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INSURGENT LEARNING*

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Abstract

Over the past decade the United States has invested substantial economic resources in protecting its troops against improvised explosive devices (IEDs). Yet we know little about the impact of these investments on combat tactics and soldier safety. We introduce a model of insurgent learning where combatants adapt during an asymmetric war using defensive and offensive technological innovation. We test comparative statics of the model using declassified military records on individual IED explosions in Afghanistan from 2006 to 2014. Consistent with insurgent learning, we show that detonation and casualty rates did not decline during this period. This microlevel evidence is also consistent with the qualitative historical record from other substate conflicts. We conclude by decomposing variable input costs for defensive and offensive innovation presented in military documents.

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Counterinsurgency campaigns are difficult to manage and harder to win. Rebel tactics vary over time [Kalyvas and Balcells 2010; Wright 2016], their organization is unknown [Dorronsoro 2009], and development and military aid spending have uneven effects [Berman, Shapiro, and Felter 2011; Crost, Felter, and Johnston 2014; Beath, Christia, and Enikolopov 2016; Sexton 2016]. Conventional military strategies often seem to be counterproductive, eroding civilian support for the counterinsurgency.[1] In this article we consider an additional challenge counterinsurgents face: insurgent learning.

We focus on improvised explosive devices (IEDs), and study the conflict in Afghanistan. IEDs are responsible for a majority of Coalition casualties in Afghanistan, and are used by insurgents and terrorists throughout the world. Defeating this threat has attracted substantial economic resources: the United States launched a new defense agency, The Joint IED Defeat Organization (JIEDDO, now JIDA), with spending shown in Figure 1. Starting in 2007, an additional 50 billion dollars was allocated to producing and deploying IED-resistant vehicles in Iraq and Afghanistan [Wilson 2008]. To date, no rigorous assessment of these investments has been conducted in Afghanistan. We address this important gap. We show that, despite steadily escalating counterinsurgent investment in IED defeat technologies, IED effectiveness did not decrease.

In Section 1, we begin our analysis by providing a qualitative discussion of bomb making and emplacing techniques, followed by a formal model. Both insurgents and counterinsurgents modify their own tactics and technology in response to their adversary. A major asymmetry here, however, is that the technologies deployed by the counterinsurgency cost many billions of dollars, but these are neutralized by insurgent adaptations that are inexpensive or costless.

In Section 2, we describe the newly declassified IED microdata that we use from the

[1] See Kalyvas [2011] and Lyall [2014] for examples. States have also historically used mass killings of non-combatants to undermine logistical support for guerrillas [Valentino, Huth, and Balch-Lindsay 2004], but evidence from modern insurgencies indicate that these blunt measures may enable mobilization. Rebels may even provoke such indiscriminate state violence to radicalize the fence-sitting population [Galula 1965; Carter 2016].

Afghanistan conflict. Our data describe the location, timing, targets, and outcomes associated with 94,679 IED-related events from 2006 to 2014. This includes 36,681 IED detonations, 43,420 IED neutralizations, and 14,578 weapon cache discoveries. We are able to examine national and regional trends in IED effectiveness over the course of the campaign, as well as consider changes in effectiveness specific to different types of actors. These data allow us to track the effectiveness of IEDs over time using two different measures: first, whether an IED explodes, and second, whether an exploding IED causes casualties.

For our first measure, we use information about IEDs that were cleared before they could even be deployed, IEDs that were planted but were then neutralized by counterinsurgents, and IEDs that were successfully detonated by insurgents. For our second measure, we use information on the outcome of IED detonations: in particular, whether or not the exploding IED caused any injuries, deaths, or resulted in a vehicle immobilization. We also know whether the attacked units were Afghan government forces or Coalition forces.

In Section 3, we show that there were no substantial changes in the detonation rate during our period of study: IEDs were just as likely to explode in 2014 as they were in 2006. Similarly, conditional on detonation, IEDs at the end of the Coalition occupation were just as damaging as at the beginning. While we find no evidence of net changes in casualty rates for Coalition forces, Afghan forces experienced an increasing casualty rate over the course of the counterinsurgent campaign. To obtain these results, we use ordinary least squares, generalized linear, and generalized additive models.

In Section 4, we apply the conflict success function from our formal model to evaluate whether this stable casualty rate was more likely due to insurgents increasing the resources used for each attack, or whether it seems to reflect learning on the part of insurgents. Our results indicate that insurgent learning kept pace with technological investments made by counterinsurgents, and if anything the cost per attack for insurgents decreased. This fact is sobering given that the United States alone invested roughly 4 billion dollars a year during the study period on anti-IED research and development [U.S. Congress Oversight Subcommittee

2008].

A substantial difficulty with our investigation is the counterfactual: what would have happened in the absence of investment in IED-defeat technology? Throughout our time period, the Afghan police and unsupported Afghan military units did not generally update their technology, and implemented fewer countermeasures. For these units, the probability of detonation and, conditional on detonation, casualties significantly increased. As part of our conclusion in Section 5, we use this fact to estimate the number of additional Coalition casualties that would have occurred in the absence of counterinsurgent investments.

Although insurgents (and their state rivals) have weaponized explosive devices for centuries, the recent proliferation of online blueprints and substantial reduction in input costs for bomb production have lead to an unprecedented expansion in the use of IEDs. In addition to Afghanistan, IED use has been reported in Colombia, India, Iraq, Pakistan, Syria, Thailand, and, in more limited cases, Mexico, the United Kingdom, and the United States. With costs ranging from five to several hundred dollars, cash-poor insurgent organizations can cripple even the most sophisticated military forces. As a weapon of war, IEDs are now as ubiquitous as land mines and AK-47s. Our research makes a novel contribution to understanding insurgent learning. We take advantage of newly available microdata on individual IED events across many years, which allows for the first time the study of combat effectiveness across time in the presence of economically meaningful investments in anti-IED technologies by government forces.

This paper also brings together the rich literature in political science on learning by strategic actors with recent work on counterinsurgency. Research on learning highlights how policies diffuse across governments [Mebane and Sekhon 2002; Volden, Ting, and Carpenter 2008; Callander 2011; Makse and Volden 2011; Callander and Clark 2017], communication devices enable anti-regime protests to spread [Little 2015], ethnic kin learn from repression [Larson and Lewis 2017], unit leaders learn during deployments, and firms and individuals and firms innovate in response to productivity shocks [Bahk and Gort 1993; Young 1993;

Foster and Rosenzweig 1995; Conley and Udry 2010]. These papers highlight how actors adapt their behavior in a dynamic fashion. Our argument—drawing on qualitative evidence across a number of conflicts—similarly highlights the importance of continuous feedback in strategic settings, especially on the battlefield during a counterinsurgency campaign.

1 Insurgent Learning

Existing research provides ample qualitative evidence of learning across insurgencies [Forest 2009]. The Irish Republican Army, for example, provided bomb making and mortar design information to armed groups in Colombia, Palestine, and Spain. Before the US-led invasion, the Afghan Taliban operated a number of training camps attended by various Pakistani rebel factions as well as fighters affiliated with al Qaida.

Even in the absence of formal coordination, groups learn from one another. Al Qaida modeled their October 2000 bombing of the USS Cole on a similar, highly publicized 1995 operation carried out by the Tamil Tigers [Forest 2009]. Insurgents in the Deep South region of Thailand have based their recent explosive devices on designs developed by sectarian fighters in Iraq [Abuza 2007].

The qualitative record on innovations within insurgencies is equally rich [Jackson et al. 2005]. Often the new techniques developed do not have any incremental cost relative to older methods: for example, Thai insurgents have learned how to hide bombs in objects commonly discarded along the main traffic corridor from Yala to Pattani. Even when new inputs are purchased, these are usually inexpensive. A famous case is the Memopark timer, a simple keyfob designed to help avoid parking tickets. A dual use was discovered by the IRA, who would use it to time their IEDs for decades.

Because of the adversarial nature of warfare, an innovation by one side frequently prompts a counterinnovation by the other. A classic example of this from conventional warfare arose during the siege of Stalingrad, where attackers tried to dislodge defenders hiding inside of buildings. Initially, the attackers simply threw grenades through windows to clear the buildings. Defenders, however, responded by covering windows with chicken wire. The attackers responded to this defensive innovation by attaching fish hooks to the grenades, which became snagged in the wire mesh.[2]

Ewell and Hunt [1974] study Vietnam, and show that the initial success of American airborne tactics were not sustained over the long term due to insurgent adaptation. Improvements in American tactics were due mainly to learning by doing, rather than a centralized research program, and most improvements did not involve any additional equipment.

One of the most successful tactics was the small unit "jitterbug" helicopter attack: this and other associated tactics, "while very obvious in retrospect, was not clearly seen at the time and was arrived at by trial and error" (p. 83). Ewell and Hunt [1974] focus on the 9th infantry division, operating in the Mekong Delta. Initially the 9th infantry fought large conventional battles against the Viet Cong, but over time the insurgents switched to evading the Americans and launching only periodic offensives. This change by the insurgents changed the payoff to different American tactics.[3] Changes in tactics would thus often arise in chains. For example, American commanders noticed that enemy troops would attack helicopters as they were landing, and began laying down heavy fire before landing. The Viet Cong responded to this by hiding or escaping away from this initial fire. The Americans then in turn responded by changing the position of their attack helicopters, so as to catch enemy forces as they retreated.

In Afghanistan, IED innovations have also typically occurred in response to countermeasures taken by security forces. For example, a simple pressure-plate IED detonates when a vehicle rolls over it, thereby depressing the plate. A countermeasure for this type of IED is a roller in front of the vehicle: the IED will detonate when the roller passes over it, potentially destroying the (relatively cheap) roller, but leaving the vehicle and its occupants unharmed.

[2]This sequence of tactical innovations dates back at least to the siege of Stalingrad. Zahn [2003] reports a similar innovation from Vietnam.

[3]"When the enemy began to evade, the relationship between *activity* and *results* changed so radically that the previous statistics comparisons lost much of their pertinence" (p. 150).

An insurgent countermeasure, however, is to separate the pressure plate from the explosive, so that when the roller rolls over the pressure plate and detonates the explosive, the vehicle behind the roller is located above the explosive. This exact sequence of adaptation was observed between 2006 and 2007 [JIEDDO Report 2007]. We illustrate several other countermeasures in Figure 2.

The IED was a fundamental component of the Taliban strategy, and counter-IED efforts were thus a major element of the Coalition counterinsurgency operations. Because of the significant threat posed by IEDs, the US government allocated substantial funding towards mitigating this threat. JIEDDO was established in 2006, and grew to have an annual budget of several billion dollars.[4] JIEDDO operated until 2015, and during that time continually brought new technologies to bear on the IED threat. A sample of these include personal and vehicle mounted jamming devices to prevent remote detonation, rollers to detonate pressure-plate IEDs, robots to examine potential IEDs, radar systems to identify suicide bombers, remote detection devices including balloon- and drone-based imaging, and ground-penetrating radar.[5] Technological innovation by Coalition forces continued until the end of our sample.

Qualitative evidence strongly suggests that anti-IED equipment was not initially useless. For example, Fowler [2016] reports that "Nyala" armoured vehicles deployed with Canadian troops were initially considered to be resistant to IEDs. However, after observing the ineffectiveness of existing IEDs, the Taliban began stacking explosives together. A stack of anti-tank mines, or anti-tank mines combined with artillery shells, was able to destroy a Nyala and kill its occupants, while the traditional approach of a single anti-tank mine would have been useless.

Similarly, when metal detectors were deployed in large numbers to detect IEDs, the Taliban responded by developing IEDs that had little or no metal content.[6] Thus, although

[4]This does not include standard procurement budgets, such as the $50 billion allocated to purchase IED-resistant MRAP vehicles for deployment to Iraq and Afghanistan.

[5]For additional details, see JIEDDO Annual Reports [2006; 2007; 2008; 2009; 2010].

[6]This in turn lead to the 2010 deployment of radar, in an attempt to detect these non-metal IEDs

there was a substantial anti-IED research and development budget, it is unclear whether Coalition forces were actually becoming more effective at detecting and defeating IEDs, or whether any gains were simply undone by Taliban innovations.

We focus on learning within insurgencies, with a special emphasis on explosive devices. Rebel groups carry out bombings with a certain technology composite. Observing this bombing composite, government forces respond by introducing countermeasures. Taking into account the government's response, rebels adapt their bombing technologies. Before rebels adapt to the government's countermeasures, these security innovations should decrease the effectiveness of IEDs deployed against security forces. After rebels adapt to these countermeasures, the effectiveness of IEDs should increase. Overall, if insurgent learning offsets the tactical returns to technological investment by the government, we expect no change in IED effectiveness over time. We formalize this logic below.

1.1 A Model of Learning

Insurgencies are typically characterized by substantial asymmetries in capabilities. Armed groups must recruit, train, and arm fighters, gather intelligence on government targets and their vulnerabilities, and establish funding streams, all in the presence of more capable government forces. These government forces vary their investments in counterinsurgent technologies and institutions, including measures taken to harden stationary targets and to randomly adjust movements of mobile targets [Hayden 2013]. Rebels respond to government countermeasures through adaptation. Adaptation, on both sides, is dynamic [Jackson 2004].[7]

We focus on an conflict environment with one insurgency force A and a government-aligned counterinsurgency force G. We assume time is discrete and the conflict is expected to last T periods $t = 1, ..., T$.[8] Let us indicate with r the discount rate and with Y^A and Y^G the respective exogenous total endowments of the two actors. For realism, one can consider

[JIEDDO Report 2010].

