Can Civilian Attitudes Predict Civil War Violence?∗

Kentaro Hirose† Kosuke Imai‡ Jason Lyall§

First Draft: December 1, 2013
Current Draft: December 2, 2014

Abstract

Are civilian attitudes a useful predictor of patterns of violence in civil wars? A prominent debate has emerged among scholars and practitioners about the importance of winning civilian “hearts and minds” for influencing their wartime behavior. We argue that such efforts may have a dark side: insurgents can use pro-counterinsurgent attitudes as cues to select their targets and tactics. We conduct an original survey experiment in 204 Afghan villages and establish a positive association between pro-International Security Assistance Force attitudes and future Taliban attacks. We extend our analysis to 14,606 non-surveyed villages and demonstrate that our measure of civilian attitudes improves out-of-sample predictive performance by 20–30% over a standard forecasting model. The results are especially strong for Taliban attacks with improvised explosive devices. These improvements in predictive power remain even after adjusting for possible confounders, including past violence, military bases, and development aid.

Key Words: Civil War; Public Opinion; Survey Experiment; Out-of-sample Prediction

∗Financial support for the survey from Yale’s Institution for Social and Policy Studies’ Field Experiment Initiative and the Macmillan Center for International and Area Studies is gratefully acknowledged. Additional support from the Air Force Office of Scientific Research (Lyall; Grant #FA9550-09-1-0314) and the National Science Foundation (Imai; Grant SES-0849715) is also acknowledged. This research was approved by Yale’s Human Subjects Committee under IRB protocol #1006006952. We thank seminar participants at the University of Sydney and Princeton University for helpful comments.

†Postdoctoral Fellow, Department of Politics, Princeton University, Princeton NJ 08544. Email: hirose@princeton.edu URL: http://scholar.princeton.edu/hirose

‡Professor, Department of Politics, Princeton University, Princeton NJ 08544. Phone: 609–258–6601, Email: kimai@princeton.edu URL: http://imai.princeton.edu

§Associate Professor, Department of Political Science, Yale University, New Haven, CT 06520. Phone: 203–432–5264, Email: jason.lyall@yale.edu URL: http://www.jasonlyall.com
1 Introduction

Are civilian attitudes a useful predictor of patterns of civil war violence? The past decade has witnessed the renewal of a debate over the importance of winning “hearts and minds” in counterinsurgency wars such as Afghanistan and Iraq. Billions of dollars have been spent by militaries and development agencies on reducing insurgent violence by finding the mix of aid, services, and protection that persuades fence-sitting civilians to side with the government (Vanden Eynde, 2013; World Bank, 2012; Sambanis, Schulhofer-Wohl and Shayo, 2012; Beath, Christia and Enikolopov, 2011; Berman, Shapiro and Felter, 2011; Department of the Army, 2007).

This discussion rests on a simple premise: civilian attitudes are a reliable guide to subsequent behavior. Most of the theoretical literature on civil war violence, however, remains deeply skeptical of a link between attitudes and behavior (see, for example, Kalyvas, 2012, 2006; Stoll, 1993; Leites and Wolf, 1970). Indeed, civilians are often cast as strategic actors, shifting allegiances frequently as circumstance requires. In this view, attitudes are likely endogenous to a host of wartime dynamics, including the relative distribution of control and economic assistance, and thus hold little independent power when explaining behavior. In addition, given the difficulties of accurately measuring wartime attitudes, it is unsurprising that the role of attitudes in shaping patterns of violence has been relatively unexplored.

We demonstrate that civilian attitudes, when measured reliably at a local level, can be used to predict future patterns of civil war violence. We argue that the distribution of attitudes toward the counterinsurgent can act as “cues” for insurgents that facilitate their decision-making about where and how to stage attacks. The spatial distribution of attitudes helps insurgents prioritize their attacks against counterinsurgent forces given resource constraints while dictating how discriminate their violence must be given the local population’s prevailing views. Efforts to win “hearts and minds” may therefore have an
unintended consequence: these efforts paradoxically attract increased insurgent attacks against counterinsurgent forces in areas where counterinsurgents have made the deepest inroads.

Our interest in civilian attitudes as a predictor of insurgent violence joins a renewed call for prediction in the social sciences (e.g., Hill, Jr. and Jones 2014; Schrodt 2014; Metternich et al. 2013; Montgomery, Hollenbach and Ward 2012; Braithwaite and Johnson 2012; Goldstone et al. 2010; Weidmann and Ward 2010; Bohorquez et al. 2009; King and Zeng 2001; Beck, King and Zeng 2000). While existing prediction efforts are typically cross-national, we take a disaggregated approach to data collection and predict village-level violence over variable spatial and temporal windows as fine-grained as one kilometer and one day, respectively.

We also move beyond existing forecasting models by introducing contextual information rather than relying simply on prior violence to predict future attacks, as is often current practice (Johnson et al. 2011; Zammit-Mangion et al. 2012; Yonamine 2013). Specifically, we draw on a survey experiment in 204 villages in Afghanistan, along with two datasets recording insurgent attacks against the International Security Assistance Force (ISAF) and civilians, to test the association between attitudes and subsequent violence. Wary of the dangers of over-fitting, we also extend our analysis to out-of-sample prediction (Ward, Greenhill and Bakke 2010; King and Zeng 2001; Beck, King and Zeng 2000). We re-estimate our models using 14,606 non-surveyed villages to examine how incorporating attitudes improves predictive accuracy across three categories of insurgent violence and two different targets. To our knowledge, this paper represents the first attempt at cross-validating village-level prediction with extensive out-of-sample testing.

Three main findings emerge. First, we find that pro-counterinsurgent attitudes significantly improve the accuracy of predicting the location of insurgent direct attacks and the use of improvised explosive devices (IEDs) for up to 10 months after our survey. Specifically,
our attitudinal measure has a robust in-sample association with future violence patterns while improving the predictive performance of our out-of-sample models by 20-30%. Second, we find little evidence that pro-counterinsurgent attitudes are associated with “found” IEDs, suggesting that winning hearts and minds may not translate into actionable intelligence. Finally, these findings hold after adjusting for confounding variables such as prior insurgent violence, the location of ISAF and Afghan National Security Forces (ANSF) bases, and the distribution of economic assistance. They are also robust to multiple measures of predictive improvement and models that address potential nonlinearities.

2 The Dark Side of Winning “Hearts and Minds”

We argue that insurgents use civilian attitudes as cues when determining the location and nature of attacks against counterinsurgent forces. Faced with a wide array of possible targets, insurgents use pro-counterinsurgent attitudes as evidence that hearts and minds efforts are gaining traction. To forestall the loss of these villages, insurgents will direct their attacks against counterinsurgent forces in an attempt to derail these initiatives. We therefore expect to observe a positive association between relative support for the counterinsurgent and subsequent insurgent attacks. We also anticipate that these attacks will be relatively indiscriminate since insurgents may relax (or abandon) prohibitions against inflicting collateral damage against civilians in these pro-counterinsurgent areas. As a result, we expect insurgent violence against both the counterinsurgent forces and civilians in these pro-counterinsurgent villages to increase.

2.1 “Hearts and Minds” and Related Theories

The belief that winning over civilians is an important goal in counterinsurgency campaigns has emerged as a staple of so-called “hearts and minds” theory. Perhaps less a theory than a collection of related propositions, the hearts and minds approach counsels that a
mixture of economic assistance, service delivery, and protection can convince fence-sitting populations to support the counterinsurgent. Civilian behavior follows attitudes; win over hearts and minds, and individuals will provide information about the insurgents hiding in their midst. Civilians in this account are calculating actors, often supporting whichever side promises the most benefits despite preexisting political loyalties or coethnic affinities.

This view of civilian attitudes during wartime suggests several observable implications. Most importantly, if hearts and minds claims are correct, then we should observe a decrease in insurgent attacks as relative support for the counterinsurgent grows. The U.S. Army’s Field Manual, recently revised in May 2014, makes this connection explicit: military offensives and aid campaigns are designed to create safe spaces for the population by reducing insurgent attacks. Each phase of the Army’s “shape-clear-hold-build-transition” framework is associated with decreased insurgent attacks, though not necessarily their complete absence. Indeed, the first metric proposed for measuring hearts and mind effectiveness is the number of insurgent attacks and casualties among COIN forces and the civilian populace (Department of the Army 2014, Section 12-29; see also Figure 9-1).

While existing scholarship converges on the use of insurgent attacks to measure hearts and minds effectiveness, various mechanisms are invoked to explain this relationship. Insurgent violence may decrease, for example, as the provision of tips from civilians better enables counterinsurgents to identify and destroy rebel leaders and networks (Kalyvas 2006; Department of the Army 2007; Berman, Shapiro and Felter 2011). Cash-for-work programs and other forms of economic assistance may also raise the opportunity costs for participating in the insurgency, making recruitment difficult and driving would-be insurgents from the ranks (Blattman and Annan 2014). Increased contact with counterinsurgents may also convince wary civilians to change their beliefs and to support the counterinsurgent’s cause. Finally, an increase in counterinsurgent troop strength in an area may act as a deterrent, forcing rebels to seek targeting opportunities elsewhere (Department of the Army 2007, pp.
but see Friedman (2011).

Some or all of these mechanisms may be operating simultaneously, making it difficult to tease them apart. Nonetheless, they converge on the same empirical expectation: pro-counterinsurgent attitudes should translate into reduced insurgent violence in a given area.

2.2 Attitudes as Cues for Insurgent Targeting

While recognizing the possibility that “hearts and minds” can be won, if temporarily, we argue that such efforts also have a darker side, one typically left unacknowledged by scholars and practitioners. We hypothesize that success at influencing attitudes may come at the cost of increasing the risk that counterinsurgent forces and, by extension, civilians face from insurgent reprisals. These pro-counterinsurgent attitudes act as cues for guiding target selection in an environment where insurgents find themselves facing resource constraints and incomplete territorial control. Put differently, hearts and minds efforts may be victims of their own success, attracting the very insurgent violence that may eventually sabotage these initiatives. The result may be the abandonment of now-exposed populations after counterinsurgent forces and aid organizations shift their focus to more “favorable” areas.

