AJPS AMERICAN JOURNAL of POLITICAL SCIENCE

Is There More Violence in the Middle?

Zachary M. Jones University of Washington
Yonatan Lupu George Washington University

Abstract: *Is there more violence in the middle? Over 100 studies have analyzed whether violent outcomes such as civil war, terrorism, and repression are more common in regimes that are neither full autocracies nor full democracies, yet findings are inconclusive. While this hypothesis is ultimately about functional form, existing work uses models in which a particular functional form is assumed. Existing work also uses arbitrary operationalizations of "the middle." This article aims to resolve the empirical uncertainty about this relationship by using a research design that overcomes the limitations of existing work. We use a random forest-like ensemble of multivariate regression and classification trees to predict multiple forms of conflict. Our results indicate the specific conditions under which there is or is not more violence in the middle. We find the most consistent support for the hypothesis with respect to minor civil conflict and no support with respect to repression.*

Replication Materials: The data, code, and any additional materials required to replicate all analyses in this article are available on the *American Journal of Political Science* Dataverse within the Harvard Dataverse Network, at: https://doi.org/10.7910/DVN/LNUYXZ.

What is the relationship between regime type and political violence? Are certain forms of conflict more likely in democracies or in autocracies? A series of influential studies has suggested this relationship is curvilinear, with violence most likely in regimes in the middle range—often referred to as anocracies—that are neither fully autocratic nor fully democratic (Eck and Hultman 2007; Fein 1995; Hegre et al. 2001). We refer to these arguments, collectively, as the More Violence in the Middle Hypothesis (or MVM Hypothesis).

Despite decades of research, the extent to which such theories are empirically supported is unclear. While some early studies found that civil wars are most likely in anocracies (Hegre et al. 2001), others did not (Sambanis 2001). The debate may have appeared resolved when Vreeland (2008) showed that correcting for the extent to which measures of democracy might include indicators of violence results in no support for the MVM Hypothesis, but since then some have used his measure and found support for the hypothesis (Gleditsch and Ruggeri 2010), whereas others have confirmed his result (Peic and Reiter 2011). Likewise, some find evidence that terrorism is most common in anocracies (Wade and Reiter 2007), whereas others do not (Chenoweth 2010). With respect to repression, Davenport and Armstrong (2004) arguably settled the question by using more appropriate methods for testing this hypothesis than the bulk of the literature and finding no support for the MVM Hypothesis, but some recent work continues to find support for it (Mitchell, Ring, and Spellman 2013).

The purpose of this article is to reduce the empirical uncertainty about the MVM Hypothesis and describe the conditions under which it does or does not hold. Although existing work has made significant progress, the methods used to date have several consequential limitations. The MVM Hypothesis is a prediction about the functional form of the relationship between regime type and conflict, yet almost all existing tests of the MVM Hypothesis have been conducted using models that *assume* a particular functional form and then test whether the data allow us to reject a simpler possible relationship between regime type and conflict, such as a monotonic relationship. While such tools can allow us to reject a monotonic relationship, they are not well suited for understanding the more complex ways in which regime type

Zachary M. Jones is Postdoctoral Fellow, eScience Institute, Campus Box 351570, University of Washington, Seattle, WA 98195-1570 (zmj@zmjones.com). Yonatan Lupu is Assistant Professor, Department of Political Science, George Washington University, Monroe Hall, Room 417, 2115 G Street, NW, Washington, DC 20052 (ylupu@gwu.edu).

For comments on previous drafts, we thank Erica Chenoweth, Christian Davenport, Scott Gates, Will Moore, and Jake Shapiro, as well as participants in workshops at New York University, Uppsala University, and George Washington University. For research assistance, we thank Jack Hasler, Bryce Loidolt, and Steven Schaaf.

American Journal of Political Science, Vol. 62, No. 3, July 2018, Pp. 652–667

©2018, Midwest Political Science Association DOI: 10.1111/ajps.12373

may predict conflict. For example, such models do not capture unspecified nonlinearities and interactions, including important ways conflict dynamics have changed over time (Kalyvas and Balcells 2010). In addition, if the relationship between regime type and conflict is more complex than an inverse U, tools used in most existing work are ill suited to uncovering such complexity. Finally, existing approaches often use arbitrary operationalizations of anocracy (usually based on some range of a regime type measure) that limit what we can learn from the results about the relationship between conflict and the full range of regime types.

Building on earlier work by Davenport and Armstrong (2004), we use a flexible method, an algorithm similar to multivariate random forests, to estimate the relationship between regime type and many forms of political conflict. This methodology has several advantages. First, we do not make restrictive assumptions about the form of the regime type–conflict relationship, thus allowing us to analyze the relationship between regime type and conflict across the regime type spectrum. Our approach does not require us to arbitrarily define "the middle" of the regime type spectrum; instead, we can estimate the risk of multiple forms of political conflict across the regime type spectrum. In turn, this allows us to learn which types of anocracies, if any, are more conflict prone than democracies and autocracies.

Using a measure of regime type used by almost all existing work on the MVM Hypothesis,[1] we find that some forms of conflict are most likely in regimes that are neither fully autocratic nor fully democratic. Yet there are important qualifications on this result, and we describe the specific conditions under which the MVM Hypothesis holds. First, our results allow us to learn which types of anocracies are especially conflict-prone and which may not be more conflict-prone than democracies and autocracies. For example, we find that civil war onset risk is greatest in the range of −4 to 1 on the X-Polity scale, whereas other anocracies may not be especially conflict-prone.[2] Along similar lines, while most of our results with respect to terrorism are consistent with the MVM Hypothesis, they indicate that only anocracies that are almost fully democratic are especially terrorism-prone. This suggests the research agenda should refocus toward explaining why these particular institutional configurations may be more terrorism-prone, rather than focusing on all anocracies. Second, we find the MVM Hypothesis does not appear to hold with respect to repression of physical integrity rights, which we find consistently decreases with democracy. Third, we find that the regime type–conflict relationship has changed in important ways over time, especially with respect to civil conflicts and terrorism. Finally, we find that when we use an alternative measure that has not been widely used in this literature but that has been argued to provide a more accurate operationalization of regime type (Pemstein, Meserve, and Melton 2010), some of our findings change. Using this measure, we find support for the MVM Hypothesis with respect to civil conflicts and terrorism, but not with respect to civil wars and repression, indicating the importance of measurement concerns in tests of this hypothesis.

The MVM Hypothesis

The MVM Hypothesis gained prominence first in the repression literature (Fein 1995), and later in the civil war literature (Fearon and Laitin 2003). While theoretical justifications for the MVM Hypothesis vary in their details, many rely on claims that in regimes that are neither fully autocratic nor fully democratic, "violence is neither effectively deterred by the inability of the dissidents to mobilize for collective action nor rendered superfluous by the availability of effective peaceful forms of collective political action" (Muller and Weede 1990, 631). Along similar lines, Hegre et al. (2001, 33) argue that "semi-democracies are partly open yet somewhat repressive, a combination that invites protest, rebellion, and other forms of civil violence." More recently, formal models have generated versions of the MVM Hypothesis (e.g., Pierskalla 2010; Dragu 2011).

Because of its significant theoretical and policy implications, the MVM Hypothesis has received broad and deep empirical attention. Our survey of articles published in several key political science journals from 1995 to 2016 found 111 articles that test whether some form of political violence is more common in the middle range of the regime type spectrum.[3]

Most studies of the MVM Hypothesis use an index, often the Polity score (Marshall and Jaggers 2002), to measure regime type. Vreeland (2008) argues that some components of the Polity index take into account the types of factionalism and violence that tend to occur

[1]We use a modified version of the Polity IV data created by Vreeland (2008; X-Polity).

[2]Examples of regimes in the conflict-prone range include Indonesia under Suharto (X-Polity −4, three civil war onsets), Ethiopia under Mengistu (X-Polity −3 or −4, five civil war onsets), and Russia from 1993 to 1998 (X-Polity 1, zero civil war onsets).

[3]The supporting information provides information about these articles.

during civil wars, thus making those measures inappropriate for testing the MVM Hypothesis. After removing these components from the index, he reanalyzes the data from Hegre et al. (2001) and Fearon and Laitin (2003), but he does not find support for the hypothesis. More recently, however, others have used Vreeland's modified measure and found that anocracies are more likely to experience civil wars (Gleditsch and Ruggeri 2010), whereas others confirmed Vreeland's finding (Peic and Reiter 2011). Studies using latent variable measures of democracy have also yielded mixed results (Gibler and Miller 2014; Treier and Jackman 2008).

