BANKWEST CURTIN ECONOMICS CENTRE

WORKING PAPER SERIES

13/11: ALTERNATIVE METHODS OF ESTIMATING INTERACTION EFFECTS IN NON-LINEAR MODELS

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Bankwest Curtin Economics Centre Working Paper Series
ISSN: 2202-2791
ISBN: 978-1-925083-13-2

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Suggested Citation
Austen, Siobhan, Rachel Ong and Richard Seymour. 2013. "Alternative Methods of Estimating Interaction Effects in Non-Linear Models." Bankwest Curtin Economics Centre Working Paper 13/11, Perth: Curtin University.

Alternative Methods of Estimating Interaction Effects in Non-Linear Models

Siobhan Austen[1], Rachel Ong and Richard Seymour

1. Introduction

This paper reviews alternative methods for estimating interaction effects in non-linear models. Interaction effects refer to the way in which the relationship between two variables can differ between categories of a third variable. Many researchers attempt to measure interaction effects, understanding that the relationship between variables of interest often differs between sub-groups or across contexts. The relationship between parenthood and wage outcomes, for example, is understood to vary between men and women; and the relationship between changing interest rates and economic activity is understood to vary with the broader economic context.

Whilst the measurement of interaction effects is straightforward when the dependent variable is linear (as is usually the case for wages), Ai and Norton (2003) found that most applied researchers misinterpreted the coefficient of the interaction term in non-linear models. To address this issue, Norton, Wang and Ai (2004) developed a method for correctly estimating interaction effects in probit and logit models with a single interaction term. Seymour (2011a) makes an important addition to this literature by describing a method for computing the interaction effects in probit models where there are two or more interaction terms with the same independent variable.

This paper examines the importance and application of this innovation by reviewing the alternative approaches to studying interaction effects and by assessing the impact of using the alternative methods to estimate interaction effects. To facilitate this review, it examines a particular case study: of the employment impacts of ill-health and informal care roles, and how these impacts can vary with the work environment. The paper trials a number of alternative methods for measuring the interaction between ill-health/informal care roles and

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characteristics of the work environment in the determination of employment retention using data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey.

2. Methods of Estimating Interaction Effects

There are four alternative methods that can be used to estimate interaction effects when the dependent variable is non-linear. The first alternative is to split the data sample into sub-samples based on an independent variable of interest. The relationships between the dependent variable and other independent factors can then be estimated and compared across the sub-samples. To illustrate the method, consider the following non-linear model:

$$\begin{aligned} P[y = 1|x_1, x_2, X] &= F(\beta_1 x_1 + \beta_2 x_2 + X\beta') \\ &= F(u) \end{aligned} \tag{1}$$

, where $F(u)$ is a non-linear function, x_1 and x_2 are discrete variables, X is a vector of other independent variables, and β is a vector of other coefficients. If the focus of the research is the effect of the interaction of x_1 with x_2, then the data sample is split into two sub-samples, based on x_1, with the resulting model for each sub-sample equal to:

$$\begin{aligned} P[y = 1|x_2, X] &= F(\beta_2 x_2 + X\beta') \\ &= F(u) \end{aligned} \tag{2}$$

The marginal effect of the independent variable of interest in each sub-sample is:

$$\Delta F(u) / \Delta x_2 = F(\beta_2 + X\beta') - F(X\beta') \tag{3}$$

, and the interaction effect is equal to the difference in the marginal effects:

$$\left(F\left(\beta_{i,2} + X_i\beta_i'\right) - F(X_i\beta_i')\right) - \left(F\left(\beta_{j,2} + X_j\beta_j'\right) - F\left(X_j\beta_j'\right)\right) \tag{4}$$

where i and j indicate the two sub-samples.

