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Solving the Problem of Unattributed Political Violence

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Abstract

High rates of missing perpetrator information in political violence data pose a serious challenge for studies into militant group behavior and the microdynamics of conflict more generally. In this article we introduce multiple imputation (MI) as the best available method for minimizing the impact of missing perpetrator information on quantitative analyses of political violence, a method that can easily be incorporated into most quantitative research designs. MI will produce unbiased attributions when the reasons for missingness are known and can be controlled for using observed variables, rendering responsibility for unclaimed attacks, "missing at random" (MAR) – which we show is a reasonable assumption in the case of political violence based on current theory of militant group claiming. We lay out the logics and steps of MI, identify variables and data sources, and demonstrate that MI produced better results in the case of the Pakistani Taliban's response to drone strikes.

Keywords

civil wars, terrorism, conflict, multiple imputation, events data

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Introduction

The rise of large databases of political violence promises to greatly advance knowledge in the study of terrorism and civil war. However, identifying the actors responsible for acts of violence is a fundamental challenge in research in these areas. As of now, missing information on perpetrators presents scholars of political violence with a difficult choice: they can either ignore group responsibility and treat all violence as generated by the same process (e.g., Fearon and Laitin 2003; Pape 2005) or they can base their analyses on known group violence, a small and likely unrepresentative sample of group operations (e.g., Asal and Rethemeyer 2008; Piazza 2009). In both cases, inference may be biased. This article lays out the problems that missing perpetrator information presents for the study of political violence and shows that existing methodological tools can be leveraged to address them.

Even the best databases used by scholars investigating intrastate conflict are missing perpetrator information for a large proportion of their cases. Our review of six prominent databases of terrorist and insurgent violence found that 75 percent of attacks on average were perpetrated by unknown groups (see Table 1). Unclaimed attacks are most prevalent in data sets of global terrorism. This comes as no surprise, because perpetrators of terrorism have strong incentives to conceal their identities. Nonetheless, all scholars working with event-level political violence data should be concerned about the impact of unknown group responsibility on their findings.

Table 1. Review of Group Responsibility in Prominent Databases.

Database	Type	Total Attacks	Number Claimed	Percent Unclaimed
START global terrorism database	Global terrorism	104,689	4,877	95
NCTC worldwide incident tracking system	Global terrorism	87,453	10,441	88
RAND database of worldwide terrorism incidents	Global terrorism	40,129	13,922	65
CPOST suicide attack database	Suicide terrorism	3,399	1,302	62
ACLED projects[a]	Global insurgency	54,315	41,511	24
UCDP georeferenced event data[a]	Global insurgency	30,694	NA[b]	NA
Total from six conflict databases		289,985	72,053	75

Source: National Consortium for the START (2014); NCTC (2012); RAND Corporation (2012); CPOST (2015); Raleigh et al. (2010); Sundberg and Melander (2013).
Note: NCTC = National Counterterrorism Center; CPOST = Chicago Project on Security and Terrorism; START = Study of Terrorism and Responses to Terrorism; UCDP = Uppsala Conflict Data Program; ACLED = Armed Conflict Location & Events Data.
[a]Count excludes nonviolent events, riots, and summary events.
[b]UCDP Georeferenced Event Dataset inclusion criteria require known actor responsibility.

The objective of this article is to give scholars a methodologically credible means for minimizing the impact of missing perpetrator information on their analyses. Specifically, we demonstrate that multiple imputation (MI) is an effective method for generating attributions of group responsibility for unclaimed attacks that can easily be incorporated into most quantitative research designs. While the problem of missing information and the benefits of MI have long been recognized in other fields (Rubin 1987), scholars of political violence have not taken the problem of missing information seriously and are not well equipped to conceptualize or address its effects on their analyses. This article, therefore, contextualizes the special case of unattributed militant violence in the general framework of missing information and gives preliminary evidence for the applicability of MI to attribute political violence, demonstrating our method in the case of Pakistan.

Using MI to attribute responsibility improves our understanding of political violence by allowing scholars to capture both the most likely perpetrator and the uncertainty in their analyses. MI will produce valid attributions when the reasons for missingness are known and can be controlled for using observed variables, rendering responsibility for unclaimed attacks, in technical terms, "missing at random" (MAR). Conceptually, this assumption requires that the groups have similar observable reasons for claiming some attacks but not others. Moreover, they must also have distinguishable operational signatures for the method to attribute attacks with high confidence. There are good reasons to believe that these conditions hold in important cases, and, more generally, that MI will produce more valid results than relying on claimed attacks alone.

This article proceeds in four sections. In the first, we explain why missing perpetrator information is a serious problem for scholarly research on intrastate conflict. The second shows that MI, the most effective method for imputing missing information, is valid when the data are MAR, a reasonable assumption in the case of political violence, given the current theory and knowledge about claiming by militant groups. In the third, we demonstrate that MI can be used to attribute responsibility for militant violence in Pakistan. We validate the imputation model using standard out-of-sample procedures and also test it on unclaimed attacks for which group responsibility has been assigned by independent expert sources. In the fourth, we show that attribution by MI challenges findings in existing research about the effectiveness of drone strikes—the use of unmanned aerial vehicles by the United States to target suspected militants—on Pakistani Taliban violence. In the conclusion, we discuss the method's applicability to other domains of political violence.

The Problem of Unattributed Violence for Political Science

The high percentage of unclaimed attacks in most conflicts means that many influential studies of intrastate conflict have based their analysis on data that do not accurately reflect group behavior, risking the validity of their conclusions and hindering understanding of the microdynamics of intrastate conflict more generally.

Missing perpetrator information has two major implications for drawing causal inferences about the dynamics of intrastate conflict. First, it prevents scholars from asking important microlevel questions. Some scholars aggregate all violence happening in a conflict zone as if it was generated by the same process. Ignoring subnational variation, however, leaves scholars unable to assess the impact on political violence of multiple groups with different objectives, ideologies, capabilities, command structures, or operational environments. For instance, the well-known finding by Collier and Hoeffler (2004), that political and social grievances have little impact on the origins of civil wars, is limited by the absence of group-specific controls which could have allowed them to identify interactions between groups and the localized grievances that may motivate their behavior. New research, particularly in political geography and comparative politics, focuses on the microdynamics of conflict and argues that there are inherent limitations to using aggregate country-level analysis to explain the conduct of violence during civil wars (Raleigh, Witmer, and O'Loughlin 2010; Cederman and Gleditsch 2009). Much of this work emphasizes that group-specific characteristics have a significant impact on the conduct of violence, and these should therefore be included in research designs.

Second, missing perpetrator information undermines confidence in the studies that do exist on the microdynamics of intrastate violence. As of now, scholars seeking to test group-specific theories have little recourse except to use claimed attacks, ignoring unclaimed attacks. Yet, claimed attacks are consistently a small, and likely unrepresentative, sample of group operations. Despite this, using only claimed attacks is so common that studies rarely mention the potential problems for inference about group behavior (for an exception, see LaFree, Dugan, and Miller 2014, chap. 5). For example, Berman and Laitin (2008) argue that militant groups that provide social services are able to undertake more lethal attacks than groups that do not. They compare 160 attacks by Hamas and Hezbollah with 228 attacks undertaken by four groups that do not provide social services, finding a statistically significant difference in their average lethality. However, they ignore 427 attacks for which perpetrator information is missing. The inability to assign responsibility for so many attacks has the potential to weaken, if not overturn, their findings.

A simple example demonstrates the bias that using claimed attacks alone introduces to quantitative analysis. In this illustration, group A is a religious militant organization and group B is a secular militant organization. Group A has a slight proclivity toward suicide attacks so that two of its four attacks are suicide attacks, while only one of group B's four attacks is a suicide attack. Both groups claim all of their suicide attacks but fail to claim one of their nonsuicide attacks. To model the propensity of either organization to carry out suicide attacks, we use the linear regression $Y = B \times X + C$, where Y is the proportion of suicide attacks, perpetrated by a given group X is a dichotomous variable indicating a religious group, B is a coefficient indicating the additional probability that the religious group engages in suicide attacks, and C is the base rate of suicide attacks for both groups. If responsibility for all eight attacks were known, we would correctly estimate that 50% of a religious group's attacks are suicide attacks, in contrast to 25% for secular groups, based on the equation $Y = .25 \times X + .25$. However, excluding the unclaimed nonsuicide attacks and using only the six claimed attacks results in the equation $Y = .33 \times X + .33$. The model based on claimed attacks overestimates the proclivity of either group to use suicide attacks. Moreover, because of the model's smaller sample size, it is also less confident that the results from the sample reflect the true population.

