

## 6 Probability and Statistical Inference

### OVERVIEW

Researchers aspire to draw conclusions about the entire population of cases that are relevant to a particular research question. However, in most cases, they must rely on data from only a sample of those cases to do so. In this chapter, we lay the foundation for how researchers make inferences about a population of cases while only observing a sample of data. This foundation rests on probability theory, which we introduce here with extensive references to examples. We conclude the chapter with an example familiar to political science students – namely, the “plus-or-minus” error figures in presidential approval polls, showing where such figures come from and how they illustrate the principles of building bridges from samples we know about with certainty to the underlying population of interest.

*How dare we speak of the laws of chance? Is not chance the antithesis of all law?*  
– Bertrand Russell

### 6.1 POPULATIONS AND SAMPLES

In Chapter 5, we learned how to measure our key concepts of interest, and how to use descriptive statistics to summarize large amounts of information about a single variable. In particular, you discovered how to characterize a distribution by computing measures of central tendency (like the mean or median) and measures of dispersion (like the standard deviation or IQR). For example, you can implement these formulae to characterize the distribution of income in the United States, or, for that matter, the scores of a midterm examination your professor may have just handed back.

But it is time to draw a critical distinction between two types of data sets that social scientists might use. The first type is data about the

**population** – that is, data for every possible relevant case. In your experience, the example of population data that might come to mind first is that of the U.S. Census, an attempt by the U.S. government to gather some critical bits of data about the entire U.S. population once every 10 years.<sup>1</sup> It is a relatively rare occurrence that social scientists will make use of data pertaining to the entire population.<sup>2</sup>

The second type of data is drawn from a **sample** – a subset of cases that is drawn from an underlying population. Because of the proliferation of public opinion polls today, many of you might assume that the word “sample” implies a **random sample**.<sup>3</sup> It does not. Researchers *may* draw a sample of data on the basis of randomness – meaning that each member of the population has an equal probability of being selected in the sample. But samples may also be nonrandom, which we refer to as samples of convenience.

The vast majority of analyses undertaken by social scientists are done on sample data, not population data. Why make this distinction? Even though the overwhelming majority of social science data sets are comprised of a sample, not the population, it is critical to note that we are not interested in the properties of the sample per se; we are interested in the sample only insofar as it helps us to learn about the underlying population. In effect, we try to build a bridge from what we know about the sample to what we believe, probabilistically, to be true about the broader population. That process is called **statistical inference**, because we use what we *know* to be true about one thing (the sample) to *infer* what is likely to be true about another thing (the population).

There are implications for using sample data to learn about a population. First and foremost is that this process of statistical inference involves, by definition, some degree of uncertainty. That notion is relatively straightforward: Any time that we wish to learn something general based on something specific, we are going to encounter some degree of uncertainty. In this chapter, we discuss this process of statistical inference, including the tools that social scientists use to learn about the population that they are interested in by using samples of data. Our first step in this process is to

<sup>1</sup> The Bureau of the Census’s web site is <http://www.census.gov>.

<sup>2</sup> But we try to make inferences about some population of interest, and it is up to the researcher to define explicitly what that population of interest is. Sometimes, as in the case of the U.S. Census, the relevant population – all U.S. residents – is easy to understand. Other times, it is a bit less obvious. Consider a preelection survey, in which the researcher needs to decide whether the population of interest is all adult citizens, or likely voters, or something else.

<sup>3</sup> When we discussed research design in Chapter 4, we distinguished between the experimental notion of random assignment to treatment groups, on the one hand, and random sampling, on the other. See Chapter 4 if you need a refresher on this difference.

discuss the basics of probability theory, which, in turn, forms the basis for all of statistical inference.

## 6.2 SOME BASICS OF PROBABILITY THEORY

Let's start with an example.

Suppose that you take an empty pillowcase, and that, without anyone else looking, you meticulously count out 550 small blue beads, and 450 small red beads, and place all 1000 of them into the pillowcase. You twist the pillowcase opening a few times to close it up, and then give it a robust shake to mix up the beads. Next, you have a friend reach her hand into the pillowcase – no peeking! – and have her draw out 100 beads, and then count the red and blue beads.

