Definition and explanation in the social sciences: The case of gun violence

Anthony C. Lopez

In the social sciences, we often want to describe and expalin relationships among variables. As a political psychologist interested in warfare, I focus on identifying the many things that make political vioelnce between groups more or less likely. These can be emotions like humiliation or revenge, and they can be things like poverty or religion. The social world is marvelously complex, so there is often no shortage of potential 'variables' to identify as things that possibly 'cause' or explain the puzzles that fascinate us.

Academic research on social phenomena can appear indeterminate - that is, it can appear as though we have many competing explanations for the same phenomenon and no clear verdict as to which explanation is better. This can happen for many reasons: perhaps our theories are not sufficiently refined, or perhaps we lack sufficient data to test hypotheses in a clear and compelling way. Or it could simply be that we have very different ways of defining the thing we are trying to explain. If two research communities have very different definitions of warfare, then their explanations for it could vary wildly despite the fact that they are, ostensibly, studying the same thing.

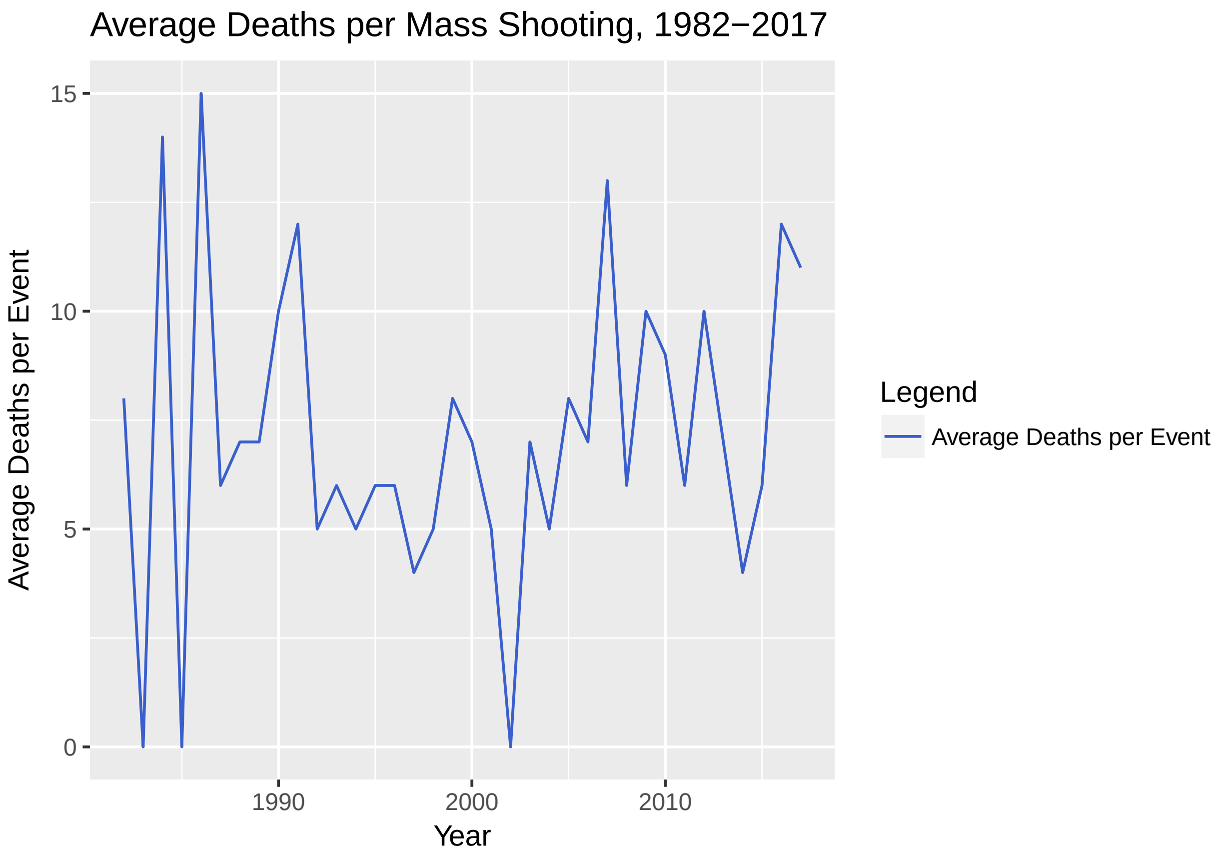
This is an underappreciated fact about social science research. Often, research in the social sciences is criticized for a lack of rigor, or inability to make strong causal inferences. Importantly, there is nothing inherent to the social world that makes this necessarily true. However, if there is contention about the very definitions we give to the variables we study, then even rigorous research is likely to fall on deaf ears.