The assumption that insurgents possess informational advantages relative to counterinsurgents is a basic premise of nearly all theories of civil war violence (Lyall and Wilson, 2009). Yet past studies have largely focused on how states overcome the “identification problem” — namely, correctly identifying insurgents hiding among civilians (Kalyvas, 2006, p. 89). In contrast, we investigate the question of how information asymmetries might influence insurgent targeting and tactics.

Insurgents typically construct elaborate monitoring systems to augment their local ties and networks. They in turn use this information to guide the location of their attacks against counterinsurgent forces. Striking disproportionately within or near villages that support the counterinsurgent makes sense as a war-fighting strategy for several reasons. The
continued erosion of insurgent support in these villages can result in the loss of information, resources, and recruits that the insurgency relies on to generate its combat power. These attacks not only preserve the insurgency’s initiative against counterinsurgent forces but also drives up the cost of defending these centers. If the insurgents are able to create the perception that the counterinsurgent cannot credibly defend the populace, then erstwhile counterinsurgent supporters may curtail their collaboration or defect (back) to the rebel side.

In addition, insurgents should attack pro-counterinsurgent villages to influence more fence-sitting villages, for two reasons. First, punishing pro-counterinsurgent villages can forestall the loss of other villages by demonstrating the costs of siding openly with the counterinsurgent. Insurgent targeting against these villages has a twin punish-deter logic; punishing these pro-counterinsurgent villages will have a deterrent effect on other, perhaps wavering, “swing” villages. Second, while insurgents are certainly interested in swing villages, they are less likely to use violence here, hoping to avoid the absolute loss of support that can accompany rebel victimization of civilian populations (Lyall, Blair and Imai, 2013). Insurgents are more likely to use redistributive mechanisms (“carrots”) in these swing villages; pro-counterinsurgent villages, on the other hand, are more likely to be punished violently (“sticks”). As a result, we predict a monotonic relationship between support and the use of violence against both counterinsurgent forces and civilian populations.

Knowledge of the distribution of civilian attitudes may also influence insurgents’ choice of tactics. Tactics that require networks within villages — notably, the use of improvised explosive devices (IEDs) and suicide bombings — may become wasting assets if the local population begins to side with the counterinsurgent. Insurgents may therefore feel compelled by a “use it or lose it” dynamic to privilege these tactics in an effort to rollback

---

1. Loss of these villages may also drive a wedge into the insurgency by creating “loyalist” faction that undercuts insurgent recruitment along ideological or ethnic lines (see Kalyvas, 2008; Lyall, 2010).
2. This claim is also broadly consistent with Kalyvas (2006)’s argument that populations under contested insurgent-counterinsurgent control are least likely to witness violence.
pro-counterinsurgent support.

These tactics are typically less discriminate than other forms of violence, raising the possibility of civilian casualties. Roadside IEDs often miss their intended military targets and instead inflict casualties on locals who had the misfortune of trailing a military convoy, for example. Yet insurgents may relax their prohibitions (if any) on killing civilians if the violence is largely restricted to the pro-counterinsurgent village. In this case, indiscriminate violence underscores the risks associated with abandoning the insurgency. Similarly, killing civilians who are actively working with counterinsurgent forces are likely to be viewed as “traitors” and thus legitimate targets.

The risks of alienating the population by killing civilians may also be negligible, or at least manageable, for insurgents. Once again, insurgents are seeking to punish, not persuade, pro-counterinsurgent villages. Moreover, civilians in swing villages may actually support these actions if the pro-counterinsurgent villages are viewed as traitors to a particular ethnopolitical cause. Insurgents may even gain support via such actions: if the counterinsurgent is provoked into retaliatory actions that harm civilians, the net effect is likely a shift in relative support toward the insurgent organization. Counterinsurgents are disproportionately punished by populations for civilian victimization if they drawn from groups outside the insurgent’s own members (Lyall, Blair and Imai 2013).

In sum, this conception of attitudes-as-targeting-cues suggests several empirical observations that sharply differ from “hearts and minds” expectations. Rather than anticipating that insurgent violence decreases in pro-counterinsurgent areas, we should expect that insurgents will disproportionately target villages that express pro-counterinsurgent sympathies. Violence against both counterinsurgents and civilians should increase in these pro-counterinsurgent villages. We expect that these cues are quite localized in nature. That is, we predict that insurgent violence clusters around the cue of a pro-counterinsurgent village; the predictive value of civilian attitudes drops as we move away from these types
of villages. Insurgents should also emphasize indiscriminate tactics when attacking these villages for their ability to maximize damage among counterinsurgent forces, their shock value among targeted civilians, and their deterrent value among neighboring villages. Pro-counterinsurgent attitudes should therefore be an important predictor of the use of improvised explosive devices.

2.3 Inferential Threats and Alternative Accounts

We face two inferential challenges when testing this attitudes-as-cues argument. First, given the skepticism of existing theories, we must demonstrate that the inclusion of attitudinal measures improves prediction of the location and timing of future insurgent violence. Second, this improvement in predictive accuracy must remain even after adjusting for confounding variables that might also explain these findings.

Indeed, there are at least four counterclaims that could be levied against our explanation. First, the conflict modeling literature has demonstrated that a leading predictor of future violence is simply the prior distribution of violence (e.g., Yonamine 2013, Zammit-Mangion et al. 2012, Montgomery, Hollenbach and Ward 2012, Bohorquez et al. 2009). In situations marked by a high frequency of events, short time frames, and repeated interaction with the same combatant, past behavior is likely to be a reliable predictor of future events, barring successful deterrence of the insurgent organization or its outright destruction. To test the validity of our theoretical argument, we must investigate whether attitudinal measures improve predictive accuracy even with prior violence included in our models.

Second, insurgent targeting may reflect the distribution of counterinsurgent forces within a given area. There are three possible mechanisms at work, none of which rely on civilian attitudes as a causal factor in explaining future insurgent attacks. The presence of bases and soldiers may alone be sufficient to guide target selection; the higher the con-
centration of forces, or the closer proximity to bases, the more likely these locations are to witness insurgent attacks. It may be that civilian attitudes are simply endogenous to base locations: more contact with the counterinsurgent may result in more support for the counterinsurgent. In addition, a higher degree of counterinsurgent control might lead to greater tips from local populations about insurgent actions and identities. As a consequence, villages close to pro-government military bases should have lower levels of insurgent violence due to better local information than villages more removed from counterinsurgent forces.

Third, pro-counterinsurgent attitudes may be associated with the presence of aid programs designed to win over fence-sitting populations. Aid programs could attract greater insurgent attacks as these groups seek to disrupt or, alternatively, violently appropriate these resources. Programs that focus on capital-intensive activities such as infrastructure development are especially likely to be subject to rent capture through violence given the substantial funding associated with those projects. We therefore must adjust for the presence of aid projects since they may account for both pro-counterinsurgent attitudes and patterns of insurgent violence.

Finally, other village characteristics might be predictive of future attacks. Rough terrain has long been associated with insurgency, for example. We might also expect a fairly mechanical relationship to exist between population size and violence; the larger the village’s population, the more targets, and the greater the likelihood of experiencing insurgent attacks.

Our empirical setting of Afghanistan helps eliminate several alternative explanations.

---

3 Note that the opposite could hold true: areas with weaker concentrations of forces may be singled out for attack by insurgents to maximize their chances of inflicting casualties while minimizing their own possible losses.

4 Kalyvas (2006) contends that selective insurgent violence should be greatest in areas that are mostly, but not completely, controlled by government forces (pp. 204–205).

5 In addition, aid may also increase locals’ willingness to provide information to the authorities about insurgent activities.
of insurgent violence. The violence in our predominantly Pashtun sample is mostly intra-ethnic, suggesting ethnicity is not facilitating insurgent targeting in this case (Fjelde and Hultman 2013; Weidmann 2009). Prewar electoral cleavages, another possible social cue for insurgent targeting, are also absent (Baicells 2011).

To be sure, we cannot rule out every confounding factor. We lack a measure for insurgent skills, for example, which may vary locally, helping to explain the selection of tactics (Asal et al. 2013). Nevertheless, our models account for major factors thought to drive insurgent behavior. If our position is correct, then we should observe improvements in predictive accuracy for insurgent violence even when accounting for these alternative explanations.

3 Data and Measurement

We use a survey experiment conducted in Afghanistan in 2011 to measure attitudes for our predictive exercise. We first briefly outline our survey design, including the multistage sampling strategy. We then detail the four indirect endorsement experiments that, when combined with a statistical model, provide a village-level measure of relative support for ISAF. Next, we introduce the declassified data used to construct measures for three types of insurgent violence. We also introduce variables to operationalize alternative predictors for insurgent violence. These predictors include: (1) prior insurgent violence; (2) the location of Afghan National Security Forces and ISAF bases; and (3) the location of counterinsurgents’ aid projects. Taken together, these three covariates constitute our “base” model for estimating the location and timing of insurgent attacks over various spatial and temporal intervals.

The Taliban are present in all five of our sampled provinces. The Haqqani network is principally active in two of our provinces, Khost and Logar (Brown and Rassler 2013).
3.1 The Survey

We measure support for ISAF and the Taliban using a survey of 2,754 adult male respondents from 204 villages in 21 districts of five Pashtun-dominated provinces of Afghanistan (Logar, Kunar, Uruzgan, Helmand, and Khost). After two large scale pilot surveys in these provinces, the survey was conducted 18 January—3 February 2011.

The sample was constructed using a multistage sampling method. Figure 1 illustrates the location of the 204 surveyed villages (blue dots) and the 14,606 non-surveyed villages.
First, the five provinces, whose borders are highlighted in the map, were randomly sampled from the 13 Pashtun-majority provinces (colored grey on the map). Within each of these five provinces, districts, and then villages, households, and finally individuals, were randomly sampled. Households were chosen using the random walk method. Owing to security considerations and cultural constraints, only male respondents aged 16 years and older were randomly selected from the sampled households using a Kish grid.

We obtained a 89% participation rate (2,754 respondents out of 3,094 approached individuals). The average respondent was a 32-year old Pashtun male who was likely married (77%), possibly employed full-time (58%), and possessed little or no formal (government) schooling and only an average of 18 months of madrassa education. Nearly all respondents were Pashtun by ethnicity (93%). Our sampling frame encompassed some of the poorest areas in Afghanistan; respondents reported possessing only 90 minutes of electricity per day, and daily income hovered between $1-6 US dollars.

