

Chapter 749

Assurance for Tests for Two Proportions in a Cluster-Randomized Design

Introduction

This procedure calculates the assurance of tests comparing the proportions of two groups (populations) when the data are collected in a cluster-randomized design. 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).

Cluster-randomized designs are often adopted when there is a high risk of contamination if cluster members were randomized individually. For example, it may be difficult for an instructor to use two methods of teaching individuals in the same class. The price of randomizing by clusters is a loss of efficiency--the number of subjects needed to obtain a certain level of precision in a cluster-randomized trial is usually much larger than the number needed when the subjects are randomized individually. Hence, the standard methods of sample size estimation cannot be used.

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.

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).

Two-Sample Z-Test of Proportions

Our formulation comes from Donner and Klar (2000). Denote a binary observation by Y_{gkm} where $g = 1$ or 2 is the group, $k = 1, 2, \dots, K_g$ is a cluster within group g , and $m = 1, 2, \dots, M_g$ is an individual in cluster k of group g . The results that follow assume an equal number of individuals per cluster. When the number of subjects from cluster to cluster are about the same, the power and sample size values should be fairly accurate. In these cases, the average number of subjects per cluster can be used.

The statistical hypothesis that is tested concerns the difference between the two group proportions, P_1 and P_2 . When necessary, we assume that group 1 is the treatment group and group 2 is the control group. With a simple modification, all of the large-sample sample size formulas that are listed in the module for testing two proportions can be used here.

When the individual subjects are randomly assigned to one of the two groups, the variance of the sample proportion is

$$\sigma_{S,g}^2 = \frac{P_g(1 - P_g)}{N_g}$$

When the randomization is by clusters of subjects, the variance of the sample proportion is

$$\begin{aligned}\sigma_{C,g}^2 &= \frac{P_g(1 - P_g)(1 + (M_g - 1)\rho)}{K_g M_g} \\ &= \sigma_{S,g}^2 [1 + (M_g - 1)\rho] \\ &= F_{g,\rho} \sigma_{S,g}^2\end{aligned}$$

The factor $[1 + (M_g - 1)\rho]$ is called the *inflation factor*. The Greek letter ρ is used to represent the *intraclass correlation coefficient (ICC)*. This correlation may be thought of as the simple correlation between any two subjects within the same cluster. If we stipulate that ρ is positive, it may also be interpreted as the proportion of total variability that is attributable to differences between clusters. This value is critical to the sample size calculation.

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The asymptotic formulas that were used in comparing two proportions (see Chapter 200, “Tests for Two Proportions”) may be used with cluster-randomized designs as well, as long as an adjustment is made for the inflation factor. The basic form of the z-test becomes

$$z = \frac{|\hat{D} - \delta_0|}{\hat{\sigma}_{\hat{D}}(\delta_0)}$$

where

$$\hat{D} = \hat{p}_1 - \hat{p}_2$$

$$\delta_0 = P_1 - P_2 | H_0 = 0$$

$$\hat{\sigma}_{\hat{D}}(\delta_0) = \sqrt{\frac{\tilde{p}_1(1 - \tilde{p}_1)F_{1,\rho}}{N_1} + \frac{\tilde{p}_2(1 - \tilde{p}_2)F_{2,\rho}}{N_2}}$$

The quantities \tilde{p}_1 and \tilde{p}_2 are the maximum likelihood estimates constrained by $\tilde{p}_1 - \tilde{p}_2 = \delta_0$.

Power Calculations

A large sample approximation may be used that is most accurate when the values of N_1 and N_2 are large. The large approximation is made by replacing the values of \hat{p}_1 and \hat{p}_2 in the z-statistic with the corresponding values of P_1 and P_2 under the alternative hypothesis, and then computing the results based on the normal distribution.

Assurance Calculation

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

Let $P_p(H|P_1, P_2, \rho, M_1, M_2)$ be the power function described above where H is the event that null hypothesis is rejected conditional on the values of the parameters. The specification of the parameters 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. Hence, the definition of assurance is

$$\begin{aligned} \text{Assurance} &= E_{P_1, P_2, \rho, M_1, M_2} \left(P_p(H|P_1, P_2, \rho, M_1, M_2) \right) \\ &= \int \int \int \int \int P_p(H|P_1, P_2, \rho, M_1, M_2) f(P_1, P_2, \rho, M_1, M_2) dP_1 \dots dM_2 \end{aligned}$$

where $f(P_1, P_2, \rho, M_1, M_2)$ is the joint prior distribution of the 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 $f(P_1, P_2, \rho, M_1, M_2)$. This provides flexibility in specifying the joint prior distribution. In the five-parameter case, six columns are entered on the spreadsheet: five for the parameters and one more 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 distributions as follows:

$$f(P_1, P_2, \rho, M_1, M_2) = f_1(P_1)f_2(P_2)f_3(\rho)f_4(M_1)f_5(M_2)$$

where $f_1(P_1)$ is the prior distribution of P_1 and so forth. This method is also available in **PASS**. In this case, the definition of assurance becomes

$$\begin{aligned} \text{Assurance} &= E_{P_1, P_2, \rho, M_1, M_2} \left(P_p(H|P_1, P_2, \rho, M_1, M_2) \right) \\ &= \int \int \int \int \int P_p(H|P_1, P_2, \rho, M_1, M_2) f_1(P_1) f_2(P_2) f_3(\rho) f_4(M_1) f_5(M_2) dP_1 \dots dM_2 \end{aligned}$$

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 $1 - \text{Prob}(\text{Min} \leq X \leq \text{Max})$ 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 $1 - \text{Prob}(\text{Min} \leq X \leq \text{Max})$ 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

Suppose that a cluster randomized study is being planned in which $P1 = 0.6$; $P2 = 0.5$; $\rho = 0.02$; $M1$ and $M2 = 7$; $\alpha = 0.05$; and $K1$ and $K2$ is in the range 20 to 100. Power is to be calculated for a two-sided test.

