Vlerick Leuven Gent Management School
the Autonomous Management School of
Ghent University and Katholieke Universiteit Leuven

Vlerick Leuven Gent Working Paper Series 2006/33

THE USE OF LIMITED DEPENDENT VARIABLE TECHNIQUES IN STRATEGY RESEARCH: ASSESSMENT AND CRITIQUE

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D/2006/6482/35

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ABSTRACT

Strategy researchers are increasingly turning their attention from examining the implications of strategic choices on firm performance to examining the factors that determine strategic choice at the firm level. This shift of research orientation has meant that researchers are increasingly faced with a limited dependent variable (LDV) that takes a limited number of usually discrete values. In such cases researchers typically use discrete LDV methods such as Logit or Probit and, in fact, the use of such methods has increased significantly in recent years. Despite their growing popularity, there appear to be widespread problems in the application, reporting, and interpretation of LDV methods and their results within the literature. We examined the use of LDV methods in 50 papers published since 2002 in two top-tier journals that are primary outlets for empirical strategy research (Strategic Management Journal and Academy of Management Journal). One particularly troublesome issue is the finding that researchers fail to correctly analyze moderating hypotheses, a situation that likely stems from a lack of familiarity with the nonlinear nature of LDV models. Based on our review of the literature, this paper provides an assessment of the use of the most common LDV methods, highlights problems and inconsistencies regarding their use and interpretation, and provides guidelines and suggestions for researchers seeking to use LDV statistical techniques.

Keywords: empirical methods, limited dependent variable, strategy research.

THE USE OF LIMITED DEPENDENT VARIABLE TECHNIQUES IN STRATEGIC MANAGEMENT RESEARCH: ASSESSMENT AND CRITIQUE

The statistical techniques used in strategic management research are becoming more sophisticated and more complex. While ordinary least squares (OLS) regression remains predominant,[1] the array of statistical techniques used has expanded significantly, with many of the newer techniques involving less familiar methods of estimation, analysis and interpretation. In part, the increased sophistication of the statistical techniques used comes in response to an increasing focus within the field on methodological issues.[2] One particular trend in strategy empirical research is the growing use of limited dependent variable (LDV) techniques. Shook, Ketchen, Cycyota and Crockett (2003), in their review of empirical research, noted that the use of Logit in published strategy research had increased more than any other non-OLS technique. Strategic choices, such as acquisitions, market exit, and joint ventures, are often modeled as a binomial (yes/no) decision whereas other choices, such as the mode of market entry or type of international expansion, are often modeled as multinomial using a limited number of discrete options (e.g. start-up, acquisition, joint venture, wholly owned subsidiary). Despite the growing use of LDV methods, to date only limited attention has been given to assessing the extent to which LDV methods are being appropriately and consistently used in strategy research, despite that such issues are of primary importance in generating valid statistical conclusions (Scandura and Williams, 2000). Not surprisingly, researchers tend to feel less at ease with specialized techniques such as Logit (Shook, et al., 2003).

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[1] According to one recent study, OLS is still used by 42% of all research studies in management, but techniques for categorical dependent variables constituted 6.9% of all research studies (Scandura and Williams, 2000).
[2] *Research Methodology in Strategy and Management*, D. Bergh and D. J. Ketchen, Jr., Series Co-Editors, Elsevier Press, 2004 as well as articles in this journal have addressed a host of specific research design and methodologically issues.

But as the use of LDV techniques becomes more prevalent, it seems warranted to undertake a critical examination and assessment of their use in strategy research. In fact, there appear to be widespread problems in the application and interpretation of LDV statistical techniques. In our review of 50 articles published in the *Strategic Management Journal* and the *Academy of Management Journal* between 2002 and 2005 that used a LDV technique,[3] we did not find one study without some type of methodological fault.[4] Our review examined several aspects of each study. First, we investigated each study's research question and design and whether or not a LDV model was appropriate or optimal for examining the phenomenon of interest. We then examined the approach and statistical methods each study used to assess its model and to conduct hypothesis tests, and finally how each study reported its results.

This paper highlights the key statistical, methodological, and interpretive issues uncovered in our review and assessment of the current use of common LDV methods in strategic management research, and it offers recommendations and guidelines regarding these issues. In this respect, this paper complements other recent articles that highlight methodological issues in management research (Scandura and Williams, 2000; Shook et al, 2003; Shook, Ketchen, Hult, and Kacmar, 2004). By broadening understanding within the profession on the use of LDV techniques for empirical investigation of strategic choices or organizational outcomes this paper seeks to enhance the field's ability to build knowledge and to provide managerial insight on important strategic issues.