Obviously, your friend knows that she is taking just a small sample of beads from the population that is in the pillowcase. And because you shook that pillowcase vigorously, and forbade your friend from looking into the pillowcase while selecting the 100 beads, her selection of 100 (more or less) represents a random sample of that population. Your friend doesn't know, of course, how many red and blue beads are in the pillowcase. She only knows how many red and blue beads she observed in the sample that she plucked out of it.

Next, you ask her to count the number of red and blue beads. Let's imagine that she happened to draw 46 red beads and 54 blue ones. Once she does this, you then ask her the key question: Based on her count, what is her best guess about the percentage of red beads versus blue beads in the entire pillowcase? The only way for your friend to know for sure how many red and blue beads are in the pillowcase, of course, is to dump out the entire pillowcase and count all 1000 beads. But, on the other hand, you're not exactly asking your friend to make some wild guess. She has some information, after all, and she can use that information to make a better guess than simply randomly picking a number between 0% and 100%.

Sensibly, given the results of her sample, she guesses that 46% of the beads in the entire pillowcase are red, and 54% are blue. (Think about it: Even though you know that her guess is wrong, it's the best guess she could have made given what she observed, right?)

Before telling her the true answer, you have her dump all 100 beads back into the pillowcase, re-mix the 1000 beads, and have her repeat the process: reach into the pillowcase again, re-draw 100 beads, and count the number of reds and blues drawn again. This time, she draws 43 red beads and 57 blue ones.

You ask your friend if she'd like to revise her guess, and, based on some new information and some quick averaging on her part, she revises her guess to say that she thinks that 44.5% of the beads are red, and 55.5% of the beads are blue. (She does this by simply averaging the 46% of red beads from the first sample and 43% of red beads from the second sample.)

The laws of probability are useful in many ways – in calculating gambling odds, for example – but in the above example, they are useful for taking particular information about a characteristic of an observed sample of data and attempting to generalize that information to the underlying and unobserved population. The observed samples above, of course, are the two samples of 100 that your friend drew from the pillowcase. The underlying population is represented by the 1000 beads in the bag.

Of course, the example above has some limitations. In particular, in the example, you knew the actual population characteristic – there were 450 red and 550 blue beads. In social reality, there is no comparable knowledge of the value of the true characteristic of the underlying population.

Now, some definitions.

An **outcome** is the result of a random observation. Two or more outcomes can be said to be **independent outcomes** if the realization of one of the outcomes does not affect the realization of the other outcomes. For example, the roll of two dice represents independent outcomes, because the outcome of the first die does not affect the outcome of the second die.

Probability has several key properties. First, all outcomes have some probability ranging from 0 to 1. A probability value of 0 for an outcome means that the outcome is impossible, and a probability value of 1 for an outcome means that the outcome is absolutely certain to happen. For example, taking two fair dice, rolling them, and adding up the sides facing up, and calculating the probability that the sum will equal 13 is 0, since the highest possible roll is 12.

Second, the sum of all possible outcomes must be exactly 1. A different way of putting this is that, once you undertake a random observation, you must observe something. If you flip a fair coin, the probability of it landing heads is  $1/2$ , and the probability of it landing tails is  $1/2$ , and the probability of landing either a head or a tail is 1, because  $1/2 + 1/2 = 1$ .

Third, if (but only if!) two outcomes are independent, then the probability of those events both occurring is equal to the product of them individually. So, if we have our fair coin, and toss it three times – and be mindful that each toss is an independent outcome – the probability of tossing three tails is  $1/2 \times 1/2 \times 1/2 = 1/8$ .

Of course, many of the outcomes in which we are interested are not independent. And in these circumstances, more complex rules of probability are required that are beyond the scope of this discussion.

Why is probability relevant for scientific investigations, and in particular, for political science? For several reasons. First, because political scientists typically work with samples (not populations) of data, the rules of probability tell us how we can generalize from our sample to the broader population. Second, and relatedly, the rules of probability are the key to identifying which relationships are “statistically significant” (a concept that we define in the next chapter). Put differently, we use probability theory to decide whether the patterns of relationships we observe in a sample could have occurred simply by chance.