To complete their sample size study, the researchers want to run an assurance analysis for a range of group sample sizes from 20 to 100. An elicitation exercise determined that the prior distribution of the $P1$ should be normal with mean 0.6 and standard deviation 0.05, the prior distribution of $P2$ should be a normal with mean 0.5 and standard deviation 0.03, the prior distribution of the ICC should be a normal with mean 0.02 and standard deviation 0.004, the prior distribution of the cluster size of group 1 should be a normal with mean 7 and standard deviation 1.5, and the prior distribution of the cluster size of group 2 should be a normal with mean 7 and standard deviation 1.5.

To reduce the runtime of this example, the number of computation points is set to 10. In practice, we recommend setting this value to 20 or more for the most accurate results.

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	Two-Sided (H1: $P1 - P2 \neq 0$)
Test Type	Z-Test (Pooled)
Alpha	0.05
K1 (Number of Clusters)	20 40 60 80 100
Prior Distribution of M1	Normal (Mean, SD)
Mean	7
SD	1.5
Truncation Boundaries	None
K2 (Number of Clusters)	K1
Prior Distribution of M2	Normal (Mean, SD)
Mean	7
SD	1.5
Truncation Boundaries	None
Prior Distribution of P1	Normal (Mean, SD)
Mean	0.6
SD	0.05
Truncation Boundaries	None
Prior Distribution of P2	Normal (Mean, SD)
Mean	0.5
SD	0.03
Truncation Boundaries	None

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Prior Distribution of ρ **Normal (Mean, SD)**Mean **0.02**SD **0.004**Truncation Boundaries **None**

Options Tab

Number of Computation Points for each **10**

Prior Distribution

Maximum K1 in Sample Size Search **1000**

Output

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

Numeric Reports

Numeric Results

Solve For: [Assurance](#)

Groups: 1 = Treatment, 2 = Control

Test Statistic: Z-Test (Pooled)

Hypotheses: $H_0: P_1 - P_2 = 0$ vs. $H_1: P_1 - P_2 \neq 0$

Prior Type: Individual Univariate Distributions

Prior Distributions

M1: Normal (Mean = 7, SD = 1.5).

M2: Normal (Mean = 7, SD = 1.5).

P1: Normal (Mean = 0.6, SD = 0.05).

P2: Normal (Mean = 0.5, SD = 0.03).

 ρ : Normal (Mean = 0.02, SD = 0.004).

Assurance*	Power‡	Sample Size			Number of Clusters			Cluster Size		Proportions		Intraclass Correlation E(ρ)	Alpha
		N1	N2	N	K1	K2	K	E(M1)	E(M2)	E(P1)	E(P2)		
0.39161	0.35485	140	140	280	20	20	40	7	7	0.6	0.5	0.02	0.05
0.56706	0.61366	280	280	560	40	40	80	7	7	0.6	0.5	0.02	0.05
0.66132	0.78712	420	420	840	60	60	120	7	7	0.6	0.5	0.02	0.05
0.71897	0.88961	560	560	1120	80	80	160	7	7	0.6	0.5	0.02	0.05
0.75768	0.94537	700	700	1400	100	100	200	7	7	0.6	0.5	0.02	0.05

* The number of points used for computation of the prior(s) was 10.

‡ Power was calculated using $M1 = E(M1) = 7$, $M2 = E(M2) = 7$, $P1 = E(P1) = 0.6$, $P2 = E(P2) = 0.5$, and $\rho = E(\rho) = 0.02$.

Assurance	The expected power where the expectation is with respect to the prior distribution(s).
Power	The power calculated using the means of the prior distributions as the values of the corresponding parameters.
N1	The number of subjects in group 1.
N2	The number of subjects in group 2.
N	The total sample size. $N = N1 + N2$.
K1	The number of clusters in group 1.
K2	The number of clusters in group 2.
K	The total number of clusters.
E(M1)	The expected average number of items (subjects) per cluster in group 1.
E(M2)	The expected average number of items (subjects) per cluster in group 2.
E(P1)	The expected response proportion in group 1 assumed by H_1 .
E(P2)	The expected response proportion in group 2.
E(ρ)	The expected intraclass correlation (ICC).
Alpha	The probability of rejecting a true null hypothesis.

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Summary Statements

A parallel two-group cluster-randomized design will be used to test whether the Group 1 (treatment) proportion (P_1) is different from the Group 2 (control) proportion (P_2) ($H_0: P_1 - P_2 = 0$ versus $H_1: P_1 - P_2 \neq 0$). The comparison will be made using a two-sided pooled variance Z-test with a Type I error rate (α) of 0.05. The prior distribution used for the average cluster size in Group 1 is Normal (Mean = 7, SD = 1.5). The prior distribution used for the average cluster size in Group 2 is Normal (Mean = 7, SD = 1.5). The prior distribution used for the response proportion in Group 1 is Normal (Mean = 0.6, SD = 0.05). The prior distribution used for the response proportion in Group 2 is Normal (Mean = 0.5, SD = 0.03). The prior distribution used for the intracluster correlation coefficient is Normal (Mean = 0.02, SD = 0.004). With 20 clusters (140 total subjects) in Group 1 (treatment) and 20 clusters (140 total subjects) in Group 2 (control), the assurance (average power) is 0.39161.