RESEARCH DESIGN CONCERNS

A discrete LDV model arises when the phenomenon of interest cannot be modeled as a continuous dependent variable, but is instead represented as a discrete array of choices or outcomes. Historically, empirical strategy research focused predominantly on organizational outcomes such as firm performance or diversification that are operationalized by continuous variables, such as ROA or the Entropy measure of diversification, and that therefore permitted the use of ordinary least squares (OLS).

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[3] We restricted review to papers that used one of the following LDV techniques: binary Logit, binary Probit, and multinomial Logit.

However, strategy researchers are increasingly examining phenomenon characterized by a discrete array of choices or organizational outcomes. Examples include international expansion operationalized as either start-up or acquisition (Vermeulen and Barkema, 2001); strategic alliances categorized into various organizational forms (Columbo, 2003); the existence or absence of certain conditions such as managerial turnover (Bloom and Michel, 2002; Shen and Cannella, 2002); the existence of a COO position (Hambrick and Canella, 2004); CEO/Chair duality (Nelson, 2003); and whether or not a new CEO differs from his predecessor (Zajac and Westphal, 1996). As researchers increasingly examine organizational phenomena that cannot be operationalized by a continuous variable, they have come to rely on LDV techniques.

For many strategy phenomena the use of a discrete measure may indeed be appropriate, but this is not always the case. Managerial choices and organizational outcomes are rarely limited to just a few discrete options. In our review, we found that while in many papers the underlying phenomenon of interest was continuous, the researcher chose to instead model it as discrete. For example, the scope of the firm in terms of its level of related diversification was modeled in terms of high versus low (Jensen and Zajac, 2004) rather than the extent of relatedness; vertical integration was modeled as a make or buy decision rather than the extent of outsourcing (Leiblein and Miller, 2003); and equity in a joint venture was modeled as being either present or absent, rather than taking into account the amount of equity (Colombo, 2003). In other cases, a multidimensional phenomenon was modeled binomially, as in the case of international expansion modeled in terms of either an acquisition or Greenfield (Anand and Delios, 2002). In some papers continuous data were gathered, but then collapsed it into discrete categories. Examples include the number of white-collar crimes (Schnatterly, 2003) and the degree of outsourcing pursued by the firm (Toulan, 2002).

The first critical issue in any research design is the choice of a measure for a model's dependent variable that best captures the underlying construct of interest. Before proceeding to use a LDV model the researcher needs to understand the true underlying distribution of the strategic phenomenon of interest and how it can best be operationalized and measured.

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[4] A list of these articles is available from the authors as well as their assessment of these articles in terms of the reporting of results, analysis, and interpretation of results.

One should not impose a discrete categorization measure on a strategic phenomenon when it does not fully represent the actual set of choices or results that one observes from managerial decisions or organizational outcomes. In addition, a researcher should not intentionally collapse a variety of outcomes into a more confined set of choices. As prior studies note, researchers rarely articulate a rationale for their approach and they often adopt measures without systematic consideration of their validity (Acar and Sankaran, 1999; Robins and Wiersema, 2002). One's choice of measure should: 1) capture the range of variation that is of interest; 2) be exhaustive in terms of the ability to classify every observation in terms of the measure; and 3) be driven by the purpose of the study.

In articulating the rationale for their choice of a measure for their dependent variable, researchers should also assess the extent to which their empirical measure adequately reflects the real meaning of the concept under consideration – what is termed content validity. Content validity cannot be empirically determined, but is assessed by determining the degree to which a measure conveys the range of meanings included within the concept, or "the strength of the deductive syllogism that links indicator to underlying concept" (Robins and Wiersema, 1995: p.281). A measure that lacks content validity precludes the researcher's ability to utilize empirical methods to address the study's theoretical concerns (Nunnally, 1978). Without adequate consideration of content validity, a study cannot fully explain the nature of organizational phenomenon or the factors driving the various strategic choices or the consequences of these choices. If researchers inappropriately utilize a discrete LDV model then the ability to contribute to an academic understanding of the phenomena as well as to provide managerial insight is lost. A clear example is when researchers operationalize corporate refocusing or portfolio relatedness, both of which are well documented to encompass a range of possible choices, by relying on just a few discrete categories.

