

Chapter 514

Two Proportions

Introduction

This program computes both asymptotic and exact confidence intervals and hypothesis tests for the difference, ratio, and odds ratio of two proportions.

Comparing Two Proportions

In recent decades, a number of notation systems have been used to present the results of a study for comparing two proportions. For the purposes of the technical details of this chapter, we will use the following notation:

	Event	Non-Event	Total
Group 1	x_{11}	x_{12}	n_1
Group 2	x_{21}	x_{22}	n_2
Totals	m_1	m_2	N

In this table, the label *Event* is used, but might instead be *Success*, *Attribute of Interest*, *Positive Response*, *Disease*, *Yes*, or something else.

The binomial proportions P_1 and P_2 are estimated from the data using the formulae

$$p_1 = \frac{x_{11}}{n_1} \quad \text{and} \quad p_2 = \frac{x_{21}}{n_2}$$

Three common comparison parameters of two proportions are the proportion difference, proportion (risk) ratio, and the odds ratio:

<u>Parameter</u>	<u>Notation</u>
Difference	$\Delta = P_1 - P_2$
Risk Ratio	$\phi = P_1 / P_2$
Odds Ratio	$\psi = \frac{O_1}{O_2} = \frac{P_1/(1-P_1)}{P_2/(1-P_2)}$

Although these three parameters are (non-linear) functions of each other, the choice of which is to be used should not be taken lightly. The associated tests and confidence intervals of each of these parameters can vary widely in power and coverage probability.

Difference

The proportion (risk) difference $\delta = P_1 - P_2$ is perhaps the most direct method of comparison between the two event probabilities. This parameter is easy to interpret and communicate. It gives the absolute impact of the treatment. However, there are subtle difficulties that can arise with its interpretation.

One interpretation difficulty occurs when the event of interest is rare. If a difference of 0.001 were reported for an event with a baseline probability of 0.40, we would probably dismiss this as being of little importance. That is, there usually is little interest in a treatment that decreases the probability from 0.400 to 0.399. However, if the baseline probability of a disease was 0.002 and 0.001 was the decrease in the disease probability, this would represent a reduction of 50%. Thus, we see that interpretation depends on the baseline probability of the event.

A similar situation occurs when the amount of possible difference is considered. Consider two events, one with a baseline event rate of 0.40 and the other with a rate of 0.02. What is the maximum decrease that can occur? Obviously, the first event rate can be decreased by an absolute amount of 0.40 while the second can only be decreased by a maximum of 0.02.

So, although creating the simple difference is a useful method of comparison, care must be taken that it fits the situation.

Ratio

The proportion (risk) ratio $\phi = p_1 / p_2$ gives the relative change in risk in a treatment group (group 1) compared to a control group (group 2). This parameter is also direct and easy to interpret. To compare this with the difference, consider a treatment that reduces the risk of disease from 0.1437 to 0.0793. Which single number is most enlightening, the fact that the absolute risk of disease has been decreased by 0.0644, or the fact that risk of disease in the treatment group is only 55.18% of that in the control group? In many cases, the percentage (100 x risk ratio) communicates the impact of the treatment better than the absolute change.

Perhaps the biggest drawback of this parameter is that it cannot be calculated in one of the most common experimental designs: the case-control study. Another drawback, when compared to the odds ratio, is that the odds ratio occurs naturally in the likelihood equations and as a parameter in logistic regression, while the proportion ratio does not.

Odds Ratio

Chances are usually communicated as long-term proportions or probabilities. In betting, chances are often given as odds. For example, the odds of a horse winning a race might be set at 10-to-1 or 3-to-2. How do you translate from odds to probability? An odds of 3-to-2 means that the event will occur three out of five times. That is, an odds of 3-to-2 (1.5) translates to a probability of winning of 0.60.

The odds of an event are calculated by dividing the event risk by the non-event risk. Thus, in our case of two populations, the odds are

$$O_1 = \frac{P_1}{1 - P_1} \quad \text{and} \quad O_2 = \frac{P_2}{1 - P_2}$$

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For example, if P_1 is 0.60, the odds are $0.60/0.40 = 1.5$. In some cases, rather than representing the odds as a decimal amount, it is re-scaled into whole numbers. Thus, instead of saying the odds are 1.5-to-1, we may equivalently say they are 3-to-2.

In this context, the comparison of proportions may be done by comparing the odds through the ratio of the odds. The odds ratio of two events is

$$\begin{aligned}\psi &= \frac{O_1}{O_2} \\ &= \frac{\frac{P_1}{1-P_1}}{\frac{P_2}{1-P_2}}\end{aligned}$$

Until one is accustomed to working with odds, the odds ratio is usually more difficult to interpret than the proportion (risk) ratio, but it is still the parameter of choice for many researchers. Reasons for this include the fact that the odds ratio can be accurately estimated from case-control studies, while the risk ratio cannot. Also, the odds ratio is the basis of logistic regression (used to study the influence of risk factors). Furthermore, the odds ratio is the natural parameter in the conditional likelihood of the two-group, binomial-response design. Finally, when the baseline event-rates are rare, the odds ratio provides a close approximation to the risk ratio since, in this case, $1 - P_1 \approx 1 - P_2$, so that

$$\psi = \frac{\frac{P_1}{1-P_1}}{\frac{P_2}{1-P_2}} \approx \frac{P_1}{P_2} = \phi$$

One benefit of the log of the odds ratio is its desirable statistical properties, such as its continuous range from negative infinity to positive infinity.

Confidence Intervals

Both large sample and exact confidence intervals may be computed for the difference, the ratio, and the odds ratio.

Confidence Intervals for the Difference

Several methods are available for computing a confidence interval of the difference between two proportions $\delta = P_1 - P_2$. Newcombe (1998) conducted a comparative evaluation of eleven confidence interval methods. He recommended that the modified Wilson score method be used instead of the Pearson Chi-Square or the Yate's Corrected Chi-Square. Beal (1987) found that the Score methods performed very well. The lower L and upper U limits of these intervals are computed as follows. Note that, unless otherwise stated, $z = |z_{\alpha/2}|$ is the appropriate percentile from the standard normal distribution.

Cells with Zero Counts

Extreme cases in which some cells are zero require special approaches with some of the tests given below. We have found that a simple solution that works well is to change the zeros to a small positive number such as 0.01. This produces the same results as other techniques of which we are aware.

