

Chapter 736

Assurance for Tests for the Ratio of Two Negative Binomial Rates

Introduction

This procedure calculates the assurance of one- or two-sided tests of the ratio of two independent negative binomial event rates. A negative binomial regression model gives the probability distribution of the number of events occurring in a specified interval of time or space. The negative binomial distribution is characterized by a single parameter which is the mean number of occurrences during the specified interval. The negative binomial distribution is often used to fit count data, such as the number of lesions on a subject's legs or the number of episodes during a year.

Count data arise from counting the number of events of a particular type that occur during a specified time interval. Traditionally, the Poisson distribution (e.g., Poisson regression) has been used to model count data. The Poisson model assumes that the mean and variance are equal, but in many clinical trials the variance is observed to be greater than the mean in a condition called *overdispersion*. When overdispersion occurs, the Poisson model provides a poor fit to the data. As an alternative, the negative binomial model is increasingly used to model overdispersed count data. While the Poisson distribution is characterized by a single parameter which represents both the mean and the variance, the negative binomial distribution includes two parameters, allowing for greater flexibility in modeling the mean-variance relationship that is observed in overdispersed, heterogeneous count data.

This procedure is based on the formulas and results outlined in Zhu and Lakkis (2014). It calculates the assurance for testing whether the ratio of two negative binomial event rates is different from one. The test is often performed using the Wald (or likelihood ratio) test statistic in the context of generalized linear models. Such an analysis is available within SAS Proc GENMOD. These asymptotic tests are appropriate when the sample size is greater than 50 per group. When the sample size is less than 50 per group, the results from this procedure can be used to obtain a rough estimate of the assurance (see Zhu and Lakkis (2014), page 381).

The calculation is based on a user-specified prior distribution of the effect size parameters. This procedure may also be used to determine the needed sample size to obtain a specified assurance. The methods for assurance calculation in this procedure are based on O'Hagan, Stevens, and Campbell (2005).

Assurance

The assurance of a design is the expected value of the power with respect to one or more prior distributions of the design parameters. Assurance is also referred to as *Bayesian assurance*, *expected power*, *average power*, *statistical assurance*, *hybrid classical-Bayesian procedure*, or *probability of success*.

The power of a design is the probability of rejecting the null hypothesis, conditional on a given set of design attributes, such as the test statistic, the significance level, the sample size, and the effect size to be detected. As the effect size parameters are typically unknown quantities, the stated power may be very different from the true power if the specified parameter values are inaccurate.

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While power is conditional on individual design parameter values, and is highly sensitive to those values, assurance is the average power across a presumed prior distribution of the effect size parameters. Thus, assurance adds a Bayesian element to the frequentist framework, resulting in a hybrid approach to the probability of trial or study success. It should be noted that when it comes time to perform the statistical test on the resulting data, these methods for calculating assurance assume that the traditional (frequentist) tests will be used.

The next section describes some of the ways in which the prior distributions for effect size parameters may be determined.

Elicitation

In order to calculate assurance, a suitable prior distribution for the effect size parameters must be determined. This process is called the *elicitation* of the prior distribution.

The elicitation may be as simple as choosing a distribution that seems plausible for the parameter(s) of interest, or as complex as combining the informed advice of several experts based on experience in the field, available pilot data, or previous studies. The accuracy of the assurance value depends on the accuracy of the elicited prior distribution. The assumption (or hope) is that an informed prior distribution will produce a more accurate estimate of the probability of trial success than a single value estimate. Because clinical trials and other studies are often costly, many institutions now routinely require an elicitation step.

Two reference texts that focus on elicitation are O'Hagan, Buck, Daneshkhah, Eiser, Garthwaite, Jenkinson, Oakley, and Rakow (2006) and Dias, Morton, and Quigley (2018).

Technical Details

The Negative Binomial Model

As in Zhu and Lakkis (2014), define y_{ij} as the number of events during time t_{ij} for subject i ($i = 1$ to n_j) in group j ($j = 1, 2$). Usually, group 1 is considered the control or reference group and group 2 is considered the treatment group. If y_{ij} follows a negative binomial distribution with mean μ_{ij} and dispersion parameter κ , the probability function for y_{ij} is

$$P(y_{ij}) = \frac{\Gamma(\kappa^{-1} + y_{ij})}{\Gamma(\kappa^{-1})y_{ij}!} \left(\frac{\kappa\mu_{ij}}{1 + \kappa\mu_{ij}} \right)^{y_{ij}} \left(\frac{1}{1 + \kappa\mu_{ij}} \right)^{1/\kappa}$$

where $\Gamma(\cdot)$ is the gamma function. Using negative binomial regression, μ_{ij} can be modeled as

$$\log(\mu_{ij}) = \log(t_{ij}) + \beta_0 + \beta_1 x_{ij}$$

such that

$$\log\left(\frac{\mu_{ij}}{t_{ij}}\right) = \beta_0 + \beta_1 x_{ij}$$

where $x_{ij} = 0$ if the i^{th} subject is in group 1 and $x_{ij} = 1$ if the i^{th} subject is in group 2.

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Further define λ_1 and λ_2 as the mean event rates per time unit for groups 1 and 2, respectively, and $RR = \lambda_2/\lambda_1$ as the ratio of event rates. Using the negative binomial model, it follows then that

$$\lambda_1 = e^{\beta_0}$$

$$\lambda_2 = e^{\beta_0 + \beta_1}$$

$$RR = \frac{\lambda_2}{\lambda_1} = e^{\beta_1}$$

If we define $\hat{\beta}_1$ as the asymptotic maximum likelihood estimate of β_1 , then the variance of $\hat{\beta}_1$ can be written as

$$\text{Var}(\hat{\beta}_1) = \frac{1}{N_1} \left[\frac{1}{\mu_t} \left(\frac{1}{\lambda_1} + \frac{1}{R\lambda_2} \right) + \frac{(1+R)\kappa}{R} \right]$$

where N_1 and N_2 are the sample sizes and λ_1 and λ_2 are the event rates from groups 1 and 2, respectively, $R = N_2/N_1$ is the sample allocation ratio, κ is the negative binomial dispersion parameter, and μ_t is the average exposure time across all subjects (i.e., $t_{ij} = \mu_t$ for all i, j).

Hypotheses

The two-sided null and alternative hypotheses for testing equality of the two event rates can be written as

$$H_0: \beta_1 = 0 \quad \text{vs.} \quad H_1: \beta_1 \neq 0$$

or equivalently in terms of $RR = \lambda_2/\lambda_1$ as

$$H_0: RR = 1 \quad \text{vs.} \quad H_1: RR \neq 1$$

The upper and lower one-sided tests, respectively, are

$$H_0: \beta_1 \leq 0 \quad \text{vs.} \quad H_1: \beta_1 > 0$$

$$H_0: \beta_1 \geq 0 \quad \text{vs.} \quad H_1: \beta_1 < 0$$

or equivalently in terms of $RR = \lambda_2/\lambda_1$ as

$$H_0: RR \leq 1 \quad \text{vs.} \quad H_1: RR > 1$$

$$H_0: RR \geq 1 \quad \text{vs.} \quad H_1: RR < 1$$

These hypotheses are most commonly tested using the Wald test statistic within generalized linear models. The likelihood ratio test statistic is also used. Such an analysis can be performed for the negative binomial distribution using SAS Proc GENMOD with a logarithmic link function and an indicator variable for group (1 or 2) as the single independent variable. For more information see Zhu and Lakkis (2014) or the SAS help manual.

