# Chapter 4:

# Testing Hypotheses: Confounds and Controls

In this chapter we will outline how we test the hypotheses which we generated from our theory. The scientific method requires that we test our theories by comparing what they predict we will observe to actual observations made in the real world. If our hypotheses are any good, they should predict what we actually see.

## Multiple Variables and Confounds

It would make our life simpler if every effect variable had only one cause, and it covaried only with one other variable. Unfortunately, this is hardly ever the case. Virtually every communication variable we can think of is associated with a number of other variables either in causal relationships or in covariance relationships. For example, the amount of time we spend watching television is determined not only by our income, but also by our age, level of education, our interests, the number of children we have, the variety of programming available to us, alternative ways of spending our leisure time and a host of other variables. Our level of public communication apprehension can be affected by age, training in public speaking, amount of experience in public communication, ego strength, status differences between ourselves and the audience, and many other factors.

If we have a number of interrelated variables, then it becomes difficult to sort out how variables affect each other. It's far too easy to confuse one cause with another, or to attribute all change to a single cause when many causal factors are operating. Similarly, having multiple variables related to each other obscures the nature of covariance relationships: if we observe covariance between two variables, we must question whether they covary because of some real relationship between the variables, or whether the covariance is merely due to the spurious effect of a third confounding variable, as was illustrated in the previous chapter. Before we can establish that a relationship exists between two variables, we have to be able to sort out the effects of all the other variables which also may be related to the two.

The process of determining whether a relationship exists between two variables requires first that we establish covariance between two variables, as we discussed in the previous chapter. In addition to verifying that the two variables change in predictable, non-random patterns, we must also be able to discount *any other variable or variables* as sources of the change. To establish a true relationship, we must be able to confidently state that we observed the relationship in the real world under conditions which eliminated the effects of any other variables.

For example, if we are interested in determining whether there is a real relationship between Exposure to Movie Violence and the Number of Violent Acts committed by adolescents, then we must observe these two variables covarying, while simultaneously eliminating the possibility that this covariance was produced by other factors. An example of a confounding factor for this relationship might be the adolescent's Predisposition to Aggressive Behavior. Adolescents inclined toward aggression may choose to watch more violent movies than adolescents who are less aggressive, and they may also be more strongly affected by violent images. In order to conduct a legitimate test of the hypothesis which links two variables, we must find ways of controlling for the effects of the confounding variables.

Graphical examples of the problem are shown in Figures 4-1 and 4-2. In Figure 4-1, we see that there are two ways that a person's Exposure to Movie Violence can covary with Number of Acts of Violence comitted by that person. There is a direct causal relationship, with movie violence viewing causing an increase in the number of acts of violence. This is the hypothesis that we're interested in testing. In this hypothesis, Exposure to Movie Violence is the independent variable and Number of Acts of Violence is the dependent variable.

But there is also a spurious relationship between such Exposure and Violent acts, which is produced by the confounding variable of Predisposition to Violence.

