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Source: *Journal of Marriage and Family*, Vol. 50, No. 4 (Nov., 1988), pp. 929-936
Published by: National Council on Family Relations
Stable URL: http://www.jstor.org/stable/352104

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Logistic Regression: Description, Examples, and Comparisons

Family studies have seen a dramatic increase in the use of statistical tools for the analysis of nominal-level variables. The general class of such models is referred to as log-linear models. When one nominal-level variable is considered to be dependent on a set of predictor variables (which may be nominal, ordinal, or interval), log-linear models are also known as logit models or logistic-regression models (Knoke and Burke, 1980).[1] In recent years, logistic regression has been used to study topics as diverse as marital formation and dissolution (Abdelrahman and Morgan, 1987; Heaton, Albrecht, and Martin, 1985; Rank, 1987; Speare and Goldscheider, 1987), contraceptive use (Bean, Williams, Opitz, Burr, and Trent, 1987; Studer and Thornton, 1987), poverty (Smith and Zick, 1986), premarital sexual experience (Newcomer and Udry, 1987), premarital pregnancy (Robbins, Kaplan, and Martin, 1985; Yamaguchi and Kandel, 1987) and spouse abuse (Kalmuss and Seltzer, 1986). Despite its growing popularity, there still exists confusion about the nature and proper use of logistic regression in family studies. We present a nontechnical discussion of logistic regression, with illustrations and comparisons to better-known procedures such as percentaging tables and OLS regression.

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Odds and Odds Ratios

The concept necessary to understand log-linear models and logistic regression is the odds ratio, a measure of association. The odds ratio, as its name suggests, is the ratio of two odds. Odds, in turn, are themselves ratios of the number of events to the number of nonevents. Although odds and odds ratios can be conceptualized without reference to tabular data (i.e., when the odds are to be related to an interval-level variable such as income), for pedagogic reasons we refer to the data in Table 1, which are taken from the National Survey of Children. Sample, measurement, and substantive issues are discussed in Furstenberg, Morgan, Moore, and Peterson (1987). For present purposes it is sufficient to note that the data are a nationally representative sample.

The event of interest is ever having intercourse, as reported by adolescents (15 and 16 years old). The odds (or likelihood) of intercourse (yes/no) is $O_m = 72/157 = .46$ for males and $O_f = 48/185 = .26$ for females. The odds ratio measures the change in these odds associated with gender. Males are $O_m/O_f = .46/.26 = 1.76$ times more likely to have had intercourse than females. Conversely, females are only $O_f/O_m = .26/.76 = .56$ times as likely as males to have had intercourse.

The odds ratio has several desirable properties as a measure of association (Fienberg, 1985):

1. It has a clear interpretation. If row totals are fixed (gender distribution taken as a given), the odds ratio gives the multiplica-

TABLE 1. ADOLESCENTS WHO HAVE EVER HAD INTERCOURSE, BY RESPONDENT'S GENDER: THE NATIONAL SURVEY OF CHILDREN

	Intercourse			Percentage			
				Row		Column	
Gender	Yes	No	Odds	Yes	No	Yes	No
Male	72	157	.46	31	69	60	44
Female	48	185	.26	21	79	40	56

tive change required to move from one odds (on intercourse) to the next (i.e., the odds of intercourse for males is equal to 1.76 times the odds of intercourse for females). An odds ratio greater than 1.0 indicates an increased likelihood of the event occurring, while an odds ratio less than 1.0 indicates a decreased likelihood of the event occurring. Thus, whether an odds ratio is greater or less than 1.0 can be thought of as its "sign."

2. It is invariant under the interchange of rows or columns (except for its "sign"). Thus, using the example above, if we interchange rows of columns, but not both, the value of O_m / O_f becomes $1/(O_m / O_f)$.
3. It is invariant under row and column multiplications. Shifts in sample size or marginal shifts do not affect its value.
4. It can be used in tables of variable sizes and dimensions (i.e., it can be used when analyzing polytomous variables or in multivariate models).

The interpretation of the odds ratio has been illustrated. Let us examine the importance of the other three properties. To begin, the most common analysis of this table would have been a simple percentaging across the dependent variable (in our example, across rows). These percentages are shown in Table 1. The difference between males and females in the percentage having intercourse is 10 points (31% minus 21%). For some problems, one might wish to examine percentages calculated across the independent variable (across columns). In this case, the percentage male shifts by 16 points (60% minus 44%) as one moves from yes to no. Thus, there are two differences that purport to describe the association in this table. The odds ratio, by contrast, is invariant to such changes.

