A COMMENT ON INTERPRETING ODDS-RATIOS
WHEN LOGISTIC REGRESSION COEFFICIENTS
ARE NEGATIVE

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Abstract
Logistic regression is widely used by many institutional researchers. One of the problems some analysts and consumers have with the results of logistic regression is interpreting odds-ratios when coefficient estimates are negative (when odds-ratios are between zero and one). This Professional File describes a way of interpreting these odds-ratios by applying a simple transformation. Dubbed the “inverse odds-ratio” or “IOR,” this statistic is designed to provide another way to interpret logistic regression results. Hopefully this transformation will make the interpretation of logistic regression results more intuitive.

Introduction
In recent years, logistic regression has emerged as a valuable tool for institutional researchers when estimating models with dichotomous outcomes. Although this technique has been used in higher education research for a long time, in recent years it has been used to study issues like the decision to apply to an institution or not (Weiler, 1994; DesJardins, Dundar, & Hendel, 1999), matriculation behavior (St. John, 1990; Brooks, 1996), persistence to graduation from college (Cabrera, Stampen, & Hansen, 1990; Dey, 1993; St. John, Paulsen, & Starkey, 1996, Bowen & Bok, 1998), how financial aid affects college enrollment (St. John & Somers, 1993; Braunstein, McGrath, & Pescatrice, 1999; DesJardins, 2001); and the intergenerational effects of paying for college (Flint, 1997).

Logistic regression is widely used by many institutional researchers. One of the problems some analysts and consumers have with the results of logistic regression is interpreting odds-ratios when coefficient estimates are negative (when odds-ratios are between zero and one). This Professional File describes a way of interpreting these odds-ratios by applying a simple transformation. Dubbed the “inverse odds-ratio” or “IOR,” this statistic is designed to provide another way to interpret logistic regression results. Hopefully this transformation will make the interpretation of logistic regression results more intuitive.

Logistic regression is widely used by many institutional researchers. One of the problems some analysts and consumers have with the results of logistic regression is interpreting odds-ratios when coefficient estimates are negative (when odds-ratios are between zero and one). This Professional File describes a way of interpreting these odds-ratios by applying a simple transformation. Dubbed the “inverse odds-ratio” or “IOR,” this statistic is designed to provide another way to interpret logistic regression results. Hopefully this transformation will make the interpretation of logistic regression results more intuitive.

There are a number of reasons why OLS regression should “not be done” when studying outcomes that are binary. When one uses OLS to study a dichotomous dependent variable, the model is what is known as a “linear probability model” (see Aldrich and Nelson, 1984 for details). Thus, we would expect the results of such a model would produce probability estimates of the outcome of interest. However, the estimates produced by using OLS when studying a dichotomous relationship may be nonsensical in that these values may be less than zero or greater than one. Clearly a probability cannot be less than zero or greater than one. As one author has noted, “Such values make no sense, and have little predictive use” (Pampel, 2000, p. 3).

Another assumption of OLS regression is the error distribution for each independent variable is normally distributed (known as the “normality” assumption). The problem is when modeling a binary dependent variable using OLS regression, the normality assumption is violated. Practically speaking, violation of the normality assumption is not egregious in large samples, but can cause problems of statistical interpretation when sample sizes are small.
A more serious problem is OLS regression assumes error distributions have constant variance (i.e., they are “homooscedastic”). When using OLS to estimate a dichotomous dependent variable, this assumption is violated because it leads to sample estimates of the standard errors being biased. The practical implication of biased standard errors is that tests of significance (like the F- and t-tests) are not valid. If these tests are not valid, the researcher cannot be confident that the relationships between the dependent and independent variables (in total and individually) are because of chance or not.

As noted above, many educational researchers now use logistic regression to study dichotomous outcomes. One of the difficulties when using logistic regression is interpreting the results of this technique. The effects of independent variables can be interpreted a number of different ways, and one of the statistics routinely produced by standard logistic regression procedures is the odds-ratio. The interpretation of odds-ratios can be especially problematic when there is a negative relationship between the dependent and independent variable (i.e., when the logistic regression coefficient estimates have a negative sign). This Professional File describes a way of interpreting odds-ratios when coefficient estimates are negative that may be more intuitive than the standard approach. Dubbed the “inverse odds-ratio,” the calculation of this statistic is demonstrated using the results of actual studies done by the author.

