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The Dataset of Countries at Risk of Electoral Violence

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ABSTRACT

Electoral violence is increasingly affecting elections around the world, yet researchers have been limited by a paucity of granular data on this phenomenon. This paper introduces and describes a new dataset of electoral violence—the Dataset of Countries at Risk of Electoral Violence (CREV)—that provides measures of 10 different types of electoral violence across 642 elections held around the globe between 1995 and 2013. The paper provides a detailed account of how and why the dataset was constructed, together with a replication of previous research on electoral violence. We introduce this dataset by demonstrating that the CREV, while measuring the same underlying phenomena as other datasets on electoral violence, provides researchers with the ability to draw more nuanced conclusions about the causes and consequences of violence that occurs in connection with the electoral process. We also present and analyze descriptive data from the CREV dataset.

KEYWORDS

Conflict; elections; electoral violence; event data

While the vast majority of countries around the world currently utilize elections as a means of transferring political power and providing legitimacy to ruling incumbents, violence continues to occur during many electoral contests. Electoral violence can have considerable implications for both security and democracy;¹ it can even culminate in revolutions leading to regime changes, as happened in Tunisia and Egypt from 2011–2012, and Ukraine in 2004. Electoral violence can also make citizens less trusting of incumbents, reducing citizen support for democracy.² Despite the problematic nature of electoral violence, we as of yet know relatively little about the causes of this phenomenon, or the effects this particular form of conflict can have on societies. Is electoral violence perpetrated mainly by state actors, or are nonstate groups such as opposition parties more likely to use violence as a means of attaining their political goals? Which political actors are most likely to undertake the most serious forms of electoral violence? Which countries are most at risk of electoral violence? Though electoral violence routinely plagues only a small minority of elections around the world, such violence exhibits wide variation across states and even across elections within states. Access to a detailed dataset of electoral violence will allow researchers to better understand this phenomenon; it will also enable practitioners to devote limited resources to preventing electoral violence in nations most at risk.

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However, the limited data on electoral violence currently in existence has impeded the development of knowledge about this destructive form of conflict.

Though electoral violence can be a broad concept,³ studies of it have usually relied on several general measures. Electoral violence has been conceptualized as violent protests against election results, political parties, or opposition groups,⁴ as well as attacks by mobs and gangs against visible manifestations of elections, like polling places.⁵ Electoral violence can occur before elections as elites strategically shift repression to pre-electoral periods in order to dissuade voters from going to the polls,⁶ or it might occur after elections if elites choose to employ violence to punish certain segments of society for voting in specific ways.⁷ And while state actors can perpetrate electoral violence, nonstate groups like opposition parties, rebels, and militants may also engage in electoral violence to advance their own objectives.⁸ Unfortunately, many broad measures of electoral violence currently in use obscure the identity of the actors involved, gloss over the tactics employed, do not report on the nature of the violence itself, or otherwise provide indicators of electoral violence at quite high levels of aggregation and generality. Because of this lack of detailed data, important puzzles still remain about the perpetrators, timing, causes, consequences, and nature of electoral violence.

We believe that electoral violence should be understood as a continuum, with a multiplicity of strategies employed, and that multiple different actors can use it at different points in the electoral cycle. We therefore collected data on various forms of electoral violence for 101 nations we deem to be at risk of electoral violence between 1995 and 2013. We introduce this data in the Countries at Risk of Electoral Violence (CREV). The CREV is a new resource that aggregates data on electorally violent events and aggregates these events monthly over a period including 6 months before each election, during the month of the election, and 3 months after the election, for a 10-month window around each national-level legislative or executive election conducted in each of the 101 nations.⁹ The CREV relies on event data aggregated by the largest automatic coder of event data yet produced, the Integrated Crisis Early Warning System, or ICEWS.¹⁰ In the future, the data will be regularly updated. In this article, we introduce this new dataset by describing the data collection process, defining electoral violence according to CREV, and presenting some descriptive statistics on how our data compare against other commonly used measures of electoral violence. We also conduct a replication of a well-known study by Hafner-Burton, Hyde, and Jablonski to demonstrate that our new dataset is measuring underlying concepts similar to those measured by previous datasets of electoral violence, such as NELDA.¹¹ Our results demonstrate that the correlates of electoral violence are sensitive to how electoral violence is coded, but that the data comprising the CREV show very similar relationships to conceptualizations of electoral violence used in previous studies.

Defining electoral violence

Electoral violence (sometimes known as “electoral conflict”) is a sub-type of political violence;¹² it is also a subtype of electoral fraud. At the most abstract level, electoral violence can be understood as any event in which the use of coercive force coincides with the electoral process. A number of more contextually-specific definitions have also been advanced. The United Nations Development Program (UNDP) defines electoral conflict

as: “acts or threats of coercion, or physical harm perpetrated to affect an electoral process or that arise in the context of electoral competition.”¹³ According to Straus and Taylor,¹⁴ electoral violence can be understood as “physical violence and coercive intimidation directly tied to an impending electoral contest or to an announced electoral result.” Fischer defines electoral violence as “any random or organized act that seeks to determine, delay, or otherwise influence an electoral process through threat, verbal intimidation, hate speech, disinformation, physical assault, forced ‘protection,’ blackmail, destruction of property, or assassination.”¹⁵ Sisk provides the most elaborate definition of what he terms “electoral-related violence”: “acts or threats of coercion, intimidation, or physical harm perpetrated to affect an electoral process or that arises in the context of electoral competition. When perpetrated to affect an electoral process, violence may be employed to influence the *process* of elections—such as efforts to delay, disrupt, or derail a poll—and to influence the *outcomes*: the determining of winners in competitive races for political office or to secure approval or disapproval of referendum questions.”¹⁶

There are two key components to all these definitions: *the temporal link* between violence and elections and *the causal link* between the two. Electoral violence is conventionally understood as violence that takes place during the electoral cycle, including the pre-electoral, electoral, and post-electoral periods. The causal link, which is often more implicit, limits electoral violence to that which is in some way connected to the electoral process, as opposed to violence that takes place during the electoral process but has no direct bearing on the election. However, most forms of collective violence in society are likely to be connected in some way to the electoral process, given the important political, social, and economic ramifications of electoral outcomes, and it has been claimed that most collective violence that takes place during an election campaign and on election day has political motives.¹⁷

With these considerations in mind, our definition of electoral violence is: *coercive force, directed towards electoral actors and/or objects, that occurs in the context of electoral competition.* This definition can be justified on the grounds that virtually all political violence that occurs during the electoral period can be expected to be conditioned by the electoral process either directly or indirectly, and conversely, the electoral process can be expected to be conditioned by virtually all political violence that occurs during this period. There can be a number of actors involved in perpetrating electoral violence.¹⁸ Because in many cases elections are the shortest route to political power, strong incentives exist for multiple actors to seize power through force.¹⁹ Opposition parties and incumbents are perhaps the most obvious perpetrators and targets of electoral violence, and these actors have been the objects of a great deal of study.²⁰