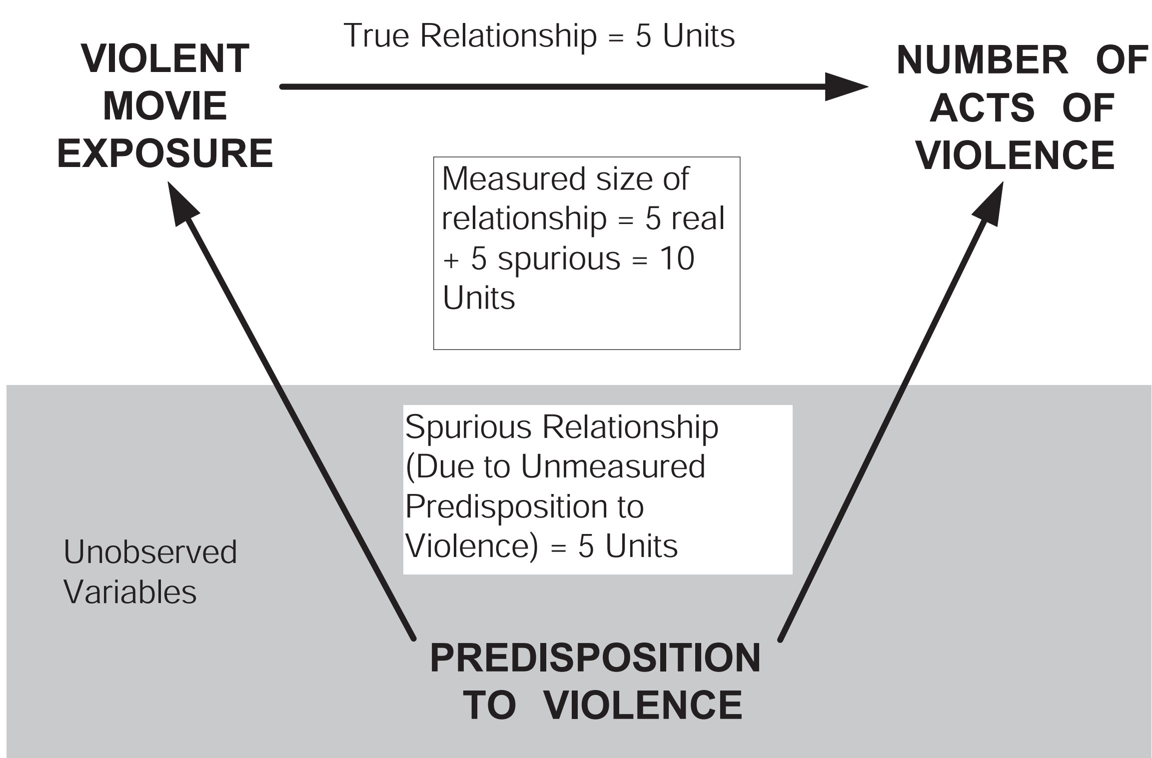


**FIGURE 4-1 Multiple variable confound: Misestimation of the size of a relationship**

Adolescents who are generally more violent are also more likely to select violent movies for viewing. This produces a spurious covariance between the independent and dependent variables.

Since we are observing only the independent (Exposure) and dependent ( # of Acts of violence) variables, we will overestimate the strength of relationship between them. If the true relationship is 5 units and the spurious relationship is also 5 units, we will conclude that the independent and dependent variables covary by 10 units. In truth, the real relationship is much smaller. If we ignore the confounding variable, we will erroneously conclude that *all* change in Number of Acts of Violence is due to the direct action of Exposure to Movie Violence. We erroneously conclude that we have strong support for our hypothesis.

Figure 4-2 illustrates an extreme way that an unobserved third variable can mislead us. Here, our original hypothesis is false—there is no relationship between Exposure to Movie Violence and Number of Acts of Violence. All covariance between the two is the result of the confounding variable Predisposition to Violence. Since we observe only the exposure and the acts of violence variables, it appears that they are covarying, so we will incorrectly conclude that we have a modest causal relation ship between viewing and violence, when we should conclude that there is no relationship.

We obviously must take steps to control all confounding variables, so that we can avoid making misestimates of the size of relationships, or even drawing the wrong conclusions from our observations. If we do not do so, we risk lending the appearance of scientific truth to falsehoods. Failure to properly control for confounding variables is a common error found in poorly done science. Critical reading of popular press accounts of "dramatic scientific breakthroughs" often reveals this error. As true scientists, you must always be skeptical of the results of *any* study. And the first thing you should speculate about when you read a scientific report (in the professional journals as well as in the popular press) is the possible presence of confounding variables which may have confused the researcher's results.