Empirical findings with respect to the relationship between regime type and repression are also mixed. Early work discovered that repression decreases in measures of democracy, although this claim was called into question by Fein's (1995) claim that repression of personal integrity rights was more likely in the middle range of regime types. Subsequent work confirmed the inverse relationship between democracy and repression (Davenport 2007; Davenport and Armstrong 2004), although others continue to find support for an inverse-U relationship (Mitchell, Ring, and Spellman 2013).

The relationship between regime type and terrorism is also likely complex. Those who have tested the MVM Hypothesis directly with respect to terrorism have found either mixed results (Wade and Reiter 2007) or no support for the hypothesis (Urdal 2006). Many scholars have argued that the type of dissident activity often coded as terrorism is most likely in democracies (Chenoweth 2010). Yet many others have focused on whether and why specific types of authoritarian or democratic regimes are more likely to be attacked (Aksoy and Carter 2014). While the bulk of existing work examines links between regime type and civil wars, terrorism, or repression, others have analyzed the relationship between anocracy and other forms of violence, including interstate conflict, violent protests, assassination, violence against civilians, and genocide.

Limitations of Existing Research

Existing research on the MVM Hypothesis uses research designs that have two important limitations with respect to the MVM Hypothesis: (1) they assume a functional form of the relationship between regime type and conflict, and (2) they require either an arbitrary operationalization of "the middle" or a polynomial regression to test the hypothesis. This section discusses these issues in more detail.

Functional Form Assumptions

The MVM Hypothesis is fundamentally an argument about functional form. It predicts that the marginal relationship between regime type and conflict takes a specific form, namely, an inverse U. With the exception of Davenport and Armstrong (2004), all of the published articles we surveyed tested the MVM Hypothesis by using a model that makes strong assumptions about the functional form of the regime type–conflict relationship as well as the relationship between control variables, regime type, and conflict. Such approaches have limitations because they do not directly estimate the functional form of the relationship. The underlying relationship may be more complex than analysts assume or theorize, in which case traditional models would not uncover such complexities.[4]

We build on Davenport and Armstrong (2004), which, in contrast to other existing work, uses tools that weaken assumptions about functional form. They first estimate the bivariate relationship between measures of regime type and repression by using a nonparametric method (LOESS), which has the advantage of not requiring the specification of a functional form. This tool does not allow for adjustments based on factors that interact with regime type. They also expand an ordered measure of regime type into a series of binary variables, which effectively allows a linear model to estimate a step function, but this results in lost information about the ordering of the regime type measure.

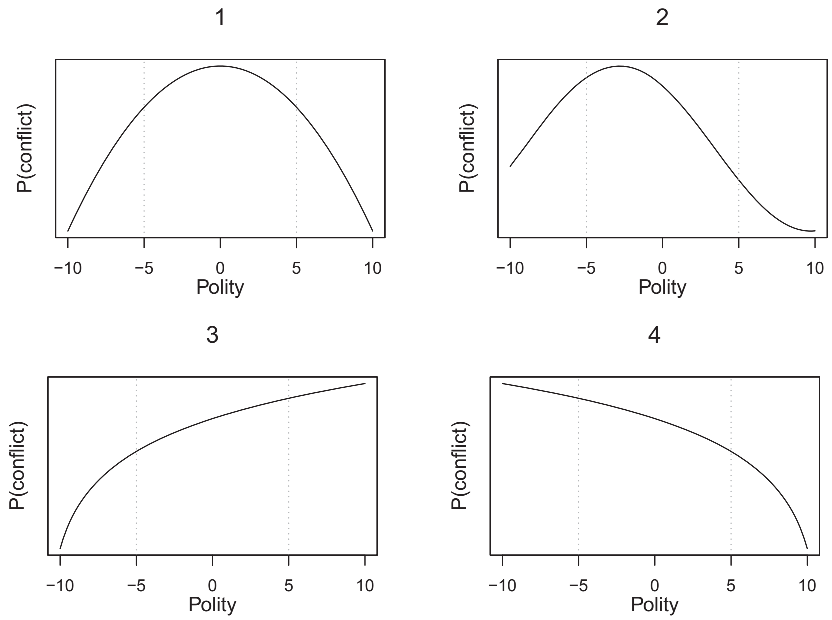
Operationalizing "The Middle"

What is "the middle"? Conceptual definitions of anocracy or semi-democracy vary; examples can be found in Hegre et al. (2001, 33), who use the term *semi-democracy* rather than *anocracy*, referring to them as "partly open yet somewhat repressive," and Regan and Bell (2010, 749), who describe them as regimes that exhibit the following conditions: "weak institutions for moderating political debate, a modicum of opportunity to make demands on these weak institutions, and politics that gravitate toward zero-sum outcomes."

Given the ambiguity of many definitions of anocracy, operationalizing the concept has proven difficult. In many cases, scholars use a binary indicator for anocracy, such as a state with a Polity score from -5 to $+5$ (e.g., Fearon

[4] In addition, the impact of mis-specifying the relationships between other predictors and the outcome(s) can be equally consequential when those predictors interact with the predictors of primary interest.

FIGURE 1 Stylized Relationships between Polity and the Probability of Conflict



and Laitin 2003). If the coefficient for this indicator is significant and positive, this is often interpreted as supporting the MVM Hypothesis. While there is much we have learned from such operationalizations of anocracy, they also have inherent limitations. First, these types of cutoffs are arbitrary. We are not aware, for example, of a theory that explicitly connects the MVM Hypothesis to the −5 to +5 range of Polity scores. Second, a binary operationalization of anocracy limits investigation of variability within the group. Finally, depending on the distribution of observations along the regime type range, a positive and significant coefficient for an indicator of some middle range of regime types may not be consistent with the MVM Hypothesis.

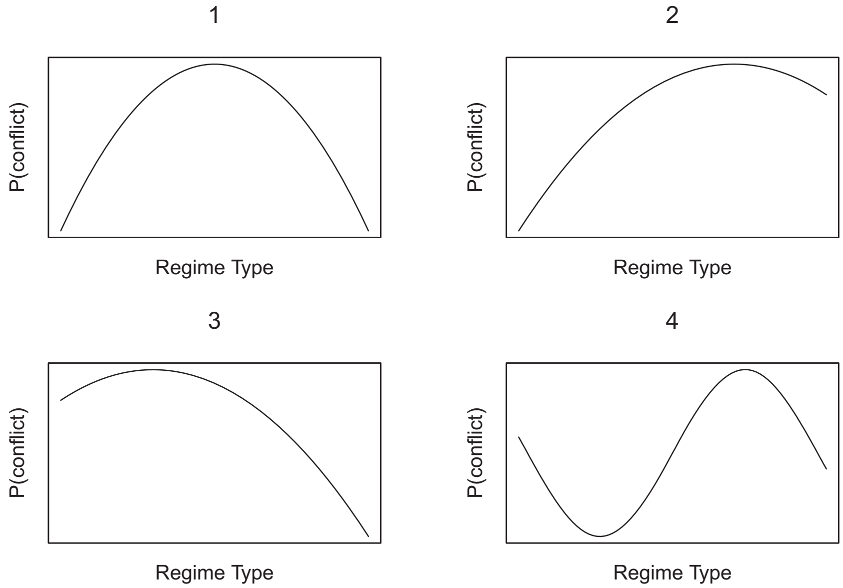
To illustrate these issues, Figure 1 provides stylized relationships between Polity and the probability of conflict. In Plot 1, the relationship between Polity and conflict is consistent with the MVM Hypothesis. A binary indicator of regimes in the −5 to +5 range would be estimated to have a significant positive relationship with the probability of conflict given enough data. Like Plot 1, the relationship in Plot 2 is consistent with the MVM Hypothesis. Nonetheless, a binary anocracy indicator, as used in the existing literature, may not distinguish between the underlying relationships in Plot 1 (in which autocracies and democracies are equally likely to experience conflict) and Plot 2 (in which autocracies are more likely than democracies to experience conflict). Plots 3 and 4 present underlying relationships that are not consistent with the MVM Hypothesis. Nonetheless, depending on the distribution of the Polity data in the sample, a binary anocracy indicator could be estimated to have a positive and significant coefficient, leading one to incorrectly infer support for the MVM Hypothesis. In Plot 3, this could occur if there are many more observations in the −10 to −5 range than there are in the 5 to 10 range, and vice versa in Plot 4.[5]

A second common approach to testing the MVM Hypothesis is to estimate a polynomial regression that includes a squared regime type measure. If the coefficient of the squared term is negative and statistically distinguishable from zero, scholars often argue, this indicates that the relationship between regime type and violence exhibits the "inverted U" shape consistent with more violence in the middle. We found 60 published articles that use this approach.