### 6.3 LEARNING ABOUT THE POPULATION FROM A SAMPLE: THE CENTRAL LIMIT THEOREM

The reasons that social scientists rely on sample data instead of on population data – in spite of the fact that we care about the results in the population instead of in the sample – are easy to understand. Consider an election campaign, in which the media, the public, and the politicians involved all want a sense of which candidates the public favors and by how much. Is it practical to take a census in such circumstances? Of course not. The adult population in the United States is approximately 200 million people, and it is an understatement to say that we can’t interview each and every one of these individuals. We simply don’t have the time or the money to do that. There is a reason why the U.S. government conducts a **census** only once every 10 years.<sup>4</sup>

Of course, anyone familiar with the ubiquitous public-opinion polls knows that scholars and news organizations conduct surveys on a sample of Americans routinely and use the results of these surveys to generalize about the people as a whole. When you think about it, it seems a little audacious to think that you can interview perhaps as few as 1000 people and then use the results of those interviews to generalize to the beliefs and opinions of the entire 200 million. How is that possible?

The answer lies in a fundamental result from statistics called the **central limit theorem**, which Dutch statistician Henk Tijms (2004) calls “the unofficial sovereign of probability theory.” Before diving into what the theorem demonstrates, and how it applies to social science research, we need to explore one of the most useful probability distributions in statistics, the **normal distribution**.

<sup>4</sup> You might not be aware that, even though the federal government conducts only one census per 10 years, it conducts sample surveys with great frequency in an attempt to measure population characteristics such as economic activity.

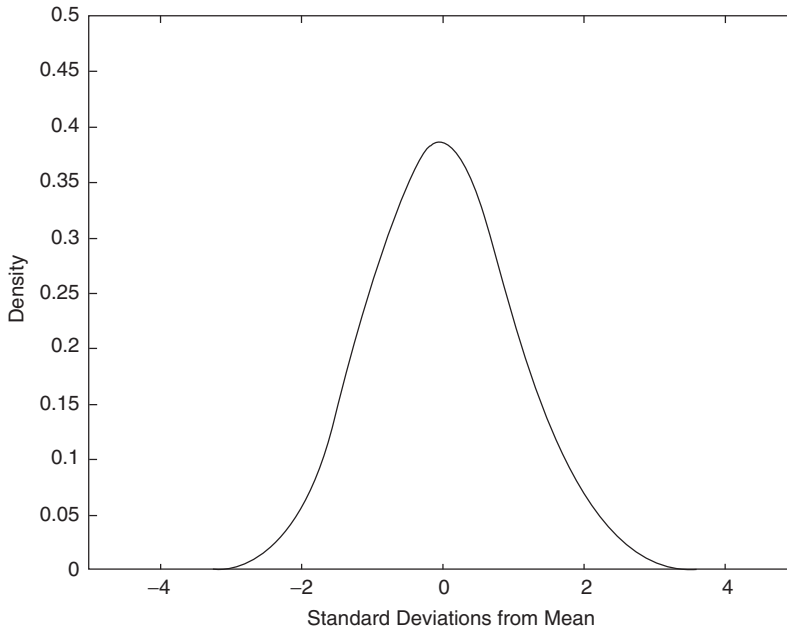


Figure 6.1. The normal probability distribution.

### 6.3.1 The Normal Distribution

To say that a particular distribution is “normal” is *not* to say that it is “typical” or “desirable” or “good.” A distribution that is not “normal” is not something odd like the “deviant” or “abnormal” distribution. It is worth emphasizing, as well, that normal distributions are not necessarily common in the real world. Yet, as we will see, they are incredibly useful in the world of statistics.

The normal distribution is often called a “bell curve” in common language. It is shown in Figure 6.1 and has several special properties. First, it is symmetrical about its mean,<sup>5</sup> such that the mode, median, and mean are the same. Second, the normal distribution has a predictable area under the curve within specified distances of the mean. Starting from the mean and going one standard deviation in each direction will capture 68% of the area under the curve. Going one additional standard deviation in each direction will capture a shade over 95% of the total area under the curve.<sup>6</sup>

<sup>5</sup> Equivalently, but a bit more formally, we can characterize the distribution by its mean and variance (or standard deviation) – which implies that its skewness and excess kurtosis are both equal to zero.

<sup>6</sup> To get exactly 95% of the area under the curve, we would actually go 1.96, not 2, standard deviations in each direction from the mean. Nevertheless, the rule of two is a handy rule of thumb for many statistical calculations.

