

Sample Size and Power


Henry Glick
www.uphs.upenn.edu/dgimhsr

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Goals of Sample Size and Power Analysis

- Sample size calculation
 - Given a desired alpha (α) and beta (β), proactively manages probability of saying a difference exists when none does
 - Type 1 error; False positive; alpha; confidence
- Power Analysis
 - Given a desired alpha and a known sample size, proactively understand probability of saying no difference exists when one does
 - Type 2 error; False negative; (1-Beta); power
- “Experiment has an 80% chance (power) of concluding with 95% confidence (alpha) that therapies differ”



Other Sample Size Traditions

- Sample size approach described here comes out of frequentist statistical tradition
- Other approaches (cost-effectiveness literature) include:
 - Bayesian (O’Hagan and Stevens)
 - Value of information (Koerkamp et al.)
 - Opportunity cost (Gafni et al.)
 - Decision model (Willan and O’Brien)

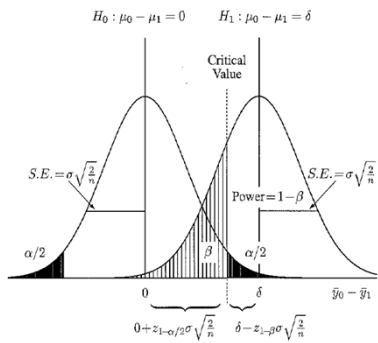


Sample Size Calculation

- Specify parameters (e.g., expected difference (Δ) and standard deviation (SD)), alpha, and beta and identify sample size per group (N)
 - Assumptions of equivalent N/group or equivalent SD can be relaxed (see later equations)



Common Sample Size/Power Figure



www.vanbelle.org/chapters%5Cwebchapter2.pdf



Common Equations

Consider an α -level test of $H_0: \mu_1 = \mu_2$ against the one-sided alternative $H_a: \mu_1 > \mu_2$. The critical region for this test is

$$\bar{X} - \bar{Y} > z_\alpha \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}} \quad (2.2.20)$$

If a power of $1 - \beta$ is required at $\mu_1 - \mu_2 = \delta (> 0)$, n_1 and n_2 must satisfy

$$P\left(\bar{X} - \bar{Y} > z_\alpha \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}} \mid \mu_1 - \mu_2 = \delta\right) = 1 - \beta. \quad (2.2.21)$$

Thus,

$$\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2} = \left[\frac{\delta}{z_\alpha + z_\beta} \right]^2. \quad (2.2.22)$$

To get a unique solution to (2.2.22), one takes $n_1 = kn_2$ and gets

$$n_2^2 = \frac{\frac{\sigma_1^2}{k} + \sigma_2^2}{\left(\frac{\delta}{z_\alpha + z_\beta} \right)^2}, \quad n_1^2 = kn_2^2. \quad (2.2.23)$$

Desu and Raghavarao, Sample Size Methodology



Not What I Am Going to Talk About

- If the graph and equations are enlightening, you may know everything you need to know
- I don't find them particularly helpful
- Hoping to provide some intuitions about power and sample size



Start with Naïve Sample Size Calculation

- Suppose we gestimate that our experiment will yield
 - Difference of 10
 - Standard deviation/group of 18.038
- If we run experiment and our data exactly match these assumptions, we need a standard error (SE) of 5.102 for a confidence interval where one confidence limit = 0 (i.e., $p = 0.05$)

$(10 - 1.96 * 5.102 = 0)$ (where $1.96 = z_{\alpha}$)
- Given we know SD, needed SE, and formula for SE – which includes sample size/group and SD – can make an initial naïve sample size estimate by substituting equation for SE and solving for N



Naïve Estimate of 25/Group

- $CL = \Delta - z_{\alpha} SE = 0$
- $\Delta / z_{\alpha} = SE$
- $SE = (2 * (SD / N^{0.5})^2)^{0.5}$
- $\Delta / z_{\alpha} = (2 * (SD / N^{0.5})^2)^{0.5}$
- Solving for N/group yields:

$$N_{naive} = \frac{2 z_{\alpha}^2 sd^2}{\Delta^2}$$
- Assuming $\Delta=10$; $sd=18.038$; $z=1.96$: $N=25$ /group