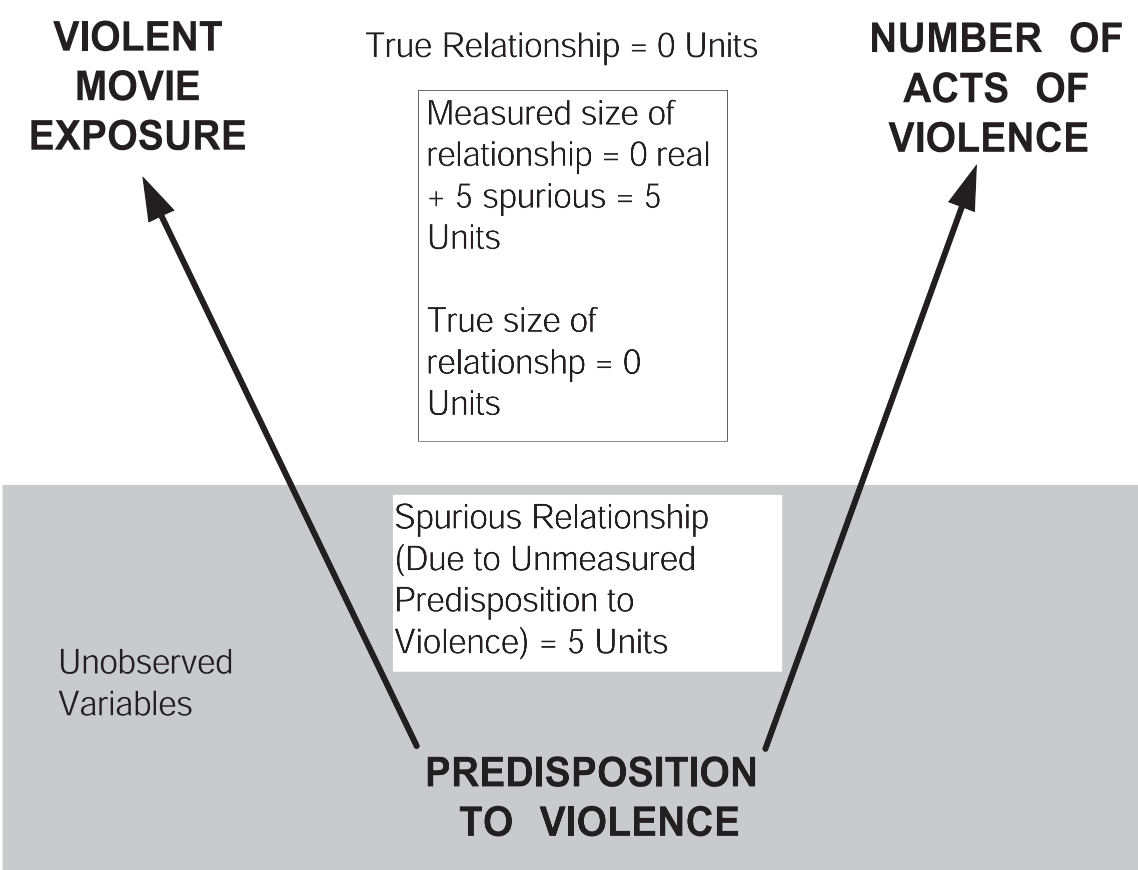


**FIGURE 4-2 Multiple variable confound: Erroneous inference**

# Controlling for Confounding Variables

We'll introduce another example to illustrate the process of determining what variables to control, and how to control them. Let's suppose that we are studying the development of children's language. We know that the age of the child and a whole variety of family interaction variables will affect both the child's Vocabulary Size and the complexity of the child's reasoning processes (which we'll label Cognitive Complexity). However, we're primarily interested in the relationship between Cognitive Complexity and Vocabulary Size, and not in family interaction variables.

## *Identifying Control Variables*

Let's start with a very wide view, and consider the idea that *any* given variable could potentially be included in our theory. We can first organize this universe of variables and reduce it enormously by classifying every variable into one of two categories: Relevant or Irrelevant to the phenomenon being investigated. This is the top stage illustrated in Figure 4-3.

The *relevant variables* are those which have already been shown to be important to understanding the phenomenon, or those for which a reasonable case can be made. For instance, if the research