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C.I. for Difference: Wald Z with Continuity Correction

For details, see Newcombe (1998), page 875.

$$L = p_1 - p_2 - z \left[\sqrt{\left(\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2} \right)} + \frac{1}{2} \left(\frac{1}{n_1} + \frac{1}{n_2} \right) \right]$$

$$U = p_1 - p_2 + z \left[\sqrt{\left(\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2} \right)} + \frac{1}{2} \left(\frac{1}{n_1} + \frac{1}{n_2} \right) \right]$$

C.I. for Difference: Wald Z

For details, see Newcombe (1998), page 875.

$$L = p_1 - p_2 - z \sqrt{\left(\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2} \right)}$$

$$U = p_1 - p_2 + z \sqrt{\left(\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2} \right)}$$

C.I. for Difference: Wilson's Score as modified by Newcombe

For details, see Newcombe (1998), page 876

$$L = p_1 - \hat{p}_2 - B$$

$$U = p_1 - \hat{p}_2 + C$$

where

$$B = z \sqrt{\frac{l_1(1-l_1)}{n_1} + \frac{u_2(1-u_2)}{n_2}}$$

$$C = z \sqrt{\frac{u_1(1-u_1)}{n_1} + \frac{l_2(1-l_2)}{n_2}}$$

and l_1 and u_1 are the roots of

$$|P_1 - p_1| - z \sqrt{\frac{P_1(1-P_1)}{n_1}} = 0$$

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and l_2 and u_2 are the roots of

$$|P_2 - p_2| - z \sqrt{\frac{P_2(1 - P_2)}{n_2}} = 0$$

C.I. for Difference: Miettinen-Nurminen Score

Miettinen and Nurminen (1985) proposed a test statistic for testing whether the odds ratio is equal to a specified value ψ_0 . Because the approach they used with the difference and ratio does not easily extend to the odds ratio, they used a score statistic approach for the odds ratio. The regular MLE's are \hat{p}_1 and \hat{p}_2 . The constrained MLE's are \tilde{p}_1 and \tilde{p}_2 . These estimates are constrained so that $\tilde{\psi} = \psi_0$. A correction factor of $N/(N-1)$ is applied to make the variance estimate less biased. The significance level of the test statistic is based on the asymptotic normality of the score statistic. The formula for computing the test statistic is

$$z_{MNO} = \frac{\frac{(\hat{p}_1 - \tilde{p}_1)}{\tilde{p}_1 \tilde{q}_1} - \frac{(\hat{p}_2 - \tilde{p}_2)}{\tilde{p}_2 \tilde{q}_2}}{\sqrt{\left(\frac{1}{N_2 \tilde{p}_1 \tilde{q}_1} + \frac{1}{N_2 \tilde{p}_2 \tilde{q}_2}\right) \left(\frac{N}{N-1}\right)}}$$

where

$$\tilde{p}_1 = \frac{\tilde{p}_2 \psi_0}{1 + \tilde{p}_2 (\psi_0 - 1)}$$

$$\tilde{p}_2 = \frac{-B + \sqrt{B^2 - 4AC}}{2A}$$

$$A = N_2(\psi_0 - 1)$$

$$B = N_1 \psi_0 + N_2 - M_1(\psi_0 - 1)$$

$$C = -M_1$$

Miettinen and Nurminen (1985) proposed inverting their score test to find the confidence interval. The lower limit is found by solving

$$z_{MND} = |z_{\alpha/2}|$$

and the upper limit is the solution of

$$z_{MND} = -|z_{\alpha/2}|$$

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C.I. for Difference: Farrington-Manning Score

Farrington and Manning (1990) proposed a test statistic for testing whether the difference is equal to a specified value δ_0 . The regular MLE's \hat{p}_1 and \hat{p}_2 are used in the numerator of the score statistic while MLE's \tilde{p}_1 and \tilde{p}_2 constrained so that $\tilde{p}_1 - \tilde{p}_2 = \delta_0$ are used in the denominator. The significance level of the test statistic is based on the asymptotic normality of the score statistic. The formula for computing the test is

$$z_{FMD} = \frac{\hat{p}_1 - \hat{p}_2 - \delta_0}{\sqrt{\left(\frac{\tilde{p}_1 \tilde{q}_1}{n_1} + \frac{\tilde{p}_2 \tilde{q}_2}{n_2}\right)}}$$

where the estimates \tilde{p}_1 and \tilde{p}_2 are computed as in the corresponding test of Miettinen and Nurminen (1985) given above.

Farrington and Manning (1990) proposed inverting their score test to find the confidence interval. The lower limit is found by solving

$$z_{FMD} = |z_{\alpha/2}|$$

and the upper limit is the solution of

$$z_{FMD} = -|z_{\alpha/2}|$$

C.I. for Difference: Gart-Nam Score

Gart and Nam (1990) page 638 proposed a modification to the Farrington and Manning (1988) difference test that corrected for skewness. Let $z_{FMD}(\delta)$ stand for the Farrington and Manning difference test statistic described above. The skewness corrected test statistic z_{GND} is the appropriate solution to the quadratic equation

$$(-\tilde{\gamma})z_{GND}^2 + (-1)z_{GND} + (z_{FMD}(\delta) + \tilde{\gamma}) = 0$$

where

$$\tilde{\gamma} = \frac{\tilde{V}^{3/2}(\delta)}{6} \left(\frac{\tilde{p}_1 \tilde{q}_1 (\tilde{q}_1 - \tilde{p}_1)}{n_1^2} - \frac{\tilde{p}_2 \tilde{q}_2 (\tilde{q}_2 - \tilde{p}_2)}{n_2^2} \right)$$

Gart and Nam (1988) proposed inverting their score test to find the confidence interval. The lower limit is found by solving

$$z_{GND} = |z_{\alpha/2}|$$

and the upper limit is the solution of

$$z_{GND} = -|z_{\alpha/2}|$$

C.I. for Difference: Chen's Quasi-Exact Method

Chen (2002) proposed a quasi-exact method for generating confidence intervals. This method produces intervals that are close to unconditional exact intervals that are available in specialized software like StatXact, but do not require as much time to compute. Chen's method inverts a hypothesis test based on Farrington and Manning's method. That is, the confidence interval is found by finding those values at which the hypothesis test that the difference is a given, non-zero value become significant. However, instead of searching for the maximum significance level of all possible values of the nuisance parameter as the exact tests do, Chen proposed using the significance level at the constrained maximum likelihood estimate of p_2 as given by Farrington and Manning. This simplification results in a huge reduction in computation with only a minor reduction in accuracy. Also, it allows much larger sample sizes to be analyzed.

Note on Exact Methods

A word of caution should be raised about the phrase *exact tests* or *exact confidence intervals*. Many users assume that methods that are based on exact methods are always better than other, non-exact methods. After all, 'exact' sounds better than 'approximate'. However, tests and confidence intervals based on exact methods are not necessarily better. In fact, some prominent statisticians are of the opinion that they are actually worse (see Agresti and Coull (1998) for one example). *Exact* simply means that they are based on exact distributional calculations. They may be, however, conservative in terms of their coverage probabilities (the probability that the confidence interval includes the true value). That is, they are wider than they need to be because they are based on worst case scenarios.