Effective α

- Using $z_{\alpha} = 1.96$
- Assuming $\alpha = 0.05$; two groups; and no adjustment for multiple tests
- Results don't depend on assumptions
- What matters is that you use correct z_{α} after adjustment when calculating both CI and p-values and when calculating N/group
 - e.g., if after adjustment you decide that $\alpha = 0.05$ when $z_{\alpha} = 2.2414$, naive sample size = 33/group

$$2 * 2.2414^2 * 18.038^2 / 10^2 = 32.69$$



Simulation to Test 25/Group

- Repeatedly draw 100,000 sets of 2 samples from normal distributions with:
 - 25/group
 - Means of 100 in group 1 and 110 in group 2 ($\Delta=10$)
 - Common SD of 18.038/group
- Basic Stata command:


```
drawnorm c1 c2, m(100 110) sd(18.038) n(25)
```




WHAT DO WE EXPECT WILL HAPPEN?



Expectations


- Group 1 mean \approx 100
- Group 2 mean \approx 110
- Mean of each SD \approx 13.038
- $\Delta \approx$ 10
- SE \approx 5.102
- % significant ???



Simulation Results

Number of draws	100,000
mean, Sample 1	99.9999
SD, Sample 1	18.0327
mean, Sample 2	109.9877
SD, Sample 2	18.0399
ΔC	9.9878
SE, ΔC	5.1280
$p < 0.05$, %	49.5


example1822.dta



Sources of (Lack of) Significance

Number of draws	100,000
% > 10	49.7
% < 5.102	48.7


- Significance
 - $\Delta > 10$; SE < 5.102
 - $\Delta > 10$; SE > 5.102; $\Delta/SE > 1.96$
 - $\Delta < 10$; SE < 5.102; $\Delta/SE > 1.96$
- Lack of significance
 - $\Delta < 10$; SE > 5.102
 - $\Delta < 10$; SE < 5.102; $\Delta/SE < 1.96$
 - $\Delta > 10$; SE > 5.102; $\Delta/SE < 1.96$



My Expectations

$\Delta C < 10; SE > 5.1$		$\Delta C < 10; SE < 5.1$		$\Delta C > 10; SE > 5.1$		$\Delta C > 10; SE < 5.1$	
$p > 0.05$	$p < 0.05$	$p > 0.05$	$p < 0.05$	$p > 0.05$	$p < 0.05$	$p > 0.05$	$p < 0.05$
25,000	0	12,500	12,500	12,500	12,500	0	25,000
0%		50%		50%		100%	


- 50% significance due to
 - ~25% of time $\Delta > 10$ and $SE < 5.102$
 - ~12.5% of time $\Delta > 10$, $SE > 5.102$, $\Delta/SE > 1.96$
 - ~12.5% of time $\Delta < 10$, $SE < 5.102$, $\Delta/SE > 1.96$



Observed


$\Delta C < 10; SE > 5.1$		$\Delta C < 10; SE < 5.1$		$\Delta C > 10; SE > 5.1$		$\Delta C > 10; SE < 5.1$	
$p > 0.05$	$p < 0.05$	$p > 0.05$	$p < 0.05$	$p > 0.05$	$p < 0.05$	$p > 0.05$	$p < 0.05$
25,694	0	21,599	3005	3207	22,379	0	24,116
0%		12.2%		87.5%		100%	

- 49.5% significance due to
 - ~25% of time $\Delta > 10$ and $SE < 5.102$
 - ~22% of time $\Delta > 10$, $SE > 5.102$, but $\Delta/SE > 1.96$
 - ~3% of time $\Delta < 10$, $SE < 5.102$, but $\Delta/SE > 1.96$




Are We Satisfied with Naïve Sample Size Estimate?

- Only if we are willing to live with designing experiments in which we are likely to detect a significant difference 50% of time




WHAT WENT WRONG?




What Went Wrong?

