>appendix9a

Complex Experimental Designs

Earlier in the chapter, we discussed true experimental designs in their most frequently used forms, but researchers often require an extension of the basic design for sophisticated experiments and market tests. Extensions differ from the traditional designs in (1) the number of different experimental stimuli that are considered simultaneously by the experimenter and (2) the extent to which assignment procedures are used to increase precision.

Before we consider the types of variations, there are some commonly used terms that should be defined. *Factor* is widely used to denote an independent variable. Factors are divided into treatment levels, which represent various subgroups. A factor may have two or more levels, such as (1) male and female; (2) large, medium, and small; or (3) no training, brief training, and extended training. These levels should be defined operationally.

Factors also may be classified by whether the experimenter can manipulate the levels associated with the participant. *Active factors* are those the researcher can manipulate by causing a participant to receive one level or another. Treatment is used to denote the different levels of active factors. With the second type, the *blocking factor,* the experimenter can only identify and classify the participant on an existing level. Gender, age group, customer status, and ethnicity are examples of blocking factors, because the participant comes to the experiment with a preexisting level of each.

Up to this point, the assumption is that experimental participants are people, but this is often not so. A broader term is *test unit;* it can refer equally well to an individual, product type, geographic market, medium of information dissemination, and innumerable other entities.*

Completely Randomized Design

The basic form of the true experiment is a completely randomized design. To illustrate its use, and that of more complex designs, consider a decision now facing the pricing manager at the Top Cannery. He would like to know what the ideal difference in price is between Top's private brand of canned vegetables and national brands such as Del Monte and Stokely's.

It is possible to set up an experiment on price differentials for canned green beans. Eighteen company stores and three price spreads (treatment levels) of 7 cents, 12 cents, and 17 cents between the company brand and national brands are used for the study. Six of the stores are assigned randomly to each of the treatment groups. The price differentials are maintained for a period, and then a tally is made of the sales volumes and gross profits of the canned green beans for each group of stores.

This design can be diagrammed as follows:

$$\begin{array}{cccc} R & O_1 & X_1 & O_2 \\ R & O_3 & X_3 & O_4 \\ R & O_5 & X_5 & O_6 \end{array} \qquad \textbf{(A1)}$$

Here, O_1, O_3, and O_5 represent the total gross profits for canned green beans in the treatment stores for the month before the test. X_1, X_3, and X_5 represent 7-cent, 12-cent, and 17-cent treatments, while O_2, O_4, and O_6 are the gross profits for the month after the test started.

We assume that the randomization of stores to the three treatment groups was sufficient to make the three store groups equivalent. When there is reason to believe this is not so, we must use a more complex design.

Randomized Block Design

If there is a single major extraneous variable, the randomized block design is used. Random assignment is still the basic way to produce equivalence among treatment groups, but the researcher may need additional assurances. First, if the sample being studied is very small, it is risky to depend on random assignment alone to guarantee equivalence. Small samples, such as the 18 company stores, are typical in field experiments because of high costs or because few test units are available. Another reason for blocking is to learn whether treatments bring different results among various groups of participants.

Consider again the canned green beans pricing experiment. Assume there is reason to believe that lower-income families are more sensitive to price differentials than are higher-income families. This factor could seriously distort our results unless we stratify the stores by customer income. Therefore, each of the 18 stores is assigned to

*Check this website for examples of industrial experiments: http://www.statsoft.com/.

one of three income blocks and randomly assigned, within blocks, to the price difference treatments. The design is shown in the following table.

Active Factor: Price Difference		Blocking Factor: Customer Income		
		High	Medium	Low
7 cents	R	X_1	X_1	X_1
12 cents	R	X_2	X_2	X_2
17 cents	R	X_3	X_3	X_3

Note: The *O*'s have been omitted. The horizontal rows no longer indicate a time sequence, but various levels of the blocking factor. However, before-and-after measurements are associated with each of the treatments.

