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Graphical Illustration of Interaction Effects in Binary Choice Models: A Note

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Abstract

Graphing procedures for evaluating power or interaction terms in binary logit and probit models are illustrated in an application to hog producers' decisions based on transaction cost economics' hypothesised positive effect of the interaction of uncertainty and asset specificity on contract use. Results support the hypothesis, particularly for producers that are otherwise on the cusp (near the 50/50 probability) of choosing either contract or spot transactions based on their responses for other variables. Such insights may not be drawn without use of the demonstrated graphing procedures.

Keywords: *Asset specificity*; *binary choice models*; *contracts*; *transaction costs economics*; *uncertainty*.

JEL classifications: *D86, C25, L14, Q13*.

1. Introduction

Agricultural economists often evaluate discrete choices of a binary nature, e.g. technology adoption, conventional or organic production, contractual or spot exchange. The challenge for agricultural economists is that in the binary logit and probit models used to examine these discrete choices, conventionally reported marginal effects of power or product terms may not be statistically significant, while the variable in fact has potentially important and economically relevant impacts. The primary purpose of this note is to demonstrate procedures for graphically assessing the marginal effects of product and power terms in binary probit and logit models, and to raise awareness of these procedures among agricultural economists. With volatile prices and growing contract use, the capital intensive hog industry offers an interesting research context

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Table 1
Asset specificity, uncertainty and the marketing/procurement decision

			Uncertainty	
		Low	*Medium*	*High*
Asset Specificity	*Low*	Market transaction	Market transaction	Market transaction
	Medium	Contract	Contract or vertical integration	Contract or vertical integration
	High	Contract	Contract or vertical integration	Vertical integration

Source: Brickley *et al*. (2009), p. 616.

for testing a central hypothesis of Williamson's (1975) transaction cost economics (TCE): greater combinations of uncertainty and asset specificity lead to more sophisticated methods of coordinating exchange (Table 1).

Transaction cost economics is a leading paradigm in management and organisational studies and is gaining application in the study of vertical coordination and integration of agricultural marketing channels. Despite the hypothesised interaction effect, management scholars commonly consider either uncertainty, asset specificity or both, but neglect their interaction (David and Han, 2004; Carter and Hodgson, 2006), which also appears to be the case for related studies in various agricultural contexts (Knoeber, 1989; Hobbs, 1996; Sykuta and Parcell, 2003; Bhuyan, 2005; Franken and Bacon, 2014). Although this well-known interaction effect makes TCE an excellent application for the graphical procedures demonstrated here, these procedures are relevant for any topic dealing with the influence of a power or product term on a binary variable of interest.

The analysis is performed on a subset of data previously analysed by Franken *et al*. (2009) to study hog contracting, and readers are directed to the study for full details on the representativeness of the sample and measurement of variables. Summary statistics are given in Table 2. *CONTRACT* equals one if the producer has a marketing contract, and zero otherwise, with the mean indicating that about 31% of producers in the sample uses contracts. *SIZE* is measured by annual sales of hogs. As identified by Franken *et al*. (2009), the sampled producers are representative of larger commercial operations. The degree of producer leverage is measured by the capital replacement and term debt repayment margin (*CRDRM*).[2] *AGE* varies from 31 to 72 years, with a mean over 50 years consistent with the ageing farmer population. *EDUCATION* equals one if the producer attended four years of college, and zero otherwise, and its mean indicates that about 38% of sampled producers have a college degree. *UNCERTAINTY* and *SPECIFICITY* are computed by applying factor analysis (Thompson, 2004) to survey items measured by Likert scales ranging from one ('low') up to nine ('high'). Hence, the summary statistics indicate a range of values that are conducive for market transactions and contracting according to the predictions of TCE (Table 1).

[2]Capital replacement and term debt repayment margin = Capital replacement and term debt repayment capacity – Principal payments on unpaid operating debts – Principal payments on current portions of term debt and capital leases, where Capital replacement and term debt repayment capacity = Net farm income from operations + Total non-farm income + Depreciation expense – Income tax expense – Withdrawals for family living.