The Logistic Regression Model

The dependent variable in a logistic regression model is the logarithm of the odds of the occurrence of a particular outcome or event (e.g., graduating from college within six years or not). Mathematically, the logistic regression model takes the form:

\[
\log \frac{P_i}{1-P_i} = a + BX_i + SY_i
\]  

(1)

where, in the example used herein, \( P_i \) is the probability that a student graduates from college within six years, \( 1-P_i \) is the probability that the person will not graduate from college within six years; \( X_i \) is a set of demographic, personal, and institutional characteristics; \( Y_i \) is a set of dummy variables indicating whether a student failed certain courses while in college and \( a, B, \) and \( S \) are the estimated coefficients of each of the independent variables included in the model.

The right-hand side of (1) may be familiar to institutional researchers because the form is similar to that describing ordinary least squares (OLS) regression. However, the left-hand side of (1) is presented in log-form; therefore, the outcome that is estimated by (1) is the log-odds of having the event (also known as the “logit” of \( P_i \)). Thus, the estimated coefficients produced by this model \( (a, B, \) and \( S) \) “represent the change in the log-odds due to unit increments in the values of the predictors” (Demaris, 1992, p.44). Because changes in the log-odds is unconventional and hard to interpret, we can transform (1) to present the results in a more convenient form. Taking the log of both sides of equation (1) produces the multiplicative version of (2) that demonstrates the non-linear nature of the model.

\[
\frac{P_i}{1-P_i} = e^a e^{B(X_i)} e^{S(Y_i)}
\]  

(2)

The coefficient estimates are defined as above and \( e \), the natural logarithm, is approximately 2.718. Transforming (1) into (2) permits us to interpret one-unit changes in the independent variables as changes in the odds of the event taking place (e.g., graduation within six years) rather than changes in the log-odds of the event happening. Since changes in the log-odds may be difficult to interpret, and people often have a more intuitive notion of what odds are, this transformation is often helpful in interpreting logistic regression results. Even so, when coefficient estimates are negative (odds-ratios are less than one), interpretation is somewhat less intuitive than when coefficient estimates are positive. The example provided below is intended to provide an alternative and more intuitive way to present odds ratios when there is a negative relationship between the dependent variable and regressors.

Empirical Examples

Empirical examples may be helpful to demonstrate the use of the inverse odds-ratio. A logistic regression model was estimated with the objective of examining the impact that failing a number of “gatekeeping” courses had on the probability that a student would graduate (within six years) from a large public institution of higher education. The sample consisted of all new freshmen (N=5,629) entering the institution in the fall of 1989 and 1991. These students were tracked for 6 years and the outcome of interest was a dichotomous variable indicating whether these students had graduated within the six-year observation period or not. A number of control variables were included as regressors to attempt to isolate the independent effects failing gatekeeping courses had on a student’s probability of graduating.

The results of this regression are displayed in Table 1. We were especially interested in comparing how failing none, one, two, or three or more gatekeeping courses affected a student’s chances of graduating at this institution. To compare the effect of failing a different number of these gatekeeping courses, we examined the odds-ratios associated with a set of dummy variables designed to inform us about differences in the odds of graduating (see Table 1 for the variable names).
The Interpretation of Individual Coefficients

Using the results from Table 1 allows us to interpret individual coefficient estimates (for example, the estimate of $B$) as a change in the log-odds for a one-unit change in the respective explanatory variable ($X_i$). For instance, the coefficient for “Engineering” is .0929 (see Table 1 below). This coefficient estimate indicates that students enrolled in the College of Engineering have log-odds of graduating in six years that are .0929 units higher than students enrolled in the College of Liberal Arts. As mentioned above, interpreting changes in the log-odds is not very intuitive, therefore, using the odds-ratio is usually more instructive. The odds-ratio corresponding to the “Engineering” coefficient is calculated by taking the natural log of .0929 ($e^{.0929}$) that results in an odds-ratio of 1.097. This odds-ratio (1.097) indicates the odds of graduating in six years are about 1.097 times (or 9.7%) higher for engineering students than for liberal arts students (see Aldrich and Nelson, 1984; Hosmer and Lemeshow, 1989; Demaris, 1992; Kleinbaum, 1994; Menard, 1995; or Long, 1997 for further discussion of the interpretation of logistic regression results). That engineering students have odds of graduating that are 1.097 higher than their liberal arts counterparts is probably more intuitive to