[7]Revolutionaries and counterrevolutionaries also learn from one another [Weyland 2016].

[8]For the case of Afghanistan, this could be equivalent to a planned and publicly announced withdrawal of troops.

it to be the case that $0 < Y^A \ll Y^G$.

In each period t, A can make an investment $0 \leq I_t^A \leq Y^A$ in attacking capability to augment its current stock AC_{t-1}. In each period t, G also makes a nonnegative investment $0 \leq I_t^G \leq Y^G$ in defensive technology to augment its current stock DF_{t-1}.

We allow both A and G to learn over time from previous conflict experience. It seems intuitive to assume that some form of learning may occur by repeated interaction, so that, for example, the past stock of defensive technology DF_{t-1} may offer opportunity of learning to A by augmenting its attacking capability AC_t. Specifically we posit for A the simple dynamic process:

$$AC_t = \alpha AC_{t-1} + \gamma DF_{t-1} + I_t^A$$

and similarly for G:

$$DF_t = \alpha DF_{t-1} + \rho AC_{t-1} + I_t^G.$$

The processes described above include a realistic component of autocorrelation in conflict capability, indexed by $0 \leq \alpha \leq 1$. In addition, learning implies that a defensive investment on the part of counterinsurgency forces at period t, I_t^G, can feedback in higher offensive capability by the insurgents in period $t+1$ by a factor $0 \leq \gamma \leq 1$ per unit of investment. Symmetrically, learning operates with a factor $0 \leq \rho \leq 1$ for the counterinsurgency forces.

We assume that in every period t there is a conflict event resolved through a conflict function of the Tullock [1980] form. It posits the probability of a victory for the insurgents equal to:

$$\Pr(A\text{'s success at } t) = \frac{AC_t}{AC_t + DF_t}. \tag{1}$$

We can think of equation (1) as a metric of "effectiveness" in conflict for the insurgent force, for which IED effectiveness (i.e. detonation rate and casualty rate) may be considered a valid empirical proxy in our context.

Finally, let us assume the cost of investment is linear at a per unit cost $c \geq 0$ for both A and G (symmetry is an assumption trivially relaxable here).

The insurgency force A will have valuation:

$$V^A = \sum_{t=1}^{T} \left[\frac{AC_t}{AC_t + DF_t} - cI_t^A \right] (1+r)^{-(t-1)},$$

which A will maximize with respect to the intertemporal investment profile $\left\{I_t^A\right\}_{t=1}^{T}$ subject to the budget constraint

$$\sum_{t=1}^{T} I_t^A (1+r)^{-(t-1)} \leq Y^A$$

and optimal response by G.[9]

In this simple theoretical environment it is possible to observe that the effectiveness in conflict of the insurgents vis-a-vis counterinsurgency forces will change over time. It is based on the countervailing effects arising from the fact that investing in offensive technology today increases the probability of success today and, with an α depreciation, tomorrow, but also increases the conflict capability of its adversary tomorrow by a factor of ρ.

To gain insight on the dynamic effects due to learning it is sufficient to set $T = 2$ and study the evolution over time of the object (1). To make our results less cumbersome, we set $AC_0 = DF_0 = 0$.

We can then prove the following proposition.

Proposition 1. *Consider the two period model. Then there exists a unique Nash Equilibrium of this game. Further, (i) the effectiveness of A is constant between period* 1 *and* 2 *only if the learning process is proportional to resources, i.e. if $\rho/\gamma = \left(Y^G/Y^A\right)^2$. (ii) The effectiveness of the insurgents, $\frac{AC_t}{AC_t+DF_t}$, increases (decreases) over time if the learning process favors the*

[9]Similarly for G we study:

$$\max_{\left\{I_t^G\right\}_{t=1}^{T}} \sum_{t=1}^{T} \left[\frac{DF_t}{AC_t + DF_t} - cI_t^G \right] (1+r)^{-(t-1)}$$

subject to

$$\sum_{t=1}^{T} I_t^G (1+r)^{-(t-1)} \leq Y^G.$$

counterinsurgency (insurgency) forces, i.e. if $\rho/\gamma > \left(Y^G/Y^A\right)^2$ *(if* $\rho/\gamma < \left(Y^G/Y^A\right)^2$*).*

The proposition posits first an intuitive result. Suppose counterfactually that $Y^A = Y^G$, then the effectiveness of the insurgent forces remains constant over time if the learning processes of A and G move at the same rate, i.e. the learning is symmetric ($\rho = \gamma$). Since however initial resources are skewed in favor of G and a large initial investment by G favors A's learning, the insurgency will be able to keep a constant effectiveness rate even with an asymmetry in learning ratio ρ/γ if ρ/γ matches the endowment imbalance $\left(Y^G/Y^A\right)^2$.

The proposition also highlights another result. The effectiveness of the insurgents will increase over time as T nears, if they operate at a learning disadvantage relative to the counterinsurgency forces ($\rho > \gamma\left(Y^G/Y^A\right)^2$).[10] The intuition is that, as A learns substantially more slowly than G in this case, then A has an incentive to initially underinvest in offensive technology in order not to excessively prop up G's success probabilities in the following periods. At the same time, because its adversary does not learn as much, G has an incentive to over-invest in defensive capacity relative to a hypothetical case without such learning effects. Hence, in this case it follows that $\frac{AC_1}{AC_1+DF_1} < \frac{AC_2}{AC_2+DF_2}$ (increasing effectiveness of A).

We can also prove the following result.

Proposition 2. *Consider the equilibrium of two period model. If the effectiveness of the insurgents,* $\frac{AC_t}{AC_t+DF_t}$*, increases over time, i.e.* $\rho/\gamma > \left(Y^G/Y^A\right)^2$*, then the growth rate of investment for insurgents is larger than the growth rate of investment for counterinsurgents, i.e.* $\frac{I_2^A}{I_1^A} > \frac{I_2^G}{I_1^G}$*. Similarly, if the effectiveness of the insurgents decreases over time, (*$\rho/\gamma < \left(Y^G/Y^A\right)^2$*), then the growth rate of investment for insurgents is smaller than the growth rate of investment for counterinsurgents, i.e.* $\frac{I_2^A}{I_1^A} < \frac{I_2^G}{I_1^G}$*.*

Proof. See Appendix E. □

Unfortunately, we do not have detailed data on insurgent investments in IED technology or the total resources available to them. We do, however, have data describing the success of

[10] The reader will note here that the restriction $\rho \geq \gamma$ seems the empirically realistic one for the Afghan case.

insurgent attacks. Below we show that, despite massive investments by the US government, insurgent success has not decreased.

2 Data

We study newly declassified military records provided to the authors by the United States Central Command. These data are more commonly referred to as the Significant Activities (SIGACTS) database. Although this data tracks dozens of types of violence, the majority of enemy action events are characterized as direct fire, indirect fire, and IEDs. This paper focuses on IEDs.[11]

For each IED event listed in SIGACTS, we know the exact location (within several meters), time (within the hour), and whether this particular IED exploded or was neutralized. For IEDs that detonate, we also know the institutional affiliation of the target (e.g. "Coalition", "Host Nation"), the type of actor (e.g. "Military", "Police"), and the outcome of the event.

Event outcomes are reported on an ordered scale. If an Afghan or Coalition security force member dies in an attack (or dies later, from wounds sustained in the attack), then the result is coded as "Killed". If no one was killed, but someone was wounded seriously enough such that they could not immediately return to duty, then the result is coded as "Wounded". If nobody was killed or wounded, but their vehicle was affected, then the result is coded as "Damaged/Disabled/Destroyed". If none of these things happened, then the result is coded as "Ineffective". When the result is left blank, this corresponds to an attack that was ineffective.[12] Information on the outcome of attacks was not always available before 2006, or after November 2014. For our analysis, we thus consider only the period from January 2006 to November 2014.

[11] Direct fire consists of machine guns, AK-47s, and other weapons that are effectively fired on a straight line from attacker to target. Indirect fire consists of mortars and other weapons that do not depend on a line of sight between the attacker and the target. See Figures SI-6 and SI-7 for a summary of the direct fire and indirect fire data.

[12] We confirmed this detail with former officers that managed the SIGACTS compilation.

Figure 3 displays trends including "found and cleared" IEDs, as well as latent IEDs that were neutralized (bomb and bomb material discoveries). Figure 4 displays outcomes for the IEDs that actually exploded. In an ideal setting, we would estimate the effect of randomly deployed anti-IED countermeasures on the effectiveness of insurgent IEDs. After more than two years of working to declassify microdata on Afghan and Coalition IED-defeat measures, we have confirmed that this data is too sensitive for public analysis. However, it is obvious from both anecdotal evidence and official government reports (see Figure 1) that enormous resources were deployed to Afghanistan during our study period. The quality of armour on vehicles, the protections designed to prevent an IED from exploding under the vehicle, and the detection technology used to clear IEDs before they explode had all been radically improved by 2014. If we do not observe any improvement over our study period in the IED clearance rate or casualty rate, then this means that either the technologies that were deployed were useless on arrival (which is highly unlikely), or that the insurgents developed effective new techniques to work around these anti-IED technologies.

The examples discussed at the end of Section 1 strongly suggest that the technologies deployed in Afghanistan would have been useful in the absence of insurgent innovation. However, it is never possible for us to show conclusively that the armour on a mine resistant vehicle would have resisted a traditional Taliban mine-based IED. An alternative interpretation of the results presented below, then, is that American investment in IED defeat technologies was simply extraordinarily inefficient and unproductive. A weakness of our analysis is thus that we cannot prove quantitatively that insurgents learned to defeat new American technology: we instead infer this indirectly.

Figure 5 shows the disposition of IEDs. An IED can be emplaced and explode, or it can be emplaced but then found and cleared, or it can be found and cleared before it is emplaced ("cache found and cleared"). Across the campaign's 94,679 unique IED events, devices exploded roughly 39% of the time.[13] Consistent with Figure 3, there are seasonal

[13] One might be concerned that various countermeasures might actually *decrease* the number of emplaced IEDs that are detected through either a detonation or neutralization event. It is important to note that

trends that map on the fighting season in Afghanistan: snow clears from mountain passes in late March and early April, and cold weather returns in late September and October. During the period of study, nearly all full-time fighters exited the country during the winter and retreat to rebel strongholds in Pakistan's border regions. The dip in IED effectiveness in the winter is consistent with a change in the composition of the fighting due to the exit of the most capable bombmakers and IED emplacement specialists during the off season. Ignoring these seasonal trends, there does not appear to be any downward trend in IED effectiveness from 2006 to 2014. If anything, there appears to be a marginal increase in the detonation rate over time.

3 Econometric Analysis

We begin our econometric analysis by looking at changes in the detonation rate of IEDs. We follow that by investigating what happens to security forces when a planted IED explodes. At the end of this section, we consider various robustness checks.

Our unit of observation will be the individual IED. Let our binary outcome variable Y be 1 if the IED exploded and 0 if it was found and cleared.[14] Our first specification will be a linear probability model of the form

$$\Pr(Y_{igm} = 1) = \beta \textsc{Time}_{igm} + \alpha_g + \gamma_m. \tag{2}$$

Here the probability of observing a given outcome (exploded vs. found and cleared) for IED i in lat-lon grid square g in month of year m is determined by the continuous variable

counterinsurgents, as a part of the broader defeat strategy, invested in advanced detection technology as well.

[14]Some IEDs are likely missing from the dataset: those that explode when nobody is around to notice or those that explode on civilian targets but happen to not be reported to the authorities. Our analysis assumes that the nature of this missing data does not change across time. In general we would expect the reporting process to improve over time, and thus the clearance rate should drop. Our finding that it is does not drop is thus more surprising given the sign of the expected bias. Emplaced IEDs are not typically retrieved from the field and replanted elsewhere.

Time (coded as 0 for midnight on 1 January 2006 and around 8.83 at the end of our sample period in November 2014). Summary statistics for these variables are given in Table 2.

Results from this regression are shown in Table 1. Positive coefficients indicate that the detonation rate is increasing (and thus the clearance rate, decreasing). Columns 1-4 show that there is no statistically significant trend in IED clearance rates over time, and that this result is the same regardless of whether grid square and month of year fixed effects are included. We interpret this time component as capturing potential returns to investments in IED-defeat technology, which was steadily increasing during this period.[15] This result is also unchanged when only emplaced IEDs are considered (that is, "cache found and cleared" observations are dropped).[16]

Alternatively, if we use a logit specification and perform the same regression given in Equation 2, the rate at which IEDs detonate appears to actually be *increasing*. These results are displayed in Columns 5-8 of Table 1. Although there is disagreement between Columns 1-4 and Columns 5-8 regarding the statistical significance of the time trend, we can reject any meaningful improvement in clearance rates at the country level.[17] Counterinsurgents do not appear to have been any better at clearing explosive threats from the field in 2014 than they were in 2006.