MODEL ASSESSMENT AND HYPOTHESIS TESTING

Methods for model assessment and hypothesis testing in the linear regression framework of OLS are widely understood and accepted, and a uniform and consistent format is used to report and interpret statistical results. In contrast, methods of model assessment and hypothesis testing are not so straightforward in a LDV framework, and in fact often differ substantively from those associated with OLS. These differences largely reflect the nonlinear nature of LDV models as well as the method (Maximum Likelihood) most often used to estimate such models. Our review indicated that as a result of these differences, the interpretation and methods of reporting the results produced by LDV techniques were highly varied, often incomplete, and in many cases incorrect. Such problems severely undermine the researchers' ability to interpret and accurately communicate his or her findings to the field and to therefore make a research contribution. Of particular concern is that because the papers evidencing such problems are published, they are often the template for later researchers who then propagate the same set of errors.

Model Assessment

The first step in any statistical analysis is model assessment, that is, assessing the extent to which the empirical model adequately represents the theoretical relationship being investigated. Such assessment usually involves testing for the joint significance of a model's explanatory variables and determining a model's predictive ability ("goodness-of-fit"). In OLS analysis, an F-statistic (the "overall F-test") is used to test the joint significance of a model's explanatory variables while a model's R-square is used to measure a model's "goodness-of-fit."

For almost all LDV techniques, including Logit and Probit, model estimation is made using the Method of Maximum Likelihood (MML). For any given model, one value produced by the MML is the maximum (or maximized) value of the likelihood function that characterizes the underlying statistical nature of the model. This maximized value is used to construct a Likelihood Ratio (LR) test of overall model significance (joint significance of all model variables) that is analogous to the overall F-test in OLS.

The specific "overall LR test" for model significance compares the maximized value of the likelihood function for the model that includes only the constant term (the "restricted" model) to the maximized value of the likelihood function of the model that includes all variables (the "full" or "unrestricted" model). The LR test statistic has a Chi-square distribution with degrees of freedom equal to the number of model variables, with a high value of the statistic pointing to rejection of the restricted model in favor of the unrestricted model – the model that includes the explanatory variables. One of the most common problems encountered in our review of LDV papers was a complete lack of discussion regarding model assessment, either in terms of overall model significance or goodness-of-fit. While most papers report the overall LR test Chi-square value in their table of results, few papers bothered to discuss the reported value or its meaning in terms of what it indicates about model significance.

Even fewer of the reviewed studies assessed the goodness-of-fit of their model. In OLS, R-square is the standard measure of model fit and it is uniformly reported and discussed. Assessing model fit is not so straightforward in LDV models since the MML does not seek to minimize error variance (or any other measure of "fit"). As a result, there is no measure of "explained variance" and hence no natural R-square measure like that in OLS regression. However, in the spirit of the OLS R-square, several "pseudo" R-square measures have been proposed for LDV models (e.g. Nagelkerke, 1991), and some are commonly computed as part of the output generated by statistical packages (e.g. SPSS, STATA) that estimate LDV models by the MML. Another indictor of fit for LDV models is the model's ability to correctly predict choices. The percentage of correctly predicted outcomes, like pseudo R-square measures, does not admit an "explained variation" interpretation, but it nonetheless provides an indication of model fit.

In our review of papers using LDV models, we found that about half the papers report some measure – predominantly a pseudo R-square measure, while the remainder fail to either report or discuss goodness-of-fit.

Despite debate about the "best" measure of goodness-of-fit for LDV models, the significant failure to report any one of a number of commonly accepted measures is a startling omission, especially since statistical programs provide these as standard output.[5] By not providing the reader with one or more measures for goodness-of-fit, the reader is uninformed (and perhaps skeptical) regarding the ability of the model to adequately describe the phenomena of interest. Unlike OLS, where there is a known analytical relationship between R-square and the overall F-statistic, knowing only the Likelihood Ratio test of overall model significance provides an incomplete picture of a model's ability to represent the underlying relationship of interest. Surely, condemnation would be swift if one omitted the R-square when reporting a model estimated using OLS. At a minimum, studies using a LDV model should report at least one goodness-of-fit measure and provide discussion of their model's predictive ability. Since the computation of many of the pseudo R-square measures, as well as the predictive ability measures, require calculations that use the underlying data, these measures cannot simply be inferred from a table of reported results. Hence, unless the researcher reports and discusses the goodness-of-fit of his or her model, the reader has no way to independently ascertain the predictive ability of the model.

