NBER WORKING PAPER SERIES

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Working Paper 23475
http://www.nber.org/papers/w23475

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2017

We thank Matilde Bombardini, Ethan Bueno de Mesquita, Hanna Halaburda, Jason Lyall, Thorsten Rogall, Oliver Vanden Eynde, and participants at the Defense and Security Economics Workshop for helpful comments. Members of the Asymmetric Warfare Group provided essential feedback. We also thank the Pearson Institute for the Study and Resolution of Global Conflicts for financial support and various government agencies for providing data. Eli Berman, Kyle Pizzey, and Jacob Shapiro are owed a particular debt of gratitude for their support of this and related projects. All errors remain our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 23475
June 2017
JEL No. O1,P48

ABSTRACT

We study a model of insurgent learning during a counterinsurgency campaign. We test empirical implications of the model using newly declassified microdata documenting improvised explosive devices (IEDs) in Afghanistan from 2006 to 2014. This period was characterized by substantial US investments in anti-IED technology and equipment. We find no evidence of decreasing effectiveness of IEDs across time. Qualitative evidence suggests that this is due to innovations in IED devices and tactics. Our results are robust to numerous alternative specifications, and yield insights on a technological revolution in insurgent violence—the proliferation and evolution of IEDs—with implications for scholarship on civil conflict and future investment in tactical countermeasures.

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1 Introduction

Counterinsurgency campaigns are difficult to manage and harder to win. Recent research in political science and economics investigates a number of difficulties security forces face during conflicts with insurgent actors. Rebel tactics vary over time [Kalyvas and Balcells 2010; Wright 2016], 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], their organization is unknown [Dorronsoro 2009; Trebbi and Weese 2015], and conventional military strategies, including aerial bombardment, can erode civilian support for the counterinsurgency [Kalyvas 2011; Lyall 2014]. Although states have historically used mass killings of non-combatants to undermine logistical support for guerrilla actors [Valentino, Huth, and Balch-Lindsay 2004], evidence from modern insurgencies indicate these blunt measures may enable mobilization. Rebels may even provoke such indiscriminate state violence to radicalize the fence-sitting population [Galula 1965; Carter 2016].

In this article, we focus on another major but understudied challenge counterinsurgents face: insurgent learning. Because it is difficult for counterinsurgents to cloak their warfighting technologies, insurgents can learn about and exploit weaknesses within deployed forces. Since counterinsurgents also directly observe insurgent innovations in the field, there are numerous opportunities for additional investment in defeat techniques.

Although insurgents can learn along many dimensions, we emphasize technological innovation with respect to explosive devices. Explosive devices, especially improvised bombs, are a frustratingly common and inexpensive tool used by rebel actors. We provide historical evidence of nuanced learning by insurgents regarding bomb making and emplacing techniques. We then model these conflict dynamics as an investment-based learning game over multiple periods. Insurgent and government actors independently invest in changes to the technology they deploy against one another. Reasonably, these investments are observed, and adjustments are made in subsequent periods. Variation in contest success (whether or not a bomb detonates) is a straightforward empirical metric for evaluating adaptation by each side over time.

We examine insurgent learning using newly declassified microdata on improvised explosive devices (IEDs) during the ongoing Afghanistan conflict. These data allow us to track the effectiveness of insurgents and counterinsurgents over time. We have information about latent IEDs cleared before they could be deployed, IEDs that have been planted but were neutralized by counterinsurgents, and IEDs that were successfully detonated by insurgents. We use this information to examine changes in the detonation rate over time, during a period of steadily escalating counterinsurgent investment in IED defeat technologies [U.S. Congress Oversight Subcommittee 2008]. Consistent with our model, we find little evidence of any substantial changes in the detonation rate. IEDs were just as likely to explode in 2014 as they were in 2006.

Our microdata also includes information on the outcomes of IED detonations, including whether or not the IED event caused any injuries or deaths or vehicle immobilization. We also know the actors who suffered from bomb damage. Our evidence indicates that, conditional on detonation, IEDs at the end of the coalition occupation were just as damaging as at the beginning. We find no evidence of net changes in casualty rates for coalition forces. On the other hand, Afghan forces who currently carry out nearly all domestic security operations, experienced a marginally increasing casualty rate over the course of the counterinsurgent campaign.

These results indicate insurgent learning kept pace with changes in the technological investments made by counterinsurgents. 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. Starting in 2007, an additional 50 billion dollars was allocated to producing and deploying IED-resistant vehicles in Iraq and Afghanistan [Wilson 2008]. The Joint IED Defeat Organization (JIEDDO, now JIDA) spent 2.3 billion dollars to develop and field an electronic signal jamming device that would thwart IED triggers using two-way radios and garage door openers [JIEDDO Report 2007]. In response, insurgents simply switched the trigger device. Yet our model suggests these investments were not necessarily wasteful. In the absence of continued investment in IED defeat operations, the detonation and casualty rates of insurgent devices would have likely increased.

Our investigation yields insights on a technological revolution in insurgent violence: the rise and evolution of IEDs. Although rebels (and their state rivals) have weaponized explosive devices for centuries, the recent proliferation of online IED blueprints and substantial reduction in input costs for bomb production have lead to an unprecedented expansion in the use of IEDs as a technology of war. IEDs have been reported in a variety of settings including Afghanistan, Colombia, India, Iraq, Pakistan, Syria, Thailand, and, in more limited cases, Mexico, United Kingdom, and United States. With costs ranging from five to several hundred U.S. dollars, poorly trained and underfunded 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.[1] Yet previous research on this technological revolution, and the learning dynamics that shape the evolving threat posed by IEDs, has been limited by the restricted nature of microdata on individual IED events.

Our data allows us to explore this technology of war in novel ways. Using newly declassified military records, we are able to examine 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 decompose changes in the rate of learning by insurgents specific to different types of actors over time.

[1]The recent use of IEDs by terrorists also highlights the changing nature of destructive technologies available to weak yet violent political actors. Attacks on London's public transportation system, Boston's 2013 marathon, and the May 2017 Manchester Arena attack were all conducted using IEDs and resulted collectively in nearly one hundred civilian deaths and some one thousand injuries. Some of the perpetrators of these attacks—for instance, the Tsarnaev brothers, responsible for the Boston attacks—had no military background or specialized educational training necessary otherwise required for the production of sophisticated explosive devices.

This paper also brings together the rich literature in political science and economics 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 government repression [Larson and Lewis 2017], unit leaders learn during deployments [Bueno de Mesquita, Price, and Shaver 2017], and firms and individuals 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 model similarly highlights the importance of continuous feedback in strategic settings, from voting and firm production to insurgent innovation. Our model of insurgent learning also yields a number of important insights about the features of a counterinsurgency campaign that we believe are not fully captured in existing models of strategic interaction between warring actors such as those of Bueno de Mesquita and Dickson [2007], Fey and Ramsay [2007], and Bueno de Mesquita [2016].

The rest of the paper is organized as follows. In the next section, we briefly outline historical evidence of learning by rebel actors. In Section 3, we present a model of sequential learning in a dynamic environment. In Section 4, we present an overview of our data and empirical strategy. Section 5 presents visual and regression-based evidence of insurgent learning. The final section concludes.

2 Insurgent 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].

Existing research provides ample qualitative evidence of learning across insurgencies [Forest 2009].[2] The Irish Republican Army (IRA), for example, transferred detailed information about bomb making and mortar design 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 2001 bombing of the USS Cole on a similar, highly publicized 1995 operation carried out by the Tamil Tigers. Insurgents in the Deep South region of Thailand have modeled 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]. To enhance the precision timing of their attacks, the Irish Republican Army adapted the Memopark timer for use in munition detonation. The Memopark timer was a simple, handheld device used for tracking remaining meter time on parked vehicles. Because this device was widely available and difficult for counterinsurgent forces to track, the IRA did not develop new timer technologies for years after the first Memopark explosive. Thai insurgents have also adapted how to design and plant roadside bombs to avoid detection, including sophisticated techniques for hiding bombs in objects commonly discarded along the main traffic corridor from Yala to Pattani.

In Iraq and Afghanistan, IED technology has rapidly advanced, from primitive wire-to-battery devices to bombs detonated through encrypted radio signals. Importantly, these innovations typically occur 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 counter-measure for this type of IED is a roller in front of the vehicle: the

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

IED will detonate when the roller passes over it, potentially destroying the (relatively cheap) roller, but leaving the vehicle and its occupants unharmed. A counter-counter-measure, 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 sequence of adaptation was observed between 2006 and 2007 [JIEDDO Report 2007].

We focus on learning within insurgencies, with a special emphasis on explosive devices. Rebel groups carry out bombings with a certain technology composite. This technology signature includes emplacement location, bomb size, explosive force, and detonation technology. Observing this bombing composite, government forces respond by introducing countermeasures. These countermeasures include randomizing force movement, enhancing vehicle and body armor, and developing signal jammers. 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. We formalize this logic below.

3 A Model of Learning

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 $t = 1, ..., T$.[3] 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 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

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

$0 \leq I_t^G \leq Y^G$ 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 $\{I_t^A\}_{t=1}^T$ subject to the budget constraint

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

and optimal response by G.[4]

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

Proof. In Appendix. □

[4]Similarly for G we study:

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

subject to

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

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 ($\rho > \gamma \left(Y^G/Y^A\right)^2$).[5] 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. In Appendix. □

This proposition focuses on an important dynamic. If the effectiveness of insurgents is increasing from one period to the next, the relative change of insurgent investment in technological innovation must exceed the change in government investments. Relatedly, any decline

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

in bomb success over periods is a function of government investments outstripping insurgent inputs in relative terms. Notice that this result also obtains if one or the other actor divests over time at a faster rate than their opponent. That is to say, if counterinsurgent forces draw down their investments between periods, while insurgent investments remain constant (or increase) between periods, attack effectiveness will increase. The inverse obtains as well.

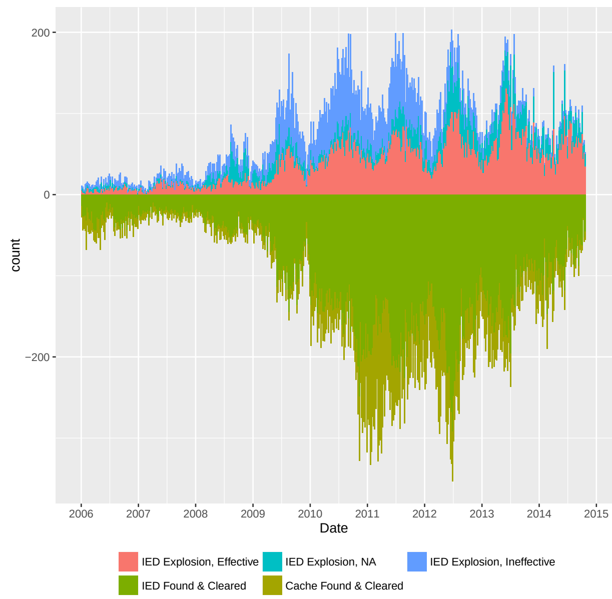
4 Data and Empirical Strategy

Our investigation exploits newly declassified conflict data from the United States Central Command. The data was retrieved by [Author] and [Author]. The detailed nature of this conflict data allows us to track insurgent activity by the hour, to within several meters of the event location. Although this data tracks dozens of types of violence, the majority of enemy action events are characterized as direct fire, indirect fire, and IED explosions. 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. IEDs consist of explosives that have already been emplaced, and are simply detonated by the attacker at the appropriate time.

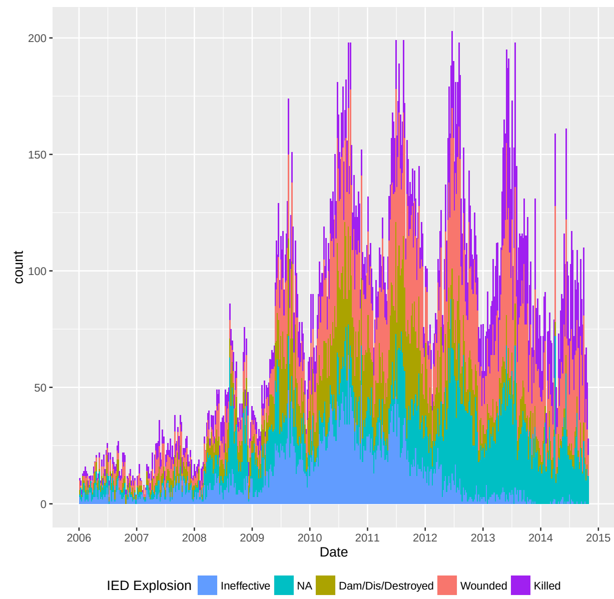
This paper focuses on insurgent learning with respect to IEDs. For each event, we know the exact location (within several meters), time (within the hour), and detonation status (whether the IED exploded or was neutralized). Importantly, emplaced IEDs are not typically retrieved from the field and replanted elsewhere. For IEDs that detonate, we also know the institutional affiliation the target (Coalition, Host Nation), the type of actor (Military, Police), and the outcome of the event (Ineffective, Damaged/Disabled/Destroyed, Injured, Killed).

