ABSTRACT. How can scholars estimate the size of armed conflicts? Thorough research only goes so far in making such assessments – there will almost always be missing data, and thus a need to draw inferences about how comprehensively violence has been recorded. This paper addresses that challenge by developing an estimation strategy based on the observation that violent events are generally distributed according to power laws, a pattern which structures expectations about what event data on armed conflict would look like if those data were complete. This technique is applied to estimate the number of Native American and U.S. casualties in the American Indian Wars between 1776 and 1890, demonstrating how scholars can use power laws to estimate conflict size, even (and perhaps especially) in cases where previous literature has been unable to do so.

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USING POWER LAWS TO ESTIMATE CONFLICT SIZE

Estimating the severity of armed conflict is generally difficult. During recent violence in Iraq, Afghanistan, and the Balkans, for instance, casualty estimates ranged widely, despite efforts to record this information objectively. These figures can be the subject of high profile controversies. More broadly, scholars’ inability to generate rigorous casualty estimates impedes their ability to describe and to analyze one of the most salient aspects of armed conflict.

One of the main difficulties of estimating conflict size is that this is not just a matter of carefully gathering information. No matter how much effort analysts put into recording violence, the available record will almost always be incomplete, and thus there will almost always be a need to estimate how comprehensively these data have been recorded.

This paper explains how power laws can be used to perform this kind of inference. A power law is a special probability distribution characterizing the relationship between the frequency and severity of many phenomena, including violent events. The notion that the distribution of violent events often resembles a power law is a well-documented empirical regularity. This paper instrumentalizes that fact to draw inferences about what the distribution of violent events might look like if the data were complete. In other words, this paper argues that it is possible to use information about the distribution of available data in order to make inferences about the comprehensiveness of those data. For demonstration, this paper uses power laws to estimate Native American and U.S. casualties during the American Indian Wars from 1776 to 1890. There are two main reasons why this is a useful experience to consider.

First, despite the central importance of the American Indian Wars to North American history, there presently exist no reliable estimates of how violent these conflicts actually were. Millions
of Native Americans died as Europeans colonized North America and the tribes were subjected, over centuries, to coercive expansion by settlers and their governments. At the same time, the majority of the tribes’ population loss was a result of disease, and in recent years, some revisionist historians have argued that the frontier was far less violent than what is commonly believed.¹ The historical significance of this violence is out of proportion with scholars’ current understanding of what it entailed.

Second, the American Indian Wars are a context in which estimating conflict size relies heavily on extrapolation. The U.S. Army kept detailed records on many phases of fighting with the tribes, and it is possible to reconstruct additional information from other sources. But it is highly unlikely that scholars will ever reach reliable estimates of the magnitude of the American Indian Wars simply by accumulating data. Many violent events – especially small-scale engagements with little historical salience in and of themselves – have presumably gone unrecorded, becoming effectively invisible to event-count methodologies. It is important to examine and assess the available record, but it is also then crucial to draw inferences about how (in)complete that record is. The approach developed below is designed to do this, indicating that roughly fifty thousand Native Americans and roughly twelve thousand U.S. forces were killed, captured, or mortally wounded during the American Indian Wars. This historical contribution is meant to reinforce the paper’s methodological purpose, which is to demonstrate how power laws can be used to estimate conflict size, even (and perhaps especially) in cases where previous literature has been unable to do so.

The paper proceeds in six sections. Section 1 provides an overview of the American Indian Wars and describes a data set covering roughly 2,500 military engagements between Native

American and U.S. forces between 1776 and 1890. These are the most comprehensive event-level data on the American Indian Wars to date, but they doubtlessly remain incomplete. Section 2 explains how it is possible to use power laws to estimate the comprehensiveness of these data. Section 3 implements this technique and Section 4 discusses the uncertainty surrounding the resulting estimates, along with their sensitivity to alternative specifications. Section 5 offers a closer look at the core distributional assumption driving the estimation strategy, and Section 6 concludes.

Section 1. Data on the American Indian Wars

When the United States declared independence, most of its population lived close to the Atlantic seaboard and the country had little ability to project military power. Settlers on the early frontier were vulnerable to attacks from nearby tribes. The tribes, in turn, suffered frequent encroachments on their territory and population. These tensions regularly produced low-grade violence which sometimes spiraled into larger conflicts. In some cases, pan-tribal military alliances opposed the United States, leading to major engagements such as the 1794 Battle of Fallen Timbers and the 1811 Battle of Tippecanoe. During the War of Independence and the War of 1812, Britain exploited these tensions by recruiting Cherokees, Shawnees, Iroquois, and other tribes to fight on its side.

During the first half of the 19th century, the United States coercively relocated dozens of tribes to lands west of the Mississippi River. In some cases (as with the Choctaws) removal entailed relatively little violence, but in other cases (as with the Seminoles), tribes fought protracted conflicts to stay on their land. As U.S. settlement expanded by mid-century, conflict ensued with
prominent tribes such as the Cheyennes and Comanches, as well as with numerous, lesser-known tribes such as the Chetcos and Kalispels. As a result of this fighting, Native Americans were often confined to reservations. Several tribes (such as the Navajos and Nez Perces) forcibly resisted the reservation policy, and some (such as Apaches and Sioux) engaged in armed conflict when factions left reservations to live, hunt, or raid elsewhere. Some battles took place within the reservations themselves. In December 1890, the U.S. Army fought Sioux conducting religious ceremonies near Wounded Knee Creek on a reservation in South Dakota. This is typically accepted by historians as marking the end of the American Indian Wars.²

The American Indian Wars thus span a wide range of time, geography, and participants. Clodfelter (2007) divides this experience into forty separate conflicts between Native Americans and the United States; Axelrod (1993) chronicles thirty-six “Indian Wars” after 1776. But as these authors readily acknowledge, dividing the period into discrete episodes can be misleading, since much of the armed conflict between the United States and Native Americans involved protracted, low-level violence throughout the broader course of U.S. expansion that took more than a century to complete.³ That movement constituted a major geopolitical shift: the United States emerged as a continental power, while previously hegemonic tribes were in some cases reduced to dependency. Yet despite the prominent role that armed conflict played in precipitating this shift, there are no reliable estimates of just how violent this conflict actually was.

³ As Axelrod (1993: 257) writes: “Wars between Indians and whites were rarely officially declared or officially concluded, and even when they ostensibly were, violence often preceded the official declaration and persisted after the official cessation of hostilities…. [M]uch white-Indian conflict was not part of any named war.”
This paper thus attempts to estimate the number of casualties – defined here as the number of people killed, captured, or mortally wounded in battle – that occurred during the American Indian Wars, both on the side of the Native Americans and on the part of the United States. To be clear about scope conditions, the analysis includes military engagements between 1776 and 1890 that took place within the continental United States or that involved pursuits into neighboring territory (such as expeditions into Mexico to capture Geronimo). The analysis includes armed engagements of any size, ranging from small-scale raids to large battles. The data include engagements fought by regular and militia forces. They include noncombatant casualties, but they do not include losses resulting from displacement or disease.

