ECON 452*: Stata 12/13 Tutorials 8 and 9

TOPIC: Estimating and Testing the Marginal Probability Effect of the Binary Variable 'dkidslt6'

DATA: mroz.dta (a *Stata*-format dataset created in *Stata 12/13 Tutorial 8*)

- The *Stata* commands that constitute the primary subject of these tutorials are:
 - probitUsed to compute ML estimates of *probit* coefficients in probit models of binary dependent
variables.dprobitUsed to compute ML estimates of the marginal *probability* effects of explanatory variables in
probit models.testUsed after probit estimation to compute *Wald tests* of linear coefficient equality restrictions on
probit coefficients.lincomUsed after probit estimation to compute and test the marginal effects of individual explanatory
variables.marginsUsed after probit estimation to compute estimates of the marginal *probability* effects of both
continuous and *categorical (binary*) explanatory variables.
- The *Stata* statistical functions used in this tutorial are:
 - **normalden**(*z*) Computes *value of the standard normal <u>density</u> function* (*p.d.f.*) for a given value *z* of a standard normal random variable.
 - **normal**(*z*) Computes *value of the standard normal <u>distribution function</u> (<i>c.d.f.*) for a given value *z* of a standard normal random variable.
 - invnormal(*p*) Computes the inverse of the standard normal <u>distribution</u> function; if normal(z) = *p*, then invnormal(p) = *z*.

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

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

- Model 2 was introduced in *Stata 12/13 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** *dkidslt6ⁱ* 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.

<u>Model 2</u> – binary explanatory variable *dkidslt6*^{*i*} enters only additively

The **probit index function**, or regression function, **for Model 2** is:

 $x_i^{T}\beta = \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \delta_0 dkidslt6_i$

- *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:

$$\left(x_i^{\mathrm{T}} \beta \left| \mathrm{dkidslt6}_i = 0 \right) = \beta_0 + \beta_1 \mathrm{nwifeinc}_i + \beta_2 \mathrm{ed}_i + \beta_3 \exp_i + \beta_4 \exp_i^2 + \beta_5 \mathrm{age}_i + \delta_0 0 \right)$$

= $\beta_0 + \beta_1 \mathrm{nwifeinc}_i + \beta_2 \mathrm{ed}_i + \beta_3 \exp_i + \beta_4 \exp_i^2 + \beta_5 \mathrm{age}_i$

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:

$$\left(x_i^{T} \beta \left| dkidslt6_i = 1 \right) = \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \delta_0 1 \right)$$

= $\beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \delta_0 1$

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^Tβ|dkidslt6_i = 1) and (2) the index function for *married women who currently have no pre-school aged children*, (x_i^Tβ|dkidslt6_i = 0):

$$\begin{split} \left(x_{i}^{T}\beta\right|dkidslt6_{i} = 1\right) &- \left(x_{i}^{T}\beta\right|dkidslt6_{i} = 0\right) \\ &= \beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}\exp_{i} + \beta_{4}\exp_{i}^{2} + \beta_{5}age_{i} + \delta_{0} \\ &- \left(\beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}\exp_{i} + \beta_{4}\exp_{i}^{2} + \beta_{5}age_{i}\right) \\ &= \beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}\exp_{i} + \beta_{4}\exp_{i}^{2} + \beta_{5}age_{i} + \delta_{0} \\ &- \beta_{0} - \beta_{1}nwifeinc_{i} - \beta_{2}ed_{i} - \beta_{3}\exp_{i} - \beta_{4}\exp_{i}^{2} - \beta_{5}age_{i} \\ &= \delta_{0} \end{split}$$

In Model 2, the marginal probability effect of the binary indicator variable dkidslt6_i is the difference between (1) the conditional probability that inlf_i = 1 for married women with one or more pre-school aged children and (2) the conditional probability that inlf_i = 1 for married women with no pre-school aged children:

$$\Pr\left(\operatorname{inlf}_{i}=1 \middle| \operatorname{dkidslt6}_{i}=1\right) - \Pr\left(\operatorname{inlf}_{i}=1 \middle| \operatorname{dkidslt6}_{i}=0\right) = \Phi\left(x_{1i}^{\mathrm{T}}\beta\right) - \Phi\left(x_{0i}^{\mathrm{T}}\beta\right)$$

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

$$\begin{aligned} \mathbf{x}_{1i}^{T} &= \left(1 \text{ nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} age_{i} 1\right) \\ \mathbf{x}_{0i}^{T} &= \left(1 \text{ nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} age_{i} 0\right) \\ \boldsymbol{\beta} &= \left(\beta_{0} \ \beta_{1} \ \beta_{2} \ \beta_{3} \ \beta_{4} \ \beta_{5} \ \delta_{0}\right)^{T} \\ \mathbf{x}_{1i}^{T} \boldsymbol{\beta} &= \beta_{0} + \beta_{1} \text{nwifeinc}_{i} + \beta_{2} ed_{i} + \beta_{3} \exp_{i} + \beta_{4} \exp_{i}^{2} + \beta_{5} age_{i} + \delta_{0} \\ \mathbf{x}_{0i}^{T} \boldsymbol{\beta} &= \beta_{0} + \beta_{1} \text{nwifeinc}_{i} + \beta_{2} ed_{i} + \beta_{3} \exp_{i} + \beta_{4} \exp_{i}^{2} + \beta_{5} age_{i} \\ \text{Pr}\left(\text{inlf}_{i} = 1 | \text{dkidslt6}_{i} = 1\right) &= \Phi\left(\mathbf{x}_{1i}^{T} \boldsymbol{\beta}\right) = \Phi\left(\beta_{0} + \beta_{1} \text{nwifeinc}_{i} + \beta_{2} ed_{i} + \beta_{3} \exp_{i} + \beta_{4} \exp_{i}^{2} + \beta_{5} age_{i} + \delta_{0}\right) \\ \text{Pr}\left(\text{inlf}_{i} = 1 | \text{dkidslt6}_{i} = 0\right) &= \Phi\left(\mathbf{x}_{0i}^{T} \boldsymbol{\beta}\right) = \Phi\left(\beta_{0} + \beta_{1} \text{nwifeinc}_{i} + \beta_{2} ed_{i} + \beta_{3} \exp_{i} + \beta_{4} \exp_{i}^{2} + \beta_{5} age_{i} + \delta_{0}\right) \\ &= \Phi\left(\beta_{0} + \beta_{1} \text{nwifeinc}_{i} + \beta_{2} ed_{i} + \beta_{3} \exp_{i} + \beta_{4} \exp_{i}^{2} + \beta_{5} age_{i}\right) \end{aligned}$$

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

$$\begin{aligned} \Pr(\operatorname{inlf}_{i} = 1 | \operatorname{dkidslt6}_{i} = 1) - \Pr(\operatorname{inlf}_{i} = 1 | \operatorname{dkidslt6}_{i} = 0) &= \Phi(x_{1i}^{T}\beta) - \Phi(x_{0i}^{T}\beta) \\ &= \Phi(\beta_{0} + \beta_{1}\operatorname{nwifeinc}_{i} + \beta_{2}\operatorname{ed}_{i} + \beta_{3}\operatorname{exp}_{i} + \beta_{4}\operatorname{exp}_{i}^{2} + \beta_{5}\operatorname{age}_{i} + \delta_{0}) \\ &- \Phi(\beta_{0} + \beta_{1}\operatorname{nwifeinc}_{i} + \beta_{2}\operatorname{ed}_{i} + \beta_{3}\operatorname{exp}_{i} + \beta_{4}\operatorname{exp}_{i}^{2} + \beta_{5}\operatorname{age}_{i}) \end{aligned}$$

<u>Model 3</u> – a full interaction model in the binary variable $dkidslt6_i$

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

 $\mathbf{x}_{i}^{\mathrm{T}}\boldsymbol{\beta} = \boldsymbol{\beta}_{0} + \boldsymbol{\beta}_{1}$ nwifeinc_i + $\boldsymbol{\beta}_{2}$ ed_i + $\boldsymbol{\beta}_{3}$ exp_i + $\boldsymbol{\beta}_{4}$ exp_i² + $\boldsymbol{\beta}_{5}$ age_i

 $+ \delta_0 dkidslt \delta_i + \delta_1 dkidslt \delta_i nwifeinc_i + \delta_2 dkidslt \delta_i ed_i + \delta_3 dkidslt \delta_i exp_i + \delta_4 dkidslt \delta_i exp_i^2 + \delta_5 dkidslt \delta_i age_i + \delta_4 dkidslt \delta_i exp_i^2 + \delta_5 dkidslt \delta_i age_i + \delta_4 dkidslt \delta_i exp_i^2 + \delta_5 dkidslt \delta_i exp_i^2 + \delta_$

- *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:

$$\left(\mathbf{x}_{i}^{\mathrm{T}}\boldsymbol{\beta}\right| \mathrm{dkidslt6}_{i} = 0\right) = \beta_{0} + \beta_{1}\mathrm{nwifeinc}_{i} + \beta_{2}\mathrm{ed}_{i} + \beta_{3}\mathrm{exp}_{i} + \beta_{4}\mathrm{exp}_{i}^{2} + \beta_{5}\mathrm{age}_{i}$$