We now consider what happens conditional on an IED exploding. Event outcomes in our data are provided as an ordered variable, and thus the most obvious specification is an ordered logit. Another option is to collapse the outcome variable to a binary variable, and analyze it using the same sort of standard linear probability model used above.

First, consider the ordered logit case. Here the observed discrete outcome Y is determined by a latent continuous variable Y^*, and an additional parameter vector μ is estimated that

[15] We recognize that time, as a general principle, is not a 'theoretical variable'. In our case, however, we believe interpreting the trend as a theoretical quantity is meaningful.

[16] Columns 2 and 4 do not have an intercept term because it is absorbed in the fixed effects.

[17] Using the coefficient reported in Column 5 of Table 1, we see that from 2006 to 2014 the log odds ratio for an IED exploding *increased* by $0.016 \times 8 = 0.128$. This means that if the odds of an IED exploding in 2006 were 37%, they rose to 40% in 2014. This is opposite to the naive prediction that spending on IED defeat technologies should have reduced the rate at which IEDs exploded.

gives cutoff values that provide the mapping of the continuous variable Y^* into the discrete variable Y. We suppose that the process determining Y^* is

$$Y^*_{igm} = \beta_1 \textsc{Time}_{igm} + \beta_2 \textsc{Type}_{igm} + \beta_3 (\textsc{Time} \times \textsc{Type})_{igm} + \alpha_g + \gamma_m + \epsilon_{igm}. \tag{3}$$

Here Time is the same continuous variable as was used above. Type is the type of the unit encountering the IED: the options here are "Afghan Military, Supported", "Afghan Military, Unsupported", "Afghan Police", "Civilian", "Coalition", and "NA", where a large portion of the "NA" explosions were IEDs that were targeting an inanimate object, such as a bridge or important building. The length of β_2 and β_3 would thus both be six, but a normalization implied in the estimation of the cutoffs μ means that only five parameters in β_2 will actually be estimated.

Table 3 shows the results of this approach. The time trends estimated in Column 4 show that there is no statistically significant relationship for Coalition outcomes over time. The (statistically insignificant) estimated parameter of 0.015 for "Time x Coalition" implies that from 2006 to 2014, the log odds ratio for Coalition forces suffering a casualty (versus no casualties) increased by only $0.015 \times 8 = 0.12$. This means that if Coalition forces suffered casualties 30% of the time in 2006, they would suffer casualties 32.5% of the time in 2014. The estimated trend over time is thus not only statistically insignificant but also small, as well as being in the opposite direction from what would be expected given the large investments made in armour and various other IED countermeasures.[18] For "Time x Afg Military, Supported", we observe a statistically significant decrease in IED effectiveness. This is due, in part, to the composition of force missions that continued to receive support until the completion of the security transition in 2014, when Operation Enduring Freedom formally ended. With Coalition troops in 'overwatch', Afghan military units may have engaged in less risky operations. This result, however, turns out not to be robust based on

[18]The time trend in "NA" type targets is probably due to a compositional trend within these targets: if some targets in the early period did not have any people near them, then casualties could not be recorded. This could result in large increases in the casualty rate as time progressed.

our next specification (Column 8).

A potential concern at this point is that the ordered logit model considered above may rely on assumptions that are violated in the data. For example, perhaps idiosyncratic shocks are not distributed according to an extreme value distribution. To assess the robustness of our results, we convert our ordered discrete outcome to a binary outcome: we classify explosions that are "Ineffective" or result in "Dam/Dis/Destroyed" as not causing a casualty, and explosions that result in "Wounded" or "Killed" as explosions that do cause a casualty. We code these as 0 and 1, respectively, and consider a linear probability model of the form

$$\Pr(Y_{igm} = 1) = \beta_1 \textsc{Time}_{igm} + \beta_2 \textsc{Type}_{igm} + \beta_3 (\textsc{Time} \times \textsc{Type})_{igm} + \alpha_g + \gamma_m. \tag{4}$$

The results of this regression are shown in Columns 5-8 of Table 3. Results are generally very similar: some of the time trends interactions reported in Column 4 are not statistically significant in Column 8, although the coefficient estimates are in the same direction. The time trend for Coalition forces in this specification is borderline statistically significant, but again is in the opposite direction compared to what would be expected: IEDs appear to be becoming more deadly for Coalition forces.

The fact that casualty rates for Coalition forces do not change or even increase slightly is a surprising result. Armoured vehicles were becoming increasingly prevalent during this period, and there were a wide variety of new anti-IED technologies being deployed by JIEDDO. The lack of improvement shown in Tables 1 and 3, then, is evidence that either this new equipment and technology was actually useless (unlikely), or that there was also substantial improvement in the quality of IEDs during this period.

3.1 Robustness checks

We might be concerned that there is some sort of non-linear trend present that is not being picked up by the linear models that we are considering. We thus consider a generalized additive model of the form

$$E[Y^*_{igm}] = f((\textsc{Time} \times \textsc{Type})_{igm}) + \alpha_g + \gamma_m, \tag{5}$$

where the time trend for each type of target is allowed to be an arbitrary non-linear function, with model constraints to ensure smoothness. Figure SI-1 shows selected coefficient estimates. While there are some short term dips in the casualty rate for Coalition forces, there is no obvious trend over the period in question. Casualty rates for the Afghan police appear to be increasing over time, as in Table 3, and there also appears to be a slight increase in the casualty rate for unsupported Afghan military forces. There is also a sharp decline in IED effectiveness against supported Afghan military units at the end of the Operation Enduring Freedom. This is consistent with a potential shift in the riskiness of missions at the end of the security transition, when foreign troops entered 'overwatch'.

Another potential concern regarding Tables 1 and 3 is that the use of the individual IED as the unit of observation is non-standard. We thus consider an alternative specification where we collapse IED activity at the district-week level. The administrative district roughly corresponds to internal divisions in insurgent leadership and the structure of rebel subunits, as well as constraining various counterinsurgent actors. We choose the week as our time unit because it allows us to examine trends without raising concerns about large-scale strategic responses by security forces, which could occur around troop deployment and rotation schedules.

We first examine the detonation rate of improvised explosives at the district-week level. This outcome is defined in district-weeks with at least one IED event and undefined otherwise. An average district-week with at least one IED attack actually experiences roughly four IED explosions. For all target types, this measure includes 28,162 district-weeks during the sample period.

We then perform a within-week analysis of detonation and casualty rates by district during the Afghan campaign. We continue to code these measures as described above. We begin with detonation rates and then decompose harm from IEDs that detonate into Coalition and Afghan casualty rates. These outcomes are only defined for district-weeks with at least one explosives attack. These rate outcomes are continuous, but bounded by zero and one. We begin with an ordinary least squares specification and confirm robustness to a generalized least squares model with binomial family and logit link functions. This latter specification is commonly used for rate outcomes. We estimate the following equation,

$$Y_{dw} = \beta_1 \text{TIME}_{dw} + \alpha_w + \gamma_d + \epsilon_{dw}, \tag{6}$$

where Y_{dw} denotes the three outcomes of interest (detonation, Coalition casualty, and Afghan casualty rates) and is defined for each district-week with positive levels of IED activity. Week of year and district fixed effects are included in all models, with even numbered columns including a year fixed effect. The coefficient of interest is β_1. If β_1 is positive, this indicates that the detonation rate or casualty rates are increasing during the campaign.

Results are shown in Tables SI-1 and SI-2. The even numbered columns in each table introduce year fixed effects. These results indicate that the likelihood of explosion is either flat or significantly increasing during the campaign. This is the case even when conditioning out district-specific but time-invariant characteristics. Regarding casualty rates for Afghan units, our results echo the conclusions in Table 3. The casualty rate is increasing in both specifications (Columns 3-4). However, we find no significant change in the casualty rates for Coalition forces in Columns 5-6.

Although we lack microlevel data on counterinsurgent investments, we incorporate newly released aggregate data on U.S. defensive investments in Afghanistan. These data were made public by the Government Accountability Office in August 2017, and tracks annual American procurement of aircraft, vehicles, small arms and other relevant equipment for Afghan national security forces.[19] These data do not include U.S. investments in Coalition

[19] See GAO-17-667R, available at https://www.gao.gov/products/GAO-17-667R.

IED-defeat technology, but help us account for other macro trends in defensive investment that might confound estimation of our time trends. The direction and statistical significance of our time trends are largely unaffected when we include these defensive investments as control variables. These results are presented in the final column of Table SI-3. We reestimate our within-week analysis, including investments as a covariate. These results are in Table SI-4. Notice that the substantive magnitude of our time trends actually increase in Table SI-4.

Returning to Table 3, a puzzling feature is that the coefficients in Columns 1-3 are larger than almost all of the coefficients in Column 4. We now inspect our data further to discover why this is the case. Figure 6 shows that the type of forces deployed has changed dramatically over the period spanned by our data. Figures SI-2 and SI-3 appear to show that IEDs have gotten deadlier over time, with about a 75% casualty rate for recent years. However, in recent years more of the IED attacks have been against Afghan government targets, which in general travel in standard pickup trucks rather than armoured vehicles. Figure SI-4 shows the numbers of IED attacks targetting Coalition forces, supported Afghan troops, and unsupported Afghan troops, respectively. For IED explosions targetting Coalition troops, there appears to be no change in casualty rates. For Afghan government forces, casualty rates appear to be increasing in recent years.

Within the Afghan military, however, certain units are supported by Coalition forces. Coalition advisors in these units not only provide advice, but also bring with them sophisticated technology. We thus might expect that Afghan military units that are supported by Coalition troops perform differently than those that are not. Figures SI-4e and SI-4f show that this is indeed the case. The casualty rate for Afghan military units with Coalition support is close to 50%, while the rate for unsupported units is closer to 75%. There is no clear trend visible in Figures SI-4e or SI-4f.

The substantial time trend reported in Columns 1-3 of Table 3 thus appears to be mainly due to a compositional trend in the target of IED attacks. From 2010 onwards, the number of Coalition troops targetted by IEDs declined. These Coalition troops were first replaced by Afghan troops supported by Coalition forces, and then later by unsupported Afghan troops. As these types of troops are more vulnerable to IED attacks, we see an increase in the overall casualty rate. Within a given type of unit, there is little to no change in casualty rates.

4 Cost of IEDs and Defensive Technology over Time

Insurgent forces operating within budgetary constraints arguably orders of magnitude smaller than the US military appear to have been able to offset almost 10 years of research and development in IED defensive technology and tens of billions of dollars in cumulative US military investment. The direct implication of this finding is both surprising and informative of the asymmetry in the technology of guerrilla warfare.

We report official US counter-IED expenditure in Figure 1, which also shows the increasing amount of US effort in activity over time. Singer (2012) reports for Brookings that "*The United States has spent roughly $17 billion on various anti-IED gear over the last decade, and that's not counting the $45 billion we've spent on mine-resistant vehicles.*"

To assess the value of this finding more transparently, define defensive effort at time 0 and time 1, D and D', respectively, and offensive effort A and A', respectively. Following from Section 1.1, assume a standard Tullock conflict function of the form:

$$Pr(DefensiveSuccess) = \frac{D}{D + \theta A}$$

where the parameter $\theta > 0$ governs the rate of relative effectiveness of offensive effort vis--vis defensive effort.

Absent insurgent learning, the parameters θ should be fixed, as customarily assumed. Under this hypothesis notice that, if $Pr(DefensiveSuccess)$ remains constant across periods

0 and 1, as proven in Section 3, this formulation implies:

$$D/(D + \theta A) = D'/(D' + \theta A'),$$

or $A/D = A'/D'$. From this, it follows that the relative growth rates of technological investment of the counter-insurgency force and insurgents have to match: $(D' - D)/D = (A' - A)/A$.

To the best of our knowledge information about cost estimates A, specifically of IED attacks, are not widely available. For this analysis, however, we are able to rely on few cost estimates released exclusively to the Danger Room, the WIRED magazine's award-winning national security site, obtained directly from JIEDDO. They are reported for 2009 in Table 4.

Table 4 above is informative along several dimensions. First, the cost of IED attacks is extremely low. Focusing on victim-activated bombs, command-wire operated bombs and remote detonated devices as representative IED attack modes on armored vehicles (as opposed to stationary targets such as government buildings or checkpoints), the cost of IEDs are dwarfed by the cost of the vehicles destroyed or disabled by them. In comparison, unit costs for a High Mobility Multipurpose Wheeled Vehicle (HMMWV) were $81,850 in 2006 and $164,660 in 2009.[20] Based on these cost ratios, one could see how a Taliban IED budget of $10 million may be sufficient to stave off defensive investment for $20 billion. More precisely, a conservative estimate of the total cost of IED incidents in Afghanistan in 2009 based on data from JIEDDO (2011) is $7,650,000 relative a budget for anti-IED activities alone of $15 billion (JIEDDO, 2011).

Also interestingly, Table 4 shows that, while victim-activated bombs, command-wire operated bombs and remote detonated devices became much cheaper over the 2006-09 due to technological progress, suicide bombers, car bombs, suicide bombers attacking in a vehicle

[20]Data is from GAO's Report on Procurement Policy for Armored Vehicles D-2007-107, p.9 Table 3 and from Pentagon procurement data for fiscal year 2009. The more expensive and armored MRAPs had unit costs of $575,000 in 2009.

substantially increased in cost, probably due to a depletion of the stock of immediately available volunteers and stock of usable vehicles. The Table 4 therefore instructive of the large changes in the cost of conflict over three crucial years of insurgency in Afghanistan (2006-09).