This approach raises several issues. First, the published work using this approach assumes a particular function form. A significant squared term is interpreted as indicating a bend in the regression function given this specified functional form. Second, a significant squared term does not indicate where that bend lies in the curve. This problem is analogous to the well-known problem with respect to interaction terms: "The point is that simply having a significant marginal effect across some values

[5]The problem could be addressed by also including an additional binary indicator for democracy or autocracy, but this would not address the problem of distinguishing which anocracies drive the result.

FIGURE 2 Stylized Relationships between Regime Type and the Probability of Conflict



of the modifying variable is not particularly interesting if real-world observations rarely fall within this range" (Brambor, Clark, and Golder 2006, 76). Only three of the published articles we surveyed provide a plot to demonstrate the shape of the curve. Third, the statistical significance of the squared term alone is insufficient to establish that the polynomial regression is more appropriate than including the linear term alone. Only five of the articles we found conducted some analysis of model fit; of these, three found that the inclusion of the polynomial term improved the fit of the model and two found that the model excluding the polynomial term resulted in a better fit.

To illustrate some of the limitations of the polynomial model approach to testing the MVM Hypothesis, Figure 2 provides stylized relationships between regime type and the probability of conflict. All of the plots in Figure 2 describe relationships that could yield a negative and significant coefficient on a squared regime type variable. In addition, they all describe relationships that are consistent with the MVM Hypothesis in the sense that the largest probability of conflict is found in regime types that are not fully autocratic or fully democratic. Nonetheless, the underlying relationships in these plots are all quite different, and the polynomial approach as practiced in the bulk of the existing literature does not allow us to distinguish between them.[6]

Research Design

We propose a research design that mitigates key limitations of existing tests of the MVM Hypothesis. Our design does not require prespecification of a functional form, thus allowing us to uncover the extent to which the relationships between regime type and forms of conflict follow the inverse-U shape. Our design estimates the extent to which different regime types are at risk of experiencing conflict and, in turn, the points in the regime type spectrum at which such risks are largest. This design also allows us to avoid arbitrary operationalization of anocracy. Existing analyses suggest conflict dynamics have changed in recent years (Kalyvas and Balcells 2010), and our design allows us to examine this interaction in detail.

Modeling Technique

We use a nonparametric multivariate regression method that can detect nonlinear, discontinuous, interactive relationships while not overfitting the data. Specifically, we use an ensemble of multivariate, randomized conditional inference trees (Hothorn, Hornik, and Zeileis 2006), which are similar to a random forest (Breiman 2001), which itself is a randomized version of bagged

[6]In Plot 4, there are two bends in the curve, which could be detected by using a cubed regime type variable. We are not aware of any study of the MVM Hypothesis that also included a cubed regime type term.

classification or regression trees (CART). These methods are described in greater detail by Jones and Linder (2016) and Friedman, Hastie, and Tibshirani (2001), and they have been used to study political violence in work by Hill and Jones (2014) and Muchlinski et al. (2016), among others.

CART. We begin with a general description of CART, followed by a description of the implementation we use. CART is a supervised machine learning algorithm that constructs a piecewise, constant approximation to the regression function. CART can detect nonlinear and interactive relationships that do not have to be prespecified by the analyst. It does so by iteratively partitioning the outcome variable(s) observations into increasingly homogenous groups using the covariates. It then predicts outcomes using a constant function of the response variable in the resulting partitions.

Suppose, for example, that we wish to predict a discrete outcome based on several covariates. First, starting with all of the data (referred to as the "root node"), a classification tree considers possible binary splits of the data using particular values of a covariate. It selects these splits and the resulting partitions by considering the reduction in prediction error that would result from differing possible partitions. CART computes predictions by summarizing the data in these possible partitions, by, for example, predicting the modal class of the data that fall into a partition. Thus, the reduction in prediction error that would result from splitting the data using a particular value of the selected covariate is the difference between (a) the prediction error in the "parent" node and (b) the sum of the prediction errors in the two resulting "child" nodes. For the selected covariate, CART chooses the partition that maximizes this reduction in prediction error. Each of the child nodes is more homogenous along the outcome variable than the root node. CART repeats this process, creating smaller partitions until a stopping criterion is met (e.g., when the difference between the prediction error computed at a current partition and the prediction error computed in a further partition is sufficiently small). The result of this process is a set of recursive partitions of the data. That is, the observations are iteratively grouped in a nonoverlapping and exhaustive manner; that is, no observation falls into more than one partition and all observations are in a partition. The smallest set of these partitions is the terminal nodes. In the terminal nodes, the prediction is a constant function of the data in those nodes. When the tree is complete, the algorithm passes each observation down the tree until a terminal node is reached. At that terminal node, the algorithm makes a prediction for that observation based on the outcome for the subset of observations at that node.

Because CART, as developed by Breiman (2001), exhibits splitting behavior biased toward covariates with many values (e.g., continuous covariates are preferred to discrete covariates even in the case where, by construction, none have any relationship with the response), we utilize the algorithm of Hothorn, Hornik, and Zeileis (2006; a conditional inference tree) to avoid this problem. This algorithm first uses a permutation statistic to measure the relationship between each covariate and the response. It then computes a multiplicity-adjusted p-value for this statistic, which is scale-invariant, avoiding the aforementioned problem of a preference for covariates with more values. This value allows it to test the global null hypothesis of no relation between the covariates in the partition. If this global null hypothesis can be rejected at a prespecified level of confidence, then the covariate with the smallest p-value is selected, and an optimal split in the selected covariate is found using a similar procedure. A split occurs when there is a statistically distinguishable relationship between at least one of the covariates and the outcome in a proposed partition, again using a permutation statistic. This becomes less likely as partitions become smaller. Eventually, we reach a stopping criterion at which there is not a significant difference between the covariates in a partition and the outcome. This algorithm grows trees that are of an optimal size in terms of bias and variance.

Conditional inference trees can be used with multivariate outcomes; that is, the relationships between the covariates and multiple outcomes can be estimated simultaneously. This produces a model fit that is similar to that of a series of univariate models, but is faster to estimate and programmatically easier to use. To extend CART or conditional inference trees to multivariate outcomes requires a measure of prediction error that encodes errors made in all of the outcome variables. Because we are using the method of Hothorn, Hornik, and Zeileis (2006), this requires us to sum the statistics, which have the same scale, for each of the outcome variables, resulting in splits that balance the importance of predicting the outcome variables equally.

Random Forests and Bagging. Thus far, we have explained how CART learns using one tree. We use an ensemble of conditional inference trees that is similar to a random forest. In this subsection, we first explain this methodology generally and then provide details about the implementation we use, which follows the implementation used by Hill and Jones (2014).

A random forest is an ensemble of many randomized trees. Each tree is grown with a randomly sampled set of data taken from the full set of data, and each node in each tree may have different predictors randomly selected to be available for a possible split. This increases the diversity of the trees' predictions, reducing the variance of the average of the trees' predictions, thus lowering overall prediction error. A nonlinear relationship between a particular covariate and the outcome can be detected because the partitioning algorithm of the individual trees can make multiple splits on the same variable in addition to making different splits in said variable across trees in the forest. The detection of interactions between covariates works similarly. This methodology does not make strong assumptions about the functional form of underlying relationships. As others (Hill and Jones 2014; Muchlinski et al. 2016) who have used this methodology in the political violence context have shown, random forests provide more accurate predictions of such outcomes than models traditionally used in political science (e.g., logit).

Such ensembles are effective relative to individual trees because they reduce the variance of predictions, which results in an overall decrease in prediction error at a rate dependent on the correlation between the trees' predictions. Random forests and similar algorithms further decrease the dependence of trees' predictions by, at each node, randomly selecting a subset of the covariates as candidates for splitting. Random forests have been empirically successful in comparison to other modern machine learning methods and are less prone to overfitting than CART or bagged CART (Fernández-Delgado et al. 2014).

We use an ensemble of 1,000 such trees. Each tree is used to learn about the underlying predictor–outcome functions independently of the other trees. We do this by first randomly creating 1,000 samples from our data by using block (country) subsampling (i.e., we draw country time-series without replacement). We combine the results of the 1,000 trees as follows. Each tree makes predictions using the data that were not in the subsample used to fit that tree. For binary outcomes, the predicted value for an observation is the most commonly predicted value for that observation across all the terminal nodes (the node at which the stopping criterion is met) in each decision tree in the forest. For continuous outcomes, the predicted value for an observation is the mean across all the terminal nodes. For discrete outcomes, the predicted probability is the proportion of observations that belong to each category averaged across all the terminal nodes.