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:

$$\left(x_i^{\mathrm{T}}\beta \right| \mathrm{dkidslt6}_i = 1 \right) = \beta_0 + \beta_1 \mathrm{nwifeinc}_i + \beta_2 \mathrm{ed}_i + \beta_3 \exp_i + \beta_4 \exp_i^2 + \beta_5 \mathrm{age}_i + \delta_0 1 + \delta_1 1 \cdot \mathrm{nwifeinc}_i + \delta_2 1 \cdot \mathrm{ed}_i + \delta_3 1 \cdot \exp_i + \delta_4 1 \cdot \exp_i^2 + \delta_5 1 \cdot \mathrm{age}_i = \beta_0 + \beta_1 \mathrm{nwifeinc}_i + \beta_2 \mathrm{ed}_i + \beta_3 \exp_i + \beta_4 \exp_i^2 + \beta_5 \mathrm{age}_i + \delta_0 + \delta_1 \mathrm{nwifeinc}_i + \delta_2 \mathrm{ed}_i + \delta_3 \exp_i + \delta_4 \exp_i^2 + \delta_5 \mathrm{age}_i = (\beta_0 + \delta_0) + (\beta_1 + \delta_1) \mathrm{nwifeinc}_i + (\beta_2 + \delta_2) \mathrm{ed}_i + (\beta_3 + \delta_3) \exp_i + (\beta_4 + \delta_4) \exp_i^2 + (\beta_5 + \delta_5) \mathrm{age}_i$$

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^T_iβ|dkidslt6_i = 1) and (2) the index function for *married women who currently have no pre-school aged children*, (x^T_iβ|dkidslt6_i = 0):

$$\left(\mathbf{x}_{i}^{\mathrm{T}}\boldsymbol{\beta} | \mathrm{dkidslt6}_{i} = 1\right) - \left(\mathbf{x}_{i}^{\mathrm{T}}\boldsymbol{\beta} | \mathrm{dkidslt6}_{i} = 0\right)$$

$$= \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \exp_i + \beta_4 \exp_i^2 + \beta_5 \text{age}_i + \delta_0 + \delta_1 \text{nwifeinc}_i + \delta_2 \text{ed}_i + \delta_3 \exp_i + \delta_4 \exp_i^2 + \delta_5 \text{age}_i \\ - \left(\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \exp_i + \beta_4 \exp_i^2 + \beta_5 \text{age}_i\right)$$

 $= \beta_0 + \beta_1 nwifeinc_i + \beta_2 ed_i + \beta_3 exp_i + \beta_4 exp_i^2 + \beta_5 age_i + \delta_0 + \delta_1 nwifeinc_i + \delta_2 ed_i + \delta_3 exp_i + \delta_4 exp_i^2 + \delta_5 age_i - \beta_0 - \beta_1 nwifeinc_i - \beta_2 ed_i - \beta_3 exp_i - \beta_4 exp_i^2 - \beta_5 age_i$

$$= \delta_0 + \delta_1 nwifeinc_i + \delta_2 ed_i + \delta_3 exp_i + \delta_4 exp_i^2 + \delta_5 age_i$$

In Model 3, the marginal probability effect of the binary indicator variable dkidslt6_i is the difference between (1) the conditional probability that inlf_i = 1 for married women with one or more pre-school aged children and (2) the conditional probability that inlf_i = 1 for married women with no pre-school aged children:

$$\Pr\left(\operatorname{inlf}_{i}=1 \middle| \operatorname{dkidslt6}_{i}=1\right) - \Pr\left(\operatorname{inlf}_{i}=1 \middle| \operatorname{dkidslt6}_{i}=0\right) = \Phi\left(x_{1i}^{\mathrm{T}}\beta\right) - \Phi\left(x_{0i}^{\mathrm{T}}\beta\right)$$

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

$$\begin{aligned} \mathbf{x}_{1i}^{T} &= \left(1 \text{ nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} \text{ age}_{i} 1 \text{ nwifeinc}_{i} \text{ ed}_{i} \exp_{i}^{2} \text{ age}_{i}\right) \\ \mathbf{x}_{0i}^{T} &= \left(1 \text{ nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} \text{ age}_{i} 0 0 0 0 0 0\right) \\ \beta &= \left(\beta_{0} \beta_{1} \beta_{2} \beta_{3} \beta_{4} \beta_{5} \delta_{0} \delta_{1} \delta_{2} \delta_{3} \delta_{4} \delta_{5}\right)^{T} \\ \mathbf{x}_{1i}^{T}\beta &= \beta_{0} + \beta_{1} \text{nwifeinc}_{i} + \beta_{2} \text{ed}_{i} + \beta_{3} \exp_{i} + \beta_{4} \exp_{i}^{2} + \beta_{5} \text{age}_{i} \\ &+ \delta_{0} + \delta_{1} \text{nwifeinc}_{i} + \delta_{2} \text{ed}_{i} + \delta_{3} \exp_{i} + \delta_{4} \exp_{i}^{2} + \delta_{5} \text{age}_{i} \end{aligned}$$

 $\mathbf{x}_{0i}^{\mathrm{T}}\boldsymbol{\beta} = \boldsymbol{\beta}_{0} + \boldsymbol{\beta}_{1} \text{nwifeinc}_{i} + \boldsymbol{\beta}_{2} \text{ed}_{i} + \boldsymbol{\beta}_{3} \exp_{i} + \boldsymbol{\beta}_{4} \exp_{i}^{2} + \boldsymbol{\beta}_{5} \text{age}_{i}$

$$\begin{aligned} &\Pr\left(\operatorname{inlf}_{i}=1 \middle| \operatorname{dkidslt6}_{i}=1\right) \\ &= \Phi \begin{pmatrix} \beta_{0} + \beta_{1} \operatorname{nwifeinc}_{i} + \beta_{2} \operatorname{ed}_{i} + \beta_{3} \exp_{i} + \beta_{4} \exp_{i}^{2} + \beta_{5} \operatorname{age}_{i} \\ + \delta_{0} + \delta_{1} \operatorname{nwifeinc}_{i} + \delta_{2} \operatorname{ed}_{i} + \delta_{3} \exp_{i} + \delta_{4} \exp_{i}^{2} + \delta_{5} \operatorname{age}_{i} \end{pmatrix} \\ &= \Phi \begin{pmatrix} (\beta_{0} + \delta_{0}) + (\beta_{1} + \delta_{1}) \operatorname{nwifeinc}_{i} + (\beta_{2} + \delta_{2}) \operatorname{ed}_{i} \\ + (\beta_{3} + \delta_{3}) \exp_{i} + (\beta_{4} + \delta_{4}) \exp_{i}^{2} + (\beta_{5} + \delta_{5}) \operatorname{age}_{i} \end{pmatrix} \\ &\Pr\left(\operatorname{inlf}_{i}=1 \middle| \operatorname{dkidslt6}_{i}=0\right) \end{aligned}$$

$$= \Phi \begin{pmatrix} \beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \exp_i + \beta_4 \exp_i^2 + \beta_5 \text{age}_i \\ + \delta_0 0 + \delta_1 0 + \delta_2 0 + \delta_3 0 + \delta_4 0 + \delta_5 0 \end{pmatrix}$$

= $\Phi (\beta_0 + \beta_1 \text{nwifeinc}_i + \beta_2 \text{ed}_i + \beta_3 \exp_i + \beta_4 \exp_i^2 + \beta_5 \text{age}_i)$

Thus, the marginal probability effect of the indicator variable $dkidslt6_i$ in Model 3 is

$$\begin{aligned} &\Pr(\operatorname{inlf}_{i}=1 | \operatorname{dkidslt6}_{i}=1) - \Pr(\operatorname{inlf}_{i}=1 | \operatorname{dkidslt6}_{i}=0) = \\ &\Phi\begin{pmatrix} \beta_{0} + \beta_{1} \operatorname{nwifeinc}_{i} + \beta_{2} \operatorname{ed}_{i} + \beta_{3} \operatorname{exp}_{i} + \beta_{4} \operatorname{exp}_{i}^{2} + \beta_{5} \operatorname{age}_{i} \\ &+ \delta_{0} + \delta_{1} \operatorname{nwifeinc}_{i} + \delta_{2} \operatorname{ed}_{i} + \delta_{3} \operatorname{exp}_{i} + \delta_{4} \operatorname{exp}_{i}^{2} + \delta_{5} \operatorname{age}_{i} \end{pmatrix} \\ &- \Phi(\beta_{0} + \beta_{1} \operatorname{nwifeinc}_{i} + \beta_{2} \operatorname{ed}_{i} + \beta_{3} \operatorname{exp}_{i} + \beta_{4} \operatorname{exp}_{i}^{2} + \beta_{5} \operatorname{age}_{i}) \end{aligned}$$

We are concerned with three aspects of the marginal probability effect of the indicator variable dkidslt6_i:

- 1. the <u>existence</u> of the marginal *probability* effect of the indicator variable *dkidslt6*_i;
- 2. the <u>direction</u> (sign) of the marginal *probability* effect of the indicator variable *dkidslt6*_i;
- 3. the magnitude (size) of the marginal probability effect of the indicator variable dkidslt6_i.