Finally, these calculations also provide another quantitative benchmark for evaluating insurgent learning. Consider the probability of success of a defensive effort in facing a victim activated IED against a HMMWV in 2006 and 2009. Taking victim-activated bombs, command-wire operated bombs and remote detonated devices as representative IED attacks on an armored vehicle as representative, we can reject constant $\theta > 0$. This can be shown governs the rate of relative effectiveness of offensive effort A vis-á-vis defensive effort D observing that

$$D/(D + \theta A) = D'/(D' + \theta' A') = 0.61$$

holds robustly in the Section 3.

Using the available proxies for A, A' in Table 4 and cost estimates for D, D' of \$81,850 in 2006 and \$164,660 in 2009, we obtain in Table 5 benchmarks for θ and θ'. Table 5 makes obvious that not only the advantage of insurgent attackers has changed over time, but that its effectiveness appears to have systematically increased across more than 94% of the attacks registered in Afghanistan in 2009 (essentially $\theta < \theta'$ for all categories excluded Car Bombs, which is likely the least representative of the IED categories). The quantitative pattern is one of substantial improvement on the rate of relative effectiveness of offensive effort vis--vis defensive efforts and the magnitudes are extremely high for a three year period, indicating sharp gain in technological advantage for insurgents. Intuitively, say for the case of Command-Wire Operated IED, between 2006 and 2006 the Taliban are able to produce an IED at one forth of the original cost producing the same level of effectiveness (which we established above) on a defensive technology that has doubled in cost. These calculations suggest evidence of substantial insurgent learning.

5 Conclusion

In this paper, we used newly declassified microdata on IEDs assembled and deployed during the ongoing Afghanistan conflict. These military records enable us to track with unparalleled detail individual explosive ordnance from 2006 to 2014, and evaluate whether they have detonated in the field, and, conditional on detonation, how much damage each bomb generated. Although we lack comparable data on anti-IED technologies, we evaluate insurgent effectiveness during a period of rapidly expanding government spending on technological responses to improvised threats. Our empirical investigation provides robust evidence that bombs were just as likely, if not more, to detonate and cause harm to combatants at the end of the conflict as they were at the beginning (and periods in between). Furthermore, using data on the costs of insurgent attacks we can see that there was no increase in per attack cost. Thus the continued success of insurgent attacks in the face of progressively more advanced countermeasures is not due to changes in the inputs expended on each attack, but is rather evidence of insurgent learning.

A remaining question is what would have happened had this spending not occurred. It is difficult to speculate about this counterfactual scenario because detailed data on the precise technologies used in insurgent attacks is not available. Qualitative evidence suggests, however, that the technology used by Afghan police forces did not change appreciably during the period being studied, offering a potential case for speculating the casualty reduction associated with Coalition investments. Drawing on Table 3 (i.e., $\beta_{\text{TIME}\times\text{Afg Police}} - \beta_{\text{TIME}\times\text{Coalition}}$), we estimate an additional 849 IED attacks causing casualties would have occurred in the absence of Coalition investments in IED-defeat technologies. If $30 billion was spent on IED defeat technologies in Afghanistan then this represents an expenditure of $35 million in order to avoid one attack causing casualties. This is a substantially higher willingness to pay to avoid injury than is normally observed, but is consistent with the results reported in Rohlfs and Sullivan [2013]. Confirmation of this number, however, must be left to future research given the uncertainty regarding our choice of "control group".

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Figure 1: U.S. Counter-IED budget, 2006-2014 (cumulative)

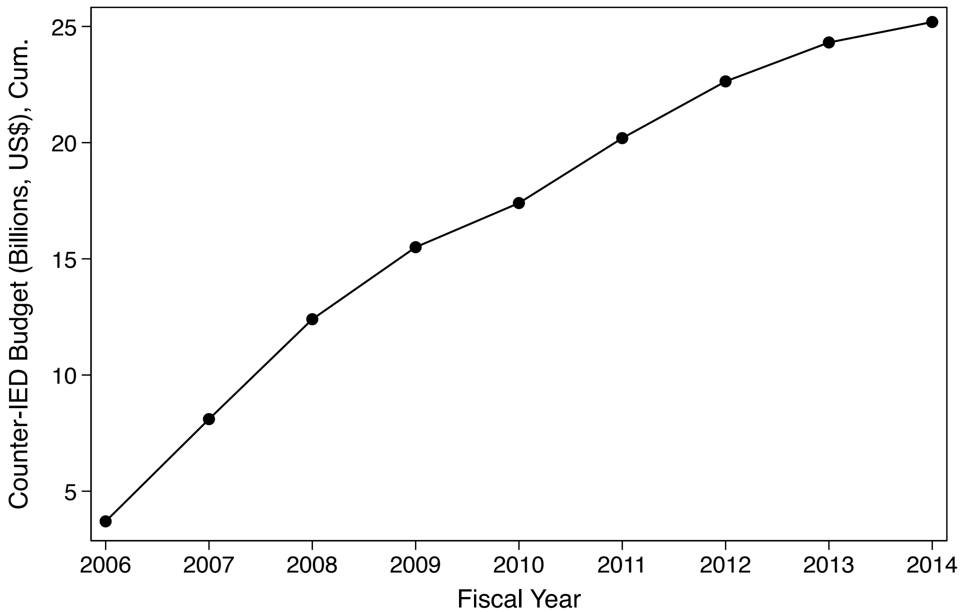
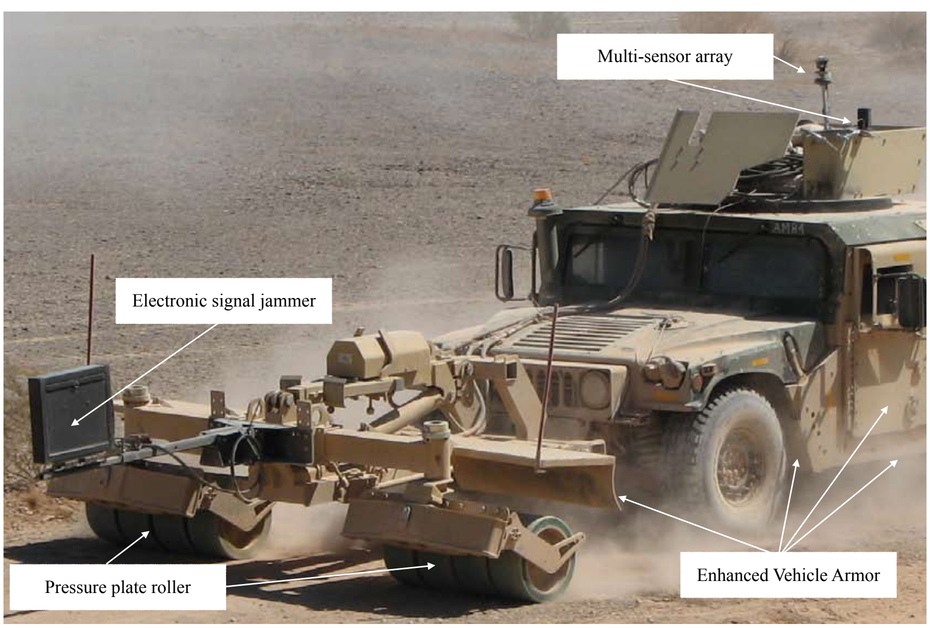
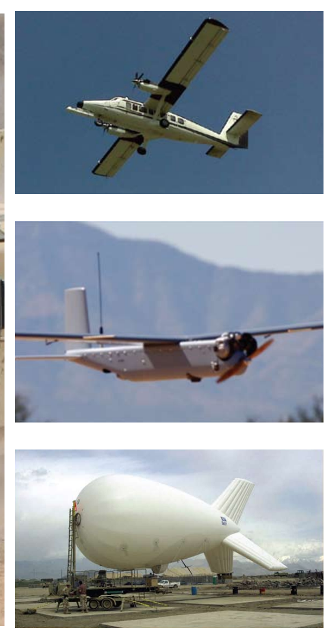


Figure 2: IED-defeat technologies implemented in Afghanistan, 2006-2014

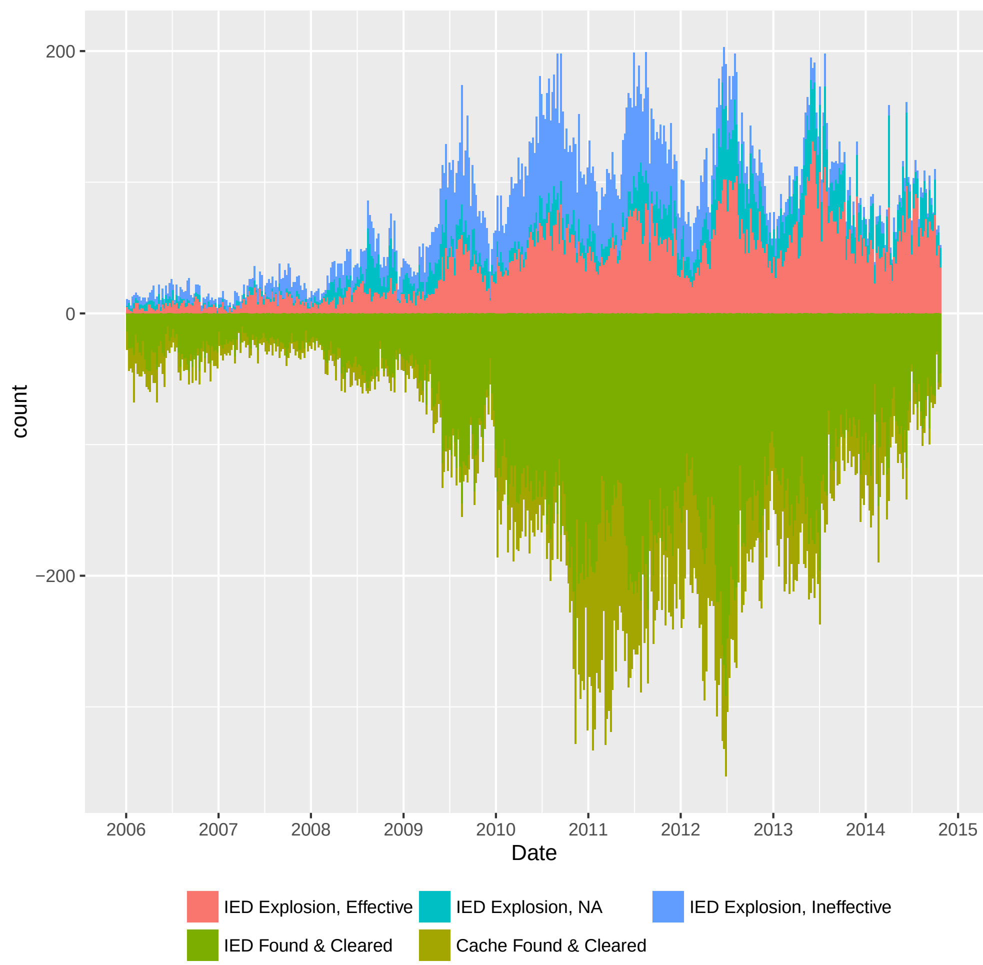


(a) IED Thwart devices on Humvee



(b) IED Detect devices

Figure 3: IED Detonation (above) vs. Clearance (below)



