Is There More Violence in the Middle?

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June 14, 2017

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" and overlooks dependencies across forms of conflict. This paper aims to resolve the empirical uncertainty about the relationship between regime type and conflict 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 simultaneously predict multiple forms of conflict using a large set of explanatory variables. Our results indicate the specific conditions under which there is or is not more violence in the middle.

1 Introduction

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 middle range – often referred to as anocracies – that are neither fully autocratic nor fully democratic (Muller, 1985; Fein, 1995; Hegre et al., 2001; Eck and Hultman, 2007). 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), while others have confirmed his result (Peic and Reiter, 2011). Likewise, some find support for the hypothesis with respect to repression (Mitchell, Ring, and Spellman, 2013), while others do not (Davenport and Armstrong, 2004; Davenport, 2007). With respect to terrorism, some find evidence that terrorism is most common in anocracies (Wade and Reiter, 2007), while others do not (Chenoweth, 2010).

The purpose of this paper is to resolve the empirical uncertainty about the MVM Hypothesis and describe the conditions under which it does or does not hold. While 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.[1] While such tools allow us to potentially reject a

[1] A key exception is Davenport and Armstrong (2004), which we discuss in detail below.

monotonic relationship, subject to strong assumptions, they limit what we can learn about the underlying relationship and are not well-suited for understanding the complex ways in which regime type may predict conflict (e.g., unspecified interaction and/or non-linearity). Additionally, while many different forms of political violence have been hypothesized to be more common in anocracies, existing studies have not accounted for the ways in which those forms of dissident-state interactions are themselves closely related to each other, for example as complements or substitutes (Davenport, 2012). 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.

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 also allows us to simultaneously learn the relationship between regime type and multiple forms of conflict, thus taking into account the ways in which those outcomes are inter-related. Finally, 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,[2] we find, with some exceptions, that conflict is most likely in regimes that are neither fully autocratic nor fully democratic. We also provide several additional results that describe the 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-

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

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. This suggests existing findings in support of the MVM Hypothesis may be driven by this particular set of regimes in the middle; we hope our results will lead to further research about why certain types of anocracies–and particularly why the institutional configurations in these regimes–may be at greater risk of civil wars. Along similar lines, while our results with respect to terrorism are consistent with the MVM Hypothesis, our results also indicate that only anocracies that are almost fully democratic are especially terrorism-prone; other types of anocracies do not appear to be at greater risk of terrorism than full democracies. Again, we hope our results will re-focus the research agenda toward explaining why these particular institutional configurations may be more terrorism-prone, rather than focusing on all anocracies. Second, while prior work left the question open, we find the MVM Hypothesis does not appear to hold with respect to repression of physical integrity rights, which we find consistently decrease 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 of regime type that has not been widely used in this literature (Pemstein, Meserve, and Melton, 2010), some of our findings change. While we continue to find that some forms of conflict are most likely in some anocracies, when we use this measure we find that the risk of civil war onset is largest for full autocracies and decreases with democracy.

2 The MVM Hypothesis

The MVM Hypothesis gained prominence first in the repression literature based on claims by Muller (1985) and Fein (1995), and later in the civil war literature based on findings by Hegre et al. (2001) and Fearon and Laitin (2003). While theoretical justifications for the MVM Hypothesis vary in their details, they generally rely on intuitions such as those expressed by Muller and Weede (1990: 631) 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.” Along similar lines, Hegre et al. (2001: 33) argue that “[s]emi-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., 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 113 articles that test whether some form of political violence is more common in the middle range of the regime type spectrum. The version of the MVM Hypothesis that has received the most scholarly attention regards the relationship between regime type and civil war or civil conflict. A series of highly cited early papers found that civil wars are more likely in anocracies (Hegre et al., 2001; Fearon and Laitin, 2003), although other work published during the same era found no evidence for this (Sambanis, 2001).

The measurement of regime type has been an important concern in this literature. Most studies 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 during civil wars, thus making those measures inappropriate for testing the MVM Hypothesis. After removing these components from the index, he re-analyzes the data from Hegre et al. (2001) and Fearon and Laitin (2003), but does not find support for the hypothesis. More recently, however, other scholars have used Vreeland's modified Polity measure in models of civil war onset, with some finding that anocracies are more likely to experience civil wars (Gleditsch and Ruggeri, 2010) and others confirming Vreeland's finding (Peic and Reiter, 2011). Compounding the extent to which the literature has found mixed results with respect to this relationship, studies using latent variable measures of democracy have also yielded inconsistent results. These latent measures of regime type are subject to the criticism made by Vreeland (2008), however, as they rely on the full Polity index.

Empirical findings with respect to the relationship between regime type and the repression of human rights are also mixed. Early work discovered that repression decreases with 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. Some subsequent work has confirmed the inverse relationship between democracy and repression (Davenport and Armstrong, 2004; Davenport, 2007), while others find support for an inverse-U relationship between regime type and repression (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 (Young and Findley, 2011; 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. Democratization – rather than the static level of democracy – has also been argued to have important effects on violence. The most prominent debate about the effects of democratization has focused on its relationship to the likelihood that a state engages in interstate war, but democratization has also been linked to civil war and violent protests.