\Box Testing the marginal *probability* effect of the binary explanatory variable *dkidslt6_i* -- *test* and *lincom*

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

$$Pr(inlf_{i} = 1 | dkidslt6_{i} = 1, nwifeinc_{i}, ed_{i}, exp_{i}, age_{i}) = Pr(inlf_{i} = 1 | dkidslt6_{i} = 0, nwifeinc_{i}, ed_{i}, exp_{i}, age_{i})?$$

Null and Alternative Hypotheses: General Formulation

The *null hypothesis* in general is:

$$H_0: \quad \Pr(inlf_i = 1 | dkidslt6_i = 1, ...) = \Pr(inlf_i = 1 | dkidslt6_i = 0, ...)$$

The *alternative hypothesis* in general is:

$$H_1: \quad \Pr(inlf_i = 1 | dkidslt6_i = 1, ...) \neq \Pr(inlf_i = 1 | dkidslt6_i = 0, ...)$$

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:

H₀:
$$Pr(inlf_i = 1 | dkidslt6_i = 1, ...) = Pr(inlf_i = 1 | dkidslt6_i = 0, ...)$$

For Model 2,

$$Pr(inlf_{i} = 1 | dkidslt6_{i} = 1, ...) = \Phi(x_{i}^{T}\beta | dkidslt6_{i} = 1)$$

$$= \Phi(\beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i} + \delta_{0})$$

$$Pr(inlf_{i} = 1 | dkidslt6_{i} = 0, ...) = \Phi(x_{i}^{T}\beta | dkidslt6_{i} = 0)$$

$$= \Phi(\beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i})$$

These two probabilities are equal if the exclusion restriction $\delta_0 = 0$ is true. In other words, a *sufficient* condition for these two probabilities to be equal is the exclusion restriction $\delta_0 = 0$.

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

$$\begin{array}{ll} H_0: & \delta_0 = 0 \\ H_1: & \delta_0 \neq 0 \end{array}$$

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

$$\Phi(\mathbf{x}_{i}^{\mathrm{T}}\beta | \mathrm{dkidslt6}_{i} = 1) = \Phi(\mathbf{x}_{i}^{\mathrm{T}}\beta | \mathrm{dkidslt6}_{i} = 0).$$

In Model 2,

$$\Phi\left(x_{i}^{T}\beta \middle| dkidslt6_{i} = 1\right) = \Phi\left(\beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i} + \delta_{0}\right)$$

 $\Phi\left(x_{i}^{T}\beta \middle| dkidslt6_{i} = 0\right) = \Phi\left(\beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i}\right)$

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

Answer: By inspection – i.e., by comparing the function $\Phi(\mathbf{x}_i^T\beta | dkidslt\mathbf{6}_i = 1)$ and the function $\Phi(\mathbf{x}_i^T\beta | dkidslt\mathbf{6}_i = 0)$ – we can see that a sufficient condition for $\Phi(\mathbf{x}_i^T\beta | dkidslt\mathbf{6}_i = 1) = \Phi(\mathbf{x}_i^T\beta | dkidslt\mathbf{6}_i = 0)$ in Model 2 is the single coefficient exclusion restriction $\delta_0 = 0$.

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

$$(\mathbf{x}_{i}^{T}\beta | dkidslt6_{i} = 1) = (\mathbf{x}_{i}^{T}\beta | dkidslt6_{i} = 0).$$

In Model 2,

$$\left(x_{i}^{T}\beta \middle| dkidslt6_{i} = 1\right) = \beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i} + \delta_{0}$$

$$\left(x_{i}^{T}\beta \middle| dkidslt6_{i} = 0\right) = \beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i}$$

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 $(x_i^T\beta | dkidslt6_i = 1)$ and the index function $(x_i^T\beta | dkidslt6_i = 0)$ – we can see that a sufficient condition for $(x_i^T\beta | dkidslt6_i = 1) = (x_i^T\beta | dkidslt6_i = 0)$ in Model 2 is the single coefficient exclusion restriction $\delta_0 = 0$.

 $\square \underline{Result}: \text{ The single coefficient exclusion restriction } \delta_0 = 0 \text{ is sufficient to make the$ *both*the marginal*probability*effect*and*the marginal*index* $effect of pre-school aged children equal to zero in Model 2.}$

u 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 H₀ against H₁ and the p-value for the calculated W-statistic, enter the following **test**, **return list** and **display** commands:

• To calculate a **two-tail asymptotic t-test** of H₀ against H₁, 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:

$$H_0: \quad \Pr(inlf_i = 1 | dkidslt6_i = 1, ...) = \Pr(inlf_i = 1 | dkidslt6_i = 0, ...)$$

For Model 3,

$$Pr(inlf_{i} = 1 | dkidslt6_{i} = 1) = \Phi(x_{i}^{T}\beta | dkidslt6_{i} = 1)$$
$$= \Phi\begin{pmatrix}\beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i} \\ + \delta_{0} + \delta_{1}nwifeinc_{i} + \delta_{2}ed_{i} + \delta_{3}exp_{i} + \delta_{4}exp_{i}^{2} + \delta_{5}age_{i} \end{pmatrix}$$

$$Pr(inlf_{i} = 1 | dkidslt6_{i} = 0) = \Phi(x_{i}^{T}\beta | dkidslt6_{i} = 0)$$
$$= \Phi(\beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i})$$

These two probabilities are equal if the six exclusion restrictions $\delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$ are true. In other words, a sufficient condition for these two probabilities to be equal is the set of six coefficient exclusion restrictions $\delta_i = 0$ for all j = 0, 1, ..., 5.

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

$$\begin{array}{ll} H_0: & \delta_j = 0 \quad \forall \ j = 0, 1, 2, 3, 4, 5 \\ \Rightarrow & \delta_0 = 0 \ and \ \delta_1 = 0 \ and \ \delta_2 = 0 \ and \ \delta_3 = 0 \ and \ \delta_4 = 0 \ and \ \delta_5 = 0 \\ H_1: & \delta_j \neq 0 \qquad j = 0, 1, 2, 3, 4, 5 \\ \Rightarrow & \delta_0 \neq 0 \ and/or \ \delta_1 \neq 0 \ and/or \ \delta_2 \neq 0 \ and/or \ \delta_3 \neq 0 \ and/or \ \delta_4 \neq 0 \ and/or \ \delta_5 \neq 0 \end{array}$$

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 if

$$\Phi(x_{i}^{T}\beta | dkidslt6_{i} = 1) = \Phi(x_{i}^{T}\beta | dkidslt6_{i} = 0).$$

In Model 3,

$$\Phi(\mathbf{x}_{i}^{T}\beta | \mathbf{dkidslt6}_{i} = 1)$$

$$= \Phi\begin{pmatrix}\beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i} \\ + \delta_{0} + \delta_{1}nwifeinc_{i} + \delta_{2}ed_{i} + \delta_{3}exp_{i} + \delta_{4}exp_{i}^{2} + \delta_{5}age_{i} \end{pmatrix}$$

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

Question: What coefficient restriction(s) are sufficient to make these two probabilities equal for any given values of nwifeinc_i, ed_i , exp_i , and 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 $\delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$.

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

$$(\mathbf{x}_{i}^{T}\beta | dkidslt6_{i} = 1) = (\mathbf{x}_{i}^{T}\beta | dkidslt6_{i} = 0).$$

In Model 3,

$$\left(x_{i}^{T}\beta \middle| dkidslt6_{i} = 1 \right) = \beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i}$$
$$+ \delta_{0} + \delta_{1}nwifeinc_{i} + \delta_{2}ed_{i} + \delta_{3}exp_{i} + \delta_{4}exp_{i}^{2} + \delta_{5}age_{i}$$

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

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 $(x_i^T\beta | dkidslt6_i = 1)$ and the index function $(x_i^T\beta | dkidslt6_i = 0)$ – we can see that a sufficient condition for $(x_i^T\beta | dkidslt6_i = 1) = (x_i^T\beta | dkidslt6_i = 0)$ in Model 3 is the set of six coefficient exclusion restrictions $\delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$.

□ <u>*Result:*</u> The six coefficient exclusion restrictions $\delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$ 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.

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

H₀: $\delta_1 = 0$ $\forall j = 0, 1, 2, 3, 4, 5 \Rightarrow \delta_0 = 0$ and $\delta_1 = 0$ and $\delta_2 = 0$ and $\delta_3 = 0$ and $\delta_4 = 0$ and $\delta_5 = 0$

• Before estimating Model 3, it is necessary to create the *dkidslt6*_i 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 H₀ against H₁ 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:

$$H_0: \quad \delta_j = 0 \quad \forall \ j = 1, 2, 3, 4, 5 \implies \delta_1 = 0 \text{ and } \delta_2 = 0 \text{ and } \delta_3 = 0 \text{ and } \delta_4 = 0 \text{ and } \delta_5 = 0$$

$$H_1: \quad \delta_j \neq 0 \qquad j = 1, 2, 3, 4, 5 \implies \delta_1 \neq 0 \text{ and/or } \delta_2 \neq 0 \text{ and/or } \delta_3 \neq 0 \text{ and/or } \delta_4 \neq 0 \text{ and/or } \delta_5 \neq 0$$

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 e	exp expsq ag	e dkidslt	6 d6nwinc	d6ed o	d6exp	d6expsq	d6ag
Iteration 0:	log likeliho	pod = -514.	8732					
Iteration 1:	log likeliho	pod = -406.4	8086					
Iteration 2:	log likeliho	pod = -402.6	3328					
Iteration 3:	log likeliho	bod = -402.6	1111					
Iteration 4:	log likeliho	pod = -402.6	1111					
Probit estimat	Fag			Number	of ob	a –	7	53
IIODIC CBCIMA				LR chi	2(11)		224	52
				Prob	chi2	_	0.00	00
Log likelihoo	d = -402.61111	l		Pseudo	R2	_	0.21	80
209 11.011.000		-		1 Deude			0.11	
inlf	Coef.	Std. Err.	Z	P> z	[95%	Conf.	Interva	1]
	+							
nwifeinc	0109103	.0056007	-1.95	0.051	0218	8874	.00006	68
ed	.1215786	.0280427	4.34	0.000	.0660	6159	.17654	13
exp	.137317	.0208939	6.57	0.000	.096	3657	.17826	82
expsq	0022349	.0006495	-3.44	0.001	003	3508	00096	19
age	0593504	.0085496	-6.94	0.000	0762	1072	04259	35
dkidslt6	-2.527031	1.267708	-1.99	0.046	-5.011	1694	04236	84
d6nwinc	0059201	.0109624	-0.54	0.589	0274	405 9	.01556	58
d6ed	.0327202	.0623143	0.53	0.600	0894	4135	.1548	54
d6exp	1128835	.0663563	-1.70	0.089	2429	9394	.01717	24
d6expsq	.0030026	.0033465	0.90	0.370	003	5564	.00956	16
d6age	.0503914	.0260813	1.93	0.053	000	7271	.10150	99
_cons	.6084091	.4961565	1.23	0.220	3640	0398	1.5808	58