Missing data also affect substantive descriptions of violence. For example, based on claimed attacks in Pakistan, the proportion of suicide attacks to nonsuicide attacks is very high, with nearly one in five attacks undertaken by a suicide bomber.[1] However, as we will show in later sections, suicide attacks are significantly more likely to be claimed than nonsuicide attacks. Including unclaimed violence reveals that suicide attacks actually constitute only one in twenty attacks. Conventional attacks are a much greater proportion of the violence in Pakistan than represented in the claims.

The best current solution is to limit analysis to geographic areas where group responsibility can reasonably be inferred, but this strategy raises questions about the generalizability of findings and precludes study of the impact of major factors such as conflict diffusion or group competition. To illustrate, Weinstein (2006) uses areas of exclusive control to attribute responsibility for unclaimed attacks in Uganda, Mozambique, and two areas of Peru. On the basis of these data, Weinstein argues that groups that form with economic endowments will engage in more indiscriminant violence than groups that form with social endowments. However, in important cases (e.g., the Peruvian civil war), he is unable to code responsibility for rebel violence in a manner that would appropriately test his theory because so much violence occurs when multiple actors are present in the same territory, a problem he recognizes (p. 241, footnote 99). Further, in three of his four cases, unclaimed attacks outnumber claimed attacks, and knowing responsibility for those events could overturn the finding. The best current solution to the problem of missing perpetrator information, therefore, has serious limitations that raise doubts about the robustness of important work.

In summary, the availability of events data is of limited help to political scientists without a way of assigning responsibility for events where perpetrators are unknown. This would seem to pose an insoluble problem, since discovering new claims for such a large number of events is unlikely. Fortunately, logics and methods have been developed to infer missing information in large data sets that apply directly to the problem at hand.

The Science of Missing Information and the Implications for Political Violence

The problem of unknown responsibility can be thought of in terms of "missing information." Statisticians have developed reliable methods to address problems of missing information that have yet to be applied to militant group responsibility. These methods can improve the validity of subsequent analysis. This article demonstrates that MI, a standard method in other fields, can be used to attribute group

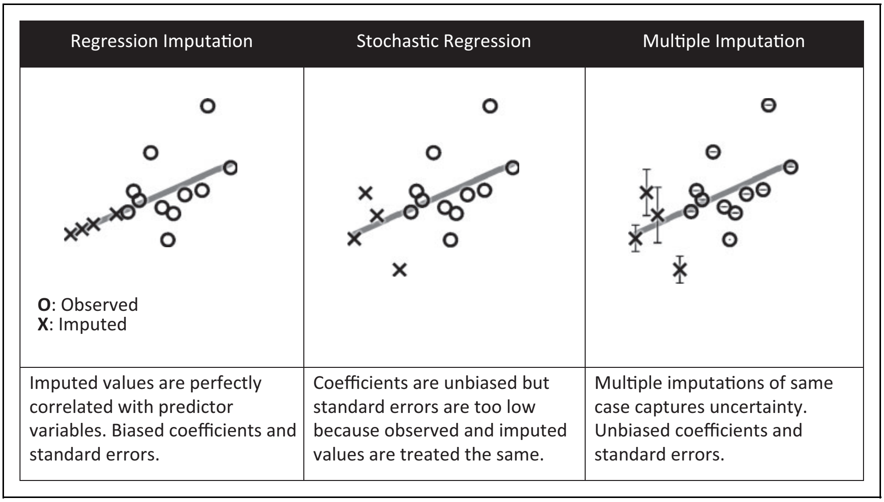

Figure 1. Comparison of imputation strategies. Adapted from C. Enders (2010).

responsibility, depending on the reasons why claims are missing. This section explains that MI is both necessary and valid when data are missing for known, systematic reasons—that is, MAR—and develops strong theoretical reasons to believe that missing perpetrator information in political violence can credibly be treated as MAR under certain conditions.

MI for Missing Information

Imputing values is a standard response to the problem of missing information. MI is a state-of-the-art technique that imputes multiple possible values for the same missing observation that reflect the uncertainty of the prediction (Rubin 1987; Little 1992; Allison 2001; King et al. 2001). As a result, this process creates unbiased estimates of coefficients and standard errors in later analysis. To illustrate the advantages of MI, we contrast it with other, less effective, methods: regression imputation and stochastic imputation. Figure 1 illustrates the differences between these methods graphically, while the following section provides a conceptual overview.

Regression imputation uses a regression model to impute possible values for the missing information based on predictors of known cases. It reports the uncertainty of the imputed values but has no means of incorporating this information into subsequent analysis. The imputed values are perfectly correlated with the predictors used in the regression, a major problem that will bias coefficients and standard errors. Stochastic regression follows a similar process but corrects for the biased coefficients by adding an additional random term to the predictions (C. Enders 2010, 44-48). As a result, the imputed values as a whole vary just as much as the observed values, and coefficients will be unbiased. However, the model still treats imputed cases the same as observed cases, and the standard errors of subsequent analysis will be too low, increasing the risk of false positives.

MI has three stages: imputation of missing values, analysis with independent imputed values, and averaging of the results. MI allows for the uncertainty of the attributions to be incorporated into subsequent analysis by generating multiple new data sets that reflect the range of possible values. Each of the imputed data sets are equivalent to stochastic regression, with the number of new data sets increasing with the degree of missing information (Graham, Olchowski, and Gilreath 2007). This process is compatible with any regression model, although less common models are generally not supported by out-of-the-box statistical software. Subsequent modeling is performed on each of these data sets separately, with the results averaged through a standard process (Rubin 1987, 76).

By capturing the spread of possible predictions, MI yields unbiased estimates of both coefficients and standard errors. However, MI requires sound logic to justify that the imputed values correspond to the actual values, which cannot be independently validated. Imputed values will be unbiased when data are missing for known, systematic reasons that can be controlled for—that is, they are MAR.

Mechanisms of Missing Information

There are three possible mechanisms of missing information that correspond to different theoretical claims about why values are missing (Brehm 1993; Schafer 1997), each with implications for the validity of imputing those values in general and for attributing group responsibility for unclaimed attacks specifically. We use the example of missing political party affiliation in survey responses from American politics to demonstrate these concepts because it shares strong parallels with militant group responsibility.

Data are *missing completely at random* (*MCAR*) if values are missing for nonsystematic reasons and any observation is just as likely to be missing as any other. If some respondents to a survey did not identify whether they were Republican or Democrat by mistake, such that this process resembled the flip of a coin, then the data would be MCAR (King et al. 2001). Respondents who did provide their affiliation would accurately reflect the partisan balance. Data that are MCAR reduce the efficiency of analysis, possibly requiring more data collection, but are a representative sample. However, data are rarely MCAR.

In the case of violent events data, claims would be MCAR if militant groups have no systematic reason for claiming or not claiming attacks. For example, claims would be MCAR if militants intended to claim every attack via cell phone and random network outages were the only reason for missing claims. In this situation, claimed attacks would be a representative sample of a group's operations, and scholars would be justified in using only claimed attacks. However, there is good reason to believe that group responsibility is missing for systematic reasons.

For voters and militant groups alike, it is more likely for data to be *MAR*, which means missing values are a function of a known systemic process. The missing observations are not omitted "randomly" in the ordinary meaning. Rather, based on prior theoretical knowledge about why values are missing, we can identify and control for observable factors which render the remaining missingness random. For example, political affiliation would be MAR if Democrats were less likely to report their political party affiliation than Republicans, but other observed variables, such as positions on polarized policies (e.g., abortion or gun control), completely predicted party affiliation.

With respect to militant groups, claims are MAR if they choose whether to claim attacks based on observed factors. If all groups claim attacks based on the same observed criteria—such as claiming suicide attacks more often than nonsuicide attacks—then the decision to claim any particular suicide or nonsuicide attack is random. When claims are MAR, claimed attacks are not representative of a group's operations, but predictions of group responsibility would be valid as long as suicide attacks were included as a control in the attribution model. Importantly, MAR is a theory about the relationship between the observed and the missing values, and neither predicted results nor model fit are sufficient evidence to justify it. However, minor violations of this assumption will still yield more accurate results than relying on claimed attacks alone (C. Enders 2010, 87).