Confidence Intervals for the Ratio

C.I. for Ratio: Miettinen-Nurminen Score

Miettinen and Nurminen (1985) proposed a test statistic for testing whether the ratio is equal to a specified value ϕ_0 . The regular MLE's \hat{p}_1 and \hat{p}_2 are used in the numerator of the score statistic while MLE's \tilde{p}_1 and \tilde{p}_2 constrained so that $\tilde{p}_1 / \tilde{p}_2 = \phi_0$ are used in the denominator. A correction factor of $N/(N-1)$ is applied to make the variance estimate less biased. The significance level of the test statistic is based on the asymptotic normality of the score statistic.

Here is the formula for computing the test

$$z_{MNR} = \frac{\hat{p}_1 / \hat{p}_2 - \phi_0}{\sqrt{\left(\frac{\tilde{p}_1 \tilde{q}_1}{n_1} + \phi_0^2 \frac{\tilde{p}_2 \tilde{q}_2}{n_2}\right) \left(\frac{N}{N-1}\right)}}$$

where

$$\tilde{p}_1 = \tilde{p}_2 \phi_0$$

$$\tilde{p}_2 = \frac{-B - \sqrt{B^2 - 4AC}}{2A}$$

$$A = N\phi_0$$

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$$B = -[N_1\phi_0 + x_{11} + N_2 + x_{21}\phi_0]$$

$$C = M_1$$

Miettinen and Nurminen (1985) proposed inverting their score test to find the confidence interval. The lower limit is found by solving

$$z_{MNR} = |z_{\alpha/2}|$$

and the upper limit is the solution of

$$z_{MNR} = -|z_{\alpha/2}|$$

C.I. for Ratio: Farrington-Manning Score

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Here is the formula for computing the test

$$z_{FMR} = \frac{\hat{p}_1/\hat{p}_2 - \phi_0}{\sqrt{\left(\frac{\tilde{p}_1\tilde{q}_1}{n_1} + \phi_0^2\frac{\tilde{p}_2\tilde{q}_2}{n_2}\right)}}$$

where the estimates \tilde{p}_1 and \tilde{p}_2 are computed as in the corresponding test of Miettinen and Nurminen (1985) given above.

Farrington and Manning (1990) proposed inverting their score test to find the confidence interval. The lower limit is found by solving

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C.I. for Ratio: Gart-Nam Score

Gart and Nam (1988) page 329 proposed a modification to the Farrington and Manning (1988) ratio test that corrected for skewness. Let $z_{FMR}(\phi)$ stand for the Farrington and Manning ratio test statistic described above. The skewness corrected test statistic z_{GNR} is the appropriate solution to the quadratic equation

$$(-\tilde{\varphi})z_{GNR}^2 + (-1)z_{GNR} + (z_{FMR}(\phi) + \tilde{\varphi}) = 0$$

where

$$\tilde{\varphi} = \frac{1}{6\tilde{u}^{3/2}} \left(\frac{\tilde{q}_1(\tilde{q}_1 - \tilde{p}_1)}{n_1^2\tilde{p}_1^2} - \frac{\tilde{q}_2(\tilde{q}_2 - \tilde{p}_2)}{n_2^2\tilde{p}_2^2} \right)$$

$$\tilde{u} = \frac{\tilde{q}_1}{n_1\tilde{p}_1} + \frac{\tilde{q}_2}{n_2\tilde{p}_2}$$

Gart and Nam (1988) proposed inverting their score test to find the confidence interval. The lower limit is found by solving

$$z_{GNR} = |z_{\alpha/2}|$$

and the upper limit is the solution of

$$z_{GNR} = -|z_{\alpha/2}|$$

C.I. for Ratio: Katz Logarithm

This was one of the first methods proposed for computing confidence intervals for risk ratios.

For details, see Gart and Nam (1988), page 324.

$$L = \hat{\phi} \exp \left(-z \sqrt{\frac{q_1}{np_1} + \frac{q_2}{np_2}} \right)$$

$$U = \hat{\phi} \exp \left(z \sqrt{\frac{q_1}{np_1} + \frac{q_2}{np_2}} \right)$$

where

$$\hat{\phi} = \frac{p_1}{p_2}$$

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C.I. for Ratio: Walters Logarithm + 1/2

For details, see Gart and Nam (1988), page 324.

$$L = \hat{\phi} \exp(-z\sqrt{\hat{u}})$$

$$U = \hat{\phi} \exp(z\sqrt{\hat{u}})$$

where

$$\hat{\phi} = \exp\left(\ln\left(\frac{x_{11} + \frac{1}{2}}{n_1 + \frac{1}{2}}\right) - \ln\left(\frac{x_{21} + \frac{1}{2}}{n_2 + \frac{1}{2}}\right)\right)$$

$$\hat{u} = \frac{1}{x_{11} + \frac{1}{2}} - \frac{1}{n_1 + \frac{1}{2}} + \frac{1}{x_{21} + \frac{1}{2}} - \frac{1}{n_2 + \frac{1}{2}}$$

$$\tilde{q}_2 = 1 - \tilde{p}_2$$

$$V = \left(\phi^2 \left(\frac{\tilde{q}_1}{n_1 \tilde{p}_1} + \frac{\tilde{q}_2}{n_2 \tilde{p}_2}\right)\right)^{-1}$$

$$\tilde{p}_1 = \phi \tilde{p}_2$$

$$\tilde{q}_1 = 1 - \tilde{p}_1$$

$$\tilde{q}_2 = 1 - \tilde{p}_2$$

$$\tilde{\mu}_3 = v^{3/2} \left(\frac{\tilde{q}_1(\tilde{q}_1 - \tilde{p}_1)}{(n_1 \tilde{p}_1)^2} - \frac{\tilde{q}_2(\tilde{q}_2 - \tilde{p}_2)}{(n_2 \tilde{p}_2)^2}\right)$$

$$v = \left(\frac{\tilde{q}_1}{n_1 \tilde{p}_1} + \frac{\tilde{q}_2}{n_2 \tilde{p}_2}\right)^{-1}$$

C.I. for Ratio: Chen's Quasi-Exact Method

Chen (2002) proposed a quasi-exact method for generating confidence intervals. This method produces intervals that are close to unconditional exact intervals that are available in specialized software like StatXact, but do not require as much time to compute. Chen's method inverts a hypothesis test based on Farrington and Manning's method. That is, the confidence interval is found by finding those values at which the hypothesis test that the difference is a given, non-zero value become significant. However, instead of searching for the maximum significance level of all possible values of the nuisance parameter as the exact tests do, Chen proposed using the significance level at the constrained maximum likelihood estimate of p_2 as given by Farrington and Manning. This simplification results in a huge reduction in computation with only a minor reduction in accuracy. Also, it allows much larger sample sizes to be analyzed.

Confidence Intervals for the Odds Ratio

The odds ratio is a commonly used measure of treatment effect when comparing two binomial proportions. It is the ratio of the odds of the event in group one divided by the odds of the event in group two. The results given below are found in Fleiss (1981).