The last three of these categories form an ordered scale, describing the effect of the insurgent attack on Afghan/Coalition forces: if an Afghan or Coalition security force member

Figure 1: IED events: detonate/clear and explosion impacts



(a) Detonates (above) vs. Clears (below)



(b) Outcomes of IED explosions

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 return to duty immediately, 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. Information on the outcome of attacks was not available before 2006, or after November 2014. For our analysis, we thus consider only the period from January 2006 to November 2014.

We also use information about IEDs planted by insurgents that were neutralized by counterinsurgents before they could detonate. Figure 1a displays trends including "found and cleared" IEDs, as well as latent IEDs that were neutralized (bomb and bomb material discoveries). Figure 1b displays outcomes only for IEDs that actually exploded.

In an ideal setting, we would estimate the effect of otherwise randomly deployed anti-IED countermeasures on the effectiveness of insurgent bomb deployment. Because no comprehensive account of IED defeat countermeasures exists, we rely on an alternative empirical strategy. We leverage a well-known, steeply increasing trend in countermeasure investment over time. That is to say, we know I^G is strictly increasing until the end of the conflict. We aim to estimate changes in the effectiveness of IED attacks, $\frac{AC_t}{AC_t+DF_t}$, over the course of the counterinsurgency campaign by examining macrolevel (and regional) trends in IED outcomes and drawing inferences about insurgent technological investments, I^A.

Although we lack microlevel information on countermeasures, our military records allow us to examine the effectiveness of explosive devices over time. As such, we present measures of IED effectiveness that take into account equilibrium offensive and defensive best responses consistent with our model. First, we assess whether an explosive device, once planted, detonates. To clarify, this outcome takes the value one if an IED, once emplaced, detonates. This outcome takes the value zero when an IED is neutralized by counterinsurgents. Across the campaign's 94,679 unique IED events, devices exploded roughly 39% of the time.

Second, we investigate what happens to security forces once a planted IED explodes. We use the explosion as our unit of observation, and examine the damage associated with each of these detonations. Initially, we classify four discrete, ordered outcomes: "Ineffective" < "Dam/Dis/Destroyed" < "Wounded" < "Killed". We examine these hierarchical outcomes in an ordered logit framework. We also collapse this outcome to a binary variable, and analyze whether an IED event causes a death (1) or not (0). These two techniques have the advantage of allowing us to examine characteristics of individual events in great detail, including how effective IEDs are against various armed actors and civilians.

We supplement these measures by collapsing insurgent 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 chose the week as our temporal unit because it allows us to examine trends (as opposed to individual events) without raising concerns about large-scale strategic responses by security forces, which could occur around troop deployment and rotation schedules. We 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 24,603 district-weeks. Our last measure decomposes the rate at which detonated IEDs cause casualties by target type. That is, once an IED explodes, how likely is it to injure or kill a member of the Afghan or Coalition security forces. This measure is similarly calculated at the district-week level, with Afghan forces experiencing a 55% casualty rate for detonated explosives, while Coalition forces are injured or killed during roughly 30% of IED explosions.

As we detail below, our primary estimations will rely on a straightforward technique for examining patterns in insurgent effectiveness: linear time trends. These trends, which we embed in a battery of alternative specifications, enable us to identify how $\frac{AC_t}{AC_t+DF_t}$ shifts as a function of time. Importantly, we know counterinsurgent investments are strictly increasing. If our trends (which we denote simply as Time) are positive, this indicates that the likelihood of detonation is increasing throughout the campaign. On the other hand, if the coefficient on Time is negative, this indicates that IEDs are less likely to explode at the end of the campaign then at the beginning. If we observe a null result, the harm caused by IEDs in 2014 cannot be distinguished from damage in 2006. **Proposition 1** implies that this null result occurs when the ratio of the rates of counterinsurgent and insurgent learning match the asymmetry in initial endowments.

To demonstrate the plausibility of a core assumption of our model (that ρ and γ are static), we introduce two key facts about the context of our study. First, the Taliban and allied fighters in Afghanistan have engaged in insurgent operations for nearly four decades. They coordinated a number of successful offensives against Soviet forces during the 1970s and 1980s, and adopted sophisticated bombmaking during this period. The Taliban are also strongly tied to the communities where they operate, hold a wealth of local intelligence, and engage in meritocratic promotion of military leaders and bombmakers. For these reasons, we find it unlikely that γ, the rate at which insurgents learn, is shifting very much. Second, when US and allied actors invaded Afghanistan in 2001, conventional military forces were not fully prepared for the dynamics of a mixed urban/rural insurgency. It took several years to resolve institutional frictions across foreign forces and establish sound explosive threat monitoring systems. By 2006, the start of our empirical analysis, security forces had streamlined the process of disseminating data to warfighters and newly created agencies (including JIEDDO) helped deployed units translate observed tactics into IED defeat countermeasures. These assets were used continuously until the end of our study. With these dynamics in mind, we expect ρ, the rate of government learning, to have increased until the start of our investigation, after which ρ remained roughly flat.

Our formal model yields another interesting result: if the coefficient on Time is positive, insurgent investments in technological innovation must have expanded rapidly. Why? For the ratio of learning to exceed the square of initial endowments, the growth rate of investment by insurgents must exceed the growth rate of counterinsurgent investment. This is **Proposition 2**. What's more, this proposition must hold under a known condition about I^G, which is that it is expanding significantly. Consequently, for the coefficient on Time to be positive and statistically significant, ΔI^A across periods must be large in relative terms.

In the following section, we evaluate insurgent learning during the ongoing Afghanistan conflict.

5 Are Insurgents "Learning"?

Because of the particular danger posed by IEDs, the US government allocated substantial funding towards mitigating this threat. JIEDDO (the Joint IED Defeat Organization) was established in 2006, and grew to have an annual budget of several billion dollars. 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. It is difficult to calculate a total cost for the anti-IED effort, but approximately half of all coalition casualties in Afghanistan resulted from IED attacks. The IED was a fundamental component of the Taliban strategy, and counter-IED efforts were thus a major component of the Coalition counterinsurgency operations.

JIEDDO operated from 2006 to 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 [JIEDDO Report 2006], rollers to detonate pressure-plate IEDs [JIEDDO Report 2007], robots to examine potential IEDs [JIEDDO Report 2008], radar systems to identify suicide bombers [JIEDDO Report 2009], and ground-penetrating radar [JIEDDO Report 2010]. Technological innovation by Coalition forces continued until the final withdrawal of foreign forces.

A major problem faced by JIEDDO was that the Taliban was also developing IED technologies at the same time. For example, metal detectors were deployed in large numbers in Afghanistan to detect IEDs. The Taliban response to this was to develop IEDs that had little or no metal content. This lead to the 2010 deployment of radar, in an attempt to detect these non-metal IEDs [.] Anecdotes such as this suggest that, although there was a substantial anti-IED research budget and significant deployments of defeat resources, it is unclear whether Coalition forces were actually becoming more effective against IEDs, or whether any gains were simply undone by Taliban innovations. Fortunately, our military records allow for an empirical investigation of this issue.

In the following subsections, we visualize violence trends in the data and perform an array of formal estimations to examine how the outcomes of explosive device shifted over the course of the Afghanistan conflict.

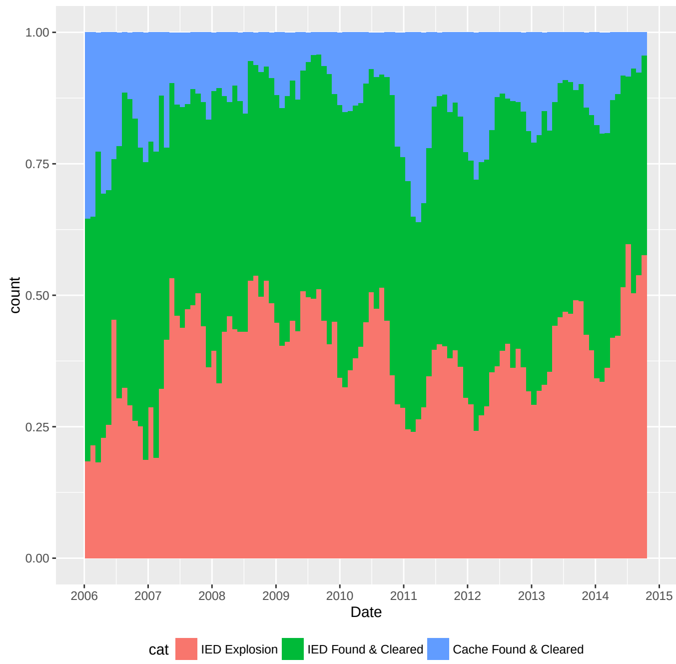
5.1 Visual evidence

We begin by visualizing the data. Figure 2 shows the disposition of planted IEDs, as well as latent IEDs (held in weapon caches). Consistent with Figure 1, notice the consistent patterns in seasonality associated with detonation rates. This seasonal trends map on the fighting season in Afghanistan, which typically begins in late March and early April (when the mountain passes clear of snow) and ends in late September and October. Nearly all full-time fighters exit the country during the winter and retreat to rebel strongholds in Pakistan's border regions. The dip in IED effectiveness 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. Once these seasonal trends are taken into account, there is no clear downward trend in IED effectiveness from 2006, the left edge of the plot, to 2014, the right edge of the plot. If anything, there appears to be a marginal increase in the detonation rate over time. We account for seasonality and evaluate these visual trends more rigorously below.

We next focus on the geography of bomb deployment in Afghanistan. Figure 3 shows the geographic distribution of IEDs across Afghanistan following a technique suggested by Grolemund and Wickham [2015].[6] Degrees of longitude are shown at the top of each chart, and degrees of latitude at the right. 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 1 is shown (for the righthand chart, this is scaled to add up to 100%). Several patterns are 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, $\frac{AC_t}{AC_t+DF_t}$, would diverge significantly across space. Yet Figure 3b shows that the effectiveness

[6] Figures SI-8 and SI-9 show these results for direct fire and indirect fire, respectively.

Figure 2: Neutralization rate of IEDs (sums to 100%), from 2006 to 2014

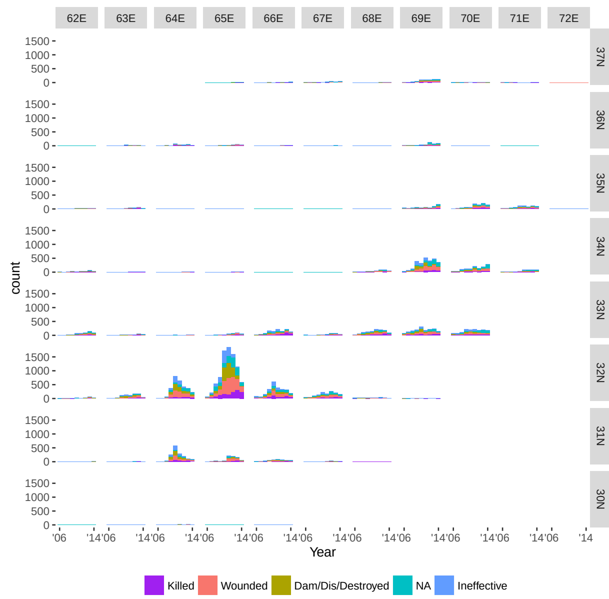


of IEDs in causing damage is nearly uniform across Afghanistan. These plots also give cursory evidence that no systematic downward trend in IED effectiveness is observable from 2006 to 2014. Instead, many plots trend upwards, indicating an increase in insurgent success as the campaign progressed.