- Did not account for fact that we cannot expect Δ and SE to equal 10 and 5.102 in repeated experiments
 - In simulation approximately 50% of time Δ and SE were above 10 and 5.102 and 50% of time Δ and SE were below
- Need to increase sample size so that expected SE is smaller than 5.102, such that we increase likelihood of:
 - $\Delta > 10$ and $SE < 5.102$ (primary mechanism)
 - $\Delta < 10$, $SE < 5.102$, $\Delta/SE > 1.96$ (secondary mechanism)




Suppose We Simulated 51/Group, Not 25

- Repeatedly draw 100,000 sets of 2 samples from normal distributions with:
 - 51/group
 - Means of 100 in group 1 and 110 in group 2 ($\Delta=10$)
 - Common SD of 18.038/group




WHAT DO WE EXPECT WILL HAPPEN?



Expectations


- Group 1 mean \approx 100
- Group 2 mean \approx 110
- Mean of each SD \approx 13.038
- $\Delta \approx$ 10
- SE < 5.102
- % significant > 50%



Simulation Results

Number of draws	100,000
mean, Sample 1	99.9777
SD, Sample 1	18.0349
mean, Sample 2	110.007
SD, Sample 2	18.0294
ΔC	10.0294
SE, ΔC	3.5804
$p < 0.05$, %	79.7
% > 10	50.45
% < 5.102	100


example218126.dta



79.4% Significant

$\Delta C < 10; SE > 5.1$		$\Delta C < 10; SE < 5.1$		$\Delta C > 10; SE > 5.1$		$\Delta C > 10; SE < 5.1$	
p > 0.05	p < 0.05	p > 0.05	p < 0.05	p > 0.05	p < 0.05	p > 0.05	p < 0.05
0	0	20,298	29,256	0	0	0	50,446
NA		59.0%		NA		100%	

- 79.4% significance due to
 - ~50.4% of time $\Delta > 10$ and $SE < 5.102$
 - ~29% of time $\Delta < 10$, $SE < 5.102$, but $\Delta/SE > 1.96$
- Further increases in sample size gain power solely from increasing proportion of time $\Delta < 10$, $SE < 5.102$, but $\Delta/SE > 1.96$



Shifting Sources of Significance

n = 5/G; power = 0.14


$\Delta C < 10; SE > 5.1$		$\Delta C < 10; SE < 5.1$		$\Delta C > 10; SE > 5.1$		$\Delta C > 10; SE < 5.1$	
p > 0.05	p < 0.05	p > 0.05	p < 0.05	p > 0.05	p < 0.05	p > 0.05	p < 0.05
49,553	0	298	25	33,498	16,308	0	318
0%		0.77		33%		100%	

n = 25/G; power = 0.5

$\Delta C < 10; SE > 5.1$		$\Delta C < 10; SE < 5.1$		$\Delta C > 10; SE > 5.1$		$\Delta C > 10; SE < 5.1$	
p > 0.05	p < 0.05	p > 0.05	p < 0.05	p > 0.05	p < 0.05	p > 0.05	p < 0.05
25,649	0	21,599	3005	3207	22,379	0	24,116
0%		12.2%		87.5%		100%	

n = 51/G; power = 0.7994

$\Delta C < 10; SE > 5.1$		$\Delta C < 10; SE < 5.1$		$\Delta C > 10; SE > 5.1$		$\Delta C > 10; SE < 5.1$	
p > 0.05	p < 0.05	p > 0.05	p < 0.05	p > 0.05	p < 0.05	p > 0.05	p < 0.05
0	0	20,298	29,256	0	0	0	50,466
NA		59.0%		NA		100%	




How Did We Come Up With 51/Group?

- Expand naïve sample size equation to include Z_β (1.96 + 0.84 = 2.80)

$$N = \frac{2(z_\alpha + z_\beta)^2 \text{sd}^2}{\Delta^2}$$


- Target SE = $10/2.8 = 3.571$ (3.58 in simulation)
- $N = 2 * 2.8^2 * 18.038^2 / 10^2 = 51/\text{group}$
- Power is typically treated as 1-tailed
 - If $Z_\beta = 0$, power = 50% (equivalent to naïve sample size); if $Z_\beta = 0.84$, power = 80%; if $Z_\beta = 1.28$, power = 90%; if $Z_\beta = 1.64$, power = 0.95



Stata sampsi Command for Sample Size


```
sampsi 100 110, sd(18.038) p(.8)

      alpha = 0.0500 (two-sided)
      power = 0.8000
      m1    = 100
      m2    = 110
      sd1   = 18.038
      sd2   = 18.038
      n2/n1 = 1.00
Estimated required sample sizes:
      n1 = 52
      n2 = 52
```