Most problematic for imputation is when data are *missing not at random* (*MNAR*), meaning that observed variables do not predict whether observations are missing. Here, observations are missing for systematic, but unknown reasons and imputed values would be unknowably biased (King et al. 2001; see also Heckman 1979; Achen 1986; Brehm 1993). Missing party identification would be MNAR if surveys contained no issue position questions that predicted party affiliation. The difference between MAR and MNAR, thus, hinges on knowing and collecting the right variables. Importantly, statistical models cannot determine the relationship between missing values and unobserved variables. Instead, substantive knowledge of the reasons why data are missing is important for determining whether data are MAR or MNAR.

In political violence, claims are MNAR if there are important predictors of claiming that are not observed or if groups differ in their reasons for claiming attacks. If groups have different logics for claiming attacks, then predicting group responsibility requires knowing the identity of the group that carried out the attack, a clear chicken-and-egg problem. This same problem makes it impossible to test whether groups have different claim logics. To give an extreme example, imagine two militant groups with the same operational pattern but opposite claim patterns. The two groups undertake the same number of suicide attacks but one group claims all of its suicide attacks while the other group claims none. A statistical algorithm, as well as an expert observer, would conclude that the unclaimed suicide attacks were perpetrated by the group which has claimed suicide attacks, exactly the wrong attribution.

Fortunately, as explained below, there are good reasons to believe that militant group claims are MAR, making MI a valid solution to the problem of missing perpetrator information.

Theory of Militant Group Claiming

In this section, we explain why the conditions for valid imputation of missing values hold in the case of missing group responsibility and identify theoretically grounded predictors of claiming that serve as the basis for attribution. The missingness mechanism is likely to be MAR when militant groups seek to balance the requirements of publicity and organizational survival. In those circumstances, groups will have similar incentives for claiming some attacks but not others that manifest themselves in consistent and observable indicators. Further, even when MAR does not hold, such that there are unobserved differences in group claim logics, these differences are likely captured by variables already included in the model so that the results of imputation are less biased than those produced using claimed attacks alone.

Crucially, the assumption of MAR is a theoretical not empirical claim. Since responsibility for specific unclaimed attacks is not known, there is no empirical evidence to test the reasons why attacks are not claimed. Instead, our confidence that the missingness mechanism is MAR depends on a sound general theory for why militant groups claim attacks, one that links observed variables to why attacks are claimed or not claimed. We present this theory below.

Why do militant groups claim attacks? A formal claim of responsibility for an attack represents a public declaration by the group that it perpetrated the attack in question. While claims are first and foremost affirmations of responsibility, they often include reasons for the attacks as well as demands. Claims thus communicate to multiple audiences: the group's enemies, its current supporters, and prospective supporters whether local or foreign (B. Hoffman and McCormick 2004).

To explain variation in the decision to claim attacks, we assume that militant groups are strategic actors, meaning that they weigh the costs and benefits of their actions for achieving their political goals (Lake 2002; Pape 2005). Militant groups must balance the activities necessary to have political impact with those that ensure their continued ability to fight (McCormick 2003; Shapiro 2013). In addition to perpetrating attacks, groups must mobilize public support while avoiding military defeat by counterinsurgent forces.

Publicity is a key resource to achieve both strategic and organizational ends, making support more likely as groups demonstrate they are achieving results (Pluchinsky 1997; Jenkins 2006). Claims contribute to groups' goals by demonstrating their strength, helping them compete for constituents and resources in often highly competitive environments. Beyond indicating responsibility for attacks, claims give groups an opportunity to present their worldview and justify their violence. Further, militant groups' ability to coerce depends on a clear link between acts of violence and the political objectives those acts are intended to promote. Explicit statements are the most effective means of drawing these connections and issuing demands (Kydd and Walter 2006; B. Hoffman and McCormick 2004; Rapoport 1997). Claiming attacks thus has clear strategic benefits for militant groups, especially when groups are in competition for resources and public support.

While the benefits to militant groups of claiming attacks are clear, many, if not most, attacks remain unclaimed for reasons that follow from the same strategic logic. First, militant groups have incentives to avoid taking responsibility for attacks that have a high risk of eroding popular support or of provoking extreme retaliation. These include attacks that intentionally, or by accident, kill many civilians or otherwise violate important community norms. By not claiming such attacks, groups seek to ensure plausible deniability, lowering the risk of backlash from supporters and the threat of reprisals (Cronin 2009, 108-10; Downes 2008, 34-35). Second, groups do not claim attacks for pragmatic reasons. Militant groups, especially large ones, perpetrate a great number of attacks on an ongoing basis. Claiming all, or even most, of the group's attacks is impractical and would exceed the capacity and interest of these organizations. Moreover, militant groups perpetrate violence to achieve a wide range of strategic and tactical objectives, not all of which would benefit from a formal claim to have the intended effect. The routine nature of much of everyday violence in a militant campaign likely explains why a sizable portion of attacks are not claimed. Finally, in conflicts with a single active militant group, claiming is simply unnecessary.

Beyond strategic, organizational and pragmatic grounds for whether to claim attacks, some attacks may appear unclaimed for reasons independent of the intentions of the militant group. Groups may have intended to claim an attack, but, for reasons outside of the group's control, the claim was either not made or not received. For example, inclement weather or the outage of a cell network might prevent claims from reaching media outlets or being uploaded to the Internet. However, such factors would not likely prevent determined groups from making their responsibility for an attack known. A more plausible reason for why an attack that was claimed is missing from data sets of political violence stems from the process by which such data sets are created. An attack may be recorded as unclaimed because the claim was not reported at the time the attack was entered into the database or because a data collector missed such reports.

In summary, because militant groups must generally balance the benefits of claiming with the potential risks, they will likely follow similar calculations in their claim decisions. Since groups' constituents and state rivals base their reaction to attacks on what they observe, groups are likely to base their decision to claim on the same observable characteristics that influence these two audiences. Accordingly, there are good reasons to believe that militant groups choose to claim attacks based on observable criteria, meaning that the missingness mechanism is MAR.[2]

Fortunately, the most important indicators of the logic of militant group claiming are captured in variables included in off-the-shelf data sets of political violence or other publicly available sources. These are summarized in Table 2.

Table 2. Variables and Missingness Mechanisms.

Variables	Specific Indicators	Mechanism	Source of Control Variables
Attack characteristics	Attack type (suicide, car bomb, IED), lethality (fatalities, collateral), and target type (security, civilian)	MAR	Off-the-shelf attack data
Strategic environment	Military operations, attack clustering, population density, and terrain	MAR	Off-the-shelf attack data, demographic data, military operations data
Random variables	Weather, cell phone reception, and data collection errors	MCAR	No controls needed
Unobserved correlated with observed variables	Group-specific factors, other correlated attack characteristics	MNAR	Unobserved; include correlated controls

Note: MNAR = missing not at random; MAR = missing at random; MCAR = missing completely at random; IED = improvised explosive device.

First, observable attack characteristics are likely good predictors of militant group claims because these are the same metrics groups are likely to use in assessing the costs and benefits of claiming. Specifically, attack type, lethality, and target type impact popular support for the group as well as the anticipation that an attack will result in a costly reprisal. For example, some attack types are more likely to be employed in a strategic context, making it more likely that they will be claimed. Suicide attacks should be especially likely to be claimed to communicate their coercive intent and to build a culture of martyrdom to attract volunteers (Pape 2005; Hafez 2006). Further, groups should be more likely to claim attacks against state security forces in order to coerce concessions from the rival state and make the group appear strong to its constituents. At the same time, groups are less likely to claim attacks that invite reprisals or threaten potential support, such as attacks on civilians (Kearns, Conlon, and Young 2014). Groups should also prefer claiming high lethality attacks because these signal their power, while conversely avoiding responsibility for failed attacks because these might signal weakness or ineptitude.

Second, observable factors in the group's strategic environment will also affect the likelihood that an attack will be claimed. The main empirical finding in the literature on claiming is that competition among militant groups increases the probability that groups will claim responsibility for their attacks (A. Hoffman 2010). Operations by other militant groups affect the claim decision because groups need to distinguish themselves from competitors (Bloom 2005, 29-31). Accordingly, when a group operates alone in a geographic area, it is likely to claim fewer attacks because responsibility can be taken for granted. Easily observable geographic variables like population density are also likely to matter for claiming. For example, groups may be more likely to claim attacks in densely populated urban environments than sparsely populated areas. Finally, operations by counterinsurgent forces can increase the likelihood that attacks will be claimed as groups seek to coerce an end to those operations.