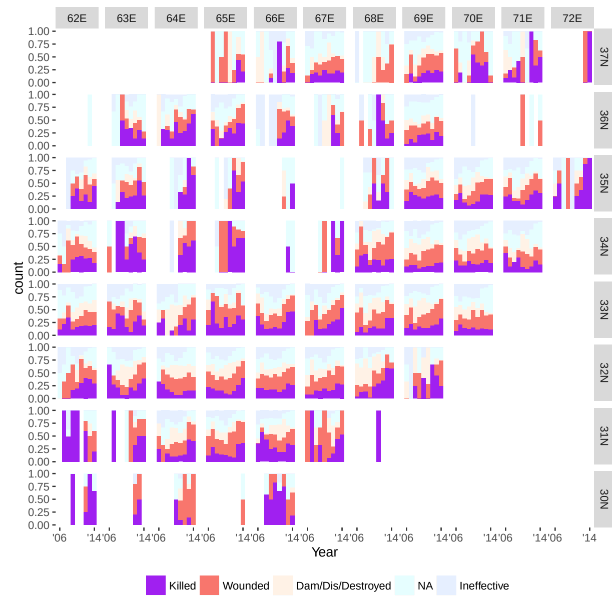
We next examine IEDs that actually exploded. Additional information is available in these cases. Did the deployment of additional armour and other technologies change the casualty rate for IED explosions? That is, do we see a downward trend across time in the effectiveness of IEDs in inflicting harm to security forces?

A major confounding factor in this analysis is that, as shown in Figure SI-1, the type of forces deployed has changed dramatically over the period spanned by our data. Figures SI-2 and SI-3 appears to show that, if anything, IEDs have gotten *deadlier* over time, with about a 75% casualty rate for recent years. However, this could be due to reductions in Coalition troop levels: 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 3: 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-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.[7]

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 sharp increase in casualty rates shown in Figures SI-2 and SI-3 thus appears to be due to a compositional trend in the target of IED attacks. From 2010 onwards, the number

[7]We provide a regression analysis of this claim in Tables A-5 and A-6.

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. We present a statistical analysis of these results below. This analysis shows that if anything there are small increases in the casualty rate (conditional on IED explosion) across time.[8]

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 a trend in Figure SI-4a, then, is evidence that either this new equipment and technology was actually useless, or that there was also substantial improvement in the quality of IEDs during this period.

5.2 Regression-based evidence

We are interested in testing whether the visual evidence reviewed above is statistically robust.

We begin with Figure 2. We examine whether Figure 2 has no substantial trend in clearance rate (fraction of IEDs that are found before they explode) or if this trend is significantly increasing or decreasing over time.

We consider our unit of observation to be the individual IED. This IED could be emplaced and explode, or it could be emplaced but then found and cleared, or it could be found and cleared before it was emplaced ("cache found and cleared"). We will use a binary variable "did IED explode?" as our outcome variable Y, coded as 0 if the IED was found and cleared.[9]

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[8]The sole exception is for coalition supported Afghan military units.

[9]Some IEDs are missing from the dataset: those that explode when nobody is around to notice, those that explode on civilian targets but happen to not be reported to the authorities, those that have neither exploded nor been found and cleared yet. 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.

A linear probability model will be used with the form

$$\Pr(Y_{igm} = \text{exploded}) = \beta \textsc{Time}_{igm} + \alpha_g + \gamma_m.$$

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 Time (coded as 0 for midnight on 1 January 2006 and around 8.83 at the end of our sample period in November 2014).

Results from this regression are shown in Table A-1. Importantly, positive coefficients indicate that the detonation rate is increasing (and, conversely, that the clearance rate is 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. This result is also unchanged when only emplaced IEDs are considered (that is, "cache found and cleared" observations are dropped).[10]

Alternatively, if we instead employ a logit model specification and replicate Table A-1, we find consistent evidence that the rate at which IEDs detonate is increasing throughout the conflict. These results are displayed in Table A-2. In principle, this functional form might be a better fit for our dichotomous outcome variable. Importantly, this increasing detonation rate is robust across columns 1-4, which vary grid square and month of year fixed effects. Although there is disagreement between Tables A-1 and A-2 over the statistical significance of the time trend, we can squarely reject a significant increase in clearance rates at the country level.[11] That is, counterinsurgents were no better at clearing explosive threats from the field in 2014 than they were in 2006.

There is no reason to believe that there is differential reporting issues in Panjwai.

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

[11]Using the coefficient reported in column 1 of Table A-2, 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.

We now consider what happens conditional on an IED exploding. The potential outcomes in this case are "Ineffective", "Dam/Dis/Destroyed", "Wounded", and "Killed".[12] We thus have four discrete ordered outcomes: "Ineffective" < "Dam/Dis/Destroyed" < "Wounded" < "Killed". One option is to analyze this as is, using an ordered logit framework. Another option is to collapse the outcome variable to a binary variable, and analyze 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 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

$$Y^*_{igm} = \beta_1 \text{TIME}_{igm} + \beta_2 \text{TYPE}_{igm} + \beta_3 (\text{TIME x TYPE})_{igm} + \alpha_g + \gamma_m + \epsilon_{igm}$$

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 targetting 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 A-3 shows the results of this approach. We see that overall IEDs are more deadly when employed against soft targets such as civilians, and less deadly when employed against Coalition forces.[13] The time trends estimated in Column 3 show that there is no statistically

[12]Some outcomes are marked as "NA". Qualitative evidence leads us to conclude that explosions classified as "NA" did not cause damage, and thus we group "NA" and "Ineffective" together and label this group as "Ineffective".

[13]The base level here is "Afghan Military, Supported", which makes the positive coefficient on "Afghan Military, Unsupported" in Column 3 surprising, since one would expect that supported troops would be a harder target than unsupported troops. This effect disappears,

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.[14]

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 then consider a linear probability model of the form,

$$\Pr(Y_{igm} = \text{casualty}) = \beta_1 \text{TIME}_{igm} + \beta_2 \text{TYPE}_{igm} + \beta_3 (\text{TIME x TYPE})_{igm} + \alpha_g + \gamma_m$$

The results of this regression are shown in Table A-4. Results are generally very similar: some of the time trends interactions reported in Table A-3 are not statistically significant in Table A-4, although the coefficient estimates are in the same direction.[15]

however, in Column 4, and instead we see a time trend that makes supported Afghan troops less likely to become casualties in later periods. One potential explanation is that initially supported Afghan troops are deployed to particularly dangerous areas, and the average danger of these areas decreases as the number of supported troops increases over time.

[14]The very large 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.

[15]The particular implementation of wild bootstrap clustered standard errors used to report

A final issue relates to Figure 3b. Careful inspection of this figure suggests that there may be time trends in casualty rates for IEDs that potentially differ from grid square to grid square. These effects appear to be due to compositional changes in targets across time. To show this, we consider a regression following Table A-4. In particular, when we condition on the type of target (Coalition, Civilian, Afghan Police, Afghan Military Supported, Afghan Military Unsupported) we find that estimated time trends at the district level are nearly indistinguishable from random noise based on an F test ($p \simeq .1$). For direct fire attacks, the distribution of casualties (Figure SI-8b) is less even across districts than for IED attacks. This could indicate greater planning in the very small number of attacks that are carried out in the north, or under-reporting of unsuccessful attacks in that region.

We conclude our examination with 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,

$$Y_{dw} = \beta_1 \textsc{Time}_{dw} + \alpha_w + \gamma_d + \epsilon_{dw},$$

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

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results in Table A-4 gives coefficient estimates for the TIME x TYPE coefficients in terms of differences from the base level of "TIME x Afghan Military, Supported". The coefficent estimate for this level is close to zero (as reported in the "TIME" row), and thus interpretation is mostly unaffected by this difference.

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.

These results are shown in tables A-5 and A-6. Recall, the even numbered columns in each table introduce year fixed effects. With respect to detonation rates, these results indicate that the likelihood of explosion is either flat or significantly increasing during the campaign. Importantly, these results obtain even when conditioning out district-specific but time-invariant characteristics. Regarding casualty rates for Afghan units, our results echo the conclusions above. The casualty rate is significantly increasing in both specifications (columns 3-4). However, we find no significant change in the casualty rates for coalition forces, and in columns 5-6, TIME flips signs across functional forms. For Afghan forces, the likelihood of severe harm was steadily increasing throughout the campaign, whereas Coalition forces appear to be no better protected from injury or death at the end of the conflict versus the beginning.

The collection of empirical evidence we have presented thus far can be reduced to two points. First, the detonation rate of explosives in Afghanistan did not significantly decline during the 9 years of our study. If anything, the likelihood an IED detonated in the field increased over time. Second, casualty rates either remained flat or significantly increased during the campaign. Host nation forces, especially those unsupported by Coalition actors, were particularly vulnerable to harm. At the macro-scale, these two robust findings indicate that insurgent success, $\frac{AC_t}{AC_t+DF_t}$, increased despite substantial counterinsurgent investment, I^G.

Qualitative evidence strongly suggests that anti-IED equipment was not initially useless. Instead, it was quickly countered by Taliban changes to their IED technology. For example, Fowler [2016] reports that "Nyala" armoured vehicles deployed with Canadian troops were initially considered to be resistant to IEDs. However, after observing this ineffectiveness, 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 would have been useless. Our findings, combined with the qualitative record, indicate that insurgents were able to quickly adapt to counterinsurgent innovations and made substantial investments of their own.

6 Conclusion

We examine an important, yet understudied dynamic in internal wars: insurgent learning. The historical record yields substantial qualitative evidence of learning by insurgents, especially regarding explosive devices. Rebels learn from one another—copying tactics and techniques—and learn from their own mistakes. Insurgents also learn from their rivals, adjusting their bomb materials and trigger mechanisms to thwart counterinsurgent innovations. Yet we know surprisingly little about how quickly and effectively insurgents respond to security force attempts to defeat their attacks. In this paper we provide evidence useful in answering such questions.

We model these strategic interactions as an investment-based learning game over multiple periods. Insurgent and government actors independently invest in changes to the technology they deploy against one another. These investments are observed, and adjustments are made in subsequent periods. Our model yields important insights regarding the capital commitments needed to continually increase attack effectiveness in the presence of counterinsurgent innovations. Although we focus specifically on learning with respect to explosive devices, the model is far more general and could enhance the microlevel study of rebellion broadly.

Our model also yields novel insights that we do not examine and leave to future research. In particular, **Proposition 1** demonstrates that a fixed time horizon (e.g., a publicly announced security transition) may induce unexpected under and/or over investment by insurgents depending on how quickly they can adapt to observed government innovations between periods. This insight of our model sheds light on another largely unexplored topic in political science and economics: how states manage foreign-to-local security transitions at the end of a military intervention. We leave this exploration to future research.

We test our model's empirical implications using newly declassified microdata on IEDs assembled and deployed during the ongoing Afghanistan conflict. These military records enable us to track 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).

Yet our results should not be taken as evidence that technological innovation by the United States and allied partners never worked or was wasteful spending. To the contrary, one of the implications of our model is that divestment by the United States and host nation forces could have led to further growth in the detonation and casualty rates. We lack sufficient evidence to fully demonstrate this point and future research should evaluate how, in the course of an ongoing insurgency, we can evaluate the impact of acquisition and installation of armor plating, body protection, signal jammers, and other defeat technologies.

Although the aggregate evidence indicates insurgents learned quickly and innovated to match counterinsurgent expenditures and equipment, the United States and host nation partners did achieve local successes. Panjwai, in Kandahar province, is one these cases. Our model and empirical investigation have primarily focused on insurgent adaptation to innovations fielded by government rivals. In Panjwai, counterinsurgents paired technological innovation with a "hearts and minds" approach to winning civilian support through foot patrols, community engagement, and development aid. In Supporting Information Section D, we introduce additional evidence from this micro case study. Although we observe no change in the casualty rate for IEDs (consistent with learning by insurgents), we do find a significant decrease in the detonation rate over time. That is, an IED remains deadly if it explodes, but IEDs are increasingly unlikely to actually explode, as they are instead found and cleared by the Afghan government or Coalition forces. Security force success in Panjwai might serve as a template for future warfighting and should motivate further investigation.

