The odds ratio is one of the most common measures used to assess the relationship between exposure to violence and adverse health outcomes, adjusting for possible confounding factors. A reason for the odds ratio's popularity is that it is relatively easy to calculate from the coefficients of a logistic regression model. For most etiologic studies of disease, the odds ratio is a suitable estimate of risk because incidence or prevalence of disease is rare (<10%). However, health outcomes studied in violence research are often more prevalent (e.g., fatigue, insomnia, stomach pain, and shortness of breath). In these cases, the odds ratio usually overestimates the strength of association, sometimes erroneously tripling the magnitude. Data from a study measuring the health effects of intimate partner violence are used to illustrate the problem of incorrectly using odds ratios. Methods to calculate relative risks and prevalence ratios from logistic regression models are presented.

Logistic Regression Analysis: When the Odds Ratio Does Not Work

An Example Using Intimate Partner Violence Data

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Many areas of research involve the investigation of events that occur frequently. Intimate partner violence (IPV) is one such event. Estimates of the prevalence in clinic populations range between 10% and 25%, and sometimes as high as 50% (Drossman et al., 1990; McCauley et al., 1995; Saunders, Hamberger, & Hovey, 1993). Health outcomes associated with IPV victimization include many common physical and psychological symptoms, including pain in the chest, stomach, pelvis, and back; fatigue; insomnia; post-traumatic stress disorder (PTSD) and gastrointestinal symptoms, among many others (Houskamp & Foy, 1991; Kemp, Green, Hovanitz, & Raulings, 1995; McCauley et al., 1995; Silva, McFarlane, Soeken, Parker, & Reel, 1997). Studies have found that more than 10% of nonabused women seen in health care and mental health settings report many of these symptoms, and abused women report these symptoms significantly more often than nonabused women (McCauley et al., 1995). Whether studying risk factors for IPV or studying the association between IPV and health symptoms, dealing with factors that are common (mathematically defined as greater than 10%) routinely occur.

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Unfortunately, some key statistical methods developed for the study of rare events are not always transferable to studies of common events. The purpose of this article is to discuss the inappropriate use of the odds ratio in studies of common events. Recently, the use of logistic regression to calculate odds ratios has gained popularity among IPV researchers. We have chosen to use numeric examples to discuss the use of the odds ratio to compare risk of adverse outcomes for abused and nonabused women, and discuss alternative methods that are appropriate when the odds ratio is not.

Prevalence Ratios and Odds Ratios: The Basics

Often researchers are interested in estimating the strength of association between a risk factor (e.g., IPV victimization) and an adverse outcome (e.g., PTSD symptoms). Using general terms, suppose that we are interested in the association between a dichotomous exposure factor (i.e., each participant is classified as exposed or unexposed) and a dichotomous outcome factor (i.e., each study participant is classified as having the outcome or being outcome free). The data can then be presented in a two-way table as shown in Figure 1. The probability of having the outcome (i.e., the prevalence) among the exposed participants is $a/(a + c)$ and the probability of having the outcome among the unexposed participants is $b/(b + d)$. The prevalence ratio is a measure of association between the exposure status and the outcome status. The prevalence ratio of the outcome among exposed participants compared to unexposed participants is

$$\text{prevalence ratio} = \frac{\frac{a}{a+c}}{\frac{b}{b+d}}.$$

Odds Ratio sometimes estimates Prevalence Ratio

Prevalence Ratio $= \dfrac{a/a+c}{b/b+d}$

Odds Ratio $= \dfrac{(a/\,a+c)\;/\;(1 - a/\,a+c)}{(b/\,b+d)\;/\;(1 - d/\,b+d)} = \dfrac{ad}{bc}$

	Exposed	Unexposed
Outcome	a	b
Outcome-free	c	d
Total	a+c	b+d

Example: When prevalence is small (<10%)
OR estimates PR

PR $= \dfrac{6/79}{4/160} = \dfrac{7.6\%}{2.5\%} = 3.0$

OR $= \dfrac{6\text{x}156}{4\text{x}73} = 3.2$

	Exposed	Unexposed
Outcome	6	4
Outcome-free	73	156
Total	79	160

Example: When prevalence is not small (>10%)
OR often overestimates PR

PR $= \dfrac{55/95}{41/180} = \dfrac{57.9\%}{22.8\%} = 2.5$

OR $= \dfrac{55\text{x}139}{41\text{x}40} = 4.7$

	Exposed	Unexposed
Outcome	55	41
Outcome-free	40	139
Total	95	180

Figure 1: An Odds Ratio May or May Not Estimate a Prevalence Ratio

For example, using hypothetical data presented in Figure 1, the probability of having the outcome among the exposed group is 6/79 or 7.6%. The probability of having the outcome among the unexposed group is 4/160 or 2.5%. The prevalence ratio equals the ratio of these proportions, about 3.0 in this case. That is, study participants who were exposed had three times the likelihood of having the outcome compared with unexposed participants.