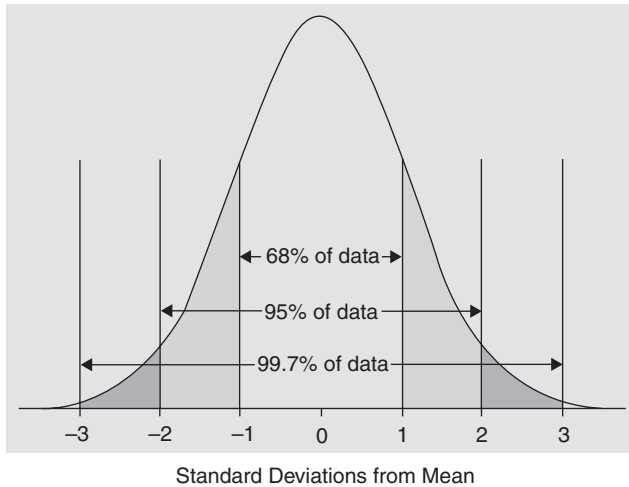


Figure 6.2. The 68–95–99 rule.

And going a third standard deviation in each direction will capture more than 99% of the total area under the curve. This is commonly referred to as the **68–95–99 rule** and is illustrated in Figure 6.2. You should bear in mind that this is a special feature of the normal distribution and does not apply to any other-shaped distribution. What do the normal distribution and the 68–95–99 rule have to do with the process of learning about population characteristics based on a sample?

A distribution of actual scores in a sample – called a **frequency distribution**, to represent the frequency of each value of a particular variable – on any variable might be shaped normally, or it might not be. Consider the frequency distribution of 600 rolls of a six-sided (and unbiased) die, presented in Figure 6.3. Note something about Figure 6.3 right off the bat: that frequency distribution does not even remotely resemble a normal distribution.<sup>7</sup> If we roll a fair six-sided die 600 times, how many 1’s, 2’s, etc., should we see? On average, 100 of each, right? That’s *pretty close* to what we see in the figure, but only pretty close. Purely because of chance, we rolled a couple too many 1’s, for example, and a couple too few 6’s.

What can we say about this sample of 600 rolls of the die? And, more to the point, from these 600 rolls of the die, what can we say about the underlying population of all rolls of a fair six-sided die? Before we answer the second question, which will require some inference, let’s answer the first, which we can answer with certainty. We can calculate the mean of these rolls of dice in the straightforward way that we learned in

<sup>7</sup> In fact, the distribution in the figure very closely resembles a uniform or flat distribution.

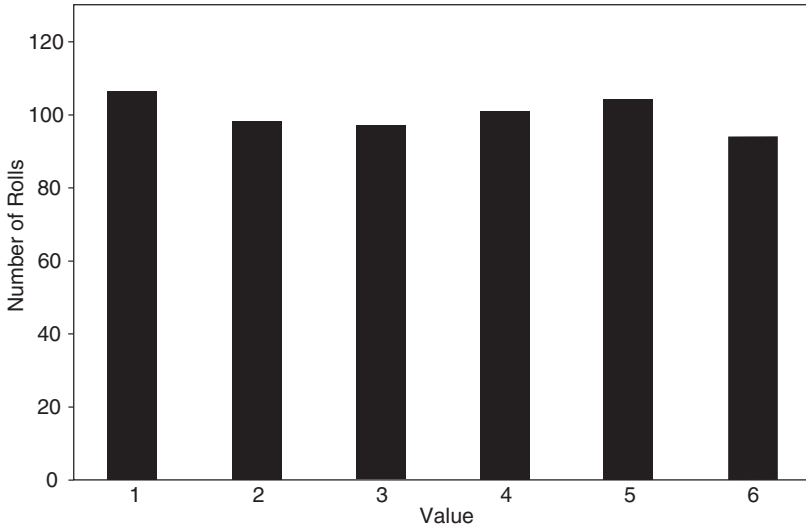


Figure 6.3. Frequency distribution of 600 rolls of a die.