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APPENDIX

— For Publication with Main Text —

A 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

$$\begin{aligned} I_2^A (1+r)^{-1} &= Y^A - I_1^A && (2) \\ I_2^G (1+r)^{-1} &= Y^G - I_1^G \end{aligned}$$

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:

$$\begin{aligned} V^A \;=\; & \left[\frac{I_1^A}{I_1^A + I_1^G} \right] + && (3) \\ & \left[\frac{\alpha I_1^A + \gamma I_1^G + \left(Y^A - I_1^A\right)(1+r)}{\alpha I_1^A + \gamma I_1^G + (Y^A - I_1^A)(1+r) + \alpha I_1^G + \rho I_1^A + (Y^G - I_1^G)(1+r)} \right] (1+r)^{-1} - cY^A \end{aligned}$$

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

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

Repeating the exercise for G, we obtain the FOC:

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

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

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

and, through the budget constraints (2), 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. ■

B Main results and summary statistics

Table A-1: Trends in IED explosions (binary outcome)

	(1) All	(2) All	(3) All	(4) All	(5) Panjwai	(6) Panjwai
Time	0.004	0.002	0.004	0.002	-0.032^{***}	-0.031^{***}
	(0.007)	(0.005)	(0.004)	(0.002)	(0.004)	(0.004)
Grid square FE	No	Yes	No	Yes	No	No
Month of year FE	No	Yes	No	Yes	No	Yes
N	94,679	94,679	80,101	80,101	6,673	6,673
R^2	0.0002	0.407	0.0002	0.469	0.011	0.408
Adjusted R^2	0.0002	0.406	0.0002	0.469	0.011	0.407

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

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). Columns 5 and 6 are restricted to the Panjwai region. Grid square fixed effects (FE) are not used because Panjwai is entirely contained in the 66E 32N grid square. Columns 1-4 use errors clustered at the grid square level. Columns 5-6 use heteroskedasticity consistent covariance matrix estimates.

Table A-2: Trends in IED explosions (binary outcome), using logit model specification

	(1) All	(2) All	(3) All	(4) All	(5) Panjwai	(6) Panjwai
Time	0.016^{***}	0.009^{***}	0.015^{***}	0.008^{**}	-0.134^{***}	-0.133^{***}
	(0.003)	(0.004)	(0.004)	(0.004)	(0.015)	(0.016)
Grid square FE	No	Yes	No	Yes	No	No
Month of year FE	No	Yes	No	Yes	No	Yes
N	94,679	94,679	80,101	80,101	6,673	6,673

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Logit model. 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). Columns 5 and 6 are restricted to the Panjwai region. Grid square fixed effects (FE) are not used because Panjwai is entirely contained in the 66E 32N grid square.

Table A-3: Outcome conditional on IED Explosion

	(1) All	(2) All	(3) All	(4) All	(5) Panjwai	(6) Panjwai	(7) Panjwai	(8) Panjwai
Time	0.157***	0.154***	0.114***		0.188***	0.190***	0.167***	
	(0.005)	(0.005)	(0.005)		(0.022)	(0.023)	(0.023)	
Afghan Military, Unsupported			0.534***	0.027			0.357**	−1.281*
			(0.063)	(0.251)			(0.175)	(0.735)
Afghan Police			0.714***	−0.019			0.831***	0.807
			(0.064)	(0.246)			(0.206)	(0.749)
Civilian			1.262***	0.514**			1.025***	0.719
			(0.064)	(0.245)			(0.180)	(0.737)
Coalition			−0.194***	−0.787***			−0.326**	−0.774
			(0.059)	(0.236)			(0.150)	(0.665)
NA			−0.639***	−4.385***			−1.423***	−6.721***
			(0.064)	(0.255)			(0.200)	(0.943)
Time × Afg Military, Supported				−0.087**				0.014
				(0.042)				(0.114)
Time × Afg Military, Unsupp.				0.030**				0.304***
				(0.014)				(0.059)
Time × Afg Police				0.062***				0.013
				(0.013)				(0.067)
Time × Civilian				0.060***				0.069
				(0.013)				(0.064)
Time × Coalition				0.015				0.088***
				(0.009)				(0.033)
Time × NA				0.554***				0.948***
				(0.016)				(0.109)
Ineffective|Dam/Dis/Destroyed	0.203***	−0.543	−1.591***	−3.335**	0.261**	0.276**	−0.011	−0.871
	(0.029)	(0.877)	(0.098)	(1.676)	(0.123)	(0.125)	(0.191)	(0.643)
Dam/Dis/Destroyed|Wounded	0.951***	0.212	−0.782***	−2.509	0.936***	0.954***	0.725***	−0.122
	(0.030)	(0.877)	(0.098)	(1.676)	(0.125)	(0.126)	(0.192)	(0.643)
Wounded|Killed	2.370***	1.654*	0.776***	−0.933	2.712***	2.738***	2.656***	1.830***
	(0.032)	(0.877)	(0.099)	(1.676)	(0.135)	(0.137)	(0.199)	(0.644)
Grid square FE	No	Yes	Yes	Yes	No	No	No	No
Month of year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	36,690	36,690	36,690	36,690	2,594	2,594	2,594	2,594

*p < .1; **p < .05; ***p < .01
Proportional-odds ordered logit regression with levels “Ineffective”, “Dam/Dis/Destroyed”, “Wounded”, “Killed”. Columns 5-8 use only data from Panjwai area. Grid square fixed effects are not used because Panjwai is contained in the 66E 32N square.

Table A-4: Outcome conditional on IED Explosion

	(1) All	(2) All	(3) All	(4) All	(5) Panjwai	(6) Panjwai	(7) Panjwai	(8) Panjwai
Time	0.046***	0.046***	0.029***	−0.014	0.051***	0.051***	0.044***	0.010
	(0.008)	(0.008)	(0.003)	(0.019)	(0.006)	(0.006)	(0.006)	(0.028)
Afghan Military, Unsupported			0.126***	0.002			0.069	−0.188
			(0.023)	(0.093)			(0.045)	(0.186)
Afghan Police			0.150***	−0.030			0.176***	0.109
			(0.019)	(0.088)			(0.050)	(0.183)
Civilian			0.259***	0.106			0.234***	0.050
			(0.023)	(0.114)			(0.044)	(0.181)
Coalition			−0.136***	−0.255**			−0.134***	−0.231
			(0.026)	(0.118)			(0.039)	(0.167)
NA			−0.114*	−0.689***			−0.274***	−0.851***
			(0.062)	(0.075)			(0.045)	(0.169)
Time × Afghan Military, Unsupported				0.027*				0.046
				(0.016)				(0.032)
Time × Afghan Police				0.035**				0.011
				(0.016)				(0.032)
Time × Civilian				0.030				0.034
				(0.020)				(0.032)
Time × Coalition				0.020				0.016
				(0.020)				(0.030)
Time × NA				0.103***				0.110***
				(0.012)				(0.031)
Grid square FE	No	Yes	Yes	Yes	No	No	No	No
Month of year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	36,690	36,690	36,690	36,690	2,594	2,594	2,594	2,594
R^2	0.033	0.048	0.132	0.147	0.029	0.037	0.127	0.138
Adjusted R^2	0.033	0.045	0.130	0.144	0.029	0.032	0.121	0.131

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Linear probability model with levels "Ineffective" and "Dam/Dis/Destroyed" coded as 0, and levels "Wounded" and "Killed" coded as 1. Columns 5-8 use only data from Panjwai area. Grid square fixed effects (FE) are not used for Panjwai columns because Panjwai is contained in the 66E 32N square. Columns 1-4 use errors clustered at the grid square level. Columns 5-8 use heteroskedasticity consistent covariance matrix estimates.

Table A-5: IED Outcomes as Rates

	Detonation Rate		Casualty Rate Afghan Units		Casualty Rate Coalition Units	
	(1)	(2)	(3)	(4)	(5)	(6)
Time	0.0000329	0.000291***	0.000551***	0.000564***	0.0000252	-0.000127
	(0.0000417)	(0.0000502)	(0.0000785)	(0.0000861)	(0.0000841)	(0.000106)
N	24603	24603	9578	9578	7730	7730
Clusters	371	371	334	334	263	263
R^2	0.0111	0.0182	0.0216	0.0516	0.00543	0.00816

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 A-6: IED Outcomes as Rates

	Detonation Rate		Casualty Rate Afghan Units		Casualty Rate Coalition Units	
	(1)	(2)	(3)	(4)	(5)	(6)
Time	0.000186	0.00122***	0.00232***	0.00247***	0.0000940	-0.000578
	(0.000163)	(0.000199)	(0.000311)	(0.000352)	(0.000387)	(0.000500)
N	24603	24603	9578	9578	7730	7730
Clusters	371	371	334	334	263	263

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 A-7: Summary Statistics for Tables A-1 and A-2

Statistic	N	Mean	St. Dev.	Min	Max
IED Explosion	94,679	0.388	0.487	0	1
Time	94,679	5.477	1.919	0.000	8.831

Table A-8: Summary Statistics for Tables A-3 and A-4

Statistic	N	Mean	St. Dev.	Min	Max
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

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 A-9: Summary Statistics for Tables A-5 and A-6

Variable	Mean	St. Dev.	Min.	Max.	N
IED detonation rate	0.498	0.427	0	1	24702
Casualty rate, Afghan forces	0.554	0.462	0	1	9638
Casualty rate, Coalition forces	0.3	0.406	0	1	7788
Time (weekly)	2669.361	118.157	2392	2851	24702

SUPPORTING INFORMATION

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A Additional visual evidence: IED attacks

Figure SI-1: Target of IED Explosions (sums to 100%)

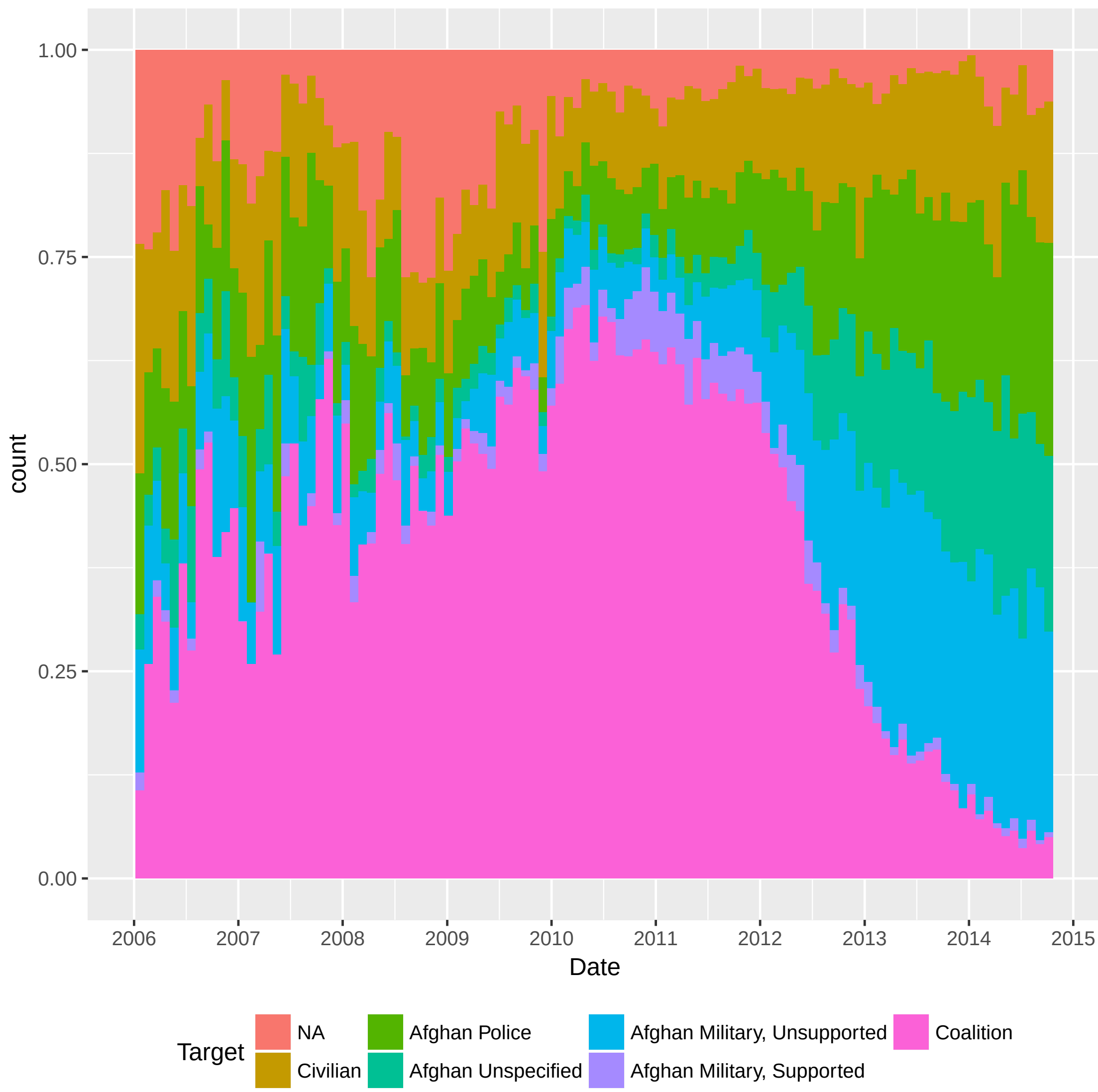


Figure SI-2: Outcome of IED Explosions (sums to 100%)