However, a key limitation of the split-sample method is that it incorrectly calculates the effect of the interaction of x_1 with x_2. To correctly calculate the effect of the interaction of x_1 with x_2, the non-linear model should be defined as:

$$\begin{aligned} P[y = 1|x_1, x_2, X] &= F(\beta_1 x_1 + \ \beta_2 x_2 + \beta_{21} x_1 x_2 + \ X\beta') \\ &= F(u) \end{aligned} \tag{5}$$

, with the interaction effect of $x_1 x_2$ found by computing the cross derivatives of x_1 and x_2 with respect to y (Ai and Norton, 2003):

$$\frac{\Delta^2 F(u)}{\Delta x_1 \Delta x_2} = \big(F(\beta_1 + \beta_2 + \beta_{12} + X\beta) - F(\beta_2 + X\beta)\big) - \big(F(\beta_1 + X\beta) - F(X\beta)\big) \tag{6}$$

Another significant limitation of the split-sample method is that the statistical significance of the observed difference in the marginal effects cannot be estimated. This is because the variance between the marginal effects cannot be calculated (because the covariance between the corresponding marginal effects in the two sub-samples is unknown). For example, the variance between the marginal effects in equation 4 is equal to:

$$var\left(\frac{\Delta F(u)}{\Delta x_{i,k}} + \frac{\Delta F(u)}{\Delta x_{j,k}}\right) = var\left(\frac{\Delta F(u)}{\Delta x_{i,k}}\right) + var\left(\frac{\Delta F(u)}{\Delta x_{j,k}}\right) + 2cov\left(\frac{\Delta F(u)}{\Delta x_{i,k}}, \frac{\Delta F(u)}{\Delta x_{j,k}}\right) \tag{7}$$

, where $\frac{\Delta F(u)}{\Delta x_{i,k}}$ and $\frac{\Delta F(u)}{\Delta x_{j,k}}$ are the marginal effects of the independent variable k in sub-samples i and j, and $cov\left(\frac{\Delta F(u)}{\Delta x_{i,k}}, \frac{\Delta F(u)}{\Delta x_{j,k}}\right)$ is the covariance between $\frac{\Delta F(u)}{\Delta x_{i,k}}$ and $\frac{\Delta F(u)}{\Delta x_{j,k}}$, which is unknown.

An alternative, commonly used method of estimating an interaction effect in a non-linear model is to estimate the marginal effect of the interaction term. To illustrate this approach, consider the following model:

$$\begin{aligned} P[y = 1|x_1, x_2, X] &= F(\beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + X\beta') \\ &= F(u) \end{aligned} \tag{8}$$

, where $F(u)$ is a non-linear function, x_1 and x_2 are continuous variables, x_1x_2 is the interaction term for x_1 and x_2, X is a vector of other independent variables, and β is a vector of other coefficients. The marginal effect of a change in the interaction term x_1x_2 in equation 8 is equal to:

$$\partial F(u) \big/ \partial(x_1x_2) = \beta_{12}F'(u) \tag{9}$$

, where $F'(u)$ is the first derivative of the non-linear function.

However, this is approach is clearly incorrect because the interaction effect of the interaction term x_1x_2 in equation 8 is equal to the cross derivative of x_1 and x_2 with respect to y (Ai and Norton, 2003):

$$\partial^2 F(u) \big/ \partial x_1 \partial x_2 = \beta_{12}F'(u) + (\beta_1 + \beta_{12}x_2)(\beta_2 + \beta_{12}x_1)F''(u) \tag{10}$$

, where $F''(u)$ is the second derivative of the non-linear function.

A method developed by Norton, Wang and Ai (2004) overcomes the above problems for non-linear models that contain a single interaction effect. The method utilises the formula shown in equation 10 for non-linear models that feature the interaction of two continuous variables and the formula in equation 6 for non-linear models that feature the interaction of two discrete variables. A third formula is devised for the interaction of a continuous variable and a discrete variable:

$$\frac{\Delta \frac{\partial F(u)}{\partial x_1}}{\Delta x_2} = (\beta_1 + \beta_{12})F'(\beta_1 x_1 + \beta_2 + \beta_{12}x_1 + X\beta) - \beta_1 F'(\beta_1 x_1 + X\beta) \tag{11}$$

Whilst the innovations of Norton, Wang and Ai (2004) represent an important advance in methods, they do not enable the computation of interaction effects in logit or probit models where the same independent variable is contained in more than one interaction term (Seymour 2011b).