As in many other conflicts, it is sometimes ambiguous whether a particular event should be seen as belonging to “the American Indian Wars” as opposed to interpersonal or intercommunal violence that was essentially nonpolitical. Scholars often disagree in defining “political violence,” and similar conceptual ambiguity applies to many aspects of fighting on the U.S. frontier. This study approaches the issue inductively by including information from a broad range of sources, and thus letting the sources “say” which engagements belong in the data. To the extent that there is disagreement, the present study thus errs on the side of inclusiveness, while following the lead of the literature on which it aims to build.

The sources for data collection comprise several anthologies recording armed conflict at the level of individual military engagements. The most comprehensive is Webb’s Chronological List of Engagements between the Regular Army of the United States and Various Tribes of Hostile Indians (1939) which lists 1,177 engagements between 1790 and 1890. Webb’s book is itself a compilation of two official records: the U.S. Army Adjutant General’s Chronological List of Actions, &c., with Indians (printed in the early 1890s) and the U.S. Army War College Historical
Figure 1. Descriptive Statistics

Time period: 1776-1890

Unit of analysis: military engagements between U.S. and Native American forces


Independent events recorded in the data: 2,537

Total recorded Native American casualties: 25,643

Total recorded U.S. casualties: 10,476

Tribes enumerated in the data set:

Section’s *Compilation of Indian Engagements* (1925). These records certainly suffer omissions and inaccuracies, but they are generally well-regarded.\(^4\)

Several additional sources flesh out the data used in this analysis. Michno’s *Encyclopedia of Indian Wars* (2003) describes 787 engagements occurring after 1850; a follow-on work, *Forgotten Fights* (Michno and Michno 2008) adds another 334 engagements dating to 1823. Axelrod’s *Chronicle of the Indian Wars* (1993) surveys 123 engagements after 1776.\(^5\) Ratjar’s *Indian War Sites* (1999) and Nunnally’s *American Indian Wars* (2007) also provide information spanning 1776 to 1890, covering 559 and 940 engagements within this period respectively. These anthologies include transparent sourcing; consistent information on the date, location, casualties, and tribe(s) involved in each engagement; and broad temporal and geographic coverage. Together, they comprise material from more than one thousand unique references. In all, these data incorporate 3,920 event reports covering 2,537 separate engagements. For 2,121 of these engagements, casualties are recorded as having been inflicted on at least one combatant.

Figure 1 offers descriptive statistics. In total, the data record 25,643 casualties sustained by Native American forces and 10,476 casualties sustained by U.S. forces.\(^6\) These data span eighty-

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\(^4\) In a related discussion, Michno (2003: 353) writes: “The numbers of casualties used in this study are inherently biased toward army estimations, since it was the army who kept the records. [But…] there is reason to be confident that the army estimates were reasonably accurate…. [T]he army lived by a strict code of honor, particularly in its official reports, and even if the unit leader tried to inflate numbers, he would face correction and perhaps ostracism by other soldier-witnesses.” Delay (2008) offers a similar discussion in describing the potential accuracy of his event-level data set covering engagements between Native Americans and Mexicans.

\(^5\) Though Axelrod’s work contains the smallest collection of engagements used for constructing data here, it is still regarded as being relatively comprehensive, and it was the source which Spirling (2011) used to define the case universe of armed conflict between the United States and the Native Americans.

\(^6\) In almost all cases, casualty counts are reproduced directly from the event reports. In cases where sources offered different estimates for the same engagement, those estimates were averaged together. There were thirty-one cases in which U.S. casualties were listed as being
one different tribes. This list emphasizes the point that most of the tribes who fought against the United States are no longer widely known, as their resistance did not achieve the kinds of historical salience attributed to groups like the Seminoles, Navajos, and Comanches. The bulk of the violence during the American Indian Wars occurred on small scales and a continual basis, which should add skepticism to the idea that this violence has been comprehensively recorded and preserved. There is surely a substantial amount of missing data, and this impedes drawing inferences about just how severe the American Indian Wars were.

How can scholars draw this kind of inference? We could examine the data and see if the results “look right,” but this requires making assumptions about the quantity we are trying to estimate. Polling subject matter experts poses a similar difficulty – since the magnitude of the American Indian Wars is the subject of scholarly debate, expert opinions are bound to differ, and the very purpose of this project is to help resolve that disagreement by producing an independent, objective estimate. We could spot check the data, using sources that discuss specific conflicts in detail in order to see how many engagements the data leave out – but then we would also have to make assumptions about the comprehensiveness of the sources being used as benchmarks as they, too, would surely be incomplete. For assessing recent conflicts, scholars can sometimes use survey methods to cross-check event counts, but this approach is not available for conflicts, like the American Indian Wars, that concluded long ago.

“several,” or “a few,” or “a number” – in each instance, this number was approximated with a coding of 5, comprising less than two percent of total recorded U.S. casualties. Seventy event reports were similarly interpolated for Native American casualties, again comprising less than two percent of total recorded casualties.

Note that there are many tribes (such as the Pequots and Wampanoags) who fought high profile conflicts against British settlers, but because those conflicts took place prior to 1776, they fall outside the scope of this study.

The bottom panel of Figure 1 summarizes temporal variations by aggregating recorded Native American and U.S. casualties annually. The data are then overlaid with curves computed via locally-weighted scatterplot smoothing.
In summary, it is unlikely that data collection alone can ever fully (or even remotely) tell us how many casualties occurred during the American Indian Wars. Analysts must ultimately make some assessment of how comprehensive their data are, and thus how the sample of available information compares to the overall population of interest. The next section outlines an approach to dealing with this challenge.

Section 2. Estimation strategy

This section describes a strategy for estimating the comprehensiveness of event data on armed conflict. This strategy revolves around the well-documented finding that violent events generally follow a special kind of probability distribution called a power law. This section explains what power laws are, how they relate to armed conflict, and how this relationship can be used to estimate conflict size.

