The Wane of Command

Evidence on drone strikes and control within terrorist organizations*

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Abstract

This paper investigates how counterterrorism targeting terrorist leaders affects terrorist attacks. This effect is theoretically ambiguous and depends on whether terrorist groups are modeled as unitary actors or not. The paper exploits a natural experiment provided by strikes by Unmanned Aerial Vehicles (drones) 'hitting' and 'missing' terrorist leaders in Pakistan. Results suggest that terrorist groups *increase* the number of attacks they commit after a drone 'hit' on their leader, compared to after a 'miss'. This increase is statistically significant for three out of six months after a hit, when it ranges between 47.7% and 70.3%. Additional analysis of heterogenous effects across groups and leaders, and the impact of drone hits on the type of attack, terrorist group infighting and splintering, suggest that principal-agent problems – (new) terrorist leaders struggling to control and discipline their operatives – account for these results better than alternative theoretical explanations.

Keywords: Terrorism; Targeted Leader Killing; Unmanned Aerial Vehicles; Drones

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1 Introduction

> The United States and its partners will *defeat* terrorist organizations of global reach by attacking their [. . .] leadership; command, control [. . .]
>
> *US National Strategy for Combating Terrorism 2003*
>
> (emphasis in original)

Targeting terrorist leaders has become a commonly used US counterterrorism policy since 9/11. According to the US National Strategy for Counterterrorism 2018, "targeting key terrorists" remains the number one priority action. This policy is also referred to as targeted leader killing or "cutting off the head of the snake" – implying that if one does so, the body dies. As illustrated by the above quote, the underlying goal of this policy is to undermine *control* within terrorist organizations: ability of terrorist leaders to determine what others in the organization do.

Terrorist leaders are primarily targeted using armed drones, or Unmanned Aerial Vehicles. These unmanned airplanes can surveil and identify individual targets, and kill them. There have been over 6700 US drones strikes worldwide to date[1]. Drone technology is spreading rapidly: 28 other countries have acquired weaponized drones in the last ten years[2].

The prominence of targeted leader killing and the proliferation of drones invite the question whether this policy works to decrease terrorist violence. This paper addresses that research question. More precisely, it investigates how drone strikes killing terrorist leaders, thereby undermining control within terrorist organizations, affect terrorist attacks[3].

The effect of killing a terrorist leader on terrorist violence is theoretically ambiguous, and depends on whether terrorist groups are modeled as unitary actors or not. Theoretical models that consider the terrorist group as unitary – as a single organism as the snake analogy would suggest – predict that killing a leader decreases the capacity of the group to commit attacks, and thereby terrorist violence (Sandler and Arce, 2003; Powell, 2007).

However, other theoretical models predict an increase in terrorist attacks after a drone hit on

[1] https://www.thebureauinvestigates.com/projects/drone-war, accessed 6 January 2020

[2] New America Foundation, "World of Drones", 15 March 2017.

[3] Defined as "the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation", following the Global Terrorism Dataset.

a terrorist leader. A first family of models treats the terrorist group as non-unitary and subject to *problems of control*. Principal-agent models by Shapiro (2013) and Abrahms and Potter (2015) suggest that leader killing undermines control of the new leader over the organization's operatives, which could lead to increased terrorist violence if operatives have a greater preference for violence than the leader. Other families of models also suggest that targeted leader killing may increase (the frequency of) terrorist violence: terrorist groups may respond to a loss in *capacity* by substituting infrequent 'big' attacks by frequent 'small' attacks, leader killings that result in civilian casualties may create *backlash* if they spur terrorist recruitment, and terrorist organizations may commit more terrorist attacks after their leader has been killed to *signal* strength.

Ambiguous theoretical predictions leave an empirical question. However, investigating the causal effect of counterterrorism on terrorist violence empirically is challenging. Although counterterrorism may well affect terrorist violence, it is equally possible that terrorist violence invites counterterrorism.

To overcome this problem, this paper exploits a natural experiment provided by drone strikes 'hitting' and 'missing' terrorist leaders in the Federally Administered Tribal Areas (FATA) of Pakistan, which is inspired by Jones and Olken (2009) and shares similarities with an analysis by Abrahms and Mierau (2017). I construct a new dataset of drone strikes targeting terrorist leaders, executing several cross-checks to safeguard data quality. This dataset captures variation across time and terrorist organizations. I argue that conditional on a drone strike targeting a terrorist leader, drone 'hits' and 'misses' are quasi-random. Drone hits and misses are not statistically significantly different from one another on an extensive range of characteristics, including pre-trends in terrorist violence. Narratives of why drones miss also suggest that misses are largely driven by chance. This enables a difference-in-difference design, investigating changes in attacks by a terrorist organization before and after a drone hit on its leader, compared to before and after a miss.

Results indicate that a drone hit on a terrorist organization's leader is associated with an increase in the number of terrorist attacks by this organization, compared to a miss. Estimates are statistically significant for three out of six months after a hit, and the increase in terrorist attacks worldwide varies between 47.7% and 70.3% for these months. This result cannot be explained by terrorist organizations 'speeding up' the timing of attacks, or by a decrease in the lethality of attacks. The result is robust to an extensive battery of robustness checks.

The paper proceeds to tests auxiliary hypotheses derived from theoretical models emphasizing problems of control, capacity, signaling and backlash. It finds more evidence in favour of hypotheses relating to problems of control than for those derived from alternative theoretical explanations. After a drone hit on a leader, those types of terrorist attacks for which we have theoretical and empirical reason to believe that they are not preferred by terrorist leaders increase most. These include attacks against civilian and private targets, echoing results by Abrahms and Mierau (2017), but also attacks by operatives that the organization does not publicly claim responsibility for. Furthermore, the effect of drone strikes on terrorist attacks is stronger for terrorist organizations and leaders that rely more strongly on central control. Finally, a drone hit is associated with terrorist infighting and a proxy for group splintering. However, evidence is also found to support some, but not all, hypotheses derived from signaling models. After a drone hit, some types of terrorist attacks that send a strong signal about the group's continued resolve increase, such as attacks on military targets and attacks the group claims responsibility for.

A considerable number of existing studies investigate empirically the impact of targeted killing of leaders of terrorist organizations, yet results are mixed. Some authors conclude that targeted leader killing is effective, because it speeds up the decline of terrorist organizations (Price, 2019) or diminishes the number or intensity of terrorist attacks (Jaeger and Paserman, 2009; Johnston, 2012). Others conclude that it has no effect or an adverse effect (Jordan, 2019; Mannes, 2008; Hafez and Hatfield, 2006; Kaplan et al., 2006; Abrahms and Potter, 2015; Abrahms and Mierau, 2017). Existing studies offer several theoretical explanations for success or failure of targeted leader killing. The former commonly revolve around the importance of leadership for terrorist groups' survival and capacity to commit attacks (Jaeger and Paserman, 2009; Price, 2019). The latter emphasize martyrdom effects, revenge, or the effect of drone strikes on terrorist recruitment (Kaplan et al., 2006; Price, 2019; Hafez and Hatfield, 2006). Several authors develop theoretical arguments explaining why targeted leader killing would be effective against some terrorist groups, but not others, depending on for example their organizational structure (Price, 2019; Jordan, 2019).

The above studies encounter some combination of three challenges. Most of these studies cannot empirically distinguish between competing theoretical explanations for their results, and do not refer to principal-agent theory as a possible explanation. Notable exception are Abrahms and Mierau (2017), to whom this paper is indebted for pioneering the study of targeted leader killing by drone in Pakistan from a principal-agent perspective. However, Abrahms and Mierau (2017) only test one implication from principal-agent theory, that relating to civilian targeting. Empirically, studies of targeted leading killing struggle to convincingly demonstrate its *causal* effect. A handful of studies employ a similar 'hit-or-miss' design as in this paper (Johnston, 2012; Abrahms and Mierau, 2017; Jaeger and Paserman, 2009), but data used lacks either variation across terrorist groups or over time. Specifically, Abrahms and Mierau (2017), are forced to consider all terrorist groups in the Afghanistan-Pakistan area as one. Hence, results hinge on the assumption that the probability of a hit is not related to trends in violence over time or across groups. These conditions could be violated in many plausible circumstances, and this paper provides evidence that the probability of a hit indeed displays a strong time trend. Unlike other studies, the present study can control for trends over time and differences across terrorist groups by including group and time-fixed effects, substantially improving causal identification.

Hence, this paper contributes to existing literature on terrorism by testing a rich set of predictions from principal-agent theory. Furthermore, it contributes to the literature on targeted leader killing by using a more rigorous identification strategy.

Finally, this paper contributes the literature on drone strikes by providing evidence on their medium-term impact on terrorist violence, across geographical areas where targeted terrorist groups are active. There is a small but growing literature on the effectiveness of drone strikes in Pakistan (Johnston and Sarbahi, 2016; Mir and Moore, 2019), generally concluding that they decrease terrorist violence in FATA. Johnston and Sarbahi (2016) argue that the week-to-week timing of drone strikes is quasi-random due to factors such as the weather, and can consequently only investigate the short-term impact of drone strikes. Mir and Moore (2019) compare areas in FATA where US drones were and were not allowed to fly over time. Given their empirical set-up, these studies cannot speak to the impact of drone strikes on violence outside FATA. This effect is arguably the more interesting one, as drone strike explicitly target terrorist organizations “of global reach”.

