# Chapter 411

# Wilcoxon Signed-Rank Tests

# Introduction

The one-sample *t*-test is used to test whether the mean of a population is greater than, less than, or not equal to a specific value. Because the *t* distribution is used to calculate critical values for the test, this test is often called the one-sample *t*-test. The *t*-test assumes that the population standard deviation is unknown and will be estimated by the data.

The nonparametric analog of the *t*-test is the *Wilcoxon Signed-Rank Test* and may be used when the one-sample *t*-test assumptions are violated.

# **Other PASS Procedures for Testing One Mean or Median**

Procedures in **PASS** are primarily built upon the testing methods, test statistic, and test assumptions that will be used when the analysis of the data is performed. You should check to identify that the test procedure described below in the Test Procedure section matches your intended procedure. If your assumptions or testing method are different, you may wish to use one of the other one-sample procedures available in **PASS**-the One-Sample Z-Tests and the One-Sample T-Tests procedures. The methods, statistics, and assumptions for those procedures are described in the associated chapters.

If you wish to show that the mean of a population is larger (or smaller) than a reference value by a specified amount, you should use one of the clinical superiority procedures for comparing means. Non-inferiority, equivalence, and confidence interval procedures are also available.

# **Assumptions for One-Sample Tests**

This section describes the assumptions that are made when you use one of the one-sample tests. The key assumption relates to normality or non-normality of the data. One of the reasons for the popularity of the *t*-test is its robustness in the face of assumption violation. However, if an assumption is not met even approximately, the significance levels and the power of the *t*-test are invalidated. Unfortunately, in practice it often happens that several assumptions are not met. This makes matters even worse! Hence, take the steps to check the assumptions before you make important decisions based on these tests.

## **One-Sample Z-Test Assumptions**

The assumptions of the one-sample *z*-test are:

- 1. The data are continuous (not discrete).
- 2. The data follow the normal probability distribution.
- 3. The sample is a simple random sample from its population. Each individual in the population has an equal probability of being selected in the sample.
- 4. The population standard deviation is known.

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## **One-Sample T-Test Assumptions**

The assumptions of the one-sample *t*-test are:

- 1. The data are continuous (not discrete).
- 2. The data follow the normal probability distribution.
- 3. The sample is a simple random sample from its population. Each individual in the population has an equal probability of being selected in the sample.

## **Paired T-Test Assumptions**

The assumptions of the paired *t*-test are:

- 1. The data are continuous (not discrete).
- 2. The data, i.e., the differences for the matched pairs, follow a normal probability distribution.
- 3. The sample of pairs is a simple random sample from its population. Each individual in the population has an equal probability of being selected in the sample.

## Wilcoxon Signed-Rank Test Assumptions

The assumptions of the Wilcoxon signed-rank test are as follows (note that the difference is between a data value and the hypothesized median or between the two data values of a pair):

- 1. The differences are continuous (not discrete).
- 2. The distribution of each difference is symmetric.
- 3. The differences are mutually independent.
- 4. The differences all have the same median.
- 5. The measurement scale is at least interval.

# Limitations

There are few limitations when using these tests. Sample sizes may range from a few to several hundred. If your data are discrete with at least five unique values, you can often ignore the continuous variable assumption. Perhaps the greatest restriction is that your data come from a random sample of the population. If you do not have a random sample, your significance levels will probably be incorrect.

# Wilcoxon Signed-Rank Test Statistic

The Wilcoxon signed-rank test is a popular, nonparametric substitute for the *t*-test. It assumes that the data follow a symmetric distribution. The test is computed using the following steps.

- 1. Subtract the hypothesized mean,  $\mu_0$ , from each data value. Rank the values according to their absolute values.
- 2. Compute the sum of the positive ranks *Sp* and the sum of the negative ranks *Sn*. The test statistic,  $W_R$ , is the minimum of *Sp* and *Sn*.
- 3. Compute the mean and standard deviation of  $W_R$  using the formulas

$$\mu_{W_R} = \frac{n(n+1)}{4}$$
$$\sigma_{W_R} = \sqrt{\frac{n(n+1)(2n+1)}{24} - \frac{\sum t^3 - \sum t}{48}}$$

where *t* represents the number of times the *i*<sup>th</sup> value occurs.