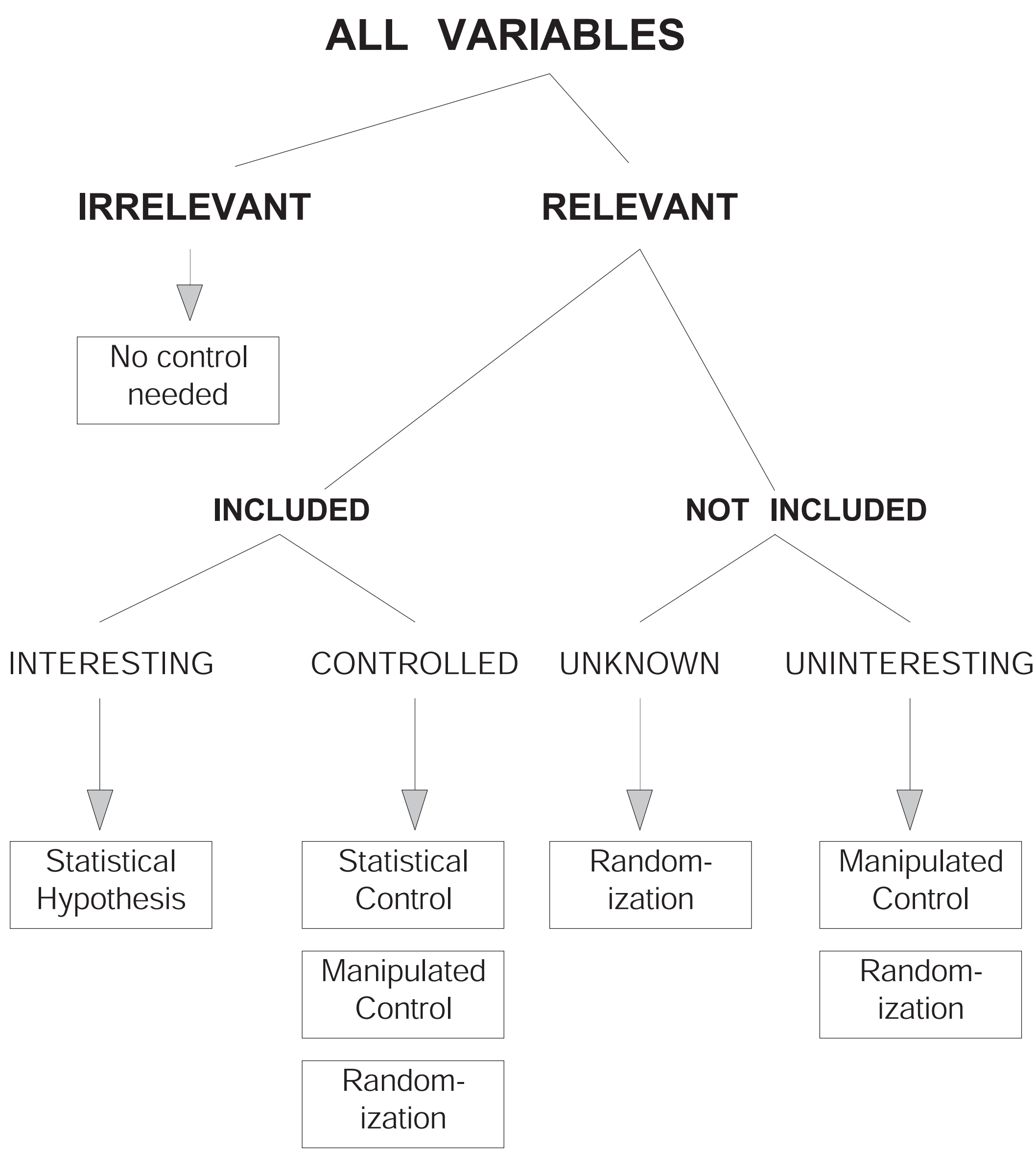


**FIGURE 4-3 Methods of controlling for confounding variables**

literature on this topic tells us that Vocabulary Size has been repeatedly observed to be associated with the Age of the child, then we will consider Age to be a relevant variable. And although no researcher may have reported it, we feel that the number of hours per week which the child spends outside the home should also be included in our theory. We'll have to justify classifying this variable as relevant, however. For the purposes of our example, let's argue that we think the additional exposure to other adults and children during the time spent outside the home should provide the child with exposure to new words, and thus expand the child's vocabulary. Note that we just provided a theoretical linkage for these two variables.

We've already covered the process of isolating and defining relevant concepts and putting them together in hypothetical relationships in Chapters 2 and 3, so we'll not spend any additional time talking about the procedure of including concepts and variables in a theory. But the *exclusion* of many concepts from consideration brings up a critical point. If we have not included a concept and its related variable in our theory, it can be because of several different reasons, and each of these reasons has important implications for the control of confounding variables.

One reason we might choose to exclude a variable is because we consider it to be irrelevant to the phenomenon we are investigating. If we classify a variable as *irrelevant*, it means that we are willing to assume that it has no systematic effect on any of the variables included in our theory. The temperature on the day that each child in our language study was born is a real variable, but we will conclude that it has no bearing on the phenomenon of children's language, and thus it will have no effect on any of the variables which we deem relevant. Irrelevant variables require no form of control, as they are not *systematically* related to any of the variables in our theory, so they will not introduce any confounding influences.

Relevant variables can be further classified into two categories: those which are explicitly measured and included in the theory, and those which are not (as shown in Figure 4-3). It's quite clear why we would include relevant variables, but why would we not include them? Again, there are two basic reasons.

First, the variables might be unknown. We, along with other researchers, might have overlooked some relevant variables. But the fact that we have missed these variables does not mean that they have no effect. So we must take precautions that insure that these unobserved, but relevant, variables do not confound our hypothesis tests. It is imperative that we take appropriate steps to insure that the effects of any unknown variables are not systematically associated with any values of the relevant variables. If they are, we will make the kinds of errors illustrated in Figures 4-1 and 4-2.

Another reason for excluding relevant variables is because they are simply not of interest. Although the researcher knows that the variable affects the phenomenon being studied, he does not want to include its effect in the theory. For example, we might decide that the effect of age on children's cognitive complexity and vocabulary is relevant—increasing age affects both variables positively—but it is not the central question being studied. We can't ignore age, however, so we must take some positive steps to control for its effect. We'll discuss methods for controlling relevant but uninteresting variables in the next section.