Data

Outcome Variables. For civil wars, we use data from the UCDP/PRIO Armed Conflict Dataset (Gleditsch et al. 2002) on intrastate conflicts in which there were 1,000 or more battle deaths. For civil conflicts, we use the UCDP/PRIO Armed Conflict Dataset to identify conflicts in which there were 25 or more battle deaths. For both civil wars and civil conflicts, we include an onset dependent variable as well as a count of ongoing conflicts. For international conflicts, we use Version 4 of the Militarized Interstate Disputes (MID) data (Palmer et al. 2015). While we estimate the relationship between regime type and all of the MID categories, we focus on MIDs in which force was used (i.e., Level 4 or higher) in our results.

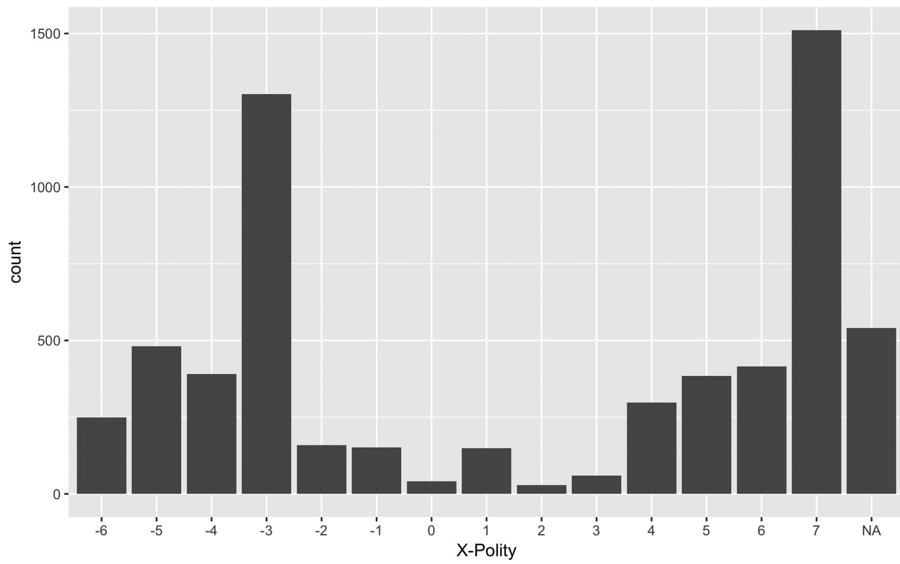
To measure terrorism, we use the data provided by the Global Terrorism Database (GTD). The GTD includes violent, intentional attacks conducted by subnational actors, such as assassinations, bombings, and assaults. The GTD data are coded based on a variety of primary news sources and secondary sources, such as books, journals, and legal materials. We include in our models country-year counts of the number of attacks and deaths from such attacks.

To measure state repression, we use the data provided by Fariss (2014).[7] Violations of physical integrity are notoriously difficult to measure. Many competing measures of these violations exist, but each is subject to measurement error. States often violate these rights in secret and have both the incentives and the means to hide evidence. Most measures of these violations also require the assumption that the standard of accountability under which violations are reported and coded has not changed over time, yet Fariss (2014) argues that it has. He provides an estimate of physical integrity rights violations based on a measurement model that takes into account information provided by multiple competing measures and relaxes assumptions about whether the standard of accountability has changed over time.

To measure violent and nonviolent dissent events, we use counts of events based on the Integrated Data for Event Analysis (IDEA) data, as compiled by Murdie and Bhasin (2011). The IDEA data are coded based on events reported in Reuters Global News Service. Based on the data set, Murdie and Bhasin (2011) created a count of violent events (e.g., assaults, shootings, and riots) with respect to which the target is a state agent or institution, and a count of nonviolent events (e.g., protest marches, demonstrations, boycotts, and sit-ins) with respect to which the target is a state agent or institution. Because the Murdie and Bhasin (2011) data end in 2004, for the years 2005–8, we use data provided by the Integrated

[7] We reverse the coding of this variable such that more repressive regimes are assigned positive values and less repressive regimes are assigned negative values.

FIGURE 3 Distribution of X-Polity, 1970–2008



Crisis Early Warning System (ICEWS; Boschee et al. 2015). These data are based on coverage in global news sources in multiple languages. Details on which ICEWS events are included in our data are provided in the supporting information.

To measure violent attacks against civilians by governments and formally organized nongovernmental armed groups, we use the UCDP One-Sided Violence Dataset (Eck and Hultman 2007). The data set provides information on the number of civilians killed by governments and other groups for those country-years in which such killings numbered 25 or more. Extrajudicial killings of individuals in government custody are excluded. Finally, we include the UCDP Non-State Conflict Dataset (Sundberg, Eck, and Kreutz 2012), which defines nonstate conflict as "the use of armed force between two organized armed groups, neither of which is the government of a state, which results in at least 25 battle-related deaths in a year." We use the geo-referenced versions of both data sets (Sundberg and Melander 2013).

Our data for most of these variables cover the years 1970–2008, but coverage for the UCDP One-Sided Violence and Non-State Conflict data begins in 1989, and coverage for the IDEA data begins in 1990. We therefore estimate two models. The temporal span for one model begins in 1970, and this model omits the One-Sided Violence, Non-State Conflict, and IDEA/ICEWS data. The temporal span for the second model begins in 1990, and this model includes all of the outcome variables. The supporting provides information about the correlations between all of our outcome variables.

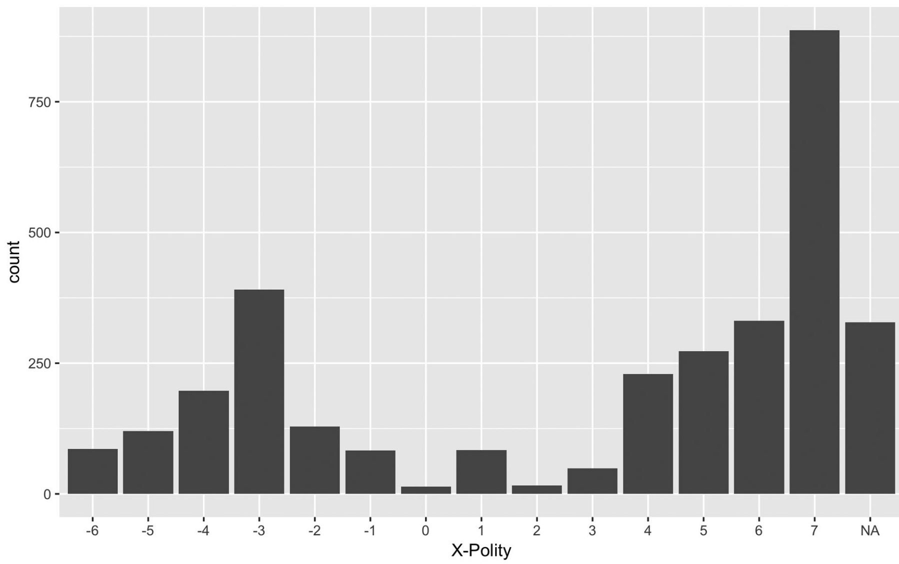
Predictor Variables. For our primary measure of regime type, we rely on the Polity data. Some version of the Polity data has been used in 96 of the 111 published articles we found that test the MVM Hypothesis. We use X-Polity, the version of the Polity data created by Vreeland (2008),[8] which removes indicators that are associated with factionalism and violence. X-Polity ranges from −6, indicating most autocratic, to 7, indicating most democratic. Figures 3 and 4 provide the distributions of the X-Polity data in our samples covering 1970–2008 and 1990–2008, respectively. X-Polity codes a plurality of country-years as fully democratic (7) and a large share of other country-years as semi-autocratic (−3).

We include several other variables that predict both regime type and conflict. Economic development is a well-known predictor of political violence in various forms and is closely associated with regime type, so we include in our models the natural log of per capita GDP using data provided by Gleditsch (2002). Larger states may be more likely to experience violent events, and this may especially be true when such events are coded by the number of fatalities. Population may also be related to regime type. We include the natural log of population using data provided by Gleditsch (2002).

We include both the ethnolinguistic fractionalization measure provided by Fearon (2003) and the excluded population measure provided by the Ethnic Power Relations Dataset (Wimmer, Cederman, and Min 2009),

[8]Vreeland's data coverage ends in 2004. We updated the data through 2015.

FIGURE 4 **Distribution of X-Polity, 1990–2008**



which provides the share of the national population that belongs to a group that is politically powerless, discriminated against, or self-excluded from politics. Because oil exports are associated with both regime type and conflict, we include a measure of per capita oil production (in barrels) provided by Wimmer, Cederman, and Min (2009). We include an indicator of whether the state is within 2 years of its independence and an indicator of whether the state has a new regime, based on the Polity data.