More important is the invariance to row and column multiplication. Let us take Table 1 and double the number of males and females who have had intercourse (multiply column 1 by 2). Ideally, changing the level of intercourse alone should not affect its association with gender—the "new residents" are distributed by gender as in the original table. Note that the odds ratio is still $O_m / O_f = .92/.52 = 1.76$, but the percentage difference across the dependent variable increases from 10 percentage points to 14 percentage points (see Table 2). If our goal is to uncover invariant relationships across groups or to properly model variable associations, we could be seriously misled were our measure of association to be influenced by the size of the sample or different levels in different subpopulations.

This point brings us to the final advantage of the odds ratio—it can be extended for use with polytomous variables and in multiway tables. Table 3 shows a three-way table of intercourse by gender and race (white vs. black). Blacks are much more likely to have had intercourse. The odds ratio (black/white) is 3.9 (1.26/.32) for males and 3.6 (.61/.17) for females. In a parallel fashion one can estimate associations between the respondents' gender and intercourse for each race. In this comparison, the race differential is slightly greater for males than females. Thus, odds ratios can be computed for different groups

TABLE 2. ADOLESCENTS WHO HAVE EVER HAD INTERCOURSE, BY RESPONDENT'S GENDER, WITH AN ARTIFICIAL DOUBLING OF THE LEVEL OF INTERCOURSE

	Intercourse		Odds	Row Percentages	
Gender	Yes	No	Yes/No	Yes	No
Male	144	157	.92	48	52
Female	96	185	.52	34	64

TABLE 3. ADOLESCENTS WHO HAVE EVER HAD INTERCOURSE, BY RESPONDENT'S GENDER AND RACE: THE NATIONAL SURVEY OF CHILDREN

		Intercourse		
Race	Gender	Yes	No	Odds
White	Male	43	134	.32
	Female	26	149	.17
Black	Male	29	23	1.26
	Female	22	36	.61

and compared.

COMPARING THE FIT OF ALTERNATIVE MODELS

So far, we have computed odds ratios and have compared odds ratios across different groups. Testing whether individual odds ratios are significantly different from 1.0 (no association), or testing whether two odds ratios are different from one another, requires use of the chi-square statistic.[2] Most readers will be familiar with the chi-square test associated with the model of independence, which is computed by comparing the expected frequencies (under a model specifying no association) with the observed frequencies (under an implicit model that allows for association). If the chi-square statistic is large (relative to the degrees of freedom), then the expected model (the model of independence) is not an adequate description of the data; that is, a large chi-square value suggests that the model of independence is an inappropriate description of the observed data. Conversely, a small chi-square value suggests that the model of independence provides a reasonable description of the data.

There can be numerous models other than independence that might be compared with the observed data. Any two models can be compared by computing the chi-square statistic that measures the fit of each (i.e., its expected frequencies) to the observed data. The goal is to find a model that fits the data well enough such that the chi-square value (which indicates deviations of observed data to data predicted by the model) is small. Logistic regression analysis allows researchers to specify a model that they think should fit the data and then allows them to test competing models. The model of independence is always one of these competing models. In Table 3, consider two competing models: one that specifies no association (i.e., the model of independence, Model 1) and a second that allows an association equal to the observed odds ratios for gender and race (Model 2). The chi-square value indicates the level of certainty with which one can reject an associated model. Model 1 fits the data poorly, while Model 2 fits extremely well. With additional variable categories and variables, the number of potential models grow rapidly. One searches for a model that is parsimonious (simpler models are better, other things equal), fits the data well and, most important, makes substantive sense.

When reviewing results from logistic-regression analyses, be careful to avoid confusion by checking the nature of the chi-square tests being reported. Some analysts report the fit of the model: the chi-square value computed from the observed and expected frequencies (a small chi-square indicates a better fit to the data). Others report the model chi-square value, which is the improvement the proposed model makes over the model of independence (a larger chi-square indicates a greater improvement in fit to the data). Note that that fit of the independence model is equal to the sum of the model chi-square and the fit of the proposed model (Table 4). These statistics can be thought of as paralleling total, residual, and model sums of squares statistics from ordinary-least-squares regression analysis.