Finally, there will always be concerns about omitted variables. To the extent that factors like weather and coder error randomly cause claims to be missing, the missingness mechanism is MCAR and claimed attacks will be representative of a group's operations. Other factors may be MNAR, such as unobserved attack characteristics and differences in group claim logics, but these factors would need to be strong predictors of unclaimed attacks to matter (Collins, Schafer, and Kam 2001, 342, 347). Variables included in the analysis that are correlated with these unobserved factors will diminish their effects even further. Finally, using MI to attribute responsibility for attacks will almost never be worse than using claimed attacks alone because the model accounts for some of the reasons why claims are missing.

Importantly, identifying statistically significant predictors of claiming alone does not prove that the model will make valid predictions about group responsibility. The validity of the imputations cannot be demonstrated empirically because group responsibility is unknown. In the absence of perpetrator information for unclaimed attacks, confidence in these results depends crucially on the theoretical relationship between these observable characteristics and their influence on the likelihood that an attack is claimed.

Application of MI to Violence in Pakistan

This section demonstrates that MI can be used to attribute responsibility for unclaimed attacks in Pakistan and that doing so improves our knowledge about substantive questions, specifically the effect of US drone strikes on Pakistani Taliban violence. Pakistan is a useful case to demonstrate the application of MI to militant violence because there are multiple insurgent movements operating in the country, and the proportion of unclaimed attacks in this conflict is particularly high. We also have plausible reasons to believe that perpetrator information is missing for systematic and observable reasons, that is, MAR. These conditions are not unique to Pakistan or drones, and we believe that MI can be productively applied to many other conflicts and to many other research questions.

After characterizing the problem of missing perpetrator information in the case of Pakistan, we use MI to evaluate the effect of drone strikes on violence by the Pakistani Taliban following a four-step process: selecting variables for the imputation process, attributing missing responsibility, validating the imputation model, and applying the data with imputed responsibility to the substantive question.

The Problem of Unclaimed Attacks for Studies of Drone Effectiveness

The escalating Pakistani Taliban insurgency in Pakistan, spearheaded by the Tehrik-i-Taliban Pakistan (TTP), has prompted significant interest in the group, its strategic objectives, and the logics behind specific targeting choices. An important substantive issue concerns the impact of drone strikes on Pakistani Taliban violence, both of which increased dramatically in 2007 when the TTP launched a major insurgent campaign to defend the tribal areas from Pakistani government incursion (Abbas 2014; Jones and Fair 2010). Proponents of the drone war (e.g., Byman 2013) have argued that drones are an indispensable tool in combating the threat of terrorism by the Pakistani Taliban, while others contend that drones are counterproductive, causing more violence than they prevent (e.g., Cronin 2013). To answer the question of effectiveness, scholars have used a range of quantitative approaches to establish whether drone strikes increase or decrease Pakistani Taliban attacks.

Despite the wealth of microlevel events data available for violence in Pakistan, a major obstacle to any group-specific analysis of drone strike effectiveness is uncertainty regarding which attacks can be attributed to which groups because the vast majority of attacks in Pakistan are unclaimed (92 percent in the data set we use). This is a problem, because, in addition to the Pakistani Taliban, there are multiple violent movements and insurgencies ongoing in Pakistan. Substantive investigation of the objectives and operations of these groups confirms that they are all concerned with the trade-off between publicity and organizational survival, consistent with our theory of claiming above. Baluchi separatist groups, most prominently the Baluchistan Liberation Army, are motivated by perceived disenfranchisement of the Baluchi ethnic group by the Punjabi dominated Pakistani government (Khan 2009; International Crisis Group 2006). The so-called Punjabi Taliban, comprising groups like Lashkar-e-Jhangvi, Jaish-e-Mohammed, and Harakat ul-Mujahidin, is motivated by an anti-Shia sectarian agenda (Abbas 2009; Grare 2007). Several other minor groups have also perpetrated and claimed attacks in Pakistan, including Al Qaeda and groups with less discernable agendas. Each of these groups contributes to an unknown portion of the unclaimed attacks.

To test the relationship between drone strikes and Pakistani Taliban violence, one needs to isolate the attacks associated with the Taliban from those perpetrated by the other groups. Previous studies of the effect of drone strikes on the Pakistani Taliban have used ad hoc strategies to isolate attacks perpetrated by the group. For example, one study uses only attacks claimed by the Pakistani Taliban (Jaeger and Siddique 2011), while another limits the analysis to Pakistani Taliban strongholds (Johnston and Sarbahi 2015). Not surprisingly, with different specifications of Pakistani Taliban violence, these studies found different results. More problematic, these strategies fail to correct for known biases and so are unlikely to produce true estimates of the Pakistani Taliban's operations. Using claimed attacks alone is particularly problematic. Apart from theoretical reasons to believe claimed attacks are not representative of Pakistani Taliban operations, drone strikes themselves could have an effect on claiming, further biasing results based on claims alone.

In short, it is common for studies to draw inferences about overall Pakistani Taliban violence from biased samples. MI mitigates these biases while accounting for the uncertainty of predictions. It is therefore a better strategy for identifying the full range of likely Pakistani Taliban attacks and a better basis to assess the impact of drones.

Data and Variable Selection

To study the impact of drones, we need data on Pakistani Taliban violence and drone strikes. Our data set of militant group violence in Pakistan combines 6,277 nonsuicide attacks from the National Counterterrorism Center's Worldwide Incident Tracking System (WITS) database, which is one of the most comprehensive sources of nonsuicide attack data from 2004 through 2010, with 280 suicide attacks from the Chicago Project on Security and Terrorism (CPOST)'s Suicide Attack Database, which maintains an exhaustive data set of suicide attacks worldwide. All attacks were coded for target type, fatality, and geolocation based on uniform coding guidelines.[3] Data on drone strikes in Pakistan were collected by the Bureau of Investigative Journalism (BIJ), widely recognized as the most reliable source on drone strikes (Ross and Serle 2014; Friedersdorf 2012). The BIJ records 231 confirmed drone strikes from 2004 through 2010.

The first step in applying MI is to identify the variables for the imputation process, in our case, variables that discriminate the Pakistani Taliban's attacks from those of the Baluchistan separatists, Punjabi Taliban, and other smaller groups. Of the 511 claimed attacks in our data set, just over half were claimed by the Pakistani Taliban (259 or 51 percent) while the Baluchi separatists claimed almost as many attacks (223 or 43 percent), and the remaining 29 attacks (6 percent) were claimed by either the Punjabi Taliban or other minor groups. Responsibility for the remaining 6,046 attacks is unknown and will be attributed to one of these three groupings. Very few attacks in our data were claimed by the Punjabi Taliban and other groups (about 7 percent combined), so to simplify the discrimination task we aggregated these into a single category of "other." An explicit assumption of the attribution process is that all violent events were carried out by one of these three groupings.[4]

We include two kinds of variables in the imputation procedure. First, we include variables that capture the claim logics and operations of militant groups. Second, we include variables specific to the research question, in this case, the timing, location, and fatalities from drone strikes. Including explanatory variables central to the substantive research design is standard procedure to control for their effect on claiming (Allison 2001). While "garbage-can" models are strongly discouraged when answering substantive questions (Achen 2005), scholars should err on the side of including as many variables as possible in the imputation model because additional observed variables may control for unobserved correlates (Rubin 1987).

Table 3 compares claimed attacks by each group to all unclaimed attacks in Pakistan, according to the variables identified in our theory of claiming. The results indicate that groups may have identifiable profiles and that there are systematic differences between claimed and unclaimed attacks.

Table 3. Group Profiles based on Claimed Attacks.

		Pakistani Taliban	Baluch Separatists	Other Groups	Unclaimed Attacks
n	Attacks	259	223	29	6,046
Attack type	Suicide	34%	0%	34%	3%
	Bombing	17%	52%	14%	37%
	Assault	49%	48%	52%	60%
Target type	Civilian	41%	65%	55%	61%
	Political	17%	11%	24%	15%
	Security	42%	24%	21%	24%
Lethality	Average fatalities	6.75	1.13	7.03	1.14
	Collateral	27%	8%	17%	8%
Geography	FATA	41%	0%	10%	23%
	NWFP	45%	0%	7%	36%
	Balochistan	1%	97%	44%	28%
	Sindh	1%	1%	14%	6%
	Punjab	7%	2%	10%	5%
	Other	5%	0%	15%	1%

Note: FATA = Federally Administered Tribal Areas; NWFP = North-West Frontier Province.