2 Background

This study focusses on drone strikes in Pakistan[4]. A drone strike is a strike by an Unmanned Aerial Vehicle, an unmanned airplane with both surveillance and strike capability. Up to September 2015, when the Pakistani government acquired armed drones, the US was the only actor conducting drone strikes on Pakistani territory – over 400 strikes to date.[5] The Central Intelligence Agency (CIA) conducts these strikes, with the consent of the Pakistani government until this was withdrawn in 2013 (Byrne, 2016). Drone strikes target terrorist leaders, both high and low level, as well as named or anonymous militants. There are no confirmed instances of conventional airstrikes by the US in Pakistan.

All but a handful of drone strikes have taken place in the Federally Administrated Tribal Areas (FATA), an area of Pakistan which borders Afghanistan. Although the Pakistani military conducts operations in FATA, there has historically been little civilian government oversight. Until it was merged into an adjacent province in 2018, FATA was administrated outside of the framework of the Pakistani constitution.[6] The region is known as a sanctuary for numerous terrorist organizations, which operate in Pakistan and transnationally. Al-Qaida and the Taliban are the best-known organizations.

Terrorist organizations in FATA are prone to splintering. Infighting between three leaders of the Tehrik-i-Taliban Pakistan (TTP) led to a split of the organization in 2009 (Crenshaw, 2012). Pakistani newspaper Dawn regularly reports on the formation of new TTP splinter factions, such as Jamaat Al-Ahrar[7] or Jundullah [8].

There is a fierce and unresolved debate about the number of civilian casualties that drone strikes

[4]There have been a substantial number of drone strikes in Afghanistan, Somalia and Yemen. Data on Afghanistan (2015-2017) overlaps insufficiently with data on terrorism. Strikes from Somalia and Yemen are excluded as these virtually exclusively target a single terrorist organization. Given this, country-specific trends cannot be controlled for and could bias the analysis.

[5]https://www.thebureauinvestigates.com/projects/drone-war/pakistan, accessed 17 April 2018.

[6]International Crisis Group, “Shaping a New Peace in Pakistan’s Tribal Areas”, 20 August 2018.

[7]Dawn, “TTP commanders form a new spliter group ‘Jamatul Ahrar”’, 26 August 2014.

[8]Dawn, “TTP claims attack on Rawalpindi Imambargah, three killed”, 18 February 2015.

cause, which is of limited relevance to this paper, since the main analysis uses data on named leaders whose relationship to terrorist groups is not disputed. A well-cited study put the civilian casualty rate at 32% between 2004-2010 (Bergen and Tiedemann, 2011). There are good reasons to doubt these and other claims. There is a tendency on the part of US officials to assume that all military-aged male casualties are militants (Byman, 2013), terrorist groups often cordon off the area of a drone strike and do not allow witnesses that might confirm or deny reports, and Pakistani media commonly publish unsubstantiated and high civilian casualty counts (Taj, 2010).

Regardless of the actual number of civilian casualties, terrorist organizations can use drone strikes hitting civilians as a propaganda tool. Al-Qaida propaganda materials portray drone strikes as causing mainly civilian deaths and as an indication of the US government attitude vis-a-vis 'ordinary' Muslims Ludvigsen (2018); Cronin (2013). This dynamic is one reason for Cronin (2013) to conclude that drone strikes are an unsuccessful counterterrorism policy.

3 Insights from theory and hypotheses

Four families of theoretical models provide hypotheses on how drone strikes killing a terrorist group's leader might affect terrorist attacks, through problems of control, terrorist capacity, backlash and signaling. According to all four of these, it is possible that a drone hit on a terrorist leader is associated with increased terrorist violence. To empirically distinguish between these theoretical models, I derive a set of auxiliary hypotheses. An overview of these hypothesis can be found in Table 1. For a more comprehensive overview of game theory and terrorism, see Sandler (2011) and Sandler (2015).

3.1 Principal-agent problems and control

This section discusses principal agent theories of terrorist groups. According to such theories, counterterrorism threatening to expose a terrorist leader may diminish leaders' control over their operatives. Depending on the preferences of leaders and operatives, this could increase terrorist violence.

Both Shapiro (2013) and Abrahms and Potter (2015) model terrorist groups as non-unitary organizations, subject to principal-agent problems. Principal-agent problems arise because leaders and operatives within terrorist organizations have different preferences regarding how many and what type of terrorist attacks to commit. Unless the leader can exert *control* over operatives, operatives might not act as the leader wants. Control refers to efforts by the leader to determine the actions of operatives, specifically: (1) communication – the leader telling operatives what to do; and (2) punishment – the leader penalizing operatives that do not follow orders or rewarding those that do (Shapiro, 2013).

Counterterrorism that threatens to expose the terrorist leader is predicted to decrease the degree of control a leader is able or willing to exert (Shapiro, 2013). Engaging in communication and punishment makes a leader more vulnerable to detection by counterterrorism agencies, so leaders may opt to exert less control as scrutiny by counterterrorism agencies intensifies. Mir (2018) illustrates qualitatively how drone strikes affect control within terrorist organizations in FATA: to avoid detection by drones, leaders eschewed use of communication devices, quit meetings and were out of contact with operatives for months. A drone strike that hits a terrorist leader plausibly decreases control more steeply than a drone strike that misses a terrorist leader. The new leader is likely less capable of exerting control, at least initially. If the new leader were better than the old leader at exerting control, presumably he would already *be* the leader. The new leader may also be less willing to exert control. The old leader evidently revealed enough information about themselves to be killed by drone. The new leader might not yet have, giving them an incentive to trade off control for secrecy.

The predicted effect of a decrease in control on terrorist violence is ambiguous: this depends on the relative preferences of the leader and the operative (Shapiro, 2013). If the operative has a greater preference for violence than the leader, decreasing the leader's control within the terrorist group is predicted to lead to *more* violence.

There are theoretical reasons to believe that terrorist operatives indeed have a greater preference for violence than terrorist leaders. The main theoretical argument is that leaders, having had longer tenure within the organization, know better that particular terrorist attacks harm the group's long-term prospects by decreasing public support (Shapiro, 2013; Abrahms and Potter, 2015). Such attacks harmful in the long term likely include attacks on civilians (Abrahms, 2012; Fortna, 2015). Alternative theoretical arguments include a selection effect – operatives are selected for their tendency towards violence whereas leaders have other qualities (Shapiro, 2013) –, or greater benefits to violence for operatives – for example in the form of pillage or promotion within the organization (Abrahms and Potter, 2015).

Empirical evidence also suggests that terrorist leaders prefer less violence than operatives, especially violence against civilians. In a study of over 1,300 individual members of radical groups in the US, Jasko and LaFree (2019) find that leaders have a lower propensity for violence than followers. Anecdotal evidence and qualitative case studies suggests a similar pattern. Intercepted letters from Al-Qaida suggests that its leaders repeatedly admonish subsidiary groups to commit less violence against Muslim civilians (Crenshaw, 2012). Al-Qaida in Iraq in particular ignored orders to halt beheadings and other tactics that eventually eroded its popular support base (Price, 2019; Jordan, 2019). Price (2019) details how the imprisonment of a Hamas leader eroded checks on who could execute suicide bombings, resulting in more attacks. Abrahms and Mierau (2017) provide a detailed case study of how leaders of the Taliban tried but on various occasions failed to stop lower level members from perpetrating indiscriminate violence against civilians. The death of TTP leader Hakimullah Mehsud reportedly sparked a debate within the group about whether civilians were legitimate targets and terrorist attacks by the TTP spiked (Crenshaw (2012)). Leaders of the TTP and Haqqani network publicly denied involvement in attacks that members of their respective organizations likely did commit, including attacks after TTP had signed a peace agreement with the Pakistani government[9] and an attack on a funeral[10].

The latter examples illustrate that leaders who cannot exert sufficient control to prevent operatives from executing attacks harmful to the group's long-term interests, may still try to do damage-control by not claiming these attacks. See Abrahms and Conrad (2017) for a formal theory of such strategic credit-claiming.

Principal agent models thus give the following hypotheses. Drone strikes that kill terrorist

[9] "Baitullah denies role in suicide bombings", Dawn, 9 February 2007

[10] "Taliban denies role in Kabul bombing", Dawn, 12 June 2017

leaders are predicted to lead to a decrease in control of leaders over operatives (H1.1). A decrease in control may be expressed empirically by an increase in terrorist attacks on civilian and private targets (H1.1a); or an increase in terrorist attacks committed, but not claimed by the organization (H1.1b).

The degree of control leaders exert affects the organizational structure of terrorist groups. Abrahms and Potter (2015) note that group structure is a standard proxy for leadership control. Groups with higher degrees of control are more centrally organized, i.e. have more ties between leaders and operatives. Robustness of central control is one of two defining characteristics in Staniland (2014)'s classification of armed group organizational structure. A group with robust central control has an effective bureaucracy to discipline members and socialize them into the "party line".