To illustrate this shortcoming of the Norton *et al*. (2004) method, consider the following extension to the base non-linear model in equation 8:

$$P[y=1|x_1,x_2,x_3,X] = F(\beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12}x_1x_2 + \beta_{13}x_1x_3 + X\beta') \quad (12)$$
$$= F(u)$$

, where x_1x_3 is the interaction term for the interaction of x_1 and x_3. If the Norton et al approach is used to estimate the interaction between x_1 and x_2, the x_1x_3 interaction term can only be treated as another variable in the X vector. This would lead to the interaction effect for the interaction term being estimated as:

$$\partial^2 F(u) \Big/ \partial x_1 \partial x_2 = \beta_{12}F'(u) + (\beta_1 + \beta_{12}x_2)(\beta_2 + \beta_{12}x_1)F''(u) \quad (13)$$

, where $u = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12}x_1x_2 + \beta_{13}x_1x_3 + X\beta'$. However, the correct interaction effect for the x_1x_2 interaction term in equation 12 is equal to:

$$\partial^2 F(u) \Big/ \partial x_1 \partial x_2 = \beta_{12}F'(u) + (\beta_1 + \beta_{12}x_2 + \beta_{13}x_3)(\beta_2 + \beta_{12}x_1)F''(u) \quad (14)$$

, where $u = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12}x_1x_2 + \beta_{13}x_1x_3 + X\beta'$.

From equations 13 and 14, it can be seen that the use of Norton *et al*.'s (2004) formula would lead to a bias in the computation of the interaction effect, with the size of the bias dependent on the magnitudes and signs of β_{13} and x_3.

To overcome the limitations of the Norton *et al*. (2004) method, Seymour (2011a) developed three matrix algebra formulas that correctly estimate the interaction effects in probit models where there are two or more interaction terms that contain the same independent variable. The three formulas are based on the following probit model:

$$P[y=1|x] = \Phi(x'\beta + x'Ax) \quad (15)$$

, where Φ is the standard normal cumulative distribution, $x = [x_1 \quad \ldots \quad x_n]$ is a vector of independent variables, without any interaction terms, $\beta = [\beta_1 \quad \ldots \quad \beta_n]$ is a vector of coefficients for the variables in *x*, and $A = \begin{bmatrix} 0 & \beta_{12} & \beta_{1n} \\ \beta_{21} & 0 & \beta_{2n} \\ \beta_{n1} & \beta_{n2} & 0 \end{bmatrix}$ is a matrix of coefficients for the interaction terms in the model. In the *A* matrix, $\beta_{ij} = \beta_{ji}$, where $i \neq j$.

The innovation in Seymour's (2011a) method is the inclusion of the interaction terms coefficients matrix, *A*, which allows the estimation of interaction effects where the same independent variable is included in multiple interaction terms.

The following formula computes the interaction effects for interactions of two continuous variables:

$$\frac{\partial \Phi(u)}{\partial x \partial x'} = \Phi'(x'\beta + x' \tfrac{1}{2} Ax)A + \Phi''(x'\beta + x' \tfrac{1}{2} Ax)[\beta + Ax][\beta' + x' A] \qquad (16)$$

, where $u = x'\beta + x' Ax$, Φ' is the first derivative of the standard normal cumulative distribution, and Φ'' is the second derivative of the standard normal cumulative distribution.