Hypothesis Testing – Direct Effects

Hypothesis testing represents the next step in any statistical analysis. Hypothesis testing in OLS is usually conducted by ascertaining the significance of one or more explanatory variables as well as by comparing alternative models in terms of their overall significance and improvement in goodness-of-fit. For a direct effect hypothesis in OLS, the importance and directional impact of a given explanatory variable on the dependent variable is assessed by the statistical significance and sign of the explanatory variable's estimated coefficient. To assess alternative models a sequential (hierarchical) approach is often used whereby the researcher compares a base model (constant and controls) to one or more partial models (addition of explanatory variables), and then to a full model (all variables). By ascertaining the improvement in goodness-of-fit (a significant increased in adjusted R-square)

[5] For example, SPSS's Logit estimation routines reports, by default, two pseudo R-square measures and a table of the percentage of correct predictions.

and the significance and sign of the coefficients in successive models, researchers can test direct hypotheses about one or more model variables.

In most of the LDV papers surveyed, hypothesis testing was problematic in that we found surprisingly few papers making the correct analysis, interpretation, or model comparison. There were two specific areas in which incorrect procedures were often followed: testing a hypothesis involving a single explanatory variable, particularly in the case of a multinomial LDV model, and testing hypotheses involving different sets of explanatory variables (i.e., testing alternative models). These two cases are discussed separately below.

Testing Hypothesis about a Single Variable

The procedures for testing a hypothesis involving a single explanatory variable can differ significantly from that of OLS depending on whether or not the LDV model is binary or multinomial. In the case of a binary LDV model, the approach for testing a direct effect hypothesis about a single variable is essentially the same as for OLS: one examines the statistical significance and directional impact of the explanatory variable's estimated coefficient. Thus a significant positive coefficient would indicate that the probability of a particular choice/outcome is greater at higher levels of the explanatory variable. However, in the case of a multinomial LDV model, testing a direct effect hypothesis is less straightforward since it first requires an additional step. Like OLS, the importance of a given explanatory variable on the dependent variable is assessed by the statistical significance of its estimated coefficient in the model. However, due to the nonlinear form of the multinomial model, an estimated coefficient does not correctly indicate the true directional impact (or magnitude) of an explanatory variable on the dependent variable, and thus one cannot test the directional influence specified in a hypothesis based on the sign (+ or -) of the estimated coefficient.

Moreover, because the model is nonlinear in all model variables, the true impact of an explanatory variable on the dependent variable is not a constant (as in OLS) but is instead a function of the values of all model variables and their estimated coefficients.[6] As a result, to test a hypothesis about a variable in a multinomial LDV model, one needs to compute the explanatory variable's *marginal effect.*[7] The marginal effect correctly measures the direction and magnitude that a change in a given explanatory variable has on the probability of making a given choice/outcome. Some statistical packages (e.g., LIMDEP, STATA, SAS) have either an option as part of their LDV model estimation routine, or a post-estimation routine, that computes variable marginal effects and associated standard errors, enabling researchers to correctly test their hypotheses in a multinomial LDV model.

In our review of papers with multinomial LDV models, most researchers incorrectly use the sign of the explanatory variable's estimated coefficient (as one would do in OLS) to test their hypothesis about the directional effect of an explanatory variable. This represents a serious error since there is no guarantee that the sign of the estimated coefficient does in fact correspond to the actual directional relationship between an explanatory variable and the dependent variable. Instead, a hypothesis regarding the direction of the relationship between a given explanatory variable and the dependent variable can only be tested by calculating the variable's marginal effect, which in turn depends on the estimated coefficients and values of all model variables. To test a direct hypothesis in a LDV multinomial model, the researcher should calculate and report in their study the explanatory variable's marginal effect on the dependent variable.[8]

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[6] This is also true in the binary Logit or Probit model. However, in these binary models the sign, but not the magnitude, of an estimated coefficient is identical to the explanatory variable's marginal effect on the dependent variable. Hence, for these binary models, hypotheses about directional effects can be based on the estimated coefficient. In fact, since a variable's marginal effect correctly indicates both the direction and magnitude of a variable's impact on the dependent variable (choice or outcome); one can always test a hypothesis in any LDV model on the basis of the variable's marginal effect and associated standard error.