Table 2
Summary statistics

	Maximum	Minimum	Mean	Standard deviation
CONTRACT (=1 if contract, 0 o.w.)	1.00	0.00	0.31	0.47
SIZE (1,000 hogs sold/year)	30.68	0.21	5.03	5.50
CRDRM†	373.92	–2,285.80	–63.93	364.00
AGE (years)	72.00	31.00	52.71	8.57
EDUCATION (=1 if 4 years college, 0 o.w.)	1.00	0.00	0.38	0.49
UNCERTAINTY‡	8.40	2.62	5.70	1.34
SPECIFICITY†	7.27	0.90	2.19	1.31

Notes: †*CRDRM* denotes capital replacement and term debt repayment margin.
‡*UNCERTAINTY* and *SPECIFICITY* are computed by applying factor analysis (Thompson, 2004) to survey items measured by Likert scales ranging from 1 ('low') up to 9 ('high'). See Franken *et al*. (2009) for details on variable measurement.

2. Empirical Methods and Results

For demonstration, we report results of a logit model of the probability of hog contracting:

$$\Pr(y = 1|\mathbf{x}) = (e^{\mathbf{x}'\boldsymbol{\beta}})/(1 + e^{\mathbf{x}'\boldsymbol{\beta}}) = F(\mathbf{x}'\boldsymbol{\beta}), \tag{1}$$

where y equals 1 if the producer sells on contract, and 0 if not, $\mathbf{x}$ and $\boldsymbol{\beta}$ are vectors of explanatory variables and coefficients, respectively, and $F(\cdot)$ is the logistic cumulative distribution function (cdf). To demonstrate potential pitfalls involved with interpreting the results of such nonlinear models, coefficients are presented alongside marginal effects in Table 3. The model's proportion of correct predictions is also included, along with the commonly reported McFadden's R^2. Following convention, we report marginal effects computed at mean values of explanatory variables, which is common practice unless particular values are of interest (Long, 1997; Sykuta, 2005). As shown below, such marginal effects are not as informative as graphing procedures for the interaction term in particular.

Briefly, we note that results for control variables are fairly consistent with the hog contracting literature (Key and McBride, 2003; Davis and Gillespie, 2007). Younger producers and those with limited ability to service additional debt are significantly more likely to contract. Though the marginal effects of *SIZE* and *EDUCATION* are consistent with anticipated positive and negative effects, they are not statistically significant at conventional levels. Finally, note that for each of these control variables, sign and statistical significance is consistent across coefficients and marginal effects – an observation that does not hold for the interacted terms.

The coefficients for *UNCERTAINTY* and *SPECIFICITY* are both significantly negative and that of their interaction is significantly positive, while each of the corresponding marginal effects are positive but statistically insignificant. Notably, the statistical significance of an interaction term and its underlying variables cannot be inferred from coefficients in nonlinear regressions like logit or probit, and its marginal effect can vary in sign, magnitude and statistical significance with the values of other explanatory variables, i.e. across observations (Hoetker, 2007). Hence, the magnitude

Table 3
Results of logit model of contract use

Variables	Coefficients	Marginal Effects
SIZE	0.17	0.03
(1,000 hogs sold/year)	(0.14)	(0.02)
CRDRM†	–0.01**	-1.22×10^{-3}**
	(3.60×10^{-3})	(5.30×10^{-4})
AGE	–0.24***	–0.04***
(Years)	(0.09)	(0.01)
EDUCATION	–0.49	–0.07
(=1 if 4 years college, 0 o.w.)	(1.01)	(0.15)
UNCERTAINTY‡	–1.98*	0.12
	(1.05)	(0.10)
SPECIFICITY‡	–7.55**	0.02
	(3.64)	(0.11)
UNCERTAINTY × *SPECIFICITY*	1.35**	0.17
	(0.63)	(0.21)
Observations	48	
Log likelihood	–16.34	
McFadden's R^2 §	0.45	
% Correctly Classified	89.58%	

