

# DIET AND LONGEVITY STUDY

## 6. Checking Model Assumptions

### 6.1 Checking the Normality Assumption

### 6.2 Checking the Assumption of Equal Variances

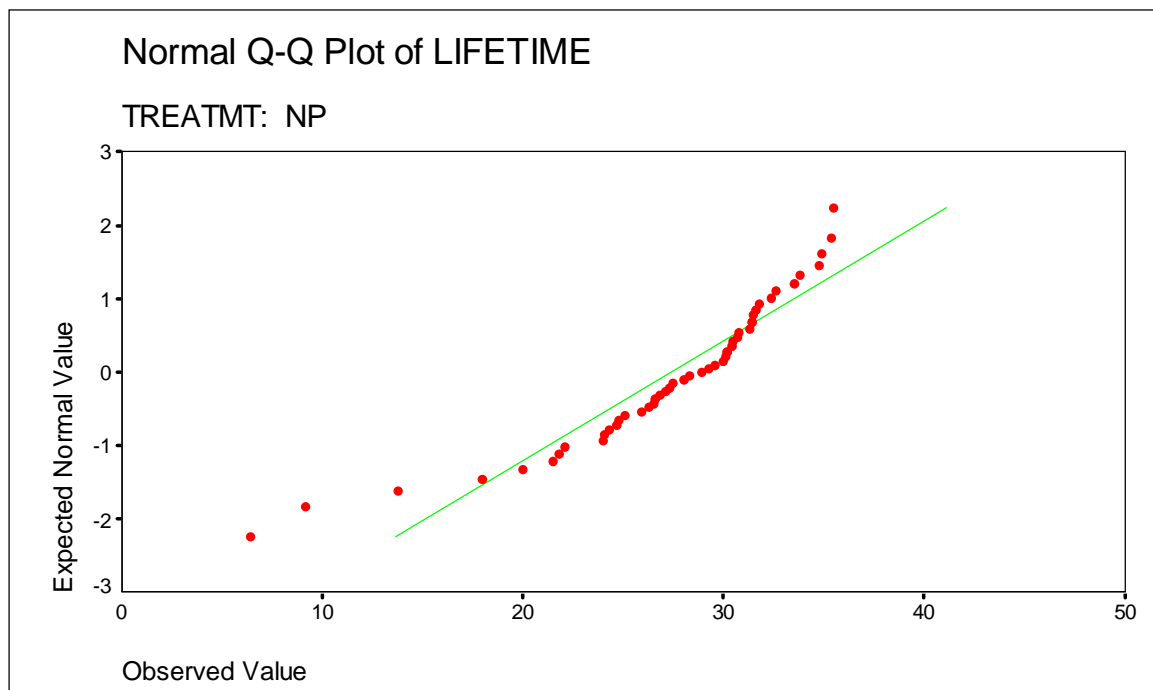
### 6.3 Checking the Independence Assumption

In order to determine whether the diet restriction has an effect on the life span of mice, we use one-way ANOVA model. However, the conclusions based on the model are valid only if the underlying assumptions are satisfied. Specifically we assume that:

1. The lifetimes have normal distributions for each of the six treatments.
2. The treatment standard deviations are all the same.
3. Observations within each group are independent of each other.
4. Observations in any one group are independent of observations in other groups.

### 6.1 Checking the Normality Assumption

In order to verify whether the assumption of normality is plausible for our data, you can use either normal quantile plot of observations or the normal quantile plot of residuals, the differences between each observation and its group mean. As SPSS doesn't provide a normal quantile plot for the residuals, we will obtain a normal quantile plot for each of the six treatment groups.