Estimating the Variance under the Null and Alternative Hypotheses

Asymptotically, the variance of $\hat{\beta}_1$ is

$$\text{Var}(\hat{\beta}_1) = \frac{1}{N_1} \left[\frac{1}{\mu_t} \left(\frac{1}{\lambda_1} + \frac{1}{R\lambda_2} \right) + \frac{(1+R)\kappa}{R} \right]$$

If we define V_1 under the alternative hypothesis using the true rates λ_1 and λ_2 as

$$V_1 = \frac{1}{\mu_t} \left(\frac{1}{\lambda_1} + \frac{1}{R\lambda_2} \right) + \frac{(1+R)\kappa}{R}$$

then the variance of $\hat{\beta}_1$ under the alternative hypothesis can be written as

$$\begin{aligned} \text{Var}_1(\hat{\beta}_1) &= \frac{1}{N_1} \left[\frac{1}{\mu_t} \left(\frac{1}{\lambda_1} + \frac{1}{R\lambda_2} \right) + \frac{(1+R)\kappa}{R} \right] \\ &= \frac{1}{N_1} [V_1] \end{aligned}$$

If we define V_0 using the rates $\tilde{\lambda}_1$ and $\tilde{\lambda}_2$ estimated under the null hypothesis as

$$V_0 = \frac{1}{\mu_t} \left(\frac{1}{\tilde{\lambda}_1} + \frac{1}{R\tilde{\lambda}_2} \right) + \frac{(1+R)\kappa}{R}$$

then the variance of $\hat{\beta}_1$ under the null hypothesis is

$$\begin{aligned} \text{Var}_0(\hat{\beta}_1) &= \frac{1}{N_1} \left[\frac{1}{\mu_t} \left(\frac{1}{\tilde{\lambda}_1} + \frac{1}{R\tilde{\lambda}_2} \right) + \frac{(1+R)\kappa}{R} \right] \\ &= \frac{1}{N_1} [V_0] \end{aligned}$$

The portion V_0 (and therefore $\text{Var}_0(\hat{\beta}_1)$) can be estimated in three ways. Define $V_{0|M}$ as the estimate of V_0 given the chosen method M . It follows then that

$$\text{Var}_{0|M}(\hat{\beta}_1) = \frac{1}{N_1} [V_{0|M}]$$

where $M = 1, 2, 3$ indicates the method used to estimate V_0 .

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The three methods for estimating V_0 are as follows:

- **Method 1: Use the Event Rate from Group 1 (λ_1)**

Under $H_0: RR = 1$, the event rates are equal (i.e., $\lambda_2 = \lambda_1$), and the null variance is estimated using

$$V_{0|1} = \frac{1+R}{\mu_t R \lambda_1} + \frac{(1+R)\kappa}{R}$$

- **Method 2: Use the True Event Rates (λ_1 and λ_2)**

The true rates λ_1 and λ_2 are used, and the null variance is estimated using

$$V_{0|2} = \frac{1}{\mu_t} \left(\frac{1}{\lambda_1} + \frac{1}{R \lambda_2} \right) + \frac{(1+R)\kappa}{R}$$

This is equivalent to the estimation of V_A under the alternative hypothesis, i.e., $V_{0|2} = V_1$.

- **Method 3: Use Maximum Likelihood Estimation**

The maximum likelihood estimate of λ under $H_0: RR = 1$, a weighted average of λ_1 and λ_2 , is used, and the null variance is estimated using

$$V_{0|3} = \frac{(1+R)^2}{\mu_t R (\lambda_1 + R \lambda_2)} + \frac{(1+R)\kappa}{R}$$

Simulation studies suggest that sample sizes calculated using methods 2 and 3 are more accurate than those calculated using method 1 (see Zhu and Lakkis (2014), page 385).

Power Calculations

From Zhu and Lakkis (2014), page 379, the power of the two-sided Wald or likelihood ratio test can be calculated at significance level α using calculation method M for V_0 as

$$Power_{2-sided} = 1 - \beta = \Phi \left(\frac{\sqrt{N_1} |\log(\lambda_2/\lambda_1)| - z_{\alpha/2} \sqrt{V_{0|M}}}{\sqrt{V_1}} \right)$$

with RR , V_1 , and $V_{0|M}$ as defined earlier. The power of the one-sided Wald or likelihood ratio test at significance level α using calculation method M for V_0 is

$$Power_{1-sided} = 1 - \beta = \Phi \left(\frac{\sqrt{N_1} |\log(\lambda_2/\lambda_1)| - z_{\alpha} \sqrt{V_{0|M}}}{\sqrt{V_1}} \right)$$

The power calculations are accurate for the Wald and likelihood ratio tests when the group sample sizes are greater than 50. When the sample size is less than 50 per group the validity of the Wald and likelihood ratio tests is questionable, and these formulas should be used only to obtain a rough estimate of the power (see Zhu and Lakkis (2014), page 381).

Assurance Calculation

This assurance computation described here is based on O'Hagan, Stevens, and Campbell (2005).

Let $P'(H|\lambda_1, \lambda_2, \mu_t, \kappa)$ be the power function described above where H is the event that null hypothesis is rejected conditional on the parameter values. The specification of $\lambda_1, \lambda_2, \mu_t$, and κ is critical to the power calculation, but the actual values are seldom known. Assurance is defined as the expected power where the expectation is with respect to a joint prior distribution for the parameters $\lambda_1, \lambda_2, \mu_t$, and κ . Hence, the definition of assurance is

$$Assurance = E_{\lambda_1, \lambda_2, \mu_t, \kappa}(P'(H|\lambda_1, \lambda_2, \mu_t, \kappa)) = \int \int \int \int P'(H|\lambda_1, \lambda_2, \mu_t, \kappa) f(\lambda_1, \lambda_2, \mu_t, \kappa) d\lambda_1 d\lambda_2 d\mu_t d\kappa$$

where $f(\lambda_1, \lambda_2, \mu_t, \kappa)$ is the joint prior distribution using the four parameters.

In **PASS**, the joint prior distribution can be specified as either a discrete approximation to the joint prior distribution, or as individual prior distributions, one for each parameter.

Specifying a Joint Prior Distribution

If the joint prior distribution is to be specified directly, the distribution is specified in **PASS** using a discrete approximation to the function $f(\lambda_1, \lambda_2, \mu_t, \kappa)$. This provides flexibility in specifying the joint prior distribution. In the four-parameter case, five columns are entered on the spreadsheet: four for the parameters and a fifth for the probability. Each row gives a value for each parameter and the corresponding parameter-combination probability. The accuracy of the distribution approximation is controlled by the number of points (spreadsheet rows) that are used.

An example of entering a joint prior distribution is included at the end of the chapter.

Specifying Individual Prior Distributions

Ciarleglio, Arendt, and Peduzzi (2016) suggest that more flexibility is available if the joint prior distribution is separated into two independent univariate distributions as follows

$$f(\lambda_1, \lambda_2, \mu_t, \kappa) = f_1(\lambda_1)f_2(\lambda_2)f_3(\mu_t)f_4(\kappa)$$

where $f_1(\lambda_1)$ is the prior distribution of λ_1 , $f_2(\lambda_2)$ is the prior distribution of λ_2 , and so on. This method is also available in **PASS**. In this case, the definition of assurance becomes

$$\begin{aligned} Assurance &= E_{\lambda_1, \lambda_2, \mu_t, \kappa}(P'(H|\lambda_1, \lambda_2, \mu_t, \kappa)) \\ &= \int \int \int \int P'(H|\lambda_1, \lambda_2, \mu_t, \kappa) f_1(\lambda_1) f_2(\lambda_2) f_3(\mu_t) f_4(\kappa) d\lambda_1 d\lambda_2 d\mu_t d\kappa \end{aligned}$$

Using this definition, the assurance can be calculated using numerical integration. There are a variety of pre-programmed, univariate prior distributions available in **PASS**.

Fixed Values (No Prior) and Custom Values

For any given parameter, **PASS** also provides the option of entering a single fixed value for the prior distribution, or a series of values and corresponding probabilities (using the spreadsheet), rather than one of the pre-programmed distributions.

Numerical Integration in PASS (and Notes on Computation Speed)

When the prior distribution is specified as independent univariate distributions, **PASS** uses a numerical integration algorithm to compute the assurance value as follows:

The domain of each prior distribution is divided into M intervals. Since many of the available prior distributions are unbounded on one (e.g., Gamma) or both (e.g., Normal) ends, an approximation is made to make the domain finite. This is accomplished by truncating the distribution to a domain between the two quantiles: $q_{0.001}$ and $q_{0.999}$.

