CHAPTER 3

The Idea of Causation in Social Research

Holographic Overview

Explanations in social science rest on the idea of causation. In both doing research and evaluating others' research conclusions, we need a solid understanding of what causation means and how it is established in social research. ■

Introduction

One of the chief goals of researchers—social or other—is to explain why things are the way they are. Typically, they do that by specifying the causes of the phenomena they observe: What things are caused by other things.

The idea of causation has been implicit in much of our discussion so far. Now we'll delve more deeply into this concept, especially as it applies to social research. We'll begin by looking at the role of determinism in social science, as contrasted with the idea of free will. Then we'll look at causation in the context of the idiographic and nomothetic modes of explanation introduced in Chapter 1. After considering the criteria for deciding that one thing causes another, we'll examine some common errors that people make in reasoning about causation. We'll conclude our discussion with a brief consideration of the link between measuring variables and determining how they are measured.

Determinism and Social Science

Scientific explanations rest on the idea that events and conditions have causes. Once we understand these causes, we know why things are the way they are: Given the occurrence of their causes, they could not be any other way. In philosophical terms, this perspective is called *determinism:* Events are determined, or caused to happen; they are not "free" to happen any other way.

In social science, this deterministic perspective contrasts with the idea of free will that you and I take for granted in our daily lives. As such, students of social research can find this basic scientific assumption troubling. The fundamental issue is this: Is our behavior the product of our freely chosen decisions and whims, or is it the product of forces and factors in the world that we cannot control and may not even recognize?

Let's begin our explanation of this issue by looking at causation in the natural sciences. Then we'll consider how this basic concept is used in the social sciences.

Causation in the Natural Sciences

The deterministic model of explanation is exemplified throughout the natural sciences. An object dropped from a tower falls to earth at a rate we can precisely determine as long as we know all the relevant factors. In the science of living things, growth is similarly caused by several factors. We can affect the growth of plants by varying the amount of light, water, and nutrients they receive; these factors, among others such as genetic inheritance, determine how the plants will grow. We also know that the growth rate of human beings is affected by the nutrients they receive. The desire to grow or not to grow is as irrelevant for humans as it is for plants. We acknowledge that genetics and nutrition greatly overshadow our free will in this matter.

The cause-and-effect, deterministic model of the natural sciences, then, is often applied to human beings as well as to plants and inanimate objects. For the most part, we accept the deterministic model as appropriate in such cases. We recognize that our free will is limited by certain constraints.

Finding Causes in Social Science

Essentially the same model is used in the social sciences. It is usually so implicit that we may forget the nature of the model we are using. Let's consider an illustration of how social science depends on a deterministic model.

Imagine that you have managed to obtain a million-dollar grant from the National Science Foundation to find out the causes of prejudice. You hope that what you discover will lead to ideas for reducing prejudice. This is certainly a laudable aim, and various government and private foundations are often willing to support such research. Let's suppose you've received the money, completed your research, and sent your report to the foundation. Here's how it reads:

> After an exhaustive examination of the subject, we have discovered that some people are prejudiced, and the reason is that they choose to be prejudiced. Other people are not prejudiced, and the reason is that they don't choose to be prejudiced.

Why would the foundation reject this conclusion as unsatisfactory? Your project aimed at finding out what causes prejudice, but your conclusion doesn't explain *why* prejudice happens. It simply pushes the explanation back into a mysterious black box labeled "choice." We are no more enlightened than we were before the research was conducted.

When we look for the causes of prejudice, we look for the reasons, or causes, that make some people prejudiced and others not. If the "explanation" is that they choose their attitudes, then we want to know why people make different choices. Satisfactory reasons might include economic competition, religious ideology, political views, childhood experiences, and amount and kind of education. Research shows, for example, that education tends to reduce prejudice. That's the kind of useful causal explanation we accept as the end product of social research.

Let's look at the logic of this kind of explanation a little more closely. What does an explanation of prejudice in terms of education and other factors say about the people who were the subjects of study? Fundamentally, it says that they turned out prejudiced or unprejudiced as a result of factors they did not control or choose. It's as though they came to a fork in the road—one path leading to prejudice and the other to the absence of prejudice—and they were propelled down one or the other by forces such as childhood experiences, level of education, economic competition, and similar factors they neither controlled nor even recognized as causing their attitudes. That is, to the extent that these factors account fully for prejudice, they turned out prejudiced or unprejudiced for reasons beyond their control.

When social scientists study juvenile delinquency, the basic model is the same: Delinquency is caused by factors other than the delinquent's free choice. They further assume that those factors can be discovered and perhaps modified so as to produce fewer delinquents in the future.

The same model applies when social scientists study behaviors that they or others consider socially desirable. What are the factors that cause a person to be altruistic, considerate, responsible? If we knew the answers, we could arrange things so that more people turned out that way—or so the implicit reasoning goes.

Reasons Have Reasons

Sometimes people protest this line of reasoning by arguing that individuals do choose those things that determine how prejudiced, delinquent, or altruistic they are. For example, let's say you are quite unprejudiced, and researchers conclude that your lack of prejudice is probably a function of all the education you've received. Didn't you choose to go to school? Aren't your own choices, therefore, the root cause of your being unprejudiced?

The problem with this view is that reasons have reasons. Why did you go to school? Initially it was probably because somebody compelled you to go. But at some point you made your own decision to continue your education at least through college. Let's say you wanted to learn about the world around you, and you thought college would be a good way to do it. That makes sense.

It makes so much sense, in fact, that we might even say your desire to learn about the world caused you to continue going to school. Given that you had such a desire, how could you not go to college?

"I might not have gone if I hadn't had enough money," you might say. True—that factor would have forced you to stay out of school. But then suppose your desire to learn about the world around you was so powerful that you overcame the lack of money. Maybe you got a scholarship or went to work for a while. In that case, we are back to your powerful desire as the cause of your going to college.

Ah, but why did you have such a strong desire to continue your education as a way of learning about the world around you? After all, you could have scraped and saved to tour the world instead. Perhaps you grew up in a family where everyone had gone to college generation after generation, and you'd have felt you were letting your family down if you didn't go to college. Or perhaps you came from a family where nobody had ever gone to college before, and they were all proud of the fact that you might be the first. In both cases, there were factors that caused your powerful desire to go to college, and that powerful desire caused you to go. Assuming that going to college caused you to be free of prejudice, this fortunate effect is ultimately produced by factors you didn't choose.

Clearly, this example oversimplifies the multiple reasons why you do something like go to college, but you can apply this line of thinking for yourself and see that there were reasons behind your behavior that explain why you did what you did. Moreover, no matter what reason you had at any specific step in the process, that reason would also have a reason. The ultimate implication of this discussion is that our attitudes and behaviors can be traced back through a long and complex chain of reasons that explain why we have turned out the way we have. If this were not the case, we would not be able to give the kinds of explanations we do in social science and see them validated by research.

Whenever we undertake explanatory social science research, then, we implicitly adopt a model of human behavior that assumes people have little individual freedom of choice. Are we therefore committed to the view that there is no such thing as free choice? Instead of answering this question with a simple yes or no, let's put the assumption of determinism in perspective.

Determinism in Perspective

The issue of determinism and freedom is quite complex—one that philosophers have debated for thousands of years and will probably debate for thousands more. It is perhaps one of those "open questions" that are more valuable asked than answered. Certainly, we are not going to resolve the issue here.

Nevertheless, as social researchers we need to recognize the role of determinism in social research and grapple with its implications. New researchers often harbor a concern about whether they are learning to demonstrate that they themselves have no free will, no personal freedom in determining the course of their own lives. To the extent that this concern grows and festers, it interferes with learning analytical skills and techniques. So it's important to confront the issue head-on.

Although explanations in social science rest on a deterministic model, we need to be clear about what is *not* part of the model. First, social scientists do not have to believe that all human actions, thoughts, and feelings are determined, nor do they lead their lives as though they believed it. But when they seek to explain things that lend themselves to social scientific study, they necessarily use the ideas of cause and effect. Second, as I've already suggested, the deterministic model does not assume that causal patterns are simple. Nor does the model assume we are all controlled by the same factors and forces: Your reasons for going to college (and the reasons for those reasons) surely differ somewhat from mine. Third, the deterministic model at the base of explanatory social science does not suggest that we now know all the answers about what causes what or that we ever will. In fact, much useful research is designed to reveal associations, or relationships, between variables without attempting to demonstrate causation.