Attack type is a set of three dichotomous variables that indicate whether the attack was a suicide attack, a nonsuicide bombing, or a direct assault (firearms, rockets, or arson). As the table shows, the Pakistani Taliban has claimed the majority of the suicide attacks in Pakistan. Target type is a set of three dichotomous variables for the target of the attack: civilian, security, or political. The Pakistani Taliban has claimed the most attacks against state security forces in response to the frequent military operations targeting them. We include two measure of lethality, total killed in the attack and whether civilians were killed. The Pakistani Taliban has claimed the highest percentage of high-casualty attacks.

We also use the precise geographic location of attacks to capture two variables related to the strategic environment: area of operations and ethnic composition in the district where attacks occurred. To create observed areas of operation for each group, we measure clustering of claimed attacks using one-year moving-window kernel densities, which helps to control for possible shifts over time.[5] As Table 2 shows, groups in Pakistan claim attacks to a large extent in mutually exclusive territorial areas. For example, the Pakistani Taliban primarily claims attacks in the Federally Administered Tribal Areas (FATA) and the North-West Frontier Province (NWFP). As a result, we expect clustering to be a particularly strong predictor of responsibility for unclaimed attacks in this case, minimizing the impact of unobserved variables. The main insurgencies in Pakistan have strong ethnic bases of support, making it important to include ethnicity as a variable to predict responsibility for attacks. To capture ethnicity, we use the percentage of Pashto, Baluchi, and

Punjabi speakers in each district from the 1998 Pakistani Census (Pakistani Population Census Organisation 1998). Results (not shown in table) indicate that groups in Pakistan primarily claim attacks in areas where coethnics predominate.

Finally, we include the number of military operations and militant fatalities in the district during the week that an attack takes place, using the BFRS data set (Shapiro et al. 2013). This is to control for the possibility that operations lead groups to claim attacks (e.g., in order to issue demands) and correlate with other changes in the strategic environment (e.g., peace deals). We also use the district's population density because groups may have less incentive to claim attacks in sparsely populated areas and a measure of rough terrain (standard deviation of elevation) because groups may have less ability to claim attacks in such areas (Pakistani Population Census Organisation 1998; Jarvis, Reuter, and Guevara 2008).

Attributing Responsibility With MI

The second step in applying MI to attributing militant group responsibility for unclaimed attacks in Pakistan is to create a statistical profile of each group's attacks based on the claimed attacks and to apply this profile to the unclaimed cases. Including variables from our theory of claiming, which predict whether attacks will be claimed, controls for the possibility that these profiles are the function of differences in claiming and not differences in actual group operations. We validate the MI model by withholding random subsets of the claimed attacks that were not used to fit the model. We also take advantage of a set of suspected attributions of responsibility made by experts on the ground, a type of information that is not traditionally available to scholars working with missing data but that is common in data sets of political violence.

The dependent variable is attacks claimed by the Pakistani Taliban, Baluchi separatists, or other minor groups. Equation 1 shows the estimation of group responsibility where i indexes the militant group, Y is the probability than an attack is carried out by a given group, C represents the base rate that any attack is carried out by that group, B_1 through B_6 represent the effect of attack type, fatalities, target type, proximate military operation, area of operation, and demography variables on the likelihood that any attack is carried out by that group, and R represents the random residual added to the predicted values to add the variability for MI.

Equation 1: Estimating equation

$$Y_i = C_i + B_{1i}X_{1i} + \ldots + B_{6i}X_{6i} + R_i.$$

We use a multinomial logit model to estimate these coefficients because it is appropriate for categorical variables and is supported by Stata's MI tools, but MI is compatible with a wide range of models accommodating different research designs. We created 100 imputations of responsibility for each attack, more than sufficient to

Table 4. The Impact of Attack Characteristics on Predicted Group Responsibility (Multinomial Logit).

Independent Variables		Pakistani Taliban versus Baluchi Separatists	Pakistani Taliban versus Other Militants	Baluchi Separatists versus Other Militants
Attack type	Suicide attack	−25.00	−0.02	25.02
	Assault	−2.48*	−0.69	1.79†
Fatalities	Fatalities	−0.05	−0.06†	−0.10
	Collateral	0.21	0.40	0.19
Target	Security target	−3.20***	−2.38**	0.81
	Political target	−2.43*	−0.43	2.00*
Area of operation	Pakistani Taliban attacks	−39.03†	0.16	39.19
	Baluchi attacks	0.33	0.03	−0.30
	Other attacks	5.94†	5.25***	−0.70
Geography	Population density	1.47	−0.12	−1.59
	Rough terrain	0.00	0.00	0.00
	Pashto %	0.40	−4.29†	−4.69
	Baluchi %	4.75*	−0.82	−5.57†
	Punjabi %	0.00	−1.47	−1.47
Military operations	COIN operations	12.90	−18.63	−31.52
	Militant fatalities	0.44	0.22	−0.22
	Drone strikes	26.47	−17.81	−44.28
Constant		4.02†	−0.79	−4.81†
Pseudo-R^2 = .815				
N = 511				

Note: COIN = counterinsurgency.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

capture the variance in predicted uncertainty given the high proportion of missing group responsibility in our data (Graham, Olchowski, and Gilreath 2007). Because suicide attack is a perfect predictor of Baluchi responsibility (Baluchi groups have never claimed one), our algorithm included a small number of ad hoc imputations to allow this variable to be included (White, Daniel, and Royston 2010). The results are presented in Table 4.

The fit of the model to the claimed cases is strong, attributing 94 percent of the claimed attacks to the correct group. Coefficients represent the change in the odds that an attack was claimed by the second group compared to the first group. Attack type, target type, area of operation, and the geography of attacks are all statistically significant predictors of group responsibility. Suicide attacks are not a statistically significant predictor because the Baluchi separatists have never claimed any and the other militants claim an equal proportion to the Pakistani Taliban. Direct assaults are more likely to have been claimed by the Pakistani Taliban than the Baluchis. Attacks against security and political targets are also less likely to have been claimed by either the Baluchi separatists or other minor groups than the Pakistani Taliban. As we would expect, areas of operation also help us predict responsibility for attacks. Claimed attacks by the Pakistani Taliban and other militants are spatially clustered in areas largely distinct from those by other groups, a pattern that is consistent over time. A greater percentage of Pashto speakers in a district makes it more likely that an attack is claimed by the other minor groups, after controlling for the other predictors. The Baluchis are more likely to claim attacks where Baluchi speakers predominate. Although some variables contribute to the profile more than others, it is only together that they predict the vast majority of claimed attacks.

Assigning responsibility to unclaimed attacks changes our substantive understanding of the nature of violence in Pakistan. Table 5 shows the difference between the claimed and the attributed attacks on key group operating characteristics. While claimed attacks were almost evenly distributed between the Pakistani Taliban and the Baluchi separatists, our model attributed 59 percent of the total attacks to the Pakistani Taliban and 33 percent of the total attacks to the Baluchi separatists. Researchers using only the claimed sample would erroneously conclude that these groups were almost equally violent. Researchers would also have come to incorrect conclusions about the types of attacks perpetrated by these groups. Groups engage in far more low-level violence against civilians than represented in their claims. This pattern of consistent violence against civilians is important to theories of territorial control (e.g., Kalyvas 2006) and civilian victimization (e.g., Downes 2008; Wood 2010) which would be difficult to validate using only claimed attacks.

Validating the Imputation Model

Using claimed attacks to predict unclaimed attacks is fundamentally a question of out-of-sample performance. While we can test how well the model predicts new, out-of-sample, claimed attacks, there is no direct way to verify how well the model correctly guesses unclaimed attacks. We implement two strategies to validate the performance of our model in generating predictions on new data, which give us confidence that the model specification we developed performs well on the unclaimed attacks and will apply to future militant violence in Pakistan.

We used 10-fold cross-validation to test how well the method predicted claimed attacks that were not used to fit the model. The process randomly partitions the claimed attacks into ten subsets, fits the model on all but one of these partitions, tests the model on the excluded partition, and then repeats the process for each subset so that all of the data are used to both fit and test the model.[6] Our model's out-of-sample performance is consistently very high, predicting the withheld claimed attacks with 93 percent accuracy. The model performed best on attacks claimed by the Pakistani Taliban or the Baluchis, with 96 percent and 98 percent accuracy, respectively,

Table 5. Impact of Attributions on Key Group Operating Characteristics.