3 Limitations of Existing Research

3.1 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 as OLS and logistic regression. Such approaches have limitations because (1) relationships may be more complex than analysts assume; (2) the parameters of the assumed functional forms may not be the only unknowns in the true relationships; and (3) they rest on strong assumptions.

In contrast to other existing work, Davenport and Armstrong (2004) use tools that weaken assumptions about functional form. First, they estimate the bivariate relationship between measures of regime type and human rights repression by using a nonparametric method (LOESS, a type of local regression), which has the advantage of not requiring the specification of a functional form. This tool cannot be used to examine multivariate relationships, and hence does not allow for adjustments based on factors that might confound the relationship between regime type and conflict. Second, they expand regime type (which is measured in an ordered categorical fashion) into a series of binary variables, which effectively allows a linear model to estimate a step function (i.e., a piecewise discontinuous function) for the relationship between regime type and repression, but this results in lost information about the ordering of the regime type measure.

3.2 Operationalizing "The Middle"

What is "The Middle"? Conceptual definitions of anocracy or semi-democracy vary, with some focusing on static characteristics and others on ongoing changes in regime characteristics. Examples of definitions can be found in Hegre et al. (2001), who use the term semi-democracy rather than anocracy, referring to them as "partly open yet somewhat repressive" (p. 33); and Regan and Bell (2009), 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" (p. 749).

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 between -5 or 5 (Fearon 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 cut-offs 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. The coefficient for such an indicator may be driven by countries within some part of the anocracy range, in which case the interpretation of the result may not be accurate with respect to the anocracy range. 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, and this result could be correctly interpreted as supporting the MVM Hypothesis. Like plot 1, the relationship in plot 2 is consistent with the MVM Hypothesis. Nonetheless, this method for testing the MVM Hypothesis, as practiced in the existing literature, does 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 indicator for the middle range of regime types 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.[3]

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

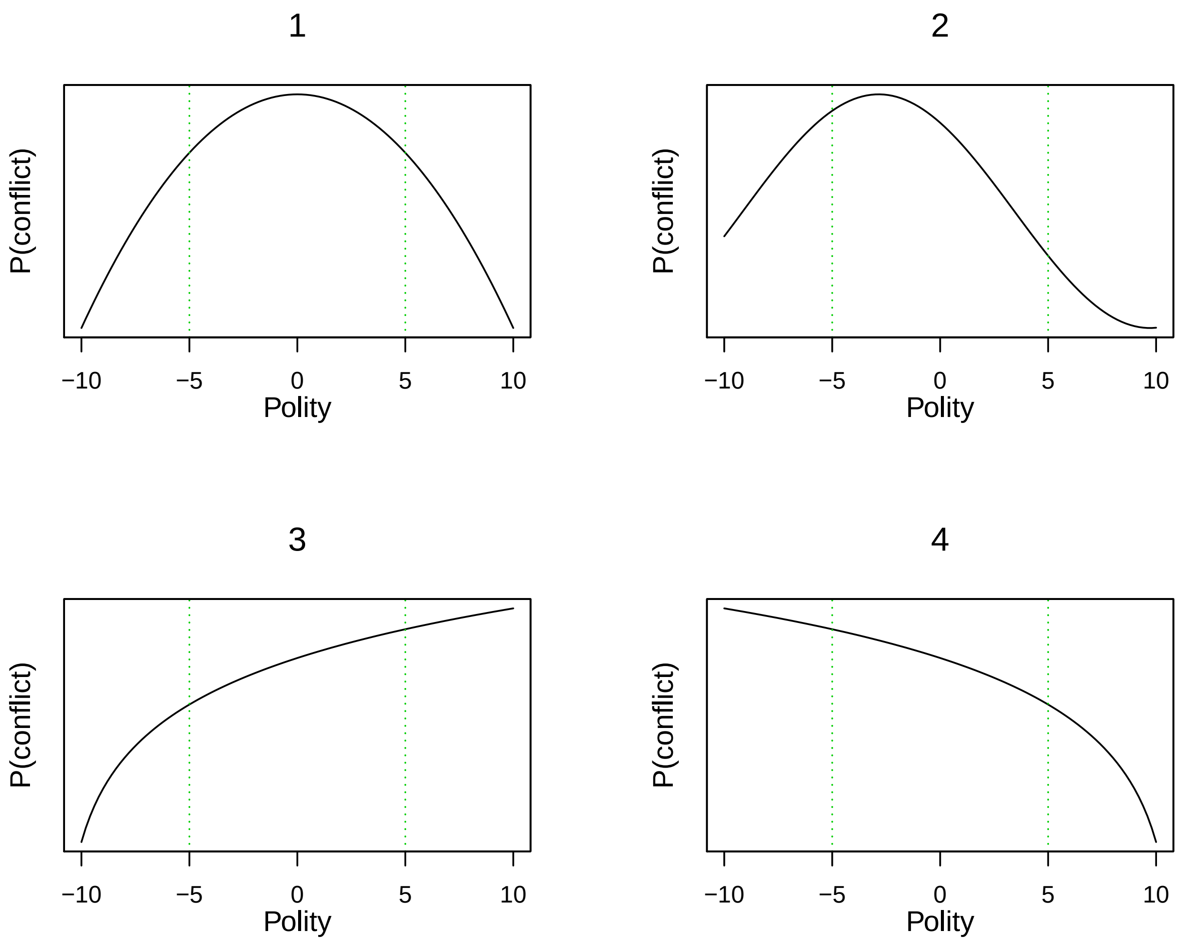

Figure 1: Stylized relationships between Polity and the probability of conflict.