Finally, as we noted earlier, social science typically operates on the basis of a causal model that is probabilistic in nature. Rather than predicting, for example, that a particular college graduate will be unprejudiced, research predicts that prejudice is more or less likely depending on people's level of education. This doesn't mean that all Ph.D.'s are free of prejudice. Nor does it mean that all school dropouts are prejudiced. It does mean that in our society prejudice is less likely to be observed among well-educated people and more likely to be found among people with less schooling.

To summarize, the kind of understanding social scientists seek when they construct causal explanations inevitably involves a deterministic model of human behavior. This model implicitly assumes that the characteristics and actions under study are determined by forces and factors that can be identified through research. Social scientists do not have to believe that every aspect of human life is totally determined, but they do need to be willing to use deterministic logic in seeking explanations for the phenomena that interest them.

Causation in Idiographic and Nomothetic Models of Explanation

The preceding discussions, with their emphasis on the multiplicity of reasons that can account for a specific behavior, provide an illustration of the idiographic model of explanation. This model aims at explanation by means of enumerating the many reasons that lie behind a particular event or action. Although in practice we never truly exhaust such reasons, the idiographic model is frequently employed in many different contexts.

Traditional historians, for example, tend to use the idiographic model, enumerating all the special causes of the French Revolution or the seemingly perpetual conflicts in the Balkans. Clinical psychologists may employ this model in seeking an explanation for the aberrant behavior of a patient. A criminal court, in response to a plea of extenuating circumstances, may seek to examine all the various factors that have played a role in the defendant's behavior.

As I indicated in Chapter 1, social researchers sometimes use this model as well. Consider the events of May 13, 1985, in Philadelphia. The city's police had been attempting to serve arrest warrants on activist members of a radical civil rights group known as MOVE. After evacuating the neighborhood and surrounding the organization's headquarters with 500 heavily armed officers, the police launched their attack. Beginning with automatic weapons, water cannons, and tear gas, the police assault culminated with a helicopter dropping explosives onto the roof, killing 11 people and destroying two urban blocks.

In shocked tones that would be echoed in the 1990s law-enforcement sieges at Waco, Texas, and Ruby Ridge, Idaho, people asked how such a tragedy could have occurred. Robin Wagner-Pacifici (1995) undertook research to find the causes. He used a technique known as *discourse analysis*, which involves dissecting the underlying meanings found in various forms of communications. In this case, the police pronouncements could be best understood as a "discourse of war." Given the perspective of the police, the resulting battle makes sense.

While the idiographic model of explanation is often used in daily life and in social research, other situations and purposes call for the nomothetic model of explanation. This model does not involve enumerating all the considerations that result in a particular action or event. Rather, it is designed to discover those considerations that are most important in explaining general classes of actions or events.

Suppose we wanted to find out why people voted the way they did in the 1996 presidential election. Each individual we talked to could give a great many reasons why he or she voted for either the Democrat, Bill Clinton, or the Republican, Bob Dole. Suppose someone gave us 99 different reasons for voting for Clinton. We'd probably feel we had a pretty complete explanation for that person's vote. In fact, if we found someone else who agreed with those 99 reasons, we would feel pretty confident in predicting that that person also voted for Clinton. This approach represents the idiographic model of explanation.

The nomothetic model, on the other hand, involves the isolation of those relatively few considerations that will provide a partial explanation for the voting behavior of many or all people. For example, political orientation—liberal or conservative—would probably be a factor of general importance in determining the voting behavior of the electorate as a whole. Most of those sharing the attribute "liberal" probably voted for Clinton in 1996, and most of those sharing the attribute "conservative" probably voted for Dole. To that extent, political orientation is one of the causes of people's voting behavior. This single consideration, however, would not provide a complete explanation of every individual's voting behavior. Some liberals voted for Dole, some conservatives for Clinton. The nomothetic model aims at providing the greatest amount of explanation with the fewest number of causal variables to uncover general patterns of cause and effect.

The nomothetic model is inevitably probabilistic in its approach to causation. Naming a few causal variables seldom, if ever, provides a complete explanation for complex behaviors. In the best of all practical worlds, the nomothetic model indicates a very high (or very low) probability that a given action will occur whenever a limited number of specified considerations are present. Adding a greater number of specified considerations to the equation typically increases the degree of explanation, but it also makes explanations more complex—perhaps so much so that they cease to be useful.

Thus, when Eric Plutzer and John Zipp (1996) set out to understand the number of votes received by feminist political candidates in the 1992 elections, they looked for variables that would make a difference in general rather than in specific cases. As you might expect, for example, they found that women were more likely than men to vote for feminist candidates. But the researchers were also interested in seeing to what extent gender-based voting conflicted with party loyalty, with some Democratic men deserting their party's feminist candidates and some Republican women supporting Democrats who were feminists. The nomothetic intent, then, was to discover which variables had the strongest impact on voting decisions.

In another illustration of nomothetic explanation, Jeremy Hein (1993:55) reviews the body of research aimed at distinguishing the experiences of refugees from other immigrants. Notice the language of causation:

> The same demographic variables predict employment status and earnings for immigrants and refugees. Both populations adapt as households and obtain income from multiple sources. Women perform the central function of bridging social networks and economic arenas. However, state intervention once again produces some important differences, particularly of access to the social welfare system. [Refugees are entitled to welfare immediately, while other immigrants must wait five years.]

Words such as *predict* and *prejudice* signal causal explanations. Notice, though, that the generalizations in these statements leave plenty of room for individual interpretations. The researchers are describing useful general patterns of cause-effect relationships that hold for a wide range of cases.

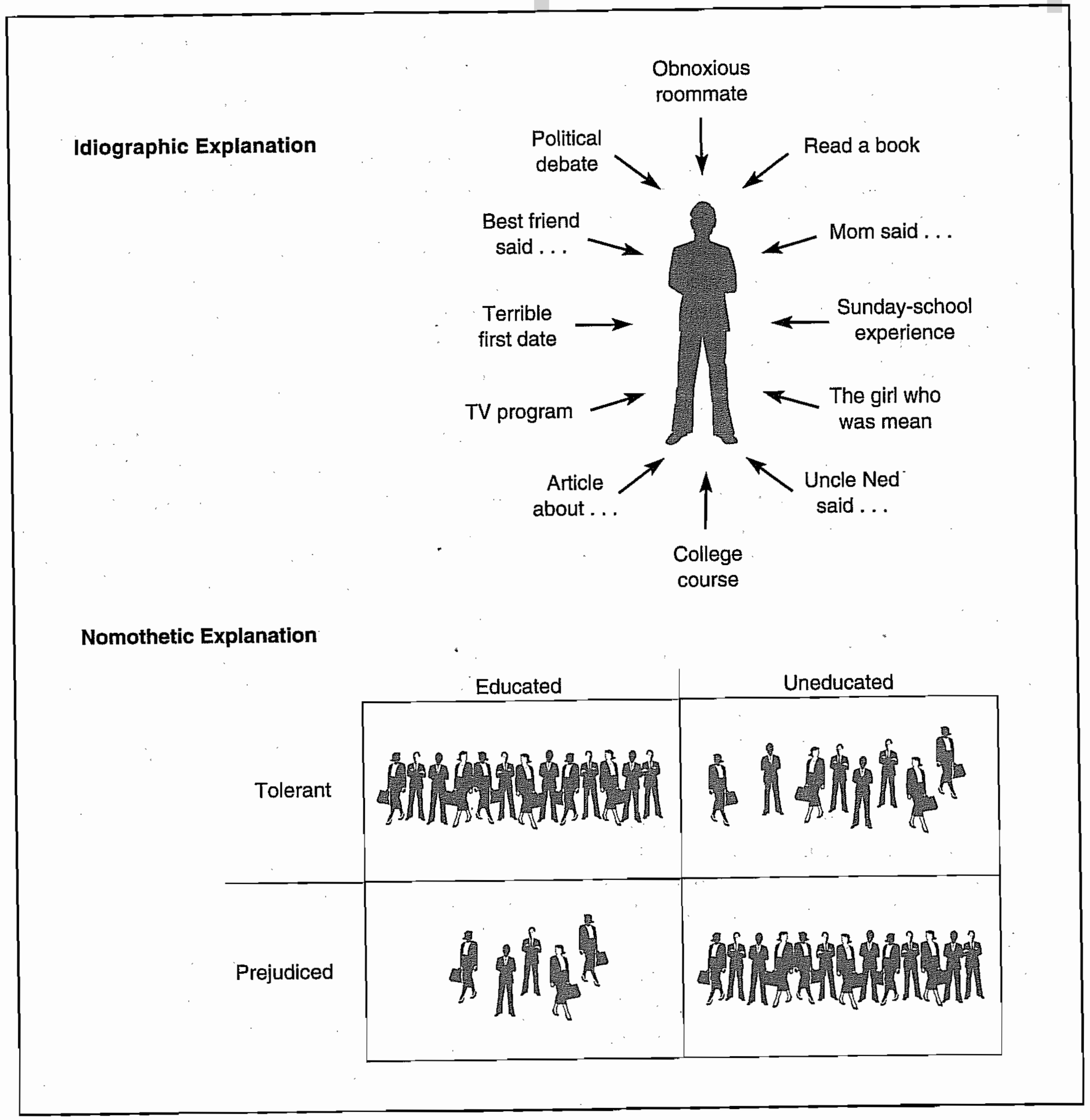
Figure 3-1 (p. 74) offers a graphic illustration of the different approaches represented by nomothetic and idiographic explanations. This diagram portrays two modes of explanation. In the idiographic case, we are attempting to understand why this one person is prejudiced, noting that a large number of idiosyncratic circumstances and experiences have contributed to her views. In the nomothetic case, we seek to discover factors that affect levels of prejudice in general. Here, we see that the more educated people are generally less prejudiced than are the uneducated.