Sample Size and Power


- Sample size and power mirror images of one another
- As previously noted, when estimating a sample size, specify parameters, alpha, and beta and identify number needed per group
- Power Analysis: specify parameters, alpha and sample size and identify power to detect a difference
- If we calculate sample size with beta=0.8 and determine 100 patients are needed per group, except for rounding, when we calculate power given 100 patients per group will see it equals 0.8



Power Equation, Continuous Variables

$$z_{\beta} = \sqrt{\frac{N \Delta^2}{2 \text{sd}^2}} - z_{\alpha}$$

- Equation yields z_{β}
- Power identified from z table
 - In stata: normal(z_{β})
- Assumes common N and common SD for each group



Power Equation, Continuous Variables

$$Z_{\beta} = \sqrt{\frac{N \Delta^2}{2 \text{sd}^2}} - Z_{\alpha} = Z_{\text{ci}=0} - Z_{\alpha}$$

where $Z_{\text{ci}=0}$ represents z-score that yields a CI for which one of CL = 0

- If know one of 90% CL equals 0 and want 95% confidence, know we have 38% power
normal(1.645-1.96) = -0.376
- Works approximately for other types of contrasts as well
– e.g., power for odds ratios
 - If one of the 90% CL equals 1 and want 95% confidence, know we have ≈ 38% power



Relaxing Some Assumptions

- Relaxing equal Ns in both groups:

$$N_2 = r N_1$$

$$Z_{\beta} = \sqrt{\frac{r N_1 \Delta^2}{(1+r) \text{sd}^2}} - Z_{\alpha}$$

- Relaxing equal SDs in both groups

$$Z_{\beta} = \sqrt{\frac{N \Delta^2}{\text{sd}_1^2 + \text{sd}_2^2}} - Z_{\alpha}$$



Stata sampsi Command for Power

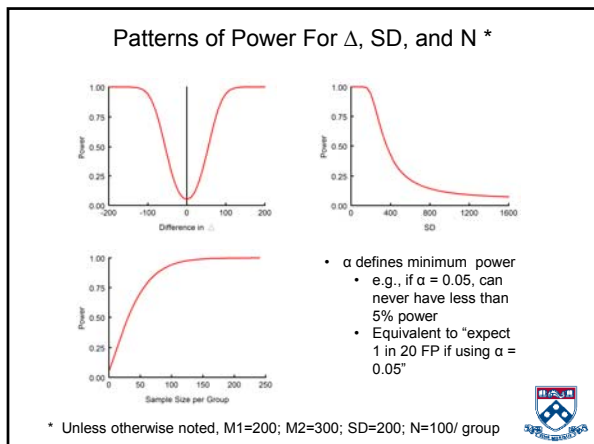
sampsi 100 110, sd(18.038) n(52)

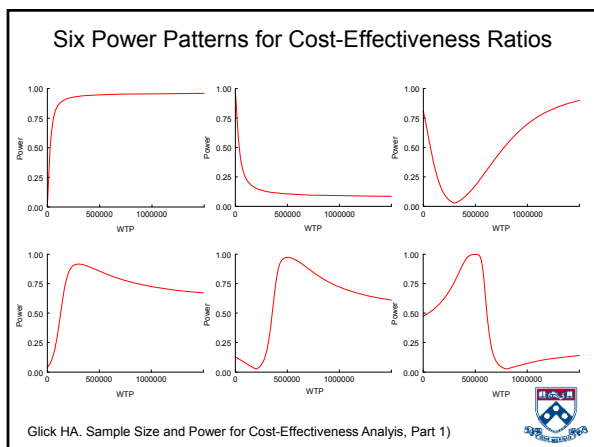
```
alpha = 0.0500 (two-sided)
m1 = 100
m2 = 110
sd1 = 18.038
sd2 = 18.038
n1 = 52
n2 = 52
n2/n1 = 1.00
```

Estimated power:

power = 0.8070







Incomplete Data (Drop Out)

- Derived sample size estimates are appropriate if we always have complete data
- If anticipate 10% with incomplete data, will want to divide sample size estimates by 0.9 to obtain "nominal" sample size from which "effective" sample size is derived