Another measure of association is the odds ratio. The *odds* is defined as a proportion divided by its complement. So the odds of having the outcome among the exposed is $(a/(a + c))/(1 - a/(a + c))$ (which equals a/c) and the odds of having the outcome among the unexposed is $(b/(b + d))/(1 - b/(b + d))$, or b/d. The odds ratio is the ratio of these odds. For the above example,

$$\text{odds ratio} = \frac{[a/(a+c)]/[1-(a/(a+c))]}{[b/(b+d)]/[1-(b/(b+d))]} = \frac{a(b+d)}{b(a+c)} = \frac{ad}{bc} = \frac{6\times 156}{73\times 4} = 3.2.$$

When the probability of having the outcome (i.e., prevalence) is less than 10%, then b is small relative to d, a is small relative to c, and the odds ratio is a reasonable approximation of the prevalence ratio. In this case, 3.2 is fairly close to 3.0. However, when the outcome is common (e.g., greater than 10%) then the odds ratio often overestimates the prevalence ratio. Notice the last example in Figure 1. The prevalence of the outcome among the exposed group is 57.9% and among the unexposed group, 22.8%. The resulting prevalence ratio is 2.5 and the odds ratio is 4.7. That is, exposed individuals are two and a half times as likely to have the outcome as unexposed individuals. In this case, the odds ratio substantially overestimates the prevalence ratio and cannot be used as a reasonable estimate.

So why bother calculating the odds ratio at all? Why not just calculate the prevalence ratio? Usually the prevalence ratio is really what we need to answer these kinds of research questions. The answer is mathematical simplicity. For the basic case where there is no need to consider the effects of other factors, the prevalence ratio is easy to calculate. There is no need to calculate the odds ratio. However, if the measure of association needs to be adjusted for other factors (by using logistic regression), then the odds ratio is much easier to calculate. And more important, the confidence intervals for the odds ratios are simpler to calculate compared with the prevalence ratios' confidence intervals. Using the knowledge that the odds ratio approximates the value of the prevalence ratio when the outcome is rare (less than 10%), the odds ratio gained popularity in scientific research. However, in the study of violence and the adverse outcomes associated with violence, this very basic and important assumption often is not met.

Why Logistic Regression Analysis Is Used

Studying life events often requires inclusion of many variables that may affect the event of interest. For example, understanding the relationship between IPV and health outcomes may require investigating this relationship in light of other factors, such as age. IPV is more common in younger women compared with older women (McCauley et al., 1995), yet adverse physical symptoms tend to increase as women get older. If the association between IPV and physical health symptoms is estimated ignoring the fact that the abused women tend to be younger than the nonabused women, the association typically would be underestimated. The effect of age can be removed from the estimated measure with statistical analysis so that a corrected measure of association is calculated.

Logistic regression analysis is chosen by many IPV researchers to estimate the strength of association between IPV and dichotomous outcomes, controlling for other factors. Although the function has an unusual S-shaped curve, medical researchers have found that this function often provides a good fit for data from studies of health outcomes and many possible risk factors. Logistic regression analysis, used correctly, is a useful and powerful tool.

Using Logistic Regression to Obtain an Estimate of Association

The need to adjust estimates of association for factors that may differ between the groups, such as differences in age and in socioeconomic distributions, leads to the use of regression techniques. The logistic function can be defined as follows:

$$\text{Probability}\,(Y = 1|x_1, x_2, x_3, \ldots, x_k) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\ldots+\beta_k x_k)}}.$$

Statistical computer programs such as SPSS and SAS can be used to estimate the parameters (the βs). If there are no interaction terms in the model, then the odds ratio for each variable is exp(β). The variance and confidence intervals are also simple to calculate and are usually provided by the statistical computer programs. If the dependent measure is rare (mathematically determined to be less than 10%), then the odds ratio is usually a reasonable estimate of the prevalence ratio. It is this simplicity that makes the odds ratio so attractive in modeling uncommon outcomes.