Of the original 204 villages, only four proved inaccessible due to a combination of Taliban hostility, the presence of criminal elements and, in two cases, the inability of enumerators to find the village. In all cases, village elders were first approached by our survey firm, Opinion Research Center of Afghanistan (ORCA), to describe the survey and to obtain permission for enumerators to enter the village. All enumerators were locals; nearly all surveys were conducted in Pashto. Informed consent was obtained in all cases orally; special permission was granted by Yale’s IRB to waive written consent requirements to avoid linking respondents to particular surveys. This helped minimize the risk of reprisal if the written forms were intercepted by the Taliban. Similarly, the names of respondents were not recorded.

---

9 The remaining eight provinces are Ghazni, Kandahar, Laghman, Nangahar, Paktia, Paktika, Wardak, and Zabul.
10 Further details about survey implementation can be found in Section A.1 of the Supporting Information and Lyall, Blair and Imai (2013).
3.2 Measuring Support

Given the sensitivity of measuring wartime support for armed combatants, we employ a battery of four indirect endorsement experiments to estimate support for ISAF and the Taliban. This approach mitigates social desirability bias and item non-response when asking questions about sensitive issues \cite{Bullock, Imai and Shapiro 2011}. Direct questions, by contrast, can endanger enumerators and respondents alike and often result in high non-response rates and biased answers.

To take one example, a recent wave of ISAF’s own Afghan National Quarterly Assessment Report (ANQAR) in November-December 2011 recorded nearly 50% non-response rate as potential respondents refused to participate. Our overall refusal rate was about 5% for our endorsement experiments, a difference we ascribe to the indirect questioning method we employed. Table 2 in Section A.3 of the Supporting Information (SI) shows the pattern of non-response rates by province. The highest non-response rate is obtained in Helmand province, which has the highest level of insurgent violence and support. We address this non-response problem in our statistical analysis by assuming that the pattern of non-response is random conditional on all observed data.

The mechanics of an endorsement experiment are straightforward. We first randomly divided a sample of respondents into groups. In the “control” group, respondents were asked to rate the level of their support for a particular policy. For those in the “treatment” group, the identical question was asked except that the policy was said to be endorsed by an actor of interest. We then take advantage of subtle cues induced by endorsements and interpret the difference in responses between the treatment and control groups as evidence of support (or lack thereof) for this actor of interest. This is based on the psychological literature, which finds that people tend to more positively (negatively) evaluate an item when paired with another item they like (dislike). In our application, we have two actors
of interest, ISAF and the Taliban, and thus the sample was randomly divided into three groups of equal size — Taliban treatment, ISAF treatment, and control — across individual respondents within each sampled village.

Typically, multiple policies in the same domain are selected so that the measurement does not rely on a single instrument. Statistical power is also increased by analyzing multiple items together. In our survey experiment, we employ four questions concerning domestic policies: prison reform, direct election of district councils, a reform of the Independent Election Committee, and the strengthening of anti-corruption policies. The exact question wording appears in Section A.1 of the SI. Elsewhere, we provide detailed justifications for the choice of these policy questions in the Afghanistan context [Lyall, Blair and Imai, 2013].

A Bayesian hierarchical factor analytic model is used to (partially) pool the responses to these four questions together, creating an estimate of individual-level support for ISAF and the Taliban [Bullock, Imai and Shapiro, 2011]. We then aggregate individual-level support values by computing the sample mean to create an estimate of village-level support for each combatant. When modeling individual-level support, we use as regressors village-level random effects and individual-level covariates such as the respondent’s age, income level, years of education, years of madrassa schooling, direct exposure to violence by the Taliban or ISAF, experience of encountering the Taliban or ISAF, the frequency in which the respondent encounters ISAF, and whether his tribe was pro-Taliban. The exact model we use is described in Section A.2 of the SI and is fitted through the open-source R package endorse [Shiraito and Imai, 2012].

The resulting measures of village-level support are numerical estimates for each combatant. The support level for the Taliban ranges from $-1.14$ to $1.42$ while that for ISAF ranges from $-1.75$ to $0.43$ with positive (negative) values, indicating support for (opposition against) the combatant. Figure 7 in Section A.3 of the SI presents the distribution of
Figure 2: Spatial distribution of the relative support for International Security Assistance Force (ISAF) in the 204 surveyed villages from the five randomly sampled Pashtun-dominated provinces. The warmer color (red) represents villages which are more supportive of ISAF than the Taliban, whereas the colder color (blue) indicates villages that are less supportive. There is a considerable degree of spatial heterogeneity in the level of relative support for ISAF. The lines within the provinces represent district borders.

Each support measure as well as the distribution of the difference between the two. The figure clearly shows that a majority of Afghan population supports Taliban over ISAF. These support measures are standardized on a latent variable scale (so called “ideal points” and “ability” parameters in the political methodology and psychometrics literatures, respectively), and so only their sign and relative magnitude can be interpreted. In addition, we validate these support measures against another measure based on the item count technique and find these two indirect questioning methods provide essentially identical findings (Blair, Imai and Lyall [2014]).

In our main analysis, we operationalize relative support for ISAF as the difference
between ISAF and Taliban support levels and use this measure as the key predictor of insurgent violence. Relative support for ISAF ranges from $-3.01$ to $0.91$, suggesting that Afghans are far more supportive of the Taliban than ISAF. Figure 2 presents the spatial distribution of relative ISAF support measure for the 204 surveyed villages in the five sampled provinces. In general, Taliban support is strongest in Uruzgan and especially Helmand, two provinces long associated with the post-2001 reemergence of the Taliban. The eastern provinces of Khost, Kunar, and Logar present a more mottled picture, with substantial pockets of support for the Taliban and ISAF.

Of particular interest is the fact that neighboring villages sometimes have different relative levels of support for these combatants. Even within the same district, some villages are supportive of ISAF while others are opposed. This local variation underscores the need to embrace disaggregated data rather than assign support values at the larger district level—as is standard operating procedure for ISAF’s own efforts to measure hearts and minds.

### 3.3 Measuring Violence

We first measure insurgent violence using declassified event data from ISAF’s Combined Information Data Network Exchange (CIDNE). These data record the date, location (using Military Grid Coordinate System) and nature of insurgent attacks against ISAF forces and installations throughout Afghanistan. Distinct from WikiLeaks’ Afghan War Diary, these data represent the most comprehensive account of insurgent attacks to date, though they are not without their limitations. These “Significant Acts” (SIGACTs) rarely cover violence against Afghan National Security Forces and exclude violence against civilians. As such, our main analysis focuses on insurgent attacks against ISAF alone. We use data from 10 months before and after our January-February 2011 survey for our prediction models; a total of 69,841 insurgent attacks were recorded over this period.
CIDNE tracks 11 discrete types of insurgent attacks that are relevant for our purposes here. We aggregate these types into three broad categories. First, we constructed an “Improvised Explosive Device (IED) Attacks” category that records 11,577 events of IED explosions, mine strikes, and premature IED detonations. IEDs represent the most lethal form of insurgent attack against ISAF forces, accounting for 54% of all soldier fatalities since 2007 [ICasualties.org, 2013], and ISAF has devoted billions of dollars in a cat-and-mouse effort to mitigate this threat.\(^{11}\)

Second, we created an “IED found” category that includes 19,093 events where ISAF forces found and cleared IEDs or mines.\(^{12}\) We make a clear distinction between “found” IEDs and “detonated” IEDs to determine whether tips from locals in pro-ISAF villages translate into higher than average timely discovery of IEDs, as anticipated by hearts and minds theory.\(^{13}\) This is an imperfect measure: found IEDs may reflect improved detection capabilities via technical means by ISAF that occurred independent of civilian support. Absent classified data on IED detection, we cautiously use this variable as a proxy for tips flowing from civilians.

Lastly, we created a “Non-IED Attacks” category that includes 39,171 insurgent attacks using small arms fire, indirect fire (e.g., mortars) and rocket fire against ISAF forces and installations.\(^{14}\) We distinguish between IED and non-IED attacks because, as explained earlier, the notion of attitudes-as-targeting-cues suggests an especially strong association between civilian attitudes and certain classes of tactics with maximum destructive value such as IEDs.

In our analysis, these three categories are operationalized as count variables recording

\(^{11}\)Specific CIDNE categories are (1) IED Explosion, (2) Premature IED Detonation, and (3) Mine Strike.

\(^{12}\)Specific CIDNE categories are (1) IED Found and Cleared, (2) IED Threat, (3) IED Cache/Find, and (4) Mine Found and Cleared.

\(^{13}\)Without disaggregating the IED category, we would also be left unable to determine whether a relative increase in IED counts in pro-ISAF villages was due to greater insurgent targeting (“detonated IEDs”), increased discovery thanks to locals, or to both mechanisms working simultaneously.

\(^{14}\)Specific CIDNE categories are (1) Direct Fire, (2) Attack, (3) Raid/Ambush, and (4) Indirect Fire.
Violence before Survey
(March – December 2010)

Violence after Survey
(March – December 2011)

<table>
<thead>
<tr>
<th>Provinces</th>
<th>Surveyed Villages</th>
<th>Non-surveyed Villages</th>
<th>ANSF/ISAF Bases</th>
<th>Aid Projects</th>
<th>IED Attack</th>
<th>IED Found</th>
<th>Non-IED Attack</th>
<th>IED Attack</th>
<th>IED Found</th>
<th>Non-IED Attack</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logar</td>
<td>19.6%</td>
<td>14.2%</td>
<td>13.3%</td>
<td>14.3%</td>
<td>5.1%</td>
<td>3.7%</td>
<td>4.9%</td>
<td>6.5%</td>
<td>5.8%</td>
<td>11.3%</td>
</tr>
<tr>
<td>Kunar</td>
<td>14.7</td>
<td>18.6</td>
<td>31.3</td>
<td>48.3</td>
<td>3.9</td>
<td>1.5</td>
<td>15.9</td>
<td>3.5</td>
<td>1.8</td>
<td>21.1</td>
</tr>
<tr>
<td>Helmand</td>
<td>29.9</td>
<td>35.9</td>
<td>22.1</td>
<td>13.2</td>
<td>79.7</td>
<td>78.2</td>
<td>72.0</td>
<td>72.1</td>
<td>75.7</td>
<td>57.6</td>
</tr>
<tr>
<td>Uruzgan</td>
<td>13.7</td>
<td>11.4</td>
<td>12.4</td>
<td>9.6</td>
<td>5.3</td>
<td>10.4</td>
<td>2.9</td>
<td>9.1</td>
<td>9.2</td>
<td>3.3</td>
</tr>
<tr>
<td>Khost</td>
<td>22.1</td>
<td>19.7</td>
<td>20.7</td>
<td>14.3</td>
<td>5.8</td>
<td>6.0</td>
<td>4.0</td>
<td>8.6</td>
<td>7.2</td>
<td>6.5</td>
</tr>
<tr>
<td>Total counts</td>
<td>204</td>
<td>4,225</td>
<td>217</td>
<td>279</td>
<td>2,765</td>
<td>3,577</td>
<td>12,841</td>
<td>2,674</td>
<td>3,979</td>
<td>9,006</td>
</tr>
</tbody>
</table>