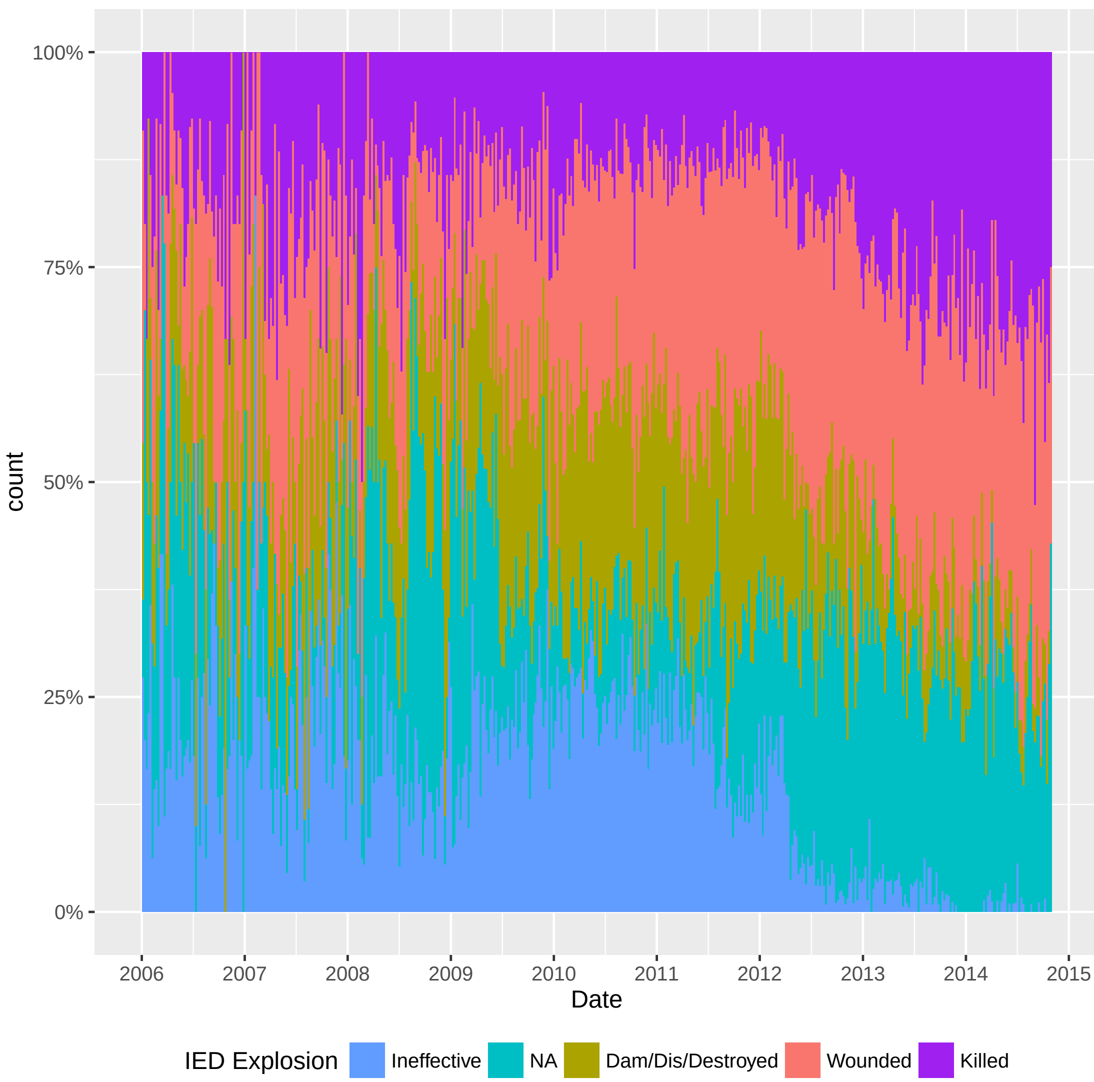


Figure SI-3: Outcome of IED Explosions by Month (sums to 100%)

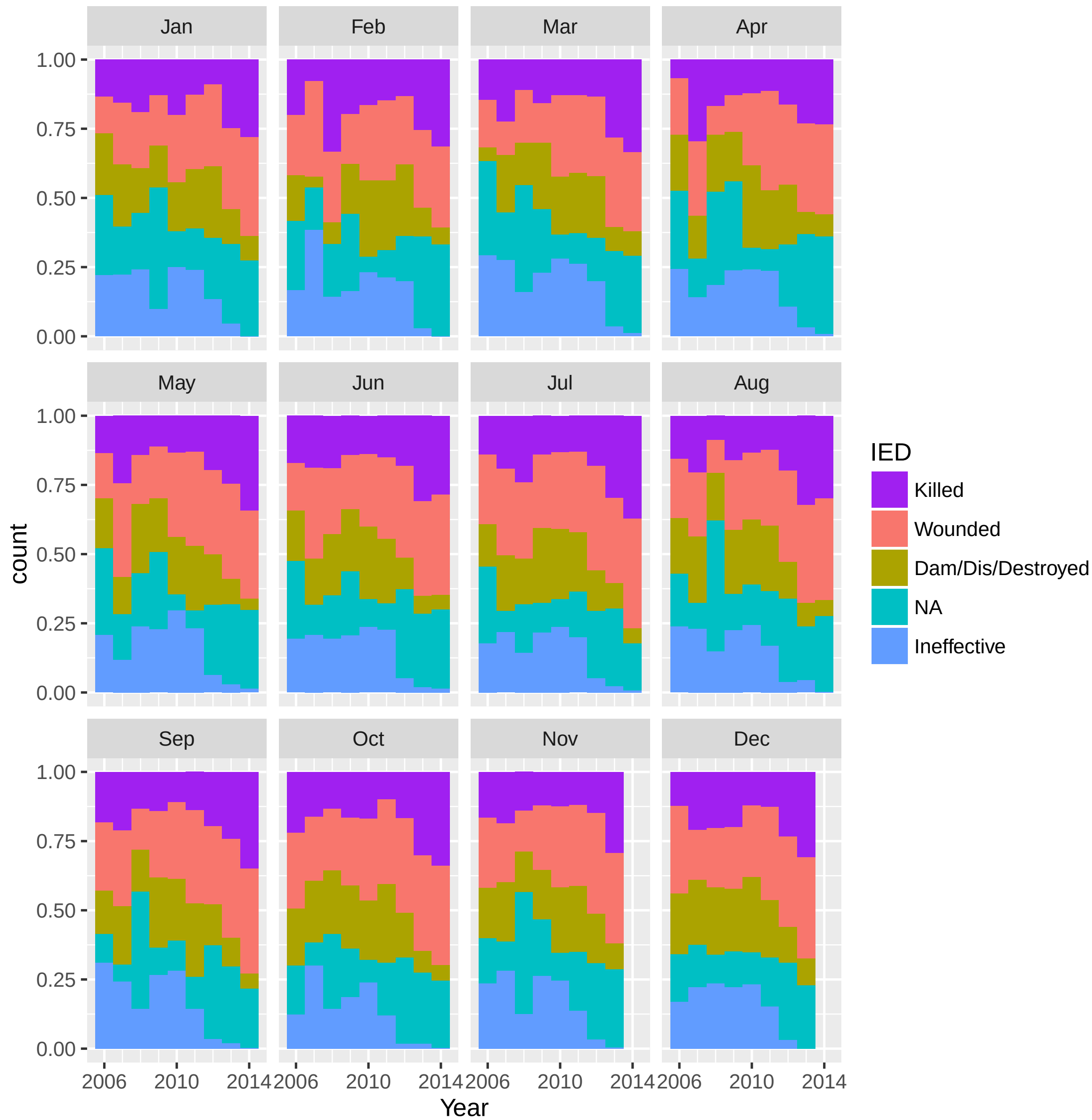
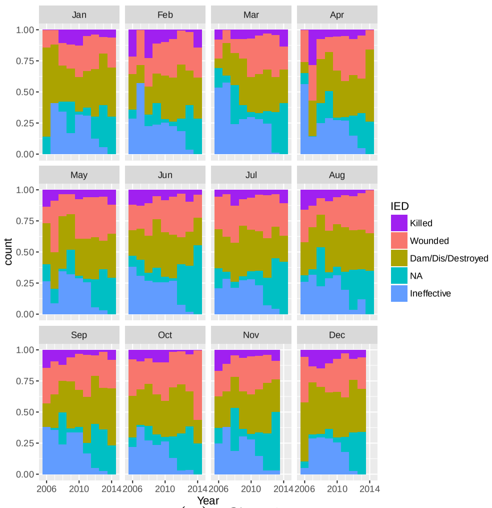
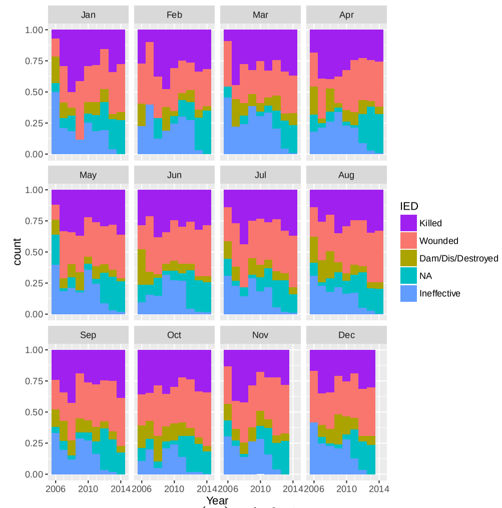


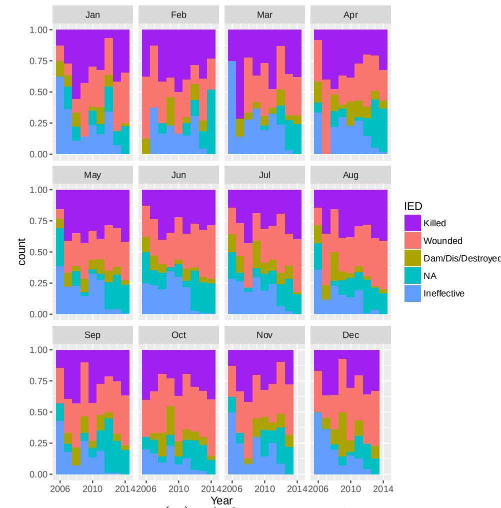
Figure SI-4: Outcome of IED Explosions by Month and Security Actor