A second common approach to testing the MVM Hypothesis is to estimate a polynomial regression that includes a squared regime type measure. We found 60 published articles that use this approach. If the coefficient of the square 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.

While this approach is simple to implement and provides useful information about underlying relationships, it raises several issues. First, the published work using this approach assumes a particular function form. A significant squared term can only be interpreted as indicating a bend in the regression function assuming the underlying functional form is correct. 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 of the modifying variable is not particularly interesting if real-world observations rarely fall within this range" (Brambor, Clark, and Golder, 2006: p.14). Only 3 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. To do this, one must analyze whether the polynomial model fits the data better. Only 5 of the articles we found conducted some analysis of model fit; of these, 3 found that the inclusion of the polynomial term improved the fit of the model and 2 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 nor 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.[4]

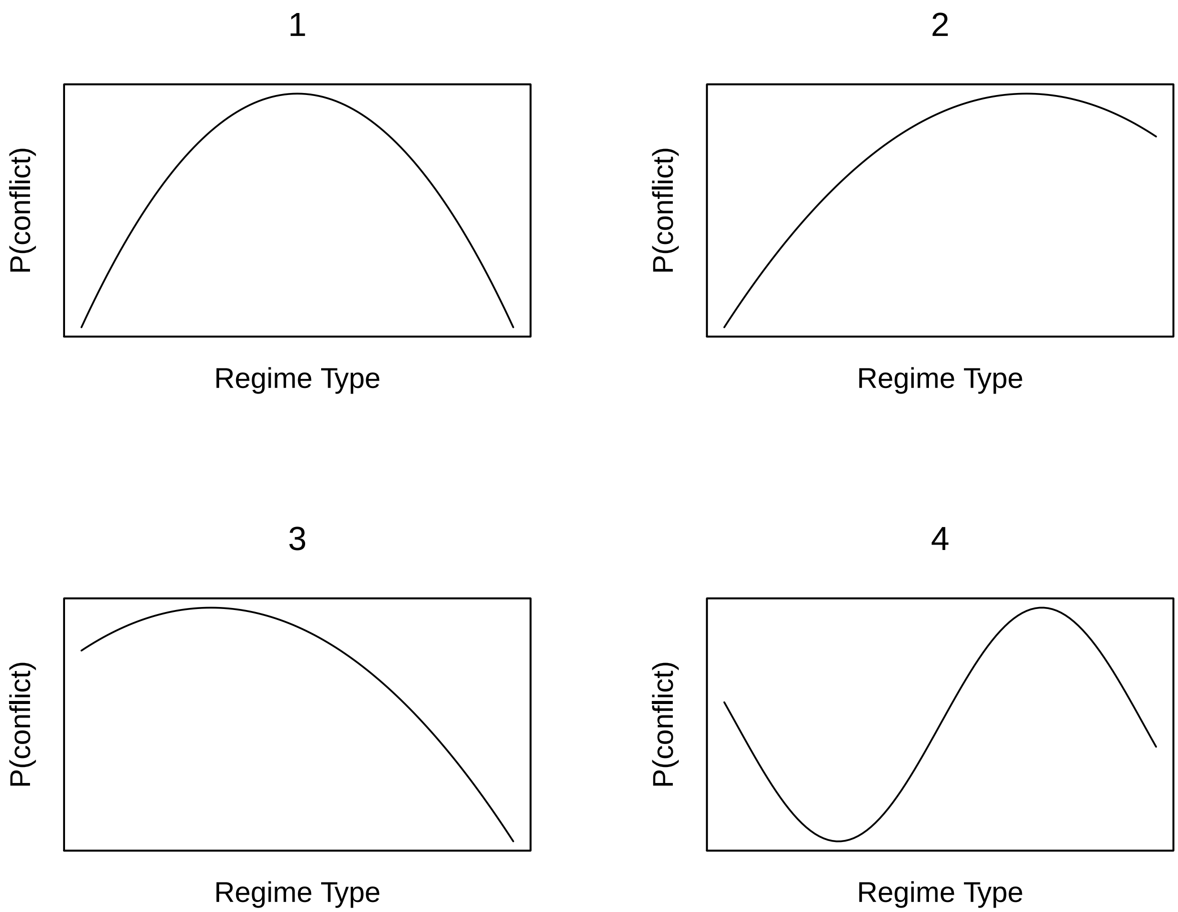

Figure 2: Stylized relationships between regime type and the probability of conflict.

[4]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.

3.3 Relationships Between Forms of Dissident-State Interaction

A third limitation in existing research is that the different forms of conflict are related to each other in many complex ways. Unfortunately, researchers in this area are often siloed into distinct communities that focus on one form of contestation or another. As Moore (2015) notes, scholars "who study 'ethnic conflict,' 'terrorism,' 'counter-insurgency,' 'civil war,' and so forth are implicitly arguing that the conflict processes that unfold in the type of dissident-state interaction they are studying are meaningfully distinct from the conflict processes that unfold in other forms of dissident-state interaction" (p. 364).