TABLE 4. FIT OF ALTERNATING MODELS, COMPARED

Item	χ^2	*df*
Fit of independent model (1)	37.5	3
Fit of proposed (additive) model (2)	.8	1
Model 1 - Model 2 chi-square	36.7	2

ESTIMATION AND PRESENTATION OF LOGISTIC-REGRESSION MODELS

Logistic-regression models can be estimated in several different ways. If all the variables are categorical, one can use weighted-least-squares or maximum-likelihood procedures (Fienberg, 1985). When the data contain continuous-level predictor variables, maximum-likelihood procedures must be used. The different ways of estimating models need not concern us, since all should produce identical results. However, the different methods of estimating models are sometimes associated with different modes of presentation, which may cause confusion. For instance, when estimated by iterative proportional fitting of rows and columns, the model for the additive effects of race and gender is: (RG) (RI) (GI), where I indicates intercourse, R indicates race, and G indicates gender. This notation means that the model is the result of fitting the joint distributions of R and G, R and I, and G and I to the data.

We suggest representation as either a multiplicative or linear prediction model (regardless of how the model was fit). A multiplicative prediction model for the data in Table 1 is:

$$Y = a \cdot b_1^{\text{GENDER}}$$

where Y is the odds of having intercourse, a is a constant, and b_1 is a coefficient for gender. Coding gender as 1 if male, 0 if female, we have:

$$Y = .26 \cdot 1.76^{\text{GENDER}} \quad (1)$$

Note that .26 is the observed odds for females, and 1.76 is the multiplicative adjustment (i.e., the odds ratio) required to produce the odds for males. To make this equation linear and estimation easier, take the natural logarithm of both sides, producing:

$$\ln(Y) = -1.34 + (.56 \cdot \text{GENDER}) \quad (2)$$

This transformation leads to a disadvantage, since log odds (also known as a *logit*; thus the term *logit models* or *logistic regression* for such models) have less intuitive appeal. Is a log odds of −1.34 low? Is an increase in the log odds of .56 large? But there are advantages. Estimated coefficients now have + and − signs, which indicate linear increases and decreases in the log odds. Thus, one can interpret them much as any regression coefficient, remembering that the dependent variable is now the logarithm of the odds of having intercourse. At the least, a variable that increases the log odds of an event occurring also increases the probability of the event occurring and vice versa.

Some investigators have chosen the linear and others the multiplicative mode of presenting results, adding to the confusion for those trying to interpret results. With a calculator that handles natural logarithms, researchers can move between models that indicate multiplicative changes in odds to models that indicate linear changes in log odds. In addition, a simple transformation yields the additive effects of the predictor variables on the probability of the event of interest occurring. Since most researchers are more comfortable thinking in terms of probabilities (P) than in terms of odds, such a translation can be useful (although the advantages of using odds and odds ratios are lost). Using the linear model for log odds, simply multiply each coefficient by $(P)(1-P)$.[3] In Table 1, the proportion experiencing intercourse is about .26, and $(P)(1-P) = .19$. Multiplying .19 times .56 (the coefficient for gender in the linear model) yields a value of approximately .10, meaning that males are about 10 percentage points more likely than females to have had intercourse.[4] Notice that this is the same percentage point difference found in the row percentages shown in Table 2. As a word of caution, however, the coefficient estimates will change as the value of P changes (just as the percentage point differential between males and females is sensitive to the proportion of adolescents having had intercourse). This sensitivity occurs because the probabilities of experiencing intercourse are nonlinear functions of the predictor variables.

Note that in Table 3 both race and gender can influence the probability of having intercourse. The results from estimating a logistic-regression model for these data are shown in Table 5. The linear model shown in the table is:

$$\ln(Y) = -1.76 + (.65 \cdot \text{GENDER}) + (1.31 \cdot \text{RACE}) \quad (3)$$

The corresponding multiplicative model is:

$$Y = .17 \cdot 1.91^{\text{GENDER}} \cdot 3.72^{\text{RACE}} \quad (4)$$

TABLE 5. LOGISTIC-REGRESSION MODEL FOR DATA IN TABLE 3

Variable	b	$b(P)(1-P)$	SE	p
Gender	.65	.12	.22	.004
Race	1.31	.25	.24	.000
Constant	−1.76			
Model χ^2	36.7			
df	2			

We know from the chi-square statistics shown above in the section on comparing alternative models that this model (e.g., a model including the effects of both gender and race) is a significant improvement over the model of independence. This model also fits the data reasonably well. What these chi-square values do not tell us is whether gender and race are both significantly related to the likelihood of intercourse. Fortunately, in addition to model chi-square values, each of the estimation routines discussed above provides the standard error of each coefficient, so that a conventional t test for the statistical significance of each coefficient can be computed. In the current case, both gender and race are significantly related to the likelihood of intercourse. Also shown in Table 5 are the linear coefficients multiplied by $P(1-P)$. These values can be interpreted as the expected percentage point differences in experience of intercourse, net of other variables in the model (and evaluated at the sample proportion experiencing intercourse).