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Standard Error</th>
<th>Wald Chi-Square</th>
<th>Pr &gt; Chi-Square</th>
<th>Standardize Estimate</th>
<th>Odds Ratio</th>
<th>Inverse Odds Ratio</th>
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<td>Intercept</td>
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<td>2.1347</td>
<td>0.144</td>
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<td>Female (Male)</td>
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<td>0.0617</td>
<td>1.7723</td>
<td>0.1831</td>
<td>-0.022597</td>
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<td>0.1659</td>
<td>17.7224</td>
<td>0.0001</td>
<td>-0.06921</td>
<td>0.497</td>
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<td>0.1528</td>
<td>1.9522</td>
<td>0.1624</td>
<td>-0.02221</td>
<td>0.808</td>
<td>1.24</td>
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<td>0.2207</td>
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<td>-0.007515</td>
<td>0.734</td>
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<td>0.2252</td>
<td>1.3221</td>
<td>0.2502</td>
<td>-0.018106</td>
<td>0.772</td>
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<td>ACT Composite</td>
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<td>0.00948</td>
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<td>0.9733</td>
<td>0.000618</td>
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<td>HSR%</td>
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<td>0.00187</td>
<td>96.8896</td>
<td>0.0001</td>
<td>0.182377</td>
<td>1.019</td>
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<td>Engineering</td>
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<td>0.1188</td>
<td>0.6116</td>
<td>0.4342</td>
<td>0.013778</td>
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<tr>
<td>(Liberal Arts)</td>
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<td>Fall 1991</td>
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<td>0.0586</td>
<td>0.1148</td>
<td>0.7348</td>
<td>-0.005469</td>
<td>0.98</td>
<td>1.02</td>
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<td>(Fall 1989)</td>
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<td>Fail 1 Gatekeeper</td>
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<td>0.0741</td>
<td>61.5299</td>
<td>0.0001</td>
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<td>Fail 2 Gatekeepers</td>
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<td>0.0949</td>
<td>108.0498</td>
<td>0.0001</td>
<td>-0.169159</td>
<td>0.373</td>
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<td>Fail 3+ Gatekeepers</td>
<td>-1.4355</td>
<td>0.1008</td>
<td>203.0022</td>
<td>0.0001</td>
<td>-0.243534</td>
<td>0.238</td>
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<td>Failed none</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
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</table>

Pseudo R2 =.10
-2Log Likelihood = 6833
Chi-square for covariates = 636 with 12 df (p=.0001)

Variables in ( ) indicate the relevant reference groups.
Understand than saying the log-odds of engineering students graduating in six years is .0929 higher than their liberal arts counterparts. Theodorsen et al. (1981) note how the base or reference group changes when the independent and dependent variable is negative. For example, the coefficient for “Failed 3+ Gatekeepers” at the institution under study is -1.4355. This means that the log-odds of graduating in six years is 1.4355 lower for students who have failed three or more gatekeeping courses than for students who did not fail a gatekeeping course (the reference group). As is the case with the example presented earlier, an odds-ratio can be calculated to help us better understand the differences in the odds of graduation between groups of students who failed gatekeeping courses and students who did not. The odds-ratio corresponding to the coefficient for “Failed 3+ Gatekeepers” is \( e^{-1.4355} \) or .238. This odds-ratio can be interpreted as meaning that students who have failed three or more gatekeeping courses (sometime in their academic career) have odds of graduating in six years that are about .238 (about 24%) that of students who did not fail such a course. Although this interpretation is probably more intuitive than trying to interpret changes in the log-odds, it still may be difficult to decipher for some analysts and readers. My experience suggests that some researchers, and many people who read our analyses, do not understand what “having .238 times the odds of graduating” really means.

The Inverse Odds-Ratio

There is a simple transformation we can do to put the odds-ratios for negatively-related coefficients on the same metric as the odds-ratios produced when estimated coefficients are positive. All one needs to do is take the inverse of the odds-ratio normally produced when estimated coefficients are negative (in the example used above, .238). For example, \( 1 / .238 = 4.20 \) which can be interpreted as meaning that students who failed no gatekeeping courses have odds of graduating that are more than 4 times greater than students who failed three or more gatekeeping courses. (It is important to note how the base or reference group changes when we invert the odd-ratio; hence the added emphasis in the preceding sentence). This “inverse odds-ratio” or “IOR” may be more intuitive than attempting to interpret odds-ratios that are less than one.