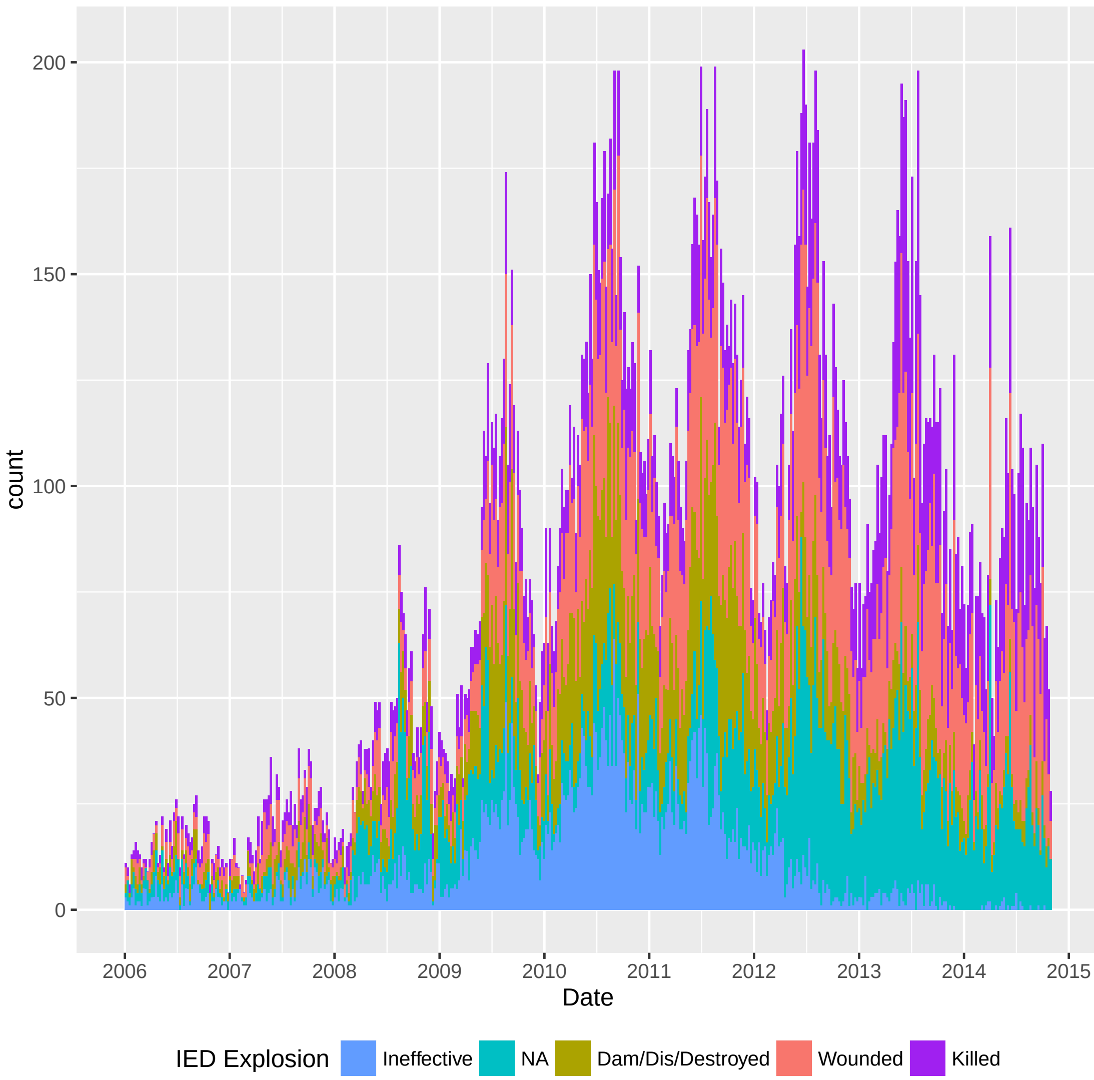


Figure 4: Outcomes of IED explosions

Figure 5: Neutralization rate of IEDs (sums to 100%), from 2006 to 2014

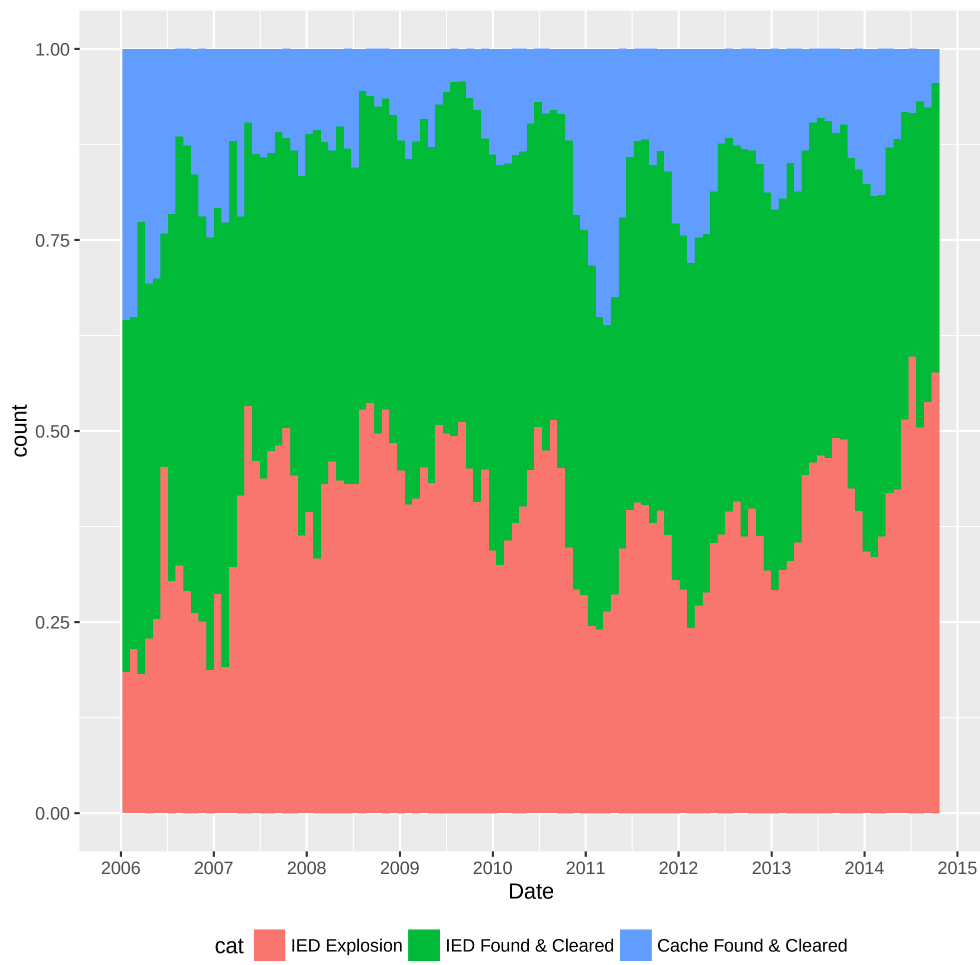


Figure 6: Target of IED Explosions (sums to 100%)

Table 1: Trends in IED explosions (binary outcome)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TIME	0.004	0.002	0.004	0.002	0.016***	0.009***	0.015***	0.008**
	(0.007)	(0.005)	(0.004)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
Grid square FE	No	Yes	No	Yes	No	Yes	No	Yes
Month of year FE	No	Yes	No	Yes	No	Yes	No	Yes
N	94,679	94,679	80,101	80,101	94,679	94,679	80,101	80,101
R^2	0.0002	0.407	0.0002	0.469				
Adjusted R^2	0.0002	0.406	0.0002	0.469				

Columns 1 and 2 consider only emplaced IEDs (coded 0 if the IED was then found and cleared, and 1 if it exploded). Columns 3 and 4 also include caches that are found and cleared (these are coded as zeros). Errors are clustered at the grid square level
Logit model: Columns 5 and 6 consider only emplaced IEDs (coded 0 if the IED was then found and cleared, and 1 if it exploded). Columns 7 and 8 also include caches that are found and cleared (these are coded as zeros).

Table 2: Summary Statistics

	Statistic	N	Mean	St. Dev.	Min	Max
Table 1	IED Explosion	94,679	0.388	0.487	0	1
	Time	94,679	5.477	1.919	0.000	8.831
Table 3	Time	36,690	5.510	1.945	0.000	8.828
	Ineffective	36,690	0.346	0.476	0	1
	Dam/Dis/Destroyed	36,690	0.178	0.382	0	1
	Wounded	36,690	0.291	0.454	0	1
	Killed	36,690	0.186	0.389	0	1
	Casualty	36,690	0.477	0.499	0	1
	Afghan Military, Supported	36,690	0.030	0.172	0	1
	Afghan Military, Unsupported	36,690	0.139	0.346	0	1
	Afghan Police	36,690	0.131	0.338	0	1
	Civilian	36,690	0.127	0.332	0	1
	Coalition	36,690	0.422	0.494	0	1
	NA	36,690	0.151	0.358	0	1

Conditional on explosion, each observation has an outcome that is one of "Ineffective", "Dam/Dis/Destroyed", "Wounded", and "Killed". "Casualty" is coded as 1 when the outcome is either "Wounded" or "Killed". Each observation has a TYPE that is one of "Afghan Military, Supported", "Afghan Military, Unsupported", "Afghan Police", "Civilian", "Coalition", and "NA".

Table 3: Outcome conditional on IED Explosion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time	0.157***	0.154***	0.114***		0.046***	0.046***	0.029***	
	(0.005)	(0.005)	(0.005)		(0.008)	(0.008)	(0.003)	
Time × Afg Military, Supported				−0.087**				-0.014
				(0.042)				(0.019)
Time × Afg Military, Unsupp.				0.030**				0.013**
				(0.014)				(0.006)
Time × Afg Police				0.062***				0.021***
				(0.013)				(0.006)
Time × Civilian				0.060***				0.015***
				(0.013)				(0.004)
Time × Coalition				0.015				0.006**
				(0.009)				(0.003)
Time × NA				0.554***				0.089***
				(0.016)				(0.011)
Ineffective|Dam/Dis/Destroyed	0.203***	−0.543	−1.591***	−3.335**				
	(0.029)	(0.877)	(0.098)	(1.676)				
Dam/Dis/Destroyed|Wounded	0.951***	0.212	−0.782***	−2.509				
	(0.030)	(0.877)	(0.098)	(1.676)				
Wounded|Killed	2.370***	1.654*	0.776***	−0.933				
	(0.032)	(0.877)	(0.099)	(1.676)				
Grid square FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month of year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Target type FE	No	No	Yes	Yes	No	No	Yes	Yes
N	36,690	36,690	36,690	36,690	36,690	36,690	36,690	36,690

Columns 1-4: Proportional-odds ordered logit regression with levels “Ineffective”, “Dam/Dis/Destroyed”, “Wounded”, “Killed”. Columns 5-8: Linear probability model with levels “Ineffective” and “Dam/Dis/Destroyed” coded as 0, and levels “Wounded” and “Killed” coded as 1. Errors are clustered at the grid square level.

Table 4: IED costs

IED Type	Average Cost per Attack 2006	2009	Share of Total Attacks in Afghanistan, 2009
Victim-Activated Bomb	$1,125	$ 265	57.9%
Command-Wire Operated	1,266	265	23.8
Remote Detonated	1,266	345	12.6
Suicide Bomber	5,966	10,032	
Car Bomb	1,675	15,320	6.0
Suicide-Car Bomb	-	19,000	

Source: Joint Improvised Explosive Device Defeat Organization (JIEDDO).

Table 5: Calibrated values of θ

IED Type	A/D (2006)	A'/D'(2009)	θ (2006)	θ' (2009)
Victim-Activated Bomb	0.014	0.002	46.516	397.262
Command-Wire Operated	0.015	0.002	41.335	397.262
Remote Detonated	0.015	0.002	41.335	305.143
Suicide Bomber	0.073	0.061	8.771	10.494
Car Bomb	0.020	0.093	31.242	6.872
Suicide-Car Bomb	-	0.115	-	5.541

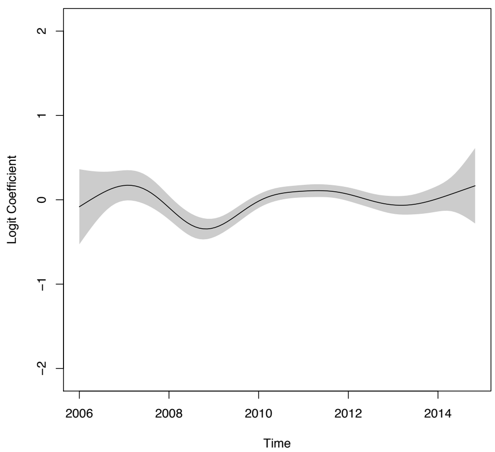
Source: Authors' calculation based on data from JIEDDO.

APPENDIX

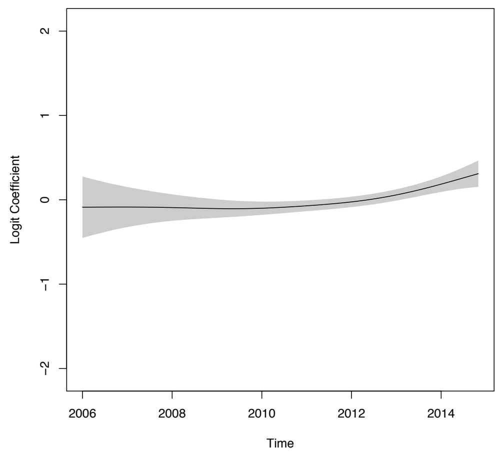
— For Online Publication Only —

A Supplemental Econometric Results

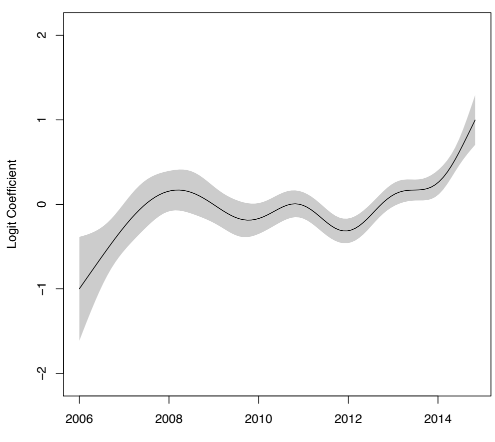
Figure SI-1: Casualty Rate by Security Actor, Nonparametric Model



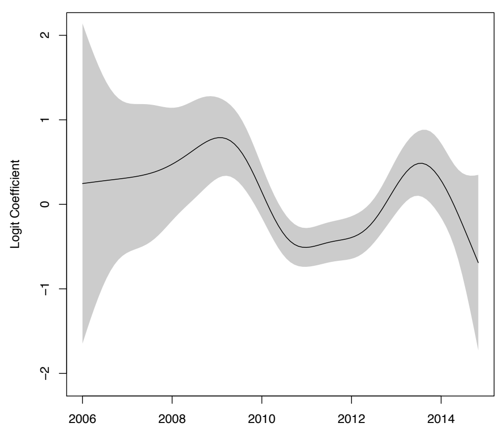
(a) Coalition



(b) Afghan Military, Unsupported



(c) Afghan Police



(d) Afghan Military, Supported

Generalized Additive Model with logit link function. Specification follows Column 8 in Table 3, except that the time interaction terms are allowed to be smooth rather than restricted to be linear.