The value of M controls the accuracy and speed of the algorithm. If only one parameter is to be given a prior distribution, then a value of M between 50 and 100 usually gives an accurate result in a timely manner. However, if two parameters are given priors, the number of iterations needed increases from M to M^2 . For example, if M is 100, 10000 iterations are needed. Reducing M from 100 to 50 reduces the number of iterations from 10000 to 2500.

The algorithm runtime increases when searching for sample size rather than solving for assurance, as a search algorithm is employed in this case. When solving for sample size, we recommend reducing M to 20 or less while exploring various scenarios, and then increasing M to 50 or more for a final, more accurate, result.

List of Available Univariate Prior Distributions

This section lists the univariate prior distributions that may be used for any of the applicable parameters when the Prior Entry Method is set to Individual.

No Prior

If 'No Prior' is chosen for a parameter, the parameter is assumed to take on a single, fixed value with probability one.

Beta (Shape 1, Shape 2, a, c)

A random variable X that follows the beta distribution is defined on a finite interval $[a, c]$. Two shape parameters (α and β) control the shape of this distribution. Two location parameters a and c give the minimum and maximum of X .

The probability density function of the beta distribution is

$$f(x|\alpha, \beta, a, c) = \frac{\left(\frac{x-a}{c-a}\right)^{\alpha-1} \left(\frac{c-x}{c-a}\right)^{\beta-1}}{(c-a)B(\alpha, \beta)}$$

where $B(\alpha, \beta) = \Gamma(\alpha) \Gamma(\beta) / \Gamma(\alpha + \beta)$ and $\Gamma(z)$ is the gamma function.

The mean of X is

$$\mu_X = \frac{\alpha c + \beta a}{\alpha + \beta}$$

Various distribution shapes are controlled by the values of α and β . These include

Symmetric and Unimodal

$$\alpha = \beta > 1$$

U Shaped

$$\alpha = \beta < 1$$

Bimodal

$$\alpha, \beta < 1$$

Uniform

$$\alpha = \beta = 1$$

Parabolic

$$\alpha = \beta = 2$$

Bell-Shaped

$$\alpha = \beta > 2$$

Gamma (Shape, Scale)

A random variable X that follows the gamma distribution is defined on the interval $(0, \infty)$. A shape parameter, κ , and a scale parameter, θ , control the distribution.

The probability density function of the gamma distribution is

$$f(x|\kappa, \theta) = \frac{x^{\kappa-1} e^{-\frac{x}{\theta}}}{\theta^{\kappa} \Gamma(\kappa)}$$

where $\Gamma(z)$ is the gamma function.

The mean of X is

$$\mu_X = \frac{\kappa}{\theta}$$

A truncated version of the distribution is constructed by dividing the density by $1 - \text{Prob}(Min \leq X \leq Max)$ where Min and Max are two truncation bounds.

Inverse-Gamma (Shape, Scale)

A random variable X that follows the inverse-gamma distribution is defined on the interval $(0, \infty)$. If $Y \sim \text{gamma}$, then $X = 1 / Y \sim \text{inverse-gamma}$. A shape parameter, α , and a scale parameter, β , control the distribution.

The probability density function of the inverse-gamma distribution is

$$f(x|\alpha, \beta) = \frac{\beta^{\alpha} x^{\alpha-1} e^{-\frac{\beta}{x}}}{\Gamma(\alpha)}$$

where $\Gamma(z)$ is the gamma function.

The mean of X is

$$\mu_X = \frac{\beta}{\alpha - 1} \text{ for } \alpha > 1$$

A truncated version of the distribution is constructed by dividing the density by $1 - \text{Prob}(Min \leq X \leq Max)$ where Min and Max are two truncation bounds.

Logistic (Location, Scale)

A random variable X that follows the logistic distribution is defined on the interval $(-\infty, \infty)$. A location parameter, μ , and a scale parameter, s , control the distribution.

The probability density function of the logistic distribution is

$$f(x|\mu, s) = \frac{e^{-\frac{x-\mu}{s}}}{s \left(1 + e^{-\frac{x-\mu}{s}}\right)^2}$$

The mean of X is

$$\mu_X = \mu$$

A truncated version of the distribution is constructed by dividing the density by $1 - \text{Prob}(Min \leq X \leq Max)$ where Min and Max are two truncation bounds.

Lognormal (Mean, SD)

A random variable X that follows the lognormal distribution is defined on the interval $(0, \infty)$. A location parameter, $\mu_{\log(X)}$, and a scale parameter, $\sigma_{\log(X)}$, control the distribution. If $Z \sim$ standard normal, then $X = e^{\mu + \sigma Z} \sim$ lognormal. Note that $\mu_{\log(X)} = E(\log(X))$ and $\sigma_{\log(X)} = \text{Standard Deviation}(\log(X))$.

The probability density function of the lognormal distribution is

$$f(x|\mu, \sigma) = \frac{e^{-\frac{1}{2}\left(\frac{\log x - \mu}{\sigma}\right)^2}}{x\sigma\sqrt{2\pi}}$$

The mean of X is

$$\mu_X = e^{\mu + \frac{\sigma^2}{2}}$$

A truncated version of the distribution is constructed by dividing the density by $1 - \text{Prob}(Min \leq X \leq Max)$ where Min and Max are two truncation bounds.

LogT (Mean, SD)

A random variable X that follows the logT distribution is defined on the interval $(0, \infty)$. A location parameter, $\mu_{\log(X)}$, a scale parameter, $\sigma_{\log(X)}$, and a shape parameter, ν , control the distribution. Note that ν is referred to as the *degrees of freedom*.

If $t \sim \text{Student's } t$, then $X = e^{\mu + \sigma t} \sim \text{logT}$.

The probability density function of the logT distribution is

$$f(x|\mu, \sigma, \nu) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{x\Gamma\left(\frac{\nu}{2}\right)\sigma\sqrt{\nu\pi}} \left(1 + \frac{1}{\nu} \left(\frac{\log x - \mu}{\sigma}\right)^2\right)^{\left(\frac{-\nu-1}{2}\right)}$$

The mean of X is not defined.

A truncated version of the distribution is constructed by dividing the density by $1 - \text{Prob}(\text{Min} \leq X \leq \text{Max})$ where Min and Max are two truncation bounds.

Normal (Mean, SD)

A random variable X that follows the normal distribution is defined on the interval $(-\infty, \infty)$. A location parameter, μ , and a scale parameter, σ , control the distribution.

The probability density function of the normal distribution is

$$f(x|\mu, \sigma) = \frac{e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}}{\sigma\sqrt{2\pi}}$$

The mean of X is

$$\mu_X = \mu$$

A truncated version of the distribution is constructed by dividing the density by $1 - \text{Prob}(\text{Min} \leq X \leq \text{Max})$ where Min and Max are two truncation bounds.

T (Mean, SD, DF)

A random variable X that follows Student's t distribution is defined on the interval $(-\infty, \infty)$. A location parameter, μ , a scale parameter, σ , and a shape parameter, ν , control the distribution. Note that ν is referred to as the *degrees of freedom* or *DF*.

The probability density function of the Student's t distribution is

$$f(x|\mu, \sigma, \nu) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sigma\sqrt{\nu\pi}} \left(1 + \frac{1}{\nu} \left(\frac{x-\mu}{\sigma}\right)^2\right)^{\left(\frac{-\nu-1}{2}\right)}$$

The mean of X is μ if $\nu > 1$.

A truncated version of the distribution is constructed by dividing the density by $1 - \text{Prob}(\text{Min} \leq X \leq \text{Max})$ where Min and Max are two truncation bounds.

Triangle (Mode, Min, Max)

Let a = minimum, b = maximum, and c = mode. A random variable X that follows a triangle distribution is defined on the interval (a, b) .

The probability density function of the triangle distribution is

$$f(x|a, b, c) = \begin{cases} \frac{2(x-a)}{(b-a)(c-a)} & \text{for } a \leq x < c \\ \frac{2}{b-a} & \text{for } x = c \\ \frac{2(b-x)}{(b-a)(b-c)} & \text{for } c < x \leq b \end{cases}$$

The mean of X is

$$\frac{a + b + c}{3}$$

Uniform (Min, Max)

Let a = minimum and b = maximum. A random variable X that follows a uniform distribution is defined on the interval $[a, b]$.