There remain two kinds of variables which are explicitly included in our hypothesis tests. The first of these are the relevant, interesting variables which are directly involved in our hypothesis test. In our example, Size of Vocabulary and Cognitive Complexity are these variables. There is also another kind of included variable called a control variable. It is explicitly included in the hypothesis test, because it affects the interesting variables. But it is included only in order to remove or control for its effect on the interesting variables. The child's Age is an example of this kind of control variable.

## Internal Validity, External Validity, and Information

Knowing what variables you need to control for is important, but even more important is the way you control for them.

Several ways of controlling variables exist, but before we discuss them it is important to understand the criteria that are used to choose among them. But prior to discussing the pro's and con's of different types of control for confounding variables, we will have to take some time to define and describe two types of research validity. Each method of control can be evaluated in terms of these validities, as well as by the amount of information about the action of control variables that is lost or gained in each method.

*Internal validity* is the degree to which we can be sure that no confounding variables have obscured the true relationship between the variables in the hypothesis test. It is the confidence that we can place in the assertion that the variables we have called causes or independent variables actually produce the effects that we observe. Internal validity is thus very closely associated with the amount of control which we exert over confounding variables. In a poorly controlled study, confounding variables may mislead us with spurious relationships. In Figure 4-2, the confounding effect of the uncontrolled variable Predisposition to Violence makes this study one that we characterize as having poor internal validity. Internal validity is also associated with the success with which we manipulate the independent variable in an experimental study. (An experimental study is one in which the independent variable or variables are deliberately manipulated by the researcher. We'll cover such studies in more detail in Chapter 14.)

*External validity* describes our ability to generalize from the results of a research study to the real world. If we have established that a relationship between two variables exists, it describes the degree to which this relationship can be generalized to groups, subjects and conditions other than those under which the research observations were made. Unfortunately, control for the effect of confounding variables, which increases internal validity, often simultaneously reduces external validity. By exercising careful control over confounding variables we may create a research environment which allows an unambiguous determination of the relationship between two variables, but at the same time creates a situation which is so artificial that any generalization to that real world is very difficult to justify.

Information. The third criterion by which we can evaluate methods of control is the *amount of information* that we can obtain about any confounding variable and its relationship with the relevant variables. We are often at least marginally interested in describing the effects of confounding variables, and some methods of control provide us with information about the action of the confounding variables on the relevant variables.

## Methods for Controlling Confounding Variables

The effects of confounding variables can be controlled with three basic methods, as was shown in Figure 4.3. The methods are *manipulated control*, *statistical control*, and *randomization*. Each method has characteristics which might be considered advantages or disadvantages. This means that they should not be used interchangeably and that the decision about which of these methods to use should be made after some thought. Internal validity, external validity, and the amount of information that can be obtained about confounding variables differs for each of these methods. An example for each of the three methods for controlling the confounding variable can be found in Table 4-1.

In this example our interest lies in studying the relationship between the method of communication used in teaching and student achievement. We want to contrast students in traditional lectures to students who are using computer-based instruction to see if there are differences in their performance. We speculate that the students in the computer-based group will be able to control the pace at which they learn and adapt it to their own abilities. Consequently we expect them to perform better than their colleagues who hear lectures, as these students cannot control the flow of information. Our hypothesis is that Teaching Method will affect Performance: specifically that the computer-using group will outperform the lecture group.

Suppose that our review of the literature has identified a variable called Previous Exposure to the Material. This variable has been shown to have a positive effect on Performance in past research studies. This classifies it as a confounding variable which we must control, so that it will not jeopardize our hypothesis test.

## Manipulated Control

Manipulated control essentially changes a variable into a constant. We eliminate the effect of a confounding variable by not allowing it to vary. If it cannot vary, it cannot produce any change in the other variables. If we use manipulated control, we will select subjects for the two conditions so that they are as similar as possible on Previous Exposure. This may mean that we will select only subjects who have no previous exposure to the course material, or we may choose only students who have already had one course in the particular subject matter. Any other variables that confound the hypothesis test can be treated in the same manner. If we can hold all confounding variables constant, we can be confident that any difference in Performance observed between the two groups is indeed due to the different teaching methods, as it could not have been due to the other variables. This gives us high internal validity for the study.