A wealth of evidence suggests that different types of interactions between dissidents and states are closely related. Civil wars are the best predictors of state repression (Hill and Jones, 2014). During civil wars, both violence against civilians and terrorism can take on more distinct logics than they do in other contexts (Findley and Young, 2012). Repression and dissent have important effects on each other, which scholars continue to uncover. Non-violent collective action is also closely related to these phenomena because it can serve as a substitute for violent dissent (Chenoweth and Stephan, 2011).

4 Research Design

We propose a research design that mitigates key limitations of existing tests of the MVM Hypothesis. Our design does not require pre-specification 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 allows us to estimate 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, as well as to discover interactions between regime type and other variables (e.g., time). A final advantage of our design is that it allows us to jointly model the relationship between regime type and multiple forms of conflict that, as noted above, are inter-related. In turn, this allows us to examine support for the MVM Hypothesis for multiple forms of conflict while taking into account the relationships between those forms of conflict.

4.1 Modeling Technique

To estimate the relationship between regime type and conflict, we use a nonparametric multivariate regression method that can detect nonlinear, discontinuous, interactive relationships while not over-fitting 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 classification or regression trees (CART) (Breiman et al., 1999). These methods are described in greater detail by Jones and Linder (2015) and Friedman, Hastie, and Tibshirani (2001). These tools have been used to study political violence in work by Hill and Jones (2014) and Muchlinski et al. (2016), among others. Cranmer and Desmarais (2017) provide a general description of the relationship between these tools and other tools often used by political scientists.

4.1.1 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 piece-wise, constant approximation to the regression function. CART can detect non-linear and interactive relationships that do not have to be pre-specified 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 estimates the univariate relationship between each covariate and the outcome variable. The algorithm then selects the covariate that best predicts the outcome variable. Next, the algorithm considers possible splits of the data into multiple nodes. It does so 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 non-overlapping and exhaustive manner, i.e., no observation falls into more than one partition and all observations are in a partition. The smallest set of these partitions are 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 pre-specified level of confidence, then the covariate with the smallest p-value is selected, and an optimal split in the selected covariate is found. A split occurs when there is a distinguishable relationship between at least one of the covariates and the outcome in a proposed partition. 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.

Second, to extend CART 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 importance of the outcome variables equally.

4.1.2 Random Forests and Bagging

Thus far, we have explained how CART learns using one tree. We use an ensemble of the aforementioned conditional inference trees which 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 non-linear 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. If the trees' predictions are independent, then averaging reduces variance at a rate of $\frac{1}{\text{no. of trees}}$. For example, consider a set of independent and identically distributed random variables $x_1, x_2, \ldots, x_n$. Because each of these random variables are identically distributed they all have the same expectation. The value of any particular observation is thus an unbiased estimator of the expectation or population average mean. However, the variance of this estimator is much larger than the variance of the sample mean, which is smaller by a factor of $\frac{1}{n}$. When there is dependence between the random variables, this efficiency gain decreases at a rate determined by the correlation between the random variables. This same idea is what motivates the use of ensembles for prediction. 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 over-fitting than CART or bagged CART (Fernández-Delgado et al., 2014).

We use an ensemble of 1000 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 1000 samples from our data by using block (country) sub-sampling (i.e., we draw country time-series without replacement).

We combine the results of the 1000 trees as follows. Each tree makes predictions using the data that were not in the sub-sample 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 criteria 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.

4.2 Data

4.2.1 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 1000 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 the relationship between 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 sub-national 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).[5] Violations of

[5]We reverse the coding of this variable such that more repressive regimes are assigned positive values

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 non-violent 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 non-violent events (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 2005-2008 we use data based on the Cross-National Time Series Archive (Banks, 2015). The Banks (2015) data are coded based on coverage in The New York Times and only include events with respect to which the number of participants meets certain thresholds.

To measure violent attacks against civilians by governments and formally organized non-governmental 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, which defines non-state conflict as "the use of armed force between two organized armed groups, neither of which is the government of a

and less repressive regimes are assigned negative values.

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 sets of models. The temporal span for one set of models begins in 1970, and these models omit the One-Sided Violence, Non-State Conflict, and IDEA data. The temporal span for the second set of models begins in 1990, and these models include all of the outcome variables. The Appendix provides information about the correlations between all of our outcome variables.

4.2.2 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 113 published articles we found that test the MVM Hypothesis. We use X-Polity, the version of the Polity data created by Vreeland (2008),[6] 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).

[6]Vreeland's version of X-Polity ends in 2004. We created an updated version of X-Polity, using the Polity IV data, with coverage through 2015.