An important problem, therefore, is that there are almost always multiple ways to define our variable of interest. To take a prominent example, look at mass killings. A recent article by Brian J. Phillips at one of my favorite blogs recently looked into the question of whether the assault weapons ban of 1994-2004 had an impact on mass killings. Again, we have to start with the question: how do you define a mass killing? As social scientists, our definitions are often a blend of intuition, theory, and methodological convenience. The role of intuition is obvious. The role of theory is to allow us to derive definitions from established clusters of knowledge. And if we want to test our hypotheses empirically, ultimately we want to define our variable in such a way that data can be gathered and tests can be replicated by anyone.

In the case of mass killings, there are already several datasets that exist. Phillips uses the Mother Jones dataset, which is an index of all mass and spree killings since 1982, and is based on an established definition of mass killings. The dataset contains information on things like gender of assailant and venue of the event, as well as the absolute number of deaths and injuries per incident and the total number of incidents per year.

Datasets such as these are a boon to social scientists and policymakers because they enable us to look more closely at the relationships among variables. For example, it might seem intuitive to hypothesize that a ban on assault weapons will reduce mass killings - but without data, we are limited in the inferences we can draw. Thus, clear definitions, combined with data collection and statistical analysis can allow us to draw inferences about the relationships among variables, and by extension, can allow us to inch closer to policy recommendations based on our understanding of those relationships.

It is in this vein that Phillips presents some descriptive statistics to help us visualize the potential effect of the assault weapons ban on mass killings. I'll begin as any researcher would - by replicating findings. So here is the first graph Phillips presents, of average deaths per mass shooting between 1982 and 2017.