This gives us a further set of hypotheses. Drone strikes undermining control may lead to a change in organizational structure: if all ties between terrorist leaders and operatives break down, parts of the group may form splinter groups (H1.1c), or fight among each other (H1.1d). Furthermore, groups that rely more on central control may be affected more strongly by drone strikes than groups that do not (H1.2a). If a group has no central control to begin with, control cannot be further undermined by killing its leader, and we would expect drone strikes to have little effect.

Finally, the effect of drone strikes on violence may be stronger for the first leader killed (H1.2b). The first leader targeted decided how much information to reveal about themselves prior to the existence of drones, and it may be too late to hide this information through decreasing control. The subsequent leader is possibly better able to trade off control for secrecy. Hence, we may expect the drop in control to be greatest after the first leader of each group is killed.

3.2 Capacity

A drone strike can be considered an example of a proactive counterterrorism policy aiming to eliminate terrorist capacity: resources needed for the execution of terrorist attacks. Consider a production function of terrorist attacks. Several resources can be inputs to this production function, for example leadership, financial capital, or operatives' labour. Assume that terrorist groups

Table 1: Hypotheses

	Hypothesis: Drone strikes killing a terrorist organization's leader are related to...	Evidence
	1. Problems of Control	
H1.1	. . . a **decrease in control** by the leader over operatives, as evidenced by:	
	(a) an increase in attacks by the organization on private and civilian targets;	(a) Yes
	(b) an increase in attacks by the organization's operatives that the organization does not claim.	(b) Yes
	(c) an increase in the probability of splintering of the terrorist organization;	(c) Yes
	(d) an increase in infighting;	(d) Yes
H1.2	. . . a **stronger increase in terrorist attacks** for:	
	(a) terrorist organizations with more initial central control.	(a) Yes
	(b) the first leader of the organization struck.	(b) Some
	2. Capacity	
H2.1	. . . a **substitution** by the terrorist organization of high-impact attacks with low-impact attacks, specifically:	
	(a) a decrease in the probability of a successful attack;	(a) No
	(b) a decrease in the number of victims per attack;	(b) No
	(c) substitution of attacks on military and US targets with attacks on private and civilian targets;	(c) No
	(d) substitution of attacks in Afghanistan and other locations outside Pakistan with attacks in Pakistan.	(d) No
	3. Signaling	
H3.1	. . . an increase in attacks by the terrorist organization that **send a strong signal**, specifically:	
	(a) attacks taking place shortly after the drone strike;	(a) No
	(b) attacks on military targets;	(b) Yes
	(c) attacks on US targets;	(c) No
	(d) attacks by the terrorist organization that the organization claims.	(d) Yes
H3.2	. . . a **stronger increase** in terrorist attacks by the organization for **more prominent leaders**.	Some
	4. Backlash	
H4.1	Drone strikes targeting a terrorist organization, yet causing **civilian casualties**, are related to an increase in attacks by that terrorist organization or by terrorist organizations generally.	No

maximize the number of terrorist attacks committed subject to their resource constraints. Drone strikes eliminating leadership tighten this resource constraint, leading to a predicted decrease in the frequency of terrorist attacks (see for example Sandler and Arce (2003); Powell (2007)).

However, capacity models considering that terrorist groups may chose between different types of attacks can predict an increase in the frequency of terrorist attacks as a result of proactive counterterrorism (Enders and Sandler, 2004). Imagine that terrorist groups maximize the political impact of their attacks. They can commit some number of low-impact attacks (requiring fewer resources) or high-impact attacks (requiring more resources). If proactive counterterrorism policies eliminate terrorist resources disproportionately required for high-impact attacks, terrorist groups may substitute away from high-impact attacks into low-impact attacks. If the increase in the number of low-impact attacks is larger than the decrease in the number of high-impact attacks, the frequency of terrorist attacks increases, despite lower capacity and lower political impact of the terrorist group.

Hence, capacity models predict that a decrease in terrorist group capacity due to a drone hit on its leader may lead to a substitution of high-impact with low-impact attacks (H2.1). This could manifest in more 'failed' terrorist attacks, smaller terrorist attacks in terms of number of victims, or substitution of attacks on military targets and US citizens or attacks abroad, with attacks on private and civilian targets or attacks in Pakistan.

3.3 Signaling

A drone strike that hits a terrorist leader may introduce uncertainty about a terrorist group's ability or resolve to continue terrorist attacks, which in turn may give terrorist groups an incentive to commit more attacks in the periods after the drone strike by way of a signal. Imagine a government must decide whether to make concessions to a terrorist group but is uncertain about the resolve or resources commanded by the terrorist group. Terrorist groups then have an incentive to commit more or larger terrorist attacks in the period soon after this uncertainty arises, in an attempt to convince the government of their strength or resolve and induce concessions (Arce and Sandler, 2007; Lapan and Sandler, 1993).

Signaling models thus hypothesize that a drone strike hitting a terrorist leader leads to an increase in terrorist attacks that send a strong signal (H3.1). The strongest signal arguably consists of terrorist attacks which immediately follow the drone strike hitting a terrorist leader, which hit a 'hard' target, such as a military target or a US citizen, and which are claimed by the terrorist organization. Furthermore, we might hypothesize that these effects are stronger for more prominent leaders (H3.2): the more prominent the leader killed by drone, the stronger the signal required to convince others of the organization's resolve.

Signaling as a theoretical explanation is difficult to empirically distinguish from revenge or retaliation. If a terrorist group wishes to avenge the death of its leader, the resulting pattern of terrorist attacks is plausibly similar to that suggested in H3.1 and H3.2.

3.4 Backlash and recruitment

Proactive counterterrorism policies may cause 'backlash' if they result in civilian collateral damage, thereby spurring terrorist recruitment. Conceptually, backlash is distinct from the effect of targeted leader killing, but in practice the two might be related if operations killing leaders disproportionately kill civilians. In this respect, drone strikes are distinct from other methods of targeted leader killing such as special operations, which may present a lower risk of civilian casualties.

Backlash could occur if terrorist organizations use civilian casualties to foment ideological opposition (Bueno de Mesquita, 2005). Alternatively, Kalyvas (2000) suggests that those facing indiscriminate violence by the hands of one party to a violent conflict, may protect themselves by joining the other. If violence is completely indiscriminate, joining does not pose additional risk, but provides the new recruit with information on when and where such indiscriminate violence might occur. A fully informed government may still wish to engage in counterterrorism creating backlash, if it trades off an increase in future attacks for a decrease in current attacks (Jacobson and Kaplan, 2007) or if it does not fully internalize the global costs of proactive counterterrorism because this increases recruitment, but displaces terrorist attacks to softer foreign targets (Rosendorff and Sandler, 2004).

Backlash need not remain limited to the terrorist organization subject to pro-active terrorism policies, but may extend to terrorist groups generally. Siqueira and Sandler (2007) provide a model in which pro-active counterterrorism measures against one terrorist group, triggers reprisal attacks by other groups.

Theoretical models considering backlash predict that drone strikes that hit civilians may lead to increased terrorist attacks, by the terrorist organization that was the target of the drone strike, or by terrorist groups in general (H4.1).

4 Data and methods

4.1 Data

This paper uses a newly constructed panel dataset of successful and failed targeted leader killings, capturing variation across thirteen terrorist groups over a period of twelve years (2004-2015). The unit of observation is the group-month. Various cross-checks have been carried out to make this dataset arguably less subject to reporting bias compared to relying on a single data source. Balance checks substantiate the assertion that drone hits and misses are quasi-random.

4.1.1 Drone strikes

To construct a dataset of successful and failed targeted killings of terrorist leaders, I code 443 narratives about individual drone strikes between 2004 and 2015 collated by the Bureau of Investigative Journalism (BIJ)[11], and cross-check these with data from the New America Foundation (NAF)[12] and information on terrorist leaders from the Mapping Militants Project at Stanford University (Crenshaw, 2012).

For each drone strike reported by the BIJ, I code whether a terrorist leader was targeted and whether this leader died. The terrorist group(s) the drone strike targeted is also recorded. This results in 379 strikes for which the group targeted can be determined from BIJ reports,[13] including 137 targeting a named individual designated by BIJ reports as 'leader'. For full coding rules, see Appendix A2.

[11] https://www.thebureauinvestigates.com/stories/2017-01-01/drone-wars-the-full-data

[12] https://www.newamerica.org/in-depth/americas-counterterrorism-wars/pakistan/

[13] The number of drone strikes targeting a group in a particular month - regardless of leader involvement - is used as a control variable in a robustness check (section 6).