We can exert manipulated control outside of a laboratory or experimental setting, too. For example, suppose that we are going to conduct a survey to determine whether there might be a relationship between the amount of information that a person recalls from Army recruiting commercials and his/her willingness to enlist. An obvious confounding variable in this relationship is age. This variable is probably related to recall of recruiting appeals because older audience members are less likely to watch such commercials (they are irrelevant to a senior citizen), so they will be less likely to remember information from them, as well as being less likely to enlist. Furthermore, younger viewers might be more willing to give up several years to serve in the Armed Forces, and they may also pay more attention to the commercials. If these things happen, we will confuse the effect of Age with the effect of the commercials. To prevent this, we might control the confounding variable Age by selecting only 17 to 19-year-olds to participate in our survey.

Another form of manipulated control is called *matching subjects*. Subjects are placed into research groups on the basis of equality on a number of characteristics, like age, sex, income, marital status, or any other set of variables which we think might confound the hypothesis tests. This ensures there are equal proportions of high and low income, married and unmarried, female and male participants in all research groups. By forcing all groups to be identical on the matched characteristics, the effects of these variables are made constant in all research groups, and thus cannot confound the relationship being tested.

Manipulated control favors internal validity. But as the number of variables that we control increases, external validity generally decreases. In the computer instruction example, if the Previous Exposure variable is controlled at "one previous course" and we find positive results for computer-based instruction, we can't say with any confidence that the same difference would exist for students with "no previous exposure" or "two previous courses". We can't generalize the results of our research as widely, so external validity is reduced. Likewise, if we find certain advertising appeals to be associated with intention to enlist for 17 to 19-year olds, we can't be sure that the same appeals will stimulate enlistment among 21-year-olds.

Manipulated control prevents the controlled variables from having any effect on the dependent variable. As a consequence we will not find out what magnitude of effect (if any) these variables will have on the dependent variable. We will not find out, for instance, whether previous experience *really* affects academic performance in computer-based instruction. We have done the proper thing and controlled for it, since we suspected that it might confound our results, but we don't know whether or not it has an effect in the real world.

## *Statistical Control*

With this method of control, we build the confounding variable into the research design as an additional measured variable, rather than forcing its value to be a constant. When we test the hypothesis, we do so with three (or more) variables, not two: the independent and dependent variables, plus the confounding (or control) variable or variables. The effect of the control variable is mathematically removed from the effect of the independent variable, but the control variable is allowed to vary naturally. We do not hold it constant by deliberately setting its value, as we would with manipulated control.

This process yields additional information about the relationship between the control variable and the other variables. In our computer-based instruction example, we could allow students to participate in our study without imposing any requirements about their Previous Exposure to the material we are going to teach. Rather than holding this variable constant at some chosen level, as with manipulated control, we will *measure* Previous Exposure for each subject and use statistical procedures to estimate its effect on student performance, and then to remove this effect from the estimate of the effect of the independent variable.

Table 4-1 shows some hypothetical data from our teaching method example. Statistical control allows us to determine whether a relationship exists between Teaching Method and Achievement by contrasting the two groups which have instructional methods in common (the two Computer groups) to the two other instructional method groups (the two Lecture groups). The data in Table 4-

1 show that students in the Computer groups outperform the students in the Lecture groups *regardless* of the level of Previous Exposure. In other words, Teaching Method has an effect *of its own* on the Achievement of students. But we also see that the groups with "Some" Previous Exposure performed at a higher level than the two groups with *no* previous exposure, and that they do this regardless of instructional method.

Statistical control thus provides us with information about the control variable. In this case evidence about the relationship between the confounding variable of Previous Exposure and the dependent variable Performance is obtained by contrasting the two "None" groups to the two "Some" groups.

We can conclude that Previous Exposure (the control variable) is related to Performance (the dependent variable) and that the nature of the relationship is positive as higher levels of Previous Exposure are associated with higher levels of Performance. The size of the effect of Previous Exposure, which reflects the strength of the relationship, is the same as the effect size of Teaching Method. Computer groups scored 10% higher on exams than did lecture groups, regardless of Previous Exposure, and students with more Previous Exposure scored 10% higher than those with none, regardless of the Teaching Method.

If we used statistical control with our other example of research on reactions to recruitment advertising, we would ask audience members to state their age. The answers could then be used to determine whether age is indeed related to recall of advertising themes and to the inclination to enlist as we suspected.

