Statistics: Concepts and Controversies

Chapter 5
Experiments, Good and Bad

Lecture Slides

Case Study: Experiments, Good and Bad 1

Reports about climate change appear frequently in the media. Climate scientists warn us that major changes will occur in the coming years. For example, scientists predict that the changing climate will probably bring more rain to California, but they don't know whether the additional rain will come during the winter wet season or extend into the long dry season in spring and summer. Is it possible to investigate the effects of possible future changes in climate now?

Case Study: Experiments, Good and Bad 2

Researchers at the University of California at Berkeley carried out an experiment to study the effects of more rain in either season.

They randomly assigned plots of open grassland to 3 treatments:

(1) add water equal to 20% of annual rainfall during January to March (winter);

(2) add water equal to 20% of annual rainfall during April to June (spring);

(3) add no water beyond normal rainfall.

Case Study: Experiments, Good and Bad 3

Eighteen circular plots of area 70 square meters were used for this study, with six plots used for each treatment.

One variable the researchers measured was total plant biomass, in grams per square meter, produced in a plot over a year. Total plant biomass for the three treatments was compared to assess the effect of increased rainfall.

Is this a good study? By the end of this chapter, you will be able to determine the strengths and weaknesses of a study such as this.

Vocabulary 1

A **response variable** is a variable that measures an outcome or result of a study.

An **explanatory variable** is a variable that we think explains or causes changes in the response variable.

The individuals studied in an experiment are often called **subjects**.

A **treatment** is any specific experimental condition applied to the subjects. If an experiment has several explanatory variables, a treatment is a combination of specific values of these variables.

Vocabulary 2

Observational studies passively collect data. Researchers observe, record, or measure, but do not impose a treatment on the subjects.

In **experiments**, the researchers intentionally intervene by imposing some treatment on the subjects in order to investigate the impact on the response variable.

To distinguish between the two types of studies ask: “Were particular treatments deliberately assigned to the subjects or were the treatments ‘self-selected’?”

Vocabulary 3

A **lurking variable** is a variable that has an important effect on the relationship among the variables in a study, but is *not* one of the explanatory variables studied.

Two variables are **confounded** when their effects on a response variable cannot be distinguished from each other.

Lurking variables exist in all studies. This poses problems when trying to establish a cause-and-effect relationship between explanatory and response variables.

Vocabulary 4

A **placebo** is a dummy treatment.

→ A placebo has no active ingredients.

Sometimes subjects respond favorably to a treatment due to the expectation of a cure. This effect is called the **placebo effect**.

The placebo effect can be confounded with the effect of a treatment. In that case, the researcher cannot distinguish which effect, treatment, or placebo effect influenced the patient responses.

An experiment in which neither subjects nor researchers recording the symptoms know which treatment was received is called **double-blind**.

Randomized Comparative Experiment 1

The goal in designing an experiment is to ensure that it will detect whether the explanatory variables **cause** changes in the response variables.

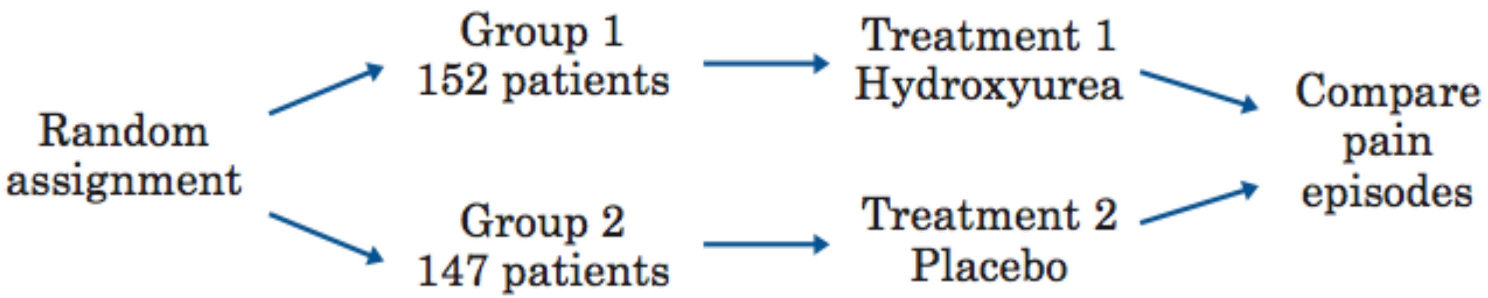
Confounding often prevents experiments with one treatment from this goal. The solution is to compare two or more treatments and assign the treatments randomly to the subjects.

Randomized Comparative Experiment 2

When confounding variables impact all subjects equally, any systematic differences in the responses of subjects receiving different treatments can be attributed to the treatments rather than random chance.

Example: Sickle-cell anemia (1 of 2)

Sickle-cell anemia is an inherited disorder of the red blood cells that in the U.S. affects mostly blacks. It can cause severe pain and many complications. A clinical trial of the drug hydroxyurea recruited 299 adult patients who had had at least three episodes of pain from sickle-cell anemia in the previous year.



The design of a randomized comparative experiment to compare hydroxyurea with a placebo for treating sickle-cell anemia.

Example: Sickle-cell anemia (2 of 2)

Figure 5.2 illustrates the simplest **randomized comparative experiment,** one that compares just two treatments. The diagram outlines the essential information about the design: random assignment to groups, one group for each treatment, the number of subjects in each group, what treatment each group receives, and the response variable being compared.

The placebo group here is called a **control group** because comparing the treatment and control groups allows the researcher to control the effects of lurking variables.

Logic of Experimental Design

Randomization produces groups of subjects that should be similar, on average, in all respects before the treatment is applied.

Comparative design exposes all groups to similar conditions, other than the treatments they receive. This ensures that any additional lurking variables operate equally on all groups and, on average, groups differ only in the treatments they receive.

Therefore, differences in the response variable are likely due to the effects of the treatments rather than random chance.

Principles in Experimental Design

Control the effects of lurking variables on the response, most simply by comparing two or more treatments.

Randomize – use impersonal chance to assign subjects to treatments.

Use enough subjects in each group to reduce chance variation in the results.

Statistical Significance

When performing a randomized comparative experiment, we compare the results of two or more treatments.

Do we expect the treatments to give the exact same results?

No, this difference could be due to the subjects chosen or the way they were assigned to treatments (chance).

How different do the results have to be to decide if one treatment is better than another?

An observed effect of a size that would rarely occur by chance is called **statistically significant.**

Statistics in Summary 1

Experiments often try to show that changing one variable (the **explanatory variable**) causes changes in another variable (the **response variable**).

In an experiment, researchers actually control the explanatory variables rather than just observe them.

Statistics in Summary 2

Observational studies fail to detect a cause-and-effect relationship because **confounding** with **lurking variables** makes it impossible to say what the effect of the treatment was on the response variable.

In a **randomized comparative experiment,** we compare two or more treatments, use chance to decide which subjects get each treatment, and use enough subjects so that the effects of chance are small.