[7] Formally, a variable's marginal effect is the first derivative of a model's conditional mean with respect to a given explanatory variable. In the case of OLS, this first derivative is just the coefficient on a given explanatory variable.

[8] Most common is to compute each variable's marginal effect when all model variables take their sample mean value.

Testing Hypotheses about a Group of Variables (Model Comparisons)

Like OLS, one can undertake model comparisons in an LDV setting by testing the statistical significance of different groups of variables. However, since LDV models are estimated using the MML, the underlying statistical basis for model comparisons is substantially different from that in an OLS framework. A failure to understand this difference accounts for many of the analytical errors found in the LDV papers we examined.

In most cases, researchers making model comparisons use a step-wise procedure that compares a base model that includes only a constant and control variables to a model that contains an additional set of explanatory variables. This hierarchical approach, common in the OLS framework, involves a step-wise procedure whereby the researcher compares a base model (constant and controls) to a more complete model (with additional explanatory variables), using a significant increase in adjusted R-square along with the significance and direction of the estimated coefficients for the explanatory variables to test the hypotheses. This step-wise approach is not correct for LDV models estimated by the MML.

Effectively, a LR test is only valid for testing nested hypotheses (models), that is, hypotheses where the model being tested (i.e., the model that is "true" under the null hypothesis) is derived by imposing constraints on the values of the coefficients of a subset of the explanatory variables contained in the full (unrestricted) model. Thus, the correct base model (alternative hypothesis) against which all other models should be compared is the full (unrestricted) model that includes all explanatory variables. This means one cannot use the hierarchical method common in OLS that begins with a restricted base model, sequentially adds variables, and then tests if these additional variables are significant by looking for a significant increase in adjusted R-square. Instead, for LDV models estimated by the MML, one begins with a full model and compares it to a partial (restricted) model formed by excluding a subset of explanatory variables that appear in the full model to determine whether or not to reject the null hypothesis that the coefficients associated with the chosen subset of variables are jointly equal to zero. A high value of the LR Chi-square statistic allows one to reject the null hypothesis - the partial model - in favor of the full model that includes all explanatory variables.

A further implication of using the MML to estimate LDV models is that one should not use a LR test to compare one partial model to another partial model. Many of the LDV papers we reviewed compared partial models, as one might do in OLS, to select a "best" model. This is an incorrect use of the LR test principle since the correct comparison for the LR test is between a partial model and the full model with all variables included.

To compare two partial models, whether each model contains only variables that are a subset of the variables in the full model or that instead contain different sets of variables (i.e., non-nested models), criteria other than the LR test should be used to select among models.[9] For example, several statistical packages (e.g. STATA) will report the Akaike Information Criterion (AIC) or Schwarz's Bayesian Information Criterion (BIC) (Judge, Griffiths, Hill, and Lee, 1984) which can be used to select among partial models. Such measures often involve the value of a model's Likelihood Ratio but use different "correction" factors, e.g. that adjust for the number of variables in a model (similar in spirit to the Adjusted R-square in OLS). Generally, these measures are used to rank alternative models in terms of the degree to which they are, in the sense defined by each particular measure, favored by the data; the best model being that which is most favored. In summary, when using a LR test to test a hypothesis about a group of explanatory variables in a LDV model, the correct alternative (base) model is the unrestricted full model that includes all explanatory variables, and the researcher should therefore report and discuss his or her results in terms of this type of model comparison.

Hypotheses Testing – Indirect (Moderating) Effects

In the framework of OLS, the analysis and interpretation of moderating or interaction hypotheses – whether the effect that an explanatory variable has on the dependent variable depends on the value of another (moderator) variable – is well documented (e.g., Jaccard, Turrisi, and Wan, 1990).

[9] However, Vuong (1989) has proposed methods that use LR test methods to make non-nested model comparisons.

Specifically, the estimated coefficient on the interaction variable (i.e., the variable formed by multiplying the values of the explanatory and moderator variable) needs to be statistically significant and the model that includes the interaction variable should explain a significant amount of the variance in the dependent variable above that explained by the model that excludes the interaction variable as indicated by a significant increase in adjusted R-square. If both of these conditions are met, then the relationship between the explanatory variable and the dependent variable is dependent on values of the moderating variable. If there is a significant moderating effect, then the sign of the estimated coefficient on the interaction variable indicates the directional influence of this moderating effect.