Other actors may also have stakes in electoral outcomes and seek to use violence as a tool to realize those outcomes. As noted by North, Wallis, and Weingast,²¹ violence is used in many less-than-democratic states as a coercive tool to penalize outgroups and reward clients. Though non-violent means such as patronage are generally preferred to the use of force, leaders must be able to commit credibly to the use of force to defend informal institutions, and their commitment means that violence does invariably play a role in the political institutions of such countries. Ethnic groups may coalesce around certain candidates, creating conditions favorable to outbreaks of inter-ethnic conflict during election periods, and incumbents may attempt to instigate diversionary conflict targeted at various ethnic or religious groups to shore up their base of support during elections.²² Politicians

may also manipulate ethnic and religious cleavages during elections to mobilize bases of support, as for instance during elections in India,²³ or they may promise certain ethnic groups favorable redistributive policies, including redistribution of pastoral land, which can influence these actors to engage in conflict with other ethnic groups to gain a greater share of resources.²⁴ Elections, especially in newly democratizing states, have also been found to encourage secessionist groups to engage in conflict, especially if such groups perceive that they will be worse off under a new regime than the status quo,²⁵ and new democracies are often more prone to destabilizing protests and violence than are authoritarian regimes.²⁶ The clientelist linkages inherent in relations among members of many ethnic groups facilitate violent mobilization of these sorts, and the credible threat of violence subtends political orders built on communal segmentation.²⁷

International organizations are regularly deployed to monitor elections in countries around the world in an effort to deter violence and other forms of electoral misconduct. Members of these observation teams may come under attack either accidentally or deliberately to discourage reporting of electoral abuses. Electoral monitors, by bringing to light instances of electoral fraud, may also inadvertently encourage opposition groups and civilians to engage in violence against incumbents, especially if levels of fraud are perceived to be severe.²⁸

As the discussion above shows, many actors can have incentives to engage in violence around elections. Elections can serve as focal points for various forms of collective action,²⁹ influencing the cost-benefit calculus of various actors who might otherwise not engage in violence. Elections, especially in newly democratizing or post-conflict states, can reignite latent social divisions, leading to a resumption of previously dormant conflicts.³⁰ When the results of an election are uncertain, electoral actors may choose to engage in violence as a complement to other, more legitimate, forms of electoral participation including protests.³¹ Because a wide array of social and political actors have incentives to make use of force during electoral contests, previous research shows the necessity of casting a wide net when attempting to measure and catalogue the diverse typologies of violence that affect elections.

Typologies of electoral violence

There are many different ways in which coercive force can intervene in the electoral process, which suggests a need to break electoral violence down into its component parts. The phenomenon can be categorized as to a) the point in the electoral process at which it occurs, b) the actors involved (perpetrators and victims), and c) the forms that violence takes. We can distinguish between violence that occurs before, during, and after the month in which the election occurs, violence perpetrated by state, non-state, and international actors, and violence that causes actual physical harm, or is instead employed to coerce, restrict, or otherwise influence electoral processes through methods that fall short of physical force. For instance, incumbent politicians may hire threatening-looking militias to stand outside polling places in opposition-friendly areas in order to depress turnout. While this behavior is designed to intimidate voters, it is quite different from militias engaging in organized violence and physically assaulting voters at polling stations.

For the purposes of this study, we focus on violence and threats of violence against people, but not property. We adopt a “who-did-what-to-whom” framework, where each

Table 1. Examples of electoral violence by type.

	Threats	Attacks
State-on-nonstate	Government threatens to use military force against protesters Military surrounds polling places in opposition neighborhoods	Police beat voters at polling stations State security forces assault opposition candidates
Nonstate-on-state	Terrorists threaten to bomb polling stations	Opposition partisans attack military and police forces
Nonstate-on-nonstate	Militias issue statement threatening to carry out attacks on voters Ethnic group X threatens to attack ethnic group Y Supporters of party A forcibly displace supporters of party B	Ethnic separatists attack members of the government Campaign rallies by activists supporting opposing parties turn violent
International actor on any actor	A neighboring state increases its military posture on the border	Foreign military exchange fire with the state military Transnational criminal groups or insurgencies attack election facilities.
Any actor on international actor	The government threatens to expel international election observers	Ethnic militias attack election observers

incident of electoral violence is understood as being characterized by a) a perpetrator, b) a victim, and c) an action that varies in intensity. On the basis of the above discussion, we disaggregate electoral violence into two broad categories: *Threats*, including threats, incitement, and coercion falling short of actual bodily harm; and *Attacks*, including violence taking the form of assaults and violent physical confrontations. This distinction is fine-grained enough to capture varieties of electoral violence, but not so detailed as to pose insuperable obstacles to operationalization. Following conventions common to the study of political violence, we categorize actors into three types: state (including incumbent parties/politicians as well as formal state institutions like the police and military), non-state (including opposition party actors, ethnic and religious groups, ordinary citizens), and international (intergovernmental and transnational organizations). The resulting typology can be illustrated by the matrix in **Table 1**, which includes descriptors of each type of violence together with hypothetical examples.

Electoral violence data and coding procedures

The Dataset of Countries at Risk of Electoral Violence includes measures for each national-level (presidential or legislative) election in each of 101 states between 1995 and 2013. We follow the NELDA scheme for the coding of elections. We code elections as being legislative, executive, or concurrent. To avoid double-counting of violence, we collapse each concurrent legislative and executive election into a single electoral event. Where elections had multiple rounds, as for instance, in elections with run-offs, we code violence only for the decisive round of that election, since actors have more incentive to initiate violence in order to influence elections in decisive rounds.

We code violence only for elections we believe to be at risk of electoral violence. We adopt an exclusion criterion to determine the potential for which a country may be at risk of electoral violence. All countries with a Polity IV “polity” score of 10 throughout the entire period 1995–2013 are excluded from our data. Electoral violence is exceedingly rare in fully established democracies, and we therefore believe that their exclusion from this

dataset is justified on the grounds that such countries are not at significant risk of electoral violence.

We aggregate our measures of electoral violence from the Integrated Crisis Early Warning System, or ICEWS, event data project developed by Lockheed Martin Advanced Technology Laboratories.³² To account for the fact that the automated ICEWS coder may simply not code violent events in countries where media coverage is scarce (for instance in very authoritarian countries with state-controlled media), we also exclude countries from the dataset that had an average of less than one event per day, peaceful or conflictual, during the year of the observed election. We believe this exclusion is justified on the basis that such limited sources of data for the automated coder to collect make our ability to draw inferences regarding violent trends in these countries exceedingly difficult.

Because the automated coder used to compile the ICEWS event data codes news reports from various countries, it is possible, and indeed substantiated, that certain countries may be reported on more frequently in the data than others.³³ In this way, elections may appear to be more violent, when in reality, a greater number of media sources for the coder to intake may artificially inflate the true number of violent events. To account for this possible source of bias, we have included in the dataset a weight that users can employ to weight the event data by a per capita measure of media coverage.

To calculate this weight we recorded the total number of coded events in the ICEWS data in which the country conducting an election was the target country of an event, then divided this number by the population of the country in question (in millions). We invert this variable and center the mean of this measure on 1 such that elections with less media coverage are weighted upwards, and elections in countries with more media coverage are weighted downwards.

The data take the format of actor-action-target triples (i.e., who-did-what-to-whom). We aggregate the raw ICEWS event data according to the actors involved and the type of violence instigated.³⁴ The ICEWS dataset codes events according to the Conflict and Mediation Event Observations (CAMEO) ontology.³⁵ Specifically, we utilize the following CAMEO codes: Threaten, Exhibit Military Posture, Coerce, Assault, and Fight. We aggregate events belonging to these codes into two mutually exclusive categories of electoral violence: Verbal Conflict (includes CAMEO codes Threaten, Exhibit Military Posture, and Coerce), and Material Conflict (Assault and Fight). We are thus left with two aggregations of the original underlying event data, which are now explained in greater detail.