The probability density function of the uniform distribution is

$$f(x|a, b) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq x \leq b \end{cases}$$

The mean of X is

$$\frac{a + b}{2}$$

Weibull (Shape, Scale)

A random variable X that follows the Weibull distribution is defined on the interval $(0, \infty)$. A shape parameter, κ , and a scale parameter, λ , control the distribution.

The probability density function of the Weibull distribution is

$$f(x|\kappa, \lambda) = \frac{\kappa}{\lambda} \left(\frac{x}{\lambda}\right)^{\kappa-1} e^{-\left(\frac{x}{\lambda}\right)^\kappa}$$

The mean of X is

$$\mu_X = \kappa \Gamma\left(1 + \frac{1}{\kappa}\right)$$

A truncated version of the distribution is constructed by dividing the density by $1 - \text{Prob}(\text{Min} \leq X \leq \text{Max})$ where Min and Max are two truncation bounds.

Custom (Values and Probabilities in Spreadsheet)

This custom prior distribution is represented by a set of user-specified points and associated probabilities, entered in two columns of the spreadsheet. The points make up the entire set of values that are used for this parameter in the calculation of assurance. The associated probabilities should sum to one. Note that custom values and probabilities can be used to approximate any continuous distribution.

For example, a prior distribution of X might be

X_i	P_i
10	0.2
20	0.2
30	0.3
40	0.2
50	0.1

In this example, the mean of X is

$$\mu_X = \sum_{i=1}^5 X_i P_i$$

Example 1 – Assurance Over a Range of Sample Sizes

Researchers wish to compare two drugs to determine whether there is a meaningful difference in the event rates as measured by their event rate ratio. In this case, higher rates are worse. They will analyze the data using a negative binomial regression model. The one-sided test of the regression coefficient identifying the treatment group will have a significance level of 0.025.

To complete their sample size study, the researchers want to run an assurance analysis for a range of group sample sizes from 100 to 500. An elicitation exercise determined that $\lambda_1 \sim N(1.4, 0.05^2)$, $\lambda_2 \sim N(0.9, 0.15^2)$, $\mu_t \sim N(1.0, 0.03^2)$, and $\kappa \sim N(1.8, 0.04^2)$.

Setup

If the procedure window is not already open, use the PASS Home window to open it. The parameters 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.

Design Tab

Solve For	Assurance
Prior Entry Method	Individual (Enter a prior distribution for each applicable parameter)
Alternative Hypothesis	One-Sided (H1: $\lambda_2 / \lambda_1 < 1$)
Null Variance Calculation Method	Use True Event Rates (λ_1 and λ_2)
Alpha	0.025
Prior Distribution of $\mu(t)$	Normal (Mean, SD)
Mean	1
SD	0.03
Truncation Boundaries	None
Group Allocation	Equal (N1 = N2)
Sample Size Per Group	100 200 300 400 500
Prior Distribution of λ_1	Normal (Mean, SD)
Mean	1.4
SD	0.05
Truncation Boundaries	None
Prior Distribution of λ_2	Normal (Mean, SD)
Mean	0.9
SD	0.15
Truncation Boundaries	None
Prior Distribution of κ	Normal (Mean, SD)
Mean	1.8
SD	0.04
Truncation Boundaries	None

Options Tab

Number of Computation Points for each	20
Prior Distribution	
Maximum N1 in Sample Size Search	5000

Output

Click the Calculate button to perform the calculations and generate the following output.

Numeric Reports

Numeric Results

Solve For: [Assurance](#)
Hypotheses: $H_0: \lambda_2 / \lambda_1 \geq 1$ vs. $H_1: \lambda_2 / \lambda_1 < 1$
Null Variance Calculation Method: Use the assumed true event rates (λ_1 and λ_2)
Prior Type: Independent Univariate Distributions

Prior Distributions

$\mu(t)$: Normal (Mean = 1, SD = 0.03).
 λ_1 : Normal (Mean = 1.4, SD = 0.05).
 λ_2 : Normal (Mean = 0.9, SD = 0.15).
 κ : Normal (Mean = 1.8, SD = 0.04).

Assurance*	Power†	Sample Size			Expected Average Exposure Time $E(\mu(t))$	Expected Event Rate Group 1 $E(\lambda_1)$	Expected Event Rate Group 2 $E(\lambda_2)$	Rate Ratio RR	Expected Dispersion $E(\kappa)$	Alpha
		N1	N2	N						
0.48822	0.47485	100	100	200	1	1.4	0.9	0.64286	1.8	0.025
0.70487	0.76505	200	200	400	1	1.4	0.9	0.64286	1.8	0.025
0.81030	0.90750	300	300	600	1	1.4	0.9	0.64286	1.8	0.025
0.86770	0.96666	400	400	800	1	1.4	0.9	0.64286	1.8	0.025
0.90202	0.98874	500	500	1000	1	1.4	0.9	0.64286	1.8	0.025

* The number of points used for computation of the prior(s) was 20.

† Power was calculated using $\lambda_1 = E(\lambda_1) = 1.4$, $\lambda_2 = E(\lambda_2) = 0.9$, $\mu(t) = E(\mu(t)) = 1$, and $\kappa = E(\kappa) = 1.8$.

Assurance The expected power where the expectation is with respect to the prior distribution(s).
Power The power calculated using the parameter values shown in the footnote. Note that these parameter values may be different from those shown in the report.
N1 The number of subjects in group 1.
N2 The number of subjects in group 2.
N The total sample size. $N = N1 + N2$.
 $E(\mu(t))$ The expected value over its prior distribution of the average exposure time across subjects in both groups.
 $E(\lambda_1)$ The expected value over its prior distribution of the group 1 mean event rate.
 $E(\lambda_2)$ The expected value over its prior distribution of the group 2 mean event rate.
RR The ratio of the average event rates (λ_2 / λ_1).
 $E(\kappa)$ The expected value over its prior distribution of the dispersion parameter.
Alpha The probability of rejecting a true null hypothesis.

Summary Statements

A parallel two-group design will be used to test whether the Group 2 (treatment) event rate is less than the Group 1 (control) event rate ($H_0: \lambda_2 / \lambda_1 \geq 1$ versus $H_1: \lambda_2 / \lambda_1 < 1$). The comparison will be made using a one-sided, two-sample negative binomial regression coefficient test of the rate ratio, with a Type I error rate (α) of 0.025. The variance of the regression coefficient to be tested will be calculated using the assumed true event rates (λ_1 and λ_2). The prior distribution used for the Group 1 event rate is Normal (Mean = 1.4, SD = 0.05). The prior distribution used for the Group 2 event rate is Normal (Mean = 0.9, SD = 0.15). The prior distribution used for the average exposure time is Normal (Mean = 1, SD = 0.03). The prior distribution used for the dispersion factor is Normal (Mean = 1.8, SD = 0.04). With sample sizes of 100 for Group 1 (control) and 100 for Group 2 (treatment), the assurance (average power) is 0.48822.

Assurance for Tests for the Ratio of Two Negative Binomial Rates

Dropout-Inflated Sample Size

Dropout Rate	Sample Size			Dropout-Inflated Enrollment Sample Size			Expected Number of Dropouts		
	N1	N2	N	N1'	N2'	N'	D1	D2	D
20%	100	100	200	125	125	250	25	25	50
20%	200	200	400	250	250	500	50	50	100
20%	300	300	600	375	375	750	75	75	150
20%	400	400	800	500	500	1000	100	100	200
20%	500	500	1000	625	625	1250	125	125	250

Dropout Rate	The percentage of subjects (or items) that are expected to be lost at random during the course of the study and for whom no response data will be collected (i.e., will be treated as "missing"). Abbreviated as DR.
N1, N2, and N	The evaluable sample sizes at which power is computed (as entered by the user). If N1 and N2 subjects are evaluated out of the N1' and N2' subjects that are enrolled in the study, the design will achieve the stated power.
N1', N2', and N'	The number of subjects that should be enrolled in the study in order to obtain N1, N2, and N evaluable subjects, based on the assumed dropout rate. N1' and N2' are calculated by inflating N1 and N2 using the formulas $N1' = N1 / (1 - DR)$ and $N2' = N2 / (1 - DR)$, with N1' and N2' always rounded up. (See Julious, S.A. (2010) pages 52-53, or Chow, S.C., Shao, J., Wang, H., and Lohknygina, Y. (2018) pages 32-33.)
D1, D2, and D	The expected number of dropouts. $D1 = N1' - N1$, $D2 = N2' - N2$, and $D = D1 + D2$.