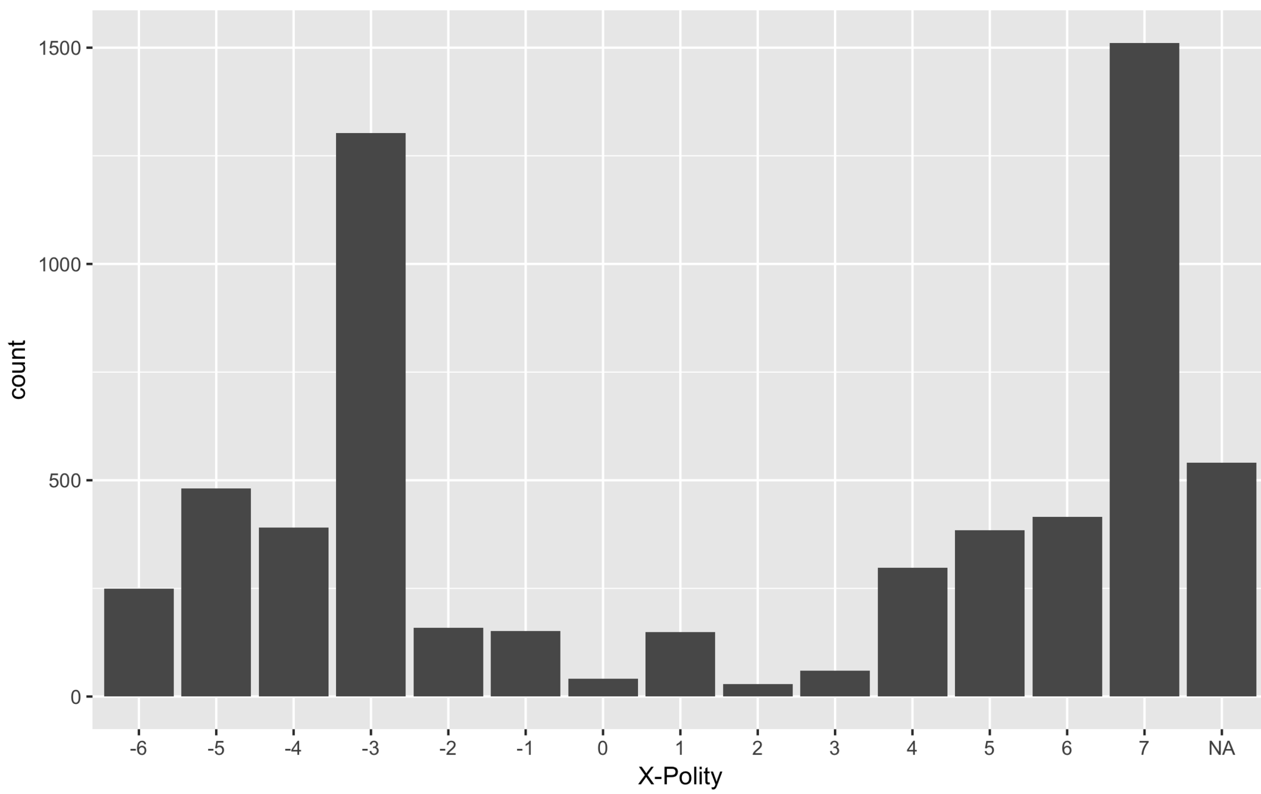

Figure 3: Distribution of X-Polity, 1970-2008.

We include both the ethno-linguistic fractionalization measure provided by Fearon (2003) and the excluded population measure provided by the Ethnic Power Relations Dataset (Wimmer, Cederman, and Min, 2009), which provides the share of the national population that belongs to a group that is politically powerless, discriminated against, or self-excluded from politics–factors which are undoubtedly related to both regime-type and conflict. 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 also include an indicator of whether the state is within two years of its independence. We also include an indicator if 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 rela-