4. Compute the *z*-value using

$$z_W = \frac{W_R - \mu_{W_R}}{\sigma_{W_R}}$$

The significance of the test statistic is determined by computing the p-value using the standard normal distribution. If this p-value is less than a specified level (usually 0.05), the null hypothesis is rejected in favor of the alternative hypothesis. Otherwise, no conclusion can be reached.

# **Population Size**

This is the number of subjects in the population. Usually, you assume that samples are drawn from a very large (infinite) population. Occasionally, however, situations arise in which the population of interest is of limited size. In these cases, appropriate adjustments must be made.

When a finite population size is specified, the standard deviation is reduced according to the formula:

$$\sigma_1^2 = \left(1 - \frac{n}{N}\right)\sigma^2$$

where *n* is the sample size, *N* is the population size,  $\sigma$  is the original standard deviation, and  $\sigma_1$  is the new standard deviation.

The quantity *n*/*N* is often called the sampling fraction. The quantity  $\left(1 - \frac{n}{N}\right)$  is called the *finite population correction factor*.

# Power Calculation for the Wilcoxon Signed-Rank Test

The power calculation for the Wilcoxon signed-rank test is the same as that for the one-sample *t*-test except that an adjustment is made to the sample size based on an assumed data distribution as described in Al-Sunduqchi and Guenther (1990). The sample size n' used in power calculations is equal to

$$n'=n/W$$
,

where W is the Wilcoxon adjustment factor based on the assumed data distribution.

The adjustments are as follows:

Distribution	W
Uniform	1
Double Exponential	2/3
Logistic	$9/\pi^{2}$
Normal	$\pi/3$

The power is calculated as follows for a directional alternative (one-tailed test) in which  $\mu_1 > \mu_0$ .

- 1. Find  $t_{\alpha}$  such that  $1 T_{df}(t_{\alpha}) = \alpha$ , where  $T_{df}(t_{\alpha})$  is the area under a central-*t* curve to the left of *x* and df = n' 1.
- 2. Calculate:  $X_1 = \mu_0 + t_\alpha \frac{\sigma}{\sqrt{n'}}$ .
- 3. Calculate the noncentrality parameter:  $\lambda = \frac{\mu_1 \mu_0}{\frac{\sigma}{\sqrt{n'}}} = \frac{\delta_1}{\frac{\sigma}{\sqrt{n'}}}$
- 4. Calculate:  $t_1 = \frac{X_1 \mu_1}{\frac{\sigma}{\sqrt{n'}}} + \lambda$ .
- 5. Power =  $1 T'_{df,\lambda}(t_1)$ , where  $T'_{df,\lambda}(x)$  is the area to the left of *x* under a noncentral-*t* curve with degrees of freedom *df* and noncentrality parameter  $\lambda$ .

# Example 1 – Power after a Study

This example will cover the situation in which you are calculating the power of a Wilcoxon Signed-Rank test on data that have already been collected and analyzed. For example, you might be playing the role of a reviewer, looking at the power of a Wilcoxon Signed-Rank test from a study you are reviewing. In this case, you would not vary the means, standard deviation, or sample size since they are given by the experiment. Instead, you investigate the power of the significance tests. You might look at the impact of different alpha values on the power.

Suppose an experiment involving 100 individuals yields the following summary statistics:

Hypothesized mean (µ0)	100.0
Sample mean (µ1)	110.0
Sample standard deviation	40.0
Sample size	100

Given the above data, analyze the power of a Wilcoxon Signed-Rank test which tests the hypothesis that the population median is 100 versus the alternative hypothesis that the population median is 110. Consider the power at significance levels 0.01, 0.05, 0.10 and sample sizes 20 to 120 by 20 when the assumed data distribution is Logistic.