In papers that use OLS, most researchers assess the directional influence of a moderating effect by computing the *total marginal effect* of the explanatory variable[10] and also depict the relationship graphically as a pair of straight lines, one line for a "high" value of the moderator variable and one for a "low" value of the moderator variable. Such an analysis provides a quick visual insight into how the relationship between the explanatory variable and the dependent variable changes at low and high values of the moderator variable.

Testing moderating effects in LDV models is far less documented, and it is therefore not surprising that analysis of moderating effects was particularly problematic in the LDV papers we examined. In fact, we could not find a single LDV study with a moderator hypothesis that performed the correct analysis. Given lack of clarity on this issue, it is not surprising that researchers relied on familiar OLS procedures to guide them in interpreting their interaction hypothesis, despite the fact that these procedures are not correct in the context of a LDV model. This is especially alarming since moderator hypotheses are increasingly common in strategy research.

The key issue for testing a moderating hypothesis in LDV models is that the estimated coefficient on an interaction variable is, unlike in OLS, not the "true" interaction coefficient (Ai and Norton, 2003). The issue of a true interaction coefficient arises because, unlike OLS, the underlying LDV model is non-linear in the model variables.

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[10] In OLS, the total marginal effect of a variable equals its estimated coefficient (direct effect) plus the estimated coefficient on the interaction variable times the moderator variable (indirect effect). See Jaccard, Turrisi, and Wan, 1990 for how to test the significance of a total marginal effect at different values of the moderator variable.

This means that the moderating or indirect effect does not equal the coefficient on the interaction variable times the moderator variable.[11] Furthermore, the true interaction coefficient is not a constant, but instead depends on the value of the moderator variable and the values of all other model variables and their estimated coefficients. Hence, unlike OLS, there is not just one single value of the true interaction coefficient. Thus the sign (and value) of the true interaction coefficient in a LDV model may be very different than that of the estimated coefficient on the interaction variable, and hence one cannot use the sign (+ or -) of this estimated coefficient to test a moderating hypothesis. This makes the analysis and interpretation of a moderating hypothesis in a LDV model both complex and more difficult.

The correct procedure for testing a moderating hypothesis in a LDV model is as follows. As with OLS, one first determines if the estimated coefficient on the interaction variable in the model is statistically significant. If so, one can then proceed to derive the *expression* for the true interaction coefficient to assess the directional influence of the moderator variable. This expression will normally involve all model variables and their estimated coefficients. Using this expression, one calculates the value of the true interaction coefficient and assesses its significance,[12] at a high, mean, and low value of the moderator variable (holding all other model variables fixed at some selected values, usually their sample mean value).[13] If the sign of the true interaction coefficient at each of these three values of the moderator variable is the same, and each coefficient is significantly different from zero, then one can reasonably conclude that, as in OLS, there is a consistent and significant moderating effect.[14]

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[11] In general, the expression for the true interaction coefficient associated with explanatory variable X and moderator variable Z is the cross partial derivative of the conditional mean of the LDV model being used with respect to these variables, i.e., $\partial^2 E[Y \mid X, Z]/\partial X\, \partial Z$. In the linear regression model this cross-partial derivative equals the coefficient on the interaction variable $X*Z$. In general, this is not true for LDV models since conditional mean for these models is a non-linear function of model variables. Instead, one must derive the cross-partial derivative and compute its value at different values of the moderator holding the values of all other model variables fixed (Ai and Norton, 2003).

[12] The procedure for assessing the significance of the interaction coefficient involves calculation of the standard error of the true interaction coefficient using the "delta method." See Ai and Norton (2003) for details.

[13] The value of the true interaction coefficient varies continuously with the value of the moderator. We suggest use of a low, mean, and high value in lieu of computing all values of the true interaction coefficient over all values of the moderator.

[14] If the true interaction coefficient is significant at one value of the moderator, but not at other values, then this fact should be noted.

As in OLS, one can then compute the *total marginal effect* of the explanatory variable at a high, mean, and low value of the moderator variable (holding all other variables fixed at their sample mean value) and test whether the total marginal effect is statistically significant. However, such calculations should keep in mind whether the true interaction effect is significantly different from zero at the value of the moderator that is used to compute the particular value of the total marginal effect. In interpreting a moderator or interaction hypothesis in a LDV model, the researcher can report and discuss the significance of the total marginal effect at low, mean, and high values of the moderator variable. Unlike OLS, we do not recommend graphical depiction of the moderating effect since a visual comparison to detect the influence of the moderator variable is more complex due to the non-linear nature of the resulting relationship between an explanatory variable and the dependent variable.