Finally, we include the year of the observation, which allows us to account for the possibility of differing relationships between regime type and conflict over time. Nonparametric methods like the one we use here are capable of automatically estimating whether the relationships between the covariates and outcomes vary across time (year in this case) because year is treated in a manner similar to other covariates.

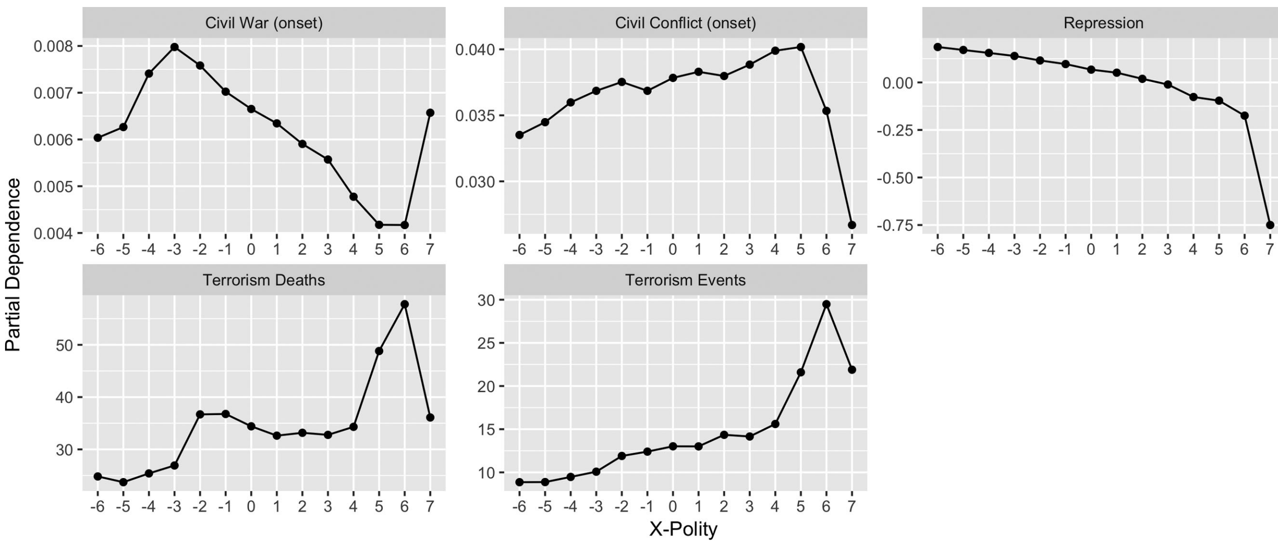
Missing Data. Missingness is an issue with several of our predictor and outcome variables. This missingness is likely to be nonrandom, although some of the reasons for missingness may be correlated to other variables in our models. Such missingness can be a problem with decision trees when a predictor with missing observations is selected for a split. In such a scenario, it would be unclear in which partition to put the observations with missing observations. We minimize the impact of missingness on our models by using surrogate splitting. Surrogate splitting treats missingness as a classification problem. It uses the other predictor variables to model the relationship between a given observation's being in the one partition versus another partition and chooses the option that minimizes the difference between the candidate partition and a partition that would ignore missingness.

Results

We focus on examining the extent to which the relationship between regime type and conflict is or is not consistent with the inverse U predicted by the MVM Hypothesis. We do not conduct formal tests of whether a parameter differs from zero, and thus we need not assume the independence of observations necessary for common estimates of sampling variability.

The algorithm generates predictions for each outcome variable as a function of the covariates in a way that minimizes the expected error on new data from the same historical data-generating process. The estimated function, that is, the output, is not directly interpretable. While CART are directly interpretable with a univariate response, viewed as a tree, such tree diagrams are less interpretable with a multivariate response. Ensembles of univariate CART and, thus, ensembles of multivariate CART are not interpretable directly, as, in our case, our output is 1,000 multivariate conditional inference trees, each of which has used different covariates and was estimated on random country subsamples of the data. We can, however, calculate approximations to the marginal relationship between regime type and conflict estimated from the data. These approximations to the marginal relationship give the partial dependence of conflict on regime

FIGURE 5 Partial Dependence of X-Polity and Conflict, 1970–2008



type, adjusted for the estimated effects of the control variables previously mentioned. The partial dependence of a covariate on the model gives the marginal relationship between said covariate and the outcomes as estimated by the model, and it gives the exact form of the relationship if/when the function being approximated can be factorized as an additive or multiplicative function of the covariate(s) in question. These plots are similar to average marginal effects in the sense that they show the predicted probability or expected value of some outcome given a covariate, averaging over the estimated effects of the other covariates.

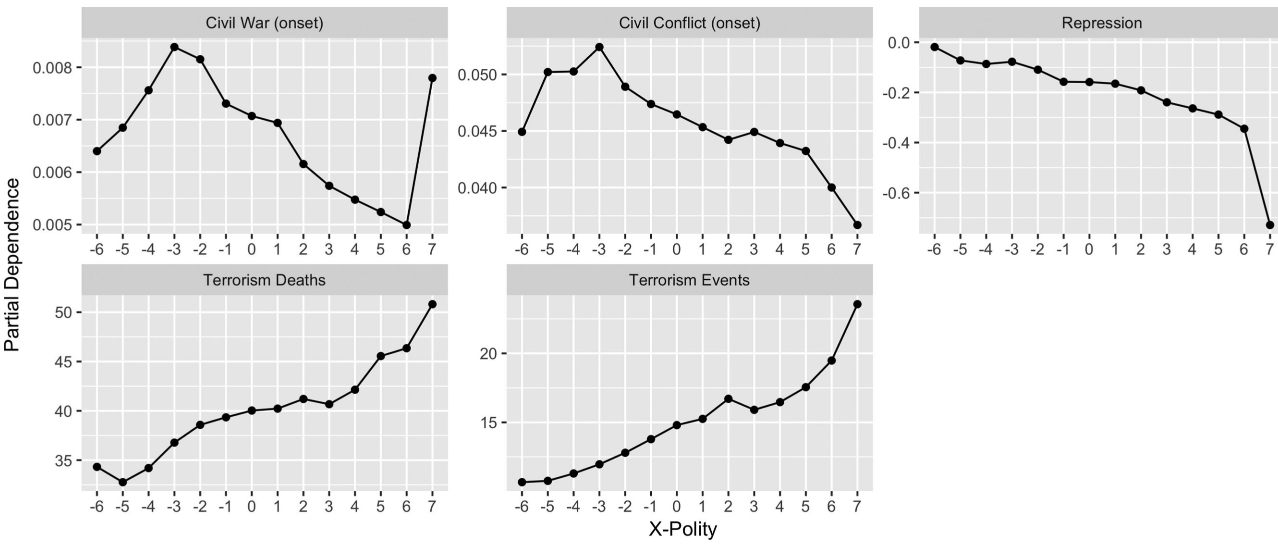
A more technical explanation of partial dependence plots follows. Partial dependence marginalizes the estimated model, specifically by averaging over the features that are not of interest, and is equivalent to average marginal effects, but can be applied in situations (e.g., when using a method like random forests) where derivatives are not available. Specifically, partial dependence computes $\hat{f}_{\mathbf{X}_s}(\mathbf{X}) = \frac{1}{N}\sum_{i=1}^{N} \hat{f}(\mathbf{X}_S, \mathbf{X}_{-S}^{(i)})$, where $\hat{f}$ is the estimated model and $\mathbf{X}_s$ represents covariates that are of interest. Partial dependence was first proposed by Friedman (2001) and is further described in Friedman, Hastie, and Tibshirani (2001) and Jones and Linder (2016). Although typically applied to estimated functions that map a multivariate set of covariates to a univariate response, its application to a function mapping multivariate covariates to a multivariate response requires no modification.

Because of space considerations, we focus our discussion on the outcome variables that have received the most attention in existing work: civil conflict/war onset, terrorism events, terrorism deaths, and repression. For these outcome variables, Figures 5 and 6 provide the partial dependence plots from our models for the years 1970–2008 and 1990–2008, respectively.[9] Each set of plots is the result of one multivariate ensemble of conditional inference trees and demonstrates the marginal relationships between the applicable measure of regime type and the outcome variables according to the fitted model. Each plot shows the extent to which states at different points on the regime type spectrum are at risk for the applicable form of conflict, averaged over the other predictor variables. We do not average over the other forms of conflict in producing a given partial dependence plot; however, the CART model learns the relationship between regime type and all of the outcome variables simultaneously.