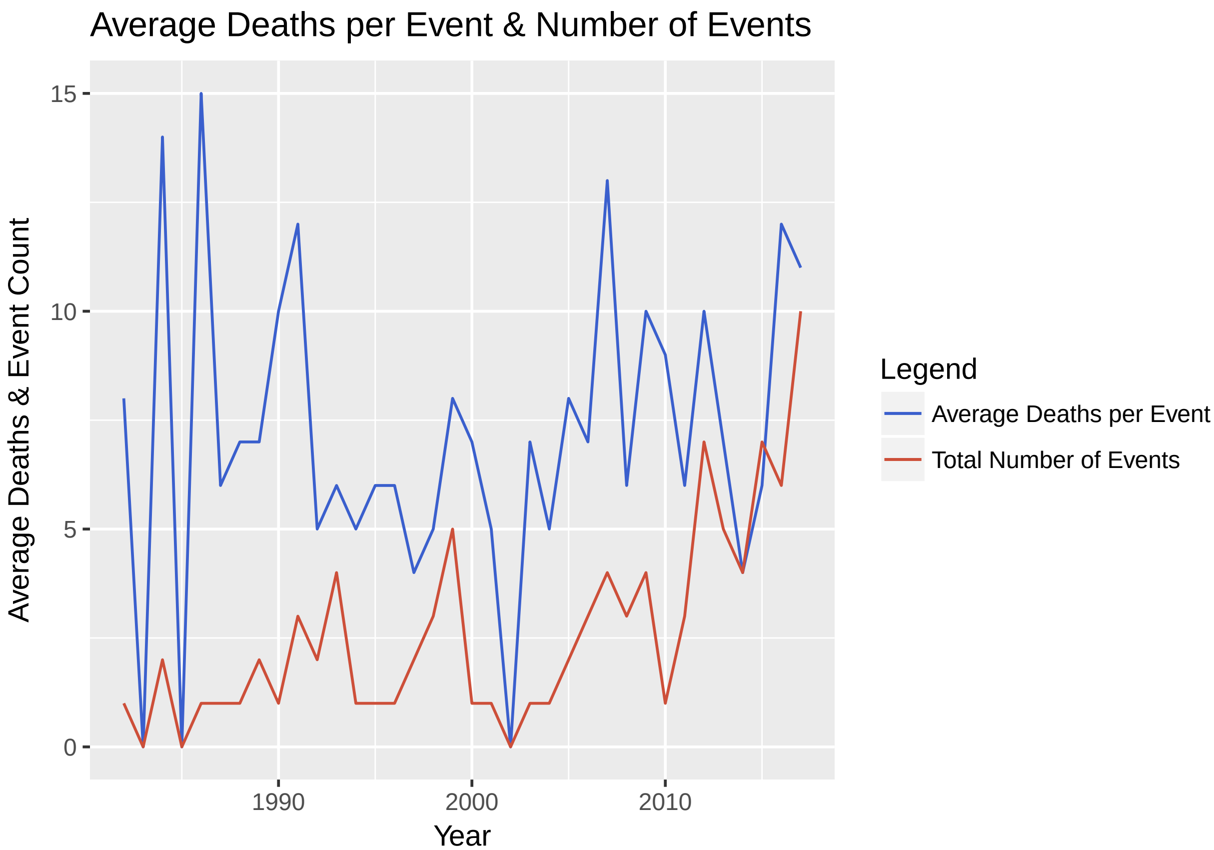


The first thing you'll notice is that my graph appears slightly more 'erratic' than the one produced by Phillips. The reason for this is that there are three years in the range in which there are zero mass killings - which of course produces an 'average deaths per event' of zero for each of these years: 1983, 1985, and 2002. These are represented as the 'dips' to the floor of the x axis in the graph for these years. I can't say why these 'dips' aren't in the graphs Phillips presents, but I also don't see why it would dramatically change the conclusions.

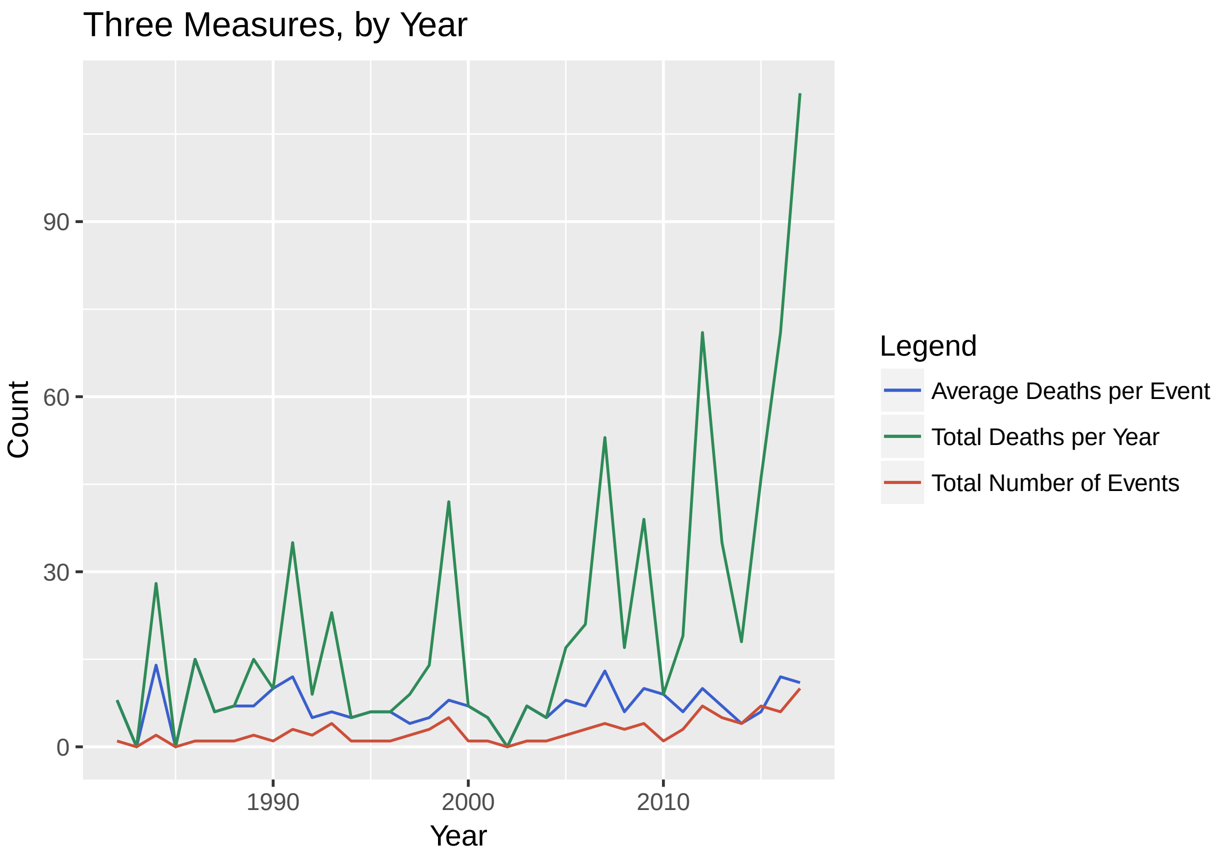
Average deaths per mass shooting is one way to measure the dependent variable. Given this dataset, there are at least two other ways to measure it: the total number of deaths of all incidents in a year, and the total number of incidents in a year. In other words, in a given year 1) how many people, total, died from all mass killings, and; 2) how many mass killings were there? This means we have three ways to examine our dependent variable using only this dataset:

- The combined number of deaths of all incidents;
- The average number of deaths per incident;
- The number of incidents.