The IOR is easy to calculate and can be produced a number of ways. The simplest way to produce an IOR is to reverse the way dichotomous variables are defined in the logistic regression equation and rerun the model. For example, in the model displayed in Table 1 the dichotomous independent variable “Failed 3+ Gatekeepers” is defined as equal to one (1) if the student failed three or more gatekeeping courses and is coded as zero (0) otherwise. Reversing this coding scheme and rerunning the model would produce a “new” set of statistics for this variable (coefficient estimates, etc.), one of which would be an odds-ratio of 4.20 (the IOR associated with this variable under the original coding scheme). This begs the question: Why not just code the variable this way from the onset of the project? If the researcher has conceptual theory or empirical evidence from past studies to suggest there is likely to be a negative relation between the outcome and a dichotomous independent variable, then the “revised” coding discussed above may be more appropriate. If, however, the researcher is not sure of the likely relationship between the outcome and explanatory variable a priori, then one will have to revert to other methods.

Another way to produce the IOR using statistical packages that include logistic regression is by outputting the conventional odds-ratios typically produced by these procedures to a temporary data file, then applying the IOR transformation to all variables negatively related to the dependent variable. If the statistical package being used does not permit the analyst to output odds-ratios to a temporary file, the IOR can be produced very easily in a spreadsheet (like Excel). The coefficient estimates normally produced by logistic regression (like those presented in column 1 of Table 1) can be copied to a spreadsheet and the following formula (an Excel “function”) can be applied to produce the IOR

\[
\text{IOR} = 1 / (\exp(-1.4355))
\]  

where -1.4355 is the unstandardized logistic regression coefficient estimate associated with the “Failed 3+ Gatekeepers.” The results of this function produce an IOR of 4.20, as demonstrated above and displayed in Table 1.

If, however, the standard logistic regression output routinely includes odds-ratios (as SAS and SPSS both do), one simply needs to apply the following formula

\[
\text{IOR} = 1 / (.238)
\]  

where .238 is the odds-ratio corresponding to the “Failed 3+ Gatekeepers,” the negatively-related variable of interest. The results of equation (4) also produce an IOR of 4.20.

An example of how the IOR makes interpretation of logistic regression results easier to understand is presented below. The coefficient estimates of the dummy variables that explain the effect of gatekeeping course failure are all negatively related to graduation (see Table 1). The odds-ratios for these variables are, therefore, all less than one as displayed in Table 1. Also presented in Table 1 is the IOR that corresponds to each of these gatekeeping course dummy variables. Interpretation of these variables is as follows: Students at the study...
institution who did not fail any gatekeeping courses have odds of graduating that are about 1.8 times (IOR=1.79) greater than students who failed one of these courses. Students who did not fail any gatekeeping courses have odds of graduating in six years that are about 2.7 (IOR=2.68) times higher than students who failed two gatekeeping courses. Finally, and as noted above, students who did not fail a gatekeeping course have odds of graduating that are about 4 times (IOR=4.20) higher than their counterparts who failed three or more gatekeeping courses. Using the IOR to interpret the effects of gatekeeping course failure may be more intuitive than trying to figure out what very small odds-ratios (.559, .373, and .238, respectively) mean.

Also, by using the IOR it may be easier to interpret differences in the magnitude of the respective coefficients on the event of interest. In our example used above, the odds-ratios for failing one, two, and three or more gatekeeping courses (relative to failing none) are .559, .373, and .238, respectively. Some individuals may be able to interpret the differences in the magnitude of these effects without the IOR conversion. Others may find the IOR conversion (shown in Table 2) more useful in comparing the relative strength of each of these effects. For instance, the results in Table 2 indicate that as the number of gatekeeping courses failed increases, the odds of not graduating increase quite dramatically.

### Table 2
Comparison of the Odds of Not Graduating in Six Years

<table>
<thead>
<tr>
<th>Number of Gatekeeping Courses Failed</th>
<th>Odds of Not Graduating Relative to Failing No Gatekeeping Courses</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.79</td>
</tr>
<tr>
<td>2</td>
<td>2.68</td>
</tr>
<tr>
<td>3 or more</td>
<td>4.20</td>
</tr>
</tbody>
</table>

Table 2
Comparison of the Odds of Not Graduating in Six Years

Often times logistic regression models also contain regressors measured on a continuous scale. The interpretation of the odds-ratio is no different when this is the case, and the conversion to the IOR remains the same. A unit change in the value of the independent variable changes the odds of the event happening by a factor of \(e^x\) where \(x\) is the coefficient value for the regressor in question. One suggestion: when using odds-ratios or the IOR to interpret changes in continuous variables, evaluate a change in the regressor \(x\) that makes some theoretical or intuitive sense.