Power laws and violent events

Power laws characterize the relationship between the frequency and the severity of certain phenomena. If data are distributed according to a power law, then when they are represented on a “log-log” plot (in which the logarithm of the event’s severity is given on the x-axis and the logarithm of the probability of an event being at least that severe is given on the y-axis), the data will form a straight line. This property is called scale invariance, because the frequency of events with magnitude log(x) is invariantly proportional to the frequency of events with magnitude log(x + 1). Power laws are formally expressed by distribution functions where the probability of seeing an event of at least a certain magnitude x is given by the expression

\[
\frac{1}{\alpha x^\alpha}
\]
Pr(X ≥ x) = F(x) = Cx^{−α}, where C is a constant ensuring that F(x_{min}) = 1.0, and α is called the scaling parameter. The scaling parameter gives the slope of the line that power law-distributed data form on log-log plots, since \log F(x) = \log(C) − α \cdot \log(x).

Power laws appear to characterize many phenomena. The sizes of cities, earthquakes, moon craters, and annual incomes have all been represented using power laws (Newman 2005). Richardson (1948) originally observed that violent events – ranging from homicides to world wars – also seem to be scale invariant. Power laws characterize inter-state wars (Cederman 2003) and terrorist attacks (Clauset, Young, and Gleditsch 2007). In a prominent paper appearing in the journal *Nature*, Bohorquez et al. (2009) plotted data on insurgent attacks in Afghanistan, Iraq, Colombia, and Peru; in each case, the data resembled power laws.

These findings have powerful implications. Bohorquez et al., for instance, demonstrated that it is possible to describe the entire distribution of insurgent violence within a conflict simply by giving the overall number of attacks and a scaling parameter. Clauset, Young, and Gleditsch (2007: 59) explain the significance of similar findings with respect to terrorism: “The frequency-severity statistics of terrorist events are scale invariant, and consequently, there is no fundamental difference between small and large events; both are consistent with a single underlying distribution. This fact indicates that there is no reason to expect that major or more severe terrorist attacks should require qualitatively different explanations than less salient forms of terrorism.”
The upper-left panel from Cederman (2003) shows data on interstate wars. The upper-right panel from Clauset, Young, and Gleditsch (2007) shows data on terrorist attacks. The panels below from Bohorquez et al. (2009) show data on insurgent attacks in four different conflicts. In all cases, the relationship between the frequency and severity of violent events resembles a power law.
Figure 3. Power laws in data on the American Indian Wars

**RAW DATA**

![Graph A](image1)

![Graph B](image2)

**RAW DATA OVERLAID WITH ESTIMATES OF SCALE INVARarlance**

![Graph C](image3)

![Graph D](image4)

**DATA PROJECTED TO MAINTAIN SCALE INVARarlance**

![Graph E](image5)

![Graph F](image6)
Figure 2 reproduces findings from these papers. In general, the notion that power laws characterize violent events is a well-known empirical regularity in the study of armed conflict, and it is a finding that has also received substantial attention in literature intended for broader audiences.9

Figure 3 then demonstrates that event-level data on the American Indian Wars also fit the power law distribution reasonably well. Panels A and B plot the (logged) severity of an armed engagement on the x-axis along with the (logged) probability that a randomly-chosen engagement is at least that severe on the y-axis; Panel A represents casualties sustained by Native American forces, Panel B represents casualties sustained by U.S. forces, and both plots resemble straight lines. Engagement-level data on the American Indian Wars thus correspond with a well-documented empirical finding that data on violent events tend to resemble power laws.

*Using power laws to extrapolate missing data*

Yet even if these plots resemble linear relationships, they are not linear exactly. In particular, it is clear that the left-tail of the data in Panel A, representing casualties sustained by Native Americans, “sags” below what we would expect to see if the distribution were truly linear. This means the data contain fewer engagements causing low numbers of casualties than what we would see if the data truly followed a power law.

This is consistent with the expectation that these smaller-scale engagements are the ones that tend to be least comprehensively recorded. It is probably reasonable to expect that most of the

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larger engagements are recorded in these data. Events like Andrew Jackson’s Battle of Horseshoe Bend against the Creeks (1814), or George Custer’s Last Stand against the Sioux (1876) were high-profile episodes: they were widely known and discussed at the time, and it is unlikely that many events of this magnitude are missing from the data. But the data are surely missing many small-scale engagements that have little historical significance. The data appear to reflect this assumption in the way that they compare to a true power law distribution.

Panel B, by comparison, containing data on casualties sustained by U.S. forces, is not as noticeably concave on the left-tail. This again makes sense given that U.S. casualties are more likely to have been documented at the time and preserved by available sources (especially since those sources include official U.S. Army records). Together, Panels A and B thus reinforce the expectation that when data on violent events are better-measured, they should more closely approximate power laws.

This suggests a strategy for estimating the comprehensiveness of available conflict data. Given a wide range of previous scholarship (and the way that the data themselves shape up), we can assume that violent events during the American Indian Wars were distributed roughly according to power laws. In addition, we expect that the data are relatively comprehensive when it comes to capturing violent events of relatively high intensity, since those events are most likely to have been recorded and preserved. Since power laws are characterized by scale invariance, it should thus be possible to use the data that we do see on right side of these distributions in order to develop an estimate of what we should see on the left if the data were complete.

This inference relies on a key distributional assumption: since we cannot directly observe a counterfactual, comprehensive data set for the American Indian Wars or any other conflict, we
cannot directly verify the notion that the left tails of these distributions should in fact conform to power laws. Yet most strategies of statistical inference rely on assumptions about probability distributions and functional forms, and the key assumption invoked here is supported by clear empirical evidence, both in general (by way of previous scholarship showing that distributions of violent events typically resemble power laws) and in this specific context (we have observed that the data on U.S. casualties, which are presumably more comprehensively measured, also approximate a power law more closely throughout).

Moreover, the notion that power laws can be used as a tool for extrapolating data is not unique to this study, but rather is an approach which scholars have already employed in a range of fields. Seismologists, for instance, use related methods to estimate the likelihood of extremely large earthquakes. Earthquakes exceeding 8.0 on the Richter scale, for instance, are far too rare to generate meaningful risk projections, especially when assessing those risks in any particular area. In order to estimate the propensity for such extreme events, researchers rely on the notion that earthquakes are typically distributed according to power laws. Researchers can thus use the data that do exist on the incidence of smaller-scale earthquakes in order to project the potential incidence of larger-scale earthquakes (Bak 1996: 87-88). Clauset and Woodard (2012) use the same approach to estimate the risk of extremely large terrorist attacks.

This paper presents a similar estimation strategy, albeit in reverse. Previous scholars have used power law relationships to estimate the potential incidence of extreme events that have yet to be observed. Using related logic, this paper uses power law relationships to estimate the prior incidence of small-scale events that have previously gone unobserved.