The next step we could take is just to add them all to the graph and compare. However, since the combined number of deaths will be a much larger number than either the average deaths per incident or the number of incidents, I'll start by comparing the latter two measures:



If we were to 'eyeball' the graph, we might be tempted to observe that the average deaths per event seems to fluctuate fairly wildly, but is also fairly closely tied to between 5-10 deaths per event. At first blush we might also conclude that the number of mass killings per year seems to be steadily rising. If we now include total deaths per year due to mass killings, we see yet a more complicated picture. Although this measure, like the other two, is subject to significant fluctuation, an increasing trend can be observed.



Now, what of the claim that the 1994-2004 ban on assault weapons reduced mass killings during this period? An initial response would be to simply observe, as Phillips does, whether the period of the assault weapons ban coincides with a drop in average deaths per event. Strictly speaking, however, this is not really a test of the hypothesis (as Phillips correctly notes) but it certainly could help to indicate whether a rigorous test is worth pursuing. I would agree with Phillips that there does seem to be some visual evidence that the period 1994-2004 is meaningfully different, particularly if you are looking at average deaths per event. The next step would therefore be hypothesis testing.

A statistical model testing the hypothesis that the assault weapons ban caused a decrease in average deaths per event should identify and control for potentially confounding variables. However, doing so often requires and spawns complex and long-lasting research programs - and rightfully so. For my purposes here, I begin more modestly by identifying a statistical model and testing the bivariate relationship between the assault weapons ban and the three measures identified above. If our test allows us to reject the hypothesis that there is no difference between years with and without the assault ban, then we are at least warranted in pursuing the matter further with a more extensive model.

Statistical models vary based on the nature of the variables being tested. Each of the three measures of the dependent variable identified above are known as 'count data', while the independent variable is a nominal categorical variable with two values: "Ban" or "No Ban". Thus, I've chosen a Poisson regression, which is often more appropriate for modeling count data.[1] A simple bivariate Poisson regression yields the following output:

Table 1:

	Dependent variable:		
	Average Deaths per Event	Total Deaths per Year	Number of Events
	(1)	(2)	(3)
Weapons Ban	-0.412^{**}	-1.044^{**}	-0.690^{*}
	(0.183)	(0.487)	(0.352)
Constant	2.074^{***}	3.309^{***}	1.125^{***}
	(0.087)	(0.179)	(0.150)
Observations	36	36	36
Residual Deviance (df = 34)	69.510	627.153	57.370
Null Deviance (df = 35)	77.692	754.420	64.972
Note:			*p<0.1; **p<0.05; ***p<0.01

The results of the statistical analysis show that the independent variable (Weapons Ban) has a negative relationship with each of the dependent variables. In other words, and generally speaking, since I have defined years without the ban as the “reference category” in the model, the results tell us that value of the dependent variable is lower in years in which the ban was in effect relative to years in which the ban was not in effect.

Importantly, the independent variable (Weapons Ban) could be related to each of the three versions of the dependent variable (total deaths; average deaths; number of events) in various ways. For example, assuming the motives for mass killings are constant across the period examined, an assault weapons ban would most likely have an effect on the average deaths per event, and by extension, on total deaths per year. If, for example, underlying motives for mass killings became stronger for some exogenous reason, this could result in a higher number of events and a higher total death rate, but not necessarily a higher *average* death rate per event. Thus, if our interest is the specific effect of an assault weapons ban on mass killings, we are probably justified in focusing on average and total deaths rather than number of events. Yet, as the model above shows, the weapons ban did indeed have a meaningful effect on the total number of events, which suggests that we probably benefit from examinimg as many versions of the dependent variable as are theoretically plausible.

In terms of useful and necessary control variables, we could again turn to both intuition and theory, which I think lead us to obvious national-level variables such as average/median income and unemployment rate. Let’s also not forget that the period of the assault weapons ban was one of relative calm in terms of threats to American international status. Observers of many stripes were quick to laud the triumph of liberalism and the unipolar moment of American hegemony, if not the outright end of history itself - a period that lasted from roughly 1991-2001. In other words, we can and should be creative, open-minded and theoretically rigorous about identifying potentially confounding variables. We lose nothing at this point from thinking openly and broadly about this very complex social problem.

Mass killings are a public health priority. As researchers continue to gather data on these events, we only move closer to a better understanding of the conditions that make such disasters more likely. Datasets such as these allow researchers, and indeed the public at large, to replicate findings themselves and improve upon existing models by asking better questions, offering clearer definitions, and ideally, developing useful policy instruments based on fine-grained analysis rather than blunt ideological suspicion. I encourage all of you to take a look at the data and start getting creative.

Anthony C. Lopez
Washington State Univeristy
November 12, 2017

[1]: I implement a quasi Poisson regression to account for overdispersion in the model, which returns corrected standard errors.