Note that we have set  $\mu$ 1 equal to the sample mean. In this case, we are studying the power of the Wilcoxon Signed-Rank test for a mean difference the size of that found in the experimental 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 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	Power
Alternative Hypothesis	Two-Sided (H1: μ ≠ μ0)
Data Distribution	Logistic
Population Size	Infinite
Alpha	0.01 0.05 0.10
N (Sample Size)	20 to 120 by 20
μ0 (Null or Baseline Mean)	100
µ1 (Actual Mean)	110
σ (Standard Deviation)	40

# Output

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

### **Numeric Reports**

Numeric Rest	ults			
Solve For:	Power			

	1 00001		
Hypotheses:	H0: μ = μ0	vs.	H1: µ ≠ µ0
Data Distribution:	Logistic		

	Samula		Mear	ı	Stondard		
Power	Sample Size N	Null µ0	Actual µ1	Difference μ1 - μ0	Standard Deviation σ	Effect Size	Alpha
0.06416	20	100	110	10	40	0.25	0.01
0.15855	40	100	110	10	40	0.25	0.01
0.27019	60	100	110	10	40	0.25	0.01
0.38634	80	100	110	10	40	0.25	0.01
0.49768	100	100	110	10	40	0.25	0.01
0.59833	120	100	110	10	40	0.25	0.01
0.19362	20	100	110	10	40	0.25	0.05
0.36033	40	100	110	10	40	0.25	0.05
0.51014	60	100	110	10	40	0.25	0.05
0.63526	80	100	110	10	40	0.25	0.05
0.73462	100	100	110	10	40	0.25	0.05
0.81063	120	100	110	10	40	0.25	0.05
0.29827	20	100	110	10	40	0.25	0.10
0.48781	40	100	110	10	40	0.25	0.10
0.63672	60	100	110	10	40	0.25	0.10
0.74816	80	100	110	10	40	0.25	0.10
0.82865	100	100	110	10	40	0.25	0.10
0.88524	120	100	110	10	40	0.25	0.10

Power The probability of rejecting a false null hypothesis when the alternative hypothesis is true.

N The size of the sample drawn from the population.

μ0 The value of the population mean under the null hypothesis.μ1 The actual value of the population mean at which power and sample size are calculated.

 $\mu$ 1 The actual value of the population mean at which population mean

 $\sigma$  The standard deviation of the population. It measures the variability in the population.

Effect Size The relative magnitude of the effect. Effect Size =  $|\mu 1 - \mu 0|/\sigma$ .

Alpha The probability of rejecting a true null hypothesis.

#### **Summary Statements**

A single-group design will be used to test whether the location (distribution center) is different from 100 (H0:  $\mu$  = 100 versus H1:  $\mu \neq$  100). The comparison will be made using a two-sided, one-sample Wilcoxon Signed-Rank test, with a Type I error rate ( $\alpha$ ) of 0.01. The underlying data distribution is assumed to be Logistic. The underlying distribution standard deviation is assumed to be 40. To detect a mean of 110 (corresponding to a difference of 10) with a sample size of 20, the power is 0.06416.

#### Wilcoxon Signed-Rank Tests

#### **Dropout-Inflated Sample Size**

Dropout Rate	Sample Size N	Dropout- Inflated Enrollment Sample Size N'	Expected Number of Dropouts D
20%	20	25	5
20%	40	50	10
20%	60	75	15
20%	80	100	20
20%	100	125	25
20%	120	150	30

 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.

 N
 The evaluable sample size at which power is computed (as entered by the user). If N subjects are evaluated out of the N' subjects that are enrolled in the study, the design will achieve the stated power.

 N'
 The total number of subjects that should be enrolled in the study in order to obtain N evaluable subjects, based on the assumed dropout rate. N' is calculated by inflating N using the formula N' = N / (1 - DR), with N' always rounded up. (See Julious, S.A. (2010) pages 52-53, or Chow, S.C., Shao, J., Wang, H., and Lokhnygina, Y. (2018) pages 32-33.)

 D
 The expected number of dropouts. D = N' - N.