Events

Events in the ICEWS data represent the action, or “did what” designation of the data.³⁶ One example would be if supporters of the Orange Democratic Movement (ODM) attacked partisans of the Party of National United (PNU) in Nairobi, Kenya in 2007. This event would be coded as an Attack-type event. There are 20 different event types in the ICEWS data, though for CREV, we are interested only in the five previously listed. The descriptions of these event types are described according to the Conflict and Mediation Event Observations (CAMEO) ontology.³⁷ Each event type in the ICEWS data has a

numerical value ascribed to it. These numerical values range from -10 (signifying the most conflictual events in the data) to +10 (signifying the most peaceful events). These numbers are called “Goldstein values,” and they were originally developed for the World Event/Interaction Survey (WEIS) event data project.³⁸ Since CREV records only electorally violent events, we exclude all events in ICEWS with Goldstein Scores greater than -1, since events with Goldstein Scores from 0 to +10 represent neutral to cooperative events, and therefore are excluded from a dataset which measures only electoral violence.

We now describe in greater detail the exact nature of the events specified in the CREV according to the CAMEO code for each event. First, we describe the Verbal Conflict events falling into the first category of electoral violence.

CAMEO code *Threaten* refers to events coded in ICEWS as “all threats, coercive or forceful warnings with serious potential repercussions.” Threats are verbal acts. While threats may incite other actors to violence, or the same actor that issues a threat may later follow up that threat with physical violence, the threat event itself is not an event in which physical violence is inflicted on a target actor. An example of this kind of electoral violence would be if an incumbent political party threatened to ban opposition parties from campaigning during an election.

The second category of violence in the Verbal Conflict category is *Exhibit Military Posture*. This event is coded according to the CAMEO ontology as, “all military or police moves that fall short of the actual use of force.” Events where military or police forces actually use force are coded as different events. An example of this type of event would be if a national military imposed a curfew in opposition-friendly areas to prevent supporters of the opposition from voting during election day.

The final category in our Verbal Conflict typology is *Coerce*. This event is defined according to the CAMEO ontology as, “repression, violence against civilians, or their rights or properties.” While this is the most violent type of event catalogued in our verbal conflict category, not all instances of these events result in civilian injury or death, which are coded elsewhere (as detailed in the following paragraph). An example of this event is when political incumbents ban other political parties in advance of an election, or when a national military destroys civilian homes in an area of the country supportive of the opposition.

Our second typology of electoral violence codes physically violent events that result in physical harm short of fatalities, or physical harm leading to fatalities.³⁹ We refer to this category of events as Attacks. The first type of event in this category is designated by the CAMEO code *Fight*. The CAMEO codebook defines this type of event as “all uses of conventional force and acts of war typically by organized armed groups.” Killings of any kind that occur when the type of weapons are not specified are also coded in this category, though murders that occur in the context of everyday crime are excluded. An example of this type of event would be if partisans of incumbent and opposition parties engaged in a violent confrontation. These events need not involve deaths in order to be coded as fights.

The second event type we code in the Attack category is *Assault*. The CAMEO codebook defines these events as “use of unconventional forms of violence which do not require high levels of organization typical of state military establishments or conventional weaponry.” An example of this type of event is ethnic violence around elections, such as members of an ethnic group in Zambia who are supportive of one political party attacking a neighboring ethnic group supportive of another party with unconventional weapons like machetes.

Actors

Actors have specific definitions in the ICEWS data. Actors are defined as the “who” and “whom” parts of the event. In ICEWS terminology, actors are defined as the *source* of the event and the *target* of the event. Actors are always nouns and formally defined in the ICEWS Actor Dictionary. Actors are broken down into two groups: *named actors* and *composite actors*. An actor is any person, “group, country, or location that may potentially serve as the source or target of an event.”⁴⁰ Actors have a variety of information associated with them including their common name, patterns (text that represents various ways in which these actors may be identified in news reports), memberships (used to associate actors with their known affiliations, either in the context of a specific timeframe or in a more general sense), and type (classified as individuals, groups, or locations).

There are a myriad of named and composite actors in the ICEWS data. A named actor can be a politician, such as Barack Obama. It can also be a recognized political party, such as the French Socialists, or the Orange Democratic Movement during the 2007 Kenyan election. Essentially, named actors are recognized political entities defined with a proper noun, meaning they have internationally recognized titles and some sense of domestic (and international) recognition. Actors are defined in the ICEWS Dictionaries with seven sources of information.⁴¹

First, actors are given an affiliation for which country or territory the actor is primarily associated, but special non-country values including “International,” “Non-governmental organization,” and “International militarized group” may also be listed. This first row of information is for reference purposes only. The second row in the dictionary gives the actor’s name. This is the name of the actor as used in the ICEWS system, for instance Barack Obama, or al-Shabaab. Third, the actor type is listed. It takes on one of two values: “individual,” or “group,” depending on whether the actor is singular or plural. The fourth row in the actor dictionary lists the sector or group with which the actor is affiliated. Sectors are hierarchical and include, for example in descending order of rank, National Sectors, Government, Executive, Executive Office, and Department of the Interior; sectors are a general expressions of membership.

For example, Sally Jewell, Barack Obama’s Secretary of the Interior, would be defined as affiliated not only with the Department of the Interior in ICEWS, but also affiliated with all ancestor nodes as well. Actors can also be affiliated with groups. For example, Abdul Salam Zaeef has an affiliation with the group “Taliban,” while Abu Bakr al-Baghdadi has an affiliation with the group “Islamic State of Iraq and the Levant.” When an actor is affiliated with a group, they inherit all sector affiliations of that group during the appropriate time periods, meaning al-Baghdadi would belong to ISIL, as well as more general affiliations including “international militarized group.” The fifth row in the dictionary lists the date on which the affiliation began, while the sixth row lists the affiliation end date. The seventh row lists all other aliases used by the actor.

Composite actors are actors that are not listed in the ICEWS actor dictionary, but are instead formed by combining an actor with either an agent or a sector.⁴² An example would be the Egyptian military. Composite actors may also be more general. For instance, “Muslim” is an unaffiliated ICEWS sector that does not have a designation with any country or national sector, allowing Muslims to be an agent in any country.

ICEWS filters the raw event data into monadic event aggregations, which form the basis for aggregation into CREV. This is done to gather a count of events within a given country for some interval of time. This is carried out in two steps: first, determine a set of events to aggregate based on the source actor, target actor, event type, and date. This is known as filtering the events. ICEWS secondly provides a numerical value of the filtered data by, for instance, counting the number of events that occurred between the target and source actor. This is called aggregating the events. We further filter these aggregations into our dyads such as nonstate actors and state actors. This filtering is done on the basis of the source sector affiliation. So, for instance, if an actor has a source affiliation of “Government,” or “Party,” or “Democratic Party,” ICEWS will filter all events where this actor is the source of the event into “Government” and record the number of events where this actor interacted with any other actor. So, for example, if this actor fought against a target actor with a source code like “Opposition,” “Party,” these events will be filtered and aggregated into the ICEWS dyad of “Government to Opposition.”

We filter these aggregations further on the basis of traditional distinctions made in the literature. The ICEWS aggregations we use to form our dyads are listed in the Online Appendix. We define as state-based actors all those actors in the ICEWS dictionary as having affiliations in “Government” including “Parties” with ancestral affiliations belonging to “Government”; this excludes opposition parties whom we aggregate elsewhere. We aggregate into our nonstate actor category all actors with a source affiliation with a religion (Buddhist, Christian, Hindu, and Muslim), an ethnic affiliation, actors with affiliations in separatist groups, actors affiliated with the political “Opposition” (an official ICEWS sector affiliation), and dissident actors, an ICEWS affiliation in which generally unorganized political actors who tend to engage in violence fall. Our category of international actors includes only international organizations with the source code “International Organization.”