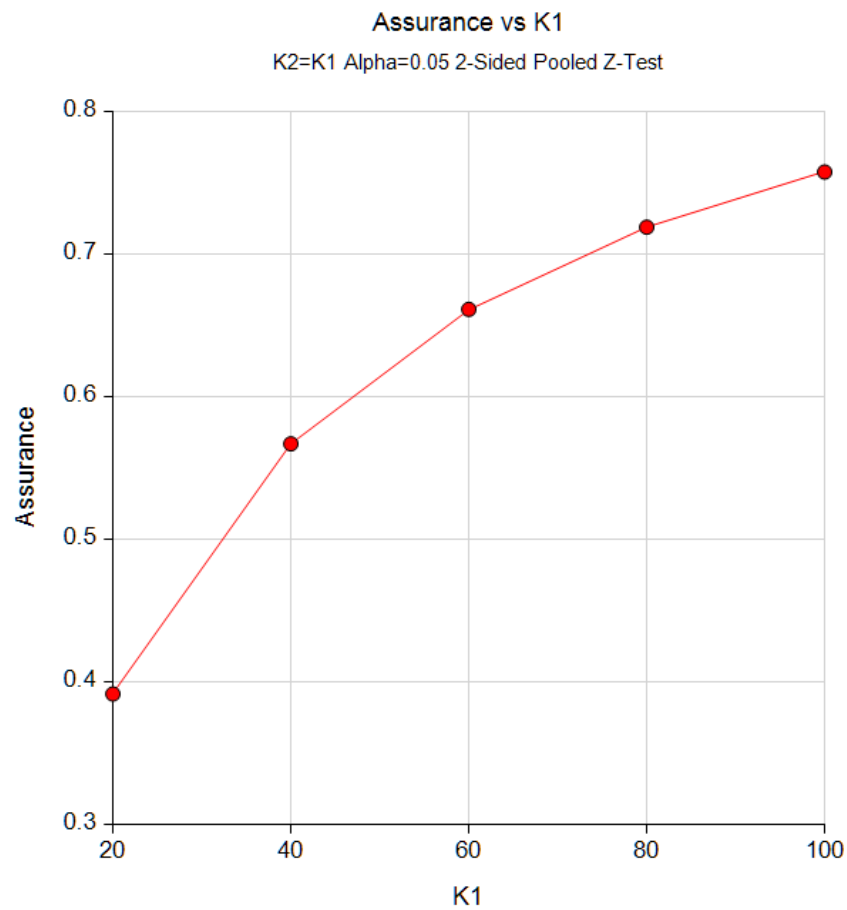
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This report shows the assurance values obtained by the various sample sizes.

Plots Section

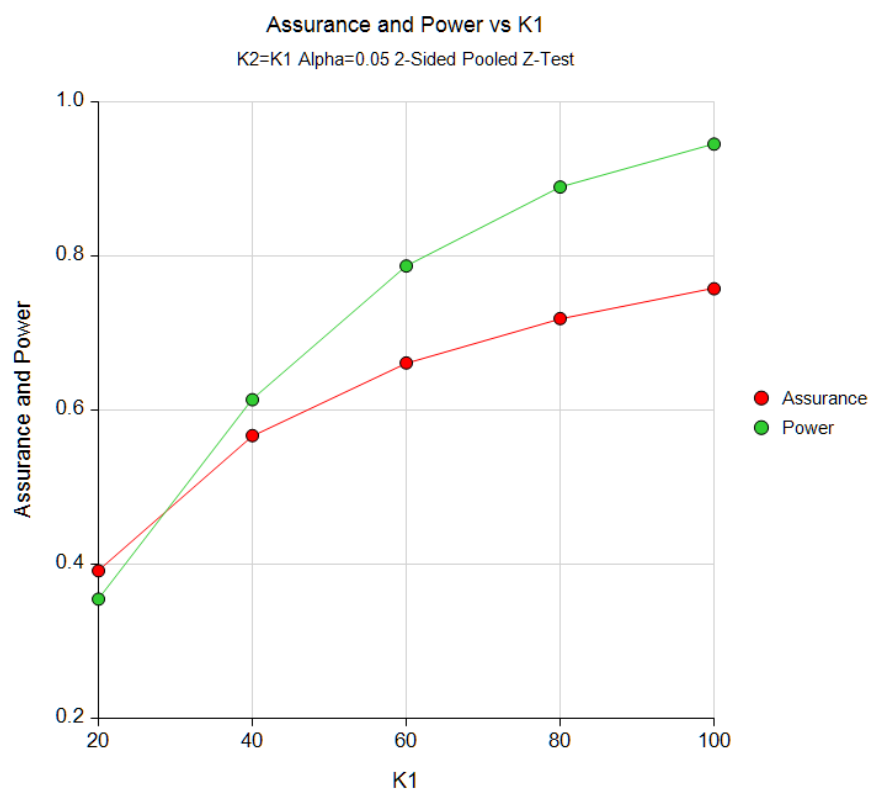
Plots



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

Comparison Plots Section

Comparison Plots



This plot compares the assurance and power across values of sample size.