Why Not OLS Regression?

From Equations 1 and 2, it is evident that logistic-regression models are multiplicative in the odds and linear in the logits. It can also be shown that the logistic-regression model is nonlinear in terms of predicting P (the proportion of respondents having had intercourse). The prediction equation for P based on Equations 1 and 2 is:[5]

$$P = \exp(a + b_1X)/(1 + \exp[a + b_1X]) \quad (5)$$

The question becomes, why not estimate an OLS regression model for the data? When OLS regression is used, the model is linear in predicting the proportion of individuals (or sample units) experiencing the event in question. This is an alluring interpretation, as most researchers prefer to think in terms of proportions and linearity (rather than multiplicative odds or linear logits). In part, this is the rationale for multiplying logistic-regression coefficients by (P) $(1-P)$. Also, many researchers have heard that OLS regression will provide as much information as logistic regression, especially if the "split" on the dependent variable is not too skewed (i.e., if about 15%–85% of the sample has experienced the event in question).

While this claim may be true in most cases, the consequences of it being false are severe, and there is no way to evaluate the claim without estimating both OLS regression models and logistic-regression models. The following are some of the pitfalls of using OLS regression (Hanushek and Jackson, 1977):

1. Predicted values may be outside the (0,1) range of the dependent variable, even though the probability of the event must lie between 0 and 1.
2. Heteroscedasticity; that is, estimated standard errors of the coefficients will be incorrect, leading to inappropriate conclusions regarding statistical significance.
3. The fitted relationship will be very sensitive to the values taken by the predictor variables. Moreover, in OLS and related models, a change in one of the predictor variables has a constant marginal effect on the probability of the event occurring.

The first two problems are familiar to many researchers, although the importance of the second problem has too often been ignored. Logistic regression overcomes the first two problems by using a functional form for the dependent variable that always yields predicted probabilities between 0 and 1 and by yielding unbiased estimates of the standard errors of coefficients. The third problem is less well known but deserves comment. OLS regression posits that an increase in an independent variable is accompanied by a constant increase in the dependent variable throughout the range of the predictor variable. In some cases, this may not be a valid assumption, as an effect may decrease at low and high levels of the independent variable (e.g., declining marginal effects). In OLS regression, one may overcome this problem by transforming the scale of the independent variable (e.g., by taking its logarithm). Logistic-regression models, however, while linear in predicting log odds, are nonlinear in the prediction of probabilities, such that marginal effects decrease at the tails of the distributions of the independent variables. In other words, one accounts for declining marginal effects in logistic regression without having to transform the scale of the independent variables.

The Probit Model

Some researchers have analyzed dichotomous dependent variables using probit models (cf. Bilsborrow, McDevitt, Kossoudji, and Fuller, 1987; Hanson, Myers, and Ginsburg, 1987). Logistic-regression and probit analysis are closely related, both being related functional forms for analyzing the likelihood of an event occurring. In most cases, probit and logistic-regression coefficients will differ only by a scalar factor.[6] For most research questions, the choice of probit versus logistic regression will be one of software availability, with the logistic specification being more common because of its link to log-linear models. In more complex analysis problems, one may have reason to choose one form of analysis over the other, but that is beyond the scope of this article. We do note that probit analysis is not applicable to nominal-level variables with more than two categories (it is appropriate, however, when the polytomous dependent variable is ordinal). A comparison of logit and probit models is provided by Aldrich and Nelson (1984).

Extensions of the Basic Logistic-Regression Model

In our example, we have used only nominal-level predictor variables. As noted, though, logistic-regression easily deals with continuous-level independent variables. If, for instance, parental income were included as a predictor variable in the model for intercourse, its coefficient would have a straightforward interpretation. In terms of Equation 2, the coefficient for parental income would indicate the increase (or decrease) in the log odds of having had intercourse for each unit increase in income.

In our example, we have assumed that the dependent variable of interest is a dichotomy. However, suppose a substantial number of adolescents refused to respond to the question on ever having intercourse. The dependent variable may then be coded as having three possible categories: yes, don't know/refused (dk) and no. Multinomial logistic regression is a procedure by which one can obtain estimates of the net effects of a set of predictor variables on all dependent variable contrasts. In our current example, we could estimate the following contrasts: yes/no, yes/dk, and dk/no (only two of these contrasts are independent). An example of multinomial logistic regression can be found in Robins and Dickinson (1985).