Some descriptive data from CREV

In this section we describe some aspects of the CREV and show how the data we have collected compare with other widely used event datasets including the Armed Conflict Location and Event Data Project (ACLED),⁴³ the Social Conflict in Africa Database (SCAD),⁴⁴ the National Elections across Democracies and Autocracies (NELDA) dataset, and the Varieties of Democracy (V-DEM) dataset.⁴⁵ Because Africa is the only region of the world for which ACLED, SCAD, and CREV overlap and have sufficient temporal coverage, we report only events for elections in Africa from 1995–2013 when comparing these datasets.⁴⁶ V-DEM and NELDA, however, overlap in their temporal coverage with CREV, and are global in coverage, so we do not limit our analysis only to Africa with these datasets. We show that our data record a larger number of events per election than do ACLED or SCAD, making CREV the most comprehensive event dataset of electoral violence currently available. We also compare these three event dataset’s fluctuations of violent events over time, and for multiple countries, demonstrating CREV captures trends in violence between elections within various African countries and also between these countries. CREV demonstrates that not only do different countries in Africa experience different levels of electoral violence, but countries also experience different trends in

violence from election to election, suggesting factors unique to elections may influence patterns of violence. We discuss the implications of this in this section, and elsewhere.

We choose these datasets because they are well known, and have been used extensively to examine electoral violence. Daxecker uses ACLED when measuring violent events to examine how the presence of election monitors shifts the timing of state-led violence against civilians in Africa. Fjelde and Höglund employ SCAD to measure the relationship between electoral institutions and electoral violence in Africa.⁴⁷ Goldsmith also uses ACLED to measure electoral violence for his study on the link between newly democratizing states and electoral violence.⁴⁸ Hafner-Burton, Hyde, and Jablonski employ NELDA to examine trends in electoral violence, as do Daxecker, and Fjelde and Höglund.⁴⁹

The greatest benefit of utilizing CREV to measure electoral violence is its breadth and granularity of coverage. CREV contains data on a larger number of actor dyads than any of these other datasets, making its measurement of electoral violence more comprehensive. Previous work has shown that a number of different actors from ethnic groups, incumbent governments, and even international actors can engage in, or become targets of, electoral violence.⁵⁰ CREV acknowledges the diversity of violent actors, measuring violence across 48 actor dyads.⁵¹ Because both SCAD and ACLED were created to measure different types of violence including violence during civil war, these datasets contain a more limited number of actors, making data derived from these datasets less than ideal for the study of electoral violence.

Another benefit of CREV is its granularity of focus. The ICEWS data, upon which CREV is based, uses over 300 different news sources to code violent events.⁵² This allows CREV to examine electoral violence in greater detail than other datasets which use a relatively smaller number of sources. Both ACLED and SCAD also rely on human coders, while CREV is based on machine-coded data. Both methods accurately measure violent trends and capture a similar number of true positives, while avoiding false positives, though machine coded data is slightly more accurate because it avoids issues like fatigue and biases that inevitably influence human coders.⁵³ Because it codes information from a large number of international and local news sources, CREV captures a greater number of true positives than projects that are hand coded, as many events may be exclusively reported in local news sources that newswires might miss. CREV therefore offers a more detailed analysis of violent trends within states. CREV, due to coding local newswire reports, also includes information on more localized and low-level violence, a type of violence that the coders of ACLED admit is often undercounted by that dataset.⁵⁴

To ensure maximum comparability between SCAD, ACLED, and CREV, we first eliminate nonviolent events from the former two datasets. From SCAD, we removed event codes 1 and 2 (organized demonstration and spontaneous demonstration) as these are peaceful events according to SCAD. We also removed event codes 3 and 4 (protests/riots). Though these are violent events, we do not code protest activity as part of CREV, and including such data here would produce an inaccurate comparison. Finally, we remove event codes 6 and 7 (general strike/limited strike) as no equivalent events are coded in CREV. We also do the same for ACLED to facilitate comparison. From ACLED we remove event codes Headquarters or Base Established, Strategic Development, and Nonviolent Transfer of Territory. All of these events are nonviolent.

In addition, we compare CREV against two other well-known datasets commonly used in studies of electoral violence. The first is the National Elections Across Democracy and

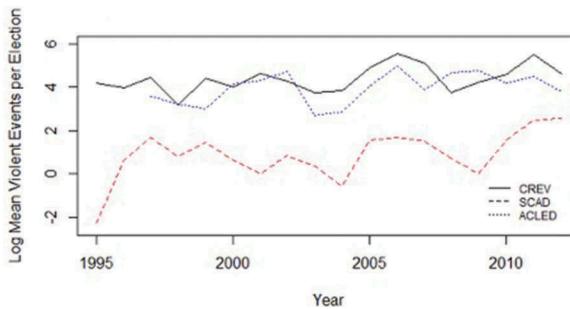


Figure 1. Comparing CREV to ACLED and SCAD.

Autocracy (NELDA) dataset. NELDA contains two variables that measure whether any kind of violence occurred during an election, and are compatible with our coding of electoral violence: *NELDA 15*, which asks if the government “harassed” the opposition, and *NELDA 33*, which asks if there was any significant violence involving civilian deaths before, during, or after the elections.⁵⁵ Because our measure of electoral violence is continuous, and these variables dichotomous, we use a poly-serial correlation coefficient to measure the strength of association between these measures of electoral violence. Additionally, due to the heavy tails in CREV—elections where extremely high levels of violence occurred—we log-transform our continuous measures of violent events before computing our correlations. This helps minimize the influence of outliers and facilitates easier comparison between the various measures of electoral violence.

Because CREV and NELDA have the same temporal coverage, we analyze all elections cross-nationally for this comparison. We also compare our measures of electoral violence against the variables *v2elpeace* and *v2elintim* in the Varieties of Democracy (V-DEM) dataset. These variables record whether actors other than the state or its military engaged in any violence during the election, or whether state-based actors threatened or intimidated members of the political opposition.

Figure 1 shows the temporal trends of electoral violence among CREV, ACLED, and SCAD. The y-axis shows the natural log of the average number of violent events per election in each African country per year, while the x-axis measures the temporal range of our dataset. We use the natural log of violent events in Figure 1 because there is a wide difference in the total number of events recorded by the three datasets. Plotting the natural log of the number of events gives a better visual display of the relationship between the three datasets.

According to Figure 1, all three datasets display similar trends in violence across Africa from 1995–2013. For the majority of years in the data, CREV contains more data on electoral violence than either ACLED or SCAD. While CREV consistently outpaces SCAD in its depth of coverage, CREV tracks ACLED, a more comprehensive event-based dataset, more closely. The correlations between CREV and the other two datasets are high. The correlation between CREV and SCAD is 0.60, and the correlation between CREV and ACLED is 0.46. Further, CREV not only tracks other datasets closely for all of Africa, but also displays similar trends to SCAD and ACLED across elections in individual countries.