Example 2 – Validation using Hand Computation

We could not find a validation example in the literature for procedure, so we have developed a validation example of our own.

Suppose a two-sided, pooled z-test will be used in which $K1 = K2 = 30$ and the significance level is 0.05.

The prior distribution of P1 is approximated by the following table. These are loaded into C1 and C2.

<u>P1</u>	<u>Prob</u>
0.6	0.4
0.7	0.6

The prior distribution of the P2 is approximated by the following table. These are loaded into C3 and C4.

<u>P2</u>	<u>Prob</u>
0.5	0.4
0.55	0.6

The prior distribution of the p is approximated by the following table. These are loaded into C5 and C6.

<u>p</u>	<u>Prob</u>
0.01	0.5
0.02	0.5

The prior distribution of the M1 is approximated by the following table. These are loaded into C7 and C8.

<u>M1</u>	<u>Prob</u>
7	0.5
9	0.5

The prior distribution of the M2 is approximated by the following table. These are loaded into C9 and C10.

<u>M2</u>	<u>Prob</u>
7	0.5
9	0.5

To run this example, the spreadsheet will need to be loaded with the following 10 columns corresponding to the values listed above.

<u>C1</u>	<u>C2</u>	<u>C3</u>	<u>C4</u>	<u>C5</u>	<u>C6</u>	<u>C7</u>	<u>C8</u>	<u>C9</u>	<u>C10</u>
0.6	0.4	0.5	0.4	0.01	0.5	7	0.5	7	0.5
0.7	0.6	0.55	0.6	0.02	0.5	9	0.5	9	0.5

Assurance for Tests for Two Proportions in a Cluster-Randomized Design

The *Tests for Two Proportions in a Cluster-Randomized Design* procedure is used to compute the power for each of the 32 combinations the parameters. The results of these calculations are shown next.

Numeric Results for Testing Two Proportions (Cluster-Randomized)

Solve For: Power

Groups: 1 = Treatment, 2 = Control

Test Statistic: Z-Test (Pooled)

Hypotheses: H0: P1 - P2 = 0 vs. H1: P1 - P2 ≠ 0

Power	Number of Clusters			Cluster Size		Sample Size			Proportion		Difference D1	Intraclass Correlation ICC	Alpha
	K1	K2	K	M1	M2	N1	N2	N	P1	P2			
0.51631	30	30	60	7	7	210	210	420	0.6	0.50	0.10	0.01	0.05
0.56045	30	30	60	7	9	210	270	480	0.6	0.50	0.10	0.01	0.05
0.49454	30	30	60	7	7	210	210	420	0.6	0.50	0.10	0.02	0.05
0.53466	30	30	60	7	9	210	270	480	0.6	0.50	0.10	0.02	0.05
0.56212	30	30	60	9	7	270	210	480	0.6	0.50	0.10	0.01	0.05
0.61366	30	30	60	9	9	270	270	540	0.6	0.50	0.10	0.01	0.05
0.53629	30	30	60	9	7	270	210	480	0.6	0.50	0.10	0.02	0.05
0.58301	30	30	60	9	9	270	270	540	0.6	0.50	0.10	0.02	0.05
0.17140	30	30	60	7	7	210	210	420	0.6	0.55	0.05	0.01	0.05
0.18520	30	30	60	7	9	210	270	480	0.6	0.55	0.05	0.01	0.05
0.16470	30	30	60	7	7	210	210	420	0.6	0.55	0.05	0.02	0.05
0.17682	30	30	60	7	9	210	270	480	0.6	0.55	0.05	0.02	0.05
0.18659	30	30	60	9	7	270	210	480	0.6	0.55	0.05	0.01	0.05
0.20420	30	30	60	9	9	270	270	540	0.6	0.55	0.05	0.01	0.05
0.17809	30	30	60	9	7	270	210	480	0.6	0.55	0.05	0.02	0.05
0.19329	30	30	60	9	9	270	270	540	0.6	0.55	0.05	0.02	0.05
0.98416	30	30	60	7	7	210	210	420	0.7	0.50	0.20	0.01	0.05
0.99146	30	30	60	7	9	210	270	480	0.7	0.50	0.20	0.01	0.05
0.97911	30	30	60	7	7	210	210	420	0.7	0.50	0.20	0.02	0.05
0.98777	30	30	60	7	9	210	270	480	0.7	0.50	0.20	0.02	0.05
0.99135	30	30	60	9	7	270	210	480	0.7	0.50	0.20	0.01	0.05
0.99610	30	30	60	9	9	270	270	540	0.7	0.50	0.20	0.01	0.05
0.98767	30	30	60	9	7	270	210	480	0.7	0.50	0.20	0.02	0.05
0.99373	30	30	60	9	9	270	270	540	0.7	0.50	0.20	0.02	0.05
0.87234	30	30	60	7	7	210	210	420	0.7	0.55	0.15	0.01	0.05
0.90501	30	30	60	7	9	210	270	480	0.7	0.55	0.15	0.01	0.05
0.85377	30	30	60	7	7	210	210	420	0.7	0.55	0.15	0.02	0.05
0.88670	30	30	60	7	9	210	270	480	0.7	0.55	0.15	0.02	0.05
0.90601	30	30	60	9	7	270	210	480	0.7	0.55	0.15	0.01	0.05
0.93606	30	30	60	9	9	270	270	540	0.7	0.55	0.15	0.01	0.05
0.88793	30	30	60	9	7	270	210	480	0.7	0.55	0.15	0.02	0.05
0.91916	30	30	60	9	9	270	270	540	0.7	0.55	0.15	0.02	0.05