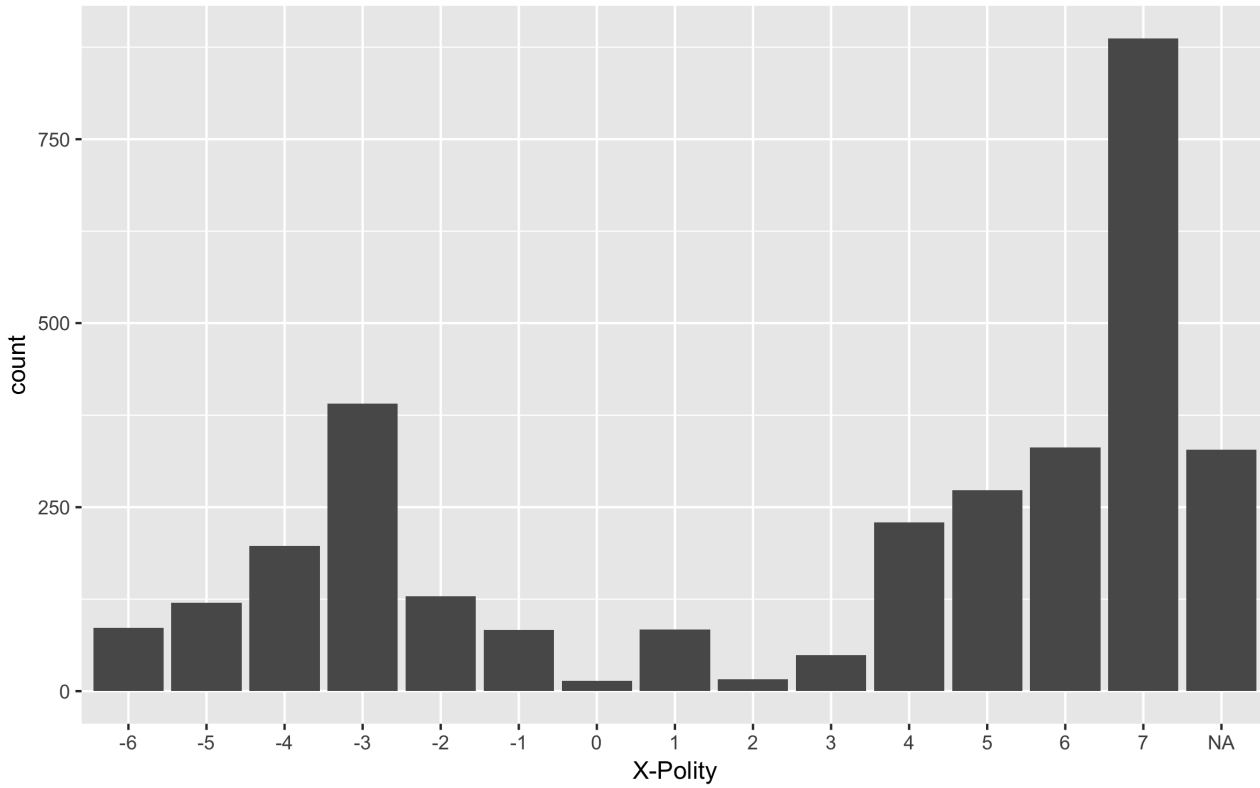

Figure 4: Distribution of X-Polity, 1990-2008.

tionships between the covariates and outcomes vary across time (year in this case) because year is treated in a manner similar to other covariates.[7]

4.2.3 Missing Data

Missingness is an issue with several of our predictor and outcome variables. This missingness is likely to be non-random, 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

[7]We do not include lagged outcome variables or other corrections for serial correlation because our methodology does not require us to assume observations are independent.

variables to model the relationship between a given observation 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.

5 Results

We focus on examining the extent to which the functional form 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 1000 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-type, adjusted for the 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 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 effects of the other covariates.

A more technical explanation of partial dependence plots follow. 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 (such as 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 (2015). 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. We use the Monte-Carlo Methods for Prediction Functions (*mmpf*) package in R (Jones, 2017).

Because of space considerations, we focus our discussion of results to the outcome variables that have received the most attention in existing work: civil war onset, civil conflict 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.[8] 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. 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, so in that sense the partial dependence plots represent the relationship between the explanatory variables and the outcome variables collectively.

[8]Partial dependence plots for the other outcome variables are provided and discussed in the Appendix.

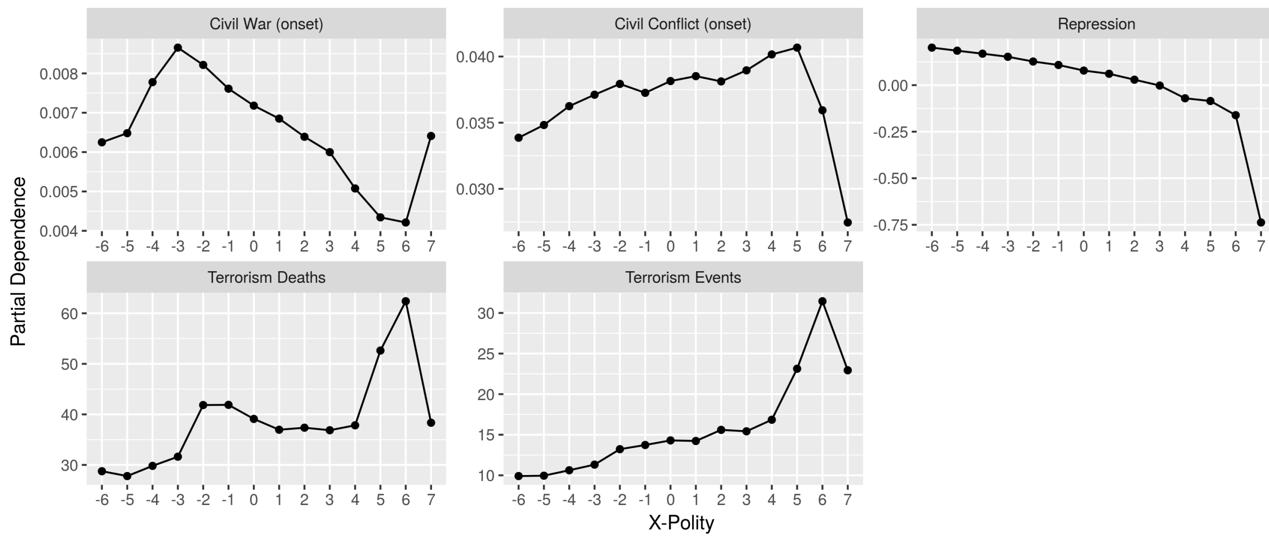

Figure 5: Partial dependence of X-Polity and conflict, 1970-2008.