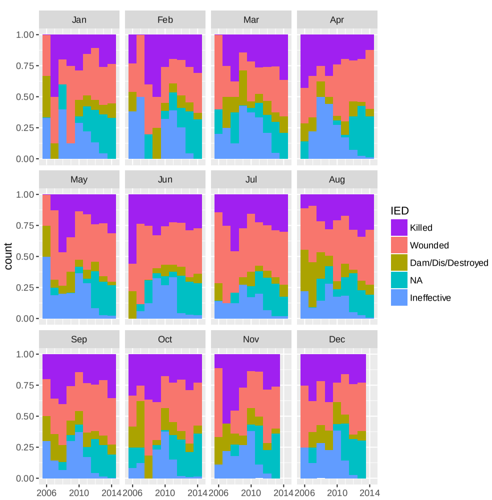
(a) Coalition



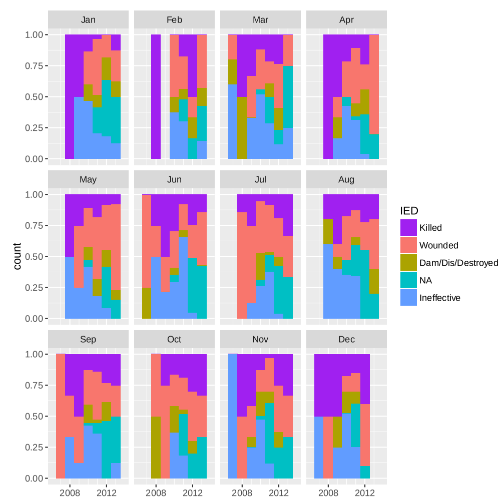
(b) Afghan



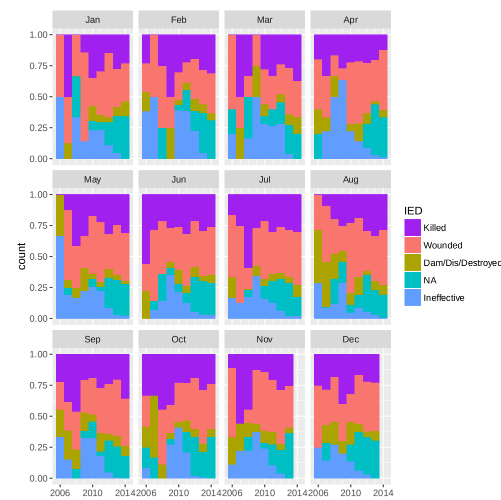
(c) Afghan Police



(d) Afghan Military



(e) Afghan Military, Supported



(f) Afghan Military, Unsupported

B Supplemental visual evidence: non-IED attacks

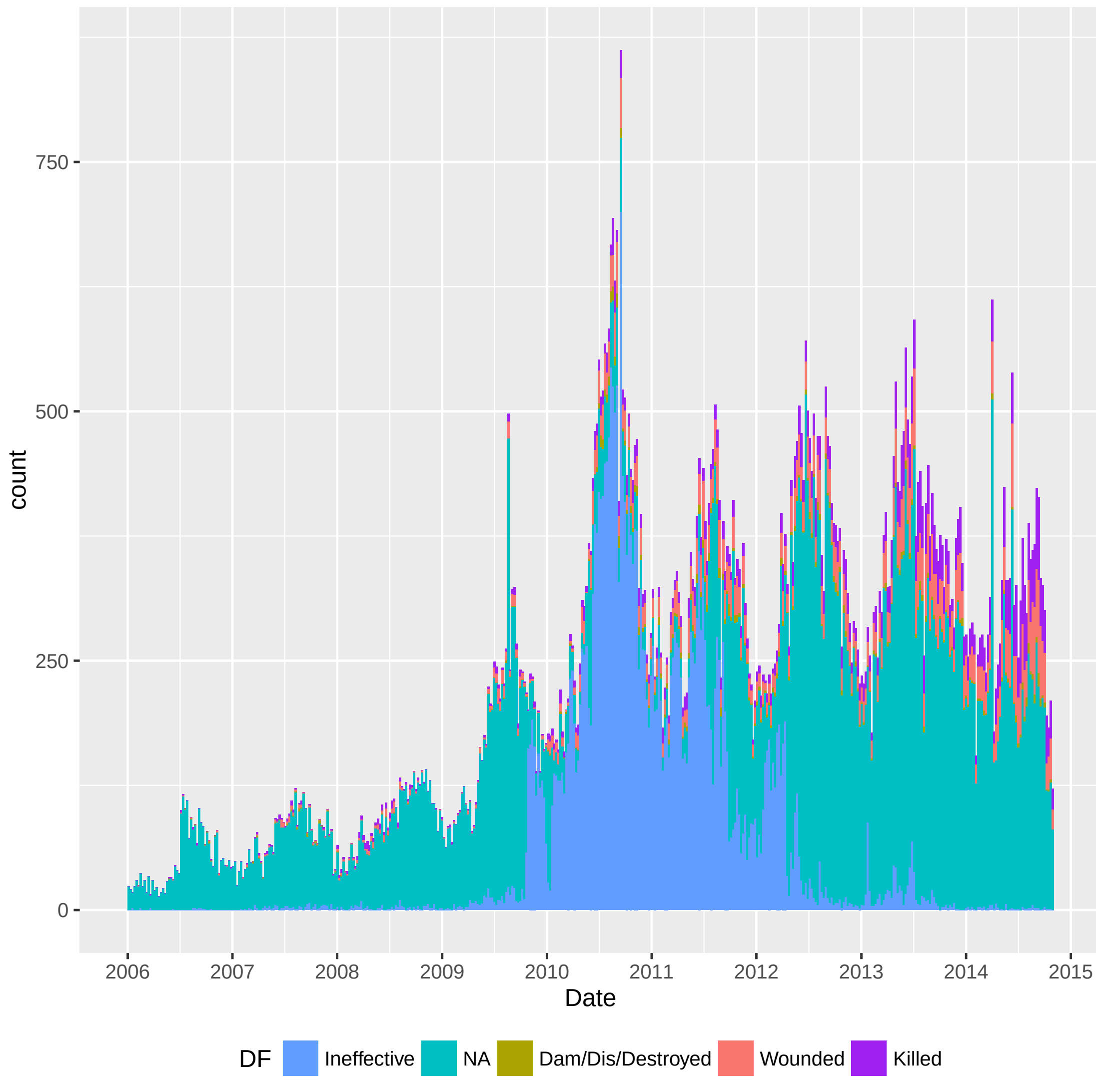


Figure SI-5: Direct Fire attacks (all of Afghanistan)

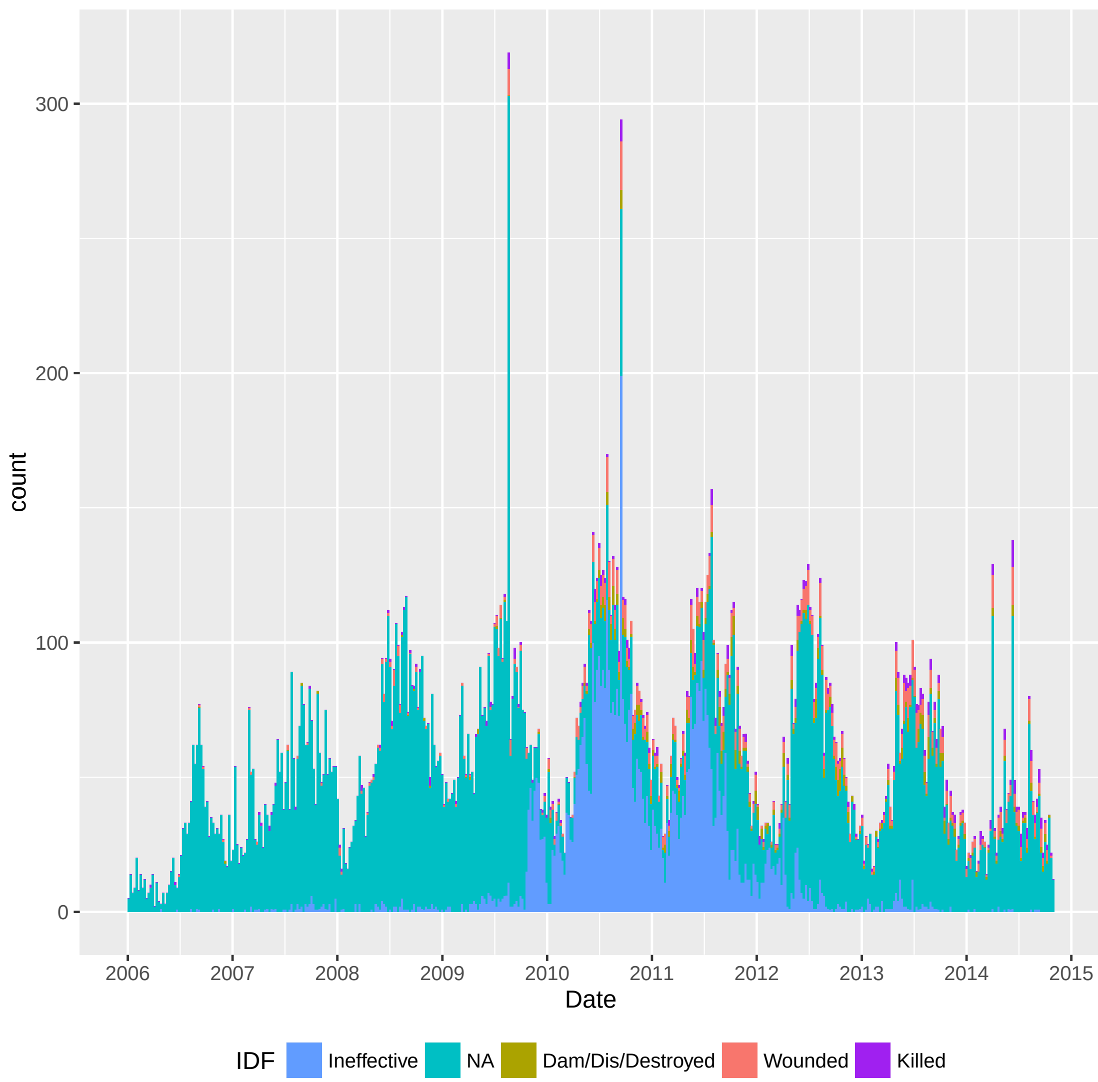
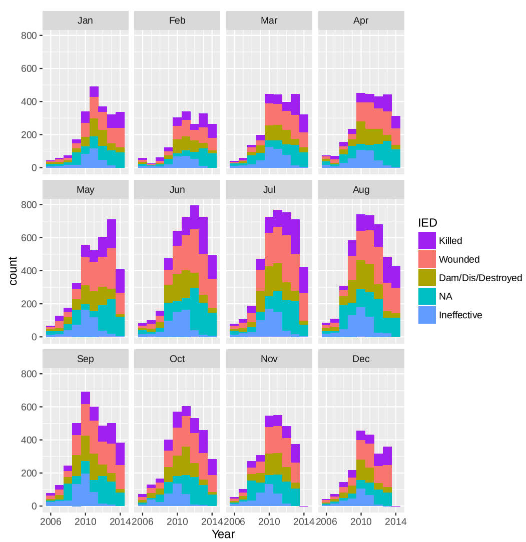
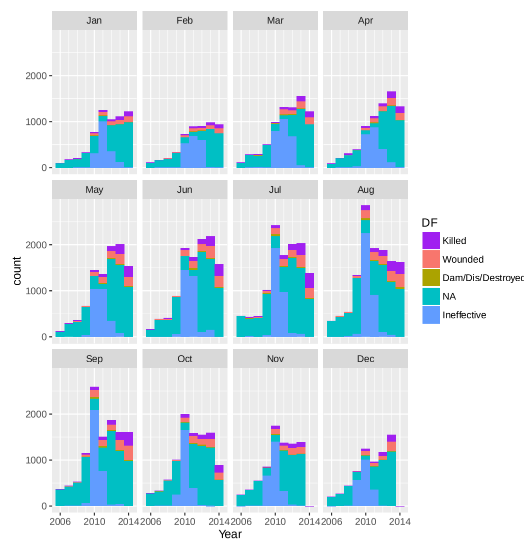


Figure SI-6: Indirect Fire attacks (all of Afghanistan)

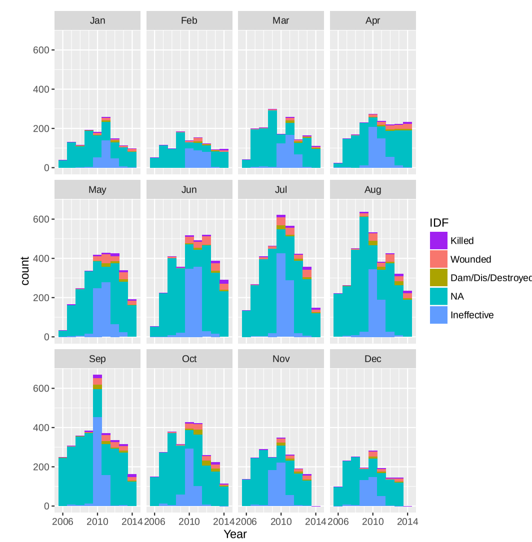
Figure SI-7: Outcomes of violent events across Afghanistan campaign by Month