Table 1: Distribution of villages, violence, ANSF and ISAF bases, and aid projects. The second and third columns, respectively, indicate the proportion of surveyed and non-surveyed villages in each of the randomly selected five provinces. The fourth and fifth columns present the proportion of counterinsurgent bases that were present at the time of our survey and aid projects started before the survey. The last six columns show the percentage of insurgent attacks in each province during 10 months before and after the survey. The last row gives total counts. In our out-of-sample prediction, we use the 13,381 non-surveyed villages in other Pashtun dominated provinces as well as the 4,225 non-surveyed villages in the randomly selected five provinces shown in the table.
the number of relevant events in specified temporal windows before and after the survey in each village. We also test across different spatial radii around villages. We therefore aim to predict the aggregate number of attacks of each category within defined spatial and temporal windows around sampled and then non-sampled villages. Table 1 illustrates the pre- and post-survey distribution of insurgent violence across five provinces. The locations of ANSF and ISAF bases and aid projects are also noted. Among the randomly sampled five provinces, most insurgent violence (57% ∼ 80%) is centered on Helmand, while most ISAF bases (31%) and aid projects (48%) are clustered in Kunar.

### 3.4 Other Predictors

As discussed in Section 3.4, we must first take into account leading factors known to be associated with insurgent violence to test whether civilian attitudes have predictive power.

Our measure of prior insurgent violence is straightforward. We draw on the same declassified CIDNE data as used for our dependent variable and simply mirror the spatial and temporal windows on either side of the survey date for a given village. For example, if we examine the effect of village-level support on the number of IED attacks occurring within a $x$ km radius around each village during $y$ months post-survey, we also include the number of past IED attacks that have occurred within the same spatial and temporal windows.

Insurgent attacks may also occur in villages that are closer to ANSF and ISAF military installations; that is, after all, where the majority of counterinsurgent targets are found. We therefore use geo-referenced base location data to adjust for the number of ANSF and ISAF military installations present in the pre-survey period (June 2007 ∼ December 2010) within a three kilometer radius of each village. The choice of three kilometers is somewhat arbitrary. As a result, in our analysis we use varying radii to examine the robustness of our findings.
We lack a direct measure of ISAF and ANSF force size or patrol rate; these data are either classified or do not exist. That said, we believe our data on base location does a credible job in controlling for ISAF presence. Many of these bases are small combat outposts (COPs) that patrolling forces sortie to and from; a five kilometer radius is likely to capture all but the most distant (and infrequent) patrol. The Taliban have also expressed a preference for ambushing tired counterinsurgent forces when they arriving back at their bases (Meyerle and Malkasian, 2009, 6). Far from viewing these military bases as oases of calm, they have historically been the site of concerted Taliban efforts to harass or breach their defenses, often via suicide bombing.

Figure 8 in Section A.3 of the SI presents the bivariate relationship between ISAF support and the number of ANSF/ISAF bases. We observe that regardless of the choice of radii there is a small degree of positive relationship between them; villages which have a larger number of bases tend to be more supportive of ISAF. This highlights the importance of adjusting for base locations when attempting to isolate the independent role of civilian attitudes.

Finally, insurgents may also launch attacks to derail the counterinsurgent’s use of aid projects to influence civilians. This dynamic was observed in the Philippines, for example, in response to the government’s KALAHI-CIDSS Community Driven Development (CDD) anti-poverty program. Insurgents timed their attacks to the announcement and initial phase of aid programming in CDD-villages to prevent the erosion of their popular support (Crost, Felter and Johnston, Forthcoming). To account for this possibility, we adjust for the number of USAID Community Development Program (CDP) using geo-referenced data for all projects initiated within one kilometer of each village. The large-scale, $250 million CDP program was designed to foster stability using cash-for-work initiatives in areas where insurgents had been forcibly evicted through military operations during 2010-12. In Figure 9 in Section A.3 of the SI, we present the bivariate association between the
aid projects (with varying radii from villages) and village level support for ISAF. While there appears to be quite weak correlation between two variables, we nonetheless include this variable in our base model.

4 Empirical Results

We begin our empirical analysis by establishing a robust association between civilian attitudes and future insurgent violence based on our original sample of 204 villages. We then assess the improvement gained by introducing civilian attitudes to our predictive models of insurgent violence by extending the analysis to nearly 15,000 out-of-sample villages. The latter analysis cross-validates the predictive power of our civilian attitudes measure.

4.1 In-Sample Prediction Performance

Throughout our in-sample analysis, we use a linear regression model to quantify the association between relative support for ISAF and subsequent insurgent violence after the survey. Note that each village has a slightly different start and end date given their survey order. This results in different temporal windows (of the same size) across villages. Specifically, we regress the number of future insurgent attacks within certain temporal and spatial windows on its relative support level for ISAF as well as the other possible confounders discussed in Section 3.4. We vary the size of time and distance windows in order to examine the robustness of our findings. We also explore the possibility of nonlinearity but we find a simple linear model captured most of the systematic variation.

Findings. As an illustrative example, we present our model’s results using a temporal window of five months pre- and post-survey. We use a 15km radius around each sampled village to calculate the number of insurgent attacks. Figure 3 demonstrates that a strong positive association exists between relative support for ISAF and future insurgent attacks even after accounting for prior violence, counterinsurgent bases, and CDP aid projects.
Figure 3: Positive association between the number of future insurgent attacks and relative ISAF support. The plots present statistically significant association between the number of insurgent attacks that have occurred within 15km of each village during the five months after the fielding of our survey in each village (vertical axis) and its relative level of ISAF support (horizontal axis) while adjusting for the number of insurgent attacks that have occurred (again within a 15km around each village) five months prior to our survey, the number of counterinsurgent bases within a 3km radius of each village, and the number of aid programs within a 1km radius of each village. The results are based on the linear regression model estimated separately for each of the three violence categories where the number of future insurgent attacks is regressed on the relative level of ISAF support and the other covariates (i.e., past violence, counterinsurgent bases, and aid projects). The dashed lines represent 95% confidence intervals based on robust standard errors.

This is particularly true for IED attacks in the leftmost plot, where the coefficient is most precisely estimated. A village that has modest relative support for ISAF (equivalent to a 0.5 value) is predicted to have an additional 13 IED attacks on average over the next five months (with a 95% confidence interval of [7, 20] using a heteroskedasticity-consistent standard error) when compared to a village strongly opposed to ISAF (equivalent to a −2.5 value).

We observe a similar pattern in the association between relative support and non-IED attacks (the rightmost plot). A village with modest relative support is expected to have 34 more non-IED attacks on average than a village with strong opposition, although the 95% confidence interval [3, 64] is quite large. The number of “found” IEDs in the middle plot does not follow this pattern, however. Shifting a village’s support from modestly pro-ISAF to strongly opposed actually yields an average increase of eight found IEDs, though the
estimate is not statistically significant different from zero. More generally, the association between relative support and found IEDs is relatively weak, raising doubt about the linkage between pro-counterinsurgent attitudes and the provision of tips. To be sure, not all IEDs are discovered through tips, and we cannot rule out the possibility that local ANSF and ISAF vary in their ability to detect such devices without local assistance. Yet the weakness of this finding suggests that pro-counterinsurgent attitudes may not necessarily translate into positive (from the counterinsurgent’s view) local action.

The positive association between relative support and future IED attacks is robust to the choice of temporal and spatial windows. We repeat the analysis by varying the temporal window from one to ten months and changing the radius around the surveyed village from 1km to 60km. Figure 4 presents contour plots of the t-statistics for the estimated coefficient of the relative ISAF support measure. We continue to observe a positive and statistically
significant association between ISAF support and insurgent IED attacks while controlling for prior insurgent attacks, counterinsurgent bases, and CDP projects.

As Figure 4 illustrates, we observe important variation in the model’s ability to predict insurgent violence. The positive relationship between pro-ISAF sentiment and insurgent IED attacks is strongest at the 4 month interval and about 40 kilometers around the surveyed village. Similarly, the relatively large t-statistics for non-IED attacks can be seen over similar temporal and spatial windows. Comparing t-values across attack types, it is apparent that our model is especially well-suited to predicting IED emplacement, with peak t-values approaching 4.5 compared to a still sizable 2.5 for non-IED attacks. In addition, our results also hold if we analyze the absolute (rather than relative) level of support for each group separately. We find that insurgent violence is positively associated with the absolute measure of ISAF support, while it is negatively correlated with the absolute levels of Taliban support (see Figures 10 and 11 in Section A.4 of the SI).

The positive association between relative ISAF support and insurgent IED attacks is robust to various modeling assumptions. In Figure 12 of the SI, we present additional results based on matching to enable flexible covariate adjustment rather than simple linear adjustment [Ho et al. 2007]. Using Mahalanobis metric matching, villages are first paired according to prior insurgent attacks, counterinsurgent bases, and the number of CDP projects. We then regress the pairwise difference in future violence on the pairwise differences in relative ISAF support, prior violence, counterinsurgent bases, and CDP projects. The association between ISAF support and IED attacks remains strong even using this nonparametric analysis. By contrast, the results for the other two types of attacks do not appear to hold for this matching analysis, indicating the lack of robustness for IED found and Non-IED attacks.