Table SI-1: IED Outcomes as District-Week Rates (OLS)

	Detonation Rate		Casualty Rate Afghan Units		Casualty Rate Coalition Units	
	(1)	(2)	(3)	(4)	(5)	(6)
TIME	0.0000219	0.000306***	0.000566***	0.000539***	0.0000171	-0.000154
	(0.0000417)	(0.0000484)	(0.0000740)	(0.0000853)	(0.0000802)	(0.000105)
N	28162	28162	10899	10899	8857	8857
Clusters	376	376	339	339	266	266
R^2	0.0111	0.0184	0.0221	0.0517	0.00620	0.00865

Standard errors in parentheses

$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All models include district and week-of-year fixed effects (FE). Standard errors are clustered by district. Even numbered columns include a year fixed effect. Time is a linear trend. The model is estimated using ordinary least squares.

Table SI-2: IED Outcomes as District-Week Rates (GLM)

	Detonation Rate		Casualty Rate Afghan Units		Casualty Rate Coalition Units	
	(1)	(2)	(3)	(4)	(5)	(6)
TIME	0.000130	0.00127***	0.00237***	0.00236***	0.0000721	-0.000719
	(0.000163)	(0.000193)	(0.000294)	(0.000346)	(0.000373)	(0.000499)
N	28162	28162	10899	10899	8857	8857
Clusters	376	376	339	339	266	266

Standard errors in parentheses

$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All models include district and week-of-year fixed effects (FE). Standard errors are clustered by district. Even numbered columns include a year fixed effect. Time is a linear trend. The model is estimated using generalized least squares, with a binomial family and logit link functions.

Table SI-3: Outcome conditional on IED Explosion, accounting for aggregate trends in military spending

	(1)	(2)	(3)	(4)
TIME	0.157***	0.154***	0.114***	
	(0.005)	(0.005)	(0.005)	
TIME × Afg Military, Supported				−0.268**
				(0.110)
TIME × Afg Military, Unsupp.				0.166***
				(0.040)
TIME × Afg Police				0.192***
				(0.037)
TIME × Civilian				0.152***
				(0.037)
TIME × Coalition				0.045
				(0.035)
TIME × NA				0.756***
				(0.041)
Ineffective|Dam/Dis/Destroyed	0.203***	−0.543	−1.591***	−4.571**
	(0.029)	(0.877)	(0.098)	(1.703)
Dam/Dis/Destroyed|Wounded	0.951***	0.212	−0.782***	−3.739**
	(0.030)	(0.877)	(0.098)	(1.703)
Wounded|Killed	2.370***	1.654*	0.776***	−2.152
	(0.032)	(0.877)	(0.099)	(1.703)
Grid square FE	No	Yes	Yes	Yes
Month of year FE	No	Yes	Yes	Yes
Target type FE	No	No	Yes	Yes
US Gov't annual support	No	No	No	Yes
N	36,690	36,690	36,690	36,690

*p < .1; **p < .05; ***p < .01

Proportional-odds ordered logit regression with levels "Ineffective", "Dam/Dis/Destroyed", "Wounded", "Killed".

Table SI-4: IED Outcomes as Rates, accounting for aggregate trends in military spending

	Detonation Rate		Casualty Rate Afghan Units		Casualty Rate Coalition Units	
	(1)	(2)	(3)	(4)	(5)	(6)
Time	0.0000686	0.000549	0.000782***	0.00187$^{\gamma}$	0.000117	-0.000517
	(0.0000720)	(0.000580)	(0.000116)	(0.00109)	(0.000189)	(0.00130)
N	27223	27223	10725	10725	8670	8670
Clusters	375	375	338	338	263	263
R^2	0.0312	0.0316	0.0905	0.0917	0.0536	0.0539

Standard errors in parentheses

$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All models include district and week-of-year fixed effects (FE). Standard errors are clustered by district. Even numbered columns include a year fixed effect. Time is a linear trend. The model is estimated using ordinary least squares.

Table SI-5: Summary Statistics for Tables SI-1 and SI-2

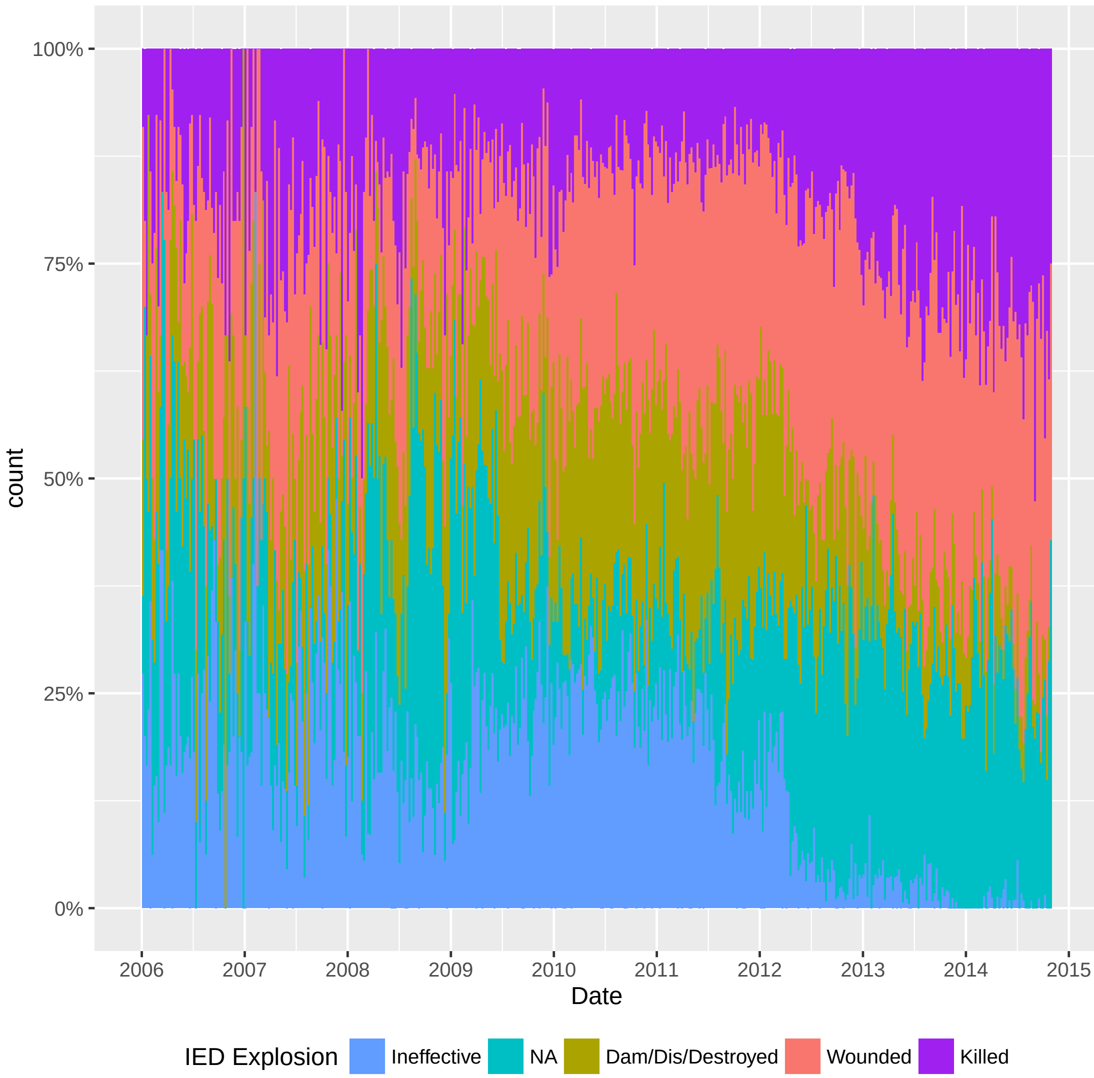
Variable	Mean	St. Dev.	Min.	Max.	N
IED detonation rate	0.493	0.426	0	1	28162
Casualty rate, Afghan forces	0.548	0.463	0	1	10899
Casualty rate, Coalition forces	0.297	0.405	0	1	8857
Time (weekly)	2669.758	116.069	2392	2851	28162

B Additional Visualization of IED Operations/Outcomes

Here we consider the geography of bomb deployment in Afghanistan. Figure SI-5 shows the geographic distribution of IEDs across Afghanistan following a technique suggested by Grolemund and Wickham [2015]. Degrees of longitude are shown at the top of each chart, and degrees of latitude at the right.[21] The count of all IED events is on the left edge and the time range is on the bottom edge. Similar to the previous plots, we examine the period from 2006 to 2014. The maximum observed number of IED events in a given cell-year is just over 1600. For each longitude-latitude combination, a histogram following Figure 4 is shown (for the righthand chart, this is scaled to add up to 100%). Several patterns are

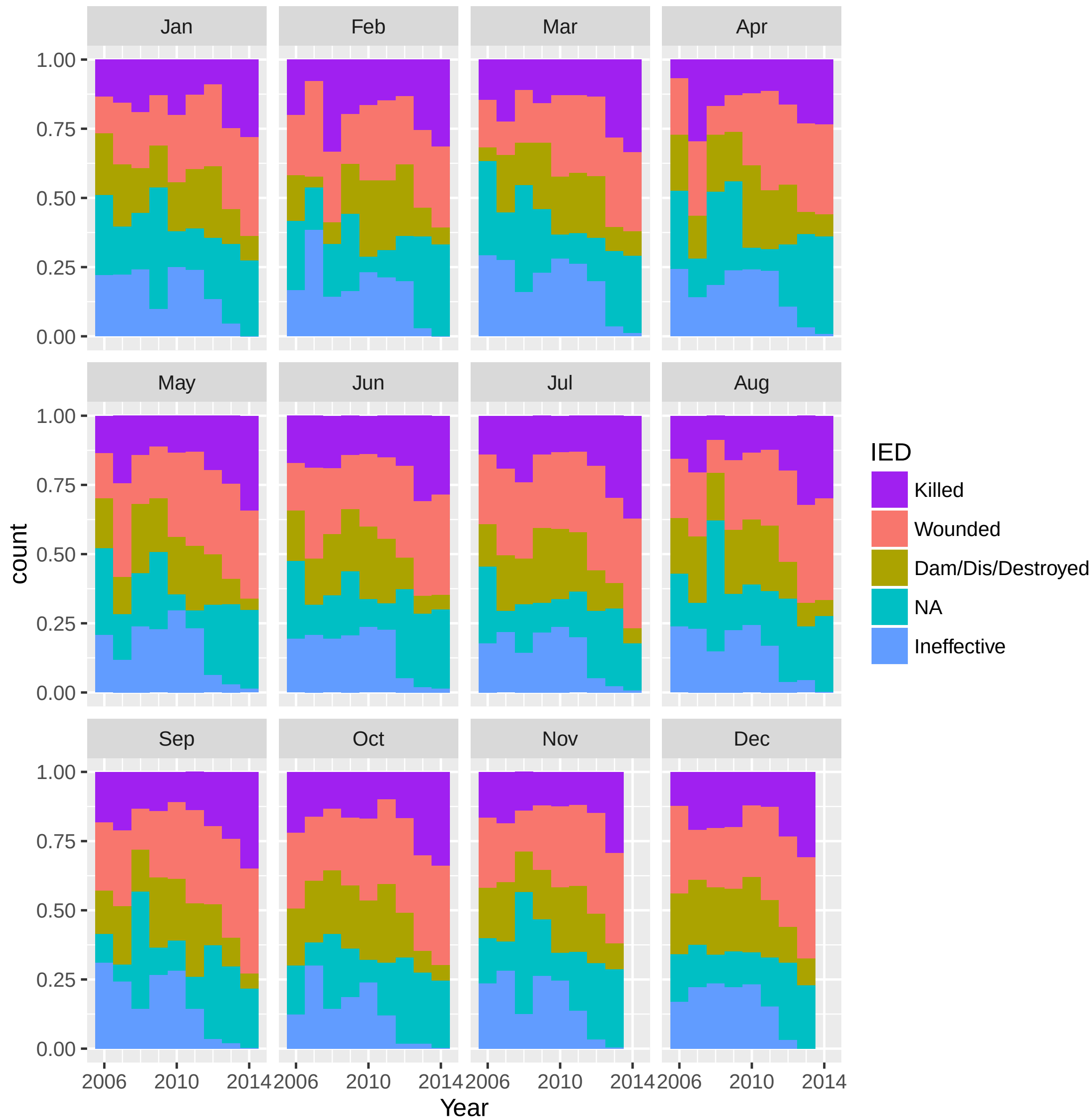
[21]Due to the varying geographic scale of provinces, however, producing a comparable map based on a breakdown by province would largely illegible. Alternatively, one could generate 34 separate plots, one for each province. We prefer for a simpler visualization.