(a) IED Explosions by Month

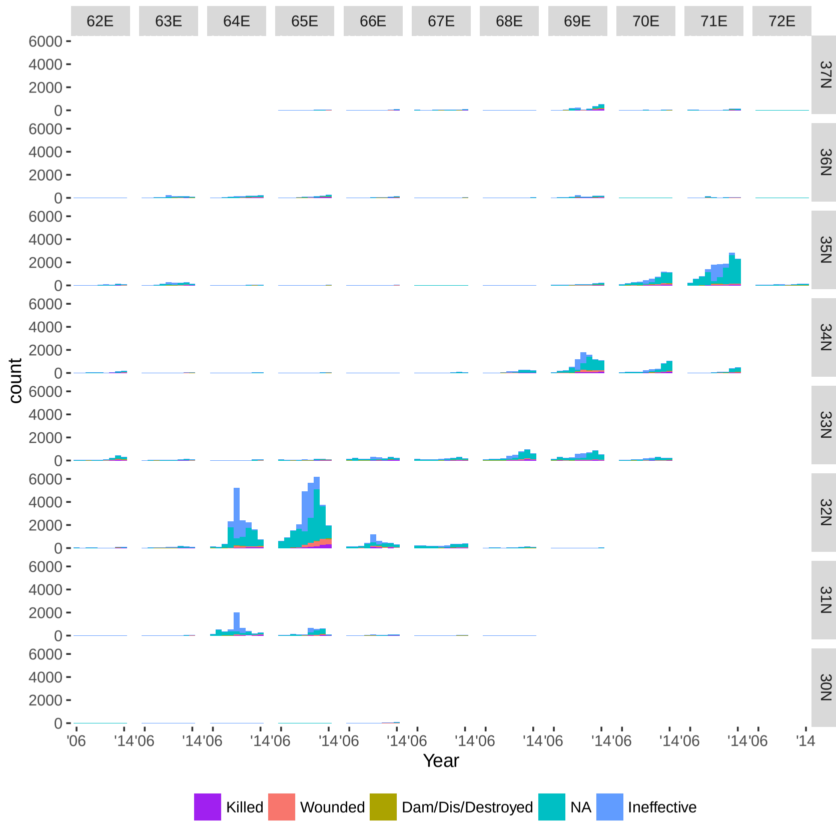


(b) Direct Fire Attacks by Month

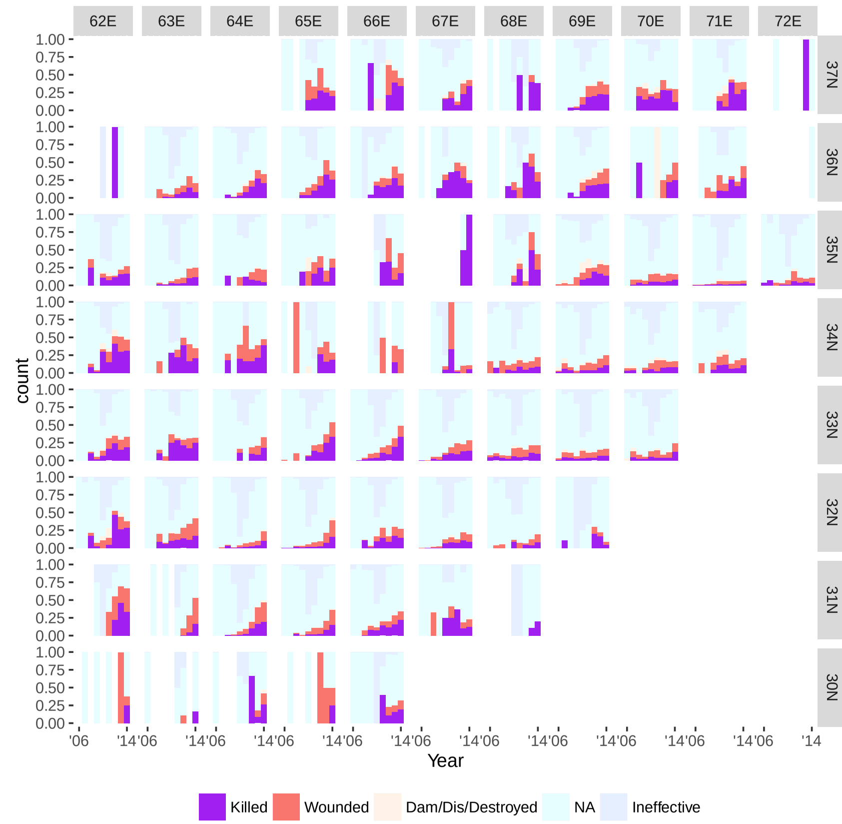


(c) Indirect Fire Attacks by Month

Figure SI-8: Direct Fire attacks, by Lat-Lon grid square

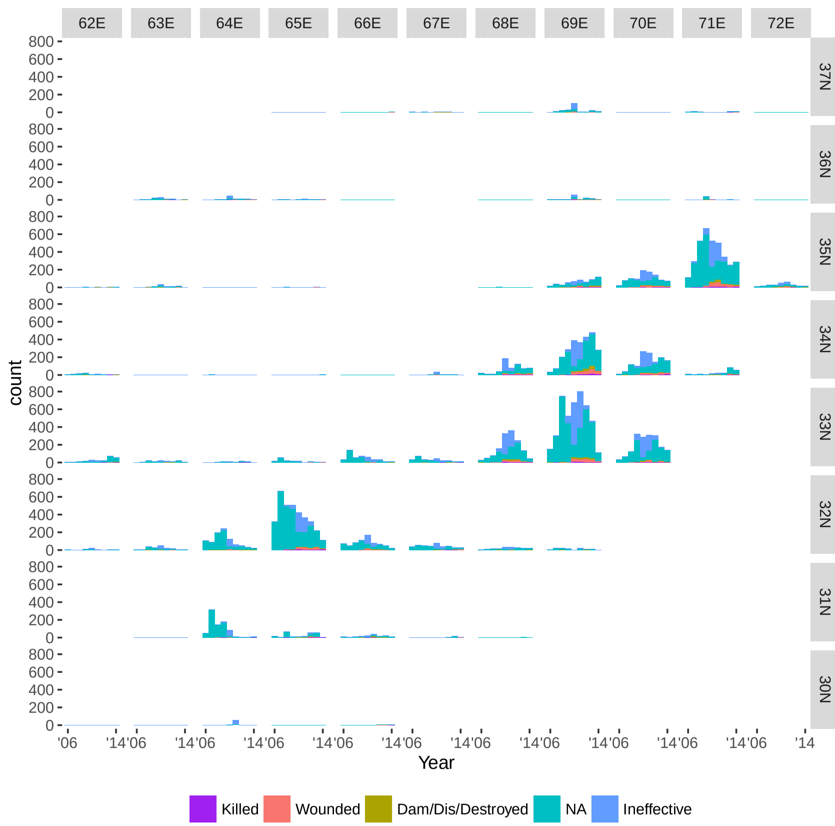


(a) Number of attacks, by outcome

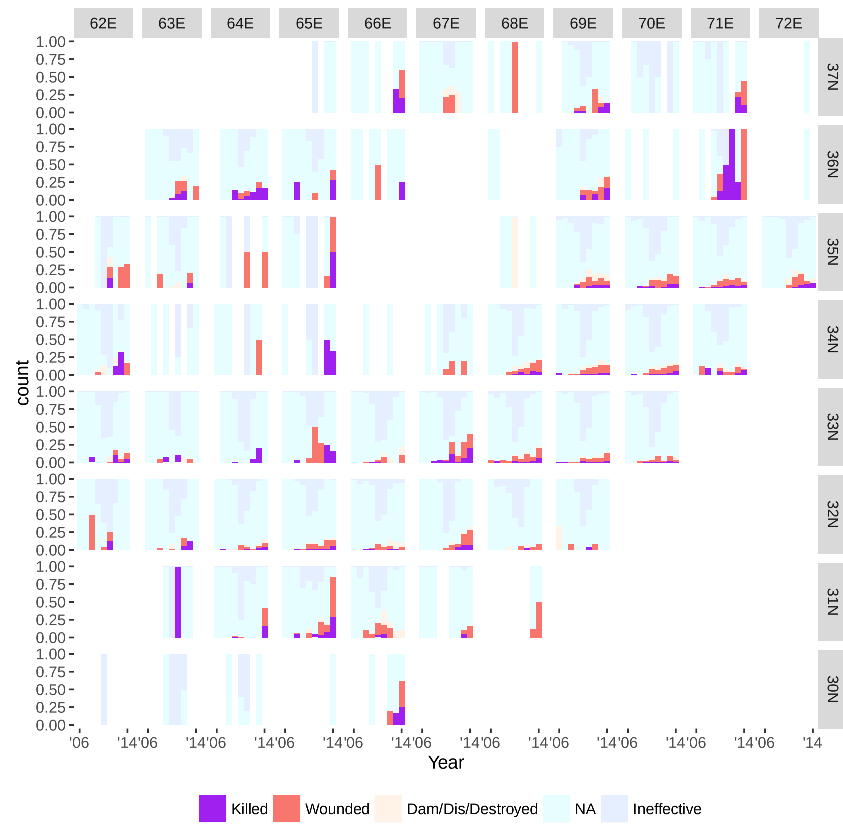


(b) Outcome shares (sums to 100%)

Figure SI-9: Indirect Fire attacks, by Lat-Lon grid square



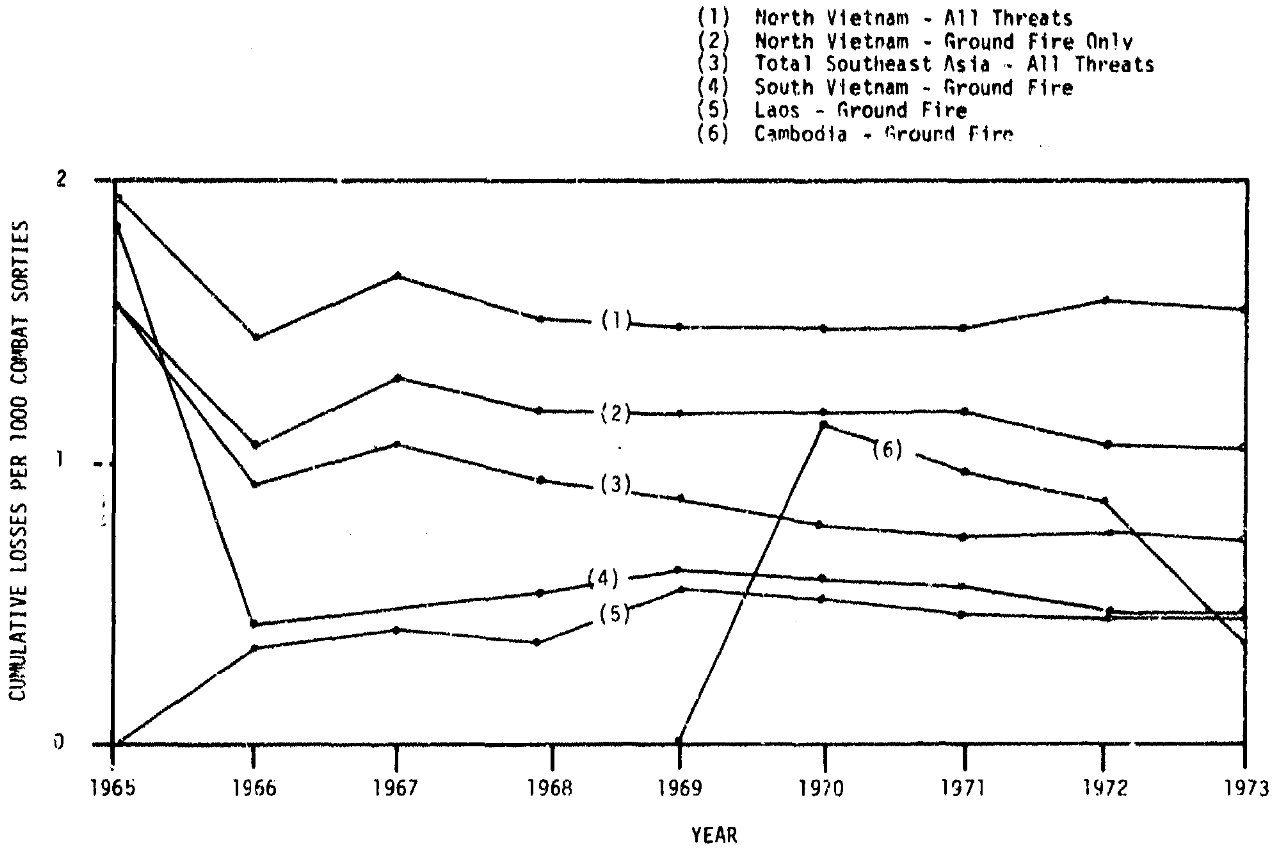
(a) Number of attacks, by outcome



(b) Outcome shares (sums to 100%)

C Supplemental visual evidence: Vietnam losses

Figure SI-10: Casualty rates in Vietnam [Gabbert and Streets 1977]



(C) Figure 2. F-4 Cumulative Loss Rates per 1,000 Combat Sorties by Year and Country (U)*

D Additional evidence: Panjwai Success

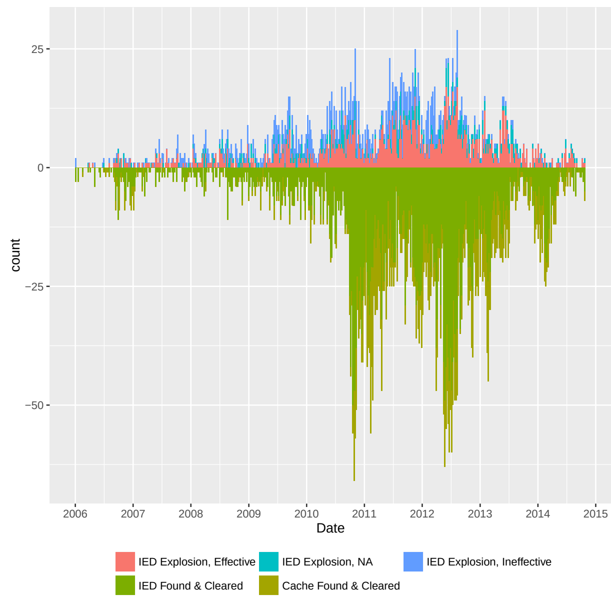
In asymmetric warfare the insurgency generally wins not by defeating its opponents militarily, but rather by inflicting sufficient casualties such that a political decision to withdraw is made. The Vietnam war is the canonical example of this situation. A complete victory by the government against the insurgency generally looks like the Malayan emergency: insurgent attacks fall to zero, and the government controls all territory. It is obvious at the end of a conflict which side has won. While the conflict is ongoing, however, it is more difficult to assess who is "winning".