As the above suggests, testing a moderating hypothesis in a LDV model is substantially more complicated that in the linear world of OLS. Making matters more difficult is that, to our knowledge, no statistical package includes as part of its standard routines for LDV model estimation the capability to automatically request calculation of either the true interaction coefficient or the total marginal effect of a variable when this effect is moderated (i.e., when the variable also appears as part of an interaction variable), or that computes the significance of either of these effects.[15] This makes it extremely difficult for researchers to easily test their moderator hypotheses and, not surprisingly, not a single study did so correctly.

[15] Norton, Wang and Ai (2004) present a supplemental routine for STATA to calculate and test significance of the true interaction coefficient for binary Logit and Probit models when there is a single moderator hypothesis.

CONCLUSION

LDV techniques can be expected to appear more frequently in the strategic management literature as researchers become increasingly interested in models that explain strategic choices and outcomes. Our review of recent strategic management research that has used a LDV model indicates a number of methodological problems related to the use, interpretation, and reporting of the results obtained from the most common LDV techniques. Model assessment and hypotheses testing are significant problem areas, with many researchers erroneously applying the methods learned from the OLS framework to interpret and present their statistical results. As a result, many of the published LDV studies we reviewed incorrectly tested their theoretical hypotheses and made judgments about model fit that were not based on sound methodological procedures. Not a single paper reviewed with moderator hypotheses performed the correct analysis. Since the use of LDV models, and the inclusion of moderating hypotheses, is becoming increasingly common in strategic management research, there is an acute need for greater awareness of the methodological issues one faces when conducting a LDV analysis and in interpreting the results of such an analysis. This paper, by reviewing four years of recent empirical work that has utilized the most common LDV models, contributes to the strategy field by highlighting the most common set of problems and also suggesting standardization in the way LDV models are analyzed and reported. These suggestions are summarized in Table 1. We hope these suggestions will prevent researchers from perpetuating the same set of errors when using LDV techniques.

Insert Table 1 About Here

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TABLE 1. SUGGESTED GUIDELINES FOR LDV MODEL ANALYSIS AND REPORTING

DEPENDENT VARIABLE	**Discrete and Dichotomous (Binary Logit or Probit)**	**Discrete, Multivariate and Unordered (Multinomial Logit)**
Model Assessment: What to Report	• Model Significance o Maximized value of log-likelihood o LR Chi-square statistic testing model with only a constant term against full model with all explanatory variables included • Model Goodness-of-Fit o Pseudo-R-square o Percent of correctly predicted choices	
Hypothesis Testing: Direct Effects	• Model Comparison: o Use LR Chi-square statistic to test a partial model (formed by excluding a subset of variables in full model) against the full model. o To compare two partial models (nested or non-nested) use the Akaike Information Criterion or other similar measure. • Hypothesis Test: o Examine significance of estimated coefficient. o Examine sign of directional influence of coefficient to interpret hypothesis.	• Model Comparison: o Use LR Chi-square statistic to test a partial model (formed by excluding a subset of variables in the full model) against the full model. o To compare two partial models (nested or non-nested) use the Akaike Information Criterion or other similar measure. • Hypothesis Test: o Examine significance of estimated coefficient. If significant then proceed to calculate marginal effect. o Calculate marginal effect of explanatory variable when all model variables take their sample mean value o Examine sign of directional influence of marginal effect to interpret hypothesis.
Hypothesis Testing: Indirect (Moderating) Effects	• Model Comparison: o Use LR Chi-square statistic to test restricted model that excludes interaction variable(s) against unrestricted (full) model • Hypothesis Test: o Cannot use sign or value of the estimated coefficient on interaction variable to test interaction hypothesis. o Examine significance of estimated interaction coefficient. If significant, proceed to derive expression for true interaction coefficient, else conclude that there is no moderating effect. o Use expression for true interaction coefficient to compute its value at low, mean, and high values of moderator variable (set all other model variables to their sample mean value). o Assess significance and sign of true interaction coefficient at each value of moderator to interpret moderator hypothesis. o Can compute value and assess significance of total marginal effect of the explanatory variable at different values of moderator variable (noting if true interaction is significant at the selected value of the moderator).	