The resulting data on terrorist leaders was cross-checked with data from the NAF. This organization also provides information on terrorist leaders targeted by drone, which is used by previous studies (e.g. Abrahms and Mierau (2017); Johnston and Sarbahi (2016)). This data has substantial downsides. The NAF for unknown reasons does not report unsuccessful strikes on leaders between 2012-2015 and is extremely broad-brushed when classifying terrorist groups. For example, the Afghan Taliban, local (Pakistani) Taliban, Tehrik-i-Taliban Pakistan (TTP) and the Punjabi Taliban are all coded as 'Taliban'. This forces authors using NAF leaders data to consider all groups targeted as a single unit and truncate the data in 2011 (Abrahms and Mierau, 2017), creating a single short time series. By contrast, coding BIJ narratives results in information on thirteen different terrorist groups, forming a panel dataset covering a longer period. An overview of these thirteen groups can be found in Appendix A1. Note that two of these thirteen groups do not exist for part of the research period.

Cross-checking data between the BIJ and the NAF gives insight in how information from single data sources might be biased. Although both BIJ and NAF are nonpartisan and construct their data on the basis of (often the same) reputable news sources, when reading between the lines, the NAF appears to have a more positive outlook on use of drones than the BIJ. This gives the NAF a stronger tendency to portray those killed by a drone strike as a leader. I cross-check all named individuals the NAF classifies as 'leaders killed'. Deaths of all but one of these individuals are also found in the BIJ data, within two days of the NAF-recorded data. However, the BIJ does not always classify these individuals as 'leaders'.

To mitigate bias in the interpretation of who is a leader, I cross-check data coded with leaders mentioned by the Stanford Mapping Militants project. US counterterrorism agencies have an incentive to inflate the importance of individuals once they are killed by drone strike, which affects both NAF and BIJ data, as these are based on strike reports. By contrast, the Mapping Militants project creates profiles of terrorist groups independent of drone strikes, based on open-source information it selects to "maximize veracity and reliability". Names of the group's leaders are a fixed element of each profile.

Confirming the suspicion that the importance of individuals is inflated by drone strike reports, the 'leader' as classified by BIJ is only recognized as such by the Mapping Militants Project for approximately one third of strikes (45 out of 137). In the preferred specification only the 45 strikes involving leaders who are considered as such by the Stanford project are coded as a drone strike targeting a leader. Fifteen of these succeeded in killing the target. Ten leaders were both missed and hit (see Appendix A3 for details). Results using the BIJ definition, giving 137 drone strikes targeting a leader, are included as a robustness check.

Note that it is the rule rather than the exception for the death of a leader, especially those leaders recognized by the Stanford project, to be confirmed by *both* sources in the US government and the terrorist organization. Terrorist organizations commonly publish statements about the death of their leader, put out eulogies, or place online pictures of his funeral. This does not hold for those marked as 'leaders' by the NAF or BIJ only, who are sometimes only identified by some less-than-unique nickname.

It is possible that a terrorist group has leaders that are not publicly known. These would not be included in reports by BIJ, NAF or Mapping Militants, which are all based on open-source information. Drone strikes on these individuals are counted as strikes not involving a group's leader in the present analysis. As results are driven by the difference between drone hits and misses on a leader, this is not likely to bias the analysis.

I supplement the dataset of terrorist leaders with information on the importance of a leader within a terrorist group. Two metrics are used. First, an indicator equalling one if the Stanford Mapping Militants Project indicates an individual was ever 'first in command' or similar of a terrorist group. Secondly, the maximum reward amount offered for information on a terrorist leader by the US Department of State's Reward for Justice Programme.

The identification strategy of this paper relies on the quasi-randomness of hits and misses: indeed, there is virtually no evidence that there is a pattern to hits and misses. Table 2 displays the mean of a large set of variables for group-months with a drone hit and a drone miss respectively, and the p-value for a t-test of the difference between both. Results indicate that the probability of a hit is not driven by prior drone activity, Pakistani military action or peace agreements between the terrorist groups and the Pakistani government, all of which could reveal information about

Table 2: Difference between group-months with a drone hit and a drone miss

Variable	(1) Mean miss	(2) Mean hit	(3) p-value difference
Strikes in previous 6 mths	4.867	5.067	0.868
'Hits' in previous 6 mths	0.200	0.267	0.622
'Misses' in previous 6 mths	0.333	0.333	1.000
Pak. military action in previous 6 mths	0.333	0.200	0.364
# Pak. military action days in previous 6 mths	3.367	2.133	0.437
Peace agreement in force previous 6 mths	0.467	0.400	0.680
Peace agreement start previous 6 mths	0.267	0.133	0.322
Peace agreement end previous 6 mths	0.133	0.133	1.000
Strikes in next 6 mths	5.100	3.333	0.100*
'Misses' in next 6 mths	0.267	0.200	0.633
'Hits' in next 6 mths	0.200	0.267	0.689
Pak. military action in next 6 mths	0.367	0.133	0.108
# Pak. military action days in next 6 mths	3.567	1.200	0.103
Peace agreement in force next 6 mths	0.500	0.267	0.141
Peace agreement start next 6 mths	0.100	0.000	0.214
Peace agreement end next 6 mths	0.100	0.000	0.214
Year	2,010.033	2,012.267	0.001***
Leader reward (M$)	2.433	1.467	0.573
First in command	0.300	0.133	0.229
Total casualties - low est.	12.967	5.600	0.153
Total casualties - high est.	18.167	10.200	0.193
Civilian casualties - low est.	4.633	0.933	0.352
Civilian casualties - high est.	7.467	2.400	0.314
Child casualties - low est.	3.267	0.533	0.407
Child casualties - high est.	3.467	0.533	0.387
Injuries - low est.	3.833	2.333	0.396
Injuries - high est.	5.933	3.733	0.333
Number leaders involved	1.033	1.000	0.486
area==Bajaur Agency	0.100	0.000	0.214
area==Khyber Agency	0.000	0.067	0.160
area==Khyber Pakhtunkhwa province	0.000	0.067	0.160
area==North Waziristan	0.600	0.667	0.672
area==Orakzai Agency	0.033	0.000	0.486
area==South Waziristan	0.267	0.200	0.633
targettype==Vehicle	0.133	0.000	0.145
targettype==Building	0.567	0.467	0.537
targettype==Both	0.133	0.267	0.281
groupid==Al-Qaida	0.267	0.400	0.374
groupid==Harkatul Jihad-e-Islami	0.133	0.067	0.513
groupid==Haqqani Network	0.133	0.200	0.571
groupid==Taliban	0.033	0.067	0.619
groupid==Tehrik-i-Taliban Pakistan	0.433	0.267	0.288
Observations	30	15	

terrorist leaders and make a hit more likely. Table 2 also finds no evidence that the probability of a hit is statistically significantly different when Pakistani military action or a peace agreement might be anticipated. The probability of a hit does not significantly differ by importance of the leader, number of leaders involved, district, target type or terrorist group. Hits do not cause a significantly higher or lower number of (civilian) casualties. There is some evidence that terrorist groups are less likely to be the target of a drone strike after a drone hit on their leaders. Therefore, all specifications will control for drone strikes not targeting leaders. There is strong evidence that the probability of a hit increased over time. This highlights the importance of including time-fixed effects, which will be included in all specifications.

Anecdotally, drone misses seem to be mostly driven by chance. They fall into three broad categories: drone strikes hitting locations where the targeted leader is not yet or no longer present, instances when the targeted leader is merely wounded and instances when reports of a leader's death are credible enough to be taken up by reputable news sources only for the leader to later show up alive. To mitigate concerns that misses are underreported, results using an alternative definition of a 'miss' will be presented as a robustness check.

4.1.2 Terrorist violence and other data

Data on drone strikes targeting the thirteen terrorist groups mentioned by BIJ is linked to data on terrorist attacks by these groups from the Global Terrorism Database (GTD). GTD relies on open source media accounts of terrorist attacks, and attributes terrorist incidents to a group based on these accounts where possible. Hence, unclaimed terrorist attacks are attributed to a group if media reports name the group as perpetrator, and 'lone wolf' attacks claimed by some terrorist group are *not* attributed to this group if open source media accounts judge this claim not to be credible. GTD also records instances of infighting - terrorists fighting other terrorists.

Relying on open-source reports introduces possible biases, but simulations suggest that the extent of these biases would have to be substantial to completely drive this paper's main results. First, bias could arise if media are more likely to report terrorist attacks by a group in the six months after a hit on its leader, compared to after a miss. Appendix B.2.1 suggests that, if drone hits in fact had no effect on terrorist violence, media would have to report all terrorist attacks by a group for six months after a drone hit on its leader and only approximately 65% of attacks after a drone miss, to obtain a single statistically significant coefficient with 95% certainty. The actual analysis obtains three significant coefficients. Secondly, measurement error might bias the analysis, as attacks committed by an unknown perpetrator are excluded from the analysis. This may introduce bias if there is a group-specific time trend in the likelihood that GTD ascribes an attack to a particular group, that correlates to the probability of a drone hit. Appendix B.2.2 shows that drone hits are uncorrelated to the logged number of unattributed terrorist attacks. Furthermore, it gives results of simulations that attribute attacks by unknown perpetrators to the groups in the main dataset: 88% of simulated regressions still give at least one statistically significant coefficient.