**Table 4-1** Examples of Control Methods

| **Manipulated Control** | | | | |
|---|---|---|---|---|
| *Previous Exposure:* | *None* | | *Some* | |
| Teaching Method: | Computer | Lecture | Computer | Lecture |
| Performance (% correct on exam) | 85 | 75 | NO DATA COLLECTED | |
| Effect of Teaching Method: | (85-75=10%) | | | |

| **Statistical Control** | | | | |
|---|---|---|---|---|
| *Previous Exposure:* | *None* | | *Some* | |
| Teaching Method: | Computer | Lecture | Computer | Lecture |
| Performance (% correct on exam) | 85 | 75 | 95 | 85 |
| Effect of Teaching Method | (85-75=10%) | | (95-85=10%) | |
| Effect of Prior Exposure: | Computer (95-85=10%) | | | |
| | Lecture (85-75=10%) | | | |

| **Randomization Control** | | |
|---|---|---|
| *Previous Exposure:* | *Random Assignment* | |
| Teaching Method: | Computer | Lecture |
| Performance (% correct on exam) | 90 | 80 |
| Effect of Teaching Method: | (90-80=10%) | |

In addition to the additional information about the confounding variables that statistical control provides, it also has some real advantages over manipulated control in external validity. External validity is improved, because the confounding variables are allowed to vary naturally, as they would in the real world. In our computer-based instruction experiment, we don't need to guess whether any relationship we find holds for students with different levels of Previous Exposure, because we have the answer in front of us in numerical form. We can see that the results generalize to students with different levels of Previous Exposure.

Internal validity is not compromised to achieve this advantage. We have still accounted for the effect of the confounding variable, so we will not confuse the effect of Previous Exposure with the effect of Teaching Method.

In general, statistical control provides us with much more information about the problem we are researching than does manipulated control. But most advantages in one area usually have a cost in another, and this is no exception. An obvious large drawback of the method lies in the increased complexity of the measurement and statistical analysis which will result from the introduction of larger numbers of variables.

## *Randomization*

The third method of controlling for confounding variables is to randomly assign the units of analysis (experimental subjects) to experimental groups or conditions. The rationale for this approach is quite straightforward: any confounding variables will have their effects spread evenly across all groups, and so they will not produce any consistent effects that can be confused with the effect of the independent variable. This is not to say that the confounding variables produce *no* effects in the dependent variable—they do. But the effects are approximately equal for all groups, so the confounding variables produce *no systematic* effects on the dependent variable. This can be easily illustrated by using some numbers.

Assume that 100 students are to be assigned to the two teaching conditions in our Teaching Methods experiment. Of these 100 students, 50 have never taken a course in the same area before; the other 50 have taken at least one course. In order to assign students to one of the two conditions we are going to flip a coin: tails, to the computer-based group; heads, to the lecture hall. If a student stands before the experimenter waiting for the coin to be flipped, he or she has a 50% chance of going into the computer-based group and a 50% chance of attending lectures. Now, if the coin flipping experiment works perfectly, 50 students will be assigned to each of the two groups (because heads will occur just as frequently as tails). Because each student assigned to a group is just as likely to have has some Previous Exposure as to have no Previous Exposure, we would expect half of the 50 students each group to have some exposure and the other half to have none. The conditions are balanced, and Prior Exposure will have the same effect on the Performance of both groups, so it will not be confused with the effect of Teaching Method.

Randomization techniques are also used in non-experimental, or observational research (research in which the values of the independent variable are only observed by the experimenter, and are not manipulated), but not to the same extent as in experimental research. In telephone interviewing, for instance, once a number has been reached, we may flip a coin to decide whether we should talk to the male or female head of the household. If we did not do this, we would be likely to interview more females than males, since women tend to answer the phone more often than men in most households. This would introduce a systematic bias in the information we obtain. Flipping the coin introduces a random element which removes systematic effects of unmeasured confounding variables like the sex of the respondent.

The key difference between randomization and the other two techniques is that randomization does not involve identifying or measuring the confounding variables. If we use manipulated control, we must identify and measure the level of the confounding variable in order to hold it constant or ensure that it is matched across groups. Statistical control likewise requires explicit measurement of the confounding variable. But randomization works for *all* variables which are related to the relevant variables, as it will equalize all systematic covariation. Randomization is the only control method in which all confounding variables are controlled, without our even having to be aware of them.

Let's look at our computer-based instruction experiment again. Since the same effects of any confounding variable are represented in the two experimental groups in the same proportions, we know that any effect of the confounding variables will be the same in both experimental conditions. Consequently, any difference in Performance observed between the two experimental groups is due only to differences in Teaching Method. Since half the students have some Previous Exposure, they will score an average of 95 in the Computer group and 85 in the Lecture group. But half of each of these groups will also be made up of students with no Previous Exposure, who will score 85 and 75, respectively (10% lower, due to the effect of Previous Exposure). So the average score for the Computer group will be the average of 25 students who score 95 and 25 students who score 85, for an overall average score of 90. The overall average score for the Lecture group will be the average of 25 students who score 85 and another 25 who score 75, or 80, as illustrated in Table 4-1.