. 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)	:	1×12
e(V)	:	12 x 12

functions:

e(sample)

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

<pre>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</pre>							
Probit est	imates				Numb LR c	er of obs hi2(11)	= 753 = 224.52
Log likelihood = -402.61111 Prob > chi2 = 0.0 Pseudo R2 = 0.2							= 0.0000 = 0.2180
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							

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. ereturn list

scalars:

e(N)	=	753
e(ll_0)	=	-514.8732045671461
e(11)	=	-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)	:	1×12
e(V)	:	12×12
e(se_dfdx)	:	1 x 11
e(dfdx)	:	1 x 11

functions:

e(sample)

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 dkidslt $6_i = 0$); and (2) the probit coefficients for married women who have one or more pre-school aged children (for whom dkidslt $6_i = 1$).

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

$$\begin{aligned} \mathbf{x}_{i}^{\mathrm{T}}\boldsymbol{\beta} &= \boldsymbol{\beta}_{0} + \boldsymbol{\beta}_{1} \mathbf{n} \mathbf{w} \mathbf{i} \mathbf{f} \mathbf{e} \mathbf{i} \mathbf{c}_{i} + \boldsymbol{\beta}_{2} \mathbf{e} \mathbf{d}_{i} + \boldsymbol{\beta}_{3} \mathbf{e} \mathbf{x} \mathbf{p}_{i} + \boldsymbol{\beta}_{4} \mathbf{e} \mathbf{x} \mathbf{p}_{i}^{2} + \boldsymbol{\beta}_{5} \mathbf{a} \mathbf{g} \mathbf{e}_{i} \\ &+ \delta_{0} \mathbf{d} \mathbf{k} \mathbf{i} \mathbf{d} \mathbf{s} \mathbf{l} \mathbf{t} \boldsymbol{\delta}_{i} + \delta_{1} \mathbf{d} \mathbf{k} \mathbf{i} \mathbf{d} \mathbf{s} \mathbf{l} \mathbf{t} \boldsymbol{\delta}_{i} \mathbf{n} \mathbf{w} \mathbf{i} \mathbf{f} \mathbf{e} \mathbf{i} \mathbf{c}_{i} + \delta_{2} \mathbf{d} \mathbf{k} \mathbf{i} \mathbf{d} \mathbf{s} \mathbf{l} \mathbf{t} \boldsymbol{\delta}_{i} \mathbf{e} \mathbf{d}_{i} \\ &+ \delta_{3} \mathbf{d} \mathbf{k} \mathbf{i} \mathbf{d} \mathbf{s} \mathbf{l} \mathbf{t} \boldsymbol{\delta}_{i} \mathbf{e} \mathbf{x} \mathbf{p}_{i} + \delta_{4} \mathbf{d} \mathbf{k} \mathbf{i} \mathbf{d} \mathbf{s} \mathbf{l} \mathbf{t} \boldsymbol{\delta}_{i} \mathbf{e} \mathbf{x} \mathbf{p}_{i}^{2} + \delta_{5} \mathbf{d} \mathbf{k} \mathbf{i} \mathbf{d} \mathbf{s} \mathbf{l} \mathbf{t} \boldsymbol{\delta}_{i} \mathbf{a} \mathbf{g} \mathbf{e}_{i} \end{aligned}$$

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:

 $\left(x_{i}^{T}\beta \left| dkidslt6_{i} = 0\right) = \beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i}\right)$

Implication: The probit coefficient estimates for married women who have no pre-school aged children (for whom dkidslt $6_i = 0$) are given directly by the coefficient estimates of the first six terms in the above index function.

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

$$\beta_0$$
 = the intercept coefficient for women for whom dkidslt $6_i = 0$

- β_1 = the slope coefficient of nwifeinc; for women for whom dkidslt $\beta_i = 0$
- β_2 = the slope coefficient of ed_i for women for whom dkidslt6_i = 0
- β_3 = the slope coefficient of exp_i for women for whom dkidslt6_i = 0
- β_4 = the slope coefficient of exp_i² for women for whom dkidslt6_i = 0
- β_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:

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

$$+ \delta_0 + \delta_1 nwifeinc_i + \delta_2 ed_i + \delta_3 exp_i + \delta_4 exp_i^2 + \delta_5 age_i$$

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:

- $\beta_0 + \delta_0$ = the intercept coefficient for women for whom dkidslt $6_i = 1$ $\beta_1 + \delta_1$ = the slope coefficient of nwifeinc_i for women for whom dkidslt $6_i = 1$ $\beta_2 + \delta_2$ = the slope coefficient of ed_i for women for whom dkidslt $6_i = 1$ $\beta_3 + \delta_3$ = the slope coefficient of exp_i for women for whom dkidslt $6_i = 1$ $\beta_4 + \delta_4$ = the slope coefficient of exp_i² for women for whom dkidslt $6_i = 1$ $\beta_5 + \delta_5$ = the slope coefficient of age_i for women for whom dkidslt $6_i = 1$.
- 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 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 + d6 \exp = 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) \exp g + d \exp g = 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
```

□ Marginal *probability* effects of *binary* explanatory variable *dkidslt6* in Model 2 – *dprobit* with *at(vecname)* option

• Use the **dprobit** command *without* the **at**(*vecname*) option to compute the marginal probability effects in Model 2 at the **sample** *mean* **values of the regressors**, i.e., at $x_i^T = \overline{x}^T$. Enter the following command:

dprobit inlf nwifeinc ed exp expsq age dkidslt6

• The next series of *Stata* commands will demonstrate how to use the **dprobit** command with the **at**(*vecname*) option to compute the **marginal** *probability* **effect of the dummy variable** *dkidslt6_i* **in Model 2** for married women whose non-wife family income is \$20,000 per year (nwifeinc_i = 20), who have 14 years of formal education (ed_i = 14) and 10 years of actual work experience (exp_i = 10, expsq_i = 100), and who are 40 years of age (age_i = 40):

$$\begin{aligned} &\Pr(\inf_{i} = 1 | dkidslt6_{i} = 1) - \Pr(\inf_{i} = 1 | dkidslt6_{i} = 0) \\ &= \Phi(x_{1i}^{T}\beta) - \Phi(x_{0i}^{T}\beta) \\ &= \Phi(\beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{i} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i} + \delta_{0}) \\ &- \Phi(\beta_{0} + \beta_{1}nwifeinc_{i} + \beta_{2}ed_{2} + \beta_{3}exp_{i} + \beta_{4}exp_{i}^{2} + \beta_{5}age_{i}) \\ &= \Phi(\beta_{0} + \beta_{1}20 + \beta_{2}14 + \beta_{3}10 + \beta_{4}100 + \beta_{5}40 + \delta_{0}) \\ &- \Phi(\beta_{0} + \beta_{1}20 + \beta_{2}14 + \beta_{3}10 + \beta_{4}100 + \beta_{5}40) \end{aligned}$$

<u>A Three Step Procedure</u>: The procedure for this computation consists of three steps.

<u>Step 1</u>: Compute an estimate of the probability of labour force participation for married women with the specified characteristics who have *one or more* dependent children under 6 years of age, for whom dkidslt $6_i = 1$: i.e., compute an estimate of

$$\begin{split} \Phi(\mathbf{x}_{1i}^{T}\beta) &= \Phi(\beta_{1}\text{nwifeinc}_{i} + \beta_{2}\text{ed}_{i} + \beta_{3}\exp_{i} + \beta_{4}\exp_{i}^{2} + \beta_{5}\text{age}_{i} + \delta_{0} + \beta_{0}) \\ &= \Phi(\beta_{1}20 + \beta_{2}14 + \beta_{3}10 + \beta_{4}100 + \beta_{5}40 + \delta_{0}1 + \beta_{0}1) & \text{in Stata format} \\ \text{where } \mathbf{x}_{1i}^{T} &= \left(\text{nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} \operatorname{age}_{i} 1 1\right) = (20\ 14\ 10\ 100\ 40\ 1\ 1). \end{split}$$

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

$$\Phi(\mathbf{x}_{0i}^{T}\beta) = \Phi(\beta_{1}\text{nwifeinc}_{i} + \beta_{2}\text{ed}_{i} + \beta_{3}\exp_{i} + \beta_{4}\exp_{i}^{2} + \beta_{5}\text{age}_{i} + \delta_{0} + \beta_{0})$$

= $\Phi(\beta_{1}20 + \beta_{2}14 + \beta_{3}10 + \beta_{4}100 + \beta_{5}40 + \delta_{0}0 + \beta_{0}1)$ in *Stata* format
where $\mathbf{x}_{0i}^{T} = (\text{nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} \text{ age}_{i} 0 1) = (20 \ 14 \ 10 \ 100 \ 40 \ 0 \ 1)$

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

<u>Step 1</u>: Use the dprobit command *with* the at(*vecname*) option to compute the marginal probability effects in Model 2 for married women whose non-wife family income is \$20,000 per year (nwifeinc_i = 20), who have 14 years of formal education (ed_i = 14) and 10 years of actual work experience (exp_i = 10, expsq_i = 100), who are 40 years of age (age_i = 40), and who have *one or more* dependent children under 6 years of age (dkidslt6 = 1). You will first have to create a vector containing the specified values of the regressors for Model 2, since the dprobit command does not permit number lists in the at() option. Note that in *Stata* format, the vector x^T_{1i} with the dummy variable *dkidslt6_i* = 1 is written as:

 $\mathbf{x}_{1i}^{T} = (nwifeinc_{i} ed_{i} exp_{i} exp_{i}^{2} age_{i} 1 1) = (20 \ 14 \ 10 \ 100 \ 40 \ 1 \ 1).$

Enter the following commands:

```
matrix xlvec = (20, 14, 10, 100, 40, 1, 1)
matrix list xlvec
dprobit inlf nwifeinc ed exp expsq age dkidslt6, at(xlvec)
ereturn list
```

Display and save the value of $\Phi(\mathbf{x}_{1i}^{T}\hat{\boldsymbol{\beta}})$ generated by the above **dprobit** command, where $\Phi(\mathbf{x}_{1i}^{T}\hat{\boldsymbol{\beta}})$ is an estimate of $\Pr(\inf_{i} = 1 | \text{dkidslt6}_{i} = 1)$. Enter the commands:

```
display e(at)
scalar PHIx1vec = e(at)
scalar list PHIx1vec
. display e(at)
.41935631
. scalar PHIx1vec = e(at)
. scalar list PHIx1vec
PHIx1vec = .41935631
```

<u>Step 2</u>: Now use the **dprobit** command *with* the **at**(*vecname*) option to compute the marginal probability effects in Model 2 for married women whose non-wife family income is \$20,000 per year (nwifeinc_i = 20), who have 14 years of formal education (ed_i = 14) and 10 years of actual work experience (exp_i = 10, expsq_i = 100), who are 40 years of age (age_i = 40), and **who have** *no* **dependent children under 6 years of age (dkidslt6 = 0)**. First, you will have to create a vector containing the specified values of the regressors for Model 2; the **dprobit** command does not permit number lists in the **at**() option. Note that in *Stata* format, the vector x^T_{0i} with the dummy variable *dkidslt6_i* = **0** is written as:

$$\mathbf{x}_{0i}^{\mathrm{T}} = (\text{nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} \operatorname{age}_{i} 0 1) = (20 \ 14 \ 10 \ 100 \ 40 \ 0 1)$$

Enter the following commands:

```
matrix x0vec = (20, 14, 10, 100, 40, 0, 1)
matrix list x0vec
dprobit inlf nwifeinc ed exp expsq age dkidslt6, at(x0vec)
ereturn list
```

Display and save the value of $\Phi(\mathbf{x}_{0i}^{T}\hat{\boldsymbol{\beta}})$ generated by the above **dprobit** command, where $\Phi(\mathbf{x}_{0i}^{T}\hat{\boldsymbol{\beta}})$ is an estimate of $\Pr(\inf_{i} = 1 | \text{dkidslt6}_{i} = 0)$. Enter the commands:

```
display e(at)
scalar PHIx0vec = e(at)
scalar list PHIx0vec
. display e(at)
.79350221
. scalar PHIx0vec = e(at)
. scalar list PHIx0vec
PHIx0vec = .79350221
```

• <u>Step 3</u>: Finally, compute the estimate of the difference $\Phi(x_{1i}^T\beta) - \Phi(x_{0i}^T\beta)$, which is the marginal probability effect of having one or more dependent children under 6 years of age for married women who have the specified characteristics. Enter the commands:

```
scalar diffPHI = PHIx1vec - PHIx0vec
scalar list PHIx1vec PHIx0vec diffPHI
. scalar list PHIx1vec PHIx0vec diffPHI
PHIx1vec = .41935631
PHIx0vec = .79350221
diffPHI = <u>-.3741459</u>
```

• Carefully compare the results of this three-step procedure with the output of the two **dprobit** commands you have estimated. Enter the following commands:

```
* Model 2 at x0vec: dprobit
dprobit inlf nwifeinc ed exp expsq age dkidslt6, at (x0vec)
* Model 2 at x1vec: dprobit
dprobit inlf nwifeinc ed exp expsq age dkidslt6, at (x1vec)
```

The *Stata* output listing produced by these commands is reproduced on the following page. Note in particular the highlighted results in the output listing for these two **dprobit** commands.

. * Model . dprobit	2 at x0vec: inlf nwifein	dprobit c ed exp exp	sq age o	dkidslt6,	at (:	x0vec)		
Iteration Iteration Iteration Iteration	0: log lik 1: log lik 2: log lik 3: log lik	elihood = - elihood = -4 elihood = -4 elihood = -4	514.8732 10.52123 07.00272 06.98832	2 3 2 2				
Probit regression, reporting marginal effectsNumber of obs =75LR chi2(6)=215.7Prob > chi2=0.000Log likelihood = -406.98832Pseudo R2=						= 753 = 215.77 = 0.0000 = 0.2095		
inlf	dF/dx	Std. Err.	Z	P> z		x	[95%	C.I.]
nwifeinc ed exp expsq age dkidslt6*	0032397 .0347428 .0334919 0005032 0152501 3741459	.0013341 .0061286 .0050403 .0001622 .0021914 .0527655	-2.39 4.92 6.32 -2.94 -6.73 -7.04	0.017 0.000 0.000 0.003 0.000 0.000		20 14 10 100 40 0	005854 .022731 .023613 000821 019545 477564	000625 .046755 .043371 000185 010955 270728
obs. P pred. P pred. P	.5683931 .583103 .7935022	(at x-bar) (at x)						

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

. * Model . dprobit	2 at x1vec: inlf nwifein	dprobit c ed exp exp;	sq age dł	cidslt6, a	at (xlvec)	
Iteration (output omitted	0: log lik d)	elihood = -!	514.8732				
Iteration	3: log lik	elihood = -4	06.98832				
Probit reg	Probit regression, reporting marginal effects LR chi2(6) = 215.77 Prob > chi2 = 0.0000						
Log likeli	.hood = -406.	98832			Pseu	do R2	= 0.2095
inlf	dF/dx	Std. Err.	z	P> z	x	[5 C.I.]
nwifeinc	0044364	.0018708	-2.39	0.017	20	008103	300077
ea exp	.04/5/65 0458635	.0100112	4.92	0.000	14 10	.02/955	060861 060861
expsq	0006891	.0002397	-2.94	0.003	100	001159)000219
age	0208833	.0029759	-6.73	0.000	40	026716	5015051
dkidslt6*	3741459	.0527655	-7.04	0.000	1	 477564	4270728
obs. P	.5683931						
pred. P pred. P	.583103 .4193563	(at x-bar) (at x)					
(*) 러파/러파	(*) dr/dr is for discrete charge of dumme revisible from 0 to 1						

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

□ Computing marginal *probability* effect of the *binary* explanatory variable *dkidslt6* in Model 2 – using the *margins* command after *probit*

In Model 2, the explanatory variable *dkidslt6_i* is a *binary* explanatory variable that distinguishes between married women who have one or more pre-school aged children under 6 years of age (for whom *dkidslt6_i* = 1), and married women who have no pre-school aged children under 6 years of age (for whom *dkidslt6_i* = 0). This section demonstrates how to use the **margins** command to easily estimate the **marginal probability effect** of the *binary* **explanatory variable** *dkidslt6_i* at *user-specified* **values** of the *continuous* **explanatory variables in Model 2**, i.e., *nwifeinc_i*, *ed_i*, *exp_i*, and *age_i*.

• To begin, re-estimate Model 2 by Maximum Likelihood using the **probit** command with all regressors entered in factor-variable notation. Enter the **probit** command:

probit inlf c.nwifeinc c.ed c.exp c.exp#c.exp c.age i.dkidslt6

Stata output on next page

. probit inlf	c.nwifeinc	c.ed c.exp	c.exp#c.exp	c.age	i.dkidslt6	
Iteration 0: Iteration 1: Iteration 2: Iteration 3:	log likeli log likeli log likeli log likeli	hood = -51 hood = -407 hood = -406 hood = -406	4.8732 .89693 .98942 .98832			
Iteration 4:	log likeli	hood = -406	.98832			
Probit regress	sion			Numbe LR cl Prob	er of obs = ni2(6) = > chi2 =	753 215.77 0.0000
Log likelihood	1 = -406.988	32		Pseud	lo R2 =	0.2095
inlf	Coef.	Std. Err	. z	P> z	[95% Conf	. Interval]
nwifeinc	0113531	.0047493	-2.39	0.017	0206616	0020446
ed	.1217526	.0247401	4.92	0.000	.0732629	.1702423
exp	.1173689	.018582	6.32	0.000	.0809488	.153789
c.exp#c.exp	0017634	.0005991	-2.94	0.003	0029376	0005892
age	0534423	.0079365	-6.73	0.000	0689976	037887
1.dkidslt6	-1.022174	.145213	-7.04	0.000	-1.306786	7375618
_cons	.4815005	.4547181	1.06	0.290	4097307	1.372732

<u>First</u>, estimate the *conditional probability* of labour force participation in Model 2 for both married women with pre-school aged children (for whom *dkidslt6_i* = 1) and married women without pre-school aged children (for whom *dkidslt6_i* = 0), where both categories of women have non-wife family income of \$20,000 per year, have 14 years of formal education and 10 years of actual work experience, and are 40 years of age. In other words, estimate the *conditional probability* of labour force participation in Model 2 at the following selected values of the four continuous explanatory variables: nwifeinc_i = 20, ed_i = 14, exp_i = 10, age_i = 40. Enter *on one line* the following margins command:

```
margins i.dkidslt6, at(nwifeinc = (20) ed = (14) exp = (10) age = (40))
```

Stata output

```
. * Marginal probability effect of BINARY explanatory variable 'dkidslt6' in Model 2
. margins i.dkidslt6, at(nwifeinc = (20) ed = (14) exp = (10) age = (40))
```

Adjusted pred	ictions			Number	of obs	= 75	3
Model VCE	: OIM						
Expression	: Pr(inlf), p	predict()					
at	: nwifeinc	=	20				
	ed	=	14				
	exp	=	10				
	age	=	40				
							_
		Delta-method					
	Margin	Std. Err.	z	P> z	[95% Co	nf. Interval]
dkidslt6	+ 						_
0	.7935022	.0246955	32.13	0.000	.745	.841904	5
1	.4193563	.0493966	8.49	0.000	.322540	7 .51617	2
dkidslt6 0 1	 Margin .7935022 .4193563	Delta-method Std. Err. .0246955 .0493966	z 32.13 8.49	P> z 0.000 0.000	[95% Co .745 .322540	nf. Interva 1 .84190 7 .5161	- 1 - 4 7

Note that the estimated *conditional probability* of labour force participation for married women with the specified characteristics who have no pre-school aged children, for whom *dkidslt6_i* = 0, is 0.7935, while the estimated *conditional probability* of labour force participation for married women with the same specified characteristics who have one or more pre-school aged children, for whom *dkidslt6_i* = 1, is 0.4194. The difference between these two conditional probabilities is by definition the marginal probability effect of the *binary* explanatory variable *dkidslt6_i* in Model 2 for married women with the user-specified characteristics.

<u>Second</u>, estimate the marginal *probability* effect of the *binary* explanatory variable *dkidslt6_i* in Model 2 for married women whose non-wife family income is \$20,000 per year, who have 14 years of formal education and 10 years of actual work experience, and who are 40 years of age. In other words, estimate the marginal *probability* effect of *dkidslt6_i* at the following selected values of the four continuous explanatory variables: nwifeinc_i = 20, ed_i = 14, exp_i = 10, age_i = 40. Enter *on one line* the following margins command:

```
margins r.dkidslt6, at(nwifeinc = (20) ed = (14) exp = (10) age = (40))
```

Stata output

```
. margins r.dkidslt6, at(nwifeinc = (20) ed = (14) exp = (10) age = (40))
Contrasts of adjusted predictions
Model VCE : OIM
Expression : Pr(inlf), predict()
   : nwifeinc =
at
                             20
          ed
                            14
                     =
                    =
                             10
          exp
               =
                             40
          age
         df chi2 P>chi2
  dkidslt6 1
                      50.28 0.0000
            Delta-method
           Contrast Std. Err. [95% Conf. Interval]
      dkidslt6
  (1 vs 0) | -.3741459 .0527658 -.477565 -.2707268
```

Alternatively, enter *on one line* the following **margins** command:

```
margins r.dkidslt6, at(nwifeinc = (20) ed = (14) exp = (10) age = (40))
contrast(nowald effects)
```

Stata output

```
. margins r.dkidslt6, at(nwifeinc = (20) ed = (14) exp = (10) age = (40))
contrast(nowald effects)
Contrasts of adjusted predictions
Model VCE : OIM
Expression : Pr(inlf), predict()
at : nwifeinc =
                              20
14
           ed
                       =
                           10
           exp =
           age
               =
                            40
                     ------
            Delta-method
Contrast Std. Err. z P>|z| [95% Conf. Interval]
   dkidslt6
  (1 vs 0) | -.3741459 .0527658 -7.09 0.000 -.477565 -.2707268
```

Compare the results of these two alternative margins commands.

The first **margins** command performs a **Wald test** of the null hypothesis that the marginal probability effect of *dkidslt6*_i equals zero; the sample value of the Wald test statistic is labeled **chi2**.

The second **margins** command performs a **large sample t-test** of the null hypothesis that the marginal probability effect of *dkidslt6*_i equals zero; the sample value of the test statistic is labeled z.

Otherwise, these two **margins** commands yield identical results, i.e., identical point estimates of the marginal probability effect of *dkidslt6*_i and its standard error, identical 95 percent confidence limits, and identical p-values of the calculated test statistics for the null hypothesis that the marginal probability effect of *dkidslt6*_i equals zero.

□ Computing the marginal *probability* effect of the binary explanatory variable *dkidslt6*^{*i*} 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_i* 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 <u>direction</u> and <u>magnitude</u> of the marginal *probability* effect of the dummy variable $dkidslt6_i$ in Model 3.

Recall that the marginal probability effect of the dummy variable dkidslt6_i in Model 3 is given by:

$$\begin{aligned} \Pr(\operatorname{inlf}_{i} = 1 | \operatorname{dkidslt6}_{i} = 1) - \Pr(\operatorname{inlf}_{i} = 1 | \operatorname{dkidslt6}_{i} = 0) &= \Phi(\mathbf{x}_{1i}^{\mathrm{T}}\beta) - \Phi(\mathbf{x}_{0i}^{\mathrm{T}}\beta) \\ \Phi\begin{pmatrix} \beta_{0} + \beta_{1}\operatorname{nwifeinc}_{i} + \beta_{2}\operatorname{ed}_{i} + \beta_{3}\operatorname{exp}_{i} + \beta_{4}\operatorname{exp}_{i}^{2} + \beta_{5}\operatorname{age}_{i} \\ + \delta_{0} + \delta_{1}\operatorname{nwifeinc}_{i} + \delta_{2}\operatorname{ed}_{i} + \delta_{3}\operatorname{exp}_{i} + \delta_{4}\operatorname{exp}_{i}^{2} + \delta_{5}\operatorname{age}_{i} \end{pmatrix} \\ - \Phi(\beta_{0} + \beta_{1}\operatorname{nwifeinc}_{i} + \beta_{2}\operatorname{ed}_{i} + \beta_{3}\operatorname{exp}_{i} + \beta_{4}\operatorname{exp}_{i}^{2} + \beta_{5}\operatorname{age}_{i}) \end{aligned}$$

In *Stata* format, the marginal *probability* effect of the dummy variable *dkidslt6*_i in Model 3 is written with the *intercept* coefficient β_0 as the *last*, not the first, term in the probit index function:

$$\Phi(\mathbf{x}_{1i}^{\mathrm{T}}\beta) - \Phi(\mathbf{x}_{0i}^{\mathrm{T}}\beta) = \Phi\begin{pmatrix}\beta_{1}\mathrm{nwifeinc}_{i} + \beta_{2}\mathrm{ed}_{i} + \beta_{3}\exp_{i} + \beta_{4}\exp_{i}^{2} + \beta_{5}\mathrm{age}_{i} \\ + \delta_{0} + \delta_{1}\mathrm{nwifeinc}_{i} + \delta_{2}\mathrm{ed}_{i} + \delta_{3}\exp_{i} + \delta_{4}\exp_{i}^{2} + \delta_{5}\mathrm{age}_{i} + \beta_{0}\end{pmatrix} \\ - \Phi(\beta_{1}\mathrm{nwifeinc}_{i} + \beta_{2}\mathrm{ed}_{i} + \beta_{3}\exp_{i} + \beta_{4}\exp_{i}^{2} + \beta_{5}\mathrm{age}_{i} + \beta_{0})$$

We can be more specific about the *Stata* format for the regressor vectors \mathbf{x}_{1i}^{T} and \mathbf{x}_{0i}^{T} and the probit coefficient vector β for full-interaction Model 3.

• Recall that in *Stata* format the **probit** *index* **function for Model 3** is written as:

 $\mathbf{x}_{i}^{\mathrm{T}}\boldsymbol{\beta} = \boldsymbol{\beta}_{1}$ nwifeinc_i + $\boldsymbol{\beta}_{2}$ ed_i + $\boldsymbol{\beta}_{3}$ exp_i + $\boldsymbol{\beta}_{4}$ exp_i² + $\boldsymbol{\beta}_{5}$ age_i + $\boldsymbol{\delta}_{0}$ dkidslt6_i

 $+\delta_1$ dkidslt δ_i nwifeinc_i $+\delta_2$ dkidslt δ_i ed_i $+\delta_3$ dkidslt δ_i exp_i $+\delta_4$ dkidslt δ_i exp_i $+\delta_5$ dkidslt δ_i age_i $+\beta_0$

• The probit coefficient vector β for Model 3 in *Stata* format is the 12×1 column vector:

 $\boldsymbol{\beta} = \begin{pmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \delta_0 & \delta_1 & \delta_2 & \delta_3 & \delta_4 & \delta_5 & \beta_0 \end{pmatrix}^{\mathrm{T}}$

• 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** everywhere it appears in the probit index function for Model 3:

$$\begin{aligned} \mathbf{x}_{1i}^{\mathrm{T}}\boldsymbol{\beta} &= \left(\mathbf{x}_{i}^{\mathrm{T}}\boldsymbol{\beta} \middle| \mathrm{dkidslt6}_{i} = 1\right) = \boldsymbol{\beta}_{1}\mathrm{nwifeinc}_{i} + \boldsymbol{\beta}_{2}\mathrm{ed}_{i} + \boldsymbol{\beta}_{3}\exp_{i} + \boldsymbol{\beta}_{4}\exp_{i}^{2} + \boldsymbol{\beta}_{5}\mathrm{age}_{i} \\ &+ \boldsymbol{\delta}_{0} + \boldsymbol{\delta}_{1}\mathrm{nwifeinc}_{i} + \boldsymbol{\delta}_{2}\mathrm{ed}_{i} + \boldsymbol{\delta}_{3}\exp_{i} + \boldsymbol{\delta}_{4}\exp_{i}^{2} + \boldsymbol{\delta}_{5}\mathrm{age}_{i} + \boldsymbol{\beta}_{0} \end{aligned}$$

In *Stata* format, the regressor vector \mathbf{x}_{1i}^{T} is therefore the 1×12 row vector:

 $\mathbf{x}_{1i}^{\mathrm{T}} = \left(\text{nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} \text{ age}_{i} 1 \text{ nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} \text{ age}_{i} 1 \right)$

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• Again, in *Stata* format the **probit** *index* **function for Model 3** is written as:

$$\mathbf{x}_{i}^{\mathrm{T}}\boldsymbol{\beta} = \boldsymbol{\beta}_{1}$$
nwifeinc_i + $\boldsymbol{\beta}_{2}$ ed_i + $\boldsymbol{\beta}_{3}$ exp_i + $\boldsymbol{\beta}_{4}$ exp_i² + $\boldsymbol{\beta}_{5}$ age_i + $\boldsymbol{\delta}_{0}$ dkidslt $\boldsymbol{\delta}_{i}$

 $+ \delta_1 dkidslt \delta_i nwifeinc_i + \delta_2 dkidslt \delta_i ed_i + \delta_3 dkidslt \delta_i exp_i + \delta_4 dkidslt \delta_i exp_i^2 + \delta_5 dkidslt \delta_i age_i + \beta_0 dkidslt \delta_i exp_i^2 + \delta_5 dkidslt \delta_i age_i + \beta_0 dkidslt \delta_i exp_i^2 + \delta_5 dkidslt \delta_i exp_$

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 everywhere it appears in the probit index function for Model 3:

$$\begin{aligned} \mathbf{x}_{0i}^{\mathrm{T}}\beta &= \left(\mathbf{x}_{i}^{\mathrm{T}}\beta \middle| \mathbf{dkidslt6}_{i} = 0\right) \\ &= \beta_{1} \mathrm{nwifeinc}_{i} + \beta_{2} \mathrm{ed}_{i} + \beta_{3} \exp_{i} + \beta_{4} \exp_{i}^{2} + \beta_{5} \mathrm{age}_{i} + \delta_{0} 0 + \delta_{1} 0 + \delta_{2} 0 + \delta_{3} 0 + \delta_{4} 0 + \delta_{5} 0 + \beta_{0} \end{aligned}$$

In *Stata* format, the regressor vector \mathbf{x}_{0i}^{T} is therefore the 1×12 row vector:

 $\mathbf{x}_{0i}^{\mathrm{T}} = \left(\text{nwifeinc}_{i} \ \text{ed}_{i} \ \exp_{i} \ \exp_{i}^{2} \ \operatorname{age}_{i} \ 0 \ 0 \ 0 \ 0 \ 1 \right)$

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

<u>Step 1</u>: Compute an estimate of 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

$$\Phi(\mathbf{x}_{1i}^{\mathrm{T}}\boldsymbol{\beta}) = \Phi\begin{pmatrix}\beta_{0} + \beta_{1} \operatorname{nwifeinc}_{i} + \beta_{2} \operatorname{ed}_{i} + \beta_{3} \operatorname{exp}_{i} + \beta_{4} \operatorname{exp}_{i}^{2} + \beta_{5} \operatorname{age}_{i} \\ + \delta_{0} + \delta_{1} \operatorname{nwifeinc}_{i} + \delta_{2} \operatorname{ed}_{i} + \delta_{3} \operatorname{exp}_{i} + \delta_{4} \operatorname{exp}_{i}^{2} + \delta_{5} \operatorname{age}_{i} \end{pmatrix}$$

<u>Step 2</u>: Compute an estimate of 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 dkidslt $6_i = 0$: i.e., compute an estimate of

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

<u>Step 3</u>: Compute an estimate of the difference $\Phi(\mathbf{x}_{1i}^{T}\beta) - \Phi(\mathbf{x}_{0i}^{T}\beta)$, 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. For this purpose, we will 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 exp50psq = exp50p<sup>2</sup>
summarize age, detail
scalar age50p = r(p50)
scalar list nwinc50p ed50p exp50p exp50psq age50p
```