Social scientists are sometimes criticized for dehumanizing the people they study. This charge is lodged specifically against the nomothetic model of explanation; the severity of the charge increases when social scientists analyze matters of great human concern. Religious people, for example, often feel robbed of their human individuality when a social scientist reports that their religiosity is largely a function of their gender, age, marital status, and social class. Any religious person will quickly report there is much more than that to the strength of his or her convictions. And indeed there is, as the use of the idiographic model in the case of any individual person would reveal. Is the idiographic model, though, any less dehumanizing than the nomothetic model?

If a characteristic such as being religious (or free of prejudice) can be explained in terms of prior considerations, is it any more dehumanizing to seek partial but general explanations using only a few of those considerations than to seek a total explanation using them all? Logically speaking, a complete account of any individual's religiosity would still imply that it is a function of other causes—only there might be a great many of them. Perhaps what really underlies the discomfort with nomothetic explanations is that this model is more obviously deterministic. However, a careful listing of all the reasons why a particular individual is religious, or votes for Candidate X, or is free of prejudice, involves a deterministic perspective. In this respect, the idiographic model is no less deterministic than a model that permits us to specify the four variables that are most important in causing religiosity among people in general.

The difference between idiographic and nomothetic explanation relates to another distinction first introduced in Chapter 1: the distinction between

FIGURE 3-1
Idiographic versus Nomothetic Explanation: Two Examples of Prejudice



qualitative and quantitative data. Qualitative data, containing a greater depth of detailed information, lend themselves readily to idiographic explanations. Quantitative data, on the other hand, are more appropriate to nomothetic explanations. Thus, for example, an in-depth interview with one homeless person might yield a full (idiographic) understanding of the reasons for that person's fate, whereas a quantitative analysis might tell us whether education or gender was a better (nomothetic) predictor of homelessness.

In summary, both the idiographic and nomothetic modes of explanation involve the idea of causation. Both are legitimate and useful. What we learn in individual cases, moreover, can suggest general, causal relationships among variables, just as those general relationships can help to focus analyses of a particular case. Most useful of all is a combination of the two approaches—if not in the same study, then by the research community collectively.

Criteria for Causality

As I've indicated, much—though by no means all—social research is ultimately geared to revealing the causes of social phenomena. But the mere fact that variables are observed to have some relationship does not establish that the relationship is one of cause and effect. If we found that most registered Democrats prefer strawberry to vanilla ice cream, we'd be right to suspect that their party preference probably doesn't cause them to like strawberry more than vanilla, and still more that their preference for strawberry doesn't cause them to be Democrats. Most likely, any such observed association between these variables would be a coincidence.

By the same token, we might find that people with higher levels of education are more likely to own luxury cars than are people with less education. We can be quite sure that owning a luxury car doesn't cause a person to receive more schooling, and there's no obvious reason why greater schooling, in and of itself, would cause people to own luxury cars.

You might interject at this point that people with more education tend to have greater earning power than do their less-educated peers and that this would explain the greater percentage of educated people who own luxury cars. This indeed is a plausible causal explanation. We'll return shortly to this distinction between observed associations and underlying causal explanations. The point here is that, to establish causal connections, something more is required than a mere association of variables.

As we've seen, science is an activity involving both observation and logic. In these examples, logic suggests that the observed relationships, or associations, are not causal in nature. By what criteria, then, do social scientists determine that one thing causes another?

Let's take idiographic explanations first. Joseph Maxwell (1996:87–88) says that the main criteria for judging the validity of an explanation are (1) its credibility, or believability, and (2) whether alternative explanations ("rival hypotheses") were seriously considered and found wanting. The first criterion relates to logic as one of the foundations of science: We demand that our explanations make sense, even if the logic is sometimes complex. The second criterion reminds us of a famous dictum of Sherlock Holmes: When all other possibilities have been eliminated, the one that remains must be the truth.

Thus, if I offer a seemingly thorough explanation of someone's religiosity, my account passes the first test if it makes sense. But if I have not considered other explanations, perhaps you will offer one that is equally credible. Unless one of these explanations is found wanting, neither of us can claim to have found the "true" one. Perhaps the most accurate and complete explanation will combine features of both.

Regarding nomothetic explanation, Paul Lazarsfeld (1959) has suggested three specific criteria for causal relationships among variables. (We'll see later in the book how these criteria are used in research practice.) The first requirement is that the cause precede the effect. It makes no sense to imagine something being caused by something else that happened later on. Clearly, a bullet leaving the muzzle of a gun does not cause the gunpowder to explode; it works the other way around. Owning a luxury car doesn't cause one to earn enough money to afford one.

As simple and obvious as this criterion may seem, you'll discover that it generates endless problems in the analysis of social science data. Often, the order of two variables is simply unclear. Which comes first: prejudice or the trait known as authoritarianism (excessive submissiveness to authority, accompanied by rigid thinking)? Even when the time order seems essentially clear, exceptions can often be found. For example, we would normally assume that the educational level of parents would be a cause of the educational level of their children.

Yet, some parents may return to school as a result of the advanced education of their own children.

The second requirement in a causal relationship is that the two variables be empirically correlated (*empirically* means "in actual experience"). A **correlation** exists between variables when they are observed to be related. That is, when one occurs or changes, so does the other. It would make no sense to say that exploding gunpowder causes bullets to leave muzzles of guns if, in observed reality, bullets did not come out after the gunpowder exploded (or if they came out even when it didn't explode).

Again, social science research can run into difficulties stemming from this apparently obvious requirement. At least in the probabilistic world of nomothetic explanations, there are few perfect correlations. Most conservatives voted for Bob Dole in 1996, but some didn't. More women than men voted for feminists in 1992, but some women didn't—and many men did. We are forced to ask, therefore, how strong an empirical relationship must be in order to be considered causal. We'll return to this issue later in the book.