Dropout Summary Statements

Anticipating a 20% dropout rate, 125 subjects should be enrolled in Group 1, and 125 in Group 2, to obtain final group sample sizes of 100 and 100, respectively.

References

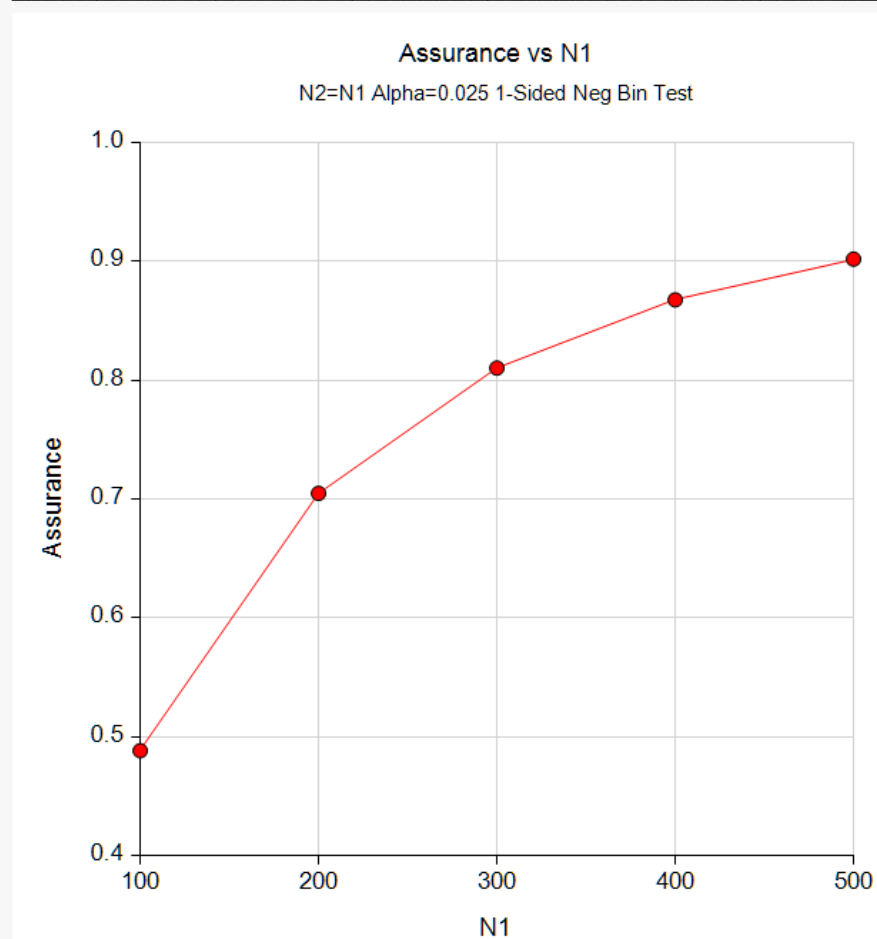
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- Zhu, H. 2017. 'Sample Size Calculation for Comparing Two Poisson or Negative Binomial Rates in Non-Inferiority or Equivalence Trials.' Statistics in Biopharmaceutical Research, 9(1), 107-115, doi:10.1080/19466315.2016.1225594.
- Zhu, H. and Lakkis, H. 2014. 'Sample Size Calculation for Comparing Two Negative Binomial Rates.' Statistics in Medicine, Volume 33, Pages 376-387.

This report shows the assurance values obtained by the various sample sizes.

Assurance for Tests for the Ratio of Two Negative Binomial Rates

Plots Section

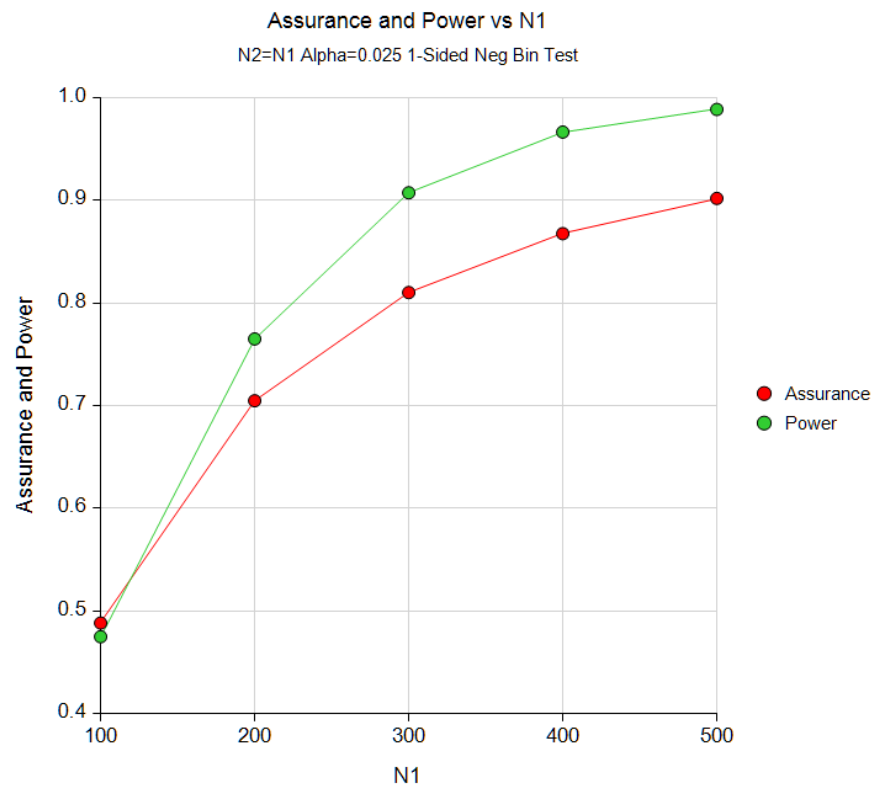
Plots



This plot shows the relationship between the assurance and sample size. Note the diminishing impact on assurance of each increase in the number of subjects.

Comparison Plots Section

Comparison Plots



This plot compares the assurance and power across values of sample size. Note that assurance does not increase nearly as fast as power.

Example 2 – Validation using Hand Computation

We could not find a validation example in the literature, so we have developed a validation example of our own. Suppose a one-sided test is used in which $N1 = N2 = 200$ and the significance level is 0.025.

The prior distribution of λ_1 is approximated by the following table.

λ_1	Prob
1.3	0.4
1.5	0.6

The prior distribution of λ_2 is approximated by the following table.

λ_2	Prob
0.6	0.4
1.2	0.6

The prior distribution of $\mu(t)$ is approximated by the following table.

$\mu(t)$	Prob
0.94	0.5
1.06	0.5

The prior distribution of κ is approximated by the following table.

κ	Prob
1.72	0.5
1.88	0.5

The *Tests for the Ratio of Two Negative Binomial Rates* procedure is used to compute the power for each of the 16 combinations of the four parameters. The results of these calculations are shown next.