Symbolically, the odds ratio is defined as

$$\psi = \frac{\frac{P_1}{1-P_1}}{\frac{P_2}{1-P_2}}$$

C.I. for Odds Ratio: Simple Technique

The simple estimate of the odds ratio uses the formula

$$\hat{\psi} = \frac{\frac{p_1}{1-p_1}}{\frac{p_2}{1-p_2}} = \frac{x_{11}x_{22}}{x_{21}x_{12}}$$

The standard error of this estimator is estimated by

$$se(\hat{\psi}) = \hat{\psi} \sqrt{\frac{1}{x_{11}} + \frac{1}{x_{21}} + \frac{1}{x_{12}} + \frac{1}{x_{22}}}$$

Problems occur if any one of the quantities x_{11} , x_{21} , x_{12} , or x_{22} are zero. To correct this problem, many authors recommend adding one-half to each cell count so that a zero cannot occur. Now, the formulas become

$$\hat{\psi}' = \frac{(x_{11} + 0.5)(x_{22} + 0.5)}{(x_{21} + 0.5)(x_{12} + 0.5)}$$

and

$$se(\hat{\psi}') = \hat{\psi}' \sqrt{\frac{1}{x_{11} + 0.5} + \frac{1}{x_{21} + 0.5} + \frac{1}{x_{12} + 0.5} + \frac{1}{x_{22} + 0.5}}$$

The distribution of these direct estimates of the odds ratio do not converge to normality as fast as does their logarithm, so the logarithm of the odds ratio is used to form confidence intervals. The formula for the standard error of the log odds ratio is

$$L' = \ln(\hat{\psi}')$$

and

$$se(L') = \sqrt{\frac{1}{x_{11} + 0.5} + \frac{1}{x_{21} + 0.5} + \frac{1}{x_{12} + 0.5} + \frac{1}{x_{22} + 0.5}}$$

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A $100(1 - \alpha)\%$ confidence interval for the log odds ratio is formed using the standard normal distribution as follows

$$\hat{\psi}_{lower} = \exp\left(L' - z_{1-\alpha/2}se(L')\right)$$

$$\hat{\psi}_{upper} = \exp\left(L' + z_{1-\alpha/2}se(L')\right)$$

C.I. for Odds Ratio: Iterated Method of Fleiss

Fleiss (1981) presents an improved confidence interval for the odds ratio. This method forms the confidence interval as all those values of the odds ratio which would not be rejected by a chi-square hypothesis test. Fleiss gives the following details about how to construct this confidence interval. To compute the lower limit, do the following.

1. For a trial value of ψ , compute the quantities X , Y , W , F , U , and V using the formulas

$$X = \psi(n_1 + m_1) + (n_2 - m_1)$$

$$Y = \sqrt{X^2 - 4n_1m_1\psi(\psi - 1)}$$

$$W = \frac{1}{A} + \frac{1}{B} + \frac{1}{C} + \frac{1}{D}$$

$$F = \left(x_{11} - A - \frac{1}{2}\right)^2 W - z_{\alpha/2}^2$$

$$U = \frac{1}{B^2} + \frac{1}{C^2} - \frac{1}{A^2} - \frac{1}{D^2}$$

$$V = T \left[\left(x_{11} - A - \frac{1}{2}\right)^2 U - 2W \left(x_{11} - A - \frac{1}{2}\right) \right]$$

where

$$A = \frac{X - Y}{2(\psi - 1)}$$

$$B = m_1 - A$$

$$C = n_1 - A$$

$$D = f - n_1 + A$$

$$T = \frac{1}{2(\psi - 1)^2} \left(Y - N - \frac{\psi - 1}{Y} [X(n_1 + m_1) - 2n_1m_1(2\psi - 1)] \right)$$

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Finally, use the updating equation below to calculate a new value for the odds ratio using the updating equation

$$\psi^{(k+1)} = \psi^{(k)} - \frac{F}{V}$$

2. Continue iterating until the value of F is arbitrarily close to zero.

The upper limit is found by substituting $+\frac{1}{2}$ for $-\frac{1}{2}$ in the formulas for F and V .

Confidence limits for the *relative risk* can be calculated using the expected counts A , B , C , and D from the last iteration of the above procedure. The lower limit of the relative risk

$$\phi_{lower} = \frac{A_{lower}n_2}{B_{lower}n_1}$$

$$\phi_{upper} = \frac{A_{upper}n_2}{B_{upper}n_1}$$

C.I. for Odds Ratio: Mantel-Haenszel

The common estimate of the logarithm of the odds ratio is used to create this estimator. That is

$$\ln(\hat{\psi}) = \ln\left(\frac{x_{11}x_{22}}{x_{21}x_{12}}\right)$$

The standard error of this estimator is estimated using the Robins, Breslow, Greenland (1986) estimator which performs well in most situations. The standard error is given by

$$se(\ln(\hat{\psi})) = \sqrt{\frac{A}{2C} + \frac{AD + BC}{2CD} + \frac{B}{2D}}$$

where

$$A = x_{11} + x_{22}$$

$$B = x_{21} + x_{12}$$

$$C = x_{11}x_{22}$$

$$D = x_{21}x_{12}$$

The confidence limits are calculated as

$$\hat{\psi}_{lower} = \exp\left(\ln(\hat{\psi}) - z_{1-\alpha/2}se(\ln(\hat{\psi}))\right)$$

$$\hat{\psi}_{upper} = \exp\left(\ln(\hat{\psi}) + z_{1-\alpha/2}se(\ln(\hat{\psi}))\right)$$

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C.I. for Odds Ratio: Miettinen-Nurminen Score

Miettinen and Nurminen (1985) proposed a test statistic for testing whether the odds ratio is equal to a specified value ψ_0 . Because the approach they used with the difference and ratio does not easily extend to the odds ratio, they used a score statistic approach for the odds ratio. The regular MLE's are \hat{p}_1 and \hat{p}_2 . The constrained MLE's are \tilde{p}_1 and \tilde{p}_2 . These estimates are constrained so that $\tilde{\psi} = \psi_0$. A correction factor of $N/(N-1)$ is applied to make the variance estimate less biased. The significance level of the test statistic is based on the asymptotic normality of the score statistic.