To determine what government success against the insurgency looks like in our data, we examine insurgent activity in Panjwai, a well-known government success story. Panjwai, located just west of Kandahar, is the birthplace of the Taliban and was a hotbed of insurgent activity during the early part of coalition operations in Afghanistan. Many of the most intense battles in Afghanistan occurred in Panjwai, including for example Operation Medusa in 2006, in which a few hundred Canadian soldiers attempted to advance into territory occupied by several thousand Taliban militants [Bradley and Maurer 2011]. Combat operations continued during the US troop surge, with a major American offensive in 2010 seizing control of the area but suffering continued attacks from insurgents blending in with the civilian population. However, by 2014 the local population was exhausted by the conflict and had turned against the Taliban. The Afghan military assumed control over the area, and insurgent presence fell to near zero. This victory in Panjwai conforms to classic "hearts and minds" counter-insurgency doctrine: peace was established only when the population turned against the insurgents.

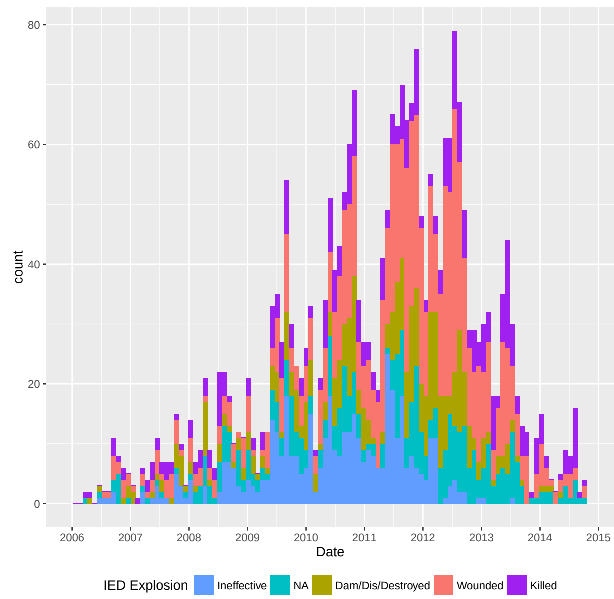
D.1 Visual evidence

As is the case in Afghanistan as a whole, the most deadly weapon used by the insurgents in Panjwai was the IED. Figure SI-11b shows that IEDs remained deadly throughout the

Figure SI-11: IED events: detonate/clear and explosion impacts, Panjwai only



(a) Detonates (above) vs. Clears (below)



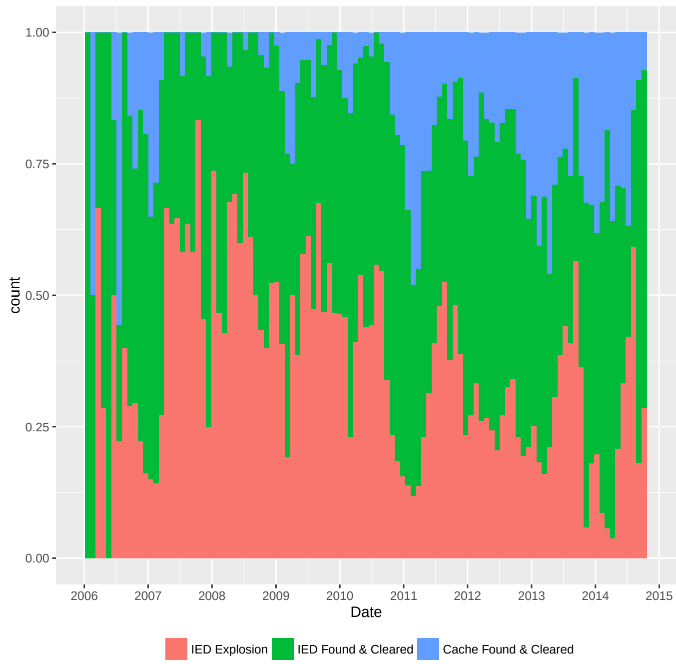
(b) Outcomes of IED explosions

conflict, in the sense that an exploding IED continued to inflict casualties at about the same (or even somewhat higher) rate. The major change in Panjwai appears to be the fraction of IEDs that exploded. Figure SI-11a shows that in 2007 more than 50% of IEDs that were emplaced exploded, whereas by 2012 or 2013 this fraction had fallen to 25%. The success of an IED attack relies on the local population remaining silent: if tips are provided to the government regarding the location of emplaced IEDs, then these can be rapidly found and cleared.

Figure SI-12 shows a dramatic improvement in the clearance rate, concurrent with qualitative reports of local towns and villages turning against the insurgents. This clearance rate is improving even in years when total IED attacks are the highest ever.[16] Looking at only the number of attacks, the government victory in Panjwai is visible only after it has already occurred. Looking at the clearance rate, however, we can see evidence that the government is winning several years before attacks decline.

[16] Figure SI-11b shows that attacks peaked around 2012.

Figure SI-12: Neutralization rate of IEDs (sums to 100%) in Panjwai, from 2006 to 2014



D.2 Regression-based evidence

The results below correspond to the estimating equations and functional form specifications reported in the main text.

In Table A-1, Columns 5 and 6 show that in Panjwai there is a positive time trend in the clearance rate: that is, the percentage of IEDs that explode is decreasing over time. This trend is the same when controlling for seasonality by adding month of year fixed effects.

In Table A-3, Columns 5-8 consider only IED explosions in the Panjwai area. Results in Columns 5-8 are the same as those in Columns 1-3. We see that over time, IEDs have become deadlier; however, as discussed in the main text, this appears to be mainly due to a compositional change away from coalition forces and towards more vulnerable Afghan troops.

Column 8 shows some differences between Panjwai and Afghanistan as a whole. In particular, the positive trend in coalition casualty rates is larger and statistically significant.[17]

[17]Note, however, that this effect is statistically insignificant in the alternate specification

That is, we observe increasing casualty rates in an environment that we know qualitatively resulted in a coalition victory.[18] This suggests that casualty rates would be an extremely poor tool to use to assess whether an insurgency is winning or loosing a conflict. Figure SI-10 suggests that this is true in other cases as well: historical data on casualty rates from the Vietnam war does not show rising success rates against US sorties.[19]

Several explanations are possible here. First, coalition forces might have been more careful in a known battle zone than in an area that is generally regarded as secured. For example, they may use lighter vehicles or may dismount from their vehicles more frequently. Second, insurgents launching many IED attacks may have used IEDs at times or locations that are not optimal, while a much smaller insurgent force could act only on the best opportunities. Third, the incentives for insurgents may be very different in an area where they have lost control, when compared to an area where there is a high intensity battle. For example, in a battle with known front lines, pressure plate IEDs can be emplaced to discourage movement in certain areas, and this tactic could be effective even when the casualty rate from these

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presented in Table A-4.

[18]Quantitatively, this trend is equivalent to an increase in casualty rates from 50% to 67%, which matches fairly well with Figure SI-13. We do not conduct a formal test of the proportionality assumption of the ordered logit regression.

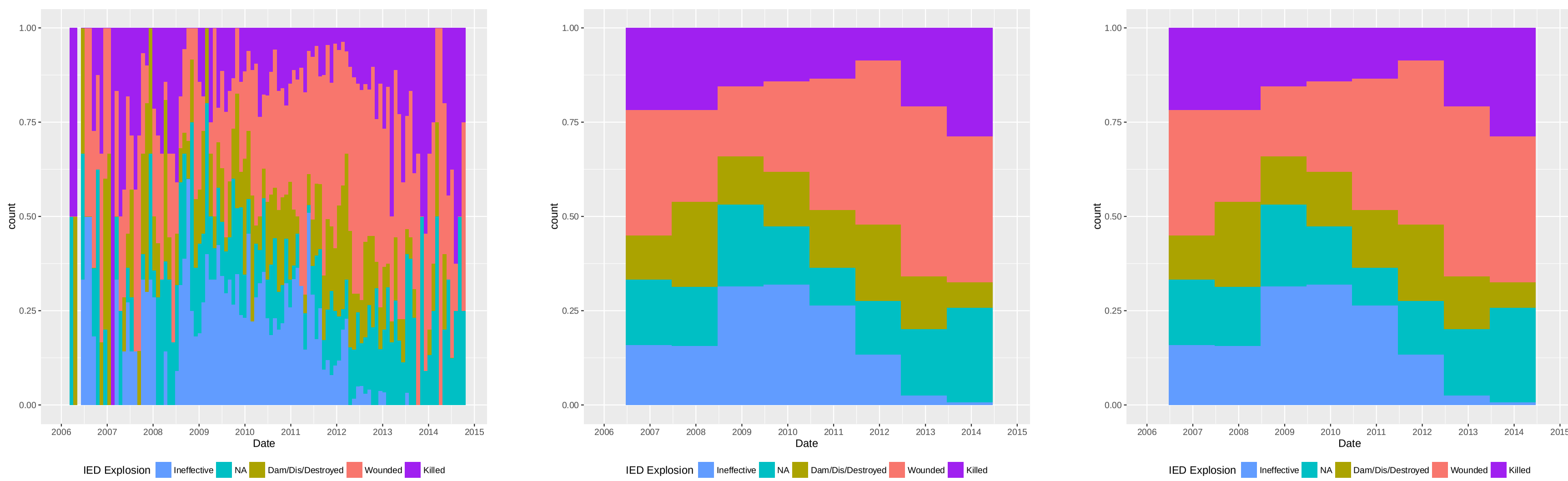
[19]There is a notable contrast between flat casualty rates in asymmetric warfare such as Afghanistan and Vietnam, and sharply changing kill ratios in air combat in world war II [Mersky 1993]. Some of the change in kill ratios towards the American's favour was due to improved fighter technology. Tactical changes that were free to disseminate, however, also resulted in substantial improved performance against the Japanese Mitsubishi Zero. For example, the Thach Weave was extremely low cost to develop, effective in dogfights, and almost impossible to counter [Ewing 2013]. This sort of development in tactics is reminiscent of insurgent warfare because it originated in an asymmetry: the American wildcat fighters were noticeably less maneuverable in combat than the Japanese zeros, and thus could not take them on directly in a one-on-one dogfight.

Another well known example of tactical development in conventional warfare concerns grenades in urban combat. These are particularly useful for clearing buildings, and thus defenders sometimes seek protection by covering windows with chicken wire to deflect thrown grenades. The appropriate response, (re-)discovered repeatedly around the world from the 19th century onwards, is to attach fishhooks to the grenades. This approach was also used during asymmetric warfare in Vietnam [Zahn 2003].

IEDs is relatively low. Such a tactic has little value in a much lower intensity conflict when the government forces are clearly in control of the area.[20]

[20]Additionally, damaging or disabling a vehicle may be valuable when fighting a battle in which the absence of that vehicle on the battlefield in the following days could make a difference; in contrast, damaging a vehicle during a very low intensity conflict may be of little importance, because the vehicle will be repaired before any subsequent attacks are launched.

Figure SI-13: Outcome of IED Explosions in Panjwai



(a) Coalition

(b) Afghan Military, Supported

(c) Afghan Military, Unsupported

Note: Afghan military results are shown annually rather than monthly due to lower number of attacks.