With respect to civil wars and civil conflicts, our results indicate that onset is most likely in regimes that are neither fully autocratic nor democratic. While these results are generally consistent with the MVM Hypothesis, interpreted broadly, several second-order results are also notable. The results suggest that elevated levels of onset risk may apply only to certain types of anocracies. With respect to civil war onset, for example, we find in the 1970–2008 model that the risk peaks when X-Polity is at −3 and consistently declines with democracy until rising again for full democracies. The increased onset risk for democracies is largely driven by multiple civil war onsets in India, which X-Polity codes as full democracy in the entire time period. By contrast, with respect to civil

[9]Results for the other outcome variables are provided and discussed in the supporting information.

FIGURE 6 Partial Dependence of X-Polity and Conflict, 1990–2008



conflict onset, we find that the risk consistently increases with democracy until X-Polity is at 5, and then decreases. The two findings jointly suggest that the risk of large-scale internal conflicts decreases with democracy (up to a point), but the risk of smaller-scale internal conflicts increases with democracy (again, up to a point). In the 1990–2008 model, we continue to find that onset risk is largest in some types of anocracies, but we find a roughly equivalent risk of civil war onset for the most democratic regimes (a finding again driven by the coding of India).

With respect to terrorism, our results differ depending on the temporal scope. In the 1970–2008 model, we find that the expected numbers of terrorism deaths and events are largest when X-Polity is at 6. While this is consistent with the MVM Hypothesis in the sense that such regimes are neither fully autocratic nor fully democratic, the result reveals a more complex relationship than a simple inverse U. The result suggests that existing findings of support for the MVM Hypothesis may be driven by a particular set of regimes in "the middle" that are actually quite close to full democracies. In addition, the expected numbers of terrorism events and deaths in full democracies are greater than in full autocracies. In the 1990–2008 model, however, we find that terrorism events and deaths increase consistently with democracy. This suggests that the relationship between regime type and terrorism has changed since the Cold War, at least with respect to full democracies, a question we return to in the next subsection.

In both models, we find that the expected level of repression of physical integrity rights consistently decreases as regimes become more democratic. This is in sharp contrast to the MVM Hypothesis, and instead supports what Davenport (2007) calls the domestic democratic peace. As Hill (2016) notes, similar prior findings may have been driven by the use of the full Polity index, which includes a measure of political competition (the participation competitiveness or "parcomp" component), thus coding political violence into the independent variable. Our finding is thus noteworthy because the X-Polity measure excludes this component of the Polity index, but we nonetheless find an inverse relationship between democracy and repression.

Additional Tests

Regime Type and Conflict over Time. Have the relationships between regime type and conflict changed over time? Our results with respect to terrorism suggest the end of the Cold War is associated with a change in the regime type–terrorism relationship. In addition, important work has argued that civil conflicts during the Cold War had different characteristics than post–Cold War civil conflicts (Kalyvas 2001; Kalyvas and Balcells 2010). Our methodology allows us to analyze interactions between regime type, conflict, and time to understand whether the Cold War and/or other events are associated with changes in these relationships.

The results of these analyses, reported in the supporting information, indicate that while civil war onset risk increased at the end of the Cold War, it has remained relatively large for states in the −4 to −2 range throughout the years in question. In addition, civil war onset risk for the most democratic states has dropped throughout the era. This indicates that our finding of support for the MVM Hypothesis with respect to civil war onset is consistent for almost all of the years in our model (except the early 1970s, when the risk was largest in full democracies). On the other hand, with respect to the civil conflicts, we find that our results support the MVM Hypothesis only during the Cold War. Collectively, these findings suggest the end of the Cold War may have altered the relationship between regime type and low-intensity civil conflicts, but it may not have altered the relationship between regime type and civil wars, a finding we hope will motivate further research on this point.

We also find that, throughout the time period, semi-democratic states coded as 5 or 6 have the largest expected numbers of both terrorism deaths and events. Nonetheless, we do find that the end of the Cold War is associated with a reduction in the extent to which terrorism is most likely in such regimes. Finally, we find that, across all years, the most autocratic regimes are also the most likely to abuse physical integrity rights.

Alternative Regime Type Measure. Democracy is a notoriously difficult concept to measure. In our primary models, we use X-Polity to allow for comparability to the bulk of existing work. Yet the Polity scale has been criticized for, among other factors, coding seemingly heterogeneous regimes at similar values (Pemstein, Meserve, and Melton 2010; Treier and Jackman 2008). To begin to assess the dependence of our results on the measure of regime type, we estimate a second set of models that replace X-Polity with the Unified Democracy Scores (UDS), a latent variable measure based on several prior measures (Pemstein, Meserve, and Melton 2010). This type of measure has been argued to provide several advantages over a traditional index measure (Fariss 2014; Pemstein, Meserve, and Melton 2010; Treier and Jackman 2008). First, the latent variable approach does not assume that indicators of an unobserved measure are independent, whereas indicators such as Polity generally do. Second, the latent variable approach estimates how much weight to assign to each indicator based on the data, whereas additive indicators require the analyst to assign weights to indicators.

The full Polity data set is one of the input variables used to estimate the original version of UDS, and this creates a potential problem because some Polity indicators are associated with factionalism and violence (Vreeland 2008). We therefore construct a new version of UDS (which we refer to as X-UDS), in which we replace Polity with X-Polity. X-UDS is otherwise constructed exactly in the same manner as UDS. X-UDS is a continuous measure, with negative values indicating more autocratic regimes and positive values indicating more democratic regimes.

The distribution of X-UDS is quite different from that of X-Polity. While a plurality of observations are coded toward the extremes of the scale using X-Polity, observations cluster toward the middle of the scale using X-UDS. Thus, many regimes coded as full democracies by X-Polity fall closer to the middle of the scale of X-UDS. These include several states that have experienced frequent conflict of various forms, including India, Peru, Turkey, and South Africa. In addition, X-UDS provides an estimate of the level of democracy for the bulk of observations coded by X-Polity as experiencing an interruption, an interregnum, or a transition. The supporting information provides density plots of the X-UDS measure in our samples. Figures 7 and 8 provide the partial dependence plots from our models for the years 1970–2008 and 1990–2008, respectively.[10]

In both models, we find that the risk of civil war onset decreases as democracy increases, in sharp contrast to the MVM Hypothesis and the results of the X-Polity models. In addition, we do not find a spike in civil war onset risk for full democracies in the X-UDS models, as we did in the X-Polity models. This is likely because, unlike X-Polity, X-UDS does not code India as a full democracy. With respect to civil conflict, we find that the risk is largest in some regimes that are neither fully democratic nor autocratic. We also find that civil conflict is smallest in full democracies.

The results of the X-UDS models also differ from the X-Polity results with respect to terrorism. In the 1970–2008 period, both measures suggest that the expected numbers of deaths and events are largest in semi-democratic states. In the X-Polity models, this risk peaks at a value of 6 (almost full democracies), whereas in the X-UDS models, the risk peaks closer to the center of the spectrum. The results across the two measures differ more sharply in the 1990–2008 models. With X-UDS, we find relatively low expected values of terrorism events and deaths in full democracies, in sharp contrast to the X-Polity results, which suggest such events and deaths increase consistently with democracy. What might account for these differences? The findings may be driven by a set of country-years coded by X-Polity as a 7 (or full democracy), but coded toward the middle of the scale by X-UDS. Examples of countries that (a) have experienced many terrorist events and deaths, (b) are coded by

[10] Partial dependence plots for the other outcome variables are provided and discussed in the supporting information.