10 Section 5 will discuss this point in more detail.
Figure 3 demonstrates this estimation strategy graphically. Panels A and B provide scatterplots of the raw data discussed earlier. These data resemble power law distributions, and Panels C and D show how we can estimate their scaling parameters using a method that the next section will describe in more detail. Panels E and F then show what the plots would look like if we added observations so that the distributions maintained scale invariance throughout their left-tails. Panels E and F are thus stylized projections of what these data might look like if they were complete, and we can use these projections to estimate how much information is missing from the original data. The estimation strategy here thus leverages information about the data’s distribution in order to draw inferences about its comprehensiveness. The following section explains the strategy’s implementation and results.

Section 3. Implementation and results

The implementation here is described specifically for estimating the number of casualties sustained by Native Americans. The same procedures were repeated for estimating the number of casualties sustained by U.S. forces. Much of the implementation employs statistical techniques developed by Clauset, Shalizi, and Newman (2009, henceforth CSN). This section leverages those techniques in order to provide a new approach for estimating conflict size.

We begin by estimating the scaling parameter. In order to do this, it is important to specify the range over which this parameter should be estimated. Because observed data on small-scale events deviate from a power law distribution, using the full data set to fit a power law distribution could cause substantial bias. CSN thus present a maximum-likelihood approach to

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11 CSN provide code at http://santafe.edu/~aaronc/powerlaws/, accessed December 2012. Additional code developed for this project is available from the author on request.
determining the optimal cutoff point, $x_{\text{min}}$, below which the data do not conform to a power law, along with $\alpha$, the scaling parameter characterizing all $x \geq x_{\text{min}}$.\(^{12}\) Using this method, the optimal $x_{\text{min}}$ for the data on Native American casualties is 20 and the scaling parameter characterizing the power law distribution above and including this point is $\alpha = 2.21$. Figure 3 presents the raw data overlaid with this distribution.\(^{13}\)

Carefully defining $x_{\text{min}}$ serves an important function beyond maximizing model fit. As described above, the central thrust of the estimation technique developed here is to use observed data on the right side of a distribution (which generally conform to power laws) in order to characterize unobserved events on the left side of a distribution (where the data generally do not conform to power laws, but are presumably undermeasured). CSN’s method for defining $x_{\text{min}}$ objectively indicates where we should divide the data for this purpose. Once we have done this, and estimated the scaling parameter characterizing points $x \geq x_{\text{min}}$, we can estimate how much data are missing from the original analysis for points $x < x_{\text{min}}$.\(^{14}\)

\(^{12}\) This method works by considering each value of $x$ to be a potential cutoff; calculating the maximum likelihood scaling parameter that would characterize the data if they conformed to a power law from that point onward; and seeing which pair $(x_{\text{min}}, \alpha)$ optimizes the Kolmogorov-Smirnov goodness-of-fit statistic over $x \geq x_{\text{min}}$. This method has been used by several scholars studying power laws in armed conflict and other fields: see Clauset, Young, and Gleditsch (2007), Bohorquez et al. (2009), Bell et al. (2012), Clauset and Woodard (2012).

\(^{13}\) It is possible to specify how choosing any other values of $x_{\text{min}}$ would result in different estimates of $\alpha$ and thus different projections of conflict size. For example, taking each possible value of $x_{\text{min}}$ between 15 and 25 for the Native American data results in fitted values of $\alpha$ ranging from 2.15 to 2.23 and casualty projections with a mean of 49,736 and a standard error of 4,637. Specifying values of $x_{\text{min}}$ between 2 and 10 for the U.S. data results in fitted values of $\alpha$ ranging from 1.88 to 2.06 and casualty projections with a mean of 11,797 and a standard error of 527. The fact that casualty projections for U.S. forces are much less sensitive to choices of $x_{\text{min}}$ is consistent with the idea that better-measured violence data are more scale invariant. Sections 4 and 5 provide more explicit discussions of uncertainty associated with the estimation strategy developed here.

\(^{14}\) The method for calculating these missing data is as follows. If the data follow a power law with scaling parameter $\alpha$ over points $x \geq x_{\text{min}}$, then the probability of a randomly chosen
The results of employing this method are displayed graphically at the bottom of Figure 3, and Figure 4 examines those results in more detail. As Figure 4 shows, there are presumably a relatively large number of missing observations for events that led to few Native American casualties – in fact, more than 90 percent of the events projected to be missing from the observed data correspond to engagements causing three Native American casualties or fewer. This is consistent with the expectation that these events would not only have been the most common, but also the most poorly preserved in the historical record. Together, these events require adding a projected 19,786 casualties sustained by Native American forces to the observed data.

The projected volume of missing data tapers quickly, however, because in power law relationships, the frequency of events declines geometrically. Moreover, we expect that larger events are more likely to have been recorded. When it comes to events causing ten Native American casualties, for example, Figure 4 shows that we will only estimate there being about twenty-six engagements missing from the data (implying that there are only about 260 missing casualties associated with events of this magnitude). Events causing fifteen Native American casualties are actually overrepresented in the observed data (perhaps because this is a number to which observers or historians would have rounded uncertain estimates) and so we actually have to remove about fifty observed casualties from the data in order to make them consistent with projected values at this point.

The violent event causing \( x \) casualties is given by the function \( f(x) = x^{-\alpha} \cdot \zeta(\alpha, x_{\text{min}})^{-1} \), where \( \zeta \) is the Hurwitz zeta function, \( \zeta(\alpha, x_{\text{min}}) = \sum_{n=0}^{\infty} (n + x_{\text{min}})^{-\alpha} \). To estimate the total number of violent events with magnitude \( x < x_{\text{min}} \) that we would expect to see if the data conformed to a power law throughout, multiply \( f(x) \) by \( \lambda \), where \( \lambda \) is the total number of observed events with magnitude \( x \geq x_{\text{min}} \). Used in this fashion, \( f(x) \) no longer represents a probability per se – its purpose is simply to establish proportionality between the frequency and severity of violent events, which is what we aim to do in extending the estimated power distribution across the data’s left tail. Note that this method can be implemented using any assumed probability distribution, and see Section 5 for more on this point. Code available from the author on request.
In total, the method described here estimates that the data set is missing 16,678 engagements, which would have led to 27,718 casualties sustained by Native Americans that were not contained in the original data. After adding these figures to the observed data, we can estimate that a total of 53,361 Native Americans were killed, captured or mortally wounded during the American Indian Wars between 1776 and 1890.\textsuperscript{15}

Figure 4 also shows the results of repeating the same procedures for estimating casualties sustained by U.S. forces during the American Indian Wars. Note that the estimated $x_{min}$ cutoff is much lower, as the data correspond to a power law all the way down to engagements causing 4 U.S. casualties. This is consistent with the expectation that data on U.S. casualties would have been much more thoroughly recorded. These data are still far from being complete – overall, Figure 4 indicates the data may be missing as many engagements as they record. Nevertheless, given that most missing engagements are presumably small in size, we can project that there are fewer than 1,500 U.S. casualties missing from the data, raising our total estimate of U.S. forces killed, captured, or mortally wounded during the American Indian Wars from 10,476 to 11,889.