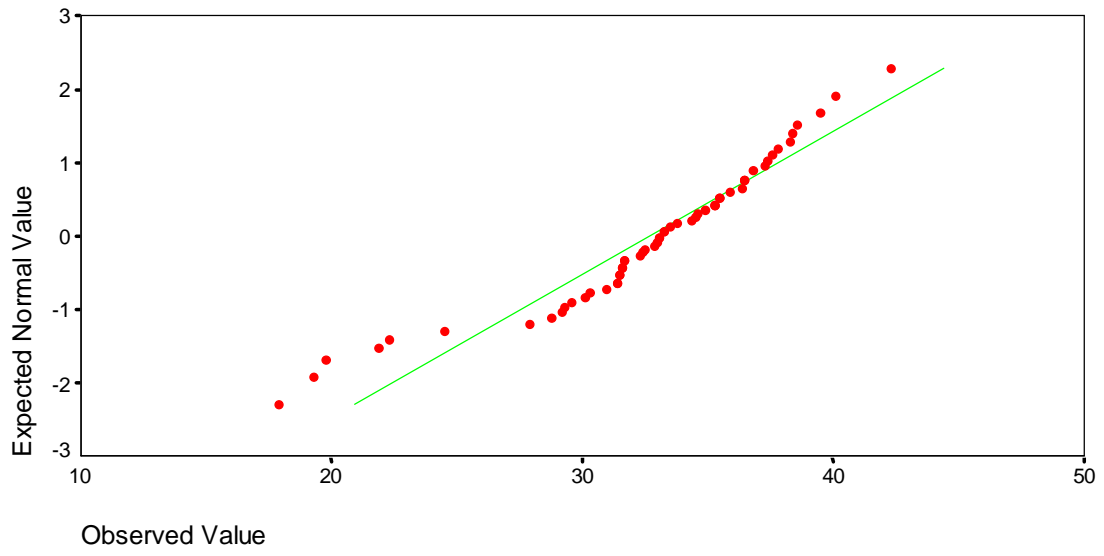


In the normal quantile plot of lifetime for the NP group displayed above, most of the points lie close to a straight line, indicating that the normality assumption is not seriously violated. The three outliers fall to the left of the general linear pattern of points. Thus the assumption of normality is slightly violated. Fortunately, normality is not critical especially when the sample sizes are relatively large.

Let us examine the plots for the remaining treatment groups.