Numeric Results

Solve For: [Power](#)
 Alternative Hypothesis: One-Sided ($H_0: RR \geq 1$ vs. $H_a: RR < 1$)
 Null Variance Calculation Method: Use True Event Rates (λ_1 and λ_2)

Power	Sample Size			Average Exposure Time $\mu(t)$	Average Event Rate		Event Rate Ratio RR	Negative Binomial Dispersion κ	Alpha
	N1	N2	N		λ_1	λ_2			
0.99366	200	200	400	0.94	1.3	0.6	0.46154	1.72	0.025
0.99132	200	200	400	0.94	1.3	0.6	0.46154	1.88	0.025
0.07202	200	200	400	0.94	1.3	1.2	0.92308	1.72	0.025
0.07001	200	200	400	0.94	1.3	1.2	0.92308	1.88	0.025
0.99962	200	200	400	0.94	1.5	0.6	0.40000	1.72	0.025
0.99937	200	200	400	0.94	1.5	0.6	0.40000	1.88	0.025
0.28989	200	200	400	0.94	1.5	1.2	0.80000	1.72	0.025
0.27547	200	200	400	0.94	1.5	1.2	0.80000	1.88	0.025
0.99540	200	200	400	1.06	1.3	0.6	0.46154	1.72	0.025
0.99348	200	200	400	1.06	1.3	0.6	0.46154	1.88	0.025
0.07335	200	200	400	1.06	1.3	1.2	0.92308	1.72	0.025
0.07119	200	200	400	1.06	1.3	1.2	0.92308	1.88	0.025

Assurance for Tests for the Ratio of Two Negative Binomial Rates

0.99976	200	200	400	1.06	1.5	0.6	0.40000	1.72	0.025
0.99959	200	200	400	1.06	1.5	0.6	0.40000	1.88	0.025
0.29883	200	200	400	1.06	1.5	1.2	0.80000	1.72	0.025
0.28340	200	200	400	1.06	1.5	1.2	0.80000	1.88	0.025

The assurance calculation is made by summing the quantities

$$\left[(power_{i,j,k,l}) (p(\lambda_{1i})) (p(\lambda_{2j})) (p(\mu_k)) (p(\kappa_l)) \right]$$

as follows

$$\begin{aligned} Assurance &= (0.99366 \times 0.4 \times 0.4 \times 0.5 \times 0.5) + (0.99132 \times 0.4 \times 0.4 \times 0.5 \times 0.5) + \dots \\ &\quad + (0.28340 \times 0.6 \times 0.6 \times 0.5 \times 0.5) \\ &= 0.51933 \end{aligned}$$

To run this example, the spreadsheet will need to be loaded with the following eight columns in which the first two are for λ_1 , the second two are for λ_2 , and so on.

C1	C2	C3	C4	C5	C6	C7	C8
1.3	0.4	0.6	0.4	0.94	0.5	1.72	0.5
1.5	0.6	1.2	0.6	1.06	0.5	1.88	0.5

Setup

If the procedure window is not already open, use the PASS Home window to open it. The parameters for this example are listed below and are stored in the **Example 2** settings file. To load these settings to the procedure window, click **Open Example Settings File** in the Help Center or File menu.

Design Tab

Solve For	Assurance
Prior Entry Method	Individual (Enter a prior distribution for each applicable parameter)
Alternative Hypothesis	One-Sided (H1: $\lambda_2 / \lambda_1 < 1$)
Null Variance Calculation Method	Use True Event Rates (λ_1 and λ_2)
Alpha	0.025
Prior Distribution of $\mu(t)$	Custom (Values and Probabilities in Spreadsheet)
Column of Values	C5
Column of Pr(Values)	C6
Group Allocation	Equal (N1 = N2)
Sample Size Per Group	200
Prior Distribution of λ_1	Custom (Values and Probabilities in Spreadsheet)
Column of Values	C1
Column of Pr(Values)	C2
Prior Distribution of λ_2	Custom (Values and Probabilities in Spreadsheet)
Column of Values	C3
Column of Pr(Values)	C4

Assurance for Tests for the Ratio of Two Negative Binomial Rates

Prior Distribution of κ**Custom (Values and Probabilities in Spreadsheet)**Column of Values**C7**Column of Pr(Values).....**C8**

Options Tab

Number of Computation Points for each.....**20**

Prior Distribution

Maximum N1 in Sample Size Search**5000**

Input Spreadsheet Data

Row	C1	C2	C3	C4	C5	C6	C7	C8
1	1.3	0.4	0.6	0.4	0.94	0.5	1.72	0.5
2	1.5	0.6	1.2	0.6	1.06	0.5	1.88	0.5

Output

Click the Calculate button to perform the calculations and generate the following output.

Numeric Results

Solve For: [Assurance](#)
Hypotheses: $H_0: \lambda_2 / \lambda_1 \geq 1$ vs. $H_1: \lambda_2 / \lambda_1 < 1$
Null Variance Calculation Method: Use the assumed true event rates (λ_1 and λ_2)
Prior Type: Independent Univariate Distributions

Prior Distributions

 $\mu(t)$: Point List (Values = C5, Probs = C6).

C5: 0.94 1.06

C6: 0.5 0.5

 λ_1 : Point List (Values = C1, Probs = C2).

C1: 1.3 1.5

C2: 0.4 0.6

 λ_2 : Point List (Values = C3, Probs = C4).

C3: 0.6 1.2

C4: 0.4 0.6

 κ : Point List (Values = C7, Probs = C8).

C7: 1.72 1.88

C8: 0.5 0.5

Assurance	Power‡	Sample Size			Expected Average Exposure Time $E(\mu(t))$	Expected Event Rate Group 1 $E(\lambda_1)$	Expected Event Rate Group 2 $E(\lambda_2)$	Rate Ratio RR	Expected Dispersion $E(\kappa)$	Alpha
		N1	N2	N						
0.51933	0.66805	200	200	400	1	1.42	0.96	0.67606	1.8	0.025

‡ Power was calculated using $\lambda_1 = E(\lambda_1) = 1.42$, $\lambda_2 = E(\lambda_2) = 0.96$, $\mu(t) = E(\mu(t)) = 1$, and $\kappa = E(\kappa) = 1.8$.

PASS has also calculated the assurance as 0.51933 which validates the procedure.

Example 3 – Finding the Sample Size Needed to Achieve a Specified Assurance

Continuing with Example 1, the researchers want to investigate the sample sizes necessary to achieve assurances of 0.4, 0.5, 0.6, 0.7, and 0.8.

Setup

If the procedure window is not already open, use the PASS Home window to open it. The parameters for this example are listed below and are stored in the **Example 3** settings file. To load these settings to the procedure window, click **Open Example Settings File** in the Help Center or File menu.

Design Tab

Solve For	Sample Size
Prior Entry Method	Individual (Enter a prior distribution for each applicable parameter)
Alternative Hypothesis	One-Sided ($H_1: \lambda_2 / \lambda_1 < 1$)
Null Variance Calculation Method	Use True Event Rates (λ_1 and λ_2)
Assurance	0.4 0.5 0.6 0.7 0.8
Alpha	0.025
Prior Distribution of $\mu(t)$	Normal (Mean, SD)
Mean	1
SD	0.03
Truncation Boundaries	None
Group Allocation	Equal ($N_1 = N_2$)
Prior Distribution of λ_1	Normal (Mean, SD)
Mean	1.4
SD	0.05
Truncation Boundaries	None
Prior Distribution of λ_2	Normal (Mean, SD)
Mean	0.9
SD	0.15
Truncation Boundaries	None
Prior Distribution of κ	Normal (Mean, SD)
Mean	1.8
SD	0.04
Truncation Boundaries	None

Options Tab

Number of Computation Points for each	20
Prior Distribution	
Maximum N_1 in Sample Size Search	5000

Output

Click the Calculate button to perform the calculations and generate the following output.

Numeric Reports

Numeric Results

Solve For: [Sample Size](#)
Hypotheses: $H_0: \lambda_2 / \lambda_1 \geq 1$ vs. $H_1: \lambda_2 / \lambda_1 < 1$
Null Variance Calculation Method: Use the assumed true event rates (λ_1 and λ_2)
Prior Type: Independent Univariate Distributions

Prior Distributions

$\mu(t)$: Normal (Mean = 1, SD = 0.03).
 λ_1 : Normal (Mean = 1.4, SD = 0.05).
 λ_2 : Normal (Mean = 0.9, SD = 0.15).
 κ : Normal (Mean = 1.8, SD = 0.04).