A further formula computes the interaction effects for interactions involving a continuous and a discrete variable:

$$\frac{\Delta \frac{\partial \Phi(u)}{\partial x}}{\Delta x_i} = (\Phi'(x'\beta + x' \tfrac{1}{2} Ax)[\beta + Ax]) - (\Phi'(x0'\beta + x0' \tfrac{1}{2} Ax0)[\beta + Ax0]) \qquad (17)$$

, where $x = [x_1 \quad \cdots \quad x_n]$ is a vector of independent variables with the discrete variable $x_i = 1$, and $x0 = [x_1 \quad \cdots \quad x_n]$ is a vector of independent variables with the discrete variable $x_i = 0$.

A third formula computes the interaction effects for interactions involving two discrete variables:

$$\frac{\Delta^2\Phi(u)}{\Delta x_i \Delta x_j} = \left(\Phi\left(j'\beta + j'\tfrac{1}{2}Aj\right) - \Phi\left(k'\beta + k'\tfrac{1}{2}Ak\right)\right) - \left(\Phi\left(l'\beta + l'\tfrac{1}{2}Al\right) - \Phi\left(m'\beta + m'\tfrac{1}{2}Am\right)\right) \tag{18}$$

, where, $j = [x_1 \quad \cdots \quad x_n]$ is a vector of independent variables with the discrete variables $x_i = 1, x_j = 1$; $k = [x_1 \quad \cdots \quad x_n]$ is a vector of independent variables with the discrete variables $x_i = 0, x_j = 1$; $l = [x_1 \quad \cdots \quad x_n]$ is a vector of independent variables with the discrete variables $x_i = 1, x_j = 0$; and $m = [x_1 \quad \cdots \quad x_n]$ is a vector of independent variables with the discrete variables $x_i = 0, x_j = 0$.

3. The Impact of Alternative Approaches on the Estimation of Interaction Effects in Non-linear Models

The importance of adopting more technically sophisticated methods to estimate interaction effects can be gauged by comparing the estimates generated by the alternative techniques. We attempt this by using each of the above four methods to examine the interaction of work environment factors with both ill-health and informal care roles in the determination of employment outcomes for Australian mid-life women. Our case study uses data from the 2001-2009 HILDA survey.

The HILDA survey is a probability-based sample of Australian households that included 15,127 individuals aged 15 and over in its first wave in 2001[i]. Since its inception, additional waves of survey data have been collected each year. The longitudinal data base now contains extensive information on the labour market characteristics of the survey respondents, including their labour force status in each year, and, where appropriate, the characteristics of their work environment, such as the type of employment contract used. Also included are data on the respondents' health and informal care roles, in addition to their age, co-residents (such as partners), human capital (such as education and labour market experience), year and place of residence (to proxy current labour market conditions).

Using data from the first nine waves of the HILDA survey, Austen and Ong (2013) estimated a random effects probit model of employment retention on a pooled sample of 5,127 person-year observations of employed mid-life women. The general aim of this analysis was to measure the correlations between employment transitions and changes in ill-health and informal care roles respectively. A related objective was to identify whether (and to what extent) these correlations differ between women employed on permanent contracts and those on casual contracts; and between women employed in higher and lower status occupational roles. Ill-health and informal care roles have been identified as important barriers to employment for mid-life people (see Austen and Ong 2010; Cai and Kalb 2006; Berecki-Gisolf et al. 2008; Leigh 2010; Larsen 2010; Mann, Cooke et al. 2011). However, these impacts are likely to be mediated by the occupational status of the worker, her access to paid holiday and sick leave, and other aspects of the work environment. The nature of these relationships is relevant to the design of policy and other initiatives aimed at boosting the workforce participation rates of mid-life women (see Berecki et al. 2007; Carney 2009; Larsen 2010).

The random effect probit model, as applied to these issues, measures the effect of ill-health[2] and increased informal care roles[3] on the probability that a mid-life woman who is in paid work in wave t will retain this involvement through to the next survey period (wave $t+1$)[ii]. By making use of the longitudinal elements of the data set, issues of reverse causation (such as the possibility that informal care roles might be determined by employment status rather than vice versa) can be addressed.