The formula for computing the test statistic is

$$z_{MNO} = \frac{\frac{(\hat{p}_1 - \tilde{p}_1)}{\tilde{p}_1 \tilde{q}_1} - \frac{(\hat{p}_2 - \tilde{p}_2)}{\tilde{p}_2 \tilde{q}_2}}{\sqrt{\left(\frac{1}{N_2 \tilde{p}_1 \tilde{q}_1} + \frac{1}{N_2 \tilde{p}_2 \tilde{q}_2}\right) \left(\frac{N}{N-1}\right)}}$$

where

$$\tilde{p}_1 = \frac{\tilde{p}_2 \psi_0}{1 + \tilde{p}_2 (\psi_0 - 1)}$$

$$\tilde{p}_2 = \frac{-B + \sqrt{B^2 - 4AC}}{2A}$$

$$A = N_2 (\psi_0 - 1)$$

$$B = N_1 \psi_0 + N_2 - M_1 (\psi_0 - 1)$$

$$C = -M_1$$

Miettinen and Nurminen (1985) proposed inverting their score test to find the confidence interval. The lower limit is found by solving

$$z_{MNO} = |z_{\alpha/2}|$$

and the upper limit is the solution of

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Two Proportions

C.I. for Odds Ratio: Farrington-Manning Score

Farrington and Manning (1990) indicate that the Miettinen and Nurminen statistic may be modified by removing the factor $N/(N-1)$.

The formula for computing this test statistic is

$$z_{FMO} = \frac{\frac{(\hat{p}_1 - \tilde{p}_1)}{\hat{p}_1 \hat{q}_1} - \frac{(\hat{p}_2 - \tilde{p}_2)}{\hat{p}_2 \hat{q}_2}}{\sqrt{\left(\frac{1}{N_2 \tilde{p}_1 \tilde{q}_1} + \frac{1}{N_2 \tilde{p}_2 \tilde{q}_2}\right)}}$$

where the estimates \tilde{p}_1 and \tilde{p}_2 are computed as in the corresponding test of Miettinen and Nurminen (1985) given above.

Farrington and Manning (1990) proposed inverting their score test to find the confidence interval. The lower limit is found by solving

$$z_{FMO} = |z_{\alpha/2}|$$

and the upper limit is the solution of

$$z_{FMO} = -|z_{\alpha/2}|$$

C.I. for Odds Ratio: Conditional Exact

The conditional exact confidence interval of the odds ratio is calculated using the noncentral hypergeometric distribution as given in Sahai and Khurshid (1995). That is, a $100(1 - \alpha)\%$ confidence interval is found by searching for ψ_L and ψ_U such that

$$\frac{\sum_{k=x}^{k_2} \binom{n_1}{k} \binom{n_2}{m_1 - k} (\psi_L)^k}{\sum_{k=k_1}^{k_2} \binom{n_1}{k} \binom{n_2}{m_1 - k} (\psi_L)^k} = \frac{\alpha}{2}$$

$$\frac{\sum_{k=k_1}^x \binom{n_1}{k} \binom{n_2}{m_1 - k} (\psi_U)^k}{\sum_{k=k_1}^{k_2} \binom{n_1}{k} \binom{n_2}{m_1 - k} (\psi_U)^k} = \frac{\alpha}{2}$$

where

$$k_1 = \max(0, m_1 - n_1) \text{ and } k_2 = \min(n_1, m_1)$$

Hypothesis Tests

A wide variety of statistical tests are available for testing hypotheses about two proportions. Some tests are based on the *difference* in proportions, others are based on the *ratio* of proportions, and still others are based on the *odds ratio*. Some tests are *conditional*, while others are *unconditional*. Some tests are said to be *large sample*, while others are said to be *exact*. In this section, some of these distinctions are explained.

Types of Hypothesis Tests

Hypothesis tests concerning two proportions can be separated into three categories: large sample, conditional exact, and unconditional exact.

Large Sample Tests

Large sample (or asymptotic) tests are based on the central limit theorem (CLT) which states that for large samples, the distribution of many of these test statistics approach the normal distribution. Hence, significance levels can be computed using the normal distribution which has been extensively tabulated and can now be easily computed.

A difficult determination when deciding whether to use a large sample test is whether or not the sample is large enough for the CLT to properly take effect.

Exact Tests in General

Because of the inaccuracy of applying a large sample procedure to a small sample study, another class of tests has been devised called *exact tests*. The significance levels of these tests are calculated from their exact distribution, usually by considering either the binomial or the hypergeometric distribution. No appeal is made to the CLT. Because these tests are computationally intensive, they have increased in popularity with increase of the computational abilities of computers.

Even with the availability of modern computers, approximate large sample techniques cannot be abandoned completely in favor of exact tests, due to the assumptions required by the exact tests.

The distribution of the proportions in a 2-by-2 table involves two parameters: p_1 and $p_1 + \delta$ in the case of the difference and p_1 and p_1 / ϕ in the case of the ratio. The hypothesis only involves one parameter, the difference, or the ratio. The other parameter, p_1 , is called a *nuisance parameter* because it is not part of the hypothesis of interest. That is, the hypothesis that $\delta = 0$ or $\phi = 1$ does not involve p_1 . In order to test hypotheses about the parameter of interest, the nuisance parameter must be eliminated. This may be accomplished either by conditional methods or unconditional methods.

Conditional Exact Test

The nuisance parameter can be eliminated by conditioning on a sufficient statistic. Fisher's exact test is an example of this. The conditioning occurs by considering only those tables in which the row and column totals remain the same as for the data. This removes the nuisance parameter p_1 from the distribution formula. This has drawn criticism because most experimental designs do not fix both the row and column totals. Others have argued that since the significance level is preserved unconditionally, the test is valid.

Unconditional Exact Test

The unconditional exact test approach is to remove the nuisance parameter by computing the significance level at all possible values of the nuisance parameter and choosing the largest (worst case). That is, find the value of p_1 which gives the maximum significance level (least significant) for the hypothesis test. That is, these tests find an upper bound for the significance level.

The problem with the unconditional approach is that the upper bound may occur at a value of p_1 that is far from the true value. For example, suppose the true value of p_1 is 0.711 where the significance level is 0.032. However, suppose the maximum significance level of 0.213 occurs at $p_1 = 0.148$. Hence, near the actual value of the nuisance value, the results are statistically significant, but the results of the exact test are not! Of course, in a particular study, we do not know the true value of the nuisance parameter. The message is that although these tests are called exact tests, they are not! They are approximate tests computed using exact distributions. Hence, one cannot say broadly that exact tests are always better than the large-sample test counterparts.

Hypothesis Test Technical Details

The sections that follow give formulaic details of the hypothesis tests associated with this procedure.

Notation for Hypothesis Test Statistics

The following notation is used in the formulas for the test statistics.

	Event	Non-Event	Total	Sample Proportion
Group 1	x_{11}	x_{12}	n_1	$p_1 = x_{11}/n_1$
Group 2	x_{21}	x_{22}	n_2	$p_2 = x_{21}/n_2$
Total	m_1	m_2	N	$p = m_1/N$

Hypotheses for Inequality Tests of Proportion Difference

One should determine in advance the direction of the null and alternative hypothesis of the test.