Figure SI-2: Outcome of IED Explosions (sums to 100%)



apparent from these plots. First, almost all recorded attacks happen in the eastern and southern portions of Afghanistan, with very little activity in the north and west. IEDs are particularly concentrated in Hilmand and Kandahar provinces. A major reason for this is the ethnic composition of the country. The southern and eastern portions of the country are densely populated by Pashtuns (i.e., Taliban co-ethnics). Second, given the spatial concentration of IED activity, one might expect that the rate of insurgent effectiveness would diverge significantly across space. Yet Figure SI-5b shows that the effectiveness of IEDs in causing damage is nearly uniform across Afghanistan. No systematic downward

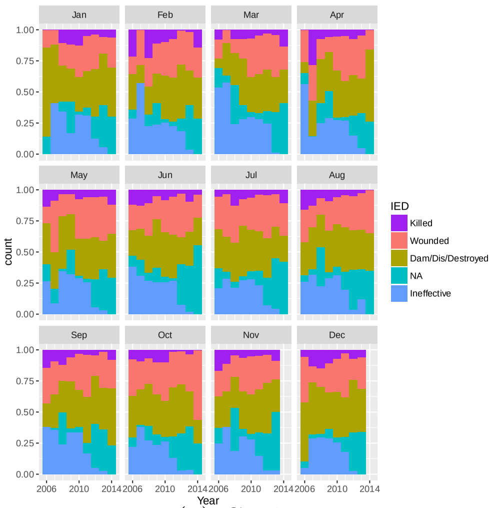
Figure SI-3: Outcome of IED Explosions by Month (sums to 100%)



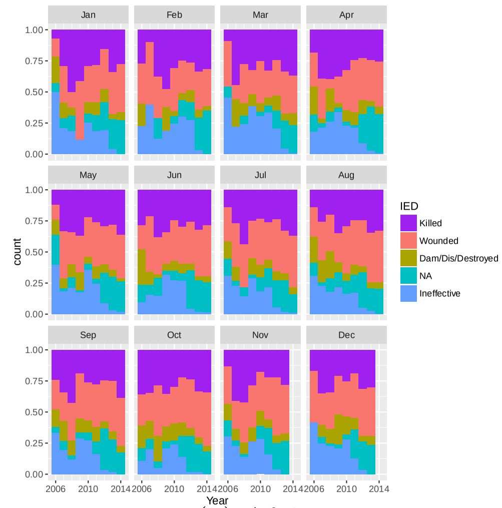
trend in IED effectiveness is visible in any part of Afghanistan. Instead, many plots trend upwards, indicating an increase in insurgent success as the campaign progressed.

C Additional Outcomes in Military Records

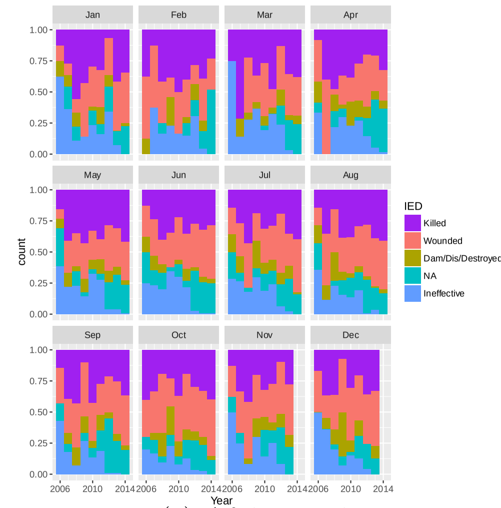
Figure SI-4: Outcome of IED Explosions by Month and Security Actor



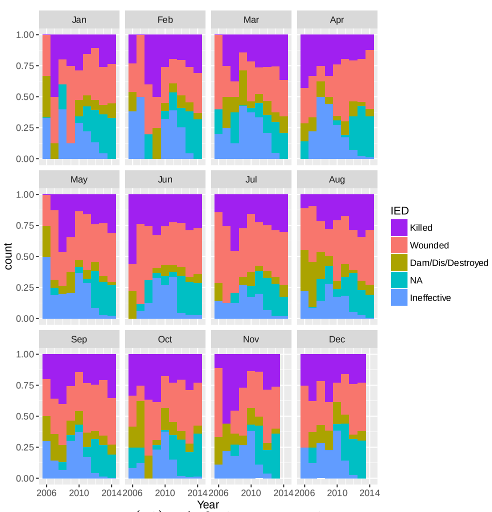
(a) Coalition



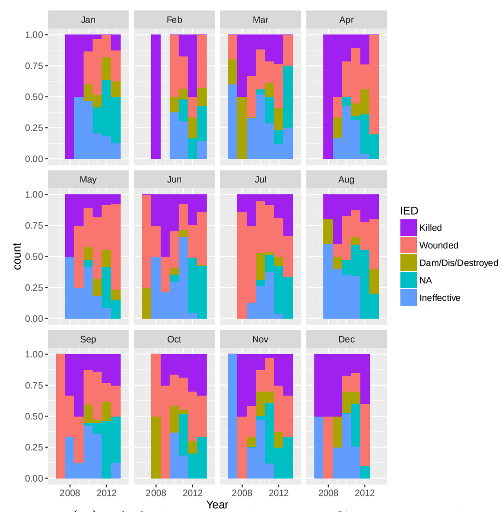
(b) Afghan



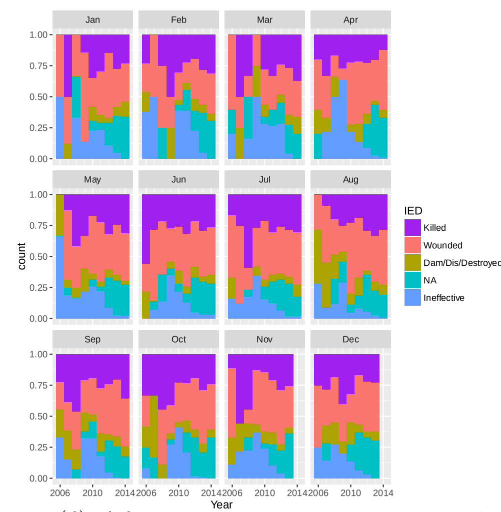
(c) Afghan Police



(d) Afghan Military

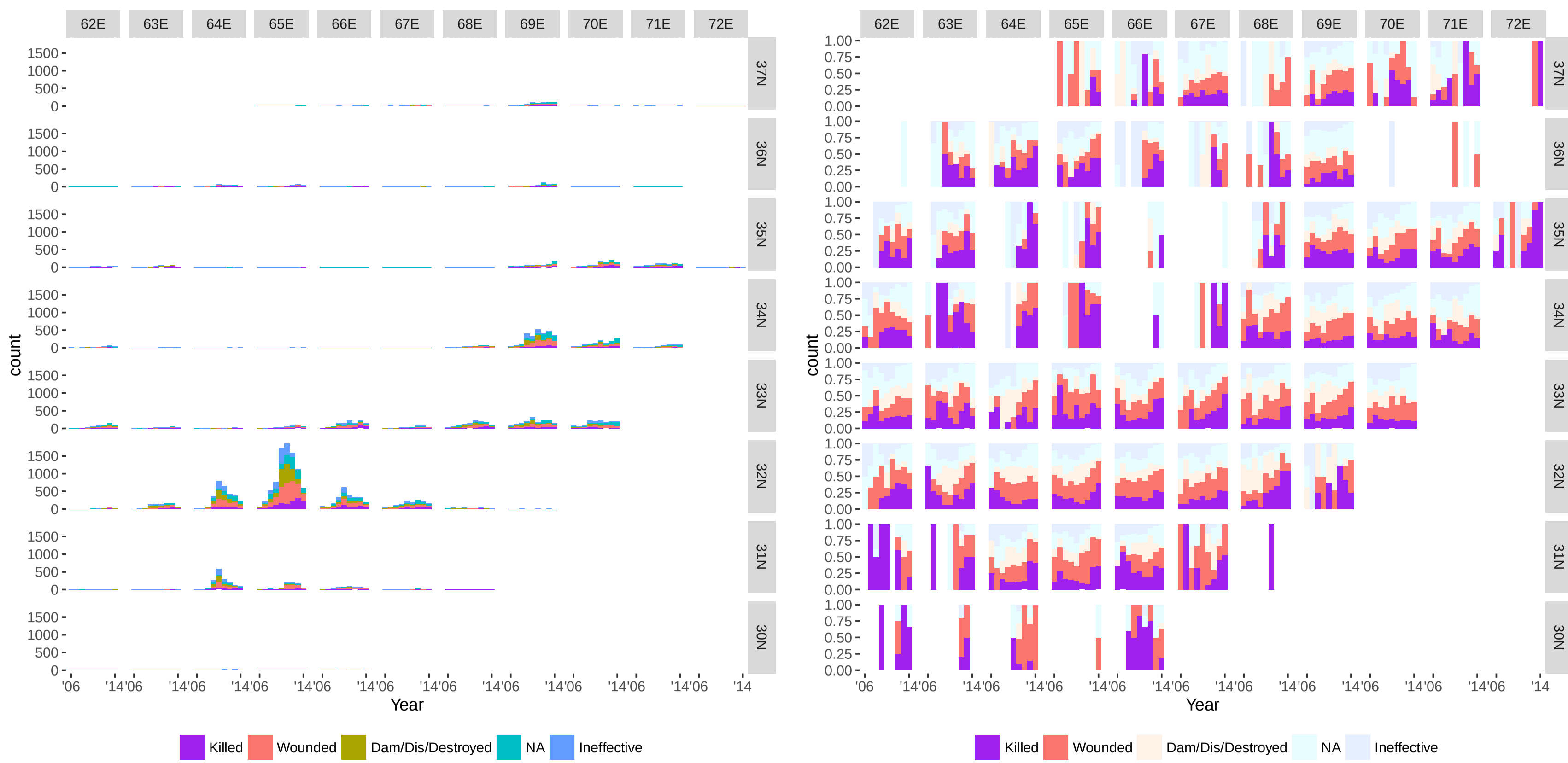


(e) Afghan Military, Supported



(f) Afghan Military, Unsupported

Figure SI-5: Outcomes of IED explosions in Afghanistan by Lat-Lon grid square



(a) Number of explosions with each outcome

(b) Outcome shares (sums to 100%)

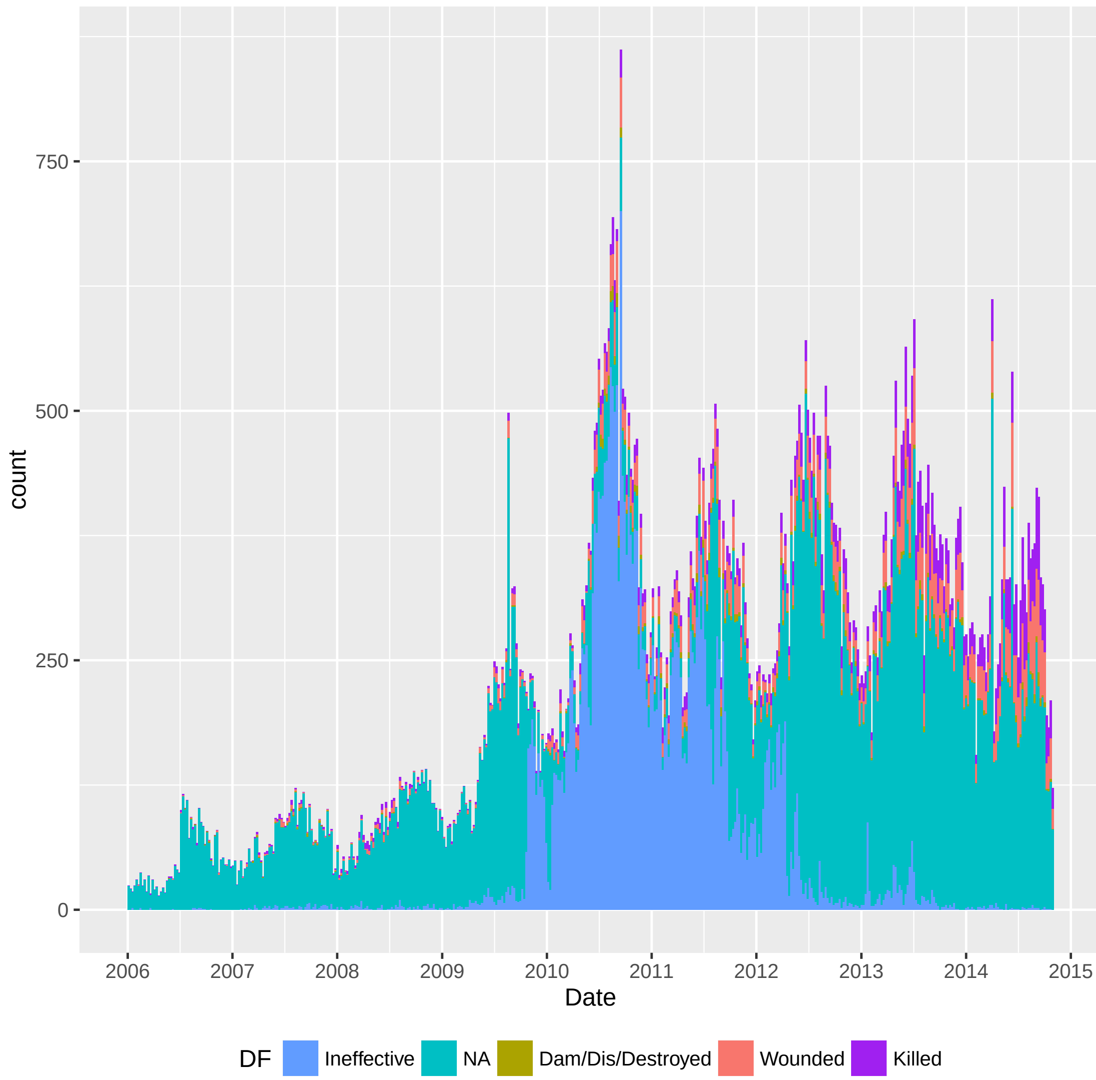


Figure SI-6: Direct Fire attacks (all of Afghanistan)