Notes: ***, **, *denote significance at the 1%, 5% and 10% levels, respectively. Standard errors in parentheses.
†*CRDRM* denotes capital replacement and term debt repayment margin.
‡*UNCERTAINTY* and *SPECIFICITY* are computed by applying factor analysis (Thompson, 2004) to survey items measured by Likert scales ranging from 1 ('low') up to 9 ('high'). See Franken *et al*. (2009) for details on variable measurement.
§McFadden's R^2 = 1 – [(log likelihood of the fitted model)/(log likelihood of the null or empty model)].

and significance of the marginal effect of the interaction of *UNCERTAINTY* and *SPECIFICITY* for each observation in the sample is depicted graphically in Figure 1 following Norton *et al*. (2004) and Wiersema and Bowen (2009) and simulated values are shown in Figure 2 following Zelner (2009). Readers are directed to these papers for further details on derivations of marginal effects and standard errors and for easily implemented procedures in the STATA software package for constructing the graphs.

Figure 1 depicts marginal interaction effects for each observation using * and × to denote statistical significance at 5% and 10% levels and ◇ to denote statistically insignificant values. Marginal effects, which may be positive or negative, are given on the vertical axis, and are plotted against probabilities of contracting (implied by values of other explanatory variables) on the horizontal axis. Marginal effects for the interaction term are mostly positive, except at extreme probabilities of contracting near zero and 100%. Most of the statistically significant effects occur at observations lying between probabilities of contracting of 30% and 60%. For producers whose values on other variables put them within this range of probabilities, a unit increase in the interaction of *UNCERTAINTY* and *SPECIFICITY* may increase their probability of contracting by over 30%.

The S-shaped logit cdf reflects this intuitive outcome: 'A given change in probability is more difficult to obtain when the probability is closer to the limits of 0 (the floor)

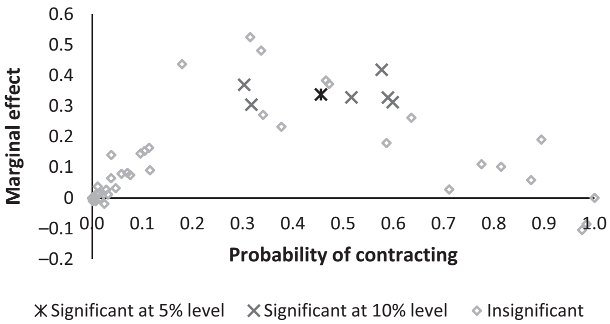

Figure 1. Marginal interaction effects of uncertainty and physical asset specificity

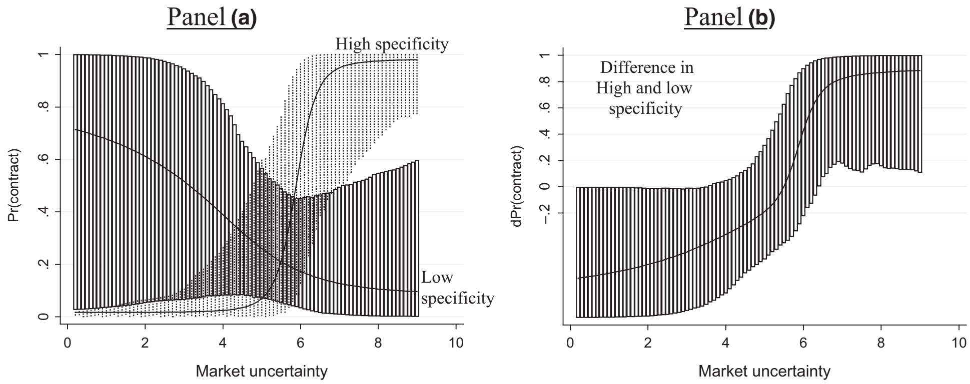

Figure 2. Marginal effect of physical asset specificity given level of uncertainty