\textsuperscript{15} An alternative, Bayesian approach (suggested by Colin Gillespie in correspondence about this paper) is to model “missingness” in the data directly by assuming the data are distributed according to a power law and then estimating simultaneously the scaling parameter along with the parameters of a function that gives the probability that an event with magnitude $x$ will be recorded. This approach does not require estimating $x_{min}$, and it can explicitly account for the possibility that the data may be undermeasured at any value of $x$, though this approach is potentially sensitive to assumptions about the reporting function. Implementing this technique on an exploratory basis with the reporting function defined as a second-order polynomial resulted in estimates close to those presented here (for example, an estimated 58,000 Native American casualties, with a standard error of roughly 7,000).
Figure 4. Extrapolating data on Native American and U.S. casualties

OBSERVED VS. PROJECTED DATA ON NATIVE AMERICAN CASUALTIES

Estimated $x_{\text{min}}$: 20
Estimated $\alpha$: 2.21

<table>
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<tr>
<th>Casualties</th>
<th>Observed $N$</th>
<th>Projected $N$</th>
<th>Estimated missing obs.</th>
<th>Estimated missing casualties</th>
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<tr>
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<td>11,945</td>
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</tr>
<tr>
<td>2</td>
<td>138</td>
<td>2,618</td>
<td>2,479</td>
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<td>1,068</td>
<td>961</td>
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</tr>
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<td>15</td>
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<td>19</td>
<td>6</td>
<td>18</td>
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<td>230</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>1,297</strong></td>
<td><strong>17,976</strong></td>
<td><strong>16,679</strong></td>
<td><strong>27,718</strong></td>
</tr>
</tbody>
</table>

Estimated total casualties sustained by Native American forces: 53,361
(See Sections 4 and 5 for discussions of uncertainty surrounding this estimate and its underlying parameters)

OBSERVED VS. PROJECTED DATA ON U.S. CASUALTIES

Estimated $x_{\text{min}}$: 4
Estimated $\alpha$: 2.00

<table>
<thead>
<tr>
<th>Casualties</th>
<th>Observed $N$</th>
<th>Projected $N$</th>
<th>Estimated missing obs.</th>
<th>Estimated missing casualties</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>430</td>
<td>1,490</td>
<td>1,060</td>
<td>1,060</td>
</tr>
<tr>
<td>2</td>
<td>247</td>
<td>373</td>
<td>126</td>
<td>251</td>
</tr>
<tr>
<td>3</td>
<td>132</td>
<td>166</td>
<td>34</td>
<td>101</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>1,233</strong></td>
<td><strong>2,075</strong></td>
<td><strong>1,220</strong></td>
<td><strong>1,413</strong></td>
</tr>
</tbody>
</table>

Estimated total casualties sustained by U.S. forces: 11,889
(See Sections 4 and 5 for discussions of uncertainty surrounding this estimate and its underlying parameters)
Figure 5. Bootstrapped estimates of $x_{min}$, $\alpha$, and total casualties

Mean alpha: 2.17 (Std. Dev.=.10)

Mean Xmin: 16.31 (Std. Dev.=5.70)

Mean alpha: 1.98 (Std. Dev.=.09)

Mean Xmin: 3.67 (Std. Dev.=2.13)

Mean=50,994
Std. Dev.=13,330

Mean=11,849
Std. Dev.=1,485
Section 4. Uncertainty and sensitivity analysis

This section examines the sensitivity of previous estimates to 1) uncertainty in underlying parameters, 2) varying the range over which projected data are added to observed data, and 3) breaking the data into subsets by time, geography, and tribal population, analyzing each of those subsets independently, and then aggregating the results together.

Parameter uncertainty

The estimation technique developed in this paper requires defining a scaling parameter, $\alpha$ and a lower-bound for data analysis, $x_{\text{min}}$. Nonparametric bootstrapping can quantify the uncertainty associated with these parameters and how this affects resulting casualty projections. For example, there are 1,297 engagements in the data set that resulted in recorded casualties sustained by Native American forces and 1,233 engagements in the data set that resulted in recorded casualties sustained by U.S. forces. We can generate “bootstrapped” data sets of the same size by randomly sampling with replacement from these distributions. For each bootstrap sample, we can estimate optimal values of $\alpha$ and $x_{\text{min}}$, resulting in the joint distributions shown in the top panels of Figure 5. Then for each ordered pair of parameters, we can project the total number of casualties sustained by Native American and U.S. forces, resulting in the histograms plotted at the bottom of Figure 5.\(^\text{16}\)

As expected, Figure 5 shows that there is substantially more uncertainty associated with estimating Native American casualties. While the standard deviations in bootstrapped estimates

\(^\text{16}\) The histogram representing bootstrapped estimates of Native American casualties is truncated for clarity. There were eighty-six samples that produced casualty estimates greater than 100,000, with a maximum estimate of 236,475.
of the scaling parameter $\alpha$ are essentially the same, the standard deviation for the estimated $x_{min}$ cutoff is more than twice as large for the Native American casualties data (5.70) relative to the U.S. casualties data (2.13). This drives more dispersion across bootstrapped casualty projections for Native American forces ($\mu/sd$ of 3.83 versus 7.98 for the Native American and U.S. data, respectively).

As shown in the bottom of Figure 5, bootstrap samples return mean casualty estimates that are close to the projections provided earlier: the mean estimate of 50,994 Native American casualties is roughly four percent less than the projection given in Section 3, and the mean estimate of 11,849 U.S. casualties is within one percent of the baseline model. Across 10,000 bootstrap samples, the standard error for estimates of total Native American casualties is 13,330, and the standard error for estimates of total U.S. casualties is 1,485.

*Varying the extrapolation range*

The estimates generated in Section 3 entailed dividing the data into two parts: events with magnitude greater than or equal to a cutoff point $x_{min}$, which were used to fit a power law, and events lying below this cutoff, where data were projected so as to maintain the scale invariance that characterized the rest of the distribution.

Would anything be different if we projected data across the entire distribution, such that the plots exactly conformed to a power law throughout? To give a sense of how this will affect overall estimates, Figure 6 compares the actual number of observations for events of any size against the projected number of observations that we would see if the data were perfectly scale invariant. Observed values tend to sag below the projection line towards the left-tail of the
Figure 6. Observed vs. projected numbers of observations

Projected vs. Observed numbers of observations for Casualties Sustained by Native American Forces, per engagement.

Projected vs. Observed numbers of observations for Casualties Sustained by U.S. Forces, per engagement.
distribution, where we expect violent events to be undermeasured. Observed values then straddle the projection line in the center of the distribution, which is what we expect to see since this is the principal body of evidence that the power laws were estimated to fit.