Two-Sided

$$H_0: P_1 = P_2 \text{ vs. } H_a: P_1 \neq P_2$$

One-Sided (Lower)

$$H_0: P_1 \geq P_2 \text{ vs. } H_a: P_1 < P_2$$

One-Sided (Upper)

$$H_0: P_1 \leq P_2 \text{ vs. } H_a: P_1 > P_2$$

Large-Sample (Asymptotic) Inequality Tests of Proportion Difference

The traditional approach was to use the Pearson chi-square test for large samples, the Yates chi-square for intermediate sample sizes, and the Fisher Exact test for small samples. Recently, some authors have begun questioning this solution. For example, based on exact enumeration, Upton (1982) and D'Agostino (1988) caution that the Fisher Exact test and Yates test should never be used.

Wald Z-Test (One- and Two-Sided)

The z statistic for the Wald z-test is computed as follows

$$z = \frac{p_1 - p_2}{\sqrt{p(1-p)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

Wald Z-Test with Continuity Correction (One- and Two-Sided)

With the continuity correction, the z statistic becomes

$$z = \frac{|p_1 - p_2| - \frac{1}{2}\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}{\sqrt{p(1-p)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \text{sign}(p_1 - p_2)$$

Chi-Square Test of Difference (Two-Sided Only) or Independence

This hypothesis test takes its place in history as one of the first statistical hypothesis tests to be proposed. It was first proposed by Karl Pearson in 1900. The two-sided test is computed as

$$\chi^2 = \frac{N(x_{11}x_{22} - x_{21}x_{12})^2}{n_1n_2m_1m_2}$$

where this statistic is compared to a chi-square distribution with one degree of freedom.

Chi-Square Test with Continuity Correction of Difference (Two-Sided Only) or Independence

With the continuity correction, the chi-square test statistic becomes

$$\chi^2 = \frac{N(|x_{11}x_{22} - x_{21}x_{12}| - \frac{1}{2}N)^2}{n_1n_2m_1m_2}$$

which also is compared to a chi-square distribution with one degree of freedom.

Two Proportions

Conditional Mantel Haenszel Test of Difference (One- and Two-Sided)

The conditional Mantel Haenszel test, see Lachin (2000) page 40, is based on the *index frequency*, x_{11} , from the 2x2 table. The formula for the z-statistic is

$$z = \frac{x_{11} - E(x_{11})}{\sqrt{V_c(x_{11})}}$$

where

$$E(x_{11}) = \frac{n_1 m_1}{N}$$

$$V_c(x_{11}) = \frac{n_1 n_2 m_1 m_2}{N^2(N-1)}$$

Likelihood Ratio Test of Difference (Two-Sided Only) or Independence

In 1935, Wilks showed that the following quantity has a chi-square distribution with one degree of freedom. This test is presented, among other places, in Upton (1982). The expression for the statistic can be reduced to

$$LR = 2 \ln \left(\frac{x_{11}^{x_{11}} x_{21}^{x_{21}} x_{12}^{x_{12}} x_{22}^{x_{22}} N^N}{n_1^{n_1} n_2^{n_2} m_1^{m_1} m_2^{m_2}} \right)$$

Small-Sample (Exact) Inequality Tests of Proportion Difference**Fisher's Exact Test of Difference (One- and Two-Sided) or Independence**

Fisher's Exact test consists of enumerating all 2-by-2 tables that have the same marginal frequencies as the observed table and then summing the probability of the observed table and all those that have probability less than or equal to the observed table. The probability of an individual table is derived from the hypergeometric probability distribution, where

$$\Pr(x_{11}, x_{12}, x_{21}, x_{22}) = \frac{n_1! n_2! m_1! m_2!}{N! x_{11}! x_{12}! x_{21}! x_{22}!}$$

General Form of the Other Exact Tests in NCSS

All of the exact tests follow the same pattern. We will present the general procedure here, and then give the specifics for each test.

Two Proportions

Specify the Null and Alternative Hypotheses

The first step is to select a method to compare the proportions and determine if the test is to be one-, or two-, sided. These may be written in general as

$$H_0: h_j(P_1, P_2) = \theta_0$$

$$H_1: h_j(P_1, P_2) \neq \theta_0$$

where ' \neq ' (for two-sided tests) could be replaced with '<' or '>' for a one-sided test and the index j is defined as

$$h_1(P_1, P_2) = P_1 - P_2.$$

$$h_2(P_1, P_2) = P_1 / P_2$$

$$h_3(P_1, P_2) = \frac{P_1 / (1 - P_1)}{P_2 / (1 - P_2)}$$

Specify the Reference Set

The next step is to specify the *reference set* of possible tables to compare the observed table against. Two reference sets are usually considered. Define Ω as the complete set of tables that are possible by selecting n_1 observations from one group and n_2 observations from another group. Define Γ as the subset from Ω for which $x_{11} + x_{21} = m_1$. Tests using Ω are unconditional tests while tests using Γ are conditional tests.

Specify the Test Statistic

The next step is to select the test statistic. In most cases, the score statistic is used which has the general form

$$D(x) = \frac{h_j(p_1, p_2) - \theta_0}{\sqrt{\tilde{V}_{h_j}(\theta_0)}}$$

where x represents a table with elements $x_{11}, x_{12}, x_{21}, x_{22}$ and $\tilde{V}_{h_j}(\theta_0)$ is the estimated variance of the score numerator with the constraint that the null hypothesis is true.

Select the Probability Distribution

The probability distribution an unconditional test based on the score statistic is

$$f_{p_1, p_2}(x) = \binom{n_1}{x_{11}} \binom{n_2}{x_{21}} p_1^{x_{11}} (1 - p_1)^{x_{12}} p_2^{x_{21}} (1 - p_2)^{x_{22}}$$

The probability distribution of a conditional test based on the score statistic is

$$f_{\psi}(x) = \frac{\binom{n_1}{x_{11}} \binom{n_2}{x_{21}} \psi^{x_{11}}}{\sum_{x \in \Gamma} \binom{n_1}{x_{11}} \binom{n_2}{x_{21}} \psi^{x_{11}}}$$

Two Proportions

Calculate the Significance Level

The significance level (rejection probability) is found by summing the probabilities of all tables that for which the computed test statistic is at least as favorable to the alternative hypothesis as is the observed table. This may be written as

$$p(y) = \sum_{I(D(y), D(x))} f_{p_1, p_2}(x)$$

where $I(D(y), D(x))$ is an indicator function.

Maximize the Significance Level

The final step is to find the maximum value (supremum) of the significance level over all possible values of the nuisance parameter. This may be written as

$$p_{\sup p_2}(x) = \sup_{0 < p_2 < 1} \left(\sum_{I(D(y), D(x))} f_{p_1, p_2}(x) \right)$$

Note that the choice of either p_1 or p_2 as the nuisance parameter is arbitrary.

Fisher, Pearson, and Likelihood Ratio Conditional Exact Test of the Difference = 0

Here, there are three conditional exact tests for testing whether the difference is zero. The most famous of these uses Fisher's statistic, but similar tests are also available using Pearson's statistic and the likelihood ratio statistic.