\footnote{For IED and non-IED attacks, the variation in t-values mainly stems from the variation in the effect sizes rather than the standard errors. In contrast, the variation in t-values for IED found comes from both the effect sizes and the standard errors.}

\footnote{We also explored the non-parametric estimation of the effects of relative ISAF support on insurgent
We also conducted robustness checks with various distance-to-base windows. In Figure 13 of the SI, we conduct the same analysis as above but using a set of different distance windows (1km, 5km, and 10km) when counting the number of bases around each village. Similarly, we examine the robustness of our finding to the choice of distance window for the presence of aid programs. In Figure 14 of the SI, we use alternative distance windows (3km, 5km, and 10km) and repeat the same analysis. All of these robustness checks support our conclusion that a strong positive association exists between pro-ISAF sentiment and future insurgent IED attacks.

4.2 Out-of-sample Prediction Performance

To further examine the predictive power of civilian attitudes, we evaluate their out-of-sample predictive performance using 14,606 non-surveyed villages. Doing so reduces the possibility of false discovery by ensuring that the results of our in-sample results are not due to over-fitting to a particular sample of surveyed villages. We first predict relative ISAF support for these out-of-sample villages using village-level covariates. We then forecast the number of insurgent attacks with these predicted support levels and then compare our forecasts with actual insurgent attacks. As before, our aim is to examine whether these predicted support levels improve forecasting performance of future insurgent violence even while controlling for prior insurgent attacks and the presence of counterinsurgent bases and aid projects.

The out-of-sample prediction proceeds in two steps. First, using the 204 surveyed villages, we estimate the ISAF support model by regressing the relative ISAF support level and a set of available village- and district-level covariates. These covariates include village population size and elevation as well as several district-level factors, including ISAF’s own measure of its relative control in that district, the existence of Taliban-run sharia courts attacks using natural cubic splines (the results not shown). However, the cross-validation indicated that the data set is too small to reliably estimate such a nonparametric model, favoring a simple linear model.
Figure 5: Out-of-sample prediction procedure. In Step 1 (left panel), using in-sample villages, we estimate the ISAF support model (blue arrow) and the Insurgent violence model (red arrow). For the former model, we regress ISAF relative support $S$ on village- and district-level covariates $Z$ such as log population, log elevation, ISAF control, Pakistan border, and Taliban Sharia. For the latter model, we regress future violence $Y$ on $S$ as well as village-level control variables ($X$) such as past violence, ANSF/ISAF bases, and aid projects. In Step 2 (right panel), we predict the ISAF support level for out-of-sample villages and then future violence using the models fitted in Step 1. For each out-of-sample village, we first estimate the ISAF relative support level $S$ (blue squiggly arrow) using the covariates $Z$ and then predict $Y$ with this estimated support level $\hat{S}$ and the other covariates $X$.

(as a measure of Taliban control), and whether the district bordered Pakistan (to control for differences arising from cross-border spillover). Using the same set of covariates, we can now estimate ISAF support level for each of the out-of-sample villages based on the fitted model. We rescale the relative support estimate for out-of-sample villages so that their standard deviation is identical to that of the original village sample.$^{17}$

Second, we estimate the Insurgent violence model, which is the same linear regression model as that used in Section 4.1. Together with the estimated ISAF support from the previous step, we can now forecast future insurgent attacks for out-of-sample villages. Finally, we compare the predicted insurgent attacks with actual attacks for each out-of-sample village to evaluate our model’s predictive performance.

Figure 5 uses a diagram to summarize our procedure for out-of-sample prediction. Be-

---

$^{17}$Such rescaling is not necessary if we do not use multistage sampling and instead use a simple random sample of villages. However, we used multistage sampling due to the cost of sending enumerators to different parts of Afghanistan.
low, we also provide the details about the entire prediction procedure,

**Step 1:** Building prediction models using in-sample villages

Step 1a: Regress ISAF support $S$ on village-level covariates $Z$ to estimate the *ISAF support model* (blue arrow in the left panel), $g(S \mid Z; \theta)$

Step 1b: Regress future violence $Y$ on ISAF support $S$ and other control variables $X$ to estimate the *Insurgent violence model* (red arrow in the left panel), $f(Y \mid S, X; \beta, \lambda)$

**Step 2:** Predicting future violence using out-of-sample villages and the estimated models from Step 1

Step 2a: Using the village-level covariates $Z$ for out-of-sample villages and the estimated *ISAF support model* from Step 1b, $g(S \mid Z; \hat{\theta})$, obtain the predicted ISAF support for out-of-sample villages $\hat{S}$ (blue squiggly arrow in the right panel)

Step 2b: Using the predicted ISAF support from Step 2a, $\hat{S}$, and control variables $X$, obtain the predicted insurgent violence for each out-of-sample village, $\hat{Y}$, based on the estimated *Insurgent violence model* from Step 1a, $f(Y \mid S, X; \hat{\beta}, \hat{\lambda})$ (red squiggly arrows in the right panel)

Step 2c: Compare the predicted insurgent violence $\hat{Y}$ against the actual insurgent violence $Y$ for each out-of-sample village

We assess the accuracy of our out-of-sample prediction by comparing our forecast with the actual level of insurgent attacks. To measure the degree to which political attitudes improve forecasting performance, we compute the *mean absolute forecasting error* (MAFE) for two models: (1) one with prior attacks, ANSF/ISAF bases, and CDP projects as the predictors of future violence and (2) one with these three covariates and the estimated
Figure 6: Out-of-sample forecasting performance. The upper panels present the forecasting improvement rates of adding the estimated ISAF relative support level to the baseline model with past violence, counterinsurgent bases, and aid projects. Prediction improvement is measured by the mean absolute forecasting errors derived from the baseline model (MAFE\textsubscript{2}) and the model with the estimated support level (MAFE\textsubscript{1}) — i.e., \((\text{MAFE}_2 - \text{MAFE}_1) / \text{MAFE}_1 \times 100\%\). The lower panels show the forecasting improvement rates of adding to the baseline model the village- and district-level covariates, such as log population, log elevation, ISAF control, Pakistan border, and Taliban Sharia, used to estimate the ISAF support level of non-surveyed villages.

We then compute the percent improvement obtained by adding the estimated relative ISAF support level to the model with only prior insurgent attacks, ANSF/ISAF bases, and aid programs.\(^{18}\)

\(^{18}\)This quantity is formally defined as \(\sum_{i=1}^{N} |Y_i - \hat{Y}_i| / N\), where \(Y_i\) represents the number of observed future insurgent attacks for an out-of-sample village \(i\) and \(\hat{Y}_i\) is its prediction from a forecasting model.

\(^{19}\)Specifically, we compute \((\text{MAFE}_2 - \text{MAFE}_1) / \text{MAFE}_1 \times 100\%\), where MAFE\textsubscript{1} and MAFE\textsubscript{2} are obtained from the model with and without the estimated relative ISAF support level variable, respectively.
Findings. We demonstrate the additional predictive gains from incorporating our measure of relative ISAF support level in the upper panel of Figure 6. Similar to Figure 4, we examine our forecasting performance across a wide range of temporal and spatial windows using contour plots for each category of insurgent violence. The inclusion of our estimate of relative support for ISAF improves predictions of the location and timing of IED attacks by up to 30%, a substantial improvement. This improvement is especially apparent in areas within 30km of the village’s center in the three months following the survey. Our model also improves, though to lesser extent, predictions of the location and timing of non-IED attacks by up to 14%, again with the greatest improvement occurring near the 30km distance mark. These patterns are consistent with our in-sample analysis (see Figure 4).

Do these improvements stem from the introduction of village and district-level covariates $Z$, which we use, along with the survey data, to predict the estimated support level? To address this concern, we plot the percentage improvement attributable to these additional covariates alone in the lower panel of Figure 6. These covariates in fact lead to over-fitting and add little out-of-sample predictive power. For IED attacks, there is a modest improvement in predictive performance with a small temporal window, though the magnitude of the improvement is much less than the model with our measure of ISAF support. For non-IED attacks and IED found, the inclusion of these covariates actually worsens the predictive power of the models. Our analysis shows that while the estimated ISAF support for out-of-sample villages is a linear function of these covariates, these covariates are relatively poor predictors of future violence.

We emphasize that this comparison is possible only with respect to out-of-sample prediction performance. The Gauss-Markov theorem implies that the inclusion of these (or any other) covariates always improves the in-sample predictive performance (Hastie, Tibshirani and Friedman [2009]). Nevertheless, this does not mean that out-of-sample predictive performance always improves by adding more covariates. Indeed, what is striking about this
finding is that these noisy covariates, which by themselves worsen out-of-sample predictive performance, can improve it when combined with our survey data.

These out-of-sample predictive improvements are once again robust to different modeling assumptions. In the SI, we present corresponding results for models that interact relative ISAF support with prior violence, ISAF bases, and aid (see Figures 16, 17, and 18 respectively). For IED attacks, the inclusion of interaction terms does not improve predictive accuracy of future violence. In contrast, the use of the interaction term between support and past non-IED attacks and the interaction term between support and counterinsurgent bases increases our ability to predict future non-IED attacks.

We also consider the robustness of our finding using an alternative method of assessing predictive improvement. In the SI (see Figure 15), we present results based on the root mean squared forecasting error (RMSFE). Though RMSFE is more sensitive to outliers, the results largely agree with those presented above for IED attacks. The prediction improvement, however, does not exist for IED found and non-IED attacks. As before, adding village and district covariates instead of the predicted support measure to the base model generally does not increase predictive performance. In fact, these covariates worsen the predictive accuracy of the base model for all three types of attacks.

Despite its clear methodological advantages, the use of out-of-sample testing remains relatively rare in the study of civil war violence. Yet this approach can yield powerful insights that are missed by relying solely on statistical significance to assess the importance of different covariates (Ward, Greenhill and Bakke 2010). In particular, our out-of-sample modeling reveals that standard covariates in studies of civil war violence—including population size and terrain—add little to our predictive success. If anything, our village and district-level covariates actually worsen our predictive accuracy. Instead, much of the predictive improvement stems from fine-grained covariates, including civilian attitudes, that

This measure is formally defined as $\sqrt{\sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2 / N}$.  

30
track the spatial distribution of combatants and their actions.

5 Insurgent Violence Against Civilians

Our theory suggests a second observable implication: insurgents use pro-counterinsurgent attitudes to guide their punishment strategy against civilians. To test this claim, we draw on a new dataset of civilian violence—SIGACTs track only violence against ISAF—and repeat the analysis above, beginning with in-sample testing before moving to out-of-sample predictions. We use data from iMMAP, a non-governmental organization that collates reports of civilian victimization across Afghanistan; data are provided by multiple NGOs and are inputted according to a standardized coding scheme via online data portal.