Logistic regression can also be used to estimate certain specialized statistical models. Much has been written in the past few years about proportional hazards models and event history analysis (Allison, 1984; Teachman, 1982). In many cases, the researcher can consider the occurrence or nonoccurrence of an event in a series of periods, durations, ages, and so on, sequentially dropping from the sample individuals who have already experienced the event or who are otherwise not at risk. In each period, duration, and so on, the odds of experiencing the event can be calculated, and since these odds are asymptotically independent, they may be pooled and analyzed by using a single logistic-regression equation (Allison, 1984; Morgan and Rindfuss, 1985; Rindfuss, Morgan, and Swicegood, 1984).

Receiving less attention, but equally important to family researchers, is the issue of sample selectivity. For example, suppose we are interested in the likelihood of experiencing intercourse among adolescents between two survey points, that is, over a period of two years. Over this two-year period, the sample is likely to suffer from attrition. If the likelihood of attrition is related to predictor variables that are in turn related to the likelihood of having intercourse, sample selection bias will occur. In other words, estimates of the effects of the predictor variables on the likelihood of having intercourse will not be correct. Logistic regression procedures (or probit regression) can be used to form a correction for such bias by providing a model of the attrition process (Berk, 1983; Heckman, 1979). More generally, sample selection bias is a potential problem whenever the sample being analyzed is dependent on the occurrence of some event (e.g., the wages of women are dependent on their prior choice regarding labor force participation). Logistic regression can be used to model and control for the selection event. For example, see Berk, Newton, and Berk (1986) and Ferber and Green (1985).

Finally, logistic regression has been used in several more sophisticated modeling exercises. Econometricians have used the procedure to model utility maximization (McFadden, 1973; Manski and Wise, 1983). Other researchers have used logistic regression to construct path models for data containing nominal-level endogenous or exogenous variables (Winship and Mare, 1983). Extended information about additional issues and uses for logistic regression can be found in Aldrich and Nelson (1984), Judge, Griffiths, Hill, Lutkepohl, and Lee (1985), and Maddala (1983).

Conclusion

Logistic regression can be a powerful statistical procedure when used appropriately. Nominal-level dependent variables are common in family research, and logistic-regression models appropriately model the impact of predictor variables on these outcomes. Moreover, with the proliferation of computer software for estimating logistic-regression models (procedures are available in most of the commonly used software packages such as SAS, SPSSX, GLIM, BMDP), the use of this technique is likely to expand. As with any new statistical technique, some investment of time and energy is required to master it. However, the advantages of logistic regression make the effort worthwhile. Readers interested in additional, nontechnical discussions of logistic regression are referred to Cleary and Angel (1984) or Walsh (1987).

Notes

We wish to thank Paul Allison and several reviewers of the special section on methodology for their many helpful comments. Any errors remain the responsibility of the authors.

1. *Log-linear analysis* refers to a set of procedures by which the association between nominal-level variables can be analyzed. If one of these nominal-level variables is chosen to be the dependent variable of interest, the log-linear analysis reduces to or becomes equivalent to logit models. Some authors reserve the term *logit models* for the case when all variables are measured at the nominal level, and use the term *logistic regression* when one or more of the predictor variables are measured at the continuous level (Feinberg, 1985).
2. Sometimes the chi-square statistic is referred to as the likelihood-ratio chi-square or the likelihood-ratio statistic. Most of the estimation routines for logistic regression utilize procedures that produce a likelihood-ratio statistic, which is used to test that the model being estimated is correct versus the unrestricted alternative. It so happens that -2 times the logarithm of the likelihood-ratio statistic is distributed as a chi-square distribution. If the researcher reports values that are based on -2 times the logarithm of the likelihood-ratio statistic, interpretation may proceed as with conventional chi-square values (for example, see Hwang and Albrecht, 1987). Occasionally, however, researchers will report the likelihood-ratio statistic itself. Chi-square values can easily be calculated from this statistic.
3. Formally, this procedure is equal to calculating the first derivative of P with respect to the independent variable in question. Thus, one is calculating the rate of change in P that is associated with the independent variable, evaluated at that level of P. As P changes, so does the marginal effect of the independent variable.
4. This procedure holds for coefficients of the independent variables and not the constant term.
5. Equation 5 can be used to predict the probability of the event occurring. Alternatively, Equation 4 can be used to predict the log odds and these can be easily translated into probabilities according to the following:
$$P = \text{antilog } [1n(y)\ ]/1 + \text{antilog } [1n(y)]\ )$$
6. Multiplication by 1.8 yields results that are approximate for estimated models.

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