On the right side of the plots, however, observed values are all above their projected frequencies. This is because once the size of violent events gets sufficiently high, then these events also become sufficiently rare that we expect to see less than one of each in expectation. Thus while there may be many values of $x$ for which the data do not contain recorded observations (there are no engagements in the data set, for instance, which inflicted exactly 337 casualties on Native American forces) we only need to add a fractional observation here in order to match the power law’s projection. By the same logic, every time we see a high-magnitude event (for instance, the 1832 Battle of Bad Axe, which killed an estimated 173 Sauks), we have to remove a substantial number of those casualties in order to make the data scale invariant.

For data on Native American casualties, this addition and subtraction balances out almost exactly: if we replace the data with projected observations for all values of $x$, then we would infer a total of 53,158 Native American casualties during the American Indian Wars, a figure that is within one percent of the original estimate. For the data on U.S. casualties, there are enough events with unusually high U.S. casualty counts (such as Little Turtle’s 1791 defeat of U.S. forces in the Algonquin War, the Shawnee attack on Fort Meigs in 1813, or Custer’s Last Stand in 1876) that replacing observed data with fitted values above the $x_{\text{min}}$ cutoff makes more of a difference, and the resulting projection of 10,451 is about twelve percent less than the original estimate.
Figure 7. Analysis of Time Period Subsets

**ENGAGEMENTS BETWEEN 1776-1814**

- \( x_{\text{min}}: 11 \)
- Scaling parameter: 1.68
- Observed N: 68
- Projected Total N: 282
- Observed Casualties: 4,163
- Projected Total Casualties: 4,605

**ENGAGEMENTS BETWEEN 1815-1864**

- \( x_{\text{min}}: 20 \)
- Scaling parameter: 2.16
- Observed N: 531
- Projected Total N: 7,060
- Observed Casualties: 12,547
- Projected Total Casualties: 23,729

**ENGAGEMENTS BETWEEN 1865-1890**

- \( x_{\text{min}}: 13 \)
- Scaling parameter: 2.38
- Observed N: 698
- Projected Total N: 12,806
- Observed Casualties: 8,933
- Projected Total Casualties: 27,355
Analyzing the data by subset

Given that the American Indian Wars spanned violent events across a range of time, space, and tribes, it makes sense to examine whether results would be meaningfully different if the estimation strategy were applied to subsets of the data rather than to all of them at once. In Figure 7, for example, the data are plotted for each of three time periods – 1776 to 1814, 1815 to 1864, and 1865 to 1890. These time periods correspond to logical historical breakpoints. As described in Section 1, Britain played a prominent role in backing tribes who fought the United States between the War of Independence and the War of 1812. After the Treaty of Paris, Britain cut off this military support and the continent’s interior was opened to rapid U.S. settlement (along with escalating demands for resettling tribes). Once the Civil War ended, the United States had a greatly expanded military infrastructure that it used to confine tribes to reservations. These time periods thus had different political and military dynamics. Yet when the estimation strategy developed in this paper is applied to each subset individually and the results are then aggregated together, the projection of 55,689 total Native American casualties is just four percent larger than the output of the full-sample analysis. The projection of 13,669 U.S. casualties is about fifteen percent larger than the original estimate.

Similar procedures were used to analyze data that were divided into Eastern, Plains, and Western regional subsets. Each engagement was assigned to a region depending on the “culture area” to which the tribes in the engagement belonged as recorded in the Smithsonian’s *Handbook of North American Indians* (Sturtevant 1978-). Culture areas are standard designations in North American anthropology. The “Eastern region” in this analysis comprises the Northeast and Southeast culture areas; the “Plains region” comprises the Northern and Southern Plains culture areas, and the “Western region” comprises the Southwest, California, Great Basin, Plateau, and Northwest culture areas. In cases where the tribe involved in the fighting was unidentified, the region of the engagement was determined by the state or territory in which the engagement took place.
behavior: in the east, for instance, tribes often fought on foot using woodlands for cover and concealment, while tribes on the open Plains were more likely to fight on horseback, and armed conflict in the West often took place on more rugged terrain. Tribes living in different parts of the continent also had systematic social and cultural differences: for example, tribes living on the Pacific Coast tended to have relatively decentralized social structures compared to those in the East. Yet when these regional subsets are analyzed separately and the results are aggregated together, they once again return estimates fairly close to the original figures. The overall projections of 55,507 Native American casualties and 13,323 U.S. casualties are about four percent and eleven percent higher than the baseline estimates, respectively.

A third way to divide the data into subsets is based on the population of the tribes involved in each military engagement. The eighty-one tribes recorded in the data set varied widely on this score, from tribes with fewer than 500 members (such as the Modocs and Walla Wallas) to those with more than 15,000 (such as the Creeks and Cherokees). The mean tribe in these data had a population of about 5,000, and the standard deviation is roughly 4,000.¹⁸ There are several reasons to think that tribes of different sizes might have varied in their military behavior, with the most obvious being that larger tribes would have been more able, ceteris paribus, to sustain and inflict larger numbers of casualties. If we divide the data into quartiles based on the populations of the tribes involved in each engagement, analyze each of these subsets individually and then aggregate the estimates together, then this would project a total of 62,122 Native

¹⁸ Population data are also from the Smithsonian’s *Handbook of North American Indians*. For this analysis, a tribe’s population is coded based on estimates that were provided as close as possible to the initiation of contact between the tribe and the United States, as this is when the tribe would have entered the sample as having the potential to wage an “American Indian War.” In cases where the tribe participating in the engagement was unidentified, a population estimate was interpolated based on the average population of tribes that appeared in the data set within each particular culture area. All of these population estimates are inexact, which should add imprecision to the resulting estimates.
American casualties during the American Indian Wars, a figure roughly sixteen percent higher than the original estimate. The projection for U.S. casualties based on these subsets of the data is 11,902, a figure almost identical to the estimate developed in Section 3.

**Summary**

Table 1 summarizes the estimates described in this section. As we expect, changing the data and estimated parameters, varying the extrapolation range, and breaking the data into subsets leads to different projections for the severity of the American Indian Wars. Yet of the fourteen different estimates provided in Table 1, all are within thirty percent of the baseline model; eleven are within fifteen percent of the original projection and six are within five percent.