		Pakistani Taliban		Baluch Separatists		Other Groups	
		Only Claimed	Claimed and Attributed	Only Claimed	Claimed and Attributed	Only Claimed	Claimed and Attributed
n	Attacks	259	3,861 ± 139	223	2,186 ± 111	29	510 ± 120
Attack type	Suicide	34%	6% ± 0.3%	0%	0% ± 0%	34%	7% ± 2%
	Bombing	17%	30% ± 2%	52%	51% ± 3%	14%	27% ± 8%
	Assault	49%	64% ± 2%	48%	49% ± 3%	52%	65% ± 8%
Target	Civilian	41%	53% ± 1%	65%	72% ± 2%	55%	64% ± 7%
	Political	17%	17% ± 1%	11%	10% ± 1%	24%	23 ± 6%
	Security	42%	30% ± 1%	24%	18% ± 1%	21%	13% ± 4%
Lethality	Average fatalities	6.75	1.8 ± 0.1	1.13	0.6 ± 0.1	7.03	1.9 ± 0.3
	Collateral	27%	11% ± 1%	8%	5% ±1%	17%	9% ±2%
Geography	FATA	41%	35% ± 1%	0%	3% ± 1%	10%	17% ± 4%
	NWFP	45%	53% ± 1%	0%	6% ± 2%	7%	26% ± 5%
	Balochistan	<2%	2% ± <1%	97%	81% ± 4%	44%	20% ± 5%
	Sindh	1%	4% ± <1%	1%	6% ± 2%	14%	22% ± 5%
	Punjab	7%	5% ± 1%	2%	3% ±1%	10%	9% ± 3%
	Other	5%	1% ± <1%	0%	<1% ± <1%	15%	6% ± 1%

Mean and standard deviation

Note: FATA = Federally Administered Tribal Areas; NWFP = North-West Frontier Province.

because it could leverage a large number of claimed attacks to build robust profiles for these groups. In contrast, the model varies significantly in the percentage of attacks correctly attributed to other minor groups depending on the cross-fold size and variables included in the model, but generally attributes only a small percentage of such attacks correctly. These findings demonstrate that the method will perform best on groups that exceed a minimum threshold of claimed attacks.

While model fit statistics give us confidence that the model was able to isolate profiles for the Pakistani Taliban and Baluchis, neither model fit nor model performance on claimed cases proves that the missing data mechanism is MAR or that the attributions of unclaimed cases are correct. We used suspected attacks to test accuracy on the unclaimed attacks. In addition to claims, the WITS and CPOST data capture suspected responsibility for 706 unclaimed attacks.[7] These suspicions are made by police, government officials, and locals on the ground that are then reported by new sources and subsequently captured by the databases. The ability to test imputed values against expert inferences is an added benefit for studies of militant violence. The model's overall accuracy on suspected attacks was 91 percent and, as with the cross-validation test, it performed best on suspected Baluchi and Pakistani Taliban attacks. The results of our two validation strategies give us confidence that the attributions of responsibility are valid, and by extension, that the assumptions supporting the model are correct.

Analysis of Drone Strike Effectiveness

The final step is to analyze the impact that attribution has on the pattern of Pakistani Taliban violence in response to drones. For multiple imputed data, subsequent analysis is performed on each of the imputed data sets separately. The results are then combined by a standard process to capture differences across the data sets (Rubin 1987, 76). To demonstrate the value of MI, we compare the results of the MI approach to other ad hoc attribution strategies using a standard time series method and find a weak but consistent suppressive effect that only appears in the MI data.

We start our analysis in February 2008 to correspond with the introduction of "signature" drone strikes, a new strategy targeting suspected militants based on profiles rather than confirmed identities, allowing the United States to greatly expand its use of drones in Pakistan's tribal areas (Williams 2010). Our analysis ends after December 2010, the last month for which we collected data on militant violence. We aggregate events at the week level so that our data are not limited by zeros (Shellman 2004), for a total of 154 week observations. We believe that a week is enough time for drone strikes to have an impact on the ability of the Pakistani Taliban to carry out attacks. We also include the measure of Pakistani military operations as a third time series to capture possible exogenous shifts in violence not related to drone strikes.

To show that the choice of attribution strategy affects subsequent findings, we compare the results of the same time series model on three distinct samples of

Table 6. Vector Auto Regression Estimates by Attribution Strategy.

	Claimed	FATA	Multiple Imputation
DV: Violence	Coefficient	Coefficient	Coefficient
Violence	0.02	0.09	0.47***
$t-2$	0.03	0.07	0.20*
Drones	0.14†	0.06	0.16
$t-2$	−0.09	−0.22	−0.94*
Military	−0.01	−0.01	−0.25†
$t-2$	−0.00	0.03	0.30*
Constant	1.39***	6.33***	7.3
DV: Drones	Coefficient	Coefficient	Coefficient
Violence	0.08	−0.08**	−0.02
$t-2$	0.05	0.04	0.01
Drones	0.26***	0.30***	0.26***
$t-2$	0.30***	0.29***	0.30***
Military	−0.01	−0.00	0.00
$t-2$	−0.00	−0.00	−0.01
Constant	0.53*	0.96**	1.01**
DV: Military	Coefficient	Coefficient	Coefficient
Violence	−0.05	−0.01	0.10†
$t-2$	0.01	−0.11	−0.02
Drones	−0.44	−0.52†	−0.36
$t-2$	0.26	0.28	0.31
Military	0.51***	0.51***	0.48***
$t-2$	0.26***	0.27***	0.27***
Constant	1.80*	2.68**	0.07
n	152	152	152

Note: FATA = Federally Administered Tribal Areas; DV = dependent variable.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

Pakistani Taliban attacks: claimed attacks, attacks in FATA, and attacks attributed to the Pakistani Taliban by MI. We analyze the data using vector auto regression (VAR), a method to model the relationship between multiple time series. VAR is well suited to modeling the dynamics of reactionary violence between militant groups and counterinsurgent operations. The resulting system of equations allows for complex interactions between the time series where the value of any given dependent variable is determined by lagged values of the independent and dependent variables (W. Enders 2009, 297-99). The VAR estimates for each of the three attribution strategies are presented in Table 6.[8] The MI results presented are the average of the 100 independent regressions combined using Rubin's rules. Importantly, VAR results were similar across each of the iterations, meaning variation between the imputed data sets did not significantly impact results.

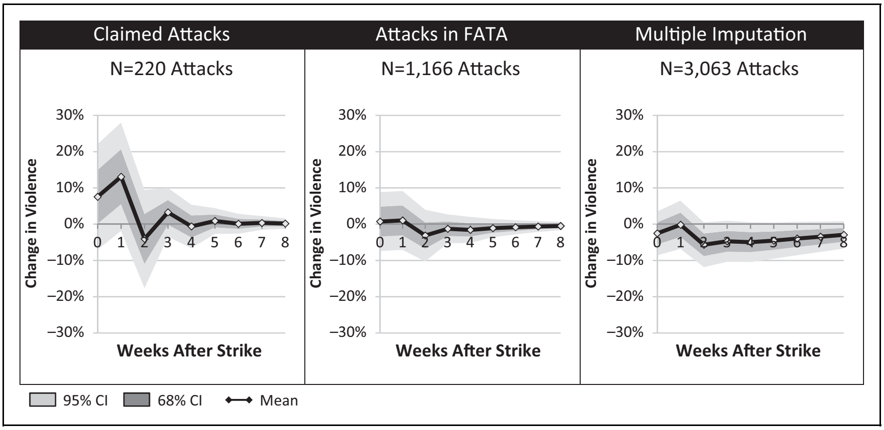

Figure 2. Results of the impulse response functions.

These three different models produced significantly different estimates of the variables that predict militant violence. Using claimed attacks finds only a weak positive correlation between drone strikes and the level of violence ($p > .05$). Using attacks in FATA finds no statistically significant predictors of violence ($p > .1$). Finally, using MI finds a negative correlation between drone strikes and violence ($p < .05$) but also a statistically significant effect of Pakistani military operations ($p < .05$) and the previous level of violence ($p < .001$), the latter presumably revealed by aggregating more data. MI yields substantively different and more credible results, more credible because MI allows for the use of all the violence rather than a small, unrepresentative subset.

VAR, however, is a complex system of equations that does not, by itself, specify the independent effect of these variables on each other. This task is accomplished using an impulse response function (IRF) that estimates the effect of an independent increase of one variable on another while keeping others constant (Lütkepohl 2007, 51). In order to identify this independent effect, we must specify the steps in the causal chain (W. Enders 2009, 309). The most plausible ordering is that Pakistani military operations immediately affect the number of drone strikes and that drone strikes in turn affect the level of Pakistani Taliban violence in that same period but not vice versa.[9] We tested the effect of drone strikes on the level of violence in the following eight weeks. The results of the IRF are presented graphically in Figure 2. As with the VAR, the MI results presented are the average of 100 independent IRFs combined using Rubin's rules, with the results highly consistent across each of the iterations.