Assurance	Power‡	Sample Size			Expected Average Exposure Time $E(\mu(t))$	Expected Event Rate Group 1 $E(\lambda_1)$	Expected Event Rate Group 2 $E(\lambda_2)$	Rate Ratio RR	Expected Dispersion $E(\kappa)$	Alpha
		N1	N2	N						
0.40188	0.37554	75	75	150	1	1.4	0.9	0.64286	1.8	0.025
0.50052	0.48982	104	104	208	1	1.4	0.9	0.64286	1.8	0.025
0.60201	0.62111	143	143	286	1	1.4	0.9	0.64286	1.8	0.025
0.70047	0.75880	197	197	394	1	1.4	0.9	0.64286	1.8	0.025
0.80011	0.89500	287	287	574	1	1.4	0.9	0.64286	1.8	0.025

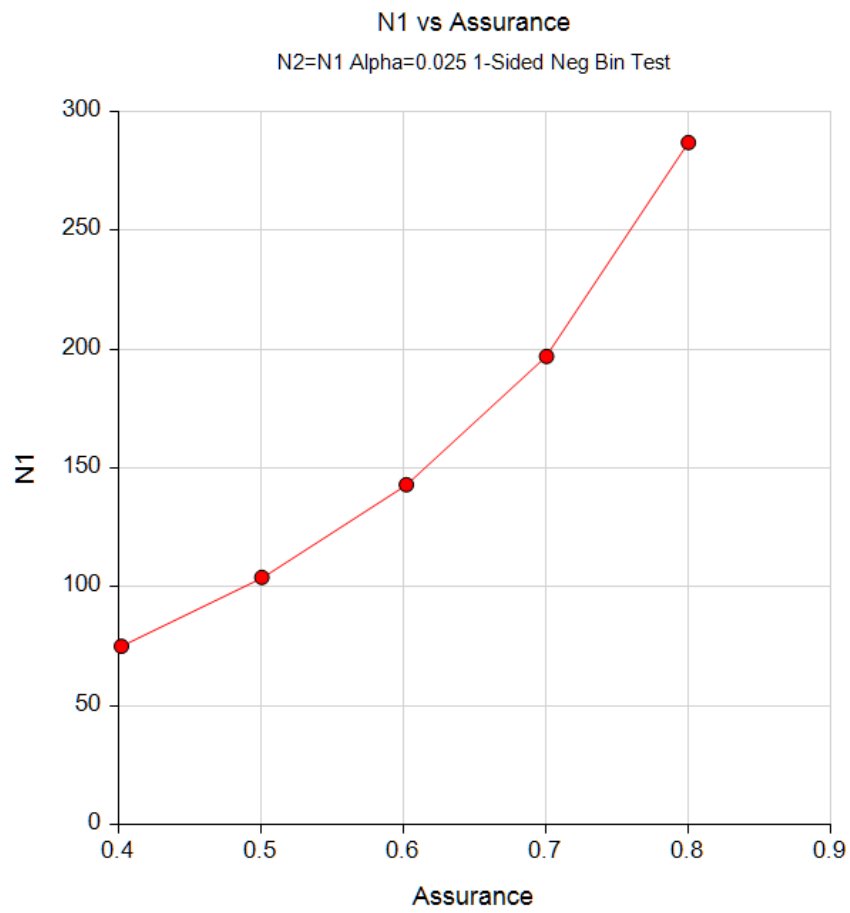
* The number of points used for computation of the prior(s) was 20.

‡ Power was calculated using $\lambda_1 = E(\lambda_1) = 1.4$, $\lambda_2 = E(\lambda_2) = 0.9$, $\mu(t) = E(\mu(t)) = 1$, and $\kappa = E(\kappa) = 1.8$.

This report shows the required sample size for each assurance target.

Plots Section

Plots



This plot shows the relationship between the sample size and assurance.

Example 4 – Joint Prior Distribution

The following example shows the complexity required to specify a joint distribution for four parameters.

Suppose a one-sided test will be used in which $N_1 = N_2 = 200$ and the significance level is 0.025.

Further suppose that the joint prior distribution of the λ_1 (control), λ_2 (treatment), $\mu(t)$, and κ is approximated by the following table. In a real study, the values in this table would be provided by an elicitation study.

Note that the program will rescale the probabilities so they sum to one.

λ_1	λ_2	$\mu(t)$	κ	Prob
1.3	0.6	0.94	1.72	0.03
1.3	0.6	0.94	1.88	0.06
1.3	1.2	0.94	1.72	0.08
1.3	1.2	0.94	1.88	0.09
1.5	0.6	0.94	1.72	0.13
1.5	0.6	0.94	1.88	0.06
1.5	1.2	0.94	1.72	0.08
1.5	1.2	0.94	1.88	0.09
1.3	0.6	1.06	1.72	0.12
1.3	0.6	1.06	1.88	0.06
1.3	1.2	1.06	1.72	0.08
1.3	1.2	1.06	1.88	0.09
1.5	0.6	1.06	1.72	0.14
1.5	0.6	1.06	1.88	0.06
1.5	1.2	1.06	1.72	0.08
1.5	1.2	1.06	1.88	0.09

To run this example, the spreadsheet will need to be loaded with the following five columns.

<u>C1</u>	<u>C2</u>	<u>C3</u>	<u>C4</u>	<u>C5</u>
1.3	0.6	0.94	1.72	0.03
1.3	0.6	0.94	1.88	0.06
1.3	1.2	0.94	1.72	0.08
1.3	1.2	0.94	1.88	0.09
1.5	0.6	0.94	1.72	0.13
1.5	0.6	0.94	1.88	0.06
1.5	1.2	0.94	1.72	0.08
1.5	1.2	0.94	1.88	0.09
1.3	0.6	1.06	1.72	0.12
1.3	0.6	1.06	1.88	0.06
1.3	1.2	1.06	1.72	0.08
1.3	1.2	1.06	1.88	0.09
1.5	0.6	1.06	1.72	0.14
1.5	0.6	1.06	1.88	0.06
1.5	1.2	1.06	1.72	0.08
1.5	1.2	1.06	1.88	0.09

Setup

If the procedure window is not already open, use the PASS Home window to open it. The parameters for this example are listed below and are stored in the **Example 4** settings file. To load these settings to the procedure window, click **Open Example Settings File** in the Help Center or File menu.

Design Tab

Solve For **Assurance**
 Prior Entry Method **Combined (Enter parameter values and probabilities on spreadsheet)**
 Alternative Hypothesis **One-Sided ($H_1: \lambda_2 / \lambda_1 < 1$)**
 Null Variance Calculation Method **Use True Event Rates (λ_1 and λ_2)**
 Alpha **0.025**
 Column of $\mu(t)$ Values **C3**
 Group Allocation **Equal ($N_1 = N_2$)**
 Sample Size Per Group **200**
 Column of λ_1 Values **C1**
 Column of λ_2 Values **C2**
 Column of κ Values **C4**
 Column of Pr(Values) **C5**

Options Tab

Number of Computation Points for each **20**
 Prior Distribution
 Maximum N_1 in Sample Size Search **5000**

Input Spreadsheet Data

Row	C1	C2	C3	C4	C5
1	1.3	0.6	0.94	1.72	0.03
2	1.3	0.6	0.94	1.88	0.06
3	1.3	1.2	0.94	1.72	0.08
4	1.3	1.2	0.94	1.88	0.09
5	1.5	0.6	0.94	1.72	0.13
6	1.5	0.6	0.94	1.88	0.06
7	1.5	1.2	0.94	1.72	0.08
8	1.5	1.2	0.94	1.88	0.09
9	1.3	0.6	1.06	1.72	0.12
10	1.3	0.6	1.06	1.88	0.06
11	1.3	1.2	1.06	1.72	0.08
12	1.3	1.2	1.06	1.88	0.09
13	1.5	0.6	1.06	1.72	0.14
14	1.5	0.6	1.06	1.88	0.06
15	1.5	1.2	1.06	1.72	0.08
16	1.5	1.2	1.06	1.88	0.09

Assurance for Tests for the Ratio of Two Negative Binomial Rates

Output

Click the Calculate button to perform the calculations and generate the following output.