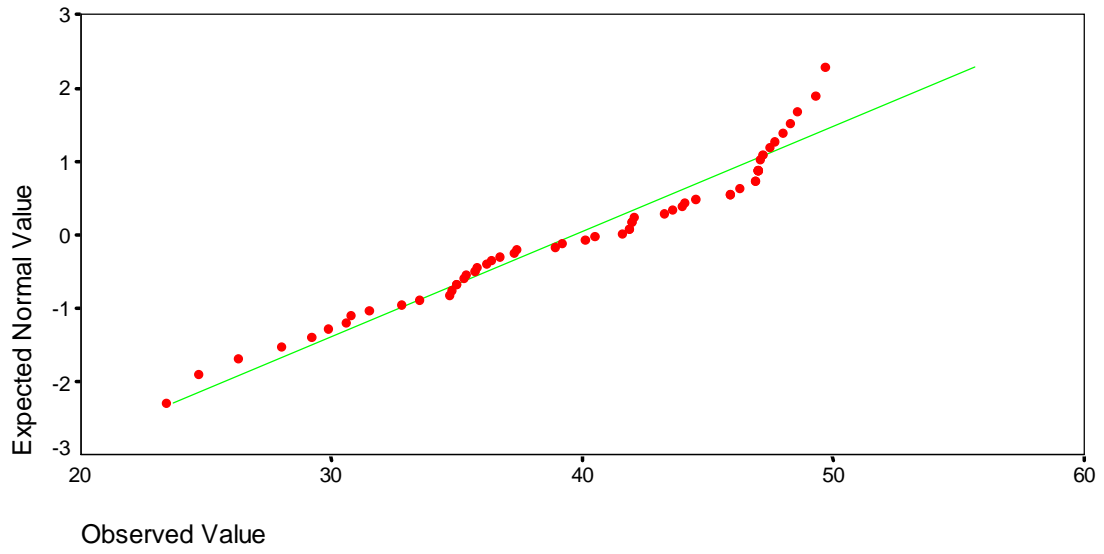
### Normal Q-Q Plot of LIFETIME

TREATMT: N/N85



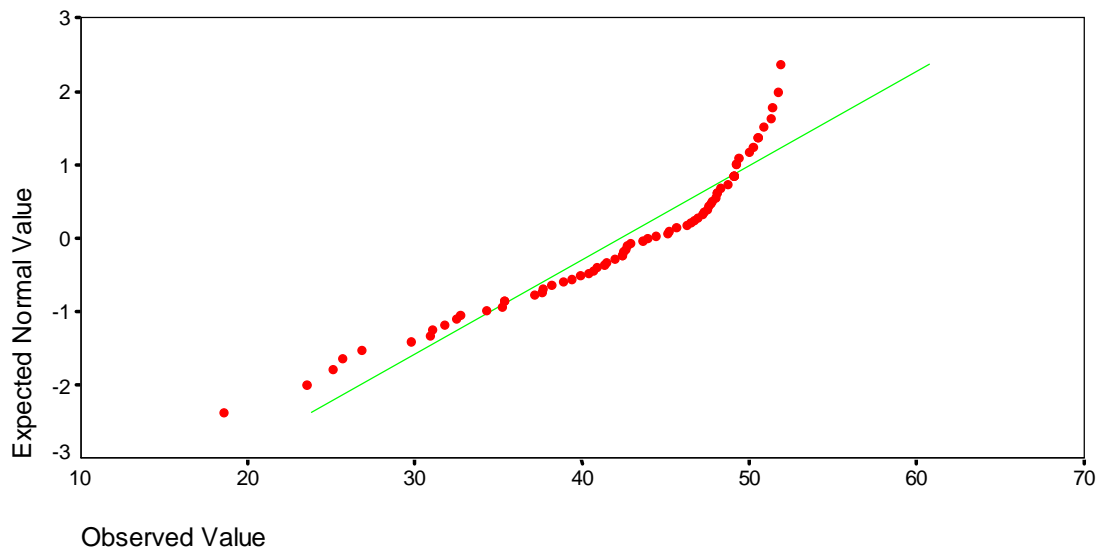
### Normal Q-Q Plot of LIFETIME

TREATMT: LOPRO



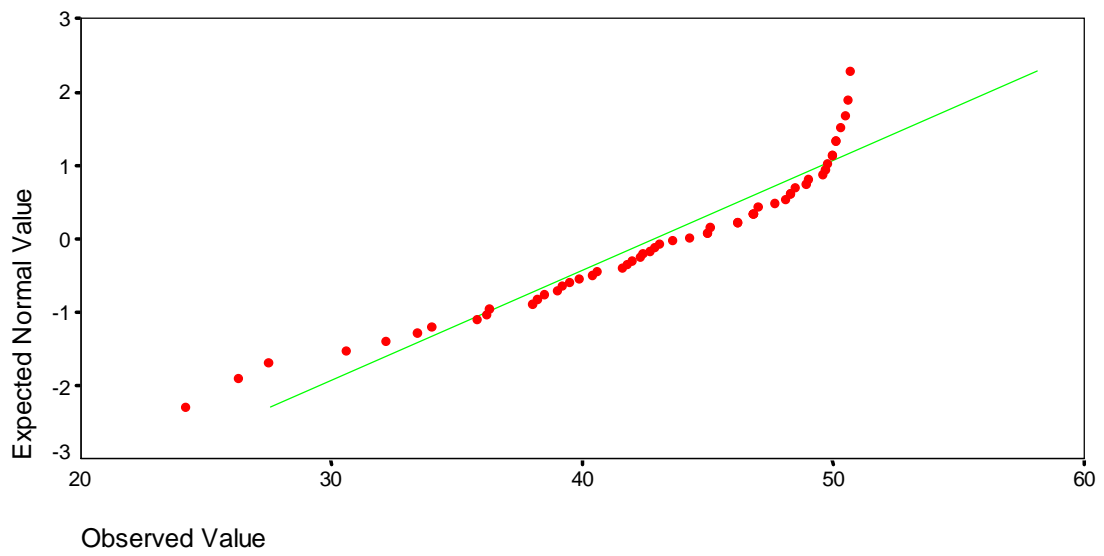
### Normal Q-Q Plot of LIFETIME

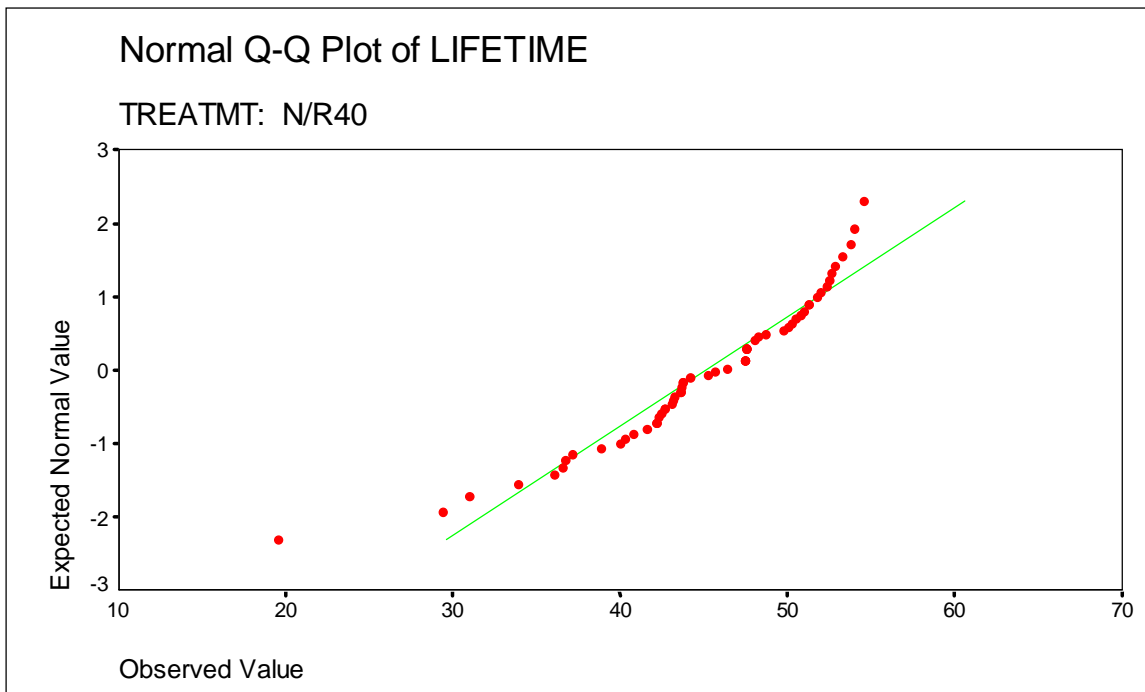
TREATMT: N/R50



### Normal Q-Q Plot of LIFETIME

TREATMT: R/R50





In each of the above plots you will also find some deviations from a straight line indicating that the assumption of normality is slightly violated. The violations do not pose any threat to our model because the sample sizes are relatively large.

## 6.2 Checking the Assumption of Equal Variances

Now we examine the assumption of equal variances. The assumption is crucial while making any inferences about the data. The side-by-side boxplots obtained in Section 4.1 indicate that the normality assumption might be slightly violated.

Formal tests for the equality of standard deviation in several groups share lack of robustness against nonnormality. Because ANOVA procedures are not extremely sensitive to unequal standard deviations, it is not recommended to carry out a formal test of equality of standard deviations as a preliminary to the ANOVA. Instead, the following rule of thumb is used: If the ratio of the largest sample standard deviation to the smallest sample standard deviation is less than 2, the assumption of equal standard deviations is plausible.

In Section 5 we obtained the following summary statistics:

Group	Count	Mean	Standard Deviation
NP	49	27.4020	6.1337