Chapter 5: Add up all of the “scores” – that is, the 1’s, 2’s, and so on – and divide by the total number of rolls, which in this case is 600. That will lead to the following calculation:

$$\begin{aligned}\bar{Y} &= \frac{\sum_{i=1}^n Y_i}{n} \\ &= \frac{\sum (1 \times 106) + (2 \times 98) + (3 \times 97) + (4 \times 101) + (5 \times 104) + (6 \times 94)}{600} = 3.47.\end{aligned}$$

Following the formula for the mean, for our 600 rolls of the die, in the numerator we must add up all of the 1’s (106 of them), all of the 2’s (98 of them), and so on, and then divide by 600 to produce our result of 3.47.

We can also calculate the standard deviation of this distribution:

$$s_Y = \sqrt{\frac{\sum_{i=1}^n (Y_i - \bar{Y})^2}{n-1}} = \sqrt{\frac{1753.40}{599}} = 1.71.$$

Looking at the numerator for the formula for the standard deviation that we learned in Chapter 5, we see that  $\sum (Y_i - \bar{Y})^2$  indicates that, for each observation (a 1, 2, 3, 4, 5, or 6) we subtract its value from the mean (3.47), then square that difference, then add up all 600 squared deviations from the mean, which produces a numerator of 1753.40 beneath the square-root sign. Dividing that amount by 599 (that is,  $n-1$ ), then taking the square root, produces a standard deviation of 1.71.

As we noted, the sample mean is 3.47, but what should we have *expected* the mean to be? If we had exactly 100 rolls of each side of the die, the mean would have been 3.50, so our sample mean is a bit lower than we



would have expected. But then again, we can see that we rolled a few “too many” 1’s and a few “too few” 6’s, so the fact that our mean is a bit below 3.50 makes sense.

What would happen, though, if we rolled that same die another 600 times? What would the mean value of those rolls be? We can’t say for certain, of course. Perhaps we would come up with another sample mean of 3.47, or perhaps it would be a bit above 3.50, or perhaps the mean would hit 3.50 on the nose. Suppose that we rolled the die 600 times like this not once, and not twice, but an infinite number of times. Let’s be clear: We do not mean *an infinite number of rolls*, we mean *rolling the die 600 times for an infinite number of times*. That distinction is critical. We are imagining that we are taking a sample of 600, not once, but an infinite number of times. We can refer to a hypothetical distribution of sample means, such as this, as a **sampling distribution**. It is hypothetical because scientists almost never actually draw more than one sample from an underlying population at one given point in time.

If we followed this procedure, we could take those sample means and plot them. Some would be above 3.50, some below, some right on it. Here is the key outcome, though: The sampling distribution would be normally shaped, even though the underlying frequency distribution is clearly not normally shaped.

That is the insight of the central limit theorem. If we can envision an infinite number of random samples and plot our sample means to each of these random samples, those sample means would be distributed normally. Furthermore, the mean of the sampling distribution would be equal to the true population mean. The standard deviation of the sampling distribution is

$$\sigma_{\bar{Y}} = \frac{s_Y}{\sqrt{n}},$$

where  $n$  is the sample size. The standard deviation of the sampling distribution of sample means, which is known as the **standard error of the mean** (or simply “standard error”), is simply equal to the sample standard deviation divided by the square root of the sample size. In the preceding die-rolling example, the standard error of the mean is

$$\sigma_{\bar{Y}} = \frac{1.71}{\sqrt{600}} = 0.07.$$

Recall that our goal here is to learn what we can about the underlying population based on what we know with certainty about our sample. We know that the mean of our sample of 600 rolls of the die is 3.47 and its standard deviation is 1.71. From those characteristics, we can imagine that, if we rolled that die 600 times an infinite number of times, the resulting

sampling distribution would have a standard deviation of 0.07. Our best approximation of the population mean is 3.47, because that is the result that our sample generated.<sup>8</sup> But we realize that our sample of 600 might be different from the true population mean by a little bit, either too high or too low. What we can do, then, is use our knowledge that the sampling distribution is shaped normally and invoke the 68–95–99 rule to create a **confidence interval** about the likely location of the population mean.