Numeric Results

Solve For: [Assurance](#)
Hypotheses: $H_0: \lambda_2 / \lambda_1 \geq 1$ vs. $H_1: \lambda_2 / \lambda_1 < 1$
Null Variance Calculation Method: Use the assumed true event rates (λ_1 and λ_2)
Prior Type: Joint Multivariate Distribution

Prior Distribution

Point Lists

λ_1 : C1: 1.3 1.3 1.3 1.3 1.5 1.5 1.5 1.5 1.3 1.3 1.3 1.3 1.5 1.5 1.5 1.5
 λ_2 : C2: 0.6 0.6 1.2 1.2 0.6 0.6 1.2 1.2 0.6 0.6 1.2 1.2 0.6 0.6 1.2 1.2
 $\mu(t)$: C3: 0.94 0.94 0.94 0.94 0.94 0.94 0.94 0.94 1.06 1.06 1.06 1.06 1.06 1.06 1.06 1.06
 κ : C4: 1.72 1.88 1.72 1.88 1.72 1.88 1.72 1.88 1.72 1.88 1.72 1.88 1.72 1.88 1.72 1.88
Prob: C5: 0.03 0.06 0.08 0.09 0.13 0.06 0.08 0.09 0.12 0.06 0.08 0.09 0.14 0.06 0.08 0.09

Assurance	Power‡	Sample Size			Expected Average Exposure Time $E(\mu(t))$	Expected Event Rate		Rate Ratio RR	Expected Dispersion $E(\kappa)$	Alpha
		N1	N2	N		Group 1 $E(\lambda_1)$	Group 2 $E(\lambda_2)$			
0.58204	0.77032	200	200	400	1.00448	1.40896	0.90448	0.64195	1.79164	0.025

PASS has calculated the assurance as 0.58204.

Example 5 – Joint Prior Validation

The problem given in Example 2 will be used to validate the joint prior distribution method. This will be done by running the independent-prior scenario used in that example through the joint-prior method and checking that the assurance values match.

The joint prior distribution can be found by multiplying the four independent probabilities in each row. This results in the following discrete probability distribution.

λ_1	λ_2	$\mu(t)$	κ	Prob
1.3	0.6	0.94	1.72	0.04
1.3	0.6	0.94	1.88	0.04
1.3	1.2	0.94	1.72	0.06
1.3	1.2	0.94	1.88	0.06
1.5	0.6	0.94	1.72	0.06
1.5	0.6	0.94	1.88	0.06
1.5	1.2	0.94	1.72	0.09
1.5	1.2	0.94	1.88	0.09
1.3	0.6	1.06	1.72	0.04
1.3	0.6	1.06	1.88	0.04
1.3	1.2	1.06	1.72	0.06
1.3	1.2	1.06	1.88	0.06
1.5	0.6	1.06	1.72	0.06
1.5	0.6	1.06	1.88	0.06
1.5	1.2	1.06	1.88	0.09

To run this example, the spreadsheet is loaded with the following five columns.

C1	C2	C3	C4	C5
1.3	0.6	0.94	1.72	0.04
1.3	0.6	0.94	1.88	0.04
1.3	1.2	0.94	1.72	0.06
1.3	1.2	0.94	1.88	0.06
1.5	0.6	0.94	1.72	0.06
1.5	0.6	0.94	1.88	0.06
1.5	1.2	0.94	1.72	0.09
1.5	1.2	0.94	1.88	0.09
1.3	0.6	1.06	1.72	0.04
1.3	0.6	1.06	1.88	0.04
1.3	1.2	1.06	1.72	0.06
1.3	1.2	1.06	1.88	0.06
1.5	0.6	1.06	1.72	0.06
1.5	0.6	1.06	1.88	0.06
1.5	1.2	1.06	1.88	0.09

Setup

If the procedure window is not already open, use the PASS Home window to open it. The parameters for this example are listed below and are stored in the **Example 5** settings file. To load these settings to the procedure window, click **Open Example Settings File** in the Help Center or File menu.

Design Tab

Solve For **Assurance**
 Prior Entry Method **Combined (Enter parameter values and probabilities on spreadsheet)**
 Alternative Hypothesis **One-Sided ($H_1: \lambda_2 / \lambda_1 < 1$)**
 Null Variance Calculation Method **Use True Event Rates (λ_1 and λ_2)**
 Alpha **0.025**
 Column of $\mu(t)$ Values **C3**
 Group Allocation **Equal ($N_1 = N_2$)**
 Sample Size Per Group **200**
 Column of λ_1 Values **C1**
 Column of λ_2 Values **C2**
 Column of κ Values **C4**
 Column of Pr(Values) **C5**

Options Tab

Number of Computation Points for each **20**
 Prior Distribution
 Maximum N_1 in Sample Size Search **5000**

Input Spreadsheet Data

Row	C1	C2	C3	C4	C5
1	1.3	0.6	0.94	1.72	0.04
2	1.3	0.6	0.94	1.88	0.04
3	1.3	1.2	0.94	1.72	0.06
4	1.3	1.2	0.94	1.88	0.06
5	1.5	0.6	0.94	1.72	0.06
6	1.5	0.6	0.94	1.88	0.06
7	1.5	1.2	0.94	1.72	0.09
8	1.5	1.2	0.94	1.88	0.09
9	1.3	0.6	1.06	1.72	0.04
10	1.3	0.6	1.06	1.88	0.04
11	1.3	1.2	1.06	1.72	0.06
12	1.3	1.2	1.06	1.88	0.06
13	1.5	0.6	1.06	1.72	0.06
14	1.5	0.6	1.06	1.88	0.06
15	1.5	1.2	1.06	1.72	0.09
16	1.5	1.2	1.06	1.88	0.09

Output

Click the Calculate button to perform the calculations and generate the following output.

Numeric Results

Solve For: [Assurance](#)
Hypotheses: $H_0: \lambda_2 / \lambda_1 \geq 1$ vs. $H_1: \lambda_2 / \lambda_1 < 1$
Null Variance Calculation Method: Use the assumed true event rates (λ_1 and λ_2)
Prior Type: Joint Multivariate Distribution

Prior Distribution

Point Lists

λ_1 : C1: 1.3 1.3 1.3 1.3 1.5 1.5 1.5 1.5 1.3 1.3 1.3 1.3 1.5 1.5 1.5 1.5
 λ_2 : C2: 0.6 0.6 1.2 1.2 0.6 0.6 1.2 1.2 0.6 0.6 1.2 1.2 0.6 0.6 1.2 1.2
 $\mu(t)$: C3: 0.94 0.94 0.94 0.94 0.94 0.94 0.94 0.94 1.06 1.06 1.06 1.06 1.06 1.06 1.06 1.06
 κ : C4: 1.72 1.88 1.72 1.88 1.72 1.88 1.72 1.88 1.72 1.88 1.72 1.88 1.72 1.88 1.72 1.88
Prob: C5: 0.04 0.04 0.06 0.06 0.06 0.06 0.09 0.09 0.04 0.04 0.06 0.06 0.06 0.06 0.09 0.09

Assurance	Power‡	Sample Size			Expected Average Exposure Time $E(\mu(t))$	Expected Event Rate		Rate Ratio RR	Expected Dispersion $E(\kappa)$	Alpha
		N1	N2	N		Group 1 $E(\lambda_1)$	Group 2 $E(\lambda_2)$			
0.51933	0.66805	200	200	400	1	1.42	0.96	0.67606	1.8	0.025

‡ Power was calculated using $\lambda_1 = E(\lambda_1) = 1.42$, $\lambda_2 = E(\lambda_2) = 0.96$, $\mu(t) = E(\mu(t)) = 1$, and $\kappa = E(\kappa) = 1.8$.

PASS has also calculated the assurance as 0.51933 which matches Example 2 and thus validates the procedure.