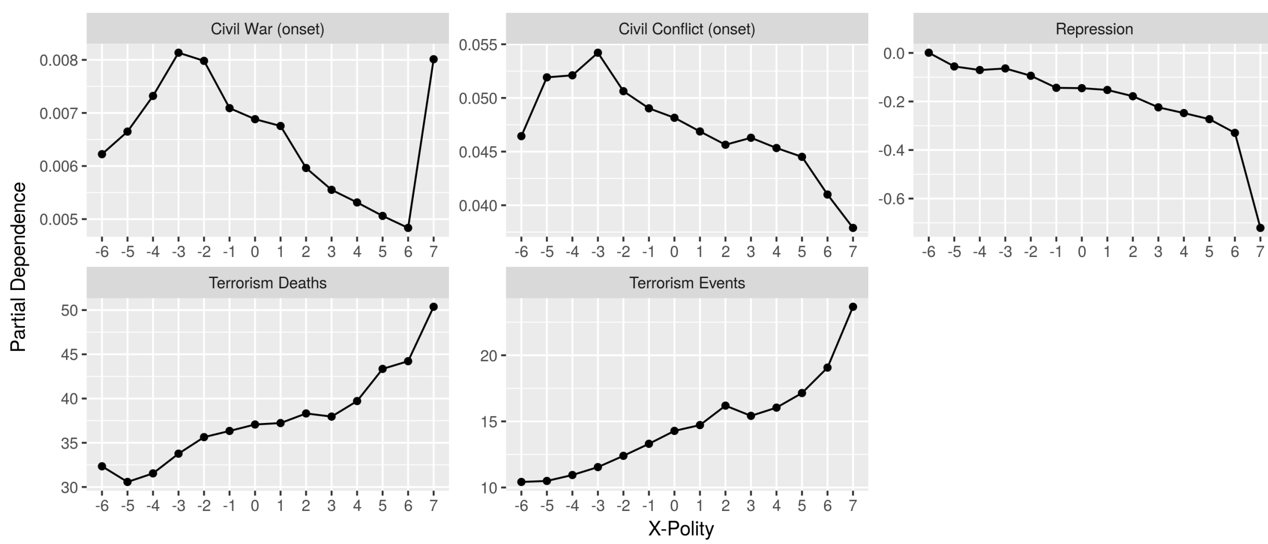

Figure 6: Partial dependence of X-Polity and conflict, 1990-2008.

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 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 find a roughly equivalent risk of civil war onset for the most democratic regimes (a finding again driven by India).

With respect to terrorism, our results differ depending on the temporal scope. In the 1970-2008 model, we find that the expected number of terrorism deaths and events is 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. The expected number 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 Section 5.1.

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.

5.1 Regime Type and Conflict over Time

Have the relationships between regime type and conflict changed over time? Our design allows us to analyze interactions between regime type, conflict, and time to answer this question. The results of these analyses, reported in the Appendix, indicate civil war onset risk 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 was not driven by a small number of years, but was consistent for almost all of the years in our model (except the early 1970s, when the risk was largest in full democracies). 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, although with respect to both the expected number dropped sharply in the early 1990s. Finally, we find that, across all years, we find that the most autocratic regimes are also the most likely to abuse physical integrity rights.

5.2 Additional Tests

5.2.1 Interruption, Interregnum, and Transition

The Polity data includes three categories of country-years that are not coded along the primary democracy-autocracy scale. Periods of interruption (coded as -66) include foreign occupations and other short-term changes in political institutions. Periods of interregnum (coded as -77) include collapses of the central government, most often during periods of civil war. Periods of transition (coded as -88) are those in which new institutions are in the process of being implemented. In our main models, we treat these observations as described in Section 4.2.3.

Conflict may intuitively appear to be likely in these country-years. To analyze this, we estimated additional models that treat X-Polity as a categorical variable for all observations. This operationalization loses information about the scale of the index, but allows us to compare the country-years coded as experiencing interruption, interregnum, or transition to the other observations. The results of these models, reported in the Appendix, indicate that civil wars, militarized interstate disputes, repression, terrorism, and both violent and non-violent dissent are especially likely during periods of interruption. During periods of interregnum, civil wars, civil conflicts, repression, and non-state violence are especially likely. During periods of transition, civil conflicts and repression are especially likely. With respect to some forms of conflict, these events are much more likely during periods of interruption, interregnum, and/or transition than they are during periods coded along the standard X-Polity scale.

5.2.2 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 heterogenous regimes at similar values (Treier and Jackman, 2008; Pemstein, Meserve, and Melton, 2010). As noted above, the plurality of country-years are coded as 7 or -3.

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). 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, interregnum, or transition. The Appendix 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.[9] In several important ways, the results from the models that use X-UDS differ from those that use X-Polity. Overall, the results of the X-UDS models are less consistent with the MVM Hypothesis than those of the X-polity models.

In both of the X-UDS 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-

[9]Partial dependence plots for the other outcome variables are provided and discussed in the Appendix.

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 number of deaths and events is largest in semi-democratic states. In the X-Polity models this risk peaks at a value of 6, almost full democracies, while 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 X-Polity results that 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 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 followed by a large decline at the fully democratic tail.