The correlations between SCAD and ACLED are positive, and show quite high levels of agreement. The correlations, however, are not perfect, demonstrating that CREV provides unique information on electoral violence not captured by these other event datasets. This

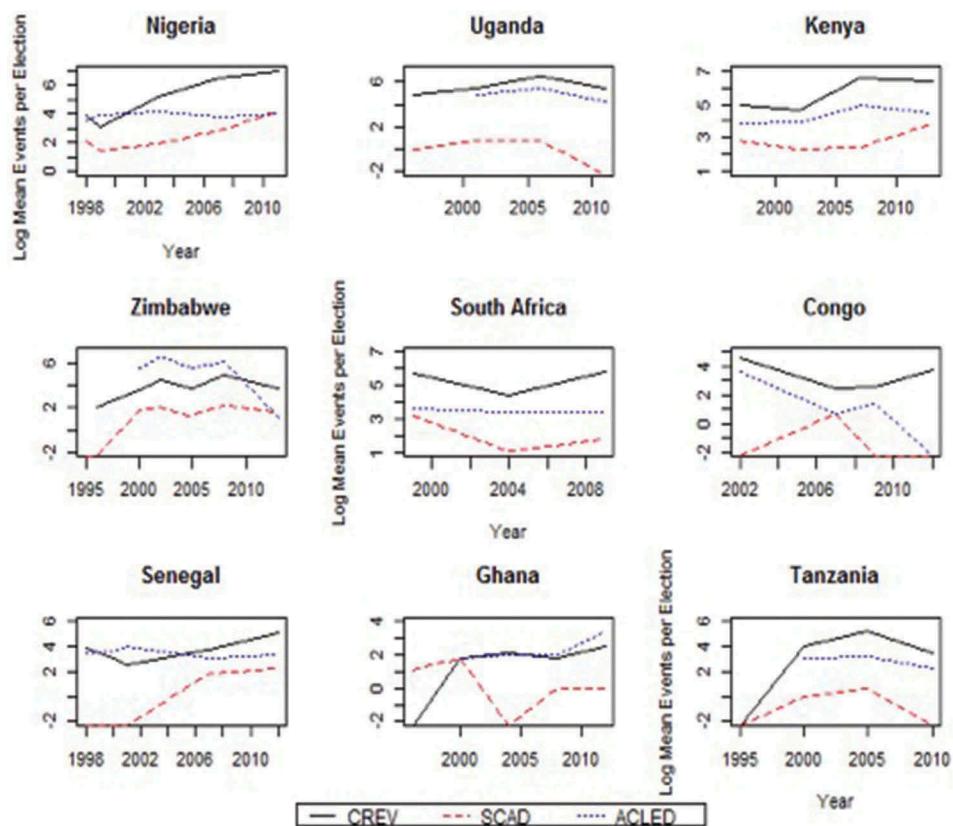


Figure 2. Electoral violence across selected African countries.

is to be expected given SCAD and ACLED were not developed for the exclusive purpose of measuring electoral violence, and the data-generating process of electoral violence may differ in fundamental ways from processes that produce other forms of political violence like insurgency, riots, and civil war. While we leave it to future research to discover the nature of this data-generation process, we discuss some possible factors that contribute to electoral violence in the conclusion.

Figure 2 shows temporal trends of electoral violence disaggregated among nine countries in Africa across the period covered by our data. According to Figure 2, CREV records a larger number of violent events per election across most countries.⁵⁶ The data in CREV also closely follow the pattern of violence found in both ACLED and SCAD. However, in Nigeria, Zimbabwe, and the Congo, trends in violence are noticeably different. One benefit of using CREV to measure electoral violence is the greater granularity of coding with regard to violent events. ICEWS, which uses the CAMEO coding ontology, records a wider array of violent events than either ACLED or SCAD, and while all three datasets show similar trends in electoral violence across many cases, CREV demonstrates trends in electoral violence that vary substantially from the other datasets in some elections. The greater number of news sources coded by ICEWS—and thus CREV—including a greater number of local sources, provides CREV with a superior ability to pick up trends in more

“competitive authoritarian” states that other datasets might miss because the news sources on which these datasets are coded do not report on such states or elections as often whether due to restrictions on media freedoms, or lack of organizational capacity, like foreign bureaus.

CREV, we believe, is a superior dataset for examining electoral violence. While CREV was created for the explicit purpose of measuring electoral violence, the other datasets compared in this section have been developed for different purposes. This can create problems when using these event datasets to measure a specific form of violence—like electoral violence—which the dataset was not created to explicitly measure. For example, one of the most violent elections in our data was the 2007 election in Kenya. During this election, over 1000 people were killed and over half a million were forcibly displaced.⁵⁷ Comparing SCAD directly to CREV, we find that SCAD recorded only eleven events corresponding to 163 deaths during the 10-month window around the 2007 election. SCAD did code a single event—tribal groups attacking other tribal groups—as lasting for the whole year, and codes the number of deaths related to that event at 300, so it still captures an important instance of electoral violence, but the data in SCAD severely underestimate the level of violence during that election. ACLED fares better, however. ACLED records one 144 violent events during the 10-month window around the election. ACLED also records 714 deaths during this period.

We know from other sources, that SCAD and ACLED most likely undercount the actual number of events and deaths that occurred during this election. CREV provides a larger number of total violent events for this as well as other elections suggesting that our data are picking up a stronger empirical signal related to electoral violence, especially in Africa. Compare the number of violent events during the Kenyan 2007 election found in ACLED and SCAD to CREV. CREV records a total of 748 events of material conflict. There were 293 events of nonstate to nonstate conflict, 134 events of conflict from nonstate groups towards state forces, and 321 events of conflict by state forces to nonstate forces. While we do not claim that the results of the CREV are the definitive account of every single violent event that took place in Kenya during this electoral cycle, we believe that our data better represent the extremely high levels of violence that wracked this election when compared with other datasets commonly used to study electoral violence.

We believe CREV will be an extremely useful resource for scholars and practitioners interested in electoral violence. Because of the underlying ICEWS data upon which CREV is based, it is able to capture more fine-grained data on electoral violence. As we have shown in regard to Africa, a region where elections are often prone to violence, CREV captures similar trends in electoral violence both across time and across different countries when compared to two other important event datasets currently in use by scholars. We now show that CREV captures similar global dynamics of electoral violence as other cross-national datasets of electoral violence currently in use, NELDA and V-DEM.

In addition to correlating strongly with existing event datasets commonly used to measure political violence, CREV also correlates positively with existing measures of electoral violence in NELDA and V-DEM. We again use poly-serial correlations. The variables we compare to our measures of electoral violence in CREV are *NELDA 33*, which is a dichotomous variable indicating whether there were any civilian deaths due to electoral violence, *NELDA 15*, a dichotomous variable indicating whether the government threatened the opposition, *v2elpeace* from V-DEM, and *v2elintim* from V-DEM. The final

two variables are ordinal measures of whether nonstate actors engaged in violence, and whether the government threatened the opposition, respectively. Because of the heavy tails in our distributions of violence, we first take the natural logarithm of our measures before dichotomizing our measures of electoral violence and computing the correlation.

Our measures of material electoral conflict—our measures of physical violence created by aggregating CAMEO codes *Fight* and *Assault*—correlate well with standard measures of electoral violence. Correlations with *NELDA 33*—one of the most commonly used measures of electoral violence—are especially robust. We create a measure of physical violence across all nonstate and state dyads by summing the relevant counts of violent events. This summed measure correlates highly with *NELDA 33* and is statistically significant at 0.53 (0.04). *NELDA 33* also correlates well with each individual measure of electoral violence. The correlation between *NELDA 33* and our measure of state to nonstate attacks is 0.49 (0.04); the correlation is the same between *NELDA 33* and attacks from nonstate actors towards other nonstate actors. The correlation between *NELDA 33* and our measure of nonstate to state violent attacks is 0.48 (0.04). Our measures also correlate well with *v2elpeace*, the variable measuring electoral conflict in V-DEM. The correlation between all attacks and *v2elpeace* is 0.35 (0.04). Correlations between this variable and nonstate to nonstate and nonstate to state attacks are 0.33 and 0.32 respectively, and also significant.