The dataset represents the best coverage of civilian victimization in Afghanistan to date. It does, however, have two major shortcomings: (1) it is noisier than SIGACT data given its multiple reporting streams and (2) the data suffer from a clear under-reporting problem, yielding far fewer recorded instances of violence against civilians than attacks against ISAF recorded in SIGACT as shown in Table 3 in the SI. Together, these limitations suggest that our findings reported in Section A.6 of the SI should be interpreted with caution.

We begin by plotting the association between relative ISAF support and two categories of insurgent violence: attacks with IEDs and those without. As an initial exploration of the data, Figure 19 in the SI plots this relationship using a negative binomial regression model for attacks within 15km of each village in the five months after our survey. As with SIGACT data, we find a positive association between relative ISAF support and both types of insurgent attacks even after adjusting for prior insurgent attacks, base locations, and aid programs. Substantively, given the low level of civilian victimization reported in the iMMAP data, the effects are fairly modest; villages at the high end of relative ISAF support will observe about three additional reported attacks within these temporal and

---

21iMMAP does not record a “found IED” category.
spatial boundaries. These findings are consistent, however, with the claim that the Taliban are willing to punish civilians for their pro-ISAF views.

Our in-sample estimates of predicted insurgent violence against civilians largely confirm the findings above. In Figure 20 of the SI, we plot the $t$ values of the association between relative ISAF support and insurgent attacks up to 60km and 10 months after the survey. For IED attacks, the association is strongest at close proximity to the village; at that distance, the positive association extends almost evenly across the 10 month post-survey period. We do note, however, a weakening of our predictive improvement at the spatial mid-range (about 30–40km). We conjecture that this weakening can be attributed to two factors: iMMAP privileges data collection on IEDs that occur within a village and rarely collects data outside of populated locations; and the average Taliban group’s operational radius is about 30–40km (see below). Non-IED attacks are strongly associated with relative ISAF support, especially relatively close to the village (at the 20-30 km mark). Taken together (the right panel), relative ISAF support is associated with attacks against civilians, particularly close to the surveyed village, a finding consistent with a punishment strategy.

Our out-of-sample forecasting based on a negative binomial model also demonstrates that including civilian attitudes significantly improves predictive performance, though the results are weaker for IEDs than non-IED attacks (see Figure 21 in the SI). For IED attacks, we find a similar pattern to our in-sample prediction: improvement is highest when violence is closest to the village at all intervals up to 10 months post-survey, though we do observe a weakening of this improvement at the 30–40km range. Once again, our predictive improvement is higher for non-IED attacks against civilians; improvement is significantly higher close to the village and extending up to 40km away. Similar to our SIGACT-based estimates, predictive performance for the pooled insurgent attacks is highest within the 10km range.
6 Qualitative Evidence

Our in-sample and out-of-sample tests converge on the same empirical finding: including civilian attitudes in our models markedly improves our ability to predict insurgent violence. Yet we require qualitative evidence of the mechanics of Taliban intelligence gathering to be confident of the link between civilian attitudes and insurgent targeting. Can the Taliban actually track civilian attitudes with reasonable precision across potentially thousands of villages? And, if so, do its commanders act upon this intelligence when choosing targets and tactics?

While information about the Taliban is necessarily incomplete, there is near universal agreement among researchers and ISAF itself that it possesses a remarkably pervasive intelligence gathering system. ISAF’s own Deputy Chief of Staff (Intelligence) publicly declared the need to drastically overhaul ISAF’s intelligence collection to compete with Taliban efforts (Flynn, Pottinger and Batchelor 2010). Similarly, a leaked classified NATO report based on nearly 27,000 interviews with 4,000 detainees in 2011 painted a stark picture of an omnipresent Taliban that had spies on ISAF bases, subverted local ANSF partners, and moved freely among locals in nominally ISAF-controlled villages (Task Force 3-10 2012).

More concretely, the Taliban has constructed an extensive surveillance system that is designed to support governance and war-fighting efforts at the village level. Each province has a shadow provincial governor and a military commission (plural, nizami); these institutions are designed to coordinate, albeit loosely, the implementation of governance programs such as Taliban-run courts while orchestrating attacks against ISAF and ANSF by small, locally-recruited, units (delgai) of 15-25 fighters. In theory, these units “scale-up” to form mahaz networks that control parts of a given district. In practice, coordination across these units is often haphazard, owing as much to ISAF efforts at disruption as local ethnic,
tribal, strategic, and other disagreements that frustrate broader cooperation (Farrell and Giustozzi 2013; Giustozzi 2013; Johnson 2013; Johnson and DuPee 2012).

The Taliban collect information about both ISAF movements and civilian attitudes via four principal mechanisms. First, the Taliban have cultivated a network of local supporters who not only provide material assistance but also information about popular opinion and troop movements. In the latter case, everything from smoke signals to information passed via radio repeater stations into Pakistan have been used to collect and disseminate timely information about ISAF actions. In one of our out-of-sample districts, Andar, located in Ghazni province, ISAF estimated that 4,000 locals (out of 150,000 individuals) actively provided information to the Taliban. Indeed, the Taliban were openly known to be running 28 schools in the district despite ISAF’s heavy presence (“In Eastern Afghanistan, at War with the Taliban’s Shadowy Rule,” New York Times, 6 February 2011).

Second, Taliban spies and sympathizers have infiltrated ISAF and ANSF bases as well as large-scale development projects. “The Taliban,” one Afghan National Police officer noted in 2011, “have spies everywhere.” Even ISAF has conceded that its facilities and, in particular, Afghan security forces, have been compromised by spies (Task Force 3-10 2012). ANSF units have been caught colluding openly with Taliban forces via local (unauthorized) ceasefire arrangements and through the provision of information about ISAF’s movements and security. “They are on top of every move we make,” one ISAF official bemoaned in 2010 (Brandt 2011 1). Extensive back-to-work projects, designed to dampen insurgency by providing steady employment for would-be fighters, are thought especially valuable to penetrate. These programs allow the Taliban to pose as wage laborers and unobtrusively gather information about village reactions toward ISAF and its “hearts and minds” efforts.

Third, the Taliban’s own efforts at providing limited governance represent a “dragnet” that gathers intelligence about local attitudes from multiple sources. These efforts includ-

ing: (1) collecting taxes (zakat) from villagers; (2) regular meetings with village elders and religious officials; (3) roadside checkpoints that provide opportunities to monitor the population; (4) the creation of complaints commissions that villagers can access for local dispute adjudication, including reporting corrupt or unruly Taliban commanders; and (5) surveillance at Friday prayers, which are typically attended by all males in a village.

As ISAF itself concluded: “Villagers commonly relay that the Taliban are continually present in their areas solving disputes, purchasing supplies at local bazaars, meeting with tribal leaders or staying overnight in guesthouses or the local mosque” (Task Force 3-10, 2012). These initiatives collectively facilitate the collection of timely information about local attitudes towards the combatants, among other topics.

Finally, by 2010 the Taliban had come to rely heavily on local recruits to staff its units. It has been estimated that between 80-90% of Taliban fighters operate in or close to their communities. Moreover, launching attacks across mahaz lines is difficult, requiring permission from both neighboring commanders and from the relevant centralized military commission (Ruttig, 2010, 13). Despite recent efforts to improve the centralization of decision-making, each group retains the authority to conduct attacks within its operating area without prior permission. As a result, the Taliban not only able to obtain local information but are likely to launch attacks in fairly constrained geographic areas.

The Taliban clearly have an impressive, if imperfect, ability to monitor civilian attitudes, one that is likely more sophisticated and extensive than ISAF’s own efforts. Does this information inform their choice of targets and tactics? Undoubtedly, yes. Indeed, it would be odd if the Taliban devoted these resources to surveillance, and to rebuilding them after ISAF counterintelligence operations, only to disregard this information when selecting targets. The Taliban has drawn on this information to launch an extensive intimidation campaign using “night letters” affixed to individual’s doors warning against continued collaboration with ISAF, for example United Nations Assistance Mission Afghanistan.
Since 2009, the Taliban has engaged in a systematic assassination campaign that has killed hundreds, including government officials, religious leaders, and individuals who have assisted ISAF in some capacity (notably, as translators or informants). As one US company commander stationed in Ghazni, an out-of-sample province, recalled: “The guy we had who was willing to give us information about the Taliban is the guy we found dead last week” after he was pulled from his vehicle and executed.

This intelligence network has proven resilient, facilitating Taliban battlefield innovation. For example, the Taliban began adopting improvised explosive devices in Helmand and then Uruzgan—both in-sample provinces—before diffusing them widely throughout Afghanistan (Malkasian, 2013; Giustozzi, 2013, 254). The move to greater IED usage was made in response to ISAF airstrikes, which made it difficult to mass units for frontal attacks. Instead, IEDs minimize Taliban casualties since they only require one or two individuals to emplace. In addition, intelligence about counterinsurgent movements allows the Taliban to strike when most effective, inflicting maximum casualties (Johnson, 2013, 13).

This discussion helps contextualize our argument that insurgents use pro-counterinsurgent attitudes as targeting cues in four ways. First, the Taliban clearly has the means to track ISAF force movements in near-real time, suggesting that striking at ISAF is feasible and a central war-fighting aim. Second, this intelligence system has the capacity to track civilian attitudes; it is realistic to assume that the Taliban is well-informed about local attitudes, not least because the bulk of its fighters are drawn from the same populations they seek to monitor. Third, the Taliban has adapted over time to become more lethal, focusing specifically on IEDs and suicide bombings that maximize the lethality of attacks against ISAF. Fourth, they have shown little hesitation in killing (suspected) informants, suggesting a willingness to consider targeting civilians. These attacks demonstrate that the Taliban can harm the counterinsurgent while also sending a message to would-be ISAF supporters:

---

continue to support the counterinsurgent, and face punishment in the form of increased (indiscriminate) violence \cite{Lyall2013}. Finally, our in- and out-of-sample findings are strongest at the 25-40 km distance from villages; these distances fit with the local nature of Taliban recruitment and the typical operating radius of its units. In short, pro-ISAF views are an invitation for, rather than a shield against, future localized insurgent violence.

7 External Generalizability

Our out-of-sample testing helps assuage concerns about generalizability. But there are natural limits to single-country studies. Do our claims about civilian attitudes and insurgent violence travel to other contexts? There are at least three ways to assess generalizability here: as a function of Afghanistan’s specific properties; the war’s characteristics; and the nature of Taliban organization.