How do we do that? First, we choose a degree of confidence that we want to have in our estimate. Although we can choose any confidence range up from just above 0 to just below 100, social scientists traditionally rely on the 95% confidence level. If we follow this tradition – and because our sampling distribution is normal – we would merely start at our mean (3.47) and move *two* standard errors of the mean in each direction to produce the interval that we are approximately 95% confident that the population mean lies within. Why *two* standard errors? Because just over 95% of the area under a normal curve lies within two standard errors of the mean. Again, to be precisely 95% confident, we would move 1.96, not 2, standard errors in each direction. But the rule of thumb of two is commonly used in practice. In other words,

$$\bar{Y} \pm 2 \times \sigma_{\bar{Y}} = 3.47 \pm (2 \times 0.07) = 3.47 \pm 0.14.$$

That means, from our sample, we are 95% confident that the population mean for our rolls of the die lies somewhere on the interval between 3.33 and 3.61.

Is it possible that we're wrong and that the population mean lies outside that interval? Absolutely. Moreover, we know exactly *how* likely. There is a 2.5% chance that the population mean is less than 3.33, and a 2.5% chance that the population mean is greater than 3.61, for a total of a 5% chance that the population mean is not in the interval from 3.33 to 3.61. For a variety of reasons, we might like to have more confidence in our estimate. Say that, instead of being 95% confident, we would be more comfortable with a 99% level of confidence. In that case, we would simply move *three* (instead of two) standard errors in each direction from our sample mean of 3.47, yielding an interval of 3.26–3.68.

Throughout this example we have been helped along by the fact that we knew the underlying characteristics of the data-generating process (a fair die). In the real world, social scientists almost never have this advantage. In the next section we consider such a case.

<sup>8</sup> One might imagine that our best guess should be 3.50 because, in theory, a fair die ought to produce such a result.

### 6.4 EXAMPLE: PRESIDENTIAL APPROVAL RATINGS

Between June 20 and 24, 2012, NBC News and the *Wall Street Journal* sponsored a survey in which 1000 randomly selected Americans were interviewed about their political beliefs. Among the questions they were asked was the following item intended to tap into a respondent's evaluation of the president's job performance:

In general, do you approve or disapprove of the job Barack Obama is doing as president?

This question wording is the industry standard, used for over a half-century by almost all polling organizations.<sup>9</sup> In June 2012, 47% of the sample approved of Obama's job performance, 48% disapproved, and 5% were unsure.<sup>10</sup>

These news organizations, of course, are not inherently interested in the opinions of those 1000 Americans who happened to be in the sample, except insofar as they tell us something about the adult population as a whole. But we can use these 1000 responses to do precisely that, using the logic of the central limit theorem and the tools previously described.

To reiterate, we know the properties of our randomly drawn sample of 1000 people with absolute certainty. If we consider the 470 approving responses to be 1's and the remaining 530 responses to be 0's, then we calculate our sample mean,  $\bar{Y}$ , as follows:<sup>11</sup>

$$\bar{Y} = \frac{\sum_{i=1}^n Y_i}{n} = \frac{\sum(470 \times 1) + (530 \times 0)}{1000} = 0.47.$$

We calculate the sample standard deviation,  $s_Y$ , in the following way:

$$\begin{aligned} s_Y &= \sqrt{\frac{\sum_{i=1}^n (Y_i - \bar{Y})^2}{n-1}} = \sqrt{\frac{470(1-0.47)^2 + 530(0-0.47)^2}{1000-1}} \\ &= \sqrt{\frac{249.1}{999}} = 0.50. \end{aligned}$$

<sup>9</sup> The only changes, of course, are for the name of the current president.

<sup>10</sup> The source for the survey was [http://www.pollingreport.com/obama\\_job2.htm](http://www.pollingreport.com/obama_job2.htm), accessed July 11, 2012.

<sup>11</sup> There are a variety of different ways in which to handle mathematically the 5% of "uncertain" responses. In this case, because we are interested in calculating the "approval" rating for this example, it is reasonable to lump the disapproving and unsure answers together. When we make decisions like this in our statistical work, it is very important to communicate exactly what we have done so that the scientific audience can make a reasoned evaluation of our work.