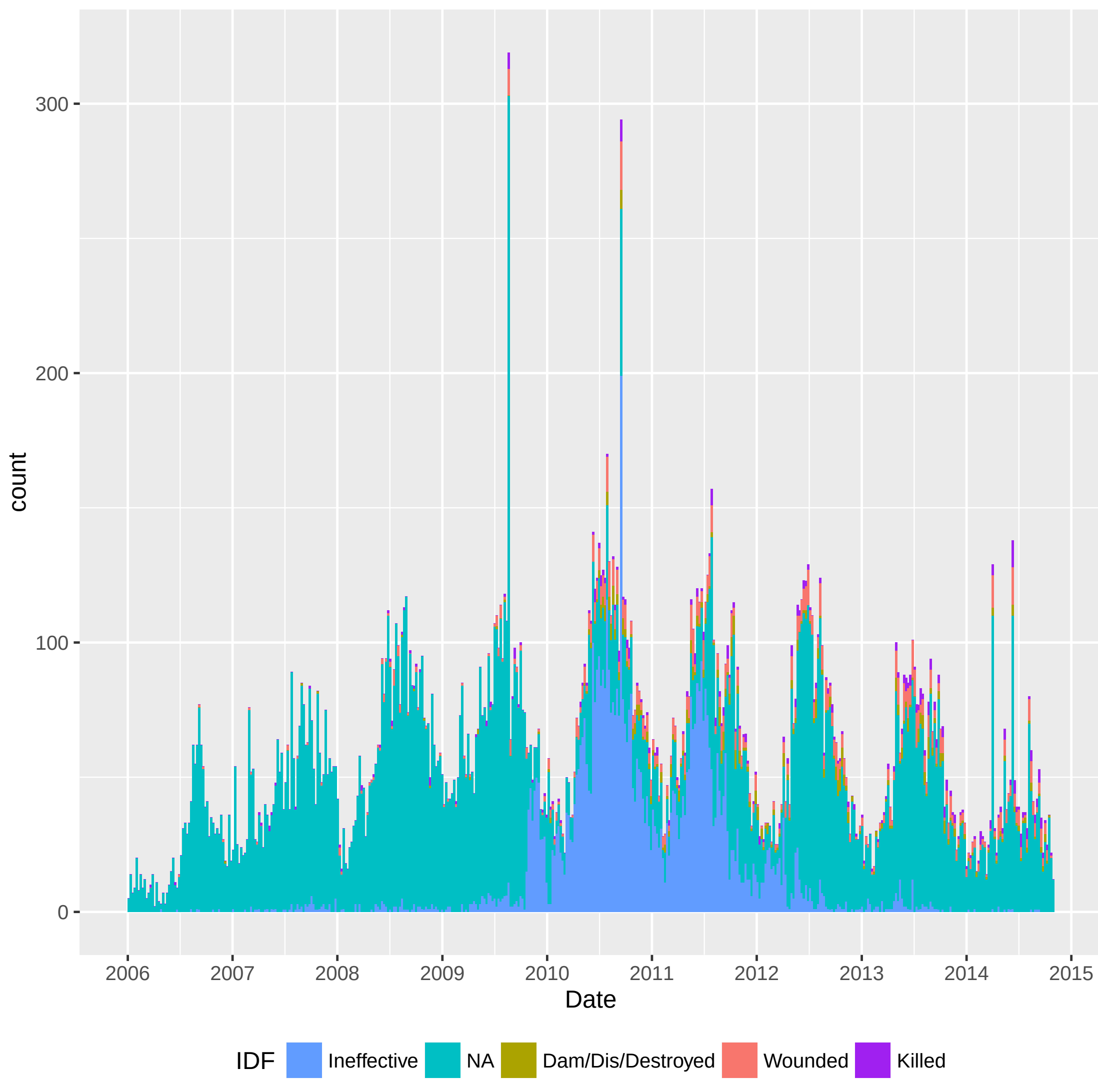


Figure SI-7: Indirect Fire attacks (all of Afghanistan)

D Potential Sources of Bias

The records were compiled by Coalition (primarily US) and host nation (Afghan) security forces. These events were collected as part of an 'operational' dataset that was intended for frequent evaluation (at an aggregate level) by commanders in the field and partner nations. The data passed through multiple points of evaluation (validation) before it entered the final version of the records which we utilize in this study. We thank Kyle Pizzey, who worked closely with the Afghanistan SIGACTS collection team, for confirming these institutional details.

We decompose four potential sources of bias: (1) underreporting of insurgent activity (in levels); (2) underreporting of casualty events by host nation (Afghan) forces; (3) underreporting of insurgent activity by Coalition forces; (4) declining quality of information during the security transition (2012-2014).

First, it is possible that the total number of attacks reported by Afghan forces in our data understates the true number of attacks, and does so to a greater extent in later years. This bias would not affect our results because we never use information on the total number of attacks in our analysis. Instead, we always analyze the outcome of an IED explosion conditional on the explosion happening, or the disposition (cleared or exploded) of an IED conditional on that IED appearing.

Second, it may be the case that Afghan forces deliberately underreported IED events that lead to casualties. This type of reporting error may have been driven by reputational concerns, particularly as districts were being evaluated for the security transition (districts were 'returned' to Afghan forces in tranches based on security assessments). If this bias were present, it would suggest that our estimates for Afghan forces are *downward* biased (i.e., casualty rates might have increased as a sharper rate than we report).

Third, Coalition forces may have similarly underreported casualty events. We find this highly unlikely as these events were rigorously vetted and reporting standards were clearly messaged to combatants. We anticipate that nearly the universe of combat activity involving

Coalition forces is present in our data (exceptions include operations that remain classified). We do not anticipate this bias would be large (if present). If present, however, our estimates would be *downward* biased here as well.

Fourth, related to our first concern, it is possible that the quality of information during the security transition declined sharply. However, as our nonparametric results suggest, our results are stable even if we exclude the transition period. To some extent, this is an empirical question that we can assess in the data. We observe a marginal decline in the completeness of our records at the tail end of 2014 (weeks 45 and above). For this reason, all our econometric results exclude this period.

E Proofs

Proof of Proposition 1. Consider

$$V^A = \sum_{t=1}^{T} \left[\frac{AC_t}{AC_t + DF_t} - cI_t^A \right] (1+r)^{-(t-1)} .$$

for $T = 2$, maximized with respect to I_1^A, I_2^A subject to

$$\begin{aligned} I_2^A (1+r)^{-1} &= Y^A - I_1^A \\ I_2^G (1+r)^{-1} &= Y^G - I_1^G \end{aligned} \tag{7}$$

and taking G's best response profile $\left\{ I_1^G, I_2^G \right\}$ as given. Once we set $AC_0 = DF_0 = 0$ and we replace the budget constraints into V^A, we obtain the unconstrained maximand:

$$\begin{aligned} V^A = & \left[\frac{I_1^A}{I_1^A + I_1^G} \right] + \\ & \left[\frac{\alpha I_1^A + \gamma I_1^G + \left(Y^A - I_1^A\right)(1+r)}{\alpha I_1^A + \gamma I_1^G + \left(Y^A - I_1^A\right)(1+r) + \alpha I_1^G + \rho I_1^A + \left(Y^G - I_1^G\right)(1+r)} \right] (1+r)^{-1} - cY^A \end{aligned} \tag{8}$$

The first order condition with respect to I_1^A is:

$$\begin{aligned}\frac{\partial V^A}{\partial I_1^A} &= \frac{I_1^G}{\left(I_1^A+I_1^G\right)^2}-\left[\frac{(1+r)^{-1}}{\left(AC_2+DF_2\right)^2}\right]\times \\ &\quad \left[(1+r-\alpha)\left(AC_2+DF_2\right)-AC_2\left(1+r-\alpha-\rho\right)\right] \\ &= 0\end{aligned}$$

Repeating the exercise for G, we obtain the FOC:

$$\begin{aligned}\frac{\partial V^G}{\partial I_1^G} &= \frac{I_1^A}{\left(I_1^A+I_1^G\right)^2}-\left[\frac{(1+r)^{-1}}{\left(AC_2+DF_2\right)^2}\right]\times \\ &\quad \left[(1+r-\alpha)\left(AC_2+DF_2\right)-DF_2\left(1+r-\alpha-\gamma\right)\right] \\ &= 0\end{aligned}$$

Define $\chi=1+r-\alpha$. Solving the system constituted of these two FOCs implies the unique equilibrium investment levels for A and G:

$$\begin{aligned}I_1^A &= \Delta\times\left[\chi Y^A+\gamma Y^G\right] \\ I_1^G &= \Delta\times\left[\chi Y^G+\rho Y^A\right]\end{aligned}$$

where

$$\begin{aligned}\Delta &= \\ &\frac{(1+r)^2(Y^A+Y^G)^2}{\begin{array}{c}Y^{A2}\left((2+r^3-2r^2(\alpha-2)+2\alpha^2+2\gamma+\gamma^2-2\alpha\left(2+\gamma\right)-\gamma\rho+r(5-6\alpha+\alpha^2+2\gamma-\gamma\rho)\right) \\ +2Y^AY^G\left((r^3-2r^2(\alpha-2)+(\alpha-1)\left(2\left(\alpha-1\right)-\gamma-\rho\right)+r(5-6\alpha+\alpha^2+\gamma+\rho-\gamma\rho)\right) \\ +Y^{G2}\left((2+r^3-2r^2(\alpha-2)+2\alpha^2+2\rho+\rho^2-2\alpha\left(2+\rho\right)-\gamma\rho+r(5-6\alpha+\alpha^2+2\rho-\gamma\rho)\right)\end{array}}\end{aligned}$$

and, through the budget constraints (7), we also have the unique equilibrium I_2^A and I_2^G. This construction proves existence and uniqueness of the Nash equilibrium.

Consider now the equilibrium insurgent effectiveness at periods 1 and 2 obtained by using the players' equilibrium investment strategies:

$$\begin{aligned}\frac{AC_1}{AC_1+DF_1} &= \frac{\chi Y^A+\gamma Y^G}{(\chi+\rho)\,Y^A+(\chi+\gamma)\,Y^G}\\ \frac{AC_2}{AC_2+DF_2} &= \frac{Y^A}{Y^A+Y^G}.\end{aligned}$$

Notice then that

$$\frac{\chi Y^A+\gamma Y^G}{(\chi+\rho)\,Y^A+(\chi+\gamma)\,Y^G}=\frac{Y^A}{Y^A+Y^G}$$

if it holds that

$$\frac{\gamma\left(Y^G\right)^2-\rho\left(Y^A\right)^2}{\left(Y^A+Y^G\right)\left((\chi+\rho)\,Y^A+(\chi+\gamma)\,Y^G\right)}=0$$

or

$$\frac{\rho}{\gamma}=\left(\frac{Y^G}{Y^A}\right)^2.$$

Notice further that

$$\begin{aligned}\frac{AC_1}{AC_1+DF_1} &< \frac{AC_2}{AC_2+DF_2}\\ &\Rightarrow\\ \left(\frac{Y^G}{Y^A}\right)^2 &< \frac{\rho}{\gamma}.\end{aligned}$$

This proves the proposition. ■

Proof of Proposition 2. Consider that

$$\rho/\gamma>\left(Y^G/Y^A\right)^2$$

implies

$$\frac{\rho\left(Y^A\right)^2-\gamma\left(Y^G\right)^2}{\chi Y^A+\gamma Y^G}>0$$

and notice that

$$\frac{\rho\left(Y^A\right)^2-\gamma\left(Y^G\right)^2}{\chi Y^A+\gamma Y^G}=\frac{I_1^G}{I_1^A}-\frac{Y^G}{Y^A}.$$

So from the argument above it holds that

$$\frac{I_1^G}{I_1^A}-\frac{Y^G}{Y^A}>0,$$

then this implies that the difference

$$\begin{aligned}\frac{I_2^G}{I_1^G}-\frac{I_2^A}{I_1^A} &= \\ \left(Y^G I_1^A - Y^A I_1^G\right)\frac{(1+r)}{Y^A Y^G} &< 0.\end{aligned}$$

This proves the proposition. ■