Drawing on \cite{FearonLaitin2003}, we first plot Afghanistan’s location in the distribution of all civil wars (1945–1999) across six characteristics: per capita income, population, mountainous terrain, the regime’s polity score, and ethnic and religious fractionalization. As Figure 22 of the SI illustrates, Afghanistan is not an outlier in any distribution.

Nor is the war itself an outlier; it shares many properties of long-running insurgencies since 1945. For example, at least one-quarter of all insurgencies since 1945 have witnessed armed intervention by a third-party counterinsurgent like ISAF \cite{LyallWilson2009}. Most of these counterinsurgency efforts—including prominent examples in Pakistan, Iraq, Colombia, Mexico, Yemen, and the Philippines—have included extensive “hearts and minds” campaigns to win over public support. And while crossnational data on civilian victimization is poor, the current war in Afghanistan is not an outlier in terms of the magnitude of civilian deaths. The best public estimates suggest that 2,000—3,000 civilians are killed each year, most by the Taliban \cite{UnitedNationsAssistanceMissionAfghanistan2011}. If our results hinge on expectations of violence among civilians, then the relatively
low level of civilian fatalities in Afghanistan suggest that our predictive improvement would be even higher in conflicts with (even) higher casualties, as in contemporary Syria.\footnote{We thank an anonymous reviewer for raising this point.}

Finally, there is little unique about the Taliban’s intelligence-gathering institutions or its governance project. Other rebel organizations, including Islamic State, FARC, LTTE, Hezbollah, and RCD, have constructed extensive intelligence networks and have sought to engage in systematic hearts and minds or governance campaigns. In fact, most insurgent organizations provide at least some basic services; the Taliban’s provision of local dispute adjudication is quite typical. But if civilian attitudes are irrelevant for combatants—i.e., the insurgent organization simply preys upon locals—then we anticipate that other considerations, notably the strategic nature of territory or the presence of lootable commodities, would likely trump attitudes in guiding targeting.

\section{Conclusion}

Civilian attitudes are an important predictor of multiple types of insurgent violence in Afghanistan. While a single study cannot definitively prove a link between attitudes and behavior, our evidence suggests that insurgents are using pro-counterinsurgent sympathies to guide their targeting and tactics. This association is especially clear in the case of improvised explosive devices against ISAF forces, where villages with pro-counterinsurgent leanings attract a disproportionate share of their use.

These findings have theoretical, methodological, and policy-relevant implications. We have only recently begun the difficult work of theorizing how (and when) combatant violence might affect civilian attitudes and subsequent behavior \cite{Romero, Magaloni and Diaz-Cayeros 2014, Beber, Roessler and Scacco 2014, Lyall, Blair and Imai 2013, Arjona 2010}. More generally, the issue of wartime attitude formation still remains understudied, leaving our theories with an impoverished view of microlevel processes such as insurgent
targeting decisions or civilian responses to counterinsurgent “hearts and minds” programs. Identifying the scope conditions for when (and why) these attitudinal processes matter for explaining civil war dynamics remains a key theoretical task.

Methodologically, these findings underscore an additional advantage of microlevel data: disaggregating our units of observation facilitates out-of-sample testing. These tests not only avoid over-fitting our models to (sparse) data but also reveal that some well-known covariates, despite their statistical significance in current civil war research, actually worsen our predictive accuracy. Our combination of in- and out-of-sample testing could be extended further by incorporating panel data on civilian attitudes. These data would provide inferential leverage on the determinants and stability of civilian attitudes over time; it would also facilitate exploring the timing of insurgent reprisals.

Finally, these findings also carry policy implications. Hearts and minds campaigns, especially successful ones, appear to have a dark side, increasing the risk faced by civilian populations by creating targeting cues for insurgents. Aid programs that aim for “quick impact” but provide little or no protection for civilians—notably, the US Army’s massive Commanders’ Emergency Response Program (CERP), along with numerous USAID programs—are likely to attract insurgent violence. Planners should anticipate the possibility that violence will increase, not decrease, at least in the early stages of programming. Instead of decamping for more favorable sites, aid programs should either work to maximize civilian protections (e.g. by close coordination with military forces) or avoid programming in areas where protection cannot be credibly extended.

More broadly, our use of attitudinal data for prediction could be extended to a host of other sensitive issues — including interethnic relations, perceptions of government legitimacy, and corruption — and associated wartime behavior. Attitudinal indicators could also form the basis of an early warning/early response (EW/ER) system that could help predict conflict onset or “hot spots” within an ongoing war [Blair, Blattman and Hartman]
Our approach also emphasizes the importance of tailored surveys that use indirect questioning techniques for measuring attitudes on sensitive issues. In-sample findings could then be cross-validated with out-of-sample predictions, leveraging the insights from a limited number of randomly chosen locations into thousands, or even tens of thousands, non-surveyed villages at reduced cost and potential harm to enumerators and respondents. In sum, the combination of attitudinal data and prediction promises to deepen our understanding of the dynamics of civil war violence while providing us with possible tools to curb its excesses.
References


Blair, Robert, Christopher Blattman and Alexandra Hartman. 2014. “Predicting Local Violence.”


A Supporting Information

A.1 The Endorsement Experiment

Our endorsement experiment uses four questions regarding domestic policy reform to estimate support levels for the Taliban and ISAF. The exact question wording is reproduced below.

Prison Reform

- CONTROL CONDITION: A recent proposal calls for the sweeping reform of the Afghan prison system, including the construction of new prisons in every district to help alleviate overcrowding in existing facilities. Though expensive, new programs for inmates would also be offered, and new judges and prosecutors would be trained. How strongly would you support this policy?

- TREATMENT CONDITION: A recent proposal by foreign forces [or the Taliban] calls for the sweeping reform of the Afghan prison system, including the construction of new prisons in every district to help alleviate overcrowding in existing facilities. Though expensive, new programs for inmates would also be offered, and new judges and prosecutors would be trained. How strongly would you support this policy?

Direct Election

- CONTROL CONDITION: It has recently been proposed to allow Afghans to vote in direct elections when selecting leaders for district councils. Provided for under Electoral Law, these direct elections would increase the transparency of local government as well as its responsiveness to the needs and priorities of the Afghan people. It would also permit local people to actively participate in local administration through voting and by advancing their own candidacy for office in these district councils. How strongly would you support this policy?

- TREATMENT CONDITION: It has recently been proposed by foreign forces [or the Taliban] to allow Afghans to vote in direct elections when selecting leaders for district councils. Provided for under Electoral Law, these direct elections would increase the transparency of local government as well as its responsiveness to the needs and priorities of the Afghan people. It would also permit local people to actively participate in local administration through voting and by advancing their own candidacy for office in these district councils. How strongly would you support this policy?
Independent Election Commission

- CONTROL CONDITION: A recent proposal calls for the strengthening of the Independent Election Commission (IEC). The Commission has a number of important functions, including monitoring presidential and parliamentary elections for fraud and verifying the identity of candidates for political office. Strengthening the IEC will increase the expense of elections and may delay the announcement of official winners but may also prevent corruption and election day problems. How do you feel about this proposal?

- TREATMENT CONDITION: A recent proposal by foreign forces [or the Taliban] calls for the strengthening of the Independent Election Commission (IEC). The Commission has a number of important functions, including monitoring presidential and parliamentary elections for fraud and verifying the identity of candidates for political office. Strengthening the IEC will increase the expense of elections and may delay the announcement of official winners but may also prevent corruption and election day problems. How do you feel about this proposal?

Anti-Corruption Reform

- CONTROL CONDITION: It has recently been proposed that the new Office of Oversight for Anti-Corruption, which leads investigations into corruption among government and military officials, be strengthened. Specifically, the Office’s staff should be increased and its ability to investigate suspected corruption at the highest levels, including among senior officials, should be improved by allowing the Office to collect its own information about suspected wrong-doing. How do you feel about this policy?

- TREATMENT CONDITION: It has recently been proposed by foreign forces [or the Taliban] that the new Office of Oversight for Anti-Corruption, which leads investigations into corruption among government and military officials, be strengthened. Specifically, the Office’s staff should be increased and its ability to investigate suspected corruption at the highest levels, including among senior officials, should be improved by allowing the Office to collect its own information about suspected wrong-doing. How do you feel about this policy?

A.2 The Statistical Model for the Endorsement Experiment

Following Bullock, Imai and Shapiro (2011), we use a statistical model to estimate support levels for ISAF and the Taliban by efficiently combining the responses to multiple endorsement experiment questions. To do so, we model each respondent’s answer to a policy
question as a function of his or her support for the endorser as well as policy preference. Specifically, we apply the following Bayesian ordered probit factor analytic model:

\[
Pr(Y_{ij} \leq l \mid T_i = k) = \Phi(-\alpha_{jl} + \beta_j(x_i + s_{ijk})),
\]

where \(Y_{ij} \in \{1, 2, 3, 4, 5\}\) represents respondent \(i\)'s answer to the \(j\)th policy question (1 = Strongly disagree, 2 = Disagree, 3 = Indifferent, 4 = Agree, and 5 = Strongly agree) and respondent \(i\)'s status regarding the randomized treatment assignment is denoted as \(T_i \in \{0, 1, 2\}\) (0 = Control, 1 = ISAF, and 2 = Taliban). The latent variable \(s_{ijk}\) measures respondent \(i\)'s support level for endorser \(k\) in policy \(j\) with a greater value of \(s_{ijk}\) indicating a higher level of support. For identification, \(s_{ij0}\) is fixed at zero. Finally, the latent variable \(x_i\) represents the degree to which respondent \(i\) is in favor of policy reform in general. The “item difficulty” parameter \(\alpha_{jl}\) measures the popularity of the \(j\)th policy reform independent of the endorser, while the “discrimination” parameter \(\beta_j\) expresses the degree to which the reform proposal differentiates pro- and anti-reform respondents. We assume \(\alpha \sim T\mathcal{N}_{[0, \infty]}(0, 25)\) and \(\beta \sim T\mathcal{N}_{[0, \infty]}(0, 25)\) as the priors.