But what can we say about the population as a whole? Obviously, unlike the sample mean, the population mean cannot be known with certainty. But if we imagine that, instead of one sample of 1000 respondents, we had an infinite number of samples of 1000, then the central limit theorem tells us that those sample means would be distributed normally. Our best guess of the population mean, of course, is 0.47, because it is our sample mean. The standard error of the mean is

$$\sigma_{\bar{Y}} = \frac{0.50}{\sqrt{1000}} = 0.016,$$

which is our measure of uncertainty about the population mean. If we use the rule of thumb and calculate the 95% confidence interval by using two standard errors in either direction from the sample mean, we are left with the following interval:

$$\bar{Y} \pm 2 \times \sigma_{\bar{Y}} = 0.47 \pm (2 \times 0.016) = 0.47 \pm 0.032,$$

or between 0.438 and 0.502, which translates into being 95% confident that the population value of Obama approval is between 43.8% and 50.2%.

And this is where the “plus-or-minus” figures that we always see in public opinion polls come from.<sup>12</sup> The best guess for the population mean value is the sample mean value, plus or minus two standard errors. So the plus-or-minus figures we are accustomed to seeing are built, typically, on the 95% interval.

#### 6.4.1 What Kind of Sample Was That?

If you read the preceding example carefully, you will have noted that the NBC-*Wall Street Journal* poll we described used a *random* sample of 1000 individuals. That means that they used some mechanism (like random-digit telephone dialing) to ensure that all members of the population had an equal probability of being selected for the survey. We want to reiterate the importance of using random samples. The central limit theorem applies *only* to samples that are selected randomly. With a sample of convenience, by contrast, we cannot invoke the central limit theorem to construct a sampling distribution and create a confidence interval.

This lesson is critical: A nonrandomly selected sample of convenience does very little to help us build bridges between the sample and the population about which we want to learn. This has all sorts of implications about “polls” that news organizations conduct on their web sites. What do

<sup>12</sup> In practice, most polling firms have their own additional adjustments that they make to these calculations, but they start with this basic logic.

such “surveys” say about the population as a whole? Because their samples are clearly not random samples of the underlying population, the answer is “nothing.”

There is a related lesson involved here. The preceding example represents an entirely straightforward connection between a sample (the 1000 people in the survey) and the population (all adults in the United States). Often the link between the sample and the population is less straightforward. Consider, for example, an examination of votes in a country’s legislature during a given year. Assuming that it’s easy enough to get all of the roll-call voting information for each member of the legislature (which is our sample), we are left with a slightly perplexing question: What is the population of interest? The answer is not obvious, and not all social scientists would agree on the answer. Some might claim that the data don’t represent a sample, but a population, because the data set contains the votes of every member of the legislature. Others might claim that the sample is a sample of one year’s worth of the legislature since its inception. Others still might say that the sample is one realization of the infinite number of legislatures that could have happened in that particular year. Suffice it to say that there is no clear scientific consensus, in this example, of what would constitute the “sample” and what would constitute the “population.”

#### 6.4.2 A Note on the Effects of Sample Size

As the formula for the confidence interval indicates, the smaller the standard errors, the “tighter” our resulting confidence intervals will be; larger standard errors will produce “wider” confidence intervals. If we are interested in estimating population values, based on our samples, with as much precision as possible, then it is desirable to have tighter instead of wider confidence intervals.

How can we achieve this? From the formula for the standard error of the mean, it is clear through simple algebra that we can get a smaller quotient either by having a smaller numerator or a larger denominator. Because obtaining a smaller numerator – the sample standard deviation – is not something we can do in practice, we can consider whether it is possible to have a larger denominator – a larger sample size.

Larger sample sizes will reduce the size of the standard errors, and smaller sample sizes will increase the size of the standard errors. This, we hope, makes intuitive sense. If we have a large sample, then it should be easier to make inferences about the population of interest; smaller samples should produce less confidence about the population estimate.

In the preceding example, if instead of having our sample of 1000, we had a much larger sample – say, 2500 – our standard errors would have been

$$\sigma_{\bar{Y}} = \frac{0.50}{\sqrt{2500}} = 0.010,$$

which is less than two-thirds the size of our actual standard errors of 0.016. You can do the math to see that going two standard errors of 0.010 in either direction produces a narrower interval than going two standard errors of 0.016. But note that the cost of reducing our error by about 1.2% in either direction is the addition of nearly another 1500 respondents, and in many cases that reduction in error will not be worth the financial and time costs involved in obtaining all of those extra interviews.