The major advantage of randomization is that we can assume that all confounding variables have been controlled. Even if we fail to identify all the confounding variables, we will still control for their effects. As these confounding variables are allowed to vary naturally, as they would in the real world, external validity is high for this method of control.

It might appear that randomization also results in high internal validity, but randomization is actually the weakest of the three control methods in this regard. This is the result of an assumption that we are forced to make. Since we don't actually measure the confounding variables, we assume that randomization produces identical effects from all confounding variables in all groups, and that this thus removes any systematic confounding effects of these variables.

But any random process will result in disproportionate outcomes occasionally. If we flip a coin 100 times, we will not always see exactly 50 heads and 50 tails. Sometimes we will get 60 heads and 40 tails, or even 70 tails and 30 heads. (We'll cover this in more detail in the next chapter).

Consequently, we have no way of knowing with absolute certainty that the randomization control procedure has actually distributed identically the effects of all confounding variables. We are trusting that it did, even though it might not have. By pure chance alone, the coin flip may have placed more students with Prior Exposure in the Computer group of our experiment, for example. If this happened, the confounding variable will exert a systematic influence on the dependent variable of Performance. This situation gives us a weaker confidence in the internal validity of our results. With manipulated control and statistical control, we can be completely confident that the effects of the confounding variables have been distributed so that no systematic influence can occur, because we can measure the effects of the confounding variable directly. There is no chance involved.

A further disadvantage of randomization is that it produces very little information about the action of any confounding variables. We assume that we have controlled for any effects of these variables, but we don't know what the variables are, or the size of their effects, if, in fact, there are any. As we'll see in Chapter 12, this lack of information makes our hypothesis test more difficult. The general problem is this: we assume that we've eliminated the *systematic* effects of the confounding variables by insuring that these effects are distributed across all values of the relevant variables. But we have not actually measured or *removed* these effects—the confounding variables will still produce change in the relevant variables. This makes it harder for us to observe the true covariance between the variables in the hypothesis test, since chance processes may not have distributed the effects of the confounding variable equally, and the confounding effects may obscure the real effects of the independent variable.

# Summary

Most communication phenomena have more than one cause for any single effect. This means that more than one cause variable is usually involved in determining the level of any dependent (effect) variable. However, we are usually interested in describing the effect of a single cause variable isolated from other confounding variables. If we blindly test for a relationship between a cause and an effect variable without controlling for the effects of the other cause variables which also affect the dependent variable, we will probably reach the wrong conclusions about the nature and strength of the true relationship. We must control for the effects of *all* variables which produce changes in the dependent variable before we can accurately describe the relationship between any one of these variables and the dependent variable.

There are three methods to control for confounding cause variables. The researcher may measure the levels of the confounding variables and design her research so that the confounding variables are held constant. This is *manipulated control*. Alternatively, she might measure the variables and use mathematical manipulations to remove their effects from her estimate of the true relationship between the independent variable and the dependent variable. This is *statistical* control. Finally, she might use research procedures to insure that the effects of all confounding variables are randomly distributed across all levels of the independent variable. This is *randomization control*.

Each of these control methods has advantages and disadvantages when we consider the internal validity, external validity, and amount of information about the controlled variables that the method produces.

Studies with high *internal validity* are those in which we can be sure that the true relationship between the independent and dependent variables are not obscured by the confounding variables. Manipulated and statistical control give high internal validity, while randomization control is a bit weaker. However, it has a distinct advantage over the other methods because the confounding variables do not have to described or measured.

Studies with high *external validity* are those in which the results can be correctly generalized to the external world. Manipulated control is weak in external validity, while statistical control and randomization control give good external validity.

Statistical control produces additional information about the size of the effects of the confounding variables on the dependent variable. The other methods do not provide this information.

Balancing the various advantages and disadvantages of these three methods for controlling for confounding variables means that the researcher must be very clear about the questions the research is to answer. Is internal validity more important than external validity? Can the confounding variables be identified and measured? Is information about the relationship between the confounding variables and the dependent variable useful? Like most decisions, the choice of control is a trade-off, with costs and benefits associated with each method.

# References and Additional Readings

Campbell, D.T. and Stanley, J.C. (1963). *Experimental and quasi-experimental designs for research*. Boston: Houghton Mifflin.

Cook, T.D. and Campbell, D.T. (1979). *QuasiExperimentation: Design and analysis issues for field settings*. (Chapter 9, “The Conduct of Randomized Experiments”).

Kish, L. (1987). *Statistical design for research*. New York: Wiley. (Chapter 1, “Representation, Randomization, and Realism”).