We model the individual-level support \(s_{ijk}\) and ideal point \(x_i\) using a hierarchical modeling technique with village-level random effect parameters \(\lambda_{\text{village}[i]}\) and \(\delta_{\text{village}[i]}\) as follows,

\[
\begin{align*}
    s_{ijk} & \sim \mathcal{N}(\lambda_{\text{village}[i]} + Z_i^\top \lambda_k^\circ, \omega_k^2) \\
x_i & \sim \mathcal{N}(\delta_{\text{village}[i]} + Z_i^\top \delta, 1)
\end{align*}
\]

where \(Z_i\) represents the set of individual-level covariates. As the priors, we assume \(\lambda \sim \mathcal{N}(0, \psi^2)\), \(\delta \sim \mathcal{N}(0, \sigma^2)\), and \(\psi^2, \sigma^2, \omega^2 \sim \text{Inv-}\chi^2(5, 2)\).

We use an R package \texttt{endorse} developed by Shiraito and Imai (2012) to fit this model. The convergence is monitored by running multiple Markov chains with over-dispersed starting values. Using the posterior simulation draws, we compute each respondent’s average support level for each endorser across the four policy areas, and then further aggregate it to village-level support by averaging the individual-level estimates.
A.3 Additional Descriptive Analyses

<table>
<thead>
<tr>
<th>Respondents</th>
<th>Non-Response Rates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ISAF Treatment</td>
</tr>
<tr>
<td>Logar</td>
<td>486</td>
</tr>
<tr>
<td>Kunar</td>
<td>396</td>
</tr>
<tr>
<td>Helmand</td>
<td>855</td>
</tr>
<tr>
<td>Uruzgan</td>
<td>387</td>
</tr>
<tr>
<td>Khost</td>
<td>630</td>
</tr>
<tr>
<td>Average</td>
<td>5.5</td>
</tr>
</tbody>
</table>

Table 2: Non-response rates in the survey experiments conducted in the randomly sampled 204 villages. Respondents were randomly assigned to one of the three conditions (ISAF treatment, Taliban treatment, and control) and asked questions about prison reform, direct election, independent election commission, and anti-corruption reform. The non-response rates are averaged over the four questions.

Figure 7: Distribution of the levels of support for Taliban and ISAF as well as the distribution of the difference between the two (ISAF–Taliban). The figure clearly shows that a majority of Afghan population supports Taliban over ISAF.
Figure 8: Bivariate relationship between relative ISAF support and the number of ANSF and ISAF bases within a 1km, 3km, 5km, or 10km radius of each surveyed village.
Figure 9: Bivariate association between relative ISAF support and the number of aid projects within a 1km, 3km, 5km, or 10km radius of each surveyed village.
A.4 Additional In-Sample Regression Results

Figure 10: $t$ values of the estimated coefficient for the *absolute* level of ISAF support. The estimated coefficient corresponds to its marginal effect on the number of future insurgent attacks, while adjusting for the prior level of insurgent violence, the number of ANSF and ISAF bases, and the number of USAID aid projects. Robust standard errors are used.

Figure 11: $t$ values of the estimated coefficient for the *absolute* level of Taliban support. The estimated coefficient corresponds to its marginal effect on the number of future insurgent attacks, while adjusting for the prior level of insurgent violence, the number of ANSF and ISAF bases, and the number of USAID aid projects. Robust standard errors are used.
Figure 12: $t$-values of the estimated coefficient of relative ISAF support derived from the Mahalanobis matching analysis. Villages are first paired according to prior violence, bases, and aid projects, and then the pairwise difference in future violence is regressed on the pairwise differences in relative ISAF support, prior violence, bases, and aid projects. Robust standard errors are used.
Figure 13: \( t \) values of the estimated coefficient of relative ISAF support, corresponding to its marginal effect on the number of future insurgent attacks, while adjusting for the prior level of insurgent violence, the number of bases, and the number of aid projects. The upper, middle, and lower panels use bases within 1km, 5km, and 10km radii of each sampled village, respectively, showing robustness of the positive association between the number of future insurgent violence and relative ISAF support. All the models use aid projects within a 1km radius of each village. Robust standard errors are used.
Figure 14: $t$ values of the estimated coefficient of relative ISAF support, corresponding to its marginal effect on the number of future insurgent attacks, while adjusting for the prior level of insurgent violence, the number of bases, and the number of aid projects. The upper, middle, and lower panels use aid projects within 3km, 5km, and 10km radii of each sampled village, respectively, showing robustness of the positive association between the number of future insurgent violence and relative ISAF support. All the models use bases within a 3km radius of each village. Robust standard errors are used.
A.5 Additional Out-of-Sample Prediction Results

Figure 15: Forecasting improvement rates based on the root mean squared forecasting error (RMSFE). The contour plots show \( \frac{(RMSFE_2 - RMSFE_1)}{RMSFE_1} \times 100\% \), where RMSFE_1 and RMSFE_2 are the root mean squared forecasting errors from the models with and without the predicted ISAF support level. Upper panels represent the forecasting improvement rates of adding the estimated ISAF support level to the baseline model with prior violence, bases, and aid programs. Lower panels show the forecasting improvement rates of adding to the baseline model the village- and district-level covariates, such as log population, log elevation, ISAF control, Pakistan border, and Taliban Sharia, used to estimate the ISAF support level of non-surveyed villages.
Figure 16: Forecasting improvement rates of adding interaction terms between estimated ISAF support level and prior violence, bases, and aid projects. The baseline model only includes ISAF support, past violence, bases, and aid projects. The contour plots show \((\text{MAFE}_2 - \text{MAFE}_1)/\text{MAFE}_1 \times 100\%\), where MAFE$_1$ and MAFE$_2$ are the mean absolute forecasting errors from the models with and without the predicted ISAF support level.
Figure 17: Forecasting improvement rates of adding interaction terms between estimated ISAF support level and prior violence, bases, and aid projects. The baseline model only includes ISAF support, past violence, bases, and aid projects. The contour plots show $(\text{MAFE}_2 - \text{MAFE}_1)/\text{MAFE}_1 \times 100\%$, where MAFE$_1$ and MAFE$_2$ are the mean absolute forecasting errors from the models with and without the predicted ISAF support level.
Figure 18: Forecasting improvement rates of adding interaction terms between estimated ISAF support level and prior violence, bases, and aid projects. The baseline model only includes ISAF support, past violence, bases, and aid projects. The contour plots show \((\text{MAFE}_2 - \text{MAFE}_1)/\text{MAFE}_1 \times 100\%\), where \(\text{MAFE}_1\) and \(\text{MAFE}_2\) are the mean absolute forecasting errors from the models with and without the predicted ISAF support level.
A.6 Violence against Civilians

<table>
<thead>
<tr>
<th>Provinces</th>
<th>IED Attack</th>
<th>Non-IED Attack</th>
<th>IED Attack</th>
<th>Non-IED Attack</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logar</td>
<td>3.1%</td>
<td>7.2%</td>
<td>3.7%</td>
<td>3.5%</td>
</tr>
<tr>
<td>Kunar</td>
<td>7.7%</td>
<td>40.0%</td>
<td>9.0%</td>
<td>68.4%</td>
</tr>
<tr>
<td>Helmand</td>
<td>38.4%</td>
<td>34.5%</td>
<td>26.3%</td>
<td>8.7%</td>
</tr>
<tr>
<td>Uruzgan</td>
<td>15.3%</td>
<td>9.1%</td>
<td>15.0%</td>
<td>3.5%</td>
</tr>
<tr>
<td>Khost</td>
<td>35.3%</td>
<td>9.1%</td>
<td>45.8%</td>
<td>15.7%</td>
</tr>
<tr>
<td>Total counts</td>
<td>195</td>
<td>55</td>
<td>133</td>
<td>57</td>
</tr>
</tbody>
</table>

Table 3: Distribution of violence against civilians. The columns show the percentage of insurgent attacks in each province during 10 months before and after the survey. The last row gives total counts. Since there was no recorded event of “IED found” by insurgents against civilians, the table only shows the distribution of IED and non-IED attacks.

Figure 19: Association between the number of future insurgent attacks against civilians and relative ISAF support. The plots show the relationship between the number of insurgent attacks that have occurred within 15km of each village during the five months after the fielding of our survey in each village (vertical axis) and its relative level of ISAF support (horizontal axis) while adjusting for the number of insurgent attacks that have occurred (again within a 15km around each village) five months prior to our survey, the number of counterinsurgent bases within a 3km radius of each village, and the number of aid programs within a 1km radius of each village. The results are based on the negative binomial regression model estimated separately for each of the violence categories where the number of future insurgent attacks is regressed on the relative level of ISAF support and the other covariates (i.e., past violence, counterinsurgent bases, and aid projects). The dashed lines represent 95% confidence intervals based on robust standard errors. Since there was no recorded event of “IED found” by insurgents against civilians, the figure only shows the results of IED and non-IED attacks.
Figure 20: \( t \) values of the association between the relative level of ISAF support and insurgent violence against civilians. The estimated coefficient corresponds to its marginal effect on the number of future insurgent attacks, while adjusting for the prior level of insurgent violence, the number of ANSF and ISAF bases, and the number of USAID aid projects. Robust standard errors are used. The estimates are derived from negative binomial regression models. Since there was no recorded event of “IED found” by insurgents against civilians, the figure only shows the results of IED and non-IED attacks.
Figure 21: Out-of-sample forecasting performance for insurgent violence against civilians. The upper panels present the forecasting improvement rates of adding the estimated ISAF relative support level to the baseline model with past violence, counterinsurgent bases, and aid projects. Prediction improvement is measured by the mean absolute forecasting errors derived from the baseline model and the model with the estimated support level. The lower panels show the forecasting improvement rates of adding to the baseline model the village- and district-level covariates, such as log population, log elevation, ISAF control, Pakistan border, and Taliban Sharia, used to estimate the ISAF support level of non-surveyed villages. In-sample coefficients are estimated through negative binomial regression models. Since there was no recored event of “IED found” by insurgents against civilians, the figure only shows the results of IED and non-IED attacks.
A.7 External Validity

Figure 22: Afghanistan is not an outlier of civil war conflicts, 1945-1999. The panels display the distributions of six factors (per capita income, population, mountainous terrain, polity score, ethnic fractionalization, and religious fractionalization) that are often deemed as important determinants of civil war conflicts. The vertical lines represent the means of Afghanistan. The sample is drawn from the data on civil wars created by Fearon and Laitin (2003).