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

nwinc50p	=	17.700001
ed50p	=	12
exp50p	=	9
exp50psq	=	81
age50p	=	43

<u>Step 1</u>: 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_i = 17.700), who have 12 years of formal education (ed_i = 12) and 9 years of actual work experience (exp_i = 9, expsq_i = 81), who are 43 years of age (age_i = 43), and **who have** *one or more* **dependent children under 6 years of age** (**dkidslt6** = 1). You will first have to create the vector x^T_{1i} containing the median values of the regressors in Model 3 when dkidslt6_i = 1, since the **dprobit** command does not permit number lists in the **at**() option.

Remember that *Stata* places the equation intercept coefficient β_0 in the *last*, not the first, element of the probit coefficient vector β , so that the coefficient vector β for Model 3 is written in *Stata* format as:

 $\boldsymbol{\beta} = \begin{pmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \delta_0 & \delta_1 & \delta_2 & \delta_3 & \delta_4 & \delta_5 & \beta_0 \end{pmatrix}^{\mathrm{T}}$

In *Stata* format, the vector \mathbf{x}_{1i}^{T} for Model 3 thus takes the form:

$$x_{1i}^{T} = \left(\text{nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} \text{ age}_{i} 1 \text{ nwifeinc}_{i} \text{ ed}_{i} \exp_{i} \exp_{i}^{2} \text{ age}_{i} 1 \right)$$

$$= \left(\begin{array}{c} \text{nwinc50p ed50p exp50p exp50psq age50p 1} \\ \text{nwinc50p ed50p exp50p exp50psq age50p 1} \end{array} \right)$$

Step 1 Stata commands are:

```
matrix x1median = (nwinc50p, ed50p, exp50p, expsq50p, age50p, 1, nwinc50p, ed50p,
exp50p, expsq50p, age50p, 1)
matrix list x1median
dprobit inlf nwifeinc ed exp expsq age dkids1t6 d6nwinc d6ed d6exp d6expsq d6age,
at(x1median)
ereturn list
```

Display and save the value of $\Phi(\mathbf{x}_{1i}^{T}\hat{\boldsymbol{\beta}})$ generated by the above **dprobit** command, where $\Phi(\mathbf{x}_{1i}^{T}\hat{\boldsymbol{\beta}})$ is an estimate of $\Pr(\inf_{i} = 1 | \text{dkidslt6}_{i} = 1)$. The value of $\Phi(\mathbf{x}_{1i}^{T}\hat{\boldsymbol{\beta}})$ is temporarily stored as the scalar **e(at)** following execution of the above **dprobit** command. Enter the commands:

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

These commands save the value of $\Phi(\mathbf{x}_{1i}^{T}\hat{\boldsymbol{\beta}})$ as the scalar **PHIx1med**.

<u>Step 2</u>: 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 (nwifeinc_i = 17.700), who have 12 years of formal education (ed_i = 12) and 9 years of actual work experience (exp_i = 9, expsq_i = 81), who are 43 years of age (age_i = 43), and **who have** *no* **dependent children under 6 years of age** (**dkidslt6 = 0**). Again, you will first have to create the vector x^T_{0i} containing the median values of the regressors in Model 3 when dkidslt6_i = 0.