However, the use of longitudinal data creates its own problems. The first relates to sample selection (the observations included in the estimation relate only to women who were employed in the initial period). This can be addressed by using results of an initial probit model[4] to calculate a generalised residual, which is then included as a regressor in the employment transition model (Heckman 2000). The second problem relates to the relatively small number of employment transitions available to study even in data sets as large as HILDA. Within the pooled sample of observations on mid-life women, for example, only 410 transitions from paid employment were recorded, representing 7.9 per cent of the sample[iii].

[2] Measured by the response to a HILDA question on whether the respondent developed a health condition in the last year, or if her health was worse than a year ago.
[3] Measured by the response to a HILDA question on the amount of time spent by the respondent caring for a disabled spouse, disabled adult relative, or an elderly parent or parent-in-law. Weekly hours of care are compared across subsequent waves to identify cases where informal care roles have increased by 5 hours or more.
[4] Results are reported in Austen and Ong (2013) and are available on request.

Importantly, this limitation increases the difficulty of precisely measuring any interaction effects.

The interactions of interest in this research are those between ill-health, informal care and different aspects of the work environment. Two work environment factors were considered: whether the contract of employment at the initial observation was permanent or casual; and occupational status[5] at the initial observation. The employment impacts of ill-health and increased informal care roles on the employment of mid-life women are expected to be negative, but the effects may be lower for women on permanent contracts than for women on casual contracts. This is because, in the Australian context at least, a permanent, but not a casual, contract contains entitlements to paid sick, parental and holiday leave. In other words, the interaction of measures of permanent contract and ill-health/increased informal care role is expected, *a priori*, to reduce the likelihood of a transition from employment, ceteris paribus. The employment impacts of ill-health and increased informal care roles may also be lower for women in higher status occupational roles than for women in lower status roles. This is because the financial incentives for, and attachment to, continued employment are likely to be greater for women in higher status roles. As such, the interaction of a measure of higher occupational status and ill-health/increased informal care role is also expected to reduce the likelihood of a transition from employment, ceteris paribus.

As noted in the previous section, several alternative methods are available to estimate the interaction effects of ill-health, informal care with different aspects of the work environment. The approach taken by Austen and Ong (2013) was to split the sample of employed mid-life women according to their work environment characteristics (contract type and occupational status) and then apply the random effects probit model (as described above) to each sample. This approach generated estimates of the marginal effects on the likelihood of an employment transition of ill-health or increased informal care responsibility for each sub-sample.

To determine the interaction effect, the marginal effects of variables relating to ill-health and informal care roles on the probability of an employment transition were compared across the

[5] Occupational status is defined using the standard occupational classification (ANZSCO). High status occupational categories include managerial and professional; lower-status occupational groupings include labourers, trade, and clerical and sales workers.

different sub-samples. This process was sequential. That is, the employment impacts of ill-health and informal care roles in the sub-samples of women employed on permanent and casual contracts were compared first. However, a new set of models needed to be estimated to examine how occupational status interacted with ill-health and informal care roles in the determination of employment transitions.

In the paragraphs below, the results derived from the split-sample approach used by Austen and Ong (2013) are compared to the other possible approaches to measuring the interaction effects: namely, the marginal effects approach; the Norton *et al.* (2004) approach; and Seymour's method. It is acknowledged that each of these alternatives, other than Seymour's method, may produce imprecise results, depending on the particular research questions. However, given that they have been used in other similar studies of interaction effects, it is useful to examine their consequences.

Table 1 shows the estimated interaction effects using the four alternative methods. It should be noted that the data relating to the Norton *et al* (2004) method in these tables were derived from applying the method sequentially. That is, a model containing a term that interacted ill-health/informal care and work contract was first estimated and a separate model was estimated to measure the interaction between ill-health/informal care and occupational status. As noted above, the split-sample method is also applied sequentially.