However, in most of our studies of IPV, the prevalences of health outcomes of interest are much greater than 10%. In these cases, the odds ratio is usually a seriously biased estimate of the prevalence ratio, overestimating it. Calculating the prevalence ratio is not difficult, although calculation of the variance needed for confidence intervals can be tedious.

The prevalence ratio comparing disease outcomes for two different categories for $x_1 = 1$ (e.g., abused) and $x_1 = 0$ (e.g., not abused) with all other variable values (for confounders such as age and socioeconomic status) staying the same is defined by

$$\text{PR} = \frac{\textit{Probability}(Y=1(\textit{adverse outcome})|x_1=1(\textit{abused}), x_2=x_2, x_3=x_3, \ldots, x_k=x_k)}{\textit{Probability}(Y=1(\textit{adverse outcome})|x_1=0(\textit{not abused}), x_2=x_2, x_3=x_3, \ldots, x_k=x_k)}.$$

Typically, statistical computer programs calculate these probabilities (often called the predicted values), leaving the simple division to be completed by the researcher. The formula for the variance is provided in the appendix and

depends on the number of variables in the model. To combine prevalence ratios for different covariate patterns (i.e., for people with different characteristics), a weighted average can be taken. Unfortunately, the variance for this measure is complicated.

For a study conducted in a primary care center and domestic violence program, we wanted to estimate the association between IPV exposure and health outcomes, adjusting for many factors. For this example, we limited the adjustment to one factor (age). Our logistic regression model had a variable that identified women who reported severe abuse by a male intimate partner (values of 0, 1). Because age as a continuous variable did not meet the assumptions of the logistic model, we grouped women into three age groups (18 to 24 years, 25 to 34 years, and older than 35 years). Using standard conventions, we then added two indicator variables in the model to adjust for the age groups. For simplicity, the results presented in Table 1 compare women 25 to 34 years of age who reported severe abuse with women reporting no abuse.

Notice the adjusted prevalence ratios are mostly about 2, whereas several of the adjusted prevalence odds ratios are greater than 5. In this study, severely abused women were about twice as likely to experience the symptoms presented, except vaginal infections, compared with nonabused women (adjusted for age), which translated to substantial morbidity and subsequent health care use. In our larger studies, adjusting for several factors simultaneously is accomplished using the same technique.

Other Methods

A simple correction method proposed by Zhang and Yu (1998) can provide insight into the magnitude of the difference between the adjusted prevalence ratio and adjusted odds ratio. To use this method, calculate the prevalence of the outcome in the unexposed group (P_0) and using logistic regression calculate the adjusted odds ratio between exposure and outcome (OR). An estimate of the prevalence ratio is

$$\text{PR} \approx \frac{OR}{(1-P_0)+(P_0 \times OR)}.$$

Although this method appears useful to approximate the prevalence ratio, no data exist to determine if the proposed confidence interval is appropriate (McNutt, Hafner, & Xue, 1999).

Another relatively simple approach to estimate an adjusted prevalence ratio is stratified analysis. Stratified analysis is widely used in the medical

TABLE 1: Intimate Partner Violence Example: Prevalence, Prevalence Odds Ratios, and Prevalence Ratios, Adjusted for Age

	n	*Percentage Positive*	*Prevalence Ratio (95% CI)*	*Prevalence Odds Ratio (95% CI)*
Pelvic pain				
No abuse	32	25.0	1	1
Severe abuse	40	55.0	2.03 (1.03, 3.97)	3.54 (1.46, 8.58)
Stomach pain				
No abuse	31	32.3	1	1
Severe abuse	41	82.9	1.92 (1.23, 2.99)	8.64 (3.07, 24.31)
Insomnia				
No abuse	30	33.3	1	1
Severe abuse	39	82.1	2.22 (1.26, 3.90)	7.78 (2.77, 21.83)
Fatigue				
No abuse	32	37.5	1	1
Severe abuse	43	83.7	2.08 (1.25, 3.46)	7.34 (2.74, 19.80)
Shortness of breath				
No abuse	32	21.9	1	1
Severe abuse	39	76.9	2.52 (1.39, 4.60)	10.09 (3.71, 27.42)
Vaginal infections				
No abuse	33	36.4	1	1
Severe abuse	36	38.9	1.02 (0.47, 2.19)	1.04 (0.43, 2.51)