The assurance calculation is made by summing the quantities

$$[(power_{i,j,k,l,m})p(P1_i)p(P2_j)p(\rho_k)p(M1_l)p(M2_m)]$$

as follows

$$\begin{aligned}
 Assurance &= (0.51631 \times 0.4 \times 0.4 \times 0.5 \times 0.5 \times 0.5) + (0.56045 \times 0.4 \times 0.4 \times 0.5 \times 0.5 \times 0.5) + \dots \\
 &\quad + (0.91916 \times 0.6 \times 0.6 \times 0.5 \times 0.5 \times 0.5) \\
 &= 0.69168.
 \end{aligned}$$

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 **Two-Sided ($H_1: P_1 - P_2 \neq 0$)**
 Test Type **Z-Test (Pooled)**
 Alpha **0.05**
 K1 (Number of Clusters) **30**
 Prior Distribution of M1 **Custom (Values and Probabilities in Spreadsheet)**
 Column of Values **C7**
 Column of Pr(Values) **C8**
 K2 (Number of Clusters) **K1**
 Prior Distribution of M2 **Custom (Values and Probabilities in Spreadsheet)**
 Column of Values **C9**
 Column of Pr(Values) **C10**
 Prior Distribution of P1 **Custom (Values and Probabilities in Spreadsheet)**
 Column of Values **C1**
 Column of Pr(Values) **C2**
 Prior Distribution of P2 **Custom (Values and Probabilities in Spreadsheet)**
 Column of Values **C3**
 Column of Pr(Values) **C4**
 Prior Distribution of ρ **Custom (Values and Probabilities in Spreadsheet)**
 Column of Values **C5**
 Column of Pr(Values) **C6**

Options Tab

Number of Computation Points for each **10**
 Prior Distribution
 Maximum K1 in Sample Size Search **1000**

Input Spreadsheet Data

Row	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
1	0.6	0.4	0.50	0.4	0.01	0.5	7	0.5	7	0.5
2	0.7	0.6	0.55	0.6	0.02	0.5	9	0.5	9	0.5

Output

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

Numeric Results

Solve For: [Assurance](#)
 Groups: 1 = Treatment, 2 = Control
 Test Statistic: Z-Test (Pooled)
 Hypotheses: $H_0: P_1 - P_2 = 0$ vs. $H_1: P_1 - P_2 \neq 0$
 Prior Type: Individual Univariate Distributions

Prior Distributions

M1: Point List (Values = C7, Probs = C8).
 C7: 7 9
 C8: 0.5 0.5
 M2: Point List (Values = C9, Probs = C10).
 C9: 7 9
 C10: 0.5 0.5
 P1: Point List (Values = C1, Probs = C2).
 C1: 0.6 0.7
 C2: 0.4 0.6
 P2: Point List (Values = C3, Probs = C4).
 C3: 0.5 0.55
 C4: 0.4 0.6
 ρ : Point List (Values = C5, Probs = C6).
 C5: 0.01 0.02
 C6: 0.5 0.5

Assurance	Power‡	Sample Size			Number of Clusters			Cluster Size		Proportions		Intraclass Correlation	Alpha
		N1	N2	N	K1	K2	K	E(M1)	E(M2)	E(P1)	E(P2)	E(ρ)	
0.69168	0.79013	240	240	480	30	30	60	8	8	0.66	0.53	0.015	0.05

‡ Power was calculated using $M1 = E(M1) = 8$, $M2 = E(M2) = 8$, $P1 = E(P1) = 0.66$, $P2 = E(P2) = 0.53$, and $\rho = E(\rho) = 0.015$.

PASS has also calculated the assurance as 0.69168 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 0.5, 0.6, and 0.7.

In order to reduce the runtime during this exploratory phase of the analysis, the number of points in the prior computation is reduced to 10. This slightly reduces the accuracy, but greatly reduces the runtime.

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	Two-Sided ($H_1: P_1 - P_2 \neq 0$)
Test Type	Z-Test (Pooled)
Assurance	0.5 0.6 0.7
Alpha	0.05
Prior Distribution of M1	Normal (Mean, SD)
Mean	7
SD	1.5
Truncation Boundaries	None
K2 (Number of Clusters)	K1
Prior Distribution of M2	Normal (Mean, SD)
Mean	7
SD	1.5
Truncation Boundaries	None
Prior Distribution of P1	Normal (Mean, SD)
Mean	0.6
SD	0.05
Truncation Boundaries	None
Prior Distribution of P2	Normal (Mean, SD)
Mean	0.5
SD	0.03
Truncation Boundaries	None
Prior Distribution of ρ	Normal (Mean, SD)
Mean	0.02
SD	0.004
Truncation Boundaries	None

Assurance for Tests for Two Proportions in a Cluster-Randomized Design

Options Tab

Number of Computation Points for each **10**

Prior Distribution

Maximum K1 in Sample Size Search..... **1000**

Output

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

Numeric Reports

Numeric Results

Solve For: [Sample Size](#)
 Groups: 1 = Treatment, 2 = Control
 Test Statistic: Z-Test (Pooled)
 Hypotheses: $H_0: P_1 - P_2 = 0$ vs. $H_1: P_1 - P_2 \neq 0$
 Prior Type: Individual Univariate Distributions

Prior Distributions

M1: Normal (Mean = 7, SD = 1.5).
 M2: Normal (Mean = 7, SD = 1.5).
 P1: Normal (Mean = 0.6, SD = 0.05).
 P2: Normal (Mean = 0.5, SD = 0.03).
 ρ : Normal (Mean = 0.02, SD = 0.004).