The third requirement for a causal relationship is that the effect cannot be explained in terms of some third variable. We already saw an instance of the "third variable" phenomenon in the case of education and ownership of luxury car. To take another example, there is a correlation between ice cream sales and deaths due to drowning: the more ice cream sold, the more drownings, and vice versa. There is, however, no direct link between ice cream and drowning. The third variable at work here is season or temperature. Most drowning deaths occur during summer—the peak period for ice-cream sales.

Here are a couple of other examples of **spurious relationships,** or ones that aren't genuine. There is a negative relationship between the number of mules and the number of Ph.D.'s in towns and cities: the more mules, the fewer Ph.D.'s and vice versa. Perhaps you can think of another variable that would explain this apparent relationship. The answer is rural versus urban settings. There are more mules (and fewer Ph.D.'s) in rural areas, whereas the opposite is true in cities.

Or, consider the a positive correlation between shoe size and math ability among schoolchildren. Here, the third variable that explains the puzzling relationship is age. Older children have bigger feet and more highly developed math skills, on average, than do younger children.

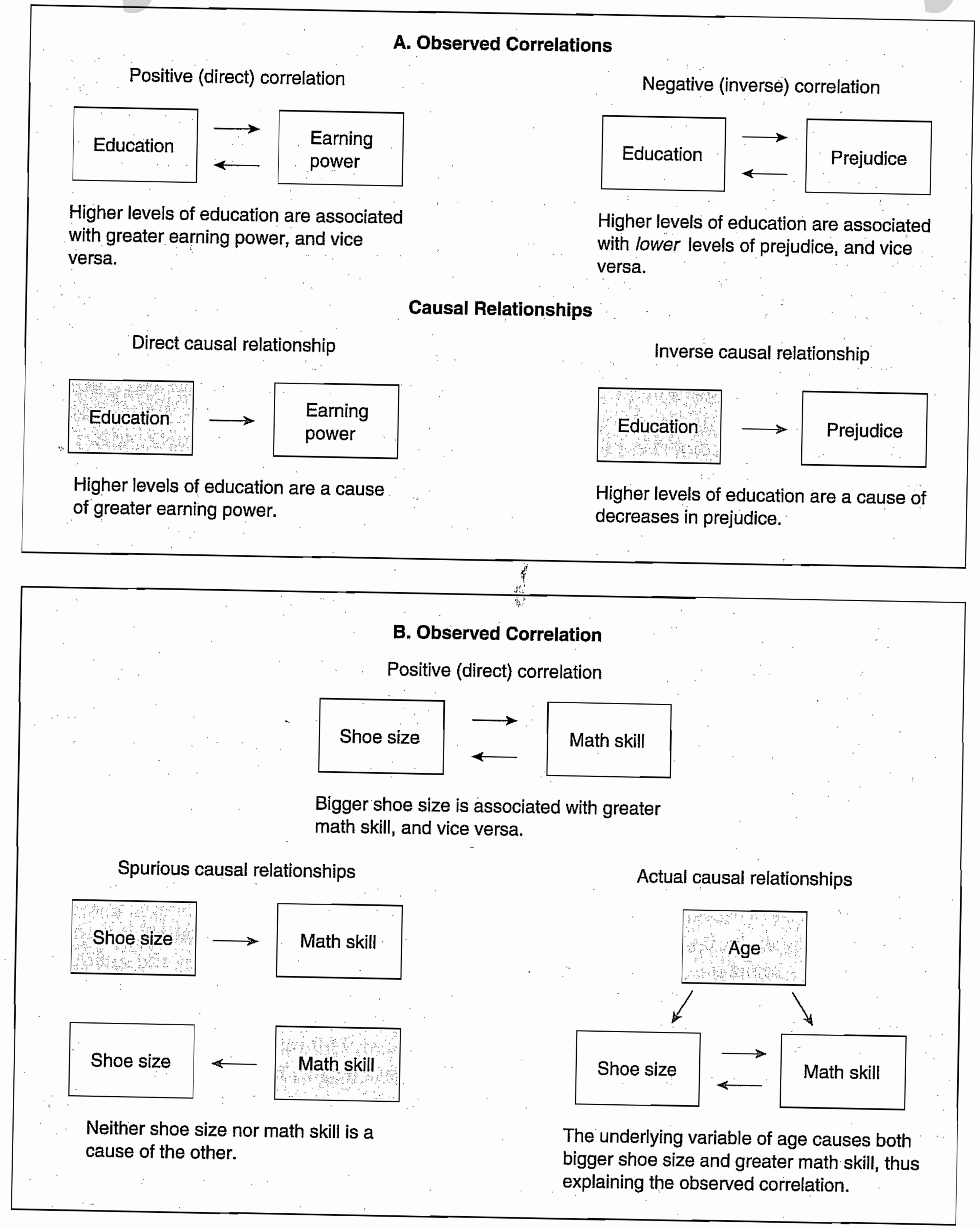
Figure 3-2 summarizes the distinctions between correlation, causation, and spurious causal relationships. Observed associations are indicated with black arrows, while causal relationships are indicated with color. Notice, too, that observed associations go in both directions. That is, as one variable occurs or changes, so does the other. But the mere fact of association does not tell us which variable causes the other, or, indeed, whether there is any causal relationship between them. In panel A, the variables do have a causal relationship, as it turns out: One variable causes the other, which explains the association we observe. In panel B, the observed association between shoe size and math skills is real enough, but a causal linkage between these variables would be spurious. In reality, a third variable explains the observed association. The box "Correlation and Causality" further illustrates the point that correlation alone does not establish a particular causal relationship.

As John and Lyn Lofland (1995 : 138–39) caution, it is important to distinguish the testing of causal relationships from conjecture about it. While it is perfectly acceptable to report our hunches or untested hypotheses about the causal processes at work in what we observe, we must distinguish between such suspicions and proven conclusions. Later on we'll go into detail on how researchers establish that suspected causal connections are real.

In summary, most social researchers consider two variables to be causally related if (1) the cause precedes the effect in time, (2) there is an empirical correlation between them, and (3) the relationship is not found to be the result of some third variable.

As we'll discuss shortly, people sometimes apply inappropriate criteria in reasoning about causality. Consequently, it's important to keep in mind that any relationship satisfying the three criteria just described is causal and that these are the only criteria.

FIGURE 3-2
Correlation, Causation, and Spurious Causal Relationships



Correlation and Causality

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Having demonstrated a statistical relationship between a hypothesized "cause" and its presumed "effect," many people (sometimes including researchers who should know better) are only too eager to proclaim "proof" of causation. Let's take an example to see why "it ain't necessarily so."

Imagine you have conducted a study on college students and have found an inverse correlation between marijuana smoking (variable M) and grade point average (variable G)—that is, those who smoke tend to have lower GPAs than those who do not, and the more smoked, the lower the GPA. You might therefore claim that smoking marijuana lowers one's grades (in symbolic form, $M \rightarrow G$), giving as an explanation, perhaps, that marijuana adversely affects memory, which would naturally have detrimental consequences on grades.

However, if an inverse correlation is all the evidence you have, a second possibility exists. Getting poor grades is frustrating; frustration often leads to escapist behavior; getting stoned is a popular means of escape; ergo, low grades cause marijuana smoking ($G \rightarrow M$)! Unless you can establish which came first, smoking or low grades, this explanation is supported by the correlation just as plausibly as the first.

Let's introduce another variable into the picture: the existence and/or extent of emotional problems (variable E). It could certainly be plausibly argued that having emotional problems may lead to escapist behavior, including marijuana smoking. Likewise it seems reasonable to suggest that emotional problems are likely to adversely affect grades. That correlation of marijuana smoking and low grades may exist for the same reason that runny noses and sore throats tend to go together—*neither* is the cause of the other, but rather, both are the consequences of some third variable ($E \lessdot^{M}_{G}$). Unless you can rule out such third variables, this explanation too is just as well supported by the data as is the first (or the second).