NOTE: Due to missing values, sample sizes were between 30 and 43 women, per group, depending on the outcome measure. Prevalence ratios listed are adjusted for age. Figures for women 25 to 34 years of age. If the analysis was not adjusted for age (using a logistic regression model in this case) then the prevalence ratio would equal the ratio of the prevalences shown.

sciences and can be performed using most statistical software (e.g., SAS, SPSS). The primary limitation of stratified analysis is that all potential confounding factors used to adjust the measure of association must be divided into categories. Converting continuous variables into categories needs to be done carefully so as not to introduce residual confounding (Brenner, 1998). From our experience with logistic regression, continuous variables often do not meet the assumption of being linear in the logit and thus also need to be divided into categories.

Effect Modification (interactions)

This article has not discussed issues related to logistic regression analysis in the presence of effect modification, such as when the association between the exposure (e.g., IPV status) and outcome (e.g., PTSD symptoms) varies for different levels of another variable (e.g., history of childhood abuse). There are many factors that actually should not be adjusted for per se, but rather included in a regression model with interaction terms. Even the variable age should be considered as an effect modifier in most studies of intimate partner violence. References useful in the analysis of data with effect modification present include Rothman and Greenland (1998) and Stokes, Davis, and Koch (1995).

CONCLUSIONS

Many articles in the violence and health literature incorrectly interpret odds ratios derived from logistic regression analysis as relative risks or prevalence ratios. When the incidence or prevalence of the health outcome is more than 10%, this will typically result in an overestimation of the effects of violence on women's health.

This measurement problem can occur when any common outcome is studied. Examples include studying risk factors for IPV, because IPV (the outcome variable in these studies) is common in many study populations. The need to improve the methods used in violence studies of common outcomes is essential to gain and maintain credibility with policy makers and ultimately decrease the amount of violence in our society.

APPENDIX

A goal of logistic regression is to estimate $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ to predict the probability of occurrence of the outcome variable using the following model:

$$\text{Probability}\,(Y = 1 | x_1, x_2, x_3, \ldots, x_k) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 + \beta_2 + \beta_3 + \ldots + \beta_k)}}.$$

Because the betas are estimated using the sample data, there is sample variation associated with these estimates. This sample variation is represented with the variance covariance matrix *V*. SAS LOGISTIC Procedure will generate this matrix when performing logistic regression. To find the variance associated with the prevalence ratio of interest,

$$\left[\frac{\partial \ln\theta}{\partial \beta_0}, \frac{\partial \ln\theta}{\partial \beta_1}, \ldots, \frac{\partial \ln\theta}{\partial \beta_k}\right]
\begin{bmatrix}
\hat{\sigma}^2_{\beta_0} & \hat{\sigma}_{\beta_0,\beta_1} & \hat{\sigma}_{\beta_0,\beta_2} & \hat{\sigma}_{\beta_0,\beta_3} & \cdots & \hat{\sigma}_{\beta_0,\beta_k} \\
 & \hat{\sigma}^2_{\beta_1} & \hat{\sigma}_{\beta_1,\beta_2} & \hat{\sigma}_{\beta_1,\beta_3} & \cdots & \hat{\sigma}_{\beta_1,\beta_k} \\
 & & \hat{\sigma}^2_{\beta_2} & \hat{\sigma}_{\beta_2,\beta_3} & \cdots & \hat{\sigma}_{\beta_2,\beta_k} \\
 & & & \hat{\sigma}^2_{\beta_3} & \cdots & \hat{\sigma}_{\beta_3,\beta_k} \\
 & & & & & \vdots \\
 & & & & & \hat{\sigma}^2_{\beta_k}
\end{bmatrix}
\begin{bmatrix}
\frac{\partial \ln\theta}{\partial \beta_0} \\
\frac{\partial \ln\theta}{\partial \beta_1} \\
\vdots \\
\frac{\partial \ln\theta}{\partial \beta_k}
\end{bmatrix}$$

APPENDIX Continued

The 95% confidence interval for the ln θ is then

$$\ln\theta \pm 1.96\sqrt{Var(\ln\theta)}.$$

With the final confidence interval for the prevalence ratio θ as

$$(e^{\ln\theta - 1.96\sqrt{Var(\ln\theta)}}, e^{\ln\theta + 1.96\sqrt{Var(\ln\theta)}}).$$

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