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

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

 $= (nwinc50p \ ed50p \ exp50p \ exp50psq \ age50p \ 0 \ 0 \ 0 \ 0 \ 1)$

Step 2 Stata commands are:

```
matrix x0median = (nwinc50p, ed50p, exp50p, exp50psq, 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 $\Phi(\mathbf{x}_{0i}^{T}\hat{\boldsymbol{\beta}})$ generated by the above **dprobit** command, where $\Phi(\mathbf{x}_{0i}^{T}\hat{\boldsymbol{\beta}})$ is an estimate of $\Pr(\inf_{i} = 1 | \text{dkidslt6}_{i} = 0)$. The value of $\Phi(\mathbf{x}_{0i}^{T}\hat{\boldsymbol{\beta}})$ is temporarily stored as the scalar **e(at)** following execution of the above **dprobit** command. Enter the commands:

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

These commands save the value of $\Phi(\mathbf{x}_{0i}^{T}\hat{\boldsymbol{\beta}})$ as the scalar **PHIx0med**.

• <u>Step 3</u>: 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

 $\Pr\left(inlf_{i}=1 \middle| dkidslt6_{i}=1\right) - \Pr\left(inlf_{i}=1 \middle| dkidslt6_{i}=0\right) = \Phi\left(x_{1i}^{T}\beta\right) - \Phi\left(x_{0i}^{T}\beta\right)$

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.

 $\texttt{diffPHImed} = \hat{P}r\big(inlf_i = 1 \big| dkidslt6_i = 1\big) - \hat{P}r\big(inlf_i = 1 \big| dkidslt6_i = 0\big) = \Phi\big(x_{1i}^T \hat{\beta}\big) - \Phi\big(x_{0i}^T \hat{\beta}\big)$

Output of Step 1 Stata Commands

. dprobit inlf nwifeinc ed exp expsq age dkidslt6 d6nwinc d6ed d6exp d6expsq d6age, at(x1median)

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

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

Log likelihood = -402.61111

inlf	dF/dx	Std. Err.	z	P> z	x	[95%	с.і.]
nwifeinc	0039009	.0020603	-1.95	0.051	17.7	(07939	.000	137
ed	.0434699	.0113882	4.34	0.000	12	. (21149	.06	579
exp	.0490971	.009644	6.57	0.000	9	. (30195	.067	999
expsq	0007991	.0002526	-3.44	0.001	81	(01294	000	304
age	0212205	.0040365	-6.94	0.000	43	(29132	013	309
dkidslt6*	6603895	.0730752	-1.99	0.046	1	8	303614	517	165
d6nwinc	0021167	.0039297	-0.54	0.589	17.7	(09819	.005	585
d6ed	.011699	.0221757	0.53	0.600	12	(31765	.055	162
d6exp	040361	.0215344	-1.70	0.089	9	(82568	.001	846
d6expsq	.0010736	.0011221	0.90	0.370	81	(01126	.003	273
d6age	.0180172	.0111044	1.93	0.053	43	(003747	.039	781
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(11_0) = -514.8732045671461
e(11) = -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);

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

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%	с.і.]
nwifeinc	004054	.0020554	-1.95	0.051	17.7	0	08083	000	025
ed	.0451757	.0104184	4.34	0.000	12	.0	24756	.065	595
exp	.0510237	.0074085	6.57	0.000	9	.0	36503	.065	544
expsq	0008305	.0002325	-3.44	0.001	81	0	01286	000	375
age	0220532	.003204	-6.94	0.000	43	0	28333	015	773
dkidslt6*	6311359	.0559456	-1.99	0.046	0	7	40787	521	485
d6nwinc	0021998	.0040816	-0.54	0.589	0	0	10199	.0	058
d6ed	.012158	.0231649	0.53	0.600	0	0	33244	.05	756
d6exp	0419448	.0245612	-1.70	0.089	0	0	90084	.006	194
d6expsq	.0011157	.0012413	0.90	0.370	0	0	01317	.003	549
d6age	.0187242	.0096966	1.93	0.053	0	0	00281	.037	729
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(11_0) = -514.8732045671461
e(11) = -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) = <u>.6469121653332525</u>
```

[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 = <u>-.32705154</u>
```

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

 $\Pr\left(\operatorname{inlf}_{i}=1 \mid \operatorname{dkidslt6}_{i}=1\right) - \Pr\left(\operatorname{inlf}_{i}=1 \mid \operatorname{dkidslt6}_{i}=0\right) = \Phi\left(x_{1i}^{\mathrm{T}}\beta\right) - \Phi\left(x_{0i}^{\mathrm{T}}\beta\right)$

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:

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

□ Computing the marginal *probability* effect of the binary explanatory variable *dkidslt6*^{*i*} in Model 3 – *probit* command followed by *margins* command

You have previously computed an estimate of the marginal probability effect of the **binary explanatory variable** *dkidslt6ⁱ* in Model 3 at the sample median values of the continuous explanatory variables; however, that procedure, while completely correct, was somewhat laborious.

This section demonstrates a much shorter and easier procedure that uses the **margins** command after Maximum Likelihood estimation of Model 3 with a **probit** command for computing the **marginal** *probability* **effect of the dummy variable** *dkidslt6_i* **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.

• <u>First</u>, use the **probit** command to re-estimate Model 3, with all regressors entered in factor-variable notation to distinguish between *continuous* and *categorical* explanatory variables. Model 3 contains four *continuous* explanatory variables, specifically nwifeinc_i, ed_i, exp_i, and age_i, and one *binary categorical* explanatory variable, **dkidslt6**_i. Enter *on one line* the following command:

```
probit inlf c.nwifeinc c.ed c.exp c.exp#c.exp c.age i.dkidslt6 i.dkidslt6#(c.nwifeinc
c.ed c.exp c.exp#c.exp c.age)
```

The following slide shows you the results of this **probit** estimation command.

```
. probit inlf c.nwifeinc c.ed c.exp c.exp#c.exp c.age i.dkidslt6
i.dkidslt6#(c.nwifeinc c.ed c.exp c.exp#c.exp c.age) ;
Iteration 0: log likelihood = -514.8732
(output omitted)
Iteration 4: log likelihood = -402.61111
Probit regression
                                       Number of obs =
                                                         753
                                       LR chi2(11) = 224.52
                                       Prob > chi2 = 0.0000
Log likelihood = -402.61111
                                       Pseudo R2 =
                                                         0.2180
            inlf
                     Coef. Std. Err. z P > |z| [95% Conf. Interval]
  nwifeinc | -.0109103 .0056007 -1.95 0.051 -.0218874 .0000668
                   .1215786 .0280427 4.34 0.000 .0666159 .1765413
              ed
                   .137317 .0208939
                                      6.57 0.000 .0963657 .1782682
             exp
       c.exp#c.exp | -.0022349 .0006495 -3.44 0.001 -.003508 -.0009619
                                            0.000 -.0761072 -.0425935
                  -.0593504 .0085496
                                      -6.94
             age
        1.dkidslt6
                  -2.527031 1.267708
                                      -1.99
                                            0.046 -5.011694 -.0423684
dkidslt6#c.nwifeinc
                                      -0.54 0.589 -.0274059 .0155658
              1
                  -.0059201 .0109624
     dkidslt6#c.ed
                   .0327202 .0623143
                                      0.53
                                            0.600 -.0894135 .154854
              1
    dkidslt6#c.exp
                                            0.089
              1
                   -.1128835 .0663563
                                      -1.70
                                                   -.2429394
                                                             .0171724
dkidslt6#c.exp#c.exp
                                            0.370
                   .0030026 .0033465
                                      0.90
                                                   -.0035564
              1
                                                            .0095616
    dkidslt6#c.age
                   .0503914 .0260813
                                            0.053 -.0007271 .1015099
                                      1.93
              1
                   .6084091 .4961565
                                      1.23
                                            0.220 -.3640398 1.580858
           _cons
```

<u>Second</u>, use a margins command with the at() option to compute estimates of the *conditional* probability of labour force participation for (1) married women with *no pre-school aged children*, for whom dkidslt6_i = 0, and (2) married women with *one or more pre-school aged children*, for whom dkidslt6_i = 1. Note that the at() option is used tell *Stata* that these conditional probabilities of labour force participation are to be computed at the sample *median* values of the four continuous explanatory variables nwifeinc_i, ed_i, exp_i, and age_i. Enter the following margins command:

margins i.dkidslt6, at((median) nwifeinc ed exp age)

Output from this **margins** command:

```
. * Marginal probability effect of 'dkidslt6' at sample medians of continuous covariates
. margins i.dkidslt6, at((median) nwifeinc ed exp age)
```

Adjusted predictions					Number	of	obs	=	753	
MODEL VCH	•	OIM								
Expression	:	<pre>Pr(inlf),</pre>	<pre>predict()</pre>							
at	:	nwifeinc	=	17.7	(median)					
		ed	=	12	(median)					
		exp	=	9	(median)					
		age	=	43	(median)					
	 		Delta-method							
	İ	Margin	a Std. Err.	Z	P> z	[95% Coi	nf.	Interval]	
dkidslt6	1									
0		.6469122	.0256601	25.21	0.000	•	5966194	4	.6972049	
1		.3198606	.0948877	3.37	0.001		1338842	2	.505837	
	·									

<u>Third</u>, use a second margins command with the at() option to compute an estimate of the *marginal* probability effect of dkidslt6_i, which by definition is the difference in the conditional probability of labour force participation between married women with pre-school aged children (for whom dkidslt6_i = 1) and married women with no pre-school aged children (for whom dkidslt6_i = 0). Enter the following margins command:

```
margins r.dkidslt6, at((median) nwifeinc ed exp age)
```

Output from this **margins** command:

```
. margins r.dkidslt6, at((median) nwifeinc ed exp age)
Contrasts of adjusted predictions
Model VCE
        : OIM
Expression : Pr(inlf), predict()
at : nwifeinc = 17.7 (median)
ed = 12 (median)
          exp
                = 9 (median)
= 43 (median)
          age
  _____
         df chi2 P>chi2
-----
  dkidslt6 | 1 11.07 0.0009
           Delta-method
  Contrast Std. Err. [95% Conf. Interval]
  dkidslt6
  (1 vs 0) -.3270515 .098296 -.5197082 -.1343949
```

• An alternative to the above *Stata* margins command uses the option **contrast(nowald effects)**. Enter the following **margins** command:

```
margins r.dkidslt6, at((median) nwifeinc ed exp age) contrast(nowald effects)
```

Output from this **margins** command:

. margins r.d	lkidslt6, at((median) nwife	inc ed	exp age)	contrast(nowald ef:	fects)
Contrasts of	adjusted pre	dictions				
Model VCE	: OIM					
Expression	: Pr(inlf),	predict()				
at	: nwifeinc	=	17.7	(median)		
	ed	=	12	(median)		
	exp	=	9	(median)		
	age	=	43	(median)		
		Delta-method				
	Contrast	Std. Err.	z	P> z	[95% Conf. Inter	rval]
dkidslt6						
(1 vs 0)	3270515	.098296	-3.33	0.001	5197082134	43949

Note that the first of the above **margins** commands reports a **Wald test** of the null hypothesis that the *marginal* **probability effect of dkidslt6**_i at sample median values of nwifeinc_i, ed_i , exp_i , and age_i is equal to zero, whereas the second **margins** command reports an equivalent **large-sample t-test** of the same null hypothesis. Otherwise, the results produced by these two **margins** commands are identical.