Then again, perhaps students smoke marijuana primarily because they have friends who smoke, and get low grades because they are simply not as bright or well prepared or industrious as their classmates, and the fact that it's the same students in each case in your sample is purely coincidental. Unless your correlation is so strong and so consistent that mere coincidence becomes highly unlikely, this last possibility, while not supported by your data, is not precluded either. Incidentally, this particular example was selected for two reasons. First of all, *every one* of the above explanations for such an inverse correlation has appeared in a national magazine at one time or another. And second, *every one* of them is probably doomed to failure because it turns out that, among college students, most studies indicate a direct correlation, that is, it is those with higher GPAs who are more likely to be marijuana smokers! Thus, with tongue firmly in cheek, we may reanalyze this finding:

1. Marijuana relaxes a person, clearing away other stresses, thus allowing more effective study; hence, $M \rightarrow G$.

   or

2. Marijuana is used as a reward for really hitting the books or doing well ("Wow, man! An 'A'! Let's go get high!"); hence, $G \rightarrow M$.

   or

3. A high level of curiosity (E) is definitely an asset to learning and achieving high grades and may also lead one to investigate "taboo" substances; hence, $E \lessdot^{M}_{G}$.

   or

4. Again coincidence, but this time the samples just happened to contain a lot of brighter, more industrious students whose friends smoke marijuana!

The obvious conclusion is this: If *all* of these are possible explanations for a relationship between two variables, then no *one* of them should be too readily singled out. Establishing that two variables tend to occur together is a *necessary* condition for demonstrating a causal relationship, but it is not by itself a *sufficient* condition. It is a fact, for example, that human birthrates are higher in areas of Europe where there are lots of storks, but as to the meaning of that relationship . . . !

Necessary and Sufficient Causes

One error people make in connection with causality is to assume that causation acquires a perfect correlation between variables. In fact, a perfect association is not a criterion of causality in social science research—or in science generally, for that matter. Put another way, exceptions, although they do not prove the rule, do not necessarily disprove the rule either. In probabilistic models, exceptions to the posited relationship almost always exist. If some liberals voted for Bob Dole and some conservatives voted for Bill Clinton, those cases would not deny the general causal relationship between political orientations and voting in the election.

Within this probabilistic model, it is useful to distinguish between necessary and sufficient causes. A *necessary cause* represents a condition that *must* be present for the effect to follow. For example, it is necessary for you to take college courses in order to get a degree. Take away the courses, and the degree never happens. However, simply taking the courses is not a sufficient cause of getting a degree. You need to take the right ones and pass them. Similarly, being female is a necessary condition of becoming pregnant, but it is not a sufficient cause. Otherwise, all women would get pregnant.

Figure 3-3 illustrates this relationship between the variables of gender and pregnancy as a matrix showing the possible outcomes of combining these variables.

A *sufficient cause*, on the other hand, represents a condition that, if it is present, guarantees the effect in question. This is not to say that a sufficient cause is the *only* possible cause of a particular effect. For example, skipping an exam in this course would be a sufficient cause for failing it, though students could fail it other ways as well. Thus, a cause can be sufficient, but not necessary. Figure 3-4 illustrates the relationship between taking or not taking the exam and either passing or failing it.

The discovery of a cause that is both necessary *and* sufficient is, of course, the most satisfying outcome in research. If juvenile delinquency were the effect under examination, it would be nice to discover a single condition that (1) must be present for delinquency to develop and (2) always results in delinquency. In such a case, you would surely feel that you knew precisely what caused juvenile delinquency.

Unfortunately, we never discover single causes that are absolutely necessary and absolutely sufficient when analyzing the nomothetic relationships among variables. It is not uncommon, however, to find causal factors that are either 100-percent

FIGURE 3-3
Necessary Cause

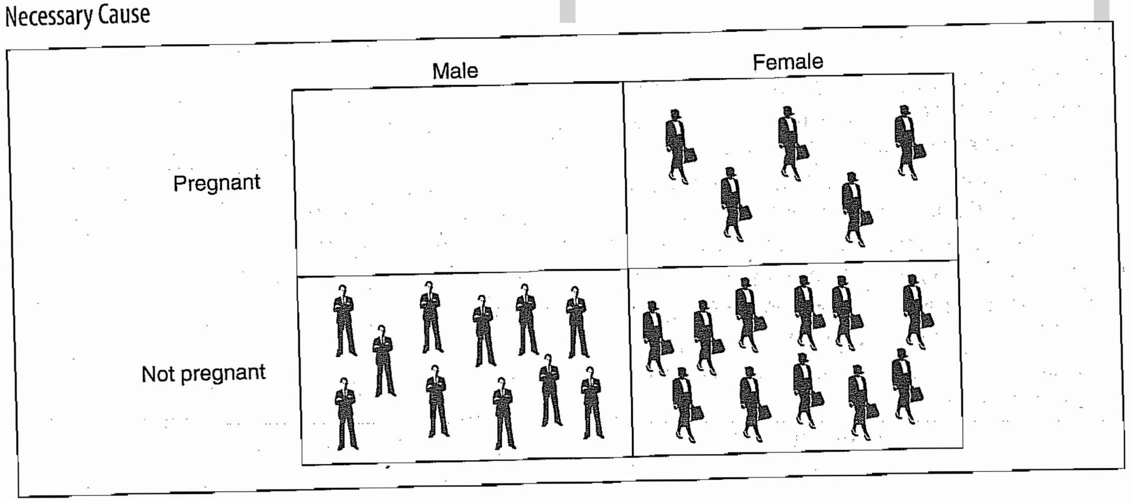
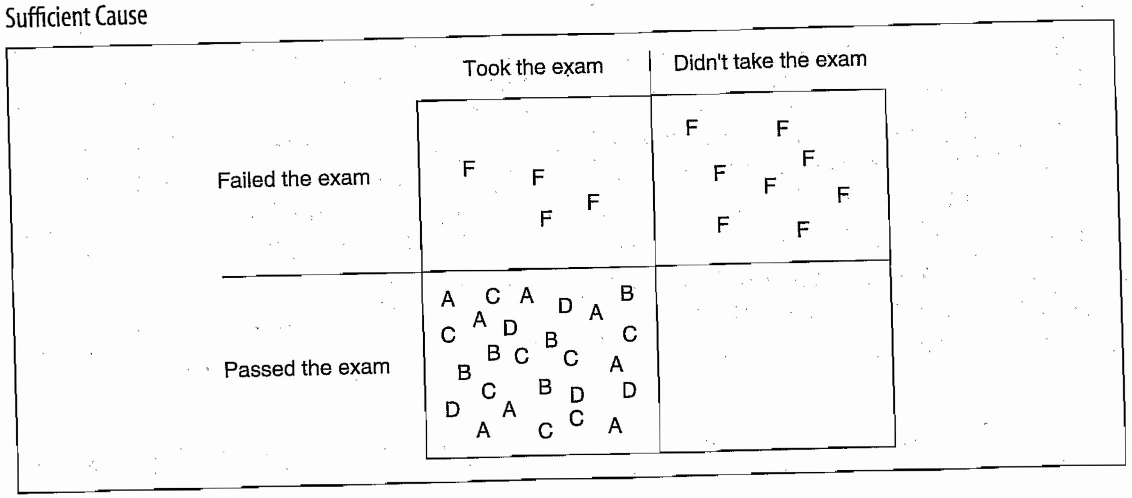


FIGURE 3-4
Sufficient Cause



necessary (you must be female to become pregnant) or 100-percent sufficient (skipping every exam will inevitably cause you to fail it).

In the idiographic analysis of single cases, you may reach a depth of explanation from which it is reasonable to assume that things could not have turned out differently, suggesting you have determined the sufficient causes for a particular result. (Anyone with all the same details of your genetic inheritance, upbringing, and subsequent experiences would have ended up going to college.) By definition, such idiographic explanations do not posit single causes, and there could always be other causal paths to the same result. Thus, the causes are sufficient but not necessary.

In general in social science, demonstrations of either necessary or sufficient causes—even imperfect ones—can be the basis for concluding that variables are causally related.

Errors in Reasoning about Causation

As we've seen, cause and effect is essential to scientific explanation. It is also fundamental to our day-to-day lives. Commonly, however, we make errors in our assessment of causation. Let's look at some examples of faulty reasoning about causation. In each case, see whether you can detect the error before reading my explanation.