<table>
<thead>
<tr>
<th>Table 1. Summary of sensitivity analyses</th>
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<tbody>
<tr>
<td>Estimated Native American Casualties</td>
</tr>
<tr>
<td>Baseline model (parameters of best fit)</td>
</tr>
<tr>
<td>Mean of bootstrapped samples</td>
</tr>
<tr>
<td>...minus one standard deviation</td>
</tr>
<tr>
<td>...plus one standard deviation</td>
</tr>
<tr>
<td>Projected data for all x</td>
</tr>
<tr>
<td>Data analyzed by</td>
</tr>
<tr>
<td>...temporal subsets</td>
</tr>
<tr>
<td>...regional subsets</td>
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<tr>
<td>...population subsets</td>
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</tbody>
</table>
Section 5. Evaluating the core distributional assumption

The estimation strategy developed in this paper depends on the assumption that when small-scale violent events are comprehensively measured, they should be approximately scale invariant. This section offers a closer look at the soundness of this claim.

To begin, it is important to reiterate that most statistical estimation strategies rely on assumptions about probability distributions and functional forms. In most regression analyses, for instance, scholars assume that error terms are distributed normally, and in most cases analysts do not submit the normality assumption to deductive or inductive inspection. Moreover, testing empirical models requires specifying what those models should be, whether linear (in the case of ordinary least squares regression), logistic (in the case of standard binary choice models), or whatever other form is thought to be best suited for the analysis. Scholars rarely claim that social phenomena are actually produced through functions like these. The operative question is not whether an empirical model is perfect, but whether its assumptions are reasonable for drawing statistical inferences. And for the purposes of this analysis, several pieces of evidence support the notion that power laws are a reasonable tool for estimating conflict size.

First, as discussed earlier, several studies have shown that data on violent events – including terrorist attacks, insurgencies, and inter-state wars – generally conform to power laws above a certain threshold. There is surely more evidence for the assumption that violent events generally resemble power laws than for the claim that error terms resemble normal distributions or that marginal effects are linearly additive in empirical studies of armed conflict.

Second, the specific data analyzed here on violent events in the American Indian Wars also conform to a power law across most of their distributions. The fit is not perfect, but we can
explicitly characterize the statistical uncertainty associated with the distribution’s parameter, and Section 4 discussed how this affects end results.

Third, while there are some phenomena for which there are theoretical reasons to expect the data to deviate from a power law distribution below the $x_{\text{min}}$ cutoff, violent events are not necessarily one of them. A previous section of the paper, for instance, described how seismologists use power laws to infer the risks of large earthquakes. Small earthquakes, however, are less frequent than what power laws suggest. This may partly reflect undermeasurement, but there is also a theoretical justification for the pattern – if tectonic forces do not meet a certain minimum energy threshold, then they may not release enough force to cause any earthquakes at all. Thus there may be geologically determined constraints on how small an earthquake can be. In the context of armed conflict, however, there is less of a theoretical reason to expect that violent events have low-end constraints. In fact, the reverse may very well be true, as there may often be logistical limits associated with the maximum amount of damage a group can cause at any given time, and yet scholars have already employed power laws to estimate the probabilities of severe terrorist events.¹⁹

Fourth, we can show that in contexts where violence data are better measured, then their left-tails are, in fact, more scale invariant. We discussed this earlier in comparing the data on Native American casualties versus U.S. casualties. We expect the U.S. data to have been much more comprehensively recorded, and we have seen that they maintain scale invariance farther out on the left-tail: while the optimal cutoff point for data on Native American forces was events

¹⁹ For instance, there is literally a maximum number of people that can be targeted in a given area, and the size and resources of armed groups probably caps their destructive potential. See Clauset and Woodard (2012) on predicting the potential frequency of terrorism.
causing twenty casualties, the data for U.S. forces held its shape all the way down to events causing four casualties.\textsuperscript{20}

We can draw similar comparisons across cases as well. There are some modern conflicts, for instance, where violence data have been much more actively (and presumably much more comprehensively) recorded than they were during the American Indian Wars. The occupation of Iraq is one such case, for which nongovernmental organizations – most prominently the British group Iraq Body Count (IBC) – have attempted to record and update information on civilian casualties as widely as possible. Figure 8 presents the IBC data on a log-log plot.\textsuperscript{21} As we would expect, these data conform to a power law even for very small-scale engagements. In fact, using

\textsuperscript{20} The bootstrapped standard errors follow a similar pattern: they are much narrower for the U.S. data, which we expect to be better-measured.

\textsuperscript{21} IBC is an organization specifically devoted to recording civilian casualties in Iraq. IBC gathers information from news reports, morgue records, and government sources.
the method described above, we can estimate that the data conform to a power law all the way down to engagements causing 2 Iraqi civilian casualties. (It is actually on the right-tail where the data break away from a power law distribution, a pattern that may reflect the fact that some armed groups like al-Qaeda have been unusually focused on – and unusually effective at – causing destruction on a large scale.22)

Another way to evaluate the way that power laws characterize the data is to examine this fit relative to other distributions. There are cases where data that appear to follow a power law also resemble other, thick-tailed distributions.23 There are obviously a wide range of distributions one might choose to examine, and Figure 9 presents four of them: the power distribution estimated earlier along with exponential, pareto, and lognormal distributions fitted to observed information on Native American casualties. All models are fitted to the same range of data (x ≥ 20), choosing parameters that optimize the Kolmogorov-Smirnov statistic using CSN’s approach.24 Figure 9 then compares each fitted distribution to actual data.25

Figure 9 clearly shows that the power law fits the data better than the exponential distribution (which significantly underpredicts violent events at lower magnitudes) and the pareto distribution (which substantially overpredicts violent events at lower magnitudes). The

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22 See Bohorquez et al. (2009) for more on how the IBC data compare to a power law.
23 On this point, see Clauset, Shalizi, and Newman (2009).
24 The exponential distribution follows the probability distribution function \( p(x) = \lambda e^{-\lambda x} \), and the optimal value of \( \lambda \) for characterizing data on recorded Native American casualties is 0.012. The pareto distribution is given by \( p(x) = \frac{\alpha x_{\text{min}}^{\alpha}}{x^{\alpha+1}} \), with an optimal \( \alpha \) of 2.248. The lognormal distribution follows \( p(x) = \left( x \sqrt{2\pi \sigma^2} \right)^{-1} \exp \left[ -\left( \ln x - \mu \right)^2 \left( 2\sigma^2 \right)^{-1} \right] \), with optimal values of \( \mu = -14.829 \) and \( \sigma = 3.940 \).
25 Consistent with the way that Kolmogorov-Smirnov statistics are calculated, Figure 9 compares empirical and projected cumulative distribution functions. Unlike previous figures, Figure 9 does not present a logarithmic y-axis, as this would make it difficult to compare empirical and projected distributions across different values of \( x \).
comparison is much closer for the lognormal and power distributions: for instance, the resulting Kolmogorov-Smirnov statistics and mean squared errors are identical to two decimal places.\textsuperscript{26} Despite these similarities in how they characterize the data plotted in Figure 9, however, the power and lognormal distributions make substantially different projections for what should lie below the $x_{min}$ cutoff. Since the lognormal distribution is thinner than a power law on its left tail, it predicts a lower volume of missing data, leading to an overall projection of 36,892 Native American casualties. This is thirty percent less than the 53,361 Native American casualties projected using power laws (but only just outside the bootstrapped standard error projection provided in Section 4). Assuming a lognormal distribution for the U.S. data returns an estimate of 11,502 casualties, only three percent less than the baseline projection based on a power law.