#### **Dropout Summary Statements**

Anticipating a 20% dropout rate, 25 subjects should be enrolled to obtain a final sample size of 20 subjects.

#### References

Al-Sunduqchi, Mahdi S. 1990. Determining the Appropriate Sample Size for Inferences Based on the Wilcoxon Statistics. Ph.D. dissertation under the direction of William C. Guenther, Dept. of Statistics, University of Wyoming, Laramie, Wyoming.

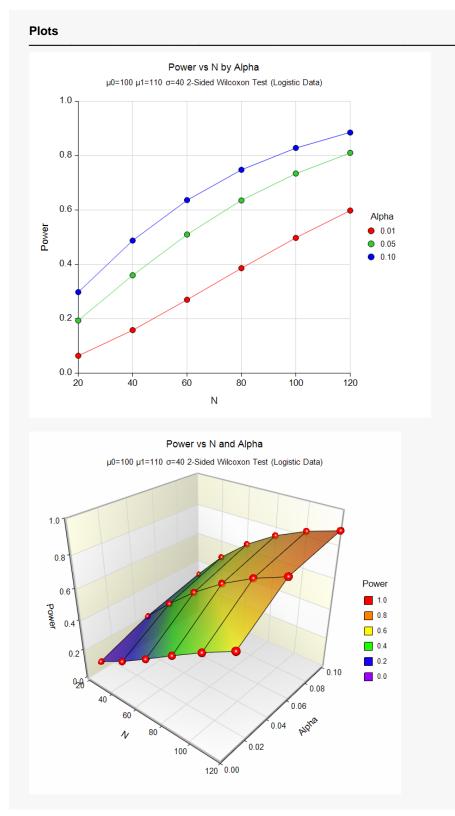
Chow, S.C., Shao, J., Wang, H., and Lokhnygina, Y. 2018. Sample Size Calculations in Clinical Research, Third Edition. Taylor & Francis/CRC. Boca Raton, Florida.

Machin, D., Campbell, M., Fayers, P., and Pinol, A. 1997. Sample Size Tables for Clinical Studies, 2nd Edition. Blackwell Science. Malden, MA.

Zar, Jerrold H. 1984. Biostatistical Analysis (Second Edition). Prentice-Hall. Englewood Cliffs, New Jersey.

This report shows the values of each of the parameters, one scenario per row. The values of power and beta were calculated from the other parameters.

## Plots Section



These plots show the relationship between sample size and power for various values of alpha.

# Example 2 – Finding the Sample Size

This example will consider the situation in which you are planning a study that will use the Wilcoxon Signed-Rank test and want to determine an appropriate sample size. This example is more subjective than the first because you now have to obtain estimates of all the parameters. In the first example, these estimates were provided by the data.

In studying deaths from SIDS (Sudden Infant Death Syndrome), one hypothesis put forward is that infants dying of SIDS weigh less than normal at birth. Suppose the average birth weight of infants is 3300 grams with a standard deviation of 663 grams. Use an alpha of 0.05 and power of both 0.80 and 0.90. How large a sample of SIDS infants will be needed to detect a drop in average weight of 25%? Of 10%? Of 5%? Note that applying these percentages to the average weight of 3300 yields 2475, 2970, and 3135.

Although a one-sided hypothesis is being considered, sample size estimates will assume a two-sided alternative to keep the research design in line with other studies. The assumed data distribution will be normal.

## 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	Sample Size
Alternative Hypothesis	Two-Sided (H1: μ ≠ μ0)
Data Distribution	Normal
Population Size	Infinite
Power	0.80 0.90
Alpha	0.05
μ0 (Null or Baseline Mean)	3300
μ1 (Actual Mean)	2475 2970 3135
$\sigma$ (Standard Deviation)	663

# Output

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

Solve For:Sample SizeHypotheses:H0: $\mu = \mu 0$ vs. H1: $\mu \neq \mu 0$ Data Distribution:Normal							
	Compl		Mean		Standard		
Power	Sample Size	e Null	Actual µ1	Difference μ1 - μ0	Standard Deviation σ	Effect Size	Alpha
0.85339	ļ	3300	2475	-825	663	1.244	0.05
0.90307	1(	3300	2475	-825	663	1.244	0.05
0.80426	30	3300	2970	-330	663	0.498	0.05
0.90409	48	3300	2970	-330	663	0.498	0.05
0.80105	130	3300	3135	-165	663	0.249	0.05
0.90070	18	3300	3135	-165	663	0.249	0.05

This report shows the values of each of the parameters, one scenario per row. Since there were three values of  $\mu$ 1 and two values of power, there are a total of six rows in the report.

