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# Six Ways to Separate Lies From Statistics

By Betsey Stevenson & Justin Wolfers - May 1, 2013

The discovery of a spreadsheet error in an influential study by Harvard University economists Carmen Reinhart and Kenneth Rogoff inevitably raises a troubling question: To what extent can we trust what any researcher claims to be true?

The unfortunate reality is that mistakes much more serious than the one committed by Reinhart and Rogoff are far too common. Superfast computers and fancy statistical models can't save us from human frailty. But that doesn't mean empirical research has nothing to offer.

The Reinhart-Rogoff incident -- in which they accidentally excluded five countries from a calculation of the average relationship between government debt and economic growth -- is in some sense the wrong launching point for a discussion about modern empirical economics. It's the perfect made-for-TV mistake: It involved a simple error in a commonly used spreadsheet program that can be explained with screen shots and laughed about with friends. Moreover, it barely affected their findings, and it isn't representative of the challenges empirical research presents.

Today's empirical analyses are more likely to be based on a mash-up of huge data sets containing millions of observations, which are processed using specialized statistical software. As a result, errors can be a lot more insidious. Often they can be found only through sophisticated forensics.

## Old Aphorism

In one important case, one of us (Wolfers) found an error in research on the effects of the death penalty buried deep in lines of code in the statistical program Stata. It turned out to make all the difference, shifting the conclusion from one that the death penalty saves lives to an inference that it may cost lives. In another case, one of us (Stevenson) found that the raw data released by the Census Bureau was flawed, a victim of a complicated program designed to preserve people's anonymity.

Given the complexity, it's understandable that people might fall for the old aphorism that "liars figure and figures lie," that you can say anything with statistics. But this is silly. You can say anything in English, too. Indeed, our nation's opinion pages are filled with slanted nonsense written entirely in English.

So how can non-experts and policy makers separate the useful research from the dross? Allow us to offer six rules.

1. Focus on how robust a finding is, meaning that different ways of looking at the evidence point to the same conclusion. Do the same patterns repeat in many data sets, in different countries, industries or eras? Are the findings fragile, changing as one makes small changes in how phenomena are measured, and do the results depend on whether particularly influential observations are included? Thanks to Moore's Law of increasing computing power, it has never been easier or cheaper to assess, test and retest an interesting finding. If the author hasn't made a convincing case, then don't be convinced.

2. Data mavens often make a big deal of their results being statistically significant, which is a statement that it's unlikely their findings simply reflect chance. Don't confuse this with something actually mattering. With huge data sets, almost everything is statistically significant. On the flip side, tests of statistical significance sometimes tell us that the evidence is weak, rather than that an effect is nonexistent. Remember, results can be useful even if they don't meet significance tests. Sometimes questions are so important that we need to glean whatever meaning we can from available data. The best bad evidence is still more informative than no evidence.

3. Be wary of scholars using high-powered statistical techniques as a bludgeon to silence critics who are not specialists. If the author can't explain what they're doing in terms you can understand, then you shouldn't be convinced. You wouldn't be convinced by an analysis just because it was written in ancient Latin, so why be impressed by an abundance of Greek letters? Sophisticated statistical methods can be helpful, but they can also hide more than they reveal.

4. Don't fall into the trap of thinking about an empirical finding as "right" or "wrong." At best, data provide an imperfect guide. Evidence should always shift your thinking on an issue; the question is how far.

5. Don't mistake correlation for causation. For instance, even after revisions and corrections, Reinhart and Rogoff have demonstrated that economic growth is typically slower when government debt is higher. But does high debt cause slow growth, or is slow growth in gross domestic product the cause of higher debt-to-GDP ratios? Or are there other important determinants, such as populist spending by a government looking to get re-elected, which is more likely when growth is slow and typically drives debt up?

6. Always ask "so what?" Are the factors that drove the observed negative correlation between debt and GDP likely to exist today, in the U.S.? Does it even make sense to speak of "the" relationship between debt and economic growth, when there are surely many such relationships: Governments

borrowing simply to fund their re-election are likely harming growth, while those investing in much-needed public works can provide the foundation for growth. The "so what" question is about moving beyond the internal validity of a finding to asking about its external usefulness.

You might be tempted to conclude that extracting meaning from data is a hopelessly difficult task. It's difficult, but it's not hopeless. The only alternative to facts is intuition, which is not only flawed but also, according to psychologists, more flawed than we think it is. Far better to base policy on imperfect analyses than on the fact-free bloviating of the ideologues, charlatans and political hucksters who would take their place.

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