Assurance*	Power‡	Sample Size			Number of Clusters			Cluster Size		Proportions		Intraclass Correlation E(ρ)	Alpha
		N1	N2	N	K1	K2	K	E(M1)	E(M2)	E(P1)	E(P2)		
0.50270	0.50744	217	217	434	31	31	62	7	7	0.6	0.5	0.02	0.05
0.60099	0.67449	322	322	644	46	46	92	7	7	0.6	0.5	0.02	0.05
0.70155	0.86026	511	511	1022	73	73	146	7	7	0.6	0.5	0.02	0.05

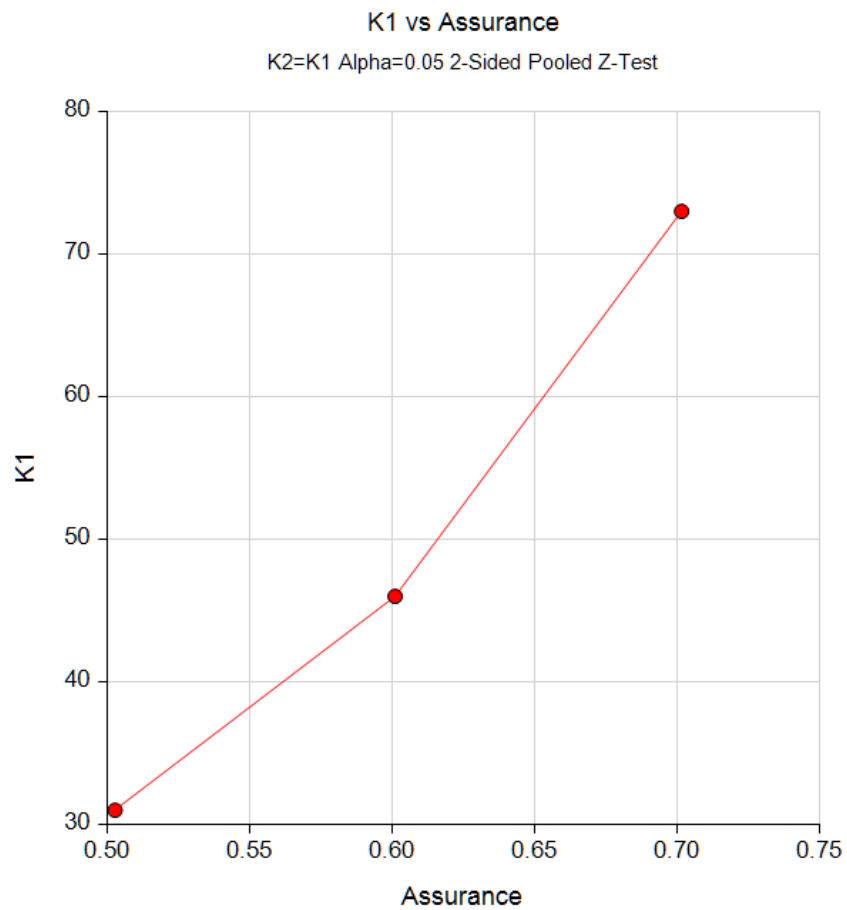
* The number of points used for computation of the prior(s) was 10.

‡ Power was calculated using $M1 = E(M1) = 7$, $M2 = E(M2) = 7$, $P1 = E(P1) = 0.6$, $P2 = E(P2) = 0.5$, and $\rho = E(\rho) = 0.02$.

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

Suppose a two-sided, pooled z-test will be used in which $K1 = K2 = (20, 40, 60, 80, 100)$ and the significance level is 0.05.

The joint prior distribution of the parameters is approximated by the following table. Note that the labels in parentheses identify the corresponding column of the spreadsheet. Also note that the prior probabilities in C6 will be automatically rescaled so that they sum to one.

P1 (C1)	P2 (C2)	p (C3)	M1 (C4)	M2 (C5)	Prob (C6)
0.7	0.5	0.01	5	5	0.25
0.7	0.5	0.02	10	10	0.2
0.68	0.45	0.01	5	5	0.25
0.68	0.45	0.02	10	10	0.2
0.65	0.5	0.01	5	5	0.65
0.65	0.5	0.02	10	10	0.6
0.62	0.45	0.01	5	5	0.65
0.62	0.45	0.02	10	10	0.6
0.6	0.5	0.01	5	5	0.45
0.6	0.5	0.02	10	10	0.4
0.58	0.45	0.01	5	5	0.45
0.58	0.45	0.02	10	10	0.4
0.55	0.5	0.01	5	5	0.25
0.55	0.5	0.02	10	10	0.2
0.53	0.45	0.01	5	5	0.25
0.53	0.45	0.02	10	10	0.2

To run this example, the spreadsheet will need to be loaded with the above data.