Early in the history of the AIDS epidemic, an article in the *San Francisco Chronicle* reported research that claimed a link between AIDS and fluoridation of the water. In part, the claim hinged on the assertion that "while half the country's communities have fluoridated water supplies and half do not, 90 percent of AIDS cases are coming from fluoridated areas and only 10 percent are coming from nonfluoridated areas." Can you see any flaws in this reasoning? Think about it for a minute before continuing.

To begin, we should always beware when data about communities are used to draw conclusions about individuals. In this instance, "half the communities" may not contain half the population. Indeed, we might imagine that large cities would be more likely to fluoridate their water than would small, rural towns. Logically, it would be possible for the fluoridated communities to have 90 percent of the nation's population, in which case they should have 90 percent of the AIDS cases even if there were no relationship between AIDS and fluoridation.

Second, progressive social values more common to cities than to small towns might affect both (1) lifestyles associated with AIDS and (2) the decision to fluoridate the water supply. In that case, AIDS and fluoridation could be statistically correlated without being causally linked.

The problems of faulty causal reasoning are not limited to statistical analyses. The examination of historical processes is equally vulnerable. Consider this example: At a news conference on August 5, 1985, then-President Ronald Reagan noted the 40th anniversary of the atomic bombing of Hiroshima by saying that that terrible example of nuclear destruction had served as "a deterrent that kept us at peace for the longest stretch we've ever known, 40 years of peace." Many people who supported an immediate end to the nuclear arms race were quick to deny the causal relationship asserted by the president, saying it was not the bombing of Hiroshima that had kept the peace. Can you spot another flaw in the causal assertion?

What seems most subject to question is not the causes of the "40 years of peace" but the very existence of this halcyon era. The period in question includes such major conflicts as the Korean War as well as the Vietnam War—not to mention scores of lesser confrontations around the world. It's difficult to maintain that the bombing of Hiroshima caused a period of peace when there was no consistent peace.

Sometimes it's possible to detect failures of causal reasoning on logical grounds alone, even when there is no possibility of examining empirical data. Again, concern about AIDS offers an example. Some people have argued that the AIDS epidemic reflects God's displeasure with certain human behaviors, specifically, homosexuality and drug use. The evangelist Don Boys spoke on the sexual issue in a guest editorial in *USA Today* (October 7, 1985):

> The AIDS epidemic indicates that morality has broken its mooring and drifted into a miasmic swamp, producing disease, degeneracy, and death. . . . God's plan is for each man to have one woman—his wife—for a lifetime, and be faithful to her.

The flaw in this case is not that AIDS has become increasingly common among heterosexual, married couples or that some hemophiliac young people have contracted AIDS through tainted blood transfusions. It is legitimate to use a probabilistic model of causation in this context, and homosexual men are, in fact, more likely to contract AIDS than are heterosexual men. However, if AIDS is an indication of "God's plan," then lesbians must be the most favored of all, because AIDS is rarest among them.

None of these illustrations of faulty causal reasoning is intended as an indictment of the perpetrators. All of us fall into such errors; it has been said that the problem with "common sense" is that it's not all that common. Rather, the purpose of these examples has been twofold. First, examples like these can sensitize us to faulty causal reasoning by revealing some of the ways it shows up in daily life. Developing a keen awareness of such flawed reasoning can help us to recognize errors in others' reasoning and avoid making similar errors ourselves. Second, these examples serve as a backdrop for understanding the power of careful, scientific reasoning. Although scientists are not immune to logical error, learning the procedures of science offers some degree of protection.

Although there is no neat set of rules for logical reasoning, an excellent book—Howard Kahane's *Logic and Contemporary Rhetoric* (1992)—outlines many of the errors people commonly make. Here are some of the pitfalls Kahane discusses.

Provincialism

All of us look at the world through glasses framed by our particular histories and current situations. There is always a danger, then, that researchers will interpret people's behavior only in ways that make sense from the researchers' own points of view. The world can look quite different to men and women, to people who grew up in different social classes, to religious and nonreligious people, and so on. This problem is particularly evident in cross-cultural research.

At the same time, Harry Wolcott (1995:164–65), in discussing "the art of fieldwork," suggests that our personal and cultural biases can work for the good. They can lend focus to an inquiry and provide insights by involving a point of view different from that of the participants being observed. The key is to be conscious of our particular views and to remain open to broadening our perspectives by recognizing that others' views may be equally valid.

Hasty Conclusion

Researchers as well as other people are susceptible to drawing hasty conclusions. Whenever a researcher offers an interpretation of data, be sure to evaluate the "weight" of evidence leading to that interpretation. Is the conclusion essentially inevitable, given the data lying behind it, or are other conclusions just as reasonable? We also need to consider all the alternative conclusions that could follow from your own data.

Questionable Cause

Whenever it seems to you that X caused Y, ask yourself if that is necessarily the case. What else could have caused Y? Kahane (1992:63) gives several examples from the economic world. If a business goes bankrupt, people often conclude that the company's president lacked business skills—even when the bankruptcy occurred during a severe recession, marked by a great many business failures. It's sometimes easy to come up with plausible causal explanations, but establishing the true cause requires eliminating other possible explanations.

Suppressed Evidence

Field researchers amass a great deal of information through direct observations, interviews, library work, and so on. To reach conclusions requires us to dismiss information as much as to select it. On the whole, a researcher dismisses information that is "not relevant"; however, that in itself is obviously a matter of judgment.

In reading research reports, take note of observations you've noted that do not figure in the conclusions, as well as observations not mentioned that you can reasonably assume were made. For example, suppose a researcher concludes that members of a neo-Nazi group were hostile to African Americans out of a fear of economic competition. If this conclusion is correct, we would expect most members to be working class or lower middle class. If the researcher has not indicated the occupations of the group's members, we might well question whether the evidence supports the conclusion.

False Dilemma

Research conclusions, like nonscientific opinions, often represent the selection of one position from alternatives. Often, selecting one seems to rule out all others, but this need not be the case. A *false dilemma* is a choice that seems to be forced but really is not. Kahane offers this example: "Economics, not biology, may explain male domination." This bold assertion seems to rule out the influence of politics, education, custom, religion, and a host of other possibilities. As Kahane puts it (1992:42):

> This statement suggests that there are just two possibilities: either biology explains male dominance (note the begged question!), or economic success does. And it suggests that the second possibility, economic success, "may" (weasel word) be the true explanation of male domination. Yet there are many other possibilities, such as social custom, religious conviction, and various combinations of economic and biological factors. By tempting us to think of the cause of male domination as either economics or biology, the quote leads us to overlook other possibilities and thus to commit the fallacy of false dilemma.

David Silverman (1993:205) sounds a similar warning in saying that a basic rule in the analysis of qualitative data is "never appeal to a single element as an explanation." The lesson is this: Always look for alternative or additional causes. We should be wary of this pitfall in reading the works of others but also be wary of falling into it ourselves.

Linking Measurement and Association

As we have seen, one of the necessary criteria for determining causation in science is an empirical correlation between the cause and the effect. Establishing correlations requires us to measure variables and determine whether and how they are associated. All too often, however, the process of measuring variables is seen as separate from the process of determining the associations between them. This view is, at best, misleading. A more useful approach is to see measurement and association as intimately linked. To illustrate this point, let's look at some examples of issues that arise in defining, measuring, and determining the relationship between variables in social research.

Practical Problems in Measuring and Associating Variables

As you recall from Chapter 2, the traditional model of the deductive scientific method proceeds from theories to theoretical expectations, or ideas to be tested in research. By operationalizing variables, the scientist arrives at a testable hypothesis. Then data are collected and analyzed to test whether the hypothesis is supported.

Although this traditional image of scientific research is a useful, idealized model, it tends to conceal some of the practical problems in working with variables that crop up in actual research. To see why, let's pursue an example.

Suppose a researcher is interested in the subject of deviant behavior and constructs a theory based on the general sociological theory of social control. This broad theory focuses on the coercive and persuasive forces that establish and maintain social order. As such, it includes a variety of concepts that would be relevant to a theory of deviant behavior.