Neither of the ad hoc attribution strategies finds strong evidence for a relationship between drone strikes and Pakistani Taliban attacks. Based on claimed attacks, Pakistani Taliban violence escalates by about 10 percent immediately following a drone strike but declines slightly several weeks thereafter. Either of these effects could be driven by changes in the likelihood that attacks are claimed rather than changes in the group's actual operations. The model indicates that the escalatory mechanism is stronger than the de-escalatory mechanism, but neither effect is long-lasting. Based on attacks in FATA, drone strikes do not have an effect on the level of Pakistani Taliban violence. The model was not confident that the number of attacks changed in either direction for the first four weeks following a drone strike but was confident that the change in attacks was close to zero in the next four-week period.

In contrast, based on the full range of Pakistani Taliban operations attributed by MI, drone strikes consistently suppress militant violence by about 5 percent over the entire eight-week period, or about one fewer attack per week. Using a larger sample of attacks significantly improved the model's confidence in comparison to using claimed attacks alone, as illustrated by the narrower confidence bounds, and very little of the remaining uncertainty was due to variation between the imputed data sets. In terms of policy, the findings produced by the MI approach suggest that drone strikes are only marginally effective at reducing militant violence in the short term, and that the effect dissipates over time.

Conclusion

Missing data are a significant challenge for research in political violence and social science in general. Although several ad hoc approaches can be followed, these are driven by the absence of a more rigorous alternative method, do not capture uncertainty in predicting missing values, and so are problematic for subsequent analysis. MI is an approach underpinned by statistical theory that is not only able to predict missing values but to capture the surrounding uncertainty. This is why many areas of social science rely on it.

This article demonstrates that MI is a valid and fruitful solution to the problem of missing perpetrator information in political violence data sets. The method depends on substantive knowledge of the case to justify its application and the availability of granular data on relevant variables. The results are likely to increase the pool of usable data and reduce the bias introduced by unclaimed attacks in subsequent research on political violence. Beyond attributing violence to militant groups, the method presented here is also applicable to scholars trying to determine responsibility for atrocities carried out by insurgents or the state.

While MI promises to advance the study of political violence, it is not appropriate in all cases. The crucial conditions are the ability to distinguish between the operations of different militant groups and reason to believe that observed variables predict why attacks are unclaimed, including that the groups in question have similar claim logics. Preliminary investigation suggests that these conditions are likely to hold in cases such as the civil wars in Iraq and Lebanon, while they are less likely to hold in Israel because Palestinian groups have nearly indistinguishable operational profiles. Attribution is not necessary in cases where only one group operates, such as the conflict in Sri Lanka after 1987, although even in this case scholars may also be interested in the method's ability to identify the violence perpetrated by specific factions of the militant group.

We hope that our article will create much needed discussion about the perils of unattributed political violence and that future work will further develop methods for attributing missing perpetrator information.

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Supplementary Material

Supplementary material is available for this article online.

Notes

1. We used Worldwide Incident Tracking System and Chicago Project on Security and Terrorism data formally introduced in the third section.
2. Preliminary research on claiming in Afghanistan, Iraq, and Pakistan finds important evidence that the variables in our model generally have the same magnitude and direction of effect across cases and militant groups but further testing is needed to determine the robustness of these findings to other conflicts, groups, and predictors of claiming.
3. We excluded 313 attacks where the location, target, or attack type was unknown. We have no reason to believe that missing data in these variables are related to group responsibility and are most likely missing completely at random.
4. As with all quantitative analysis, the results are sensitive to the choice of data set. For example, the Global Terrorism Database attributes 63 percent of claimed attacks in Pakistani to the Pakistani Taliban, 29 percent to Baluchi groups, and 6 percent to sectarian and other groups, but counts less than half the total number of claimed attacks that our composite data set (NCTC-WITS/CPOST-SAD) does in Pakistan during the same period.
5. We use 100 km bandwidth.

6. The *k*-fold validation model excludes the measures of rough terrain, population density, and Pakistani military operations, none of which were statistically significant, because some iterations failed to converge.
7. The overrepresentation of the Pakistani Taliban in the suspected attacks leads us to believe that the reporting of suspicions is politically motivated but we have no reason to believe that the suspicions themselves are inaccurate.
8. We used a standard battery of tests to determine the appropriate lag order for each of the VAR models. For consistency we used two lags for all of the MI models, which tests showed correct in all but five cases.
9. Results are not sensitive to either Cholesky decomposition or the ordering of variables, although the precise estimates do change slightly.

References

Abbas, Hassan. 2009. "Defining the Punjabi Taliban Network." *CTC Sentinel* 2 (4). Accessed July 19, 2013. http://www.ctc.usma.edu/posts/defining-the-punjabi-taliban-network.

Abbas, Hassan. 2014. *The Taliban Revival: Violence and Extremism on the Pakistan-Afghanistan Frontier*. New Haven, CT: Yale University Press.

Achen, Christopher H. 1986. *The Statistical Analysis of Quasi-experiments*. Los Angeles: University of California Press.

Achen, Christopher H. 2005. "Let's Put Garbage-can Regressions and Garbage-can Probits Where They Belong." *Conflict Management and Peace Science* 22 (4): 327-39. doi:10.1080/07388940500339167.

Allison, Paul D. 2001. *Missing Data. Quantitative Applications in the Social Sciences*. Newberry Park, CA: Sage.

Asal, Victor, and R. Karl Rethemeyer. 2008. "The Nature of the Beast: Organizational Structures and the Lethality of Terrorist Attacks." *The Journal of Politics* 70 (2): 437-49. doi:10.1017/S0022381608080419.

Berman, Eli, and David D. Laitin. 2008. "Religion, Terrorism and Public Goods: Testing the Club Model." *Journal of Public Economics* 92 (10-11): 1942-67.

Bloom, Mia. 2005. *Dying to Kill: The Allure of Suicide Terror*. New York: Columbia University Press.

Brehm, John. 1993. *The Phantom Respondents*. Ann Arbor: University of Michigan Press.

Byman, Daniel. 2013. "Why Drones Work: The Case for Washington's Weapon of Choice." *Foreign Affairs* 92 (4): 32-43.

Cederman, Lars-Erik, and Kristian Gleditsch. 2009. "Introduction to Special Issue on 'Disaggregating Civil War.'" *The Journal of Conflict Resolution* 53 (4): 487-95. doi:10.2307/20684599.

Chicago Project on Security and Terrorism (CPOST). (2015). Suicide Attack Database, April 27, 2015, Release [Data File]. Accessed April 28, 2015. http://cpostdata.uchicago.edu.

Collier, Paul, and Anke Hoeffler. 2004. "Greed and Grievance in Civil War." *Oxford Economic Papers* 56 (4): 563-95.

Collins, Linda M., Joseph L. Schafer, and Chi-Ming Kam. 2001. "A Comparison of Inclusive and Restrictive Strategies in Modern Missing Data Procedures." *Psychological Methods* 6 (4): 330-51. doi:10.1037/1082-989X.6.4.330.

Cronin, Audrey Kurth. 2009. *How Terrorism Ends: Understanding the Decline and Demise of Terrorist Campaigns*. Princeton, NJ: Princeton University Press.

Cronin, Audrey Kurth. 2013. "Why Drones Fail: When Tactics Drive Strategy." *Foreign Affairs* 92 (4): 44-54.

Downes, Alexander B. 2008. *Targeting Civilians in War*. Ithaca, NY: Cornell University Press.

Enders, Craig. 2010. *Applied Missing Data Analysis*. New York: The Guilford Press.

Enders, Walter. 2009. *Applied Econometric Time Series*. 3rd ed. Hoboken, NJ: Wiley.

Fearon, James D., and David D. Laitin. 2003. "Ethnicity, Insurgency, and Civil War." *American Political Science Review* 97 (1): 75-90. doi:10.1017/S0003055403000534.

Friedersdorf, Conor. 2012. "Flawed Analysis of Drone Strike Data Is Misleading Americans." *The Atlantic*, July 18. Accessed December 28, 2014. http://www.theatlantic.com/politics/archive/2012/07/flawed-analysis-of-drone-strike-data-is-misleading-americans/259836/.