N/N85	57	32.6912	5.1253
LOPRO	56	39.6857	6.9917
N/R50	71	42.2972	7.7682
R/R50	56	42.8857	6.6832
N/R40	60	45.1167	6.7034

A quick glance at the data ensures us that the assumption of equal variances is plausible in our case. Indeed, the smallest standard deviation is 5.1253, the largest is 7.7682, and therefore their ratio is smaller than 2. We conclude that the assumption of equal variances is not violated.

The formal test available in SPSS, the Levene's test produces the following output:

<b>Levene Test for Homogeneity of Variances</b>			
Statistic	df1	df2	2-tail Sig.
3.1463	5	343	.009

Notice that the test supports strongly the alternative hypothesis that the group standard deviations are not equal. However, as we emphasized before the test might be affected by the slight departures of our data from the normality.

**Remark:**

If the number of observations in each group is the same, inferences made about means assuming a common variance are not seriously affected by unequal population variances. Thus the experimenter should try to arrange for equal sample sizes. If we couple this requirement with our requirement for minimizing the effects of nonnormality, we should try to arrange for equal and reasonably sample sizes.

**6.3 Checking the Independence Assumption**

Of the all assumptions, independence is the most crucial. If this assumption is violated, the effect on inferences about population means can be severe. In our case, independence is assured by randomly assigning experimental units to the different levels of the factor.