Consider the opposite case. If, instead of interviewing 1000 individuals, we interviewed only 400, then our standard errors would have been

$$\sigma_{\bar{Y}} = \frac{0.50}{\sqrt{400}} = 0.025,$$

which, when doubled to get our 95% confidence interval, would leave a plus-or-minus 0.050 (or 5%) in each direction.

We could be downright silly and obtain a random sample of only 64 people if we liked. That would generate some rather wide confidence intervals. The standard error would be

$$\sigma_{\bar{Y}} = \frac{0.50}{\sqrt{64}} = 0.062,$$

which, when doubled to get the 95% confidence interval, would leave a rather hefty plus-or-minus 0.124 (or 12.4%) in each direction. In this circumstance, we would guess that Obama's approval in the population was 47%, but we would be 95% confident that it was between 34.6% and 59.4% – and that alarmingly wide interval would be just too wide to be particularly informative.

In short, the answer to the question, “How big does my sample need to be?” is another question: “How tight do you want your confidence intervals to be?”

## 6.5 A LOOK AHEAD: EXAMINING RELATIONSHIPS BETWEEN VARIABLES

Let's take stock for a moment. In this book, we have emphasized that political science research involves evaluating causal explanations, which entails examining the relationships between two or more variables. Yet, in this chapter, all we have done is talk about the process of statistical inference with a *single* variable. This was a necessary tangent, because we had to teach you the logic of statistical inference – that is, how we use samples to learn something about an underlying population.

In Chapter 7, you will learn three different ways to move into the world of bivariate hypothesis testing. We will examine relationships between two variables, typically in a sample, and then make probabilistic assessments of the likelihood that those relationships exist in the population. The logic is identical to what you have just learned; we merely extend it to cover relationships between two variables. After that, in Chapter 8, you will learn one other way to conduct hypothesis tests involving two variables – the bivariate regression model.

#### CONCEPTS INTRODUCED IN THIS CHAPTER

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- 68–95–99 rule – a useful characteristic of the normal distribution which states that moving  $\pm 1$ , 2, and 3 standard deviations from the mean will leave 68, 95, and 99% of the distribution’s area under the curve.
- census – an accounting of a population.
- central limit theorem – a fundamental result from statistics indicating that if one were to collect an infinite number of random samples and plot the resulting sample means, those sample means would be distributed normally around the true population mean.
- confidence interval – a probabilistic statement about the likely value of a population characteristic based on the observations in a sample.
- frequency distribution – a distribution of actual scores in a sample.
- independent outcomes – two or more outcomes such that the realization of one of the outcomes does not affect the realization of the other outcomes.
- normal distribution – a bell-shaped statistical distribution that can be entirely characterized by its mean and standard deviation.
- outcome – the result of a random observation.
- population – data for every possible relevant case.
- random sample – a sample such that each member of the underlying population has an equal probability of being selected.
- sample – a subset of cases that is drawn from an underlying population.
- sampling distribution – a hypothetical distribution of sample means.
- standard error of the mean – the standard deviation of the sampling distribution of sample means.
- statistical inference – the process of using what we know about a sample to make probabilistic statements about the broader population.

#### EXERCISES

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1. Go to <http://www.pollingreport.com> and find a polling statistic that interests you most. Be sure to click on the “full details” option, where available,

to get the sample size for the survey item. Then calculate the 95% and 99% confidence intervals for the population value of the statistic you have in mind, showing all of your work. Print the page from the web site and turn it in with your homework.

2. For the same survey item, what would happen to the confidence interval if the sample size were cut in half? What would happen instead if it were doubled? Assume that the sample standard deviation does not change and show your work.
3. Are larger sample sizes always better than smaller sample sizes? Explain your answer.
4. Refer back to Table 5.2, which shows the incumbent vote percentage in U.S. presidential elections. Calculate the standard error of the mean for that distribution, and then construct the 95% confidence interval for the population mean. Show your work. What does the 95% confidence interval tell us in this particular case?
5. If we take a representative draw of 1000 respondents from the population of the United States for a particular survey question and obtain a 95% confidence margin, how many respondents would you need to draw from the population of Maine to obtain the same interval, assuming that the distribution of responses is the same for both populations?