Let's assume that our researcher derives the theoretical expectation that juvenile delinquency is a function of supervision: As supervision increases, delinquency decreases. The next step is to operationalize the key variables by specifying how they will be measured. So, for instance, the researcher might operationalize "juvenile" as anyone under 18 years of age, "delinquency" as being arrested for a criminal act, and "supervision" as the presence of a nonworking adult in the home. The researcher now has a testable hypothesis: Among people under 18 years of age, those living in homes with a nonworking adult will be less likely to be arrested for a criminal act than will those without a nonworking adult in the home.

The researcher now proceeds to collect empirical data. One technique, for instance, would be to survey people under 18 years of age. The survey questionnaire would ask, among other things. whether they lived in a home with a nonworking adult and whether they had ever been arrested for a criminal act.

Finally, the researcher analyzes the collected data statistically to test the hypothesis. The statistical tests are intended to show whether, in fact—based on the data collected—juveniles with a nonworking adult in the home are less likely than others to be arrested for a crime. The confirmation or disconfirmation of the hypothesis is then used as one piece of evidence in accepting or rejecting the theory from which the hypothesis was derived.

As it probably did in Chapter 2, this process sounds neat and logical. But there are two basic problems that prevent the easy application of this model in practice.

First, theoretical concepts seldom, if ever, permit unambiguous operationalization. Because concepts are abstract and general, every specification of empirical indicators must be an approximation. In our example, it is unlikely that the general concept of supervision is adequately represented by the presence of a nonworking adult in the home. For one thing, the mere presence of such an adult does not ensure that the juvenile is actually supervised. For another thing, in some homes lacking such an adult, other arrangements may be made for the juvenile's supervision.

Consider also the operational definition of "delinquent." Being arrested for a criminal act is clearly not the same as the abstract concept of delinquency. Some juveniles may engage in delinquent behavior without being arrested; others may be arrested falsely. Finally, even the specification of "juvenile" as a person under 18 years of age is arbitrary. Other specifications might have been made, and probably none would be unambiguously correct. The problem here is not that the researcher is incompetent. Every empirical indicator has some defects; all could be improved on, and the search for better indicators is endless.

Second, the empirical associations among variables are almost never perfect. For example, if all juveniles with nonworking adults in the home had never been arrested, and all those without such adults had been arrested, we could safely conclude that the hypothesis had been confirmed. Or, if both groups had exactly the same records, we could conclude that the hypothesis had been rejected by the data. In practice, however, the results will be mixed. Nearly all variables are related empirically to one another to some extent. What counts as a strong enough association to permit valid conclusions? In practice, specifying exactly what level of association is necessary to accept or reject the hypothesis is also an arbitrary act, in the sense that different levels can be plausibly defended. (We'll consider the issue of statistical significance in detail in Chapter 17.)

Ultimately, then, scientists use imperfect indicators of theoretical concepts to discover imperfect associations that are open to imperfect interpretations. And these imperfections conspire with one another against us. Suppose that you specify a degree of association that will constitute acceptance of the hypothesis, and the empirical analysis falls short. You will quite naturally ask yourself whether different indicators of the concepts might have produced the specified extent of association. If you measured juvenile delinquency as being convicted of a crime, for example, perhaps the analysis would have turned out differently if you had used arrests rather than convictions as your indicator.

The overriding lesson here is that measurement and association are interrelated concepts. Researchers must handle both simultaneously and logically. Rather than moving through a fixed series of discrete steps, in practice scientists continually move back and forth through them. Hypotheses, operational definitions, and statistical techniques all may be refined, with one "step" confirming the others. Often, theoretical constructions are built around the previously observed associations between empirical indicators. Partial theoretical constructions may suggest new empirical data to be examined, and so forth. After each activity, researchers hope to understand their subject matter a little better. Similarly, different studies confirm subsequent efforts, and new results may change the interpretation of earlier ones. The "critical experiment" that single-handedly determines the fate of an entire theory is rare indeed—in any science.

An Example of Measurement and Association

As a final example of the linkage between measurement and association, consider the controversy that brewed many years ago concerning the relationship between religiosity and prejudice. A book by Charles Glock and Rodney Stark entitled *Christian Beliefs and Anti-Semitism* (1967) reported empirical data indicating that Christian church members holding orthodox beliefs (in God, Jesus, the Bible, and so on) were more likely to be anti-Semitic than were less-orthodox members. As you can imagine, the book's findings stirred considerable discussion within the churches. Other researchers then did follow-up projects on the same topic.

One of these research projects arrived at a conclusion directly opposite that of Glock and Stark. The researchers reported that as orthodoxy increased, prejudice decreased. On closer examination, however, orthodoxy in this second study turned out to be measured by acceptance of questionnaire statements of the traditional Christian doctrines of "All men are brothers" and "Love thy neighbor." Not surprisingly, survey respondents who accepted these doctrines appeared less prejudiced than those who rejected them.

Normally, these research findings would be (and were) challenged on the grounds of "contamination": The indicators used to operationalize religious orthodoxy and prejudice actually measured the same or similar qualities. Calling one set of indicators "orthodoxy" and the other "prejudice" does not prove that prejudice decreases with increasing orthodoxy in a more general sense. (Of course, measuring religious orthodoxy in terms of brotherly love and equality might be extremely useful in some other context.)

The discussions of this chapter suggest a somewhat different reaction to the two kinds of research findings. Asking *how* orthodoxy and prejudice are associated with each other rather than *whether* they are associated, we might conclude the following: (1) Orthodoxy measured in terms of the Glock-Stark indicators is positively associated with prejudice, and (2) orthodoxy measured as commitment to the norms of brotherly love and equality is negatively associated with prejudice. Both conclusions are empirically correct. Neither conclusion answers the more general question of whether religion and prejudice are related.

The remaining step, of course, is to evaluate the usefulness of these conclusions. The finding that orthodoxy—defined as a commitment to norms of brotherly love—is negatively associated with prejudice comes perilously close to being a logical truth, or tautology. A *tautology* is a statement that is true by definition: "People who are orthodox (believe in brotherly love) are not prejudiced (believe in brotherly love)."

Of course, the point of this example is not to settle issues of religion and prejudice: you might like to read the literature on this subject and perhaps even explore it yourself with original research someday. What the example does illustrate is that the processes of defining, measuring, and determining the relationship between variables are interrelated. A further point is that when you read the results of research, whether in professional journals or in popular media, there are many searching questions you can ask before you accept the conclusions as they are reported. How were the variables measured? (Remember, how they were measured is the only meaning they have.) How do these measurements relate to one other logically? How strong is the association between the variables? And do the conclusions, as stated, reflect exactly what the findings were, or do they stretch the findings in a way the evidence does not actually support? Naturally, all researchers should poise the same questions about their own work as well.

MAIN POINTS

- Explanatory scientific research depends implicitly on the idea of cause and effect.
- Explanatory social scientific research depends implicitly on a deterministic model of the human behavior it seeks to explain.
- Both idiographic and nomothetic models of explanation rest on the idea of causation. The idiographic model aims at a complete understanding of a particular phenomenon, using all relevant causal factors. The nomothetic model aims at a general understanding—not necessarily complete—of a class of phenomena, using a small number of relevant causal factors.
- In idiographic explanations, the principal criteria for establishing a causal relationship are (1) the credibility of the explanation and

(2) a demonstration that alternative explanations should be rejected.

- There are three basic criteria for establishing causation in nomothetic analyses: (1) The variables must be empirically associated, or correlated, (2) the causal variable must occur earlier in time than the variable it is said to affect, and (3) the observed effect cannot be explained as the effect of a different variable.
- Mere association, or correlation, does not in itself establish causation. A spurious causal relationship is an association that in reality is caused by one or more other variables.
- A perfect statistical relationship between two variables is not an appropriate criterion for causation in social research. We may say that a causal relationship exists between *X* and *Y*, then, even though *X* is not the total cause of *Y*.
- Most explanatory social research uses a probabilistic model of causation. *X* may be said to cause *Y* if it is seen to have some influence on *Y*.
- There are two important types of causes: necessary and sufficient. X is a necessary cause of *Y* if *Y* cannot happen without *X*. *X* is a sufficient cause of *Y* if *Y* always happens when *X* happens. The scientifically most satisfying discovery is a necessary and sufficient cause.
- Researchers need to guard against several common kinds of errors in reasoning about causation, including provincialism, hasty conclusions, questionable identification of causes, suppressed evidence, and false dilemmas.
- Although the idealized deductive model of science suggests that defining and measuring variables are separate from determining the associations between them, it is fruitful to see these processes as intimately linked.
- Before accepting conclusions about causality, we should examine how variables were operationalized, what their logical relationship is, how strong the association is between them, and whether the conclusions stated reflect precisely what the findings permit.