The main dataset is restricted to the thirteen groups subject to drone strikes, because the identification strategy in this paper hinges on comparing groups that had their leader hit and missed at different times. Including terrorist groups not subject to drone strikes in the sample does not contribute to the identification of the coefficients of interest, but does artificially inflate the sample size and introduces needless heteroskedasticity. Appendix B.5 illustrates that, unsurprisingly, including all terrorist groups that committed more than one attack in Afghanistan or Pakistan in the sample does not affect the main results.

To investigate group splintering, I identify all terrorist groups (other than the included thirteen) in the GTD that ever committed a terrorist attack in Afghanistan or Pakistan. Using a web search, I code these as having an affiliation to one or more of the thirteen terrorist groups in the drone strike dataset, or as unaffiliated (see Appendix A.4 for details). These groups have typically committed a small number of terrorist attacks (median 2), and anecdotally many of these groups are splinter groups of the main terrorist groups. The first attack by such a terrorist group recorded by GTD is taken as a proxy for splintering.

Data on peace agreements between the Pakistani government and terrorist groups and Pakistani military action against particular terrorist groups up to March 2013 was collected by Staniland et al. (2018).

Table 3 provides descriptive statistics for the main outcome variables of interest at the group-month level. For ease of interpretation, it displays counts of terrorist attacks. In the main analysis all count outcome variables are logged. Note that the number of observations included in the main analysis is smaller than that in Table 3, due to the inclusion of leads and lags of variables. Appendix B.1 plots terrorist attacks and drone hits and misses by group over time. Terrorist attacks fluctuate strongly over time, and no definitive pattern can be discerned by eye-balling the resulting graphs.

Table 3: Descriptive statistics

	count	mean	sd	min	max
Number of terrorist attacks	1733	5.066359	15.59163	0	175
Unclaimed attacks	1733	2.632429	7.836554	0	75
Claimed attacks	1733	2.383151	8.416812	0	109
% successful attacks	1733	.2776709	.4352409	0	1
Attack in Pakistan	1733	.8072706	3.155664	0	31
Attack in Afghanistan	1733	3.174841	14.64073	0	175
Attack in rest of the world	1733	1.079631	5.432294	0	73
Mean # victims per attack.	1733	1.442927	5.858005	0	139
Attack on private target	1733	1.577034	4.837961	0	47
Attack on civilian target	1733	5.057703	15.56407	0	175
Attack on military target	1733	2.493941	9.398454	0	126
Attack with US victim	1733	.06809	.3579882	0	5
Pakistani military action	1304	.0858896	.2803084	0	1
Peace agreement in force	1304	.2062883	.4047952	0	1
Drone strikes	1733	.2186959	.6421107	0	7
Splintering	1733	.0155799	.1238791	0	1
Infighting between terrorist groups	1733	.0230814	.2267818	0	5

4.2 Empirical strategy

The main specification of interest is the following:

$$Y_{it} = \sum_{k=-6}^{6} \beta_{i,t-k} hit_{i,t-k} + \sum_{k=-6}^{6} \delta_{i,t-k} targeted_{i,t-k} + \sum_{k=-6}^{6} \gamma_{i,t-k} X_{i,t-k} + \mu_i + \theta_t + \epsilon_{it} \quad (1)$$

where subscript t indicates a month and subscript i a terrorist group. Y_{it} is the outcome variable of interest, most commonly a logged count ($ln(count+1)$) of the number of terrorist attacks. *hit* is an indicator equaling one if a group's leader was targeted by drone and killed. *targeted* equals one if a leader was targeted by drone and killed *or* if a leader was targeted by drone and survived. X

denotes any group-specific control variables. All specifications unless otherwise indicated control for the number of drone strikes on a group regardless if they targeted a leader. μ_i and θ_t are vectors of group and month-fixed effects respectively. Standard errors are Newey-West standard errors with bandwidth twelve, although Appendix B.5 investigates the robustness of results to using different standard errors and bootstrapping test statistics using randomization inference.

Specification 1 is estimated using an Ordinary Least Squares (OLS) model. As OLS assumes normally distributed standard errors to determine the level of statistical significance of coefficients, Appendix B.4 shows that residuals obtained using specification 1 are indeed approximately normally distributed. Alternatively, negative binomial models are commonly used in the literature to analyze unlogged counts of terrorist attacks (e.g. Reese et al. (2017)). This is not the model of choice here, as results from negative binomial models are inconsistent and subject to bias in the presence of a large number of fixed effects (Hilbe, 2011; Allison, 2012). However, as the extent of this bias in the present case is unclear, Appendix B.5 also presents alternative results using two fixed effect negative binomial models.

The individual coefficients on the lags of *hit* – and the *p*-value from a Wald test of their joint significance – are the main coefficients of interest. These reflect the effect of a drone hit on a terrorist leader, compared to a drone miss.[14] In experimental terms, group-months for which $hit = 1$ and $targeted = 1$ are the treatment group, and group-months for which $hit = 0$ and $targeted = 1$ form the control group. The coefficients on the lags of *targeted* reflect the effect of a drone miss.[15]

To credibly identify the causal impact of targeted leader killing, the probability of a hit must not be driven by prior trends in the outcome variable. This would for example be the case if counterterrorist organizations would accept a higher or lower probability of a hit for terrorist groups that commit an increasing number of terrorist attacks. To verify the parallel trends assumption, each specification includes six leads of *targeted* and *hit*, in addition to six lags. If the coefficients on the leads of *hit* are statistically significant, this provides evidence that the parallel trends assumption

[14] To see this, consider the following specification: $Y_{it} = \sum_{k=-6}^{6} \beta_{i,t-k} hit_{i,t-k} + \sum_{k=-6}^{6} \delta_{i,t-k} miss_{i,t-k} + \sum_{k=-6}^{6} \gamma_{i,t-k} X_{i,t-k} + \mu_i + \theta_t + \epsilon_{it}$ where *miss* is an indicator equaling one if a terrorist group's leader was targeted by drone but survived. Coefficients on $hit_{i,t-k}$ from specification 1 are identical to $\beta_{i,t-k} - \delta_{i,t-k}$ in the above.

[15] Coefficients on *targeted* in specification 1 are identical to the coefficients on *miss* in the above specification.

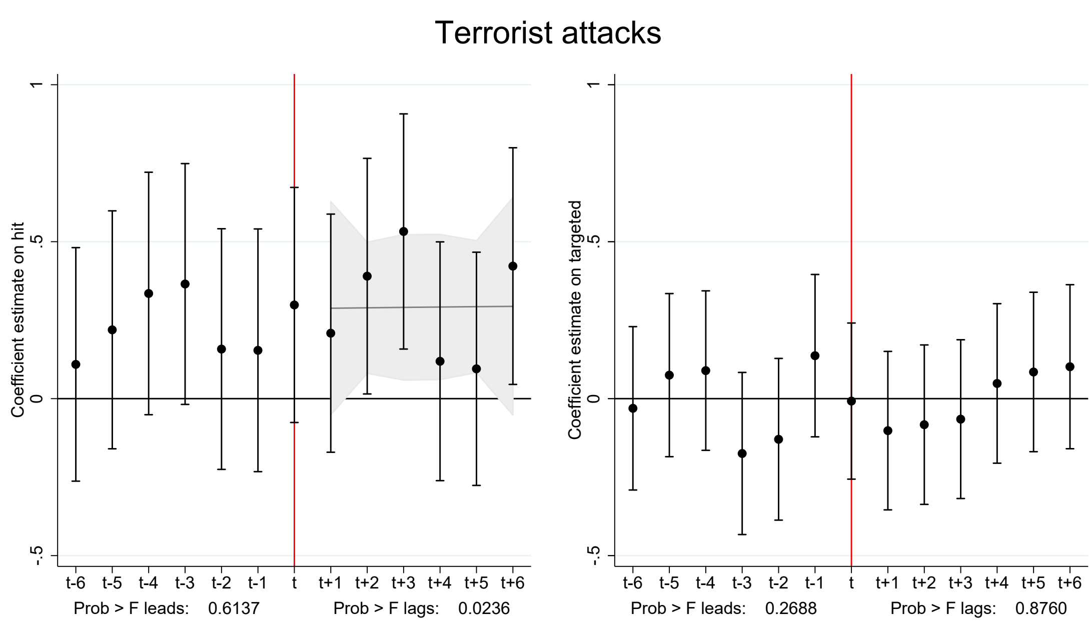
has been violated. p-values for the joint significance of leads of *hit* will be provided for all regressions.

5 Main Results

Main results suggest that the number of attacks committed by a terrorist group *increases* in the six months after a drone strike hits one of its leaders, whereas no change in terrorist violence can be detected after a strike that targets but misses a leader.

Figure 1 displays the results from specification 1. These results are also reproduced in Table 5, column 1. It displays the coefficient estimates and 95% confidence intervals for six leads and lags of the variables *hit* (left panel) and *targeted* (right panel). It also displays a quadratic trend for the six lags of *hit* and its 95% confidence interval. Recall that coefficients on the lags of *hit* reflect the effect of a drone hit compared to a miss, that coefficients on *targeted* reflect the effect of a miss, and that group and period fixed effects and control variables are included in this specification.