and 1 (the ceiling), and is easier to obtain when the indeterminacy is highest (usually at the midpoint of 0.5)' (Huang and Shields, 2000, p. 81). That is, the interaction effect has the greatest influence on choice for producers whose values on other variables put them near the 50/50% probability cutoff for the contract-or-spot decision, and therefore, likely influences predicted outcomes (i.e. contract-or-spot). The reported model correctly classifies nearly 90% of observations compared to 85% for a model excluding the interaction term. For those producers who are roughly ambivalent between contractual and arms-length spot transactions, the statistically positive marginal effect of the interaction term is consistent with the central hypothesis of TCE (Table 1).

In Figure 2, Panel (a) depicts the probability of contracting (vertical axis) associated with high and low levels of *SPECIFICITY* (95th and 5th percentiles) at given levels of *UNCERTAINTY* (horizontal axis), while Panel (b) shows differences in the probability of contracting (vertical axis) corresponding to differences in high and low *SPECIFICITY* at given levels of *UNCERTAINTY* (horizontal axis). In both panels, 95% confidence intervals (CIs) are illustrated as shaded areas. In Panel (a), the 95% CIs for high and low asset specificity overlap at lower levels of uncertainty, implying that the level of asset specificity is insignificant when uncertainty is low. However, at high levels of uncertainty, the 95% CI of high asset specificity lies above that of low asset specificity, implying that the combination of high uncertainty and high asset specificity significantly increases the probability of contracting. Similarly, in Panel (b), the 95% CI for the difference in high and low asset specificity encompasses zero at low levels of uncertainty but not at high levels. Furthermore, the value slopes upward with higher uncertainty, indicating an increasing (positive change in) probability of contracting. Hence, the results again imply that the effect of moving from low to high asset specificity on the probability of contracting is not statistically different from zero when uncertainty is low, but is statistically positive at high levels of uncertainty. In each case, the graphics support the hypothesis that the probability of contracting is significantly higher for greater combinations of asset specificity and uncertainty. Since high levels of asset specificity in our sample are actually moderate levels (i.e. around seven on a scale from one to nine), the results are consistent with TCE predictions of contract use under conditions of high uncertainty and moderate asset specificity (Table 1).

3. Discussion and Conclusions

This note demonstrates graphing methods that facilitate interpretation of interaction effects in binary logit and probit models in an application of TCE to hog producers' contracting decisions. The statistical significance of a hypothesised positive interaction effect of uncertainty and asset specificity on contract use is masked in our results when assessing marginal effects computed at mean values of explanatory variables, as is common practice, but becomes evident through broader graphical assessment. The primary purpose of this note is to illustrate these graphing procedures to the agricultural economics community.

A secondary contribution of this note relates to TCE and its use in empirical applications. Scholars commonly consider either uncertainty, asset specificity or both, but neglect their interaction in TCE studies. Our results indicate that including this often omitted but theoretically relevant interaction term results in more accurate classification of marketing decisions, which suggests that models omitting this important term may yield inaccurate inferences about the practices of businesses and may underestimate our ability to explain their choices. For instance, in our results, the interaction term is particularly significant for the decisions of hog producers that are otherwise on the cusp (near the 50/50% probability cutoff) of choosing either spot market or on contract sales, likely influencing the predicted choice for these producers. Hence, analyses that only consider marginal effects at the mean may erroneously infer that the interaction term is of little importance for the decision at hand.

An anonymous referee raises the point that such graphing of marginal effects across observations seems at odds with the *ceteris paribus* nature of hypothesis testing (i.e. holding all other variables constant) and that researchers commonly seek to ascertain the effect for the average case for the purpose of policy-making. We acknowledge that singular calculations of a marginal effect at the mean or some other value of interest for other explanatory variables may be meaningful, particularly if such cases exist in the population. However, as Hoetker (2007) notes, often no single case in the sample or population exhibits the mean of all other variables, and then it is more informative to consider the response for each observation graphically. Then, following Train (1986), the average of these responses arguably may offer a more representative average marginal effect. Hence, the suitability of the approach may depend on the application at hand, and each perspective may be consulted. Overall, this note and its findings underscore the importance of careful implementation and interpretation of empirical procedures and appropriate practices that should be considered in future work.