We were solving for the sample size, *N*. Notice that the increase in sample size seems to be most directly related to the difference between the two means. The difference in beta values does not seem to be as influential, especially at the smaller sample sizes.

Note that even though we set the power values at 0.8 and 0.9, these are not the power values that were achieved. This happens because *N* can only take on integer values. The program selects the first value of *N* that gives at least the values of alpha and power that were desired.

# **Example 3 – Finding the Minimum Detectable Difference**

This example will consider the situation in which you want to determine how small of a difference between the two means can be detected by the Wilcoxon Signed-Rank test with specified values of the other parameters.

Continuing with the previous example, suppose about 50 SIDS deaths occur in a particular area per year. Using 50 as the sample size, 0.05 as alpha, and 0.80 as power, how large of a difference between the means is detectable?

# 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.

De	sian	Tab
	e gri	100

Solve For	µ1 (Search < µ0)
Alternative Hypothesis	
Data Distribution	Normal
Population Size	Infinite
Power	0.80
Alpha	0.05
N (Sample Size)	
μ0 (Null or Baseline Mean)	
σ (Standard Deviation)	

# Output

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

Solve Fo Hypothes Data Dis	ses: HO	(Search < : μ = μ0 ormal	< μ0) vs. H1:μ≠	μO				
	Semula		Mean	1	Standard			
					Stanuaru			
Power	Sample Size N	Null µ0	Actual µ1	Difference μ1 - μ0	Deviation σ	Effect Size	Alpha	

With a sample of 50, a difference of 3023.2 - 3300 = -276.8 would be detectable.

# Example 4 – Validation using Chow, Shao, Wang, and Lokhnygina (2018)

Chow, Shao, Wang, and Lokhnygina (2018) presents an example on pages 45 and 46 of a two-sided onesample *t*-test sample size calculation in which  $\mu 0 = 1.5$ ,  $\mu 1 = 2.0$ ,  $\sigma = 1.0$ , alpha = 0.05, and power = 0.80. They obtain a sample size of 34.

The Wilcoxon Signed-Rank test power calculations are the same as the one-sample *t*-test except for an adjustment factor for the assumed data distribution. If we assume a uniform data distribution, we should get this same result. If we set the data distribution to Normal, we should get a result of N =  $34 \times \pi/3 = 35.605 = 36$ .

## 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 4a** 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
Alternative Hypothesis	Two-Sided (H1: μ ≠ μ0)
Data Distribution	Uniform
Population Size	Infinite
Power	0.80
Alpha	0.05
μ0 (Null or Baseline Mean)	<b>1.5</b>
µ1 (Actual Mean)	2
$\sigma$ (Standard Deviation)	1

## Output

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

Solve For: Hypothese Data Distr	es: H0:	nple Size μ = μ0 v form	s. H1:µ≠	μΟ				
			Mear	n	Standard			
	Sampla		mour	•	Standard			
Power	Sample Size N	Null μ0	Actual µ1	Difference μ1 - μ0	Standard Deviation σ	Effect Size	Alpha	

The sample size of 34 matches Chow, Shao, Wang, and Lokhnygina (2018) exactly.

If we now assume a Normal data distribution (**Example 4b** settings file), the results match our expected outcome.

Solve For:       Sample Size         Hypotheses:       H0: $\mu = \mu 0$ vs. H1: $\mu \neq \mu 0$ Data Distribution:       Normal         Mean								
	Sample		Ivieal	•	Standard			
Power	Size N	Null µ0	Actual µ1	Difference μ1 - μ0	Deviation σ	Effect Size	Alpha	

The sample size of 36 matches the expected result.