What should we make of this comparison? Given the way that previous scholars have documented the connection between power laws and conflict data so widely, one might be inclined to view that distribution as the logical first choice, but it is still necessary to accept the plausibility of estimates based on alternative distributions. At the very least, we can say that the core distributional assumption driving the estimation strategy in this paper is supported by empirical evidence, both within and across cases. This distributional assumption is probably more valid than some of the core assumptions driving standard statistical estimation, and it is probably no less valid than other ways in which scholars have invoked power laws in past research. And even if this section has demonstrated that varying distributional assumptions can lead to estimates ranging by thirty percent, this uncertainty still pales in comparison to the vastly different figures often given in scholarly and public debates about conflict size. The following section concludes this paper by drawing explicit connections to these broader issues.

\textsuperscript{26} The lognormal distribution has a slightly better Kolmogorov-Smirnov statistic (0.055 vs. 0.063). The power law distribution has a slightly better mean squared error (0.399 vs. 0.401).
Figure 9. Comparing alternative distributional fits

- **Power distribution fit**
- **Empirical C.D.F.**

- **Exponential distribution fit**
- **Empirical C.D.F.**

- **Lognormal distribution fit**
- **Empirical C.D.F.**

- **Pareto distribution fit**
- **Empirical C.D.F.**

Casualties Sustained by Native Americans, per engagement
Section 6. Discussion

This paper offers two main contributions: one is historical, speaking to knowledge about the American Indian Wars in particular, and the second is methodological, speaking to broader academic questions about estimating conflict size.

The principal historical relevance of this paper is to provide systematic casualty estimates for the American Indian Wars. These conflicts are central to understanding how the United States became a continental power, yet historians do not know how violent this period actually was. This is largely because any historical analysis of the subject will inevitably confront missing data and necessitate drawing difficult inferences. This paper offers a novel approach to drawing those inferences based on empirical regularities that characterize armed conflict more generally. This technique suggests that roughly fifty thousand Native Americans and roughly twelve thousand U.S. forces were killed, captured, or mortally wounded during the American Indian Wars, and previous sections explicitly discussed the uncertainty surrounding these estimates.

What should we make of these figures? If U.S. forces sustained twelve thousand casualties in the American Indian Wars, then this would be about as large as the totals from the War of Independence, the War of 1812, the Mexican-American War, and the Spanish-American War combined. This is roughly a third of combat losses U.S. forces sustained in Korea, and about twice the number of losses sustained during the occupations of Iraq and Afghanistan, as of this writing. And these comparisons are all in absolute terms. Per capita, the American Indian Wars are even more pronounced as one of the most violent periods in U.S. history.

Clodfelter (2008) gives the following totals: the War of Independence (6,824 battle deaths), the War of 1812 (2,260), the Mexican-American War (1,721), the Spanish-American War (385).
For Native Americans, these conflicts exacted a far greater toll. Fifty thousand combat casualties is about what U.S. forces sustained in Vietnam, and again, the populations in question are far different. From 1776 to 1890, the population of Native Americans living in the continental United States averaged roughly 400,000 (Reddy 1993). Considering that only about one-quarter to one-fifth of these people would have been military-aged males, a figure of fifty thousand casualties is massive, even if that total accumulated over an extended period of time. It is unclear how many other populations have sustained greater military losses per capita.

Of course, we do not need to invoke power laws to establish that the American Indian Wars were costly, especially for Native Americans – this is common knowledge. But from a historical perspective, it is useful to have an objective sense of relevant magnitudes. For instance, Pinker (2011) cites a figure of twenty million Native American deaths during his discussion of the “annihilation of the American Indians” as being one of the most violent phenomena in world history, but the vast majority of this population loss was a result of disease and not armed conflict. It is important to understand the impact of these diseases, but they were largely independent of the fighting that took place during the American Indian Wars, and the resulting population loss was so huge that it can obscure the military aspects of the conflict, which were important and devastating in their own right. This paper addresses the military costs of the American Indian Wars directly, and this is its main historical contribution.

More generally, this paper has offered a new method for estimating conflict size, a subject that has been the subject of recent and widespread controversy among scholars. During the occupation of Iraq, for instance, a study published in The Lancet (Burnham et al. 2006) used survey methods to estimate that roughly 600,000 civilians had died as a result of the war. This figure was an order of magnitude higher than contemporary estimates provided by the U.S.
government or the independent Iraq Body Count. The Lancet article received substantial public debate, as well as a rebuttal from both the U.S. government and academics.\textsuperscript{28}

Among scholars, these kinds of disagreements often go well beyond assessing individual cases, as prominent data sets that measure conflict size are often themselves the subject of dispute. For instance, Lacina and Gleditsch’s (2005) data on battle deaths is probably the most widely-used source of its kind in contemporary studies of armed conflict. In 2008, a group of medical researchers (Obermeyer et al.) criticized Lacina and Gleditch’s methodology and used a sampling technique to argue that their data had severely underestimated the scale of many conflicts. This study was then itself sharply critiqued by a third group of scholars (Spagat et al. 2009) who argued that their sampling methodology was flawed and that they had mischaracterized Lacina and Gleditsch’s work.

This paper offers a way to approach these debates from an alternative angle. The method described here is based on event counts, but it explicitly seeks to go beyond them, using the data’s distribution in order to draw inferences about their comprehensiveness. In order to explain the technique and demonstrate its utility, this paper examined how power laws can be used to estimate the severity of the American Indian Wars, but scholars can use the same methodology in order to (re)examine the size of many other conflicts as well. In order to employ this technique, event level data must be relatively comprehensive when it comes to capturing large-scale events, but one of the appealing aspects of the estimation strategy is that it is specifically designed to deal with missing data for small-scale events. Political scientists can play an important role on this score by developing objective ways of going beyond historical material or government

\textsuperscript{28} See Fischer (2010: 9) for a tabulation of Iraq casualty estimates from a range of governmental and nongovernmental sources and Spagat (2010) for a critique of the Lancet article’s methodology.
records, which are usually incomplete. It will almost always be necessary to supplement data that are available with inferences about information that has not been preserved. This paper has shown how power laws can be used as a tool for that purpose.
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