(A2)

In this design, one can measure both main effects and interaction effects. The *main effect* is the average direct influence that a particular treatment of the independent variable (IV) has on the dependent variable (DV), independent of other factors. The *interaction effect* is the influence of one factor or variable on the effect of another. The main effect of each price difference is discovered by calculating the impact of each of the three treatments averaged over the different blocks. Interaction effects occur if you find that different customer income levels have a pronounced influence on customer reactions to the price differentials. (See Chapter 17, "Hypothesis Testing.")

Whether the randomized block design improves the precision of the experimental measurement depends on how successfully the design minimizes the variation within blocks and maximizes the variation between blocks. If the response patterns are about the same in each block, there is little value to the more complex design. Blocking may be counterproductive.

Latin Square Design

The Latin square design may be used when there are two major extraneous factors. To continue with the pricing example, assume we decide to block on the size of store and on customer income. It is convenient to consider these two blocking factors as forming the rows and columns of a table. We divide each factor into three levels to provide nine groups of stores, each representing a unique combination of the two blocking variables. Treatments are then randomly assigned to these cells so that a given treatment appears only once in each row and column. Because of this restriction, a Latin Square must have the same number of rows, columns, and treatments. The design looks like the following table.

Store Size	Customer Income		
	High	Medium	Low
Large	X_3	X_1	X_2
Medium	X_2	X_3	X_1
Small	X_1	X_2	X_3

(A3)

Treatments can be assigned by using a table of random numbers to set the order of treatment in the first row. For example, the pattern may be 3, 1, 2 as shown above. Following this, the other two cells of the first column are filled similarly, and the remaining treatments are assigned to meet the restriction that there can be no more than one treatment type in each row and column.

The experiment takes place, sales results are gathered, and the average treatment effect is calculated. From this, we can determine the main effect of the various price spreads on the sales of company and national brands. The cost information allows us to discover which price differential produces the greatest margin.

A limitation of the Latin square is that we must assume there is no interaction between treatments and blocking factors. Therefore, we cannot determine the interrelationships among store size, customer income, and price spreads. This limitation exists because there is not an exposure of all combinations of treatments, store sizes, and customer income groups. Such an exposure would require a table of 27 cells, while this one has only 9. If one is not especially interested in interaction, the Latin square is much more economical.

Factorial Design

One commonly held misconception about experiments is that the researcher can manipulate only one variable at a time. This is not true; with factorial designs, you can deal with more than one treatment simultaneously. Consider again the pricing experiment. The president of the chain might also be interested in finding the effect of posting unit prices on the shelf to aid shopper decision making. The following table can be used to design an experiment that includes both the price differentials and the unit pricing.

Unit Price Information?	Price Spread		
	7 Cents	12 Cents	17 Cents
Yes	X_1Y_1	X_1Y_2	X_1Y_3
No	X_2Y_1	X_2Y_2	X_2Y_3

(A4)

This is known as a 2 × 3 factorial design in which we use two factors: one with two levels and one with three levels of intensity.* The version shown here is completely randomized, with the stores being randomly assigned to one of six treatment combinations. With such a design, it is possible to estimate the main effects of each of the two independent variables and the interactions between them. The results can help to answer the following questions:

1. What are the sales effects of the different price spreads between company and national brands?
2. What are the sales effects of using unit-price marking on the shelves?
3. What are the sales effect interrelations between price spread and the presence of unit-price information?

*We describe factorial designs used with conjoint analysis in Chapter 19.

Covariance Analysis

We have discussed direct control of extraneous variables through blocking. It is also possible to apply some degree of indirect statistical control on one or more variables through analysis of covariance. Even with randomization, one may find that the before-measurement shows an average knowledge-level difference between experimental and control groups. With covariance analysis, one can adjust statistically for this before-difference. Another application might occur if the canned green beans pricing experiment were carried out with a completely randomized design, only to reveal a contamination effect from differences in average customer income levels. With covariance analysis, one can still do some statistical blocking on average customer income after the experiment has been run.†

†We discuss the statistical aspects of covariance analysis with analysis of variance (ANOVA) in Chapter 17.