = 0.0000
Pseudo R2 = 0.2180
```

Log likelihood = -402.61111

inlf	dF/dx	Std. Err.	z	P> z	x	[	95% C.I.	]
nwifeinc	-.0039009	.0020603	-1.95	0.051	17.7	-.007939	.000137	
ed	.0434699	.0113882	4.34	0.000	12	.021149	.06579	
exp	.0490971	.009644	6.57	0.000	9	.030195	.067999	
expsq	-.0007991	.0002526	-3.44	0.001	81	-.001294	-.000304	
age	-.0212205	.0040365	-6.94	0.000	43	-.029132	-.013309	
dkidslt6*	-.6603895	.0730752	-1.99	0.046	1	-.803614	-.517165	
d6nwinc	-.0021167	.0039297	-0.54	0.589	17.7	-.009819	.005585	
d6ed	.011699	.0221757	0.53	0.600	12	-.031765	.055162	
d6exp	-.040361	.0215344	-1.70	0.089	9	-.082568	.001846	
d6expsq	.0010736	.0011221	0.90	0.370	81	-.001126	.003273	
d6age	.0180172	.0111044	1.93	0.053	43	-.003747	.039781	
obs. P	.5683931							
pred. P	.5870885	(at x-bar)						
pred. P	.3198606	(at x)						

(\*) dF/dx is for discrete change of dummy variable from 0 to 1  
z and P>|z| are the test of the underlying coefficient being 0

```
. ereturn list

scalars:
      e(N) = 753
      e(l1_0) = -514.8732045671461
      e(l1) = -402.6111063731551
      e(df_m) = 11
      e(chi2) = 224.5241963879821
      e(r2_p) = .2180383387563736
      e(pbar) = .5683930942895087
      e(xbar) = .220061785738521
      e(offbar) = 0
      e(at) = .3198606279066483
```

```
[output omitted]
```

```
. display e(at)
.31986063

. scalar PHIx1med = e(at)

. scalar list PHIx1med
  PHIx1med = .31986063
```

**Output of Step 2 *Stata* Commands**

```
. dprobit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age, at(x0median);
```

```
Iteration 0: log likelihood = -514.8732
Iteration 1: log likelihood = -406.48086
Iteration 2: log likelihood = -402.63328
Iteration 3: log likelihood = -402.61111
Iteration 4: log likelihood = -402.61111
```

Probit estimates

Number of obs = 753  
 LR chi2(11) = 224.52  
 Prob > chi2 = 0.0000  
 Pseudo R2 = 0.2180

Log likelihood = -402.61111

inlf	dF/dx	Std. Err.	z	P> z	x	[	95% C.I.	]
nwifeinc	-.004054	.0020554	-1.95	0.051	17.7	-.008083	-.000025	
ed	.0451757	.0104184	4.34	0.000	12	.024756	.065595	
exp	.0510237	.0074085	6.57	0.000	9	.036503	.065544	
expsq	-.0008305	.0002325	-3.44	0.001	81	-.001286	-.000375	
age	-.0220532	.003204	-6.94	0.000	43	-.028333	-.015773	
dkidslt6*	-.6311359	.0559456	-1.99	0.046	0	-.740787	-.521485	
d6nwinc	-.0021998	.0040816	-0.54	0.589	0	-.010199	.0058	
d6ed	.012158	.0231649	0.53	0.600	0	-.033244	.05756	
d6exp	-.0419448	.0245612	-1.70	0.089	0	-.090084	.006194	
d6expsq	.0011157	.0012413	0.90	0.370	0	-.001317	.003549	
d6age	.0187242	.0096966	1.93	0.053	0	-.000281	.037729	
obs. P	.5683931							
pred. P	.5870885	(at x-bar)						
pred. P	.6469122	(at x)						

(\*) dF/dx is for discrete change of dummy variable from 0 to 1  
 z and P>|z| are the test of the underlying coefficient being 0

```
. ereturn list

scalars:
      e(N) = 753
      e(ll_0) = -514.8732045671461
      e(ll) = -402.6111063731551
      e(df_m) = 11
      e(chi2) = 224.5241963879821
      e(r2_p) = .2180383387563736
      e(pbar) = .5683930942895087
      e(xbar) = .220061785738521
      e(offbar) = 0
      e(at) = .6469121653332525
```

```
[output omitted]
```

```
. display e(at)
.64691217

. scalar PHIx0med = e(at)

. scalar list PHIx0med
  PHIx0med = .64691217
```



### Output of Step 3 *Stata* Commands

```

.
. * Model 3: compute marginal probability effect of dkidslt6
. scalar diffPHImed = PHIx1med - PHIx0med