Table 1: Estimated Interaction Effects using Four Different Methods

Interaction Term	Split-Sample[1]	Marginal Effect of Interaction Term	Interaction Effect using Norton, Wang, and Ai (2004)	Interaction Effect using Seymour (2011a)
Health Deteriorated X Casual contract	0.0435	0.0044	0.0201	0.0208
Health Deteriorated X Lower Occupational Status	0.0039	-0.0117	0.0005	-0.0001
Informal Care Hours Increase > 5 X Casual Contract	-0.0389	-0.0693 *	-0.0705	-0.0703
Informal Care Hours Increase > 5 X Lower Occupational Status	0.0094	-0.0007	0.0032	0.0175

1. The estimates for the 'split-sample' method are based on the difference between the marginal effects estimated for each sample. The results shown here differ slightly from those reported in Austen & Ong (2013) because they are average marginal effect as opposed to the marginal effect for the average individual.
*denotes statistical significance at the 0.10 level.

Statistical significance levels cannot be estimated for the split-sample 'interaction effects'.

The data in Table 1 show a degree of consistency in the estimated marginal effects obtained from the different approaches. With the exception of the term relating to the interaction of *informal care hours and contract type*, the estimated marginal effects are all insignificant. The interaction of informal care hours and contract type is measured as significant by the marginal effect method, whilst the technically superior Seymour method shows it as insignificant. However, the sign and magnitude of the effect is similar across the marginal effect, Norton *et al.* and Seymour models.

Conclusion

This paper examined the importance reviewed four alternative approaches to estimating interaction effects in non-linear regression models. Commonly used approaches are the split-sample approach and the estimation of marginal effects of interaction terms. However, the split-sample method does not permit testing of the statistical significance of observed difference in marginal effects across split-samples, and the method of generating marginal effects from interaction terms produces biased estimates of these interaction effects. Norton *et al's* (2004) method enables the estimation of interaction effects in models that contain a single interaction term. Seymour's method allows for multiple interaction terms.

To assess how the use of these alternative methods might have impacted on the accuracy of estimates of interaction terms, this paper used a case study approach. The interaction terms related to effects of ill-health, informal care roles, occupational status and employment contract on employment retention. The data sample was mid-life Australian women. The data source was the HILDA Survey.

The findings of the evaluation of the alternative methods suggest that using a less-than-ideal method to estimate the interaction effects of informal care/ill health and contract type/occupational status on the employment transitions of mid-life Australian women has relatively small consequences – given the available data.

However, these results are specific to this data set and these research questions. Other, especially larger data sets and research questions might show larger differences between the results of the different models than those shown here. Furthermore, given that other parts of the paper demonstrate that the marginal effects from split-samples and interaction terms contain limitations/inaccuracies; even in the absence of evidence of large differences in results, it provides grounds for the adoption, wherever possible, of the superior Norton *et al*. (2004) or Seymour methods.

Further improvements in the measurement of interaction should also be sought. For example, the analysis presented in this paper has only reported the average interaction effects for all observations. However, the sign, magnitude and statistical significance of the average interaction effect provides only a partial guide to the evaluation of interaction effects as the interaction effect of x_1x_2 might be statistically significant for some observations, but insignificant for others. Furthermore, the interaction effect may be positive for some observations but negative for others. In the case where x_1 and/or x_2 are continuous variables, both Ai and Norton (2003) and Greene (2010) have proposed that graphical illustrations might best demonstrate how the interaction effect x_1x_2 might change as the values of x_1 and/or x_2 increase or decrease.

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[i] Subsequent waves of the survey featured some attrition of participants, due to refusal, death, or problems in locate them. In 2002, the survey managers secured interviews with 87 per cent of the original sample. In 2003 the retention (inverse of attrition) rate was 90 per cent; in 2004, 92 per cent; in 2005, 94 per cent; 2006 to 2008 95 per cent; 2009 96 per cent (see Melbourne Institute for Applied Economic Research 2011).

[ii] As we pool the data from the various waves of the survey, we use multiple observations on different women. For example, if a mid-life woman was observed to be employed in waves 1, 2 and 3, then the model would contain three observations on this woman.

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