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 **Two-Sided ($H1: P1 - P2 \neq 0$)**
 Test Type **Z-Test (Pooled)**
 Alpha **0.05**
 K1 (Number of Clusters) **50 100 150**
 Column of M1 Values **C4**
 K2 (Number of Clusters) **K1**
 Column of M2 Values **C5**
 Column of P1 Values **C1**
 Column of P2 Values **C2**

Assurance for Tests for Two Proportions in a Cluster-Randomized Design

Column of p Values **C3**Column of Pr(Values)..... **C6**

Options Tab

Number of Computation Points for each..... **10**

Prior Distribution

Maximum K1 in Sample Size Search..... **1000**

Input Spreadsheet Data

Row	C1	C2	C3	C4	C5	C6
1	0.70	0.50	0.01	5	5	0.25
2	0.70	0.50	0.02	10	10	0.20
3	0.68	0.45	0.01	5	5	0.25
4	0.68	0.45	0.02	10	10	0.20
5	0.65	0.50	0.01	5	5	0.65
6	0.65	0.50	0.02	10	10	0.60
7	0.62	0.45	0.01	5	5	0.65
8	0.62	0.45	0.02	10	10	0.60
9	0.60	0.50	0.01	5	5	0.45
10	0.60	0.50	0.02	10	10	0.40
11	0.58	0.45	0.01	5	5	0.45
12	0.58	0.45	0.02	10	10	0.40
13	0.55	0.50	0.01	5	5	0.25
14	0.55	0.50	0.02	10	10	0.20
15	0.53	0.45	0.01	5	5	0.25
16	0.53	0.45	0.02	10	10	0.20

Output

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

Numeric Results

Solve For: **Assurance**

Groups: 1 = Treatment, 2 = Control

Test Statistic: Z-Test (Pooled)

Hypotheses: H0: P1 - P2 = 0 vs. H1: P1 - P2 ≠ 0

Prior Type: Joint Multivariate Distribution

Prior Distribution

Point Lists

M1: C4: 5 10 5 10 5 10 5 10 5 10 5 10 5 10

M2: C5: 5 10 5 10 5 10 5 10 5 10 5 10 5 10

P1: C1: 0.7 0.7 0.68 0.68 0.65 0.65 0.62 0.62 0.6 0.6 0.58 0.58 0.55 0.55 0.53 0.53

P2: C2: 0.5 0.5 0.45 0.45 0.5 0.5 0.45 0.45 0.5 0.5 0.45 0.45 0.5 0.5 0.45 0.45

p: C3: 0.01 0.02 0.01 0.02 0.01 0.02 0.01 0.02 0.01 0.02 0.01 0.02 0.01 0.02 0.01 0.02

Prob: C6: 0.25 0.2 0.25 0.2 0.65 0.6 0.65 0.6 0.45 0.4 0.45 0.4 0.25 0.2 0.25 0.2

Assurance	Power†	Sample Size			Number of Clusters			Cluster Size		Proportions		Intraclass Correlation E(p)	Alpha
		N1	N2	N	K1	K2	K	E(M1)	E(M2)	E(P1)	E(P2)		
0.83610	0.95834	367	367	734	50	50	100	7.3	7.3	0.61625	0.475	0.01467	0.05
0.92985	0.99946	734	734	1468	100	100	200	7.3	7.3	0.61625	0.475	0.01467	0.05
0.95973	1.00000	1100	1100	2200	150	150	300	7.3	7.3	0.61625	0.475	0.01467	0.05

† Power was calculated using M1 = E(M1) = 7.3, M2 = E(M2) = 7.3, P1 = E(P1) = 0.61625, P2 = E(P2) = 0.475, and p = E(p) = 0.01467.

PASS has calculated the required number of clusters to achieve each assurance goal.

Example 5 – Joint Prior Distribution Validation

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

In Example 2, the prior distribution of P1 is given as follows.

<u>P1</u>	<u>Prob</u>
0.6	0.4
0.7	0.6

The prior distribution of the P2 is approximated by the following table.

<u>P2</u>	<u>Prob</u>
0.5	0.4
0.55	0.6

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

<u>ρ</u>	<u>Prob</u>
0.01	0.5
0.02	0.5

The prior distribution of the M1 is approximated by the following table.

<u>M1</u>	<u>Prob</u>
7	0.5
9	0.5

The prior distribution of the M2 is approximated by the following table.

<u>M2</u>	<u>Prob</u>
7	0.5
9	0.5

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

<u>M1 (C1)</u>	<u>M2(C2)</u>	<u>P1 (C3)</u>	<u>P2 (C4)</u>	<u>ρ (C5)</u>	<u>Prob (C6)</u>
7	7	0.6	0.5	0.01	0.02
7	9	0.6	0.5	0.01	0.02
7	7	0.6	0.5	0.02	0.02
7	9	0.6	0.5	0.02	0.02
9	7	0.6	0.5	0.01	0.02
9	9	0.6	0.5	0.01	0.02
9	7	0.6	0.5	0.02	0.02
9	9	0.6	0.5	0.02	0.02
7	7	0.6	0.55	0.01	0.03
7	9	0.6	0.55	0.01	0.03
7	7	0.6	0.55	0.02	0.03
7	9	0.6	0.55	0.02	0.03
9	7	0.6	0.55	0.01	0.03
9	9	0.6	0.55	0.01	0.03
9	7	0.6	0.55	0.02	0.03

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9	9	0.6	0.55	0.02	0.03
7	7	0.7	0.5	0.01	0.03
7	9	0.7	0.5	0.01	0.03
7	7	0.7	0.5	0.02	0.03
7	9	0.7	0.5	0.02	0.03
9	7	0.7	0.5	0.01	0.03
9	9	0.7	0.5	0.01	0.03
9	7	0.7	0.5	0.02	0.03
9	9	0.7	0.5	0.02	0.03
7	7	0.7	0.55	0.01	0.045
7	9	0.7	0.55	0.01	0.045
7	7	0.7	0.55	0.02	0.045
7	9	0.7	0.55	0.02	0.045
9	7	0.7	0.55	0.01	0.045
9	9	0.7	0.55	0.01	0.045
9	7	0.7	0.55	0.02	0.045
9	9	0.7	0.55	0.02	0.045

To run this example, the spreadsheet is loaded with the above data.