. scalar list PHIx1med PHIx0med diffPHImed
  PHIx1med = .31986063
  PHIx0med = .64691217
diffPHImed = -.32705154

```

The value of the scalar `diffPHImed` is the estimate for Model 3 of

$$\Pr(\text{inlf}_i = 1 | \text{dkidslt6}_i = 1) - \Pr(\text{inlf}_i = 1 | \text{dkidslt6}_i = 0) = \Phi(x_{1i}^T \beta) - \Phi(x_{0i}^T \beta)$$

In Model 3, the estimated **marginal probability effect of having one or more dependent children under 6 years of age** for married women who have the median characteristics of women in the full sample is:

$$\Phi(x_{1i}^T \hat{\beta}) - \Phi(x_{0i}^T \hat{\beta}) = -0.32705154 = -0.3271$$

---

**□ Marginal probability effects of continuous explanatory variables in Model 3 -- dprobit**


---

**Background**

- ◆ The **marginal probability effects of continuous explanatory variables in probit models** are the partial derivatives of the standard normal c.d.f.  $\Phi(x_i^T\beta)$  with respect to the individual explanatory variables:

$$\text{marginal probability effect of } X_j = \frac{\partial \Phi(x_i^T\beta)}{\partial X_{ij}} = \frac{\partial \Phi(x_i^T\beta)}{\partial x_i^T\beta} \frac{\partial x_i^T\beta}{\partial X_{ij}} = \phi(x_i^T\beta) \frac{\partial x_i^T\beta}{\partial X_{ij}}$$

where

$\phi(x_i^T\beta)$  = the **value of the standard normal p.d.f.** evaluated at  $x_i^T\beta$

$\frac{\partial x_i^T\beta}{\partial X_{ij}}$  = the **marginal index effect** of the continuous variable  $X_j$ .

- ◆ Recall that the **probit index function for Model 3** is:

$$\begin{aligned} x_i^T\beta &= \beta_0 + \beta_1 \text{nwifinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i \\ &\quad + \beta_6 \text{dkidslt6}_i + \beta_7 \text{dkidslt6}_i \text{nwifinc}_i + \beta_8 \text{dkidslt6}_i \text{ed}_i \\ &\quad + \beta_9 \text{dkidslt6}_i \text{exp}_i + \beta_{10} \text{dkidslt6}_i \text{exp}_i^2 + \beta_{11} \text{dkidslt6}_i \text{age}_i \end{aligned}$$

### **Marginal Index Effects of Continuous Explanatory Variables – Model 3**

- ♦ For Model 3, there are *two sets of marginal index effects*, one for women with no pre-school aged children (for whom  $dkidslt6_i = 0$ ), and the other for women with one or more pre-school aged children (for whom  $dkidslt6_i = 1$ ).
- ♦ The **marginal index effects** of the *continuous explanatory variables in Model 3* are obtained by partially differentiating the index function  $x_i^T \beta$  for Model 3 with respect to each of the four continuous explanatory variables  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$ .

The **probit index function**, or regression function, for **Model 3** is:

$$\begin{aligned} x_i^T \beta &= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i \\ &\quad + \beta_6 dkidslt6_i + \beta_7 dkidslt6_i nwifeinc_i + \beta_8 dkidslt6_i ed_i \\ &\quad + \beta_9 dkidslt6_i exp_i + \beta_{10} dkidslt6_i exp_i^2 + \beta_{11} dkidslt6_i age_i \end{aligned}$$

$$\begin{aligned}
 x_i^T \beta &= \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \text{exp}_i + \beta_4 \text{exp}_i^2 + \beta_5 \text{age}_i \\
 &\quad + \beta_6 \text{dkidslt6}_i + \beta_7 \text{dkidslt6}_i \text{nwifeinc}_i + \beta_8 \text{dkidslt6}_i \text{ed}_i \\
 &\quad + \beta_9 \text{dkidslt6}_i \text{exp}_i + \beta_{10} \text{dkidslt6}_i \text{exp}_i^2 + \beta_{11} \text{dkidslt6}_i \text{age}_i
 \end{aligned}$$

Now partially differentiate the index function  $x_i^T \beta$  for Model 3 with respect to each of the four continuous explanatory variables  $\text{nwifeinc}_i$ ,  $\text{ed}_i$ ,  $\text{exp}_i$ , and  $\text{age}_i$ .

1. marginal index effect of  $\text{nwifeinc}_i = \frac{\partial x_i^T \beta}{\partial \text{nwifeinc}_i} = \beta_1 + \beta_7 \text{dkidslt6}_i$
2. marginal index effect of  $\text{ed}_i = \frac{\partial x_i^T \beta}{\partial \text{ed}_i} = \beta_2 + \beta_8 \text{dkidslt6}_i$
3. marginal index effect of  $\text{exp}_i = \frac{\partial x_i^T \beta}{\partial \text{exp}_i} = \beta_3 + 2\beta_4 \text{exp}_i + (\beta_9 + 2\beta_{10} \text{exp}_i) \text{dkidslt6}_i$
4. marginal index effect of  $\text{age}_i = \frac{\partial x_i^T \beta}{\partial \text{age}_i} = \beta_5 + \beta_{11} \text{dkidslt6}_i$

**Note:** Each of these marginal *index* effects differs depending on whether  $\text{dkidslt6}_i = 0$  or  $\text{dkidslt6}_i = 1$ .

- ♦ The **marginal index effects for married women with *no pre-school aged children*** are obtained by **setting the indicator variable  $dkidslt6_i = 0$**  in expressions 1 to 4 above:

5. marginal index effect of  $nwifeinc_i = \frac{\partial x_i^T \beta}{\partial nwifeinc_i} = \beta_1$

6. marginal index effect of  $ed_i = \frac{\partial x_i^T \beta}{\partial ed_i} = \beta_2$

7. marginal index effect of  $exp_i = \frac{\partial x_i^T \beta}{\partial exp_i} = \beta_3 + 2\beta_4 exp_i$

8. marginal index effect of  $age_i = \frac{\partial x_i^T \beta}{\partial age_i} = \beta_5$

- ♦ The **marginal index effects for married women with *one or more pre-school aged children*** are obtained by **setting the indicator variable  $dkidslt6_i = 1$**  in expressions 1 to 4 above:

$$9. \text{ marginal index effect of } nwifeinc_i = \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial nwifeinc_i} = \beta_1 + \beta_7$$

$$10. \text{ marginal index effect of } ed_i = \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial ed_i} = \beta_2 + \beta_8$$

$$11. \text{ marginal index effect of } exp_i = \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial exp_i} = \beta_3 + 2\beta_4 exp_i + (\beta_9 + 2\beta_{10} exp_i) \\ = \beta_3 + \beta_9 + 2(\beta_4 + \beta_{10}) exp_i$$

$$12. \text{ marginal index effect of } age_i = \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial age_i} = \beta_5 + \beta_{11}$$

**Marginal Probability Effects of Continuous Explanatory Variables – Model 3**

- ♦ The **marginal probability effects** of the four continuous explanatory variables in Model 3 are:

$$\begin{aligned}
 1. \text{ marginal probability effect of } \text{nwifinc}_i &= \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{nwifinc}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{nwifinc}_i} \\
 &= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_1 + \beta_7 \text{dkidslt6}_i)
 \end{aligned}$$

$$\begin{aligned}
 2. \text{ marginal probability effect of } \text{ed}_i &= \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{ed}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{ed}_i} \\
 &= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_2 + \beta_8 \text{dkidslt6}_i)
 \end{aligned}$$

$$\begin{aligned}
 3. \text{ marginal probability effect of } \text{exp}_i &= \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{exp}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{exp}_i} \\