Figure 1: Main results



Results suggest that the number of terrorist attacks increases after a leader has been hit, compared to when he has been missed. This increase is statistically significant at the 5% level for the second, third and sixth lag of *hit* and the coefficients on all lags of *hit* (indicated by $t + k$) are jointly statistically significant at the 5% level. The increase in the number of terrorist attacks is substantial: the three significant lags suggest a respective 47.7%, 70.3% and 52.5% increase in terrorist attacks globally by a group that had its leader killed by drone, over an average of 7 attacks per month in the six month after a drone miss. There is no evidence that the trend in the number of terrorist attacks was already different prior to a hit, compared to prior to a miss: coefficient estimates on leads of *hit* (indicated by $t - k$) are individually and jointly insignificant.

The right panel of Figure 1 suggests that drone strikes that target but miss a leader have no statistically significant effect on the number of terrorist attacks over the next half year. Coefficients on all leads and lags of *targeted* are individually and jointly insignificant.

Further results suggest that the effect of a drone hit on terrorist attacks can be detected up to six to seven months thereafter. The analysis in Appendix B.7 varies the number of lags of all variables in specification1 between four and 15. None of the coefficients on *hit* is statistically significant beyond month seven in any of the models.

6 Robustness

6.1 Speed-up of the timing of terrorist attacks

The main results presented would not necessarily imply an increase in terrorist attacks overall, if terrorist groups merely change the timing of already planned attacks after a drone strike has hit their leader, so that attacks are concentrated in the six months after the strike. I find some evidence of this, but effects are not statistically significant and too small to explain the main results.

There is no evidence that terrorist groups commit their next attack substantially sooner after a drone hit on their leader, compared to after a miss (Table 4). If the duration to the first terrorist attack after the drone strike is decreased, this effect is small: point estimates suggest the first attack occurs about 13 days earlier after a hit compared to after a miss (column 1). The Cox hazard model presented in column 2 similarly suggests that the hazard of a first attack occurring is not significantly higher after a drone hit compared to after a drone miss.

On a longer time scale, there is some evidence of displacement of terrorist attacks over time, but this effect is not statistically significant for drone hits on a terrorist leader. Figure 2 displays results from specification 1, including fifteen leads and lags of all variables. For readability, only the coefficients on the lags of *hit* and *targeted* are displayed, in addition to a cubic trend and 95% confidence intervals. Results suggest that the number of terrorist attacks is somewhat lower in earlier and higher in later months after a drone miss, compared to similar periods not preceded by a drone strike aimed at a leader. Coefficients are significant for month three, ten and thirteen. Although coefficients on *hit* follow the opposite trend, there is no statistically significant decline in the number of terrorist attacks in month eight to fifteen after a drone hit on a terrorist leader, as we might expect if terrorist attacks planned for later periods were committed earlier in response to the hit. On average, the fifteen coefficients in the extended model still suggest a 17% increase in terrorist attacks after a drone *hit*.[16]

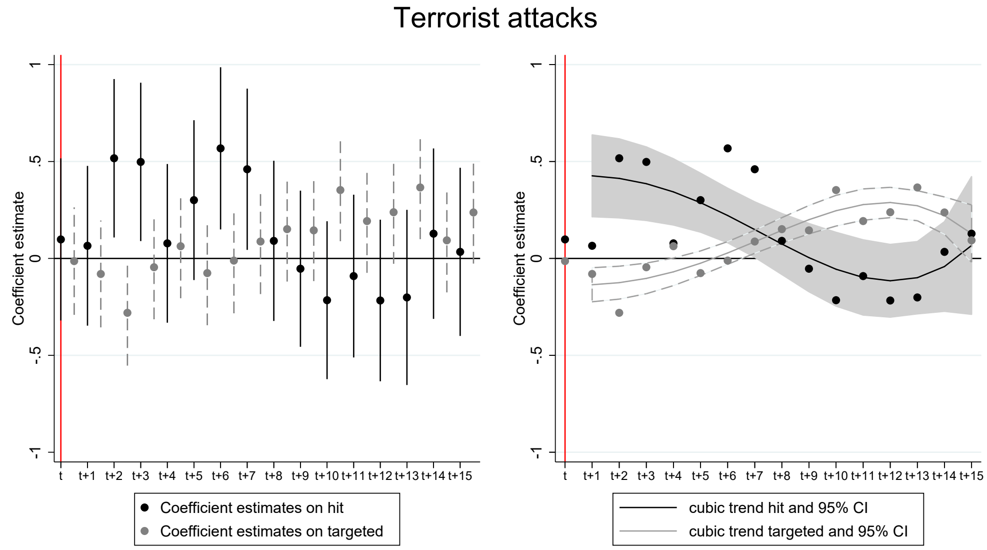
Table 4: Duration in days to first terrorist attack

VARIABLES	(1) OLS First terrorist attack	(2) cox First terrorist attack	(3) OLS First claimed attack	(4) cox First claimed attack	(5) OLS First unclaimed attack	(6) cox First unclaimed attack
Drone strike killing leader	-13.15	-0.0505	-41.56	0.354	22.10	0.318
	(36.19)	(0.283)	(32.45)	(0.314)	(29.67)	(0.248)
Constant	61.78***		99.14***		20.40	
	(12.34)		(11.06)		(10.65)	
Observations	44	44	44	44	39	39
R-squared	0.003		0.029		0.058	
Number of groups	5		5		4	
Group FE	YES	NO	YES	NO	YES	NO
Stratified on group	NO	YES	NO	YES	NO	YES

Clustered (group) standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

[16]This effect is close to half the size of that in the baseline model (36.1%), which is roughly consistent with the idea that the effect of a drone hit on terrorist attacks is null beyond month seven.

Figure 2: Timing of terrorist attacks



6.2 Alternative econometric specifications

Main results are robust to including leader-fixed effects, omitting control variables, including several additional control variables and estimating p-values for lags of *hit* through randomization inference. Similar, but somewhat weaker results are also obtained when employing an alternative definition of 'leader'. Main results are sensitive to varying which Al-Qaida branches are considered part of Al-Qaida, but not to other alternative treatments of terrorist groups.

Table 5 investigates the robustness of the main results, which are reproduced in column 1. Only lags of the variable of interest are presented to promote readability.

Omitting the number of drone strikes targeting a terrorist group as a control variable does not meaningfully affect the main results (column 2). Results are robust to including leader-fixed effects (column 3), and to controlling for six leads and lags of an indicator for Pakistani military action against a terrorist group and the existence of a peace agreement between the terrorist group and the Pakistani government (columns 4 and 5). The latter two variables are only available up to March 2013, leading to a substantial loss in observations, so these variables are not included in the baseline specifications.

The next columns of Table 5 investigate the sensitivity of main results to alternative ways of aggregating terrorist groups. The dependent variable for Al-Qaida in the baseline specification is an aggregation of terrorist attacks by all Al-Qaida branches[17]. I argue that this is the most appropriate set-up to analyse Al-Qaida terrorist attacks for several reasons. First, leaders of several of these branches are at times present in FATA. Presence of leaders of Al-Qaida in Iraq, Al-Qaida in the Arab Peninsula and Al-Qaida in the Indian Subcontinent in FATA is recorded by the BIJ.[18] Second, Al-Qaida leaders based in FATA at least attempt to control its branches (Crenshaw, 2012; Shapiro, 2013). Third, reducing attacks by branches is one motivation for drone strikes against Al-Qaida. The 2018 US counterterrorism strategy explicitly mentions that targeting key terrorists will "disrupt, degrade and prevent reconstruction of terrorist networks".[19] Nevertheless, column 6 presents results obtained if only attacks by Al-Qaida proper and Al-Qaida in the Indian Subcontinent are 'counted' as Al-Qaida terrorist attacks. Main results are clearly sensitive to this alternative treatment of Al-Qaida branches. The reader unconvinced by the arguments above may have to conclude that drone strikes on a terrorist group's leader do not affect the number terrorist attacks this group commits. However, considering Al-Qaida branches as independent organizations affiliated to Al-Qaida only strengthens the results obtained in Appendix C.1 indicating that drone strikes hitting a terrorist group's leader increase the number of terrorist attacks committed by this group's affiliates.

Main results are robust to recoding 'local Taliban' as TTP from December 2007 onwards. GTD appears to code all terrorist attacks by the Taliban in Pakistan after this date as committed by TTP, whereas the BIJ distinguishes the TTP from the 'local Taliban'. This recoding does not affect the main results (column 7).

[17]These are: Al-Qaida (30 terrorist attacks over the period under investigation); Al-Qaida in Iraq (637); Al-Qaida in Saudi Arabia (1); Al-Qaida in Yemen (12); Al-Qaida in the Arab Peninsula (907); Al-Qaida in the Indian Subcontinent (14); Al-Qaida in the Islamic Maghreb (248).

[18]Bureau of Investigative Journalism reports Ob74, Ob177, Ob348, Ob359.

[19]National Strategy for Counterterrorism of the United States of America, October 2018, available at https://www.whitehouse.gov/wp-content/uploads/2018/10/NSCT.pdf.