The correlations between the measures of physical violence and threats in CREV and other measures of threats are lower. The correlation between *v2elintim* and our measure of state to nonstate threats is 0.20 (0.05), and the correlation between *NELDA 15* and the same variable is 0.23 (0.05). These correlations are positive, indicating that our variables are measuring some similar underlying trends. However, our measures of electoral threats are measuring different concepts from either *NELDA 33* or *v2elintim*. These variables are generally measuring whether the government attempted to repress opposition parties, while our variables measure more general threatening behavior directed at a greater number of nonstate actors. Rather than measuring repression inherent in the electoral process, our variables measure more distinct verbal threats. NELDA and V-DEM conceptualize threatening behavior as repression, while ours measure a different concept. Taken together, however, these positive correlations, especially with *NELDA 33*, a widely used measure of electoral violence, indicate that the data in CREV are measuring broadly similar concepts.

Replication study with CREV

To demonstrate the theoretical and empirical validity of the underlying measures of electoral violence comprising CREV, in this section we replicate an existing cross-national study of electoral violence, Emilie Hafner-Burton, Susan Hyde, and Ryan Jablonski's analysis entitled "When Do Governments Resort to Election Violence?"⁵⁸ We find that the authors' main finding—governments resort to pre-election violence when polling indicates an electoral loss and when institutional constraints on executive power are low—is reversed. Unfavorable polling suggests that governments are *less* likely to resort to electoral violence. However, other results reported by the authors continue to hold.

Because our variable measuring electoral violence is a count variable, and shows significant over-dispersion, we utilize a negative binomial model for our analysis. To

Table 2. Replication results.

Variable	Hafner-Burton, Hyde, and Jablonski (2014)	Replication—Negative Binomial	Replication—Logit
Polling Unfavorable	2.37* (1.07)	-5.04* (1.88)	14.37* (5.45)
Executive Constraints	0.20 (0.21)	-1.06* (0.21)	-0.46 (0.51)
Polling Unfavorable X Executive Constraints	-0.49* (0.20)	0.60* (0.30)	-2.94* (1.07)
Physical Integrity	-0.44* (0.12)	-0.52* (0.12)	-3.21* (1.26)
Political Competition	-0.18 (0.10)	-0.52* (0.17)	-0.75 (0.43)
Executive Recruitment	0.31 (0.16)	-0.55* (0.22)	1.85* (0.82)
Population	0.36 (0.27)	0.30 (0.19)	1.04 (0.75)
GDP	-0.28 (0.19)	0.45* (0.18)	0.38 (0.66)
Leader Tenure	0.00 (0.01)	0.003 (0.01)	0.11 (0.51)
Leader Age	0.12 (0.17)	-0.09 (0.19)	-0.48 (0.51)
Civil War	0.54* (0.28)	0.00 (0.41)	-0.71 (1.18)
Electoral Fraud	1.60* (0.42)	0.02 (0.30)	2.45* (1.49)
Demonstrations	0.12* (0.05)	0.02 (0.05)	0.60* (0.21)
Log-Likelihood	-227.1	-253.72	-257.74
N	602	602	602

* p < 0.05

directly compare our measure of state-led electoral violence to the original model, we also dichotomize our measure. All elections with less than the mean number of violent events (45 events) are recoded as zero, while all elections with 45 or more events are recoded as one. We utilize a logistic regression, as per the original model of Hafner-Burton and colleagues, to directly compare the results of our new measure of electoral violence with their original analysis. The results of these regressions are shown in Table 2.

Our analysis of these statistical models shows that the results obtained in the original study are subject to the coding of the dependent variable. When the dependent variable is coded as a continuous count of electorally violent events, the main finding of the original study—unfavorable polling is correlated with more electoral violence—is reversed. We find that unfavorable polls for incumbents are correlated with less electoral violence. On the other hand, when we recode our continuous measure of state-led electoral violence for the logistic regression model, the results obtained in the original study continue to hold. When the dependent variable is dichotomous, polling that indicates an incumbent will lose an election is associated with more electoral violence.

On the one hand, this analysis demonstrates that CREV is picking up on the same underlying data-generating process found in datasets previously used to study electoral violence. This gives us confidence in the validity of our measures. On the other hand, CREV demonstrates something new. Our continuous measure of electoral violence shows incumbents are less willing to resort to electoral violence given unfavorable polling, but at the same time, a dichotomous version of this same variable produces results indicating the

opposite. This suggests that there may be a threshold effect for polling. If polls are very unfavorable, incumbents are loath to engage in violence since it incurs costs that are unlikely to lead to a higher chance of winning the election. If polls are only slightly unfavorable, however, the strategic use of violence may make more sense, because only a small amount may suffice to alter the outcome of the election in a way favorable to the incumbent.

A full exploration of this result is beyond the scope of this article, which aims to introduce CREV and show some descriptive statistics. We leave it to future research to more completely determine the effects of electoral competition on electoral violence. We do note in the conclusion that CREV shows a high level of variation in electoral violence *within* countries from election to election, suggesting that effects endogenous to the electoral process itself may explain a great deal of variation in electoral violence. This is in line with the result shown above in the replication study. Very unfavorable polling might cause incumbents to be less willing to engage in electoral violence, but this polling can change from election to election given the nature of the candidates in the race, prevailing sentiments expressed by public opinion, and other factors.

Conclusion

The study of electoral violence has grown substantially in recent years. Thanks to this burgeoning literature, scholars have been able to investigate many aspects of this unique category of political violence. Unfortunately, many of the datasets used to measure electoral violence have suffered from conceptual problems, making the data used to study this subject opaque. The dataset on Countries at Risk for Electoral Violence allows scholars access to more detailed data on electoral violence than any other dataset available. The nature of CREV as an event dataset means that research can now be carried out at a more detailed level of analysis than has previously been possible. CREV, in addition to a greater depth of analysis into electoral violence, also codes violent activity among a greater number of electoral actors, making it the most comprehensive dataset of electoral violence currently available.

We have demonstrated that our dataset correlates positively and closely with other datasets previously used to study electoral violence, and that results carried out on the basis of this dataset comport with previous studies, but also show novel results that can drive the field of electoral violence forward in new directions.

Our descriptive analyses of the CREV data yield some interesting findings that are worth exploring in greater detail in future research. One of the most intriguing results to emerge from the granular CREV data is the high degree of variability in levels of violence within countries from one election to the next; on virtually all of the CREV indicators, within-country variance is not much smaller than between-country variance. An aggregate measure of all types of state violence in the CREV dataset has a mean of 85.97 events, within-country variance of 131.88, and between-country variance of 149.59. The corresponding figures for an aggregate measure of all forms of nonstate violence are a mean of 156.72, within-country variance of 250.59, and between-country variance of 364.70. These data suggest that there is a large degree of variability in levels of violence across the globe—as one would expect—but that in given countries at risk of violence the number of

actual violence events that occur over any given electoral cycle is not easily predicted on the basis of that country's electoral history. This fact has implications for the way in which state and nonstate actors alike perceive the risk of violence being perpetrated against them; they may well in many cases not know how likely it is that the other side will opt to use violence as an electoral tool, and this uncertainty has strategic implications that could be usefully explored in future research.