FIGURE 7 Partial Dependence of X-UDS and Conflict, 1970–2008

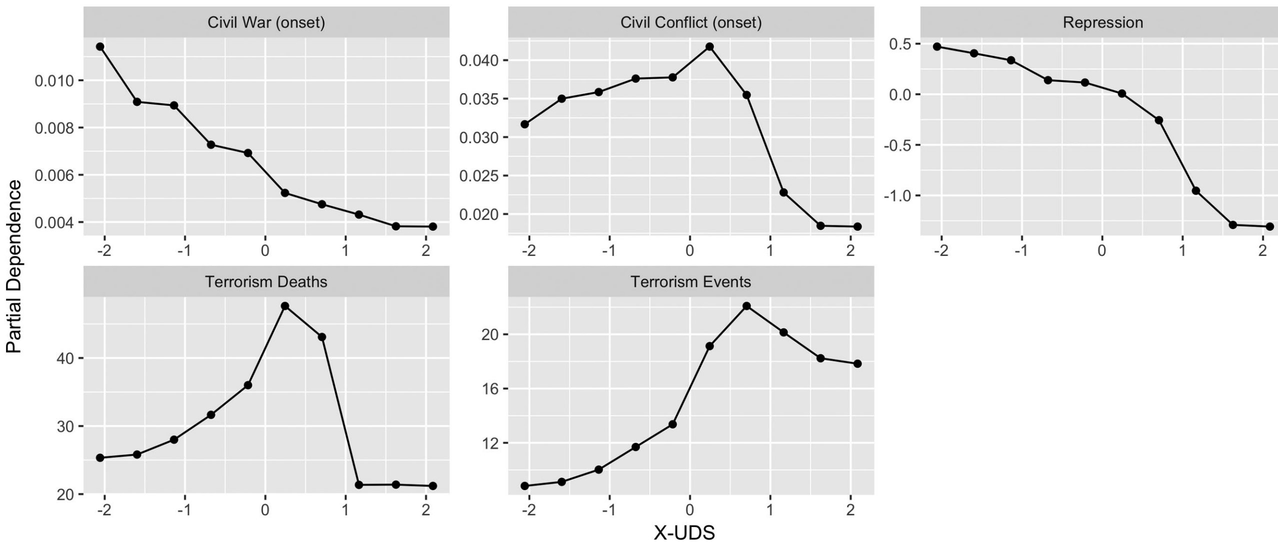
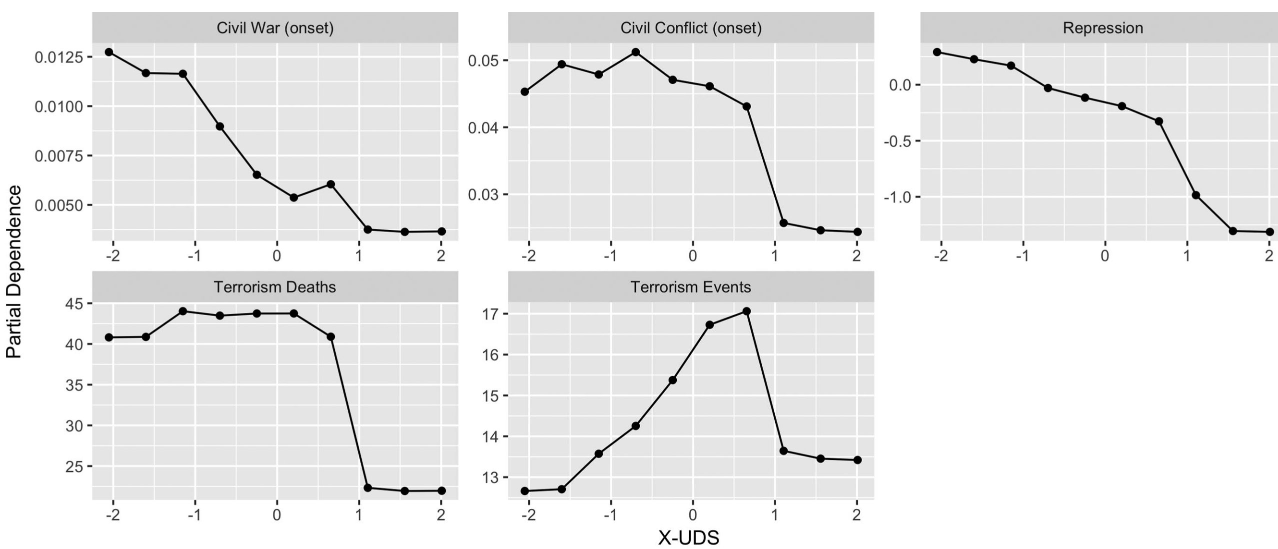


FIGURE 8 Partial Dependence of X-UDS and Conflict, 1990–2008



X-Polity as full democracies, and (c) are coded by X-UDS as semi-democracies (i.e., between 0 and 1) include India, Pakistan (early 1990s), Turkey, and South Africa (early 1990s).

Just as in the X-Polity models, the X-UDS models indicate that repression consistently decreases with democracy. Given the differences between the two regime type measures, this is a remarkable finding that suggests the robustness of the inverse relationship between democracy and repression. The only notable difference between the results across the two measures is that the expected level of repression declines more steadily with democracy along the X-UDS scale, whereas it declines more slowly along the X-Polity measure followed by a large decline at the fully democratic tail.

Interruption, Interregnum, and Transition. Our primary models treat periods of interruption, interregnum, and transition as missing data, as described earlier. Yet conflict may intuitively appear to be likely in these country-years. The supporting information therefore provides the results of alternative models that compare these missing categories in the X-Polity data to other observations.

TABLE 1 Summary of Results

	X-Polity		X-UDS	
	1970–2008	1990–2008	1970–2008	1990–2008
Civil war onset	Peaks in semi-autocracies (−4 to −2)	Peaks in semi-autocracies (−4 to −2)	Declines with democracy	Declines with democracy
Civil conflict onset	Peaks in semi-democracies (3 to 5)	Peaks in semi-autocracies (−5 to −2)	Peaks near the middle	Peaks in semi-autocracies
Repression	Declines with democracy	Declines with democracy	Declines with democracy	Declines with democracy
Terrorism deaths	Peaks in semi-democracies (6)	Increases with democracy	Peaks near the middle	Peaks near the middle
Terrorism events	Peaks in semi-democracies (6)	Increases with democracy	Peaks near the middle	Peaks near the middle

Bivariate Relationships. While our multivariable models ensure comparability with existing work by accounting for variables that could bias the relationship between regime type and conflict, analysts may also be interested in the bivariate relationships between regime type and conflict. The supporting information provides the results of bivariate models that include X-Polity as the only predictor variable.

Conclusions

The goal of this article has been to analyze the relationship between regime type and conflict using a research design that mitigates the limitations of existing work. We describe the conditions under which the MVM Hypothesis does and does not hold according to our methods. Our hope is that by providing an abundance of novel empirical results that, as we have argued, derive from a research design more appropriate for analyzing this question, this article will lead to further theorizing about the relationships between regime type and conflict and to a deeper awareness of the dependence of inferences on the choice of regime type measure. Where we do find evidence that is consistent with the MVM Hypothesis, we also find that only certain anocracies are especially conflict-prone. In some cases, a broad range of anocracies are more conflict-prone, whereas in other cases only a specific type of anocracy is especially conflict-prone. Table 1 provides a brief summary of our key results.

With respect to civil wars and civil conflicts, studies of which have perhaps most prominently analyzed the MVM directions for future research. First, as noted above, our findings depend in part on the measure of regime type. That our evidence is consistent with the MVM Hypothesis with X-Polity is in some ways surprising because the initial publication of X-Polity did not find support for the MVM Hypothesis (Vreeland 2008). We have provided possible explanations for the divergence between our X-UDS and X-Polity results with respect to civil wars, and we hope future research will examine the relationships between these measures and conflict in greater detail. An improved understanding of those differences could lead to an improved understanding of the regime type–conflict relationship. Second, even with the X-Polity measure, we find that only specific types of anocracies are especially conflict-prone. We hope this finding will spur future theoretical work about why such anocracies might be more prone to civil wars and conflicts.

We find consistent support for what Davenport (2007) calls the domestic democratic peace, that is, the notion that repression is least likely in full democracies. This finding is consistent across time and across measures of regime type. Given that we also find that civil war onset risk is relatively small in semi-democracies and democracies,[11] reading the two findings together suggests that repression and civil war onset risk have similar relationships with regime type, at least at the predictive level. This accords with a recent finding that civil wars are highly predictive of repression (Hill and Jones 2014). In addition, existing work has posited that democratic institutions condition and/or explain the relationship between civil war onset and repression (Besley and Persson 2009).[12] Our results are suggestive of a relationship among these

[11] With India, as coded by X-Polity but not by X-UDS, we find a possible exception.

[12] Others argue that democratic institutions are unlikely to constrain repression once a violent conflict has broken out (Davenport 2007).

phenomena, although further theoretical and empirical work is needed to assess causal mechanisms.

We find much evidence in support of the notion that terrorism is more likely in regimes that are neither fully autocratic nor fully democratic. This is especially interesting because terrorism scholars have not focused on the concept of anocracy to the same extent as have, for example, civil war scholars. Instead, much new work on the relationship between regime type and terrorism focuses on specific institutions. Our results are especially consistent with arguments of the type made by Aksoy and Carter (2014), indicating that states with some democratic institutions may experience more terrorism, but that additional such institutions reduce this risk. Our results suggest a similar pattern, but additional work is needed to determine which aspects of democracy contribute to the relatively large risk of terrorism in some regime types.