 &= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_3 + 2\beta_4 \text{exp}_i + (\beta_9 + 2\beta_{10} \text{exp}_i) \text{dkidslt6}_i)
 \end{aligned}$$

$$\begin{aligned}
 4. \text{ marginal probability effect of } \text{age}_i &= \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{age}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{age}_i} \\
 &= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_5 + \beta_{11} \text{dkidslt6}_i)
 \end{aligned}$$

**Notes:** There are **three features of these marginal probability effects for Model 3** that you should recognize.

1. These marginal *probability* effects differ depending on whether  $dkidslt6_i = 0$  or  $dkidslt6_i = 1$ .
2. The marginal probability effect of a continuous explanatory variable  $X_j$  is proportional to the marginal index effect of  $X_j$ , where the factor of proportionality is the standard normal p.d.f. at  $x_i^T \beta$ :

$$\text{marginal probability effect of } X_j = \phi(x_i^T \beta) \times \text{marginal index effect of } X_j$$

3. Estimation of the marginal probability effects of a continuous explanatory variable  $X_j$  requires one to choose a specific vector of regressor values  $x_i^T$ . Common choices for  $x_i^T$  are the **sample mean** and **sample median** values of the regressors.



- ♦ The **marginal probability effects for married women with no pre-school aged children** are obtained by setting the indicator variable **dkidslt6<sub>i</sub> = 0** in expressions 1 to 4 above:

$$5. \text{ marginal probability effect of } \text{nwifinc}_i = \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{nwifinc}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{nwifinc}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \beta_1$$

$$6. \text{ marginal probability effect of } \text{ed}_i = \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{ed}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{ed}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \beta_2$$

$$7. \text{ marginal probability effect of } \text{exp}_i = \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{exp}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{exp}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) (\beta_3 + 2\beta_4 \text{exp}_i)$$

$$8. \text{ marginal probability effect of } \text{age}_i = \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{age}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{age}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \beta_5$$

- ♦ The **marginal probability effects for married women with one or more pre-school aged children** are obtained by setting the indicator variable  $\mathbf{dkidslt6}_i = 1$  in expressions 1 to 4 above:

$$9. \text{ marginal probability effect of } \text{nwifinc}_i = \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{nwifinc}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{nwifinc}_i}$$

$$= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_1 + \beta_7)$$

$$10. \text{ marginal probability effect of } \text{ed}_i = \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{ed}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{ed}_i}$$

$$= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_2 + \beta_8)$$

$$11. \text{ marginal probability effect of } \text{exp}_i = \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{exp}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{exp}_i}$$

$$= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_3 + 2\beta_4 \text{exp}_i + \beta_9 + 2\beta_{10} \text{exp}_i)$$

$$= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_3 + \beta_9 + 2(\beta_4 + \beta_{10}) \text{exp}_i)$$

$$12. \text{ marginal probability effect of } \text{age}_i = \frac{\partial \Phi(\mathbf{x}_i^T \boldsymbol{\beta})}{\partial \text{age}_i} = \phi(\mathbf{x}_i^T \boldsymbol{\beta}) \frac{\partial \mathbf{x}_i^T \boldsymbol{\beta}}{\partial \text{age}_i}$$

$$= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_5 + \beta_{11})$$

---

□ **Testing for zero marginal *probability* effects of *continuous* explanatory variables in Model 3 – *probit* or *dprobit***

---

**Background:**

For any explanatory variable, there are **two distinct empirical questions** that an econometric investigation of married women's labour force participation (or any other binary outcome) should address.

- ◆ The first question concerns the ***existence of a relationship***: is a particular explanatory variable related to the probability of married women's labour force participation, conditional on other explanatory variables included in the model?

In other words, is the marginal probability effect of a particular explanatory variable on the probability of married women's labour force participation zero or non-zero?

- ◆ The second question concerns the ***direction and magnitude of the relationship***: how large a change in the conditional probability of married women's labour force participation is associated with a one-unit increase in the value of a particular continuous explanatory variable, holding constant the values of all other explanatory variables included in the model?

This section addresses the first question for each of the four continuous variables in Model 3.

***Objective:*** To test the proposition that the **marginal effect of each *continuous* explanatory variable** on the probability of married women's labour force participation **is equal to zero** for each of the **two groups of married women**:

1. married women with one or more pre-school aged children  
and
2. married women with no pre-school aged children

***Important Point:***

The marginal probability effect of a continuous explanatory variable  $X_j$  is proportional to the marginal index effect of  $X_j$ , where the factor of proportionality is the standard normal p.d.f. at  $x_i^T \beta$ :

$$\text{marginal probability effect of } X_j = \phi(x_i^T \beta) \times \text{marginal index effect of } X_j$$

***Implication:*** Any set of coefficient restrictions that is sufficient to make the **marginal index effect** of a continuous explanatory variable **equal to zero** is also sufficient to make the **marginal probability effect** of that continuous explanatory variable **equal to zero**.

In other words, testing the null hypothesis that the marginal *index* effect of a continuous explanatory variable equals zero is equivalent to testing the null hypothesis that the marginal *probability* effect of that continuous explanatory variable equals zero.

- First, re-estimate probit Model 3. Enter the **probit** command:

```
probit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age
```

♦ **Test 1 - Model 3: for married women with no pre-school aged children**

- ♦ **Proposition:** The non-wife income of the family has no effect on the probability of labour force participation for married women who have no pre-school aged children; the **marginal probability (and index) effect of  $nwifeinc_i$  equals zero** for married women for whom  $dkidslt6_i = 0$ .

- ♦ **For married women for whom  $dkidslt6_i = 0$ :** marginal probability effect of  $nwifeinc_i = \phi(x_i^T \beta) \beta_1$

A sufficient condition for the marginal probability effect of  $nwifeinc_i$  to equal zero for any given values of the regressors  $x_i^T$  is  $\beta_1 = 0$ .

- ♦ **Null and Alternative Hypotheses:**

$$H_0: \beta_1 = 0 \quad \text{versus} \quad H_1: \beta_1 \neq 0$$

- To calculate a **Wald test** of this hypothesis and the corresponding p-value for the calculated W-statistic, enter the following **test**, **return list** and **display** commands:

```
test nwifeinc      or      test nwifeinc = 0
return list
display sqrt(r(chi2))
```

- To calculate a **two-tail asymptotic t-test** of  $H_0$  against  $H_1$ , enter the following *Stata* commands:

```
lincom _b[nwifeinc]
return list
display r(estimate)/r(se)
```

The results of this two-tail t-test are identical with those of the previous Wald test.

♦ **Test 1 - Model 3: for married women with one or more pre-school aged children**

- ♦ **Proposition:** The non-wife income of the family has no effect on the probability of labour force participation for married women who have one or more pre-school aged children; the **marginal probability (and index) effect of  $nwifeinc_i$  equals zero** for married women for whom  $dkidslt6_i = 1$ .

- ♦ **For married women for whom  $dkidslt6_i = 1$ :** marginal probability effect of  $nwifeinc_i = \phi(x_i^T \beta)(\beta_1 + \beta_7)$

A sufficient condition for the marginal probability effect of  $nwifeinc_i$  to equal zero for any given values of the regressors  $x_i^T$  is  $\beta_1 + \beta_7 = 0$ .

- ♦ **Null and Alternative Hypotheses:**

$$H_0: \beta_1 + \beta_7 = 0 \quad \text{versus} \quad H_1: \beta_1 + \beta_7 \neq 0$$

- To calculate a **Wald test** of this hypothesis and the corresponding p-value for the calculated W-statistic, enter the following **test**, **return list** and **display** commands:

```
test nwifeinc + d6nwinc = 0
return list
display sqrt(r(chi2))
```

- To calculate a **two-tail asymptotic t-test** of  $H_0$  against  $H_1$ , enter the following *Stata* commands:

```
lincom _b[nwifeinc] + _b[d6nwinc]
return list
display r(estimate)/r(se)
```

The results of this two-tail t-test are identical with those of the previous Wald test.

- ◆ **Test 2 - Model 3: for married women with no pre-school aged children**
- ◆ **Proposition:** For married women who have no pre-school aged children, the probability of labour force participation does not depend on their education; the **marginal probability (and index) effect of  $ed_i$  equals zero** for married women for whom  $dkidslt6_i = 0$ .
- ◆ **For married women for whom  $dkidslt6_i = 0$ :** marginal probability effect of  $ed_i = \phi(x_i^T \beta) \beta_2$

A sufficient condition for the marginal probability effect of  $ed_i$  to equal zero for any given values of the regressors  $x_i^T$  is  $\beta_2 = 0$ .

- ◆ **Null and Alternative Hypotheses:**

$$H_0: \beta_2 = 0 \quad \text{versus} \quad H_1: \beta_2 \neq 0$$

- To calculate a **Wald test** of this hypothesis and the corresponding p-value for the calculated W-statistic, enter the following **test**, **return list** and **display** commands:

```
test ed      or      test ed = 0
return list
display sqrt(r(chi2))
```

- To calculate a **two-tail asymptotic t-test** of  $H_0$  against  $H_1$ , enter the following *Stata* commands:

```
lincom _b[ed]
return list
display r(estimate)/r(se)
```

The results of this two-tail t-test are identical with those of the previous Wald test.

- ◆ **Test 2 - Model 3: for married women with one or more pre-school aged children**
- ◆ **Proposition:** For married women who have one or more pre-school aged children, the probability of labour force participation does not depend on their education; the **marginal probability (and index) effect of  $ed_i$  equals zero** for married women for whom  $dkidslt6_i = 1$ .
- ◆ **For married women for whom  $dkidslt6_i = 1$ :** marginal probability effect of  $ed_i = \phi(x_i^T \beta)(\beta_2 + \beta_8)$

A sufficient condition for the marginal probability effect of  $ed_i$  to equal zero for any given values of the regressors  $x_i^T$  is  $\beta_2 + \beta_8 = 0$ .

- ◆ **Null and Alternative Hypotheses:**

$$H_0: \beta_2 + \beta_8 = 0 \quad \text{versus} \quad H_1: \beta_2 + \beta_8 \neq 0$$

- To calculate a **Wald test** of this hypothesis and the corresponding p-value for the calculated W-statistic, enter the following **test**, **return list** and **display** commands:

```
test ed + d6ed = 0
return list
display sqrt(r(chi2))
```

- To calculate a **two-tail asymptotic t-test** of  $H_0$  against  $H_1$ , enter the following *Stata* commands:

```
lincom _b[ed] + _b[d6ed]
return list
display r(estimate)/r(se)
```

The results of this two-tail t-test are identical with those of the previous Wald test.



- ◆ **Test 3 - Model 3: for married women with no pre-school aged children**
- ◆ **Proposition:** Years of actual work experience have no effect on the probability of labour force participation for married women who have no pre-school aged children; the **marginal probability (and index) effect of  $\text{exp}_i$  equals zero** for married women for whom  $\text{dkidslt6}_i = 0$ .
- ◆ **For married women for whom  $\text{dkidslt6}_i = 0$ :** marginal probability effect of  $\text{exp}_i = \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_3 + 2\beta_4 \text{exp}_i)$

A sufficient condition for the marginal probability effect of  $\text{exp}_i$  to equal zero for any given values of the regressors  $\mathbf{x}_i^T$  is  $\beta_3 = 0$  and  $\beta_4 = 0$ .

- ◆ **Null and Alternative Hypotheses:**

$$H_0: \beta_3 = 0 \text{ and } \beta_4 = 0 \quad \text{versus} \quad H_1: \beta_3 \neq 0 \text{ and/or } \beta_4 \neq 0$$

- To calculate a **Wald test** of this hypothesis and the corresponding p-value for the calculated W-statistic, enter the following **test**, **return list** and **display** commands:

```
test exp expsq
return list
```

- ◆ **Test 3 - Model 3: for married women with one or more pre-school aged children**
- ◆ **Proposition:** Years of actual work experience have no effect on the probability of labour force participation for married women who have one or more pre-school aged children; the **marginal probability (and index) effect of  $\text{exp}_i$  equals zero** for married women for whom  $\text{dkidslt6}_i = 1$ .

- ◆ **For married women for whom  $\text{dkidslt6}_i = 1$ :**

$$\text{marginal probability effect of } \text{exp}_i = \phi(x_i^T \beta) (\beta_3 + \beta_9 + 2(\beta_4 + \beta_{10}) \text{exp}_i)$$

A sufficient condition for the marginal probability effect of  $\text{exp}_i$  to equal zero for any given values of the regressors  $x_i^T$  is  $\beta_3 + \beta_9 = 0$  and  $\beta_4 + \beta_{10} = 0$ .

- ◆ **Null and Alternative Hypotheses:**

$$H_0: \beta_3 + \beta_9 = 0 \text{ and } \beta_4 + \beta_{10} = 0$$

$$H_1: \beta_3 + \beta_9 \neq 0 \text{ and/or } \beta_4 + \beta_{10} \neq 0$$

- To calculate a **Wald test** of this hypothesis and the corresponding p-value for the calculated W-statistic, enter the following **test** and **return list** commands:

```
test exp + d6exp = 0, notest
test expsq + d6expsq = 0, accumulate
return list
```

◆ **Test 4 - Model 3: for married women with no pre-school aged children**

- ◆ **Proposition:** For married women who have no pre-school aged children, their age has no effect on their probability of labour force participation; the **marginal probability (and index) effect of age<sub>i</sub> equals zero** for married women for whom  $dkidslt6_i = 0$ .

- ◆ **For married women for whom  $dkidslt6_i = 0$ :** marginal probability effect of  $age_i = \phi(x_i^T \beta) \beta_5$

A sufficient condition for the marginal probability effect of  $ed_i$  to equal zero for any given values of the regressors  $x_i^T$  is  $\beta_5 = 0$ .

- ◆ **Null and Alternative Hypotheses:**

$$H_0: \beta_5 = 0 \quad \text{versus} \quad H_1: \beta_5 \neq 0$$

- To calculate a **Wald test** of this hypothesis and the corresponding p-value for the calculated W-statistic, enter the following **test**, **return list** and **display** commands:

```
test age          or      test age = 0
return list
display sqrt(r(chi2))
```

- To calculate a **two-tail asymptotic t-test** of  $H_0$  against  $H_1$ , enter the following *Stata* commands:

```
lincom _b[age]
return list
display r(estimate)/r(se)
```

The results of this two-tail t-test are identical with those of the previous Wald test.

◆ **Test 4 - Model 3: for married women with one or more pre-school aged children**

- ◆ **Proposition:** For married women who have one or more pre-school aged children, their age has no effect on their probability of labour force participation; the **marginal probability (and index) effect of age<sub>i</sub> equals zero** for married women for whom  $dkidslt6_i = 1$ .

- ◆ **For married women for whom  $dkidslt6_i = 1$ :** marginal probability effect of age<sub>i</sub> =  $\phi(x_i^T \beta)(\beta_5 + \beta_{11})$

A sufficient condition for the marginal probability effect of age<sub>i</sub> to equal zero for any given values of the regressors  $x_i^T$  is  $\beta_5 + \beta_{11} = 0$ .

- ◆ **Null and Alternative Hypotheses:**

$$H_0: \beta_5 + \beta_{11} = 0 \quad \text{versus} \quad H_1: \beta_5 + \beta_{11} \neq 0$$

- To calculate a **Wald test** of this hypothesis and the corresponding p-value for the calculated W-statistic, enter the following **test**, **return list** and **display** commands:

```
test age + d6age = 0
return list
display sqrt(r(chi2))
```

- To calculate a **two-tail asymptotic t-test** of  $H_0$  against  $H_1$ , enter the following *Stata* commands:

```
lincom _b[age] + _b[d6age]
return list
display r(estimate)/r(se)
```

The results of this two-tail t-test are identical with those of the previous Wald test.

---

□ **Testing for *differences* in the marginal *probability* effects of *continuous* explanatory variables in Model 3 – *probit* or *dprobit***

---

***Objective:*** To test the proposition that the **marginal effect of each *continuous* explanatory variable** on the probability of married women's labour force participation **is equal** for the ***two* groups of married women**: married women with no pre-school aged children, for whom  $dkidslt6_i = 0$ ; and married women with one or more pre-school aged children, for whom  $dkidslt6_i = 1$ .

- ◆ **Test 5 - Model 3: equal marginal probability effects of  $nwifeinc_i$**
- ◆ **Proposition:** The marginal probability (and index) effect of  $nwifeinc_i$  is equal for zero for married women for whom  $dkidslt6_i = 1$ .

- ◆ **Marginal probability effects for  $nwifeinc_i$  are:**

$$= \phi(x_i^T \beta) \beta_1 \quad \text{when } dkidslt6_i = 0$$

$$= \phi(x_i^T \beta) (\beta_1 + \beta_7) \quad \text{when } dkidslt6_i = 1$$

A sufficient condition for the marginal probability effect of  $nwifeinc_i$  to be equal for married women with and without pre-school aged children is  $\beta_7 = 0$ .

- ◆ ***Null and Alternative Hypotheses:***

$$H_0: \beta_7 = 0 \quad \text{versus} \quad H_1: \beta_7 \neq 0$$

- To calculate a **Wald test** of this hypothesis, enter the following **test** command:

```
test d6nwinc = 0
```

- To calculate a **two-tail asymptotic t-test** of  $H_0$  against  $H_1$ , enter the following **lincom** command:

```
lincom _b[d6nwinc]
```

The results of this two-tail t-test are identical with those of the previous Wald test.

- ◆ **Test 6 - Model 3: equal marginal probability effects of  $ed_i$**
- ◆ **Proposition:** The marginal probability (and index) effect of  $ed_i$  is equal for married women with pre-school aged kids and married women with no pre-school aged kids.
- ◆ **Marginal probability effects for  $ed_i$  are:**

$$= \phi(x_i^T \beta) \beta_2 \quad \text{when } dkidslt6_i = 0$$

$$= \phi(x_i^T \beta) (\beta_2 + \beta_8) \quad \text{when } dkidslt6_i = 1$$

A sufficient condition for the marginal probability effect of  $ed_i$  to be equal for married women with and without pre-school aged children is  $\beta_8 = 0$ .

- ◆ ***Null and Alternative Hypotheses:***

$$H_0: \beta_8 = 0 \quad \text{versus} \quad H_1: \beta_8 \neq 0$$

- To calculate a **Wald test** of this hypothesis, enter the following **test** command:

```
test d6ed = 0
```

- To calculate a **two-tail asymptotic t-test** of  $H_0$  against  $H_1$ , enter the following **lincom** command:

```
lincom _b[d6ed]
```

The results of this two-tail t-test are identical with those of the previous Wald test.

- ◆ **Test 7 - Model 3: equal marginal probability effects of  $exp_i$**
- ◆ **Proposition:** The marginal probability (and index) effect of  $exp_i$  is equal for married women with pre-school aged kids and married women with no pre-school aged kids.
- ◆ **Marginal probability effects for  $exp_i$  are:**

$$= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_3 + 2\beta_4 \exp_i) \quad \text{when } dkidslt6_i = 0$$

$$= \phi(\mathbf{x}_i^T \boldsymbol{\beta})(\beta_3 + \beta_9 + 2(\beta_4 + \beta_{10}) \exp_i) \quad \text{when } dkidslt6_i = 1$$

Sufficient conditions for the marginal probability effect of  $exp_i$  to be equal for married women with and without pre-school aged children are  $\beta_9 = 0$  and  $\beta_{10} = 0$ .

- ◆ ***Null and Alternative Hypotheses:***

$$H_0: \beta_9 = 0 \text{ and } \beta_{10} = 0 \quad \text{versus} \quad H_1: \beta_9 \neq 0 \text{ and/or } \beta_{10} \neq 0$$

- To calculate a **Wald test** of this hypothesis, enter the following **test** commands:

```
test d6exp = 0
test d6expsq = 0, accumulate
```



- ◆ **Test 8 - Model 3: equal marginal probability effects of age<sub>i</sub>**
- ◆ **Proposition:** The marginal probability (and index) effect of age<sub>i</sub> is equal for married women with pre-school aged kids and married women with no pre-school aged kids.
- ◆ **Marginal probability effects for age<sub>i</sub> are:**

$$= \phi(x_i^T \beta) \beta_5 \quad \text{when } dkidslt6_i = 0$$

$$= \phi(x_i^T \beta) (\beta_5 + \beta_{11}) \quad \text{when } dkidslt6_i = 1$$

A sufficient condition for the marginal probability effect of age<sub>i</sub> to be equal for married women with and without pre-school aged children is  $\beta_{11} = 0$ .

- ◆ ***Null and Alternative Hypotheses:***

$$H_0: \beta_{11} = 0 \quad \text{versus} \quad H_1: \beta_{11} \neq 0$$

- To calculate a **Wald test** of this hypothesis, enter the following **test** command:

```
test d6age = 0
```

- To calculate a **two-tail asymptotic t-test** of  $H_0$  against  $H_1$ , enter the following **lincom** command:

```
lincom _b[d6age]
```

The results of this two-tail t-test are identical with those of the previous Wald test.

---

□ **Computing estimates of the marginal *probability* effects of *continuous* explanatory variables in Model 3 -- *dprobit***

---

**Objective**

To estimate the *magnitude* of the relationship between a continuous explanatory variable and the conditional probability of married women's labour force participation.

***Question addressed is:* How large a change in the conditional probability of married women's labour force participation is associated with a **one-unit increase in the value of a particular continuous explanatory variable**, holding constant the values of all other explanatory variables included in the model?**

This section demonstrates how to address this second question for each of the continuous explanatory variables  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$ .

**Procedure**

Recall that the **marginal probability effect of a continuous explanatory variable  $X_j$**  is **proportional to the marginal index effect of  $X_j$** , where the factor of proportionality is the standard normal p.d.f. evaluated at  $x_i^T \beta$ :

$$\text{marginal probability effect of } X_j = \phi(x_i^T \beta) \times \text{marginal index effect of } X_j$$

This expression implies that to compute estimates of the marginal *probability* effect of each *continuous* explanatory variable, we must first do two things.

- First, we must compute an estimate  $x_i^T \hat{\beta}$  of  $x_i^T \beta$ .
- Second, we must compute the value of  $\phi(x_i^T \hat{\beta})$ , i.e., the value of the standard normal density function evaluated at  $x_i^T \hat{\beta}$ .

**Which Stata command to use** Use the **dprobit** command with the **at(*vecname*)** option

**Marginal probability effects for married women for whom  $dkidslt6_i = 0$** 

Compute the marginal probability effects of the four *continuous explanatory variables* in Model 3 for married women who have the **sample median values** of  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$ , and **no pre-schooled aged children** (for whom  $dkidslt6_i = 0$ ).

- First re-estimate Model 3 using the **dprobit** command with the **at(vecname)** option. The vector to use in the **at(vecname)** option is the vector  $x_{0i}^T$  containing the median values of the regressors in Model 3 when  $dkidslt6_i = 0$ :

$$\begin{aligned} x_{0i}^T &= (nwifeinc_i \quad ed_i \quad exp_i \quad exp_i^2 \quad age_i \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1) \\ &= (nwinc50p \quad ed50p \quad exp50p \quad expsq50p \quad age50p \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1) \end{aligned}$$

You previously created the vector  $x_{0i}^T$  and named it **x0median**. So simply enter the commands:

```
dprobit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age,
at(x0median)
ereturn list
display e(at)
```

Recall that the scalar **e(at)** contains the value of  $\Phi(x_{0i}^T \hat{\beta})$  generated by the previous **dprobit** command, where  $\Phi(x_{0i}^T \hat{\beta})$  is an estimate of  $\Pr(\text{inlf}_i = 1 \mid dkidslt6_i = 0)$ .

- Second, use the *Stata* statistical function **invnormal()** to save the value of  $x_{0i}^T \hat{\beta}$ . Enter the commands:

```
scalar x0medbhat = invnormal(e(at))
scalar list x0medbhat
```

- Third, use the *Stata* statistical function **normalden()** to save as a scalar the value of  $\phi(x_{0i}^T \hat{\beta})$ , which is the standard normal density function (or p.d.f.) evaluated at  $x_{0i}^T \hat{\beta}$ . Enter the commands:

```
scalar phix0med = normalden(x0medbhat)
scalar list phix0med
```

These commands save the value of  $\phi(x_{0i}^T \hat{\beta})$  as the scalar **phix0med**.

- Compute the **estimated marginal probability effect of explanatory variable *nwifeinc*<sub>*i*</sub>** for the **median married woman who has no pre-school aged children**, which when **dkidslt6<sub>*i*</sub> = 0** is given by the function:

$$\text{estimated marginal probability effect of } nwifeinc_i = \phi(x_{0i}^T \hat{\beta}) \hat{\beta}_1$$

Enter the **lincom** command:

```
lincom phix0med*_b[nwifeinc]
```

- Compute the **estimated marginal probability effect of explanatory variable  $ed_i$**  for the ***median married woman who has no pre-school aged children***, which when  $\mathbf{dkidslt6}_i = \mathbf{0}$  is given by the function:

$$\text{estimated marginal probability effect of } ed_i = \phi(x_{0i}^T \hat{\beta}) \hat{\beta}_2$$

Enter the **lincom** command:

```
lincom phix0med*_b[ed]
```

- Compute the **estimated marginal probability effect of explanatory variable  $exp_i$**  for the ***median married woman who has no pre-school aged children***, which when  $\mathbf{dkidslt6}_i = \mathbf{0}$  is given by the function:

$$\text{estimated marginal probability effect of } exp_i = \phi(x_{0i}^T \hat{\beta}) (\hat{\beta}_3 + 2\hat{\beta}_4 \exp50p)$$

Enter the **lincom** command:

```
lincom phix0med*(_b[exp] + 2*_b[exp50p])
```

- Compute the **estimated marginal probability effect of explanatory variable  $age_i$**  for the ***median married woman who has no pre-school aged children***, which when  $\mathbf{dkidslt6}_i = \mathbf{0}$  is given by the function:

$$\text{estimated marginal probability effect of } age_i = \phi(x_{0i}^T \hat{\beta}) \hat{\beta}_5$$

Enter the **lincom** command:

```
lincom phix0med*_b[age]
```

**Marginal probability effects for married women for whom  $dkidslt6_i = 1$** 

Compute the marginal probability effects of the four *continuous explanatory variables* in Model 3 for married women who have the **sample median values** of  $nwifeinc_i$ ,  $ed_i$ ,  $exp_i$ , and  $age_i$ , and **one or more pre-schooled aged children** (for whom  $dkidslt6_i = 1$ ).

- First re-estimate Model 3 using the **dprobit** command with the **at(vecname)** option. The vector to use in the **at(vecname)** option is the vector  $x_{ii}^T$  containing the median values of the regressors in Model 3 when  $dkidslt6_i = 1$ :

$$\begin{aligned} x_{ii}^T &= (nwifeinc_i \quad ed_i \quad exp_i \quad exp_i^2 \quad age_i \quad 1 \quad nwifeinc_i \quad ed_i \quad exp_i \quad exp_i^2 \quad age_i \quad 1) \\ &= \begin{pmatrix} nwinc50p \quad ed50p \quad exp50p \quad expsq50p \quad age50p \quad 1 \\ nwinc50p \quad ed50p \quad exp50p \quad expsq50p \quad age50p \quad 1 \end{pmatrix} \end{aligned}$$

You previously created the vector  $x_{ii}^T$  and named it **x1median**. So simply enter the commands:

```
dprobit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age,
at(x1median)
ereturn list
display e(at)
```

Recall that the scalar **e(at)** contains the value of  $\Phi(x_{ii}^T \hat{\beta})$  generated by the previous **dprobit** command, where  $\Phi(x_{ii}^T \hat{\beta})$  is an estimate of  $\Pr(\text{inlf}_i = 1 \mid dkidslt6_i = 1)$ .

- Second, use the *Stata* statistical function **invnormal()** to save the value of  $x_{ii}^T \hat{\beta}$ . Enter the commands:

```
scalar x1medbhat = invnormal(e(at))
scalar list x1medbhat
```

- Third, use the *Stata* statistical function **normalden()** to save as a scalar the value of  $\phi(x_{ii}^T \hat{\beta})$ , which is the standard normal density function (or p.d.f.) evaluated at  $x_{ii}^T \hat{\beta}$ . Enter the commands:

```
scalar phix1med = normalden(x1medbhat)
scalar list phix1med
```

These commands save the value of  $\phi(x_{ii}^T \hat{\beta})$  as the scalar **phix1med**.

- Compute the **estimated marginal probability effect of explanatory variable *nwifeinc*<sub>*i*</sub>** for the **median married woman who has one or more pre-school aged children**, which when **dkidslt6<sub>*i*</sub> = 1** is given by the function:

$$\text{estimated marginal probability effect of } nwifeinc_i = \phi(x_{ii}^T \hat{\beta})(\hat{\beta}_1 + \hat{\beta}_7)$$

Enter the **lincom** command:

```
lincom phix1med*(_b[nwifeinc] + _b[d6nwinc])
```



- Compute the **estimated marginal probability effect of explanatory variable  $ed_i$**  for the **median married woman who has one or more pre-school aged children**, which when  $dkidslt6_i = 1$  is given by the function:

$$\text{estimated marginal probability effect of } ed_i = \phi(x_{1i}^T \hat{\beta}) (\hat{\beta}_2 + \hat{\beta}_8)$$

Enter the **lincom** command:

```
lincom phix1med*(_b[ed] + _b[d6ed])
```

- Compute the **estimated marginal probability effect of explanatory variable  $exp_i$**  for the **median married woman who has one or more pre-school aged children**, which when  $dkidslt6_i = 1$  is given by the function:

$$\text{estimated marginal probability effect of } exp_i = \phi(x_{1i}^T \hat{\beta}) (\hat{\beta}_3 + \hat{\beta}_9 + 2(\hat{\beta}_4 + \hat{\beta}_{10}) \exp50p)$$

Enter the **lincom** command:

```
lincom phix1med*(_b[exp] + _b[d6exp] + 2*(_b[expsq] + _b[d6expsq])*exp50p)
```

- Compute the **estimated marginal probability effect of explanatory variable  $age_i$**  for the **median married woman who has one or more pre-school aged children**, which when  $dkidslt6_i = 1$  is given by the function:

$$\text{estimated marginal probability effect of } age_i = \phi(x_i^T \beta) (\beta_5 + \beta_{11})$$

Enter the **lincom** command:

```
lincom phix1med*(_b[age] + _b[d6age])
```