Graham, John, Allison Olchowski, and Tamika Gilreath. 2007. "How Many Imputations Are Really Needed? Some Practical Clarifications of Multiple Imputation Theory." *Prevention Science* 8 (3): 206-13. doi:10.1007/s11121-007-0070-9.

Grare, Frédéric. 2007. "The Evolution of Sectarian Conflicts in Pakistan and the Ever-changing Face of Islamic Violence." *South Asia: Journal of South Asian Studies* 30 (1): 127-43. doi:10.1080/00856400701264068.

Hafez, Mohammed M. 2006. "Suicide Terrorism in Iraq: A Preliminary Assessment of the Quantitative Data and Documentary Evidence." *Studies in Conflict & Terrorism* 29 (6): 591-619. doi:10.1080/10576100600790878.

Heckman, James. 1979. "Sample Selection Bias as a Specification Error." *Econometrica: Journal of the Econometric Society* 47 (1): 153-61.

Hoffman, Aaron. 2010. "Voice and Silence: Why Groups Take Credit for Acts of Terror." *Journal of Peace Research* 47 (5): 615-26. doi:10.1177/0022343310376439.

Hoffman, Bruce, and Gordon McCormick. 2004. "Terrorism, Signaling, and Suicide Attack." *Studies in Conflict & Terrorism* 27 (4): 243-81.

International Crisis Group. 2006. "Pakistan: The Worsening Conflict in Balochistan." *Asia Report* 119. Accessed August 1, 2013. http://www.crisisgroup.org/en/regions/asia/south-asia/pakistan/119-pakistan-the-worsening-conflict-in-balochistan.aspx.

Jaeger, David, and Zahra Siddique. 2011. "Are Drone Strikes Effective in Afghanistan and Pakistan? On the Dynamics of Violence between the United States and the Taliban." Discussion Paper Series, Forschungsinstitut Zur Zukunft Der Arbeit No. 6262 (December). Accessed August 26, 2014. http://nbn-resolving.de/urn: nbn: de: 101:1-201203016420.

Jarvis, A., H. I. Reuter, and E. Guevara. 2008. "Hole-filled Seamless SRTM Data V4." *International Centre for Tropical Agriculture (CIAT)*. Accessed March 24, 2015. http://srtm.csi.cgiar.org.

Jenkins, Brian. 2006. "The New Age of Terrorism." In *Homeland Security Handbook*, edited by David G. Kamien, 117-29. New York: McGraw-Hill.

Johnston, Patrick, and Anoop Sarbahi. 2015. "The Impact of U.S. Drone Strikes on Terrorism in Pakistan and Afghanistan." *Working Paper*, April 21, 2015. Accessed June 1, 2015. http://patrickjohnston.info/materials/drones.pdf.

Jones, Seth, and Christine Fair. 2010. *Counterinsurgency in Pakistan*. Santa Monica, CA: RAND.

Kalyvas, Stathis. 2006. *The Logic of Violence in Civil War*. 1st ed. Cambridge, UK: Cambridge University Press.

Kearns, Erin, Brendan Conlon, and Joseph Young. 2014. "Lying about Terrorism." *Studies in Conflict & Terrorism* 37 (5): 422-39. doi:10.1080/1057610X.2014.893480.

Khan, Adeel. 2009. "Renewed Ethnonationalist Insurgency in Balochistan, Pakistan: The Militarized State and Continuing Economic Deprivation." *Asian Survey* 49 (6): 1071-91. doi:AS.2009.49.6.1071.

King, Gary, James Honaker, Anne Joseph, and Kenneth Scheve. 2001. "Analyzing Incomplete Political Science Data: An Alternative Algorithm for Multiple Imputation." *American Political Science Review* 95 (1): 49-70.

Kydd, Andrew, and Barbara Walter. 2006. "The Strategies of Terrorism." *International Security* 31 (1): 49-79.

LaFree, Gary, and Laura Dugan. 2007. "Introducing the Global Terrorism Database." *Terrorism and Political Violence* 19 (2): 181-204. doi:10.1080/09546550701246817.

LaFree, Gary, Laura Dugan, and Erin Miller. 2014. *Putting Terrorism in Context: Lessons from the Global Terrorism Database*. 1st ed. Abingdon, Oxon: Routledge.

Lake, David A. 2002. "Rational Extremism: Understanding Terrorism in the Twenty-First Century." *Dialogue IO* 1 (1): 15-29.

Little, Roderick. 1992. "Regression with Missing X's: A Review." *Journal of the American Statistical Association* 87 (420): 1227-37.

Lütkepohl, Helmut. 2007. *New Introduction to Multiple Time Series Analysis*. New York: Springer.

McCormick, Gordon H. 2003. "Terrorist Decision Making." *Annual Review of Political Science* 6 (1): 473-507.

National Consortium for the Study of Terrorism and Responses to Terrorism (START). (2014). Global Terrorism Database [Data file]. Accessed March 5, 2014. http://www.start.umd.edu/gtd.

National Counterterrorism Center (NCTC). (2012). Worldwide Incidents Tracking System [Data File]. Accessed February 1, 2012. http://wits.nctc.gov.

Pakistani Population Census Organisation. 1998. *1998 District Census Report of [name of District]*. Islamabad, Pakistan: Pakistan Bureau of Statistics.

Pape, Robert. 2005. *Dying to Win: The Strategic Logic of Suicide Terrorism*. New York: Random House.

Piazza, James A. 2009. "Is Islamist Terrorism More Dangerous?: An Empirical Study of Group Ideology, Organization, and Goal Structure." *Terrorism and Political Violence* 21 (1): 62-88. doi:10.1080/09546550802544698.

Pluchinsky, Dennis A. 1997. "The Terrorism Puzzle: Missing Pieces and No Boxcover." *Terrorism and Political Violence* 9 (1): 7-10.

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen. 2010. "Introducing ACLED: An Armed Conflict Location and Event Dataset." *Journal of Peace Research* 47 (5): 651-60.

Raleigh, Clionadh, Frank Witmer, and John O'Loughlin. 2010. "A Review and Assessment of Spatial Analysis and Conflict: The Geography of War." *The International Studies Encyclopedia* 10:6534-53.

RAND Corporation. 2012. "RAND Database of Worldwide Terrorism Incidents." Accessed November 20, 2013. http://smapp.rand.org/rwtid.

Rapoport, David. 1997. "To Claim or Not to Claim; That Is the Question—Always!" *Terrorism and Political Violence* 9 (1): 11-17. doi:10.1080/09546559708427383.

Ross, Alice, and Jack Serle. 2014. *Get the Data: What the Drones Strike*. London, UK: The Bureau of Investigative Journalism.

Rubin, D. B. 1987. *Multiple Imputation for Nonresponse in Surveys*. New York: Wiley.

Schafer, Joseph L. 1997. *Analysis of Incomplete Multivariate Data. Vol. 72*. London, UK: Chapman & Hall/CRC.

Shapiro, Jacob. 2013. *The Terrorist's Dilemma: Managing Violent Covert Organizations*. Princeton, NJ: Princeton University Press.

Shapiro, Jacob, Ethan Bueno de Mesquita, C. Christine Fair, Jenna Jordan, and Rasul Bakhsh Rais. 2013. "The BFRS Political Violence in Pakistan Dataset." Accessed November 20, 2013. https://esoc.princeton.edu/files/bfrs-political-violence-pakistan-dataset-0.

Shellman, Stephen M. 2004. "Time Series Intervals and Statistical Inference: The Effects of Temporal Aggregation on Event Data Analysis." *Political Analysis* 12 (1): 97-104. doi:10.1093/pan/mpg017.

Sundberg, Ralph, and Erik Melander. 2013. "Introducing the UCDP Georeferenced Event Dataset." *Journal of Peace Research* 50 (4): 523-32.

Weinstein, Jeremy. 2006. *Inside Rebellion*. Cambridge, UK: Cambridge University Press.

White, Ian, Rhian Daniel, and Patrick Royston. 2010. "Avoiding Bias Due to Perfect Prediction in Multiple Imputation of Incomplete Categorical Variables." *Computational Statistics & Data Analysis* 54 (10): 2267-75. doi:10.1016/j.csda.2010.04.005.

Williams, Brian Glyn. 2010. "The CIA's Covert Predator Drone War in Pakistan, 2004–2010: The History of an Assassination Campaign." *Studies in Conflict & Terrorism* 33 (10): 871-92. doi:10.1080/1057610X.2010.508483.

Wood, Reed M. 2010. "Rebel Capability and Strategic Violence against Civilians." *Journal of Peace Research* 47 (5): 601-14. doi:10.1177/0022343310376473.