Null Hypothesis: $P_1 - P_2 = 0$

Hypothesis Types: Both one-sided and two-sided

Reference Set: Γ

Fisher's Test Statistic: $D(x) = -2 \ln(f_1(x)) - \ln(2.51N^{-3/2} \sqrt{m_1 m_2 n_1 n_2})$

Pearson's Test Statistic: $D(x) = \sum_i^2 \sum_j^2 \frac{(x_{ij} - m_i n_j / N)^2}{m_i n_j / N}$

L.R. Test Statistic: $D(x) = 2 \sum_i^2 \sum_j^2 x_{ij} \ln \left(\frac{x_{ij}}{m_i n_j / N} \right)$

Two-Sided Test: $I(D(y), D(x)) = |D(x)| \geq |D(y)|$

Lower One-Sided Test: $I(D(y), D(x)) = D(x) \leq D(y)$

Upper One-Sided Test: $I(D(y), D(x)) = D(x) \geq D(y)$

Two Proportions

Barnard's Unconditional Exact Test of the Difference = 0

Barnard (1947) proposed an unconditional exact test for the difference between two proportions. It is interesting that two years later he retracted his article. However, the test has been adopted in spite of his retraction. Here are the details of this test:

Null Hypothesis: $P_1 - P_2 = 0$

Hypothesis Types: Both one-sided and two-sided

Reference Set: Ω .

Test Statistic: $D(x) = \frac{p_1 - p_2}{\sqrt{p(1-p)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$ where $p = \frac{y_{11} + y_{21}}{n_1 + n_2}$

Two-Sided Test: $I(D(y), D(x)) = |D(x)| \geq |D(y)|$

Lower One-Sided Test: $I(D(y), D(x)) = D(x) \leq D(y)$

Upper One-Sided Test: $I(D(y), D(x)) = D(x) \geq D(y)$

Hypotheses for Inequality Tests of Proportion Ratio

One should determine in advance the direction of the null and alternative hypothesis of the test.

Two-Sided

$H_0: P_1/P_2 = 1$ vs. $H_a: P_1/P_2 \neq 1$

One-Sided (Lower)

$H_0: P_1/P_2 \geq 1$ vs. $H_a: P_1/P_2 < 1$

One-Sided (Upper)

$H_0: P_1/P_2 \leq 1$ vs. $H_a: P_1/P_2 > 1$

Large-Sample (Asymptotic) Inequality Tests of Proportion Ratio**Wald Z-Test (One- and Two-Sided)**

The Wald z-test for the ratio given is identical to the z-test for the difference, which may not necessarily be a recommended procedure for ratios. The z statistic for the z-test is computed as follows

$$z = \frac{p_1 - p_2}{\sqrt{p(1-p)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

Small-Sample (Exact) Inequality Tests of Proportion Ratio

Barnard's Exact Test of the Ratio = 1 (One- and Two-Sided)

Barnard's exact test for the ratio is identical to that for the difference.

Hypotheses for Inequality Tests of Proportion Odds Ratio

One should determine in advance the direction of the null and alternative hypothesis of the test.

Two-Sided

$$H_0: O_1/O_2 = 1 \text{ vs. } H_a: O_1/O_2 \neq 1$$

One-Sided (Lower)

$$H_0: O_1/O_2 \geq 1 \text{ vs. } H_a: O_1/O_2 < 1$$

One-Sided (Upper)

$$H_0: O_1/O_2 \leq 1 \text{ vs. } H_a: O_1/O_2 > 1$$

Large-Sample (Asymptotic) Inequality Tests of Proportion Odds Ratio

Log Odds Ratio Test (One- and Two-Sided)

The z statistic for the log odds ratio z-test is computed as follows

$$z = \frac{\log\left(\frac{p_1/(1-p_1)}{p_2/(1-p_2)}\right)}{\sqrt{\left(\frac{1}{x_{11}} + \frac{1}{x_{21}} + \frac{1}{x_{12}} + \frac{1}{x_{22}}\right)}}$$

Mantel-Haenszel Test (One- and Two-Sided)

The z statistic for the Mantel-Haenszel z-test is computed as follows

$$z = \frac{\log\left(\frac{p_1/(1-p_1)}{p_2/(1-p_2)}\right)}{\sqrt{\frac{AC}{2C^2} + \frac{AD+BC}{2CD} + \frac{BD}{2D^2}}}$$

where

$$A = x_{11} + x_{22}$$

$$B = x_{21} + x_{12}$$

$$C = x_{11}x_{22}$$

$$D = x_{21}x_{12}$$

Small-Sample (Exact) Inequality Test of Proportion Odds Ratio

Exact Test of the Odds Ratio = 1 (One- and Two-Sided)

The exact test here follows the procedure described in Sahai and Khurshid (1995) beginning on page 37.

General Form of the Other Exact Tests in NCSS

All of the exact tests follow the same pattern. We will present the general procedure here, and then give the specifics for each test.

Specify the Null and Alternative Hypotheses

The first step is to select a method to compare the proportions and determine if the test is to be one-, or two-, sided. These may be written in general as

$$H_0: h_j(P_1, P_2) = \theta_0$$

$$H_1: h_j(P_1, P_2) \neq \theta_0$$

where ' \neq ' (for two-sided tests) could be replaced with ' $<$ ' or ' $>$ ' for a one-sided test and the index j is defined as

$$h_1(P_1, P_2) = P_1 - P_2.$$

$$h_2(P_1, P_2) = P_1/P_2$$

$$h_3(P_1, P_2) = \frac{P_1/(1 - P_1)}{P_2/(1 - P_2)}$$

Specify the Reference Set

The next step is to specify the *reference set* of possible tables to compare the observed table against. Two reference sets are usually considered. Define Ω as the complete set of tables that are possible by selecting n_1 observations from one group and n_2 observations from another group. Define Γ as the subset from Ω for which $x_{11} + x_{21} = m_1$. Tests using Ω are unconditional tests while tests using Γ are conditional tests.

Specify the Test Statistic

The next step is to select the test statistic. In most cases, the score statistic is used which has the general form

$$D(x) = \frac{h_j(p_1, p_2) - \theta_0}{\sqrt{\tilde{V}_{h_j}(\theta_0)}}$$

where x represents a table with elements $x_{11}, x_{12}, x_{21}, x_{22}$ and $\tilde{V}_{h_j}(\theta_0)$ is the estimated variance of the score numerator with the constraint that the null hypothesis is true.