References

Bhuyan, S. 'An empirical evaluation of factors determining vertical integration in US food manufacturing industries', *Agribusiness*, Vol. 21, (2005) pp. 429–445.

Brickley, J. A., Smith, C. W. and Zimmerman, J. L. *Managerial Economics and Organizational Architecture*. New York, NY: McGraw-Hill Irwin, 2009.

Carter, R. and Hodgson, G. M. 'The impact of empirical tests of transaction cost economics on the debate on the nature of the firm', *Strategic Management Journal*, Vol. 27, (2006) pp. 461–476.

David, R. J. and Han, S.-K. 'A systematic assessment of the empirical support for transaction cost economics', *Strategic Management Journal*, Vol. 25, (2004) pp. 39–58.

Davis, C. G. and Gillespie, J. M. 'Factors affecting the selection of business arrangements by US hog farmers', *Review of Agricultural Economics*, Vol. 29, (2007) pp. 331–348.

Franken, J. R. and Bacon, K. J. 'Organizational structure and operation of the Illinois wine industry', *Agricultural and Resource Economics Review*, Vol. 43, (2014) pp. 104–124.

Franken, J. R. V., Pennings, J. M. E. and Garcia, P. 'Do transaction costs and risk preferences influence marketing arrangements in the Illinois hog industry?', *Journal of Agricultural and Resource Economics*, Vol. 34, (2009) pp. 297–315.

Hobbs, J. E. 'Transaction costs and slaughter cattle procurement: Processors' selection of supply channels', *Agribusiness*, Vol. 12, (1996) pp. 509–523.

Hoetker, G. 'The use of logit and probit models in strategic management research: Critical issues', *Strategic Management Journal*, Vol. 28, (2007) pp. 331–343.

Huang, C. and Shields, T. G. 'Interpretation of interaction effects in logit and probit analyses: Reconsidering the relationship between registration laws, education, and voter turnout', *American Politics Research*, Vol. 28, (2000) p. 80.

Key, N. and McBride, W. 'Production contracts and productivity in the US hog sector', *American Journal of Agricultural Economics*, Vol. 85, (2003) pp. 121–133.

Knoeber, C. R. 'A real game of chicken: Contracts, tournaments, and the production of broilers', *Journal of Law, Economics, & Organization*, Vol. 5, (1989) pp. 271–292.

Long, J. S. *Regression Models for Categorical and Limited Dependent Variables*. Thousand Oaks, CA: Sage Publications Inc, 1997.

Norton, E. C., Wang, H. and Ai, C. 'Computing interaction effects and standard errors in logit and probit models', *The Stata Journal*, Vol. 4, (2004) pp. 103–116.

Sykuta, M. E. *New Institutional Econometrics: The Case of Contracting and Organization Research*, New Institutional Economics Working Papers, University of Missouri at Columbia, 2005.

Sykuta, M. and Parcell, J. 'Contract structure and design in identity-preserved soybean production', *Review of Agricultural Economics*, Vol. 25, (2003) pp. 332–350.

Thompson, B. *Exploratory and Confirmatory Factor Analysis: Understanding Concepts and Applications*. Washington, DC: American Psychological Association, 2004.

Train, K. *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*. Cambridge, MA: The MIT Press, 1986.

Wiersema, M. F. and Bowen, H. P. 'The use of limited dependent variable techniques in strategy research: Issues and methods', *Strategic Management Journal*, Vol. 30, (2009) pp. 679–692.

Williamson, O. E. *Markets and Hierarchies: Analysis and Antitrust Implications*. New York, NY: The Free Press, 1975.

Zelner, B. A. 'Using simulation to interpret results from logit, probit, and other nonlinear models', *Strategic Management Journal*, Vol. 30, (2009) pp. 1335–1348.