Table 5: Robustness of main results

VARIABLES	(1) Baseline Terr.att.	(2) No controls Terr.att.	(3) Baseline Terr.att.	(4) Pak. mil action 6L&Ls Terr.att.	(5) Peace agreem. 6L&Ls Terr.att.	(6) Alt. aggreg. AQ Terr.att.	(7) Alt. aggreg. TTP Terr.att.	(8) Alt. leader. coding Terr.att.
t	0.298	0.267	0.126	0.386	0.420*	0.0645	0.300	0.220*
	(0.191)	(0.190)	(0.219)	(0.239)	(0.235)	(0.164)	(0.194)	(0.128)
t+1	0.209	0.114	0.345*	0.338	0.361	0.0722	0.326*	0.184
	(0.193)	(0.192)	(0.195)	(0.241)	(0.236)	(0.166)	(0.196)	(0.128)
t+2	0.390**	0.351*	0.465**	0.595**	0.608**	-0.0849	0.403**	0.434***
	(0.191)	(0.191)	(0.201)	(0.251)	(0.246)	(0.164)	(0.194)	(0.129)
t+3	0.533***	0.578***	0.522***	0.748***	0.840***	0.186	0.529***	0.209
	(0.191)	(0.190)	(0.194)	(0.251)	(0.246)	(0.164)	(0.193)	(0.128)
t+4	0.119	0.140	0.130	0.166	0.217	-0.0557	0.134	0.0193
	(0.194)	(0.193)	(0.191)	(0.270)	(0.266)	(0.167)	(0.196)	(0.129)
t+5	0.0951	0.0550	0.0556	0.397	0.437*	0.0647	0.0501	0.0321
	(0.189)	(0.188)	(0.193)	(0.255)	(0.251)	(0.163)	(0.194)	(0.129)
t+6	0.422**	0.376*	0.469**	0.529**	0.554**	-0.0106	0.409**	0.101
	(0.192)	(0.192)	(0.193)	(0.260)	(0.257)	(0.166)	(0.196)	(0.131)
Observations	1,577	1,577	1,577	1,148	1,148	1,577	1,492	1,577
R-squared	0.850	0.847	0.860	0.848	0.852	0.861	0.852	0.852
Group FE	YES	YES	YES	YES	YES	YES	YES	YES
Period FE	YES	YES	YES	YES	YES	YES	YES	YES
Leader FE	NO	NO	YES	NO	NO	NO	NO	NO
Prob > F lags hit	0.0236	0.0137	0.0111	0.0258	0.0094	0.7231	0.0279	0.0384
Prob > F leads hit	0.6137	0.7885	0.1411	0.1414	0.1348	0.1753	0.3942	0.4063
Prob > F lags targeted	0.8760	0.7764	0.6224	0.6704	0.6045	0.5828	0.5815	0.6574
Prob > F leads targeted	0.2688	0.2747	0.0411	0.0438	0.0441	0.0795	0.3116	0.0849
Control mean	1.9450	1.9450	1.9450	1.9450	1.9450	1.1672	1.9450	1.7937

Newey-West standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

Lastly, column 8 presents results when using an alternative coding rule for who constitutes a terrorist leader. Under this alternative rule, all individuals marked by the BIJ as 'leader', 'commander', 'senior figure' or similar are considered leaders. This coding rule plausibly considers as drone hits, strikes on some individuals whose status as leader was exaggerated in the media after they have been hit. Despite this, the second lag of *hit* remains individually and all coefficients on *hit* jointly significant. Although the observed effect is somewhat weakened, which may be unsurprising if the alternative coding rule counts as 'hits' strikes on some individuals who may in reality not have a leading role, it is still in evidence.

Appendix B.3 suggests that the lack of statistical significance of individual leads and lags of *hit* in the main results is not an artefact of small sample size, implying that the first, fourth and fifth lag of *hit*, as well as all leads of *hit* are indeed null. Simulations thus suggest that the sample size would have to be radically expanded to make a meaningful difference to the main results.

Appendix B.5 furthermore shows that results are robust to: restricting the analysis to periods within 6 months of a hit or a miss, using a group-time trend instead of period fixed effects, using Discroll-Kraay standard errors, dropping two small terrorist groups, including all terrorist groups that have committed more than one attack in Afghanistan or Pakistan in the sample, and restricting the period under analysis to periods prior to Pakistan acquiring its own drone capability. Results are also robust to using alternative counterfactuals that are less subject to measurement error. To investigate concerns that results are driven by trends over time specific to world regions terrorist groups are active in, Appendix B.5 also shows results from region-group-month level regressions, including region-fixed effects, region-group fixed effects and region-period fixed effects respectively. Results are somewhat sensitive to using HAC instead of Newey-West standard errors.

However, calculating the main test statistic using randomization inference leaves results qualitatively unchanged (Appendix B.6). As randomization inference necessitates no assumptions regarding the distribution of the standard errors, this further mitigates the concern that statistically significant coefficients in the main result are an artefact of non-normally distributed residuals. Although there are doubts about whether these are consistently estimated (Hilbe, 2011; Allison, 2012), Appendix B.5 provides results from two fixed effects negative binomial models. In these models, most individual coefficients lose statistical significance, but coefficients on the lags of *hit* are still jointly significant.

7 Theoretical explanations for main results

This section explores which theory most plausibly explains the main results, by testing the hypotheses derived from theoretical models of problems of control, capacity, backlash and signaling (or revenge). Most evidence found favours problems of control as an explanation, although there is also some evidence in favour of signaling. Table 1 provides an overview of hypotheses and evidence found.

7.1 Problems of control

Principal-agent models of terrorist organizations suggest that the main results may be driven by a loss of control of terrorist leaders over operatives. I find evidence in favour of most hypotheses derived from theoretical models of problems of control.

The increase in terrorist attacks after a drone hit on a leader is driven by those types of attacks that leaders plausibly do not favour. Consistent with the idea that terrorist operatives may have a greater preference for violence against civilians than the leader (H1.1a), the number of attacks against civilian and private targets is statistically significantly higher after a drone hit on a leader compared to after a drone miss (Table 6, columns 1 and 2). This result echoes that obtained by Abrahms and Mierau (2017). Furthermore, the number of unclaimed attacks increases significantly for three out of six months after a drone hit (column 3). This is consistent with the idea that leaders may strategically not claim attacks by operatives that they fear will have negative repercussions for the terrorist group's long-term goals (H1.1b).

A decrease in control may also be expressed in a change in the organizational structure of the terrorist group. If all ties between leaders and operatives break down, a terrorist group may splinter (H1.1c), or operatives may start fighting among themselves (H1.1d). Indeed, a drone hits is associated with an increase in the third and fifth lag of a proxy for group splintering (Table 6,

Table 6: Effects on attack type and organizational changes

VARIABLES	(1) Civilian	(2) Private	(3) Unclaimed	(4) Splintering	(5) Infight	(6) Claimed
t	0.299	0.499***	0.0384	-0.0666	0.0186	0.552***
	(0.191)	(0.163)	(0.177)	(0.0449)	(0.0424)	(0.184)
t+1	0.209	0.0963	0.201	-0.0914**	-0.00110	0.361*
	(0.193)	(0.165)	(0.180)	(0.0448)	(0.0424)	(0.186)
t+2	0.382**	0.0390	0.343*	-0.0663	0.0373	0.271
	(0.191)	(0.163)	(0.178)	(0.0448)	(0.0422)	(0.184)
t+3	0.538***	0.391**	0.438**	0.0899**	0.159***	0.655***
	(0.191)	(0.163)	(0.177)	(0.0448)	(0.0422)	(0.184)
t+4	0.119	0.210	0.0254	0.0770*	0.0438	0.273
	(0.194)	(0.165)	(0.180)	(0.0448)	(0.0424)	(0.186)
t+5	0.0883	0.237	0.0692	0.144***	0.0225	0.201
	(0.189)	(0.161)	(0.176)	(0.0443)	(0.0418)	(0.182)
t+6	0.421**	0.397**	0.519***	0.00821	-0.0430	0.251
	(0.192)	(0.164)	(0.178)	(0.0458)	(0.0430)	(0.185)
Observations	1,577	1,577	1,577	1,577	1,577	1,577
R-squared	0.850	0.761	0.807	0.233	0.221	0.765
Group FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Prob > F lags hit	0.0221	0.0803	0.0036	0.0004	0.0122	0.0309
Prob > F leads hit	0.6168	0.2073	0.2383	0.3741	0.0000	0.2199
Prob > F lags targeted	0.8717	0.2355	0.1811	0.0006	0.4976	0.0705
Prob > F leads targeted	0.2580	0.7959	0.5480	0.2973	0.0133	0.4142
Control mean	1.9441	1.0720	1.4810	0.0594	0.0543	1.2292

Newey-West standard errors in parentheses
* $p<0.1$ ** $p<0.05$ *** $p<0.01$

column 4). If the first attack by a small affiliated group in Afghanistan and Pakistan is a credible indicator for splintering of the parent group, terrorist groups are more likely to splinter after a drone hit on their leader. Finally, a drone hit is associated with an increase in infighting (column 5). These results should be treated with some caution for two reasons. First, infighting is rare, there are only forty instances of infighting in 26 time periods. Second, in this specification, leads of *hit* are also strongly jointly statistically significant. However, Appendix B.8 shows that this is driven by a single coefficient, and not necessarily by consistently differing trends between a hit and a miss prior to the drone strike.