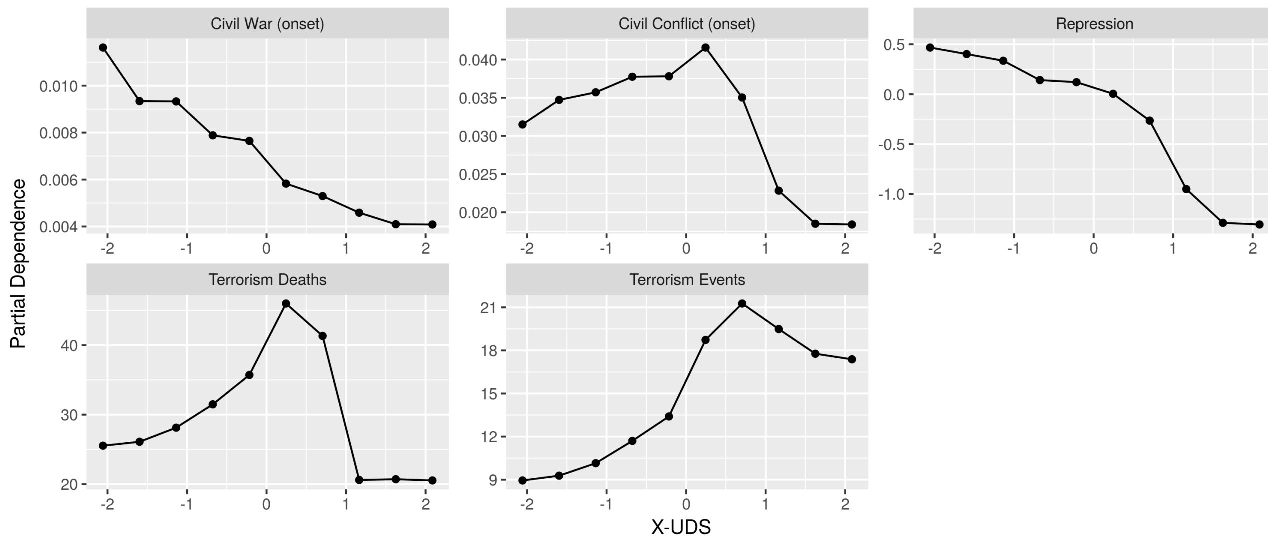

Figure 7: Partial dependence of X-UDS and conflict, 1970-2008.

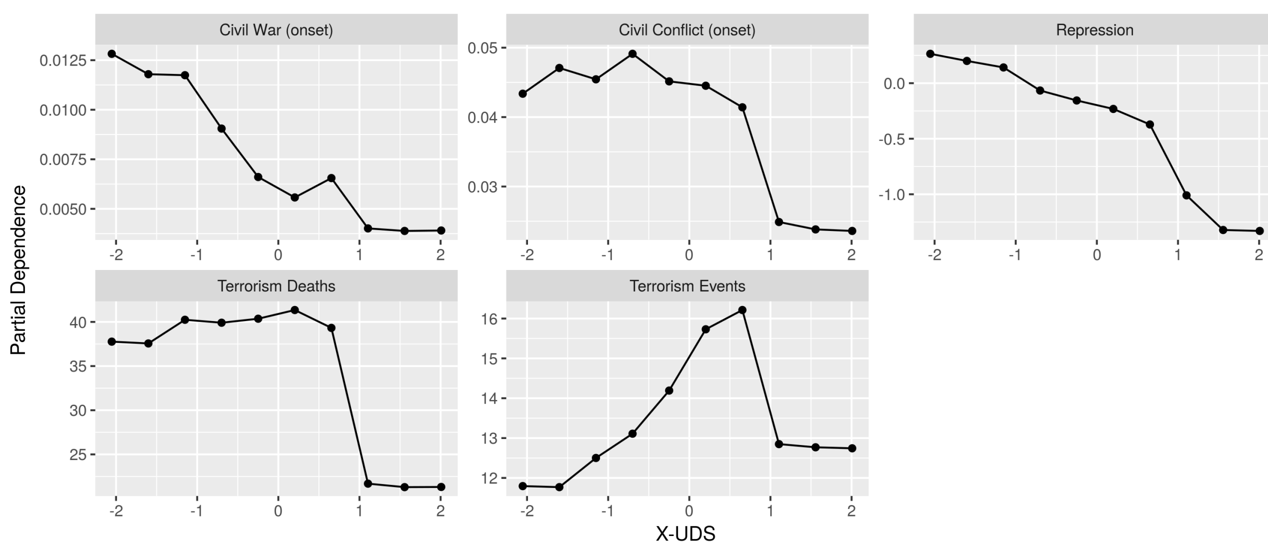

Figure 8: Partial dependence of X-UDS and conflict, 1990-2008.

5.2.3 Bivariate Relationships

While our multi-variable 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 Appendix provides the results of bivariate models that include X-Polity as the only predictor variable.

6 Conclusions

The goal of this paper has been to analyze the relationship between regime type and conflict using a research design that mitigates the limitations of existing work. We empirically describe the conditions under which the MVM Hypothesis does and does not hold. 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. Second, we find that the risk with some conflict outcomes, including repression and interstate conflict, has a direct relationship to democracy. Finally, we analyze which of these findings are robust to a measure of regime type that has not been widely used in the MVM Hypothesis literature.

With respect to civil wars and civil conflicts, studies of which have perhaps most prominently analyzed the MVM Hypothesis, our results point to two 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 difference could lead, in turn, 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.

In contrast to several other studies, we find much support for what Davenport (2007) calls the Domestic Democratic Peace, i.e., that repression is least likely in full democracies. This finding is consistent across time and across measures of regime type. This finding has broader implications. Given the prior finding that civil wars are highly predictive of repression (Hill and Jones, 2014), it is noteworthy that we find large civil war risks in full democracies but small expected levels of repression. This suggests that civil wars may be associated with more repression in non-democracies, but that, in fully democratic states, institutions and/or norms constrain the government from increasing repression to the same extent during periods of internal conflict. In turn, this suggests important distinctions between the *conduct* of civil wars in different regime types.

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, 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 semi-democratic states.

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