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	Two-Sided ($H_1: P_1 - P_2 \neq 0$)
Test Type	Z-Test (Pooled)
Alpha	0.05
K1 (Number of Clusters)	30
Column of M1 Values	C1
K2 (Number of Clusters)	K1
Column of M2 Values	C2
Column of P1 Values	C3
Column of P2 Values	C4
Column of p Values	C5
Column of Pr(Values)	C6

Options Tab

Number of Computation Points for each	10
Prior Distribution	
Maximum K1 in Sample Size Search	1000

Assurance for Tests for Two Proportions in a Cluster-Randomized Design

Input Spreadsheet Data

Row	C1	C2	C3	C4	C5	C6
1	7	7	0.6	0.50	0.01	0.020
2	7	9	0.6	0.50	0.01	0.020
3	7	7	0.6	0.50	0.02	0.020
4	7	9	0.6	0.50	0.02	0.020
5	9	7	0.6	0.50	0.01	0.020
6	9	9	0.6	0.50	0.01	0.020
7	9	7	0.6	0.50	0.02	0.020
8	9	9	0.6	0.50	0.02	0.020
9	7	7	0.6	0.55	0.01	0.030
10	7	9	0.6	0.55	0.01	0.030
11	7	7	0.6	0.55	0.02	0.030
12	7	9	0.6	0.55	0.02	0.030
13	9	7	0.6	0.55	0.01	0.030
14	9	9	0.6	0.55	0.01	0.030
15	9	7	0.6	0.55	0.02	0.030
16	9	9	0.6	0.55	0.02	0.030
17	7	7	0.7	0.50	0.01	0.030
18	7	9	0.7	0.50	0.01	0.030
19	7	7	0.7	0.50	0.02	0.030
20	7	9	0.7	0.50	0.02	0.030
21	9	7	0.7	0.50	0.01	0.030
22	9	9	0.7	0.50	0.01	0.030
23	9	7	0.7	0.50	0.02	0.030
24	9	9	0.7	0.50	0.02	0.030
25	7	7	0.7	0.55	0.01	0.045
26	7	9	0.7	0.55	0.01	0.045
27	7	7	0.7	0.55	0.02	0.045
28	7	9	0.7	0.55	0.02	0.045
29	9	7	0.7	0.55	0.01	0.045
30	9	9	0.7	0.55	0.01	0.045
31	9	7	0.7	0.55	0.02	0.045
32	9	9	0.7	0.55	0.02	0.045

Output

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

Numeric Results

Solve For: [Assurance](#)
 Groups: 1 = Treatment, 2 = Control
 Test Statistic: Z-Test (Pooled)
 Hypotheses: $H_0: P_1 - P_2 = 0$ vs. $H_1: P_1 - P_2 \neq 0$
 Prior Type: Joint Multivariate Distribution

Prior Distribution

Point Lists

M1: C1: 7 7 7 7 9 9 9 9 7 7 7 7 9 9 9 9 7 7 7 7 9 9 9 9 7 7 7 7 9 9 9 9
 M2: C2: 7 9 7 9 7 9 7 9 7 9 7 9 7 9 7 9 7 9 7 9 7 9 7 9 7 9 7 9 7 9 7 9
 P1: C3: 0.6 0.6 0.6 0.6 0.6 0.6 0.6 0.6 0.6 0.6 0.6 0.6 0.6 0.6 0.6 0.7 0.7 0.7 0.7 0.7 0.7 0.7 0.7 0.7 0.7 0.7 0.7 0.7
 P2: C4: 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.55 0.55 0.55 0.55 0.55 0.55 0.55 0.55 0.55 0.55 0.55 0.55 0.55
 0.55 0.55
 ρ : C5: 0.01 0.01 0.02 0.02 0.01 0.01 0.02 0.02 0.01 0.01 0.02 0.02 0.01 0.01 0.02 0.02 0.01 0.01 0.02 0.02 0.01 0.01 0.02 0.02 0.01 0.01
 0.02 0.02 0.01 0.01 0.02 0.02
 Prob: C6: 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.045
 0.045 0.045 0.045 0.045 0.045 0.045 0.045

Assurance	Power‡	Sample Size			Number of Clusters			Cluster Size		Proportions		Intraclass Correlation	Alpha
		N1	N2	N	K1	K2	K	E(M1)	E(M2)	E(P1)	E(P2)	E(ρ)	
0.69168	0.79013	240	240	480	30	30	60	8	8	0.66	0.53	0.015	0.05

‡ Power was calculated using $M1 = E(M1) = 8$, $M2 = E(M2) = 8$, $P1 = E(P1) = 0.66$, $P2 = E(P2) = 0.53$, and $\rho = E(\rho) = 0.015$.

PASS has calculated the assurance as 0.69168 which matches the result in Example 2. This validates the joint prior method.