References

Aksoy, Deniz, and David B. Carter. 2014. "Electoral Institutions and the Emergence of Terrorist Groups." *British Journal of Political Science* 44(1): 181–204.

Besley, Timothy, and Torsten Persson. 2009. "Repression or Civil War?" *American Economic Review* 99(2): 292–97.

Boschee, Elizabeth, Jennifer Lautenschlager, Sean O'Brien, Steve Shellman, James Starz, and Michael Ward. 2015. "ICEWS Coded Event Data." Harvard Dataverse, https://doi.org/10.7910/DVN/28075.

Brambor, Thomas, William Roberts Clark, and Matt Golder. 2006. "Understanding Interaction Models: Improving Empirical Analyses." *Political Analysis* 14(1): 63–82.

Breiman, Leo. 2001. "Random Forests." *Machine Learning* 45(1): 5–32.

Chenoweth, Erica. 2010. "Democratic Competition and Terrorist Activity." *Journal of Politics* 72(1): 16–30.

Davenport, Christian. 2007. *State Repression and the Domestic Democratic Peace.* New York: Cambridge University Press.

Davenport, Christian, and David A. Armstrong. 2004. "Democracy and the Violation of Human Rights: A Statistical Analysis from 1976 to 1996." *American Journal of Political Science* 48(3): 538–54.

Dragu, Tiberiu. 2011. "Is There a Trade-Off between Security and Liberty? Executive Bias, Privacy Protections, and Terrorism Prevention." *American Political Science Review* 105(1): 64–78.

Eck, Kristine, and Lisa Hultman. 2007. "One-Sided Violence Against Civilians in War: Insights from New Fatality Data." *Journal of Peace Research* 44(2): 233–46.

Fariss, Christopher J. 2014. "Respect for Human Rights Has Improved over Time: Modeling the Changing Standard of Accountability." *American Political Science Review* 108(2): 297–318.

Fearon, James D. 2003. "Ethnic and Cultural Diversity by Country." *Journal of Economic Growth* 8(2): 195–222.

Fearon, James D., and David D. Laitin. 2003. "Ethnicity, Insurgency, and Civil War." *American Political Science Review* 97(1): 75–90.

Fein, Helen. 1995. "More Murder in the Middle: Life-Integrity Violations and Democracy in the World, 1987." *Human Rights Quarterly* 17(1): 170–91.

Fernández-Delgado, Manuel, Eva Cernadas, Senén Barro, and Dinani Amorim. 2014. "Do We Need Hundreds of Classifiers to Solve Real World Classification Problems?" *Journal of Machine Learning Research* 15(1): 3133–81.

Friedman, Jerome H. 2001. "Greedy Function Approximation: A Gradient Boosting Machine." *Annals of Statistics* 29(5): 1189–1232.

Friedman, Jerome, Trevor Hastie, and Robert Tibshirani. 2001. *The Elements of Statistical Learning.* Vol. 1. Springer Series in Statistics. Berlin: Springer.

Gibler, Douglas M., and Steven V. Miller. 2014. "External Territorial Threat, State Capacity, and Civil War." *Journal of Peace Research* 51(5): 634–46.

Gleditsch, Kristian Skrede. 2002. "Expanded Trade and GDP Data." *Journal of Conflict Resolution* 46(5): 712–24.

Gleditsch, Kristian Skrede, and Andrea Ruggeri. 2010. "Political Opportunity Structures, Democracy, and Civil War." *Journal of Peace Research* 47(3): 299–310.

Gleditsch, Nils Petter, Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg, and Håvard Strand. 2002. "Armed Conflict 1946–2001: A New Dataset." *Journal of Peace Research* 39(5): 615–37.

Hegre, Håvard, Tanja Ellingsen, Scott Gates, and Nils Petter Gleditsch. 2001. "Toward a Democratic Civil Peace? Democracy, Political Change, and Civil War, 1816–1992." *American Political Science Review* 95(1): 33–48.

Hill, Daniel W. 2016. "Democracy and the Concept of Personal Integrity Rights." *Journal of Politics* 78(3): 822–35.

Hill, Daniel W., and Zachary M. Jones. 2014. "An Empirical Evaluation of Explanations for State Repression." *American Political Science Review* 108(3): 661–87.

Hothorn, Torsten, Kurt Hornik, and Achim Zeileis. 2006. "Unbiased Recursive Partitioning: A Conditional Inference Framework." *Journal of Computational and Graphical Statistics* 15(3): 651–74.

Jones, Zachary M., and Fridolin Linder. 2016. "edarf: Exploratory Data Analysis Using Random Forests." *Journal of Open Source Software* 1(6): 92.

Kalyvas, Stathis. 2001. "New and Old Civil Wars." *World Politics* 54(1): 99–118.

Kalyvas, Stathis N., and Laia Balcells. 2010. "International System and Technologies of Rebellion: How the End of the Cold War Shaped Internal Conflict." *American Political Science Review* 104(3): 415–29.

Marshall, Monty, and Keith Jaggers. 2002. "Polity IV Project: Political Regime Characteristics and Transitions, 1800–2002." http://www.systemicpeace.org/polity/polity4.htm.

Mitchell, Sara McLaughlin, Jonathan J. Ring, and Mary K. Spellman. 2013. "Domestic Legal Traditions and States Human Rights Practices." *Journal of Peace Research* 50(2): 189–202.

Muchlinski, David, David Siroky, Jingrui He, and Matthew Kocher. 2016. "Comparing Random Forest with Logistic Regression for Predicting Class-Imbalanced Civil War Onset Data." *Political Analysis* 24(1): 87–103.

Muller, Edward N., and Erich Weede. 1990. "Cross-National Variation in Political Violence: A Rational Action Approach." *Journal of Conflict Resolution* 34(4): 624–51.

Murdie, Amanda, and Tavishi Bhasin. 2011. "Aiding and Abetting: Human Rights INGOs and Domestic Protest." *Journal of Conflict Resolution* 55(2): 163–91.

Palmer, Glenn, Vito D'Orazio, Michael Kenwick, and Matthew Lane. 2015. "The MID4 Dataset, 2002–2010: Procedures, Coding Rules and Description." *Conflict Management and Peace Science* 32(2): 222–42.

Peic, Goran, and Dan Reiter. 2011. "Foreign-Imposed Regime Change, State Power and Civil War Onset, 1920–2004." *British Journal of Political Science* 41(3): 453–75.

Pemstein, Daniel, Stephen A. Meserve, and James Melton. 2010. "Democratic Compromise: A Latent Variable Analysis of Ten Measures of Regime Type." *Political Analysis* 18(4): 426–49.

Pierskalla, Jan H. 2010. "Protest, Deterrence, and Escalation: The Strategic Calculus of Government Repression." *Journal of Conflict Resolution* 54(1): 117–45.

Regan, Patrick M., and Sam R. Bell. 2010. "Changing Lanes or Stuck in the Middle: Why Are Anocracies More Prone to Civil Wars?" *Political Research Quarterly* 63(4): 747–59.

Sambanis, Nicholas. 2001. "Do Ethnic and Nonethnic Civil Wars Have the Same Causes? A Theoretical and Empirical Inquiry (Part 1)." *Journal of Conflict Resolution* 45(3): 259–82.

Sundberg, Ralph, and Erik Melander. 2013. "Introducing the UCDP georeferenced event dataset." *Journal of Peace Research* 50(4): 523–32.

Sundberg, Ralph, Kristine Eck, and Joakim Kreutz. 2012. "Introducing the UCDP non-state conflict dataset." *Journal of Peace Research* 49(2): 351–62.

Treier, Shawn, and Simon Jackman. 2008. "Democracy as a Latent Variable." *American Journal of Political Science* 52(1): 201–17.

Urdal, Henrik. 2006. "A Clash of Generations? Youth Bulges and Political Violence." *International Studies Quarterly* 50(3): 607–29.

Vreeland, James Raymond. 2008. "The Effect of Political Regime on Civil War: Unpacking Anocracy." *Journal of Conflict Resolution* 52(3): 401–25.

Wade, Sara Jackson, and Dan Reiter. 2007. "Does Democracy Matter? Regime Type and Suicide Terrorism." *Journal of Conflict Resolution* 51(2): 329–48.

Wimmer, Andreas, Lars-Erik Cederman, and Brian Min. 2009. "Ethnic Politics and Armed Conflict: A Configurational Analysis of a New Global Data Set." *American Sociological Review* 74(2): 316–37.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

- MVM Hypothesis Literature
- ICEWS Data
- Outcome Variable Correlations
- Additional Results
- Interactions with Time
- Interruption, Interregnum, and Transition
- X-UDS
- Bivariate Relationships