A related finding is the high degree of variation in levels of violence across countries that are in many respects relatively similar, such as those on the African continent. This comes out quite clearly in the pan-African data set out in [Figure 2](#), where there is little evidence of any kind of common trend. This, together with the variability of violence within countries, strongly suggests that violence is conditioned by factors specific to the electoral event in question. Violence appears to track electoral competitiveness in Nigeria and Zimbabwe, but there is less clear-cut evidence of a relationship of this sort in the other states displayed here. This is another topic that could be usefully probed using the CREV data.

Another question on which the CREV data would undoubtedly yield interesting insights is the way in which electoral actors mobilize others to engage in violent acts, against both cultural outgroups and political rivals. The “production” of violence has been explored extensively in case studies, but there have heretofore been few datasets with sufficiently detailed data to enable researchers to explore patterns of interactions between actors over time within and across elections.

The study of violence has for years presented challenges to researchers, as the illicit use of force is typically not widely advertised by its perpetrators, and the parties involved have strong incentives to disseminate narratives of violent events that suit their ends. Electoral violence is no exception to this general rule. In compiling the Countries at Risk of Electoral Violence dataset, we hope to have produced a resource that will be of great use to both scholars and practitioners in their quests to understand elections that are affected by conflict.

Notes

1. C. Blattman, “From Violence to Voting: War and Political Participation in Uganda,” *American Political Science Review* 103, no. 2 (2009): 231–47; D. A. O. Bekoe, *Trends in Electoral Violence in Sub-Saharan Africa*, vol. 10 (Washington, DC: United States Institute of Peace, 2010); D. Brancati and J. L. Snyder, “Time to Kill the Impact of Election Timing on Postconflict Stability,” *Journal of Conflict Resolution* 57, no. 5 (2013): 822–53; T. Dunning, “Fighting and Voting: Violent Conflict and Electoral Politics,” *Journal of Conflict Resolution* 55, no. 3 (2011): 327–39; P. Staniland, “Violence and Democracy,” *Comparative Politics* 47, no. 1 (2014): 99–118.
2. S. M. Burchard, *Electoral Violence in Sub-Saharan Africa* (Boulder, CO and London: Lynne Rienner, 2015).
3. P. Staniland, “Violence and Democracy” (see note 1).
4. S. Hyde and N. Marinov, “Which Elections Can Be Lost?,” *Political Analysis* 20, no. 2 (2012): 191–210.
5. M. Bratton, “Vote Buying and Violence in Nigerian Election Campaigns,” *Electoral Studies* 27, no. 4 (2008): 621–32.
6. U. E. Daxecker, “All Quiet on Election Day? International Election Observation and Incentives for Pre-election Violence in African Elections,” *Electoral Studies* 34 (2014): 232–43.

7. T. Bhasin and J. Gandhi, "Timing and Targeting of State Repression in Authoritarian Elections," *Electoral Studies* 32, no. 4 (2013): 620–31; E. M. Hafner-Burton, S. D. Hyde, and R. S. Jablonski, "When Do Governments Resort to Election Violence?," *British Journal of Political Science* 44, no. 1 (2014): 149–79.
8. K. Höglund, A. Jarstad, and M. S. Kovacs, "The Predicament of Elections in War-torn Societies," *Democratization* 16, no. 3 (2009): 530–57; K. Klaus and M. I. Mitchell, "Land Grievances and the Mobilization of Electoral Violence: Evidence from Côte d'Ivoire and Kenya," *Journal of Peace Research* 52, no. 5 (2015): 622–35; H. Smidt, "From a Perpetrator's Perspective: International Election Observers and Post-Electoral Violence," *Journal of Peace Research* 53, no. 2 (2016): 226–41; S. I. Wilkinson, *Votes and Violence: Electoral Competition and Communal Riots in India* (Cambridge, UK: Cambridge University Press, 2004).
9. See the Online Appendix for the list of 101 countries contained in the CREV.
10. E. Boschee, J. Lautenschlager, S. O'Brien, S. Shellman, J. Starz, and M. D. Ward, "ICEWS Coded Event Data" (2015), <http://dx.doi.org/10.7910/DVN/28075>.
11. Hafner-Burton, Hyde, and Jablonski, "When Do Governments Resort to Election Violence?" (see note 7); Hyde and Marinov, "Which Elections Can Be Lost?" (see note 4); S. Hyde and N. Marinov, "NELDA 4.0: National Elections Across Democracy and Autocracy Dataset Codebook for Version 4" (2015), <http://hyde.research.yale.edu/nelda/>.
12. European Commission and United Nations Development Program, "Introduction to Current Trends in Election-Related Violence" (2009), <https://www.ec-undp-electoralassistance.org/medias/trainings/2010-barcelona/ec-undp-jtf-04-our-trainings-2010-barcelona-day-1-3.pdf>.
13. Ibid., 4.
14. S. Straus and C. Taylor, "Democratization and Electoral Violence in Sub-Saharan Africa 1990–2008," in *Voting in Fear: Electoral Violence in Sub-Saharan Africa*, edited by D. Bekoe (Washington, DC: United States Institute of Peace Press, 2012), 15–38.
15. J. Fischer, *Electoral Conflict and Violence*, IFES White Paper 1 (Washington, DC: International Foundation for Electoral Systems, 2002).
16. T. Sisk, "Elections in Fragile States: Between Voice and Violence" (paper prepared for the International Studies Association Annual Meeting, San Francisco, California, March 24–28, 2008), 5.
17. European Commission and United Nations Development Program, "Introduction to Current Trends in Election-Related Violence," 55 (2009), <https://www.ec-undp-electoralassistance.org/medias/trainings/2010-barcelona/ec-undp-jtf-04-our-trainings-2010-barcelona-day-1-3.pdf>; Daxecker, "All Quiet on Election Day?" (see note 6): 233.
18. H. Fjelde and K. Höglund, "Electoral Institutions and Electoral Violence in Sub-Saharan Africa," *British Journal of Political Science* 46, no. 2 (2016): 297–320; Hafner-Burton, Hyde, and Jablonski, "When Do Governments Resort to Election Violence?" (see note 7); K. Höglund, "Electoral Violence in Conflict-ridden Societies: Concepts, Causes, and Consequences," *Terrorism and Political Violence* 21, no. 3 (2009): 412–27.
19. C. Boone, "Politically Allocated Land Rights and the Geography of Electoral Violence: The Case of Kenya in the 1990s," *Comparative Political Studies* 44, no. 10 (2011): 1311–42; M. Chacón, J. A. Robinson, and R. Torvik, "When Is Democracy an Equilibrium? Theory and Evidence from Colombia's la Violencia," *Journal of Conflict Resolution* 55, no. 3 (2011): 366–96; A. Chaturvedi, "Rigging Elections with Violence," *Public Choice* 125, no. 1–2 (2005): 189–202; P. Collier and P. C. Vicente, "Violence, Bribery, and Fraud: The Political Economy of Elections in Sub-Saharan Africa," *Public Choice* 153, no. 1–2 (2012): 117–47.
20. Fjelde and Höglund, "Electoral Institutions and Electoral Violence in Sub-Saharan Africa" (see note 18); Hafner-Burton, Hyde, and Jablonski, "When Do Governments Resort to Election Violence?" (see note 7); Smidt, "From a Perpetrator's Perspective" (see note 8).
21. D. C. North, J. J. Wallis, and B. R. Weingast, *Violence and Social Orders: A Conceptual Framework for Interpreting Recorded Human History* (Cambridge, UK: Cambridge University Press, 2009).
22. L. E. Cederman, K. S. Gleditsch, and S. Hug, "Elections and Ethnic Civil War," *Comparative Political Studies* 46, no. 3 (2013) 387–417; Dunning, "Fighting and Voting" (see note 1); B.