Two Proportions

Select the Probability Distribution

The probability distribution an unconditional test based on the score statistic is

$$f_{p_1, p_2}(x) = \binom{n_1}{x_{11}} \binom{n_2}{x_{21}} p_1^{x_{11}} (1 - p_1)^{x_{12}} p_2^{x_{21}} (1 - p_2)^{x_{22}}$$

The probability distribution of a conditional test based on the score statistic is

$$f_{\psi}(x) = \frac{\binom{n_1}{x_{11}} \binom{n_2}{x_{21}} \psi^{x_{11}}}{\sum_{x \in \Gamma} \binom{n_1}{x_{11}} \binom{n_2}{x_{21}} \psi^{x_{11}}}$$

Calculate the Significance Level

The significance level (rejection probability) is found by summing the probabilities of all tables that for which the computed test statistic is at least as favorable to the alternative hypothesis as is the observed table. This may be written as

$$p(y) = \sum_{I(D(y), D(x))} f_{p_1, p_2}(x)$$

where $I(D(y), D(x))$ is an indicator function.

Maximize the Significance Level

The final step is to find the maximum value (supremum) of the significance level over all possible values of the nuisance parameter. This may be written as

$$p_{sup p_2}(x) = \sup_{0 < p_2 < 1} \left(\sum_{I(D(y), D(x))} f_{p_1, p_2}(x) \right)$$

Note that the choice of either p_1 or p_2 as the nuisance parameter is arbitrary.

Data Structure

This procedure can summarize data from a database or summarized count values can be entered directly into the procedure panel in one of two ways: group sample sizes and group 'successes', or group 'successes' and group 'non-successes'.

Example 1 – Large-Sample Analysis of the Difference of Two Proportions

This section presents an example of a standard, large-sample analysis of the difference between two proportions. In this example, 2132 of 2662 receiving the standard treatment responded positively and 1995 of 2378 receiving the experimental treatment responded positively.

Setup

To run this example, complete the following steps:

1 Specify the Two Proportions procedure options

- Find and open the **Two Proportions** procedure using the menus or the Procedure Navigator.
- The settings for this example are listed below and are stored in the **Example 1** settings file. To load these settings to the procedure window, click **Open Example Settings File** in the Help Center or File menu.

Data Tab

Type of Data Input	Summary Table of Counts: Enter Row Totals and First Column
Group Heading	Treatment
Group Label of 1st Value	Experimental
Group Label of 2nd Value	Standard
Outcome Heading	Response
Outcome Label of 1st Value	Positive
Outcome Label of 2nd Value	Negative
Group 1 Total	2378
Group 1, Outcome 1 Value	1995
Group 2 Total	2662
Group 2, Outcome 1 Value	2132

Summary Reports Tab

Counts and Proportions	Checked
Proportions Analysis	Checked

Difference Reports Tab

Confidence Intervals of the Difference ($P_1 - P_2$)

Wald Z with Continuity Correction	Checked
Wilson Score with Continuity Correction	Checked

Inequality Tests of the Difference ($P_1 - P_2$)

Test Direction	Two-Sided ($H_0: P_1 = P_2$ vs. $H_a: P_1 \neq P_2$)
Wald Z	Checked

2 Run the procedure

- Click the **Run** button to perform the calculations and generate the output.

Counts and Proportions Sections

Counts and Proportions

Treatment	Response			Proportion*
	Positive Count	Negative Count	Total Count	
Experimental	1995	383	2378	p1 = 0.8389
Standard	2132	530	2662	p2 = 0.8009

* Proportion = Positive / Total

Proportions Analysis

Statistic	Value
Group 1 Event Rate (p1)	0.8389
Group 2 Event Rate (p2)	0.8009
Absolute Risk Difference p1 - p2	0.0380
Number Needed to Treat 1/ p1 - p2	26.29
Relative Risk Reduction p1 - p2 /p2	0.05
Relative Risk p1/p2	1.05
Odds Ratio o1/o2	1.29

These reports document the values that were input and give various summaries of these values.

Confidence Interval

Confidence Intervals of the Difference (P1 - P2)

Confidence Interval Name	p1	p2	Difference p1 - p2	Lower 95% C.L. of P1 - P2	Upper 95% C.L. of P1 - P2	Confidence Interval Width
Wald Z c.c.	0.8389	0.8009	0.0380	0.0165	0.0596	0.0431
Wilson Score c.c.	0.8389	0.8009	0.0380	0.0165	0.0594	0.0429

This report provides two, large sample confidence intervals of the difference based on formulas shown earlier in this chapter. In this case, they are nearly identical. The Wilson Score with continuity correction has been shown to be one of the best. The Wald Z (or Simple Z) confidence interval is often shown in elementary statistics books.

Inequality Test

Two-Sided Tests of the Difference (P1 - P2)

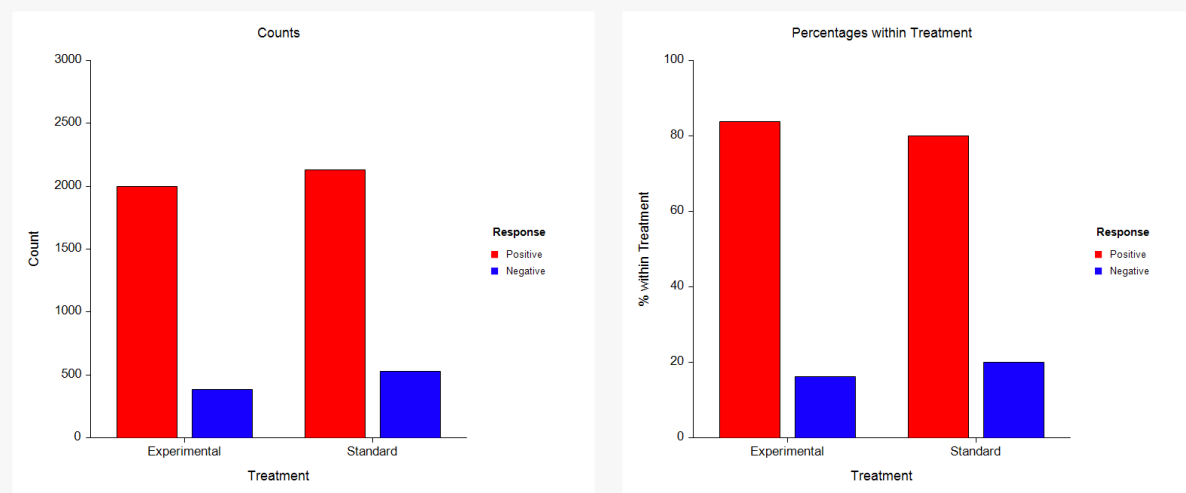
H0: P1 = P2 vs. Ha: P1 ≠ P2

Test Statistic Name	p1	p2	Difference p1 - p2	Test Statistic Value	Prob Level	Reject H0 at α = 0.05?
Wald Z	0.8389	0.8009	0.0380	3.500	0.0005	Yes

This report provides the Wald Z large-sample test. The p-value of the test is the Prob Level.

Plots

Plots Section



These bar charts show the count and row percentages of the data.