KEY TERMS

The following terms are defined in context in the chapter and can also be found in the Glossary at the back of the book.

correlation   spurious relationship

REVIEW QUESTIONS AND EXERCISES

1. Describe the conditions that would permit you to conclude that education is
   a. a necessary cause of reduction in prejudice
   b. a sufficient cause of reduction in prejudice
   c. a necessary and sufficient cause of reduction in prejudice
2. Why did you choose to attend the college you are now attending? Create an idiographic explanation by detailing as many factors as you can that led to your choice.
3. Isolate the two or three factors from your idiographic explanation of your choice of college that you think would be most relevant to explaining the choices of many other college students besides yourself. Discuss what would be gained and lost in a nomothetic explanation (of students' choice of college) based on these factors, compared with your original explanation.
4. Women earn roughly 70 percent as much as men in U.S. society. What do you suppose "causes" that difference? Describe the procedures by which you might test your conjectures.
5. Pick a topic you're interested in and use the Web to locate at least two popular reports of scientific findings concerning causal relationships (for example, in newspapers, magazines, health-oriented sites). Such reports are published in popular media almost every day. Analyze what you can tell and what you cannot tell from the report about how the variables were operationalized and tested, and whether the report accurately reflects legitimate conclusions based on the data. Would you accept the conclusions as reported? If not, what information do you need to make an intelligent judgment about them? Do you see any flaws in reasoning in the way the findings are reported in the media?

ADDITIONAL READINGS

Beck, E. M., and Stewart E. Tolnay. 1990. "The Killing Fields of the Deep South: The Market for Cotton and the Lynching of Blacks, 1882–1930." *American Sociological Review* 55:526–39. This analysis of the structural causes of lynching in the South illustrates the type of causal analysis that social scientists often undertake. Some of the variables examined are inflation, the price of cotton, and the proportion of blacks in the population.

Davis, James A. 1985. *The Logic of Causal Order.* Beverly Hills, CA: Sage. Davis examines the logical and statistical dimensions of causality in social research.

Hirschi, Travis, and Hanan Selvin. 1973. *Principles of Survey Analysis.* New York: Free Press; see especially Part II. Excellent statements on causation within a practical framework. I can think of no better discussions of causation within the context of particular research findings than these. The book is readable, stimulating, and generally just plain excellent.

Lazarsfeld, Paul. 1955. "Foreword." In Herbert Hyman, *Survey Design and Analysis.* New York: Free Press. A classic and still valid statement of causation in social science. In the context of the elaboration model, Lazarsfeld provides a clear statement of the criteria for determining causation.

Shaver, Kelly G. 1985. *The Attribution of Blame: Causality, Responsibility, and Blameworthiness.* New York: Springer-Verlag. Shaver discusses many of the aspects of causality presented in this chapter and shows how they relate to the notions of responsibility and blame.

Wallace, William A. 1972. *Causality and Scientific Explanation.* Ann Arbor: University of Michigan Press. In case you developed an interest in the question of causality, this two-volume work provides a full examination of the history of the concept within science, from medieval times to the present.

SOCIOLOGY WEB SITE

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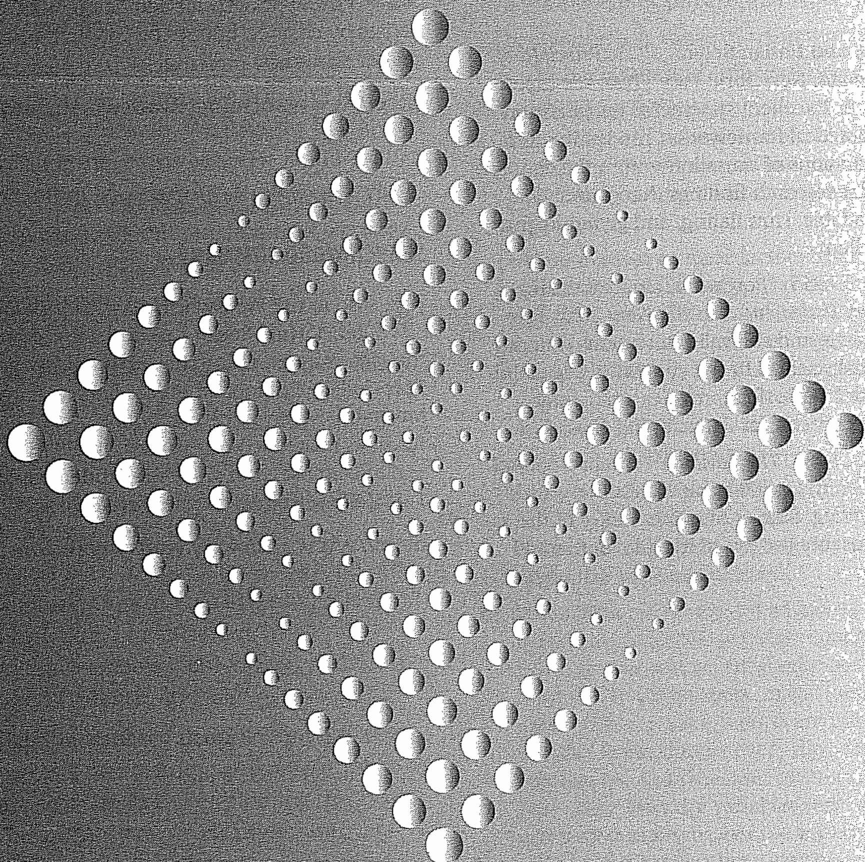
Part 2



The Structuring of Inquiry

Posing problems properly is often more difficult than answering them. Indeed, a properly phrased question often seems to answer itself. You may discover the answer to a question just in the process of making the question clear to someone else.

Part 2 considers the posing of proper scientific questions, the structuring of inquiry. Part 3 will describe some of the specific methods of social scientific observation.

Chapter 4 addresses the beginnings of research. It examines some of the purposes of inquiry, the units of analysis and points of focus in social scientific research, and the reasons scientists get involved in research projects.

Chapter 5 deals with the specification of what it is you want to measure—the processes of conceptualization and operationalization. It looks at some of the terms that you and I use quite casually in everyday life—prejudice, liberalism, happiness, and so forth—and shows how essential it is to clarify what we really mean by such terms when we do research. This process of clarification is called *conceptualization.*

Once we clarify what we mean by certain terms, we can then measure the referents of those terms. The process of devising steps or operations for measuring what we want to study is called *operationalization.* Chapter 5 deals with the topic of operationalization in general, paying special attention to the framing of questions for interviews and questionnaires.

To complete the introduction to measurement, Chapter 6 breaks with the chronological discussion of how research is conducted. In this chapter, we'll examine techniques for measuring variables in quantitative research through the combination of several indicators: indexes, scales, and typologies. As an example, we might ask survey respondents five different questions about their attitudes toward gender equality and then combine the answers to all five questions into a composite measure of gender-based egalitarianism. Although such composite measures are constructed during the analysis of data (see Part 4), the raw materials for them must be provided for in the design and execution of data collection.

Finally, we'll look at how social scientists select people or things for observation. Chapter 7, on sampling, addresses the fundamental scientific issue of generalizability. As you'll see, we can select a few people or things for observation and then apply what we observe to a much larger group of people or things. For example, by surveying 1,000 U.S. citizens about whom they favor for president of the United States, we can accurately predict how tens of millions will vote. This chapter examines techniques that increase the generalizability of what we observe.

What you learn in Part 2 will bring you to the verge of making controlled research observations. Part 3 will show how to take that next step.