Eifert, E. Miguel, and D. N. Posner, "Political Competition and Ethnic Identification in Africa," *American Journal of Political Science*, 54, no. 2 (2010): 494–510.

23. Wilkinson, *Votes and Violence* (see note 8).
24. Boone, "Politically Allocated Land Rights and the Geography of Electoral Violence" (see note 19).
25. J. L. Snyder, *From Voting to Violence: Democratization and Nationalist Conflict* (New York: Norton, 2000).
26. S. M. Saideman, D. J. Lanoue, M. Campenni, and S. Stanton, "Democratization, Political Institutions, and Ethnic Conflict: A Pooled Time-Series Analysis, 1985–1998," *Comparative Political Studies* 35, no. 1 (2002): 103–29.
27. North, Wallis, and Weingast, *Violence and Social Orders* (see note 21).
28. U. E. Daxecker, "The Cost of Exposing Cheating International Election Monitoring, Fraud, and Post-election Violence in Africa," *Journal of Peace Research* 49, no. 4 (2012): 503–16; J. G. Kelley, *Monitoring Democracy: When International Election Observation Works, and Why It Often Fails* (Princeton, NJ and Oxford, UK: Princeton University Press, 2012).
29. J. A. Tucker, "Enough! Electoral Fraud, Collective Action Problems, and Post-communist Colored Revolutions," *Perspectives on Politics* 5, no. 3 (2007): 535–51.
30. Brancati and Snyder, "Time to Kill the Impact of Election Timing on Postconflict Stability" (see note 1).
31. Dunning, "Fighting and Voting" (see note 1).
32. Boschee et al., "ICEWS Coded Event Data" (see note 10).
33. D. Chiba and K. S. Gleditsch, "The Shape of Things to Come? Expanding the Inequality and Grievance Model for Civil War Forecasts with Event Data," *Journal of Peace Research* 54, no. 2 (2017): 275–97; M. Garces, I. S. Lustick, and B. P. Levey, "Fragility and Destabilizing Protest: Combining Event and Structural Data for Improved Forecasts," *Procedia Manufacturing* 3 (2015): 4136–43.
34. For a full list of included actors, their CREV dyadic classifications, and their associated strategies of violence, see the Online Appendix.
35. See P. A. Schrot, *CAMEO: Conflict and Mediation Event Observations Event and Actor Codebook* (Pittsburgh, PA: Pennsylvania State University, 2012).
36. J. Lautenschlager, "ICEWS Events and Aggregation" (2015), <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/28117>.
37. Schrot, *CAMEO* (see note 35).
38. J. S. Goldstein, "A Conflict-Cooperation Scale for WEIS Events Data," *Journal of Conflict Resolution* 36, no. 2 (1992): 369–85.
39. The ICEWS dataset does not contain information on whether or how many deaths are associated with a particular event.
40. Lautenschlager, "ICEWS Events and Aggregation" (see note 36).
41. For some information see the ICEWS Actor Dictionaries "Read Me" at <https://dataverse.harvard.edu/file.xhtml?fileId=2548488&version=2.0> and the ICEWS Events and Aggregations "Read Me" at file:///C:/Users/k1636076/Downloads/ICEWS%20Events%20and%20Aggregations.pdf .
42. Lautenschlager, "ICEWS Events and Aggregation" (see note 36).
43. C. Raleigh, A. Linke, H. Hegre, and J. Karlsen, "Introducing ACLED: An Armed Conflict Location and Event Dataset Special Data Feature," *Journal of Peace Research* 47, no. 5 (2010): 651–60.
44. I. Salehyan, C. S. Hendrix, J. Hamner, C. Case, C. Linebarger, E. Stull, and J. Williams, "Social Conflict in Africa: A New Database," *International Interactions* 38, no. 4 (2012): 503–11.
45. Hyde and Marinov, "Which Elections Can Be Lost?" (see note 4); Hyde and Marinov, "NELDA 4.0" (see note 11); M. Coppedge, J. Gerring, S. I. Lindberg, S.-E. Skaaning, J. Teorell, D. Altman, F. Andersson, M. Bernhard, M. S. Fish, A. Glynn, A. Hicken, C. H. Knutson, K. McMann, V. Mechkova, F. Miri, P. Paxton, D. Pemstein, R. Sigman, J. Staton, and B. Zimmerman, *V-Dem Codebook v6* (Gothenburg: Varieties of Democracy (V-Dem) Project, 2016).

46. ACLED contains data only beginning from 1997. We note this in the figures produced for this section.
47. Daxecker, "All Quiet on Election Day?" (see note 6); Fjelde and Höglund, "Electoral Institutions and Electoral Violence in Sub-Saharan Africa" (see note 18).
48. A. A. Goldsmith, "Electoral Violence in Africa Revisited," *Terrorism and Political Violence* 27, no. 5 (2015): 818–37.
49. Hafner-Burton, Hyde, and Jablonski, "When Do Governments Resort to Election Violence?" (see note 7); Daxecker, "All Quiet on Election Day?" (see note 6); Fjelde and Höglund, "Electoral Institutions and Electoral Violence in Sub-Saharan Africa" (see note 18).
50. Cederman, Gleditsch, and Hug, "Elections and Ethnic Civil War" (see note 22); Hafner-Burton, Hyde and Jablonski, "When Do Governments Resort to Election Violence?" (see note 7); Daxecker, "The Cost of Exposing Cheating International Election Monitoring, Fraud, and Post-election Violence in Africa" (see note 28); Smidt, "From a Perpetrator's Perspective" (see note 8).
51. These 48 actors dyads are then aggregated into our dyads as listed in **Table 1**. Please see the Online Appendix for the full listing of actors that are aggregated into these dyads.
52. P. A. Schrodt, "Event Data in Forecasting Models: Where Does it Come from and What Can it Do?" (2015), <http://eventdata.parusanalytics.com/papers.dir/Schrodt.PRIO15.EventData.pdf>.
53. *Ibid.*
54. Raleigh et al., "Introducing ACLED" (see note 43).
55. Another variable, NELDA 29, is commonly used to measure electoral violence. This variable asks if there were any significant protests or riots after the election. Because we exclude protests from the CREV, however, we do not measure the correlation of this variable with our measures of electoral violence, as the two variables measure different types of violence, making a direct comparison difficult.
56. Since the y-axes of **Figure 2** are the natural log of the number of events across each dataset, and the natural log of zero is undefined, we replaced all instances of zero events with 0.1 events. The natural log of 0.1 is -2.3. Hence, when the graph in the figure crosses the y-axis at -2.3 that corresponds to a count of zero violent events in a given election.
57. Human Rights Watch, "Ballots to Bullets: Organized Political Violence and Kenya's Crisis of Governance" (2008), <https://www.hrw.org/report/2008/03/16/ballots-bullets/organized-political-violence-and-kenyas-crisis-governance>.
58. Hafner-Burton, Hyde, and Jablonski, "When Do Governments Resort to Election Violence?" (see note 7).

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