An example may be instructive. Logistic regression was used to study how discounting non-resident student tuition would affect enrollments at a large Research I institution (DesJardins, 2001). The results of this study indicate increases in the provision of work/study aid decreases the chances that non-resident students will enroll (coefficient value = -.00029; standard error = .000068). The odds-ratio associated with this result is \(e^{-0.00029}\) or .99. The interpretation of this result is each one-dollar change in the provision of work/study aid changes the odds of enrolling by a factor of .99, holding other variables in the model constant. However, evaluating the effect of a one-dollar change in work/study aid is not very useful. A more practical approach may be to evaluate the effect of a $500 change in work/study aid. To do this one simply calculates \(e^{-0.00029 \times 500}\) = .865. This result indicates a $500 increase in work/study aid reduces the odds of enrolling by a factor of .865. Again, some individuals may find that the IOR conversion may be helpful in understanding this relationship. Inverting .865 produces an IOR of 1.16, indicating that (other things equal) students with $500 more in work/study aid have odds of not enrolling 1.16 times higher than their counterparts. Another way to interpret this result is that an increase in work/study aid of $500 reduces the odds of enrolling by about 100 \((IOR - 1) = 100[1.16 - 1] = 16\%\).

### Limitations
If ones does not rerun the models to produce an IOR, one must be careful to do this transformation only to coefficients that are negatively related to the independent variable. As you can see in Table 1, the inverse odds-ratios were only calculated for variables that have negative logistic regression coefficients.

### Conclusion
Some analysts and readers may find it difficult to interpret the results of logistic regression when the independent and dependent variables are negatively related. The above transformation, which for lack of a better name is coined the “inverse odds-ratio” or “IOR” is a way to present these results in a different metric. One thing to keep in mind, however, is that “no single approach to interpretation can fully describe the relationship between a variable and the outcome probability. You should search for an elegant and concise way to summarize the results that does justice to the complexities of the nonlinear model” (Long, 1997, p. 61). The IOR is but one way for researchers to interpret logistic regression results. Hopefully it will help to make the results of these models more understandable and therefore more useful.
Notes:

1 The Sage Series “Quantitative Applications in the Social Science” has produced a number of valuable books on the subject of logistic regression. Readers unfamiliar with logistic regression are advised to read Pampel, 2000, the most recent installment in the Sage series.

2 Other ways to interpret the effects of the regressors on an outcome of interest are by producing partial effect measures like “marginal effects” or by examining the differences in predicted probabilities for different values of the independent variables. Another approach often used in higher education studies of financial aid effects is the delta-p (owing to Peterson, 1984; see Cabrera, 1994 for how to derive delta-p; see St. John, 1999 for an application).

3 “Gatekeeping” courses are defined as lower-level courses that had high failure rates. For more information about this project contact the author of this brief.

4 Sometimes analysts will write up results like this by using ambiguous language like “engineering students are 1.097 times more likely to graduate in six years than liberal arts students.” Many of us (including this author) are guilty of this, but it is technically incorrect because “more likely” and “less likely” are ambiguous terms, at least in a statistical sense. Does “more likely” mean an increase in the probability of graduation? Or does it mean an increase in the likelihood of graduating? Or the odds of graduating? Or the risk of graduating? Each of these concepts have specific statistical meanings so we need to be careful with our use of language when writing-up the results of logistic regression models (See Pampel, 2000 for an introductory explanation of the differences in some of these concepts. For a more advanced treatment see Long, 1997. For a discussion of problems in interpretation and expression of odds and probability ratios see Cohen, 2000). The odds ratio represents how the odds of the event (in this case graduation) changes given a unit change in the corresponding independent variable (in this case college of enrollment), holding all other variables constant.

5 Sometimes researchers either will not know the likely direction of effects or may be wrong about their a priori hypotheses. This is likely when researchers are unfamiliar with the literature of the outcome being studied or are studying subsets of data where relationships can often change. In any case, sometimes our results include negatively related coefficients.

6 If one plotted these ratios one would be able to decipher that there is a slight positive nonlinear trend. That is, the odds of not graduating increase at an increasing rate as the number of gatekeeping courses failed increases.

7 Since the continuous variables (high school rank percentile and ACT Composite score) in the results presented in Table 1 all have positive coefficients (and therefore odds-ratios greater than one), it is not possible to demonstrate the use of the IOR with these results. For expository purposes I will demonstrate the application of the IOR using the results obtained in DesJardins, (in press) to clarify how odds-ratios and the IOR can be used when continuous regressors are negatively related to the outcome of interest.
References


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