# Example 5 – Validation using Zar (1984)

Zar (1984) pages 111-112 presents an example in which  $\mu$ 0 = 0.0,  $\mu$ 1 = 1.0,  $\sigma$  = 1.25, alpha = 0.05, and N = 12. Zar obtains an approximate power of 0.72 for the one sample *t*-test.

The Wilcoxon Signed-Rank test power calculations are the same as the one-sample *t*-test except for an adjustment factor for the assumed data distribution. If we assume a uniform data distribution, we should get the same power with N = 12. If we assume a Double Exponential data distribution with N =  $12 \times 2/3 = 8$ , then the adjusted sample size would be N' = 8/(2/3) = 12 and we should get the same power as Zar (1984).

# 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 5a** 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	Power
Alternative Hypothesis	Two-Sided (H1: μ ≠ μ0)
Data Distribution	Uniform
Population Size	Infinite
Alpha	0.05
N (Sample Size)	12
μ0 (Null or Baseline Mean)	0
μ1 (Actual Mean)	1
$\sigma$ (Standard Deviation)	1.25

# Output

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

Solve For: Hypothese Data Distr		μ = μ0 ι	∕s. H1:μ≠	μΟ				
		Mean			Standard			
	Sample			•	Standard			
Power	Sample Size N	Null µ0	Actual µ1	Difference μ1 - μ0	Standard Deviation σ	Effect Size	Alpha	

The difference between the power computed by **PASS** of 0.71366 and the 0.72 computed by Zar is due to Zar's use of an approximation to the noncentral *t* distribution. Notice that the results for the Wilcoxon signed-rank test with the uniform distribution match the one-sample *t*-test results.

If we now assume a double exponential data distribution and set N = 8 (**Example 5b** settings file), the results match our expected outcome.

#### **Numeric Results**

Solve For: Hypothese Data Distri	es: H0:	er μ = μ0 vs. H1: μ ≠ μ0 ble Exponential						
	Sample	Mean			Standard			
Power	Sample Size N	Null μ0	Actual µ1	Difference μ1 - μ0	Deviation σ	Effect Size	Alpha	
0.71366	8	0	1	1	1.25	0.8	0.05	

The power of 0.71366 matches the expected result.

# Example 6 – Validation using Machin (1997)

Machin, Campbell, Fayers, and Pinol (1997) page 37 presents an example in which  $\mu$ 0 = 0.0,  $\mu$ 1 = 0.2,  $\sigma$  = 1.0, alpha = 0.05, and beta = 0.20. They obtain a sample size of 199.

As in Example 4, if we set the data distribution to Uniform, we should get this same result. If we set the data distribution to double exponential, we should get a result of  $N = 199 \times 2/3 = 132.6667 = 133$ .

## 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 6a** 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
Alternative Hypothesis	Two-Sided (H1: μ ≠ μ0)
Data Distribution	Uniform
Population Size	Infinite
Power	0.80
Alpha	0.05
μ0 (Null or Baseline Mean)	0
µ1 (Actual Mean)	0.2
$\sigma$ (Standard Deviation)	1

# Output

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

Solve For:Sample SizeHypotheses:H0: $\mu = \mu 0$ vs. H1: $\mu \neq \mu 0$ Data Distribution:Uniform								
			Mear	ı	Standard			
	Sample	-						
Power	Sample Size N	Null µ0	Actual µ1	Difference μ1 - μ0	Deviation σ	Effect Size	Alpha	

The sample size of 199 matches Machin's result.

If we now assume a double exponential data distribution (**Example 6b** settings file), the results match our expected outcome.

Solve For: Hypothese Data Distr				•				
	Sample	 Null	Mear Actual	n  Difference	Standard Deviation	Effect		
Power	Size N	μ0	μ1	μ1 - μ0	σ	Size	Alpha	

The sample size of 133 matches the expected result.