Table 7: Heterogeneous effects

VARIABLES	(1) Terr. att.	(2) Terr. att.	(3) Terr. att.	(4) Terr. att.	(5) Terr. att.	(6) Terr. att.
t	-0.102	0.312	-0.109	0.346	0.342	0.242
	(0.238)	(0.197)	(0.229)	(0.270)	(0.244)	(0.218)
t+1	0.119	0.166	0.198	0.189	0.141	0.118
	(0.243)	(0.199)	(0.234)	(0.268)	(0.246)	(0.220)
t+2	-0.249	0.309	-0.0485	0.000654	-0.0862	0.0734
	(0.241)	(0.197)	(0.231)	(0.263)	(0.246)	(0.215)
t+3	0.393	0.448**	0.508**	0.390	0.477*	0.298
	(0.241)	(0.198)	(0.230)	(0.265)	(0.244)	(0.217)
t+4	-0.519**	-0.00621	-0.281	-0.196	0.0808	0.0874
	(0.243)	(0.201)	(0.231)	(0.272)	(0.251)	(0.222)
t+5	-0.115	-0.0273	0.0262	-0.0167	0.277	-0.0112
	(0.237)	(0.196)	(0.227)	(0.275)	(0.252)	(0.219)
t+6	-0.206	0.262	0.0564	0.523*	0.271	0.409*
	(0.249)	(0.199)	(0.236)	(0.281)	(0.268)	(0.226)
Interaction	1.247***	0.381	1.423***	-0.486	0.185	-0.153
	(0.393)	(0.754)	(0.427)	(0.403)	(0.406)	(0.566)
t+1	0.568	0.883	0.516	-0.128	0.599	0.172
	(0.401)	(0.754)	(0.437)	(0.401)	(0.413)	(0.552)
t+2	1.726***	1.651**	1.543***	0.513	1.051**	0.983*
	(0.402)	(0.758)	(0.442)	(0.407)	(0.422)	(0.547)
t+3	0.583	1.449*	0.285	0.0600	0.248	0.267
	(0.405)	(0.759)	(0.448)	(0.400)	(0.416)	(0.524)
t+4	1.765***	1.747**	1.378***	0.494	0.120	-0.575
	(0.407)	(0.759)	(0.448)	(0.404)	(0.420)	(0.524)
t+5	0.889**	1.647**	0.441	0.192	-0.228	0.227
	(0.400)	(0.757)	(0.441)	(0.408)	(0.417)	(0.506)
t+6	1.779***	1.858**	1.302***	-0.178	0.455	0.0882
	(0.397)	(0.760)	(0.423)	(0.411)	(0.412)	(0.500)
Observations	1,577	1,577	1,577	1,577	1,577	1,577
R-squared	0.864	0.854	0.860	0.855	0.856	0.856
Interaction variable	central control	intregated	vanguard	1st hit	reward	1st in comm.
Group FE	YES	YES	YES	YES	YES	YES
Period FE	YES	YES	YES	YES	YES	YES
Prob > F lags hit	0.0261	0.0959	0.0632	0.0544	0.3061	0.3373
Prob > F leads hit	0.0991	0.5429	0.2143	0.7520	0.1320	0.4661
Prob > F lags inter.	0.0000	0.1257	0.0001	0.5116	0.1120	0.1616
Prob > F leads inter.	0.0000	0.5751	0.0000	0.7435	0.0143	0.0537
Control mean	1.9450	1.9450	1.9450	1.9450	1.9450	1.9450

Newey-West standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

If the main results of these study are due to aggravated problems of control, we may furthermore observe heterogeneous effects across terrorist groups and leaders. Specifically, terrorist groups that rely more strongly on central control may be more strongly affected (H1.2a), and the drop in control may be largest for the first leader killed, as they were initially not subject to incentives to trade off control for secrecy (H1.2b). Results on heterogenous effects, displayed in Table 7, should be interpreted with some caution: given the limited number of drone strikes targeting a terrorist leader and limited number of groups, statistical power to detect any interaction effects may be lacking.

Keeping this in mind, the first three columns of Table 7 suggest that the effect of a drone hit on a terrorist leader is greater for terrorist groups that rely more strongly on central control. I employ a classification by Staniland (2014), in which integrated and vanguard terrorist groups have strong central control. Staniland considers the Taliban an integrated group (p140). Al-Qaida is not explicitly classified, but its strategy of making alliances closely resembles Staniland's description of a vanguard group (p44-46). No other groups subject to drone hits and misses on their leaders are classified by Staniland as having strong central control[20]. Column 1 reveals that the effect of a drone hit on terrorist attacks is indeed stronger for these two organizations. This heterogeneous effect holds both for the Taliban, the one integrated organization (column 2), and for Al-Qaida, the only vanguard organization (column 3).

Lastly, column 4 of Table 7 provides some very tentative support for the hypothesis that the effect of a drone hit is stronger for the first leader hit. Coefficients on the second to fifth lag of the interaction term are positive and of substantial size compared to their non-interacted counterparts. They are not individually or jointly statistically significant however.

7.2 Capacity

There is no evidence that terrorist groups, in response to a drone strike hitting their leader, substitute a small number of high-impact attacks with a large number of low-impact attacks, as capacity models would suggest (H2.1).

[20]TTP is classified as a Parochial group (p.6), the Stanford mapping militants project describes Harkat-ul-Jihad-al-Islami as consisting of "small, autonomous cells", not suggesting strong central control and the Haqqani network is described by Staniland as a group with "strong social ties' (p.138).

A low-impact attack might be an 'unsuccessful' terrorist attack, i.e. the planned attack type was foiled, or an attack with a small number of victims (H2.1a and H2.1b respectively). Table 8 provides no evidence that these attack types increase after a drone hit on a terrorist leader. If anything, the percentage of 'successful' terrorist attacks (column 1) and the mean number of victims per terrorist attack (column 2) is lower for some individual months after a hit.

Furthermore, there is no evidence that terrorist groups substitute attacks against 'softer' targets for attacks against 'hard' targets (H2.1c). Even though the number of attacks against civilian or private targets does increase (Table 6), Table 8 shows no significant decline in the number of terrorist attacks against military targets (column 3) or attacks with US casualties or injured (column 4).[21]

Finally, Table 8 provides no evidence that terrorist groups are concentrating their attacks in their 'homebase' of Pakistan at the expense of attacks in Afghanistan or the rest of the world (excluding Western Europe, the US and Australia) after a drone hit on their leader (H2.1d). In fact, the main results are driven by terrorist attacks in the rest of the world (ROW, column 5)[22]. Although it would be interesting to investigate the effect of a drone hit on terrorist attacks in 'the West', there have been only eight such attacks over the research period, making this impossible.

The observation that the increase in terrorist attacks after a drone hit is concentrated in the rest of the world rather than in Pakistan or Afghanistan is interesting in light of the other three families of theoretical models. We might speculate that a new leader taking the place of a leader killed by drone has greater trouble exerting control over far-away operatives than operatives close to home. This contrasts with the backlash or signaling perspective. From either of those perspectives, we might expect a stronger reaction in Pakistan, as most civilians killed are Pakistani, and because operatives closer to the leader killed may have a greater incentive to signal strength.

[21] The coefficient on the leads of *hit* are jointly statistically significant in this specification, but a plot of the coefficients reveals a downward trend in the number of terrorist attacks with a US victim prior to a drone hit compared to a drone miss. Hence, there is no evidence that the probability of a drone hit is driven by an increasing number of attacks on US citizens.

[22] In the models presented in columns (6) and (7), the leads of *hit* are jointly statistically significant. However, they are only statistically significant at the 10% level and since this is two models among many, this may be due to multiple testing.

Table 8: Substitution of terrorist attack types

VARIABLES	(1) % success	(2) mean # vics.	(3) Military	(4) US vic.	(5) Pak.	(6) Afgh.	(7) ROW
t	0.0343	-0.238	0.230	0.0286	0.0405	0.0735	0.327***
	(0.101)	(2.194)	(0.193)	(0.0633)	(0.110)	(0.125)	(0.127)
t+1	0.0434	0.314	0.331*	-0.0559	-0.0409	-0.0539	0.175
	(0.102)	(2.193)	(0.196)	(0.0639)	(0.110)	(0.128)	(0.128)
t+2	0.0577	1.293	0.589***	0.0288	-0.117	0.01000	0.462***
	(0.101)	(2.188)	(0.194)	(0.0634)	(0.110)	(0.126)	(0.127)
t+3	0.00324	-3.753*	0.545***	0.0675	0.163	0.0699	0.331***
	(0.101)	(2.193)	(0.193)	(0.0634)	(0.110)	(0.126)	(0.127)
t+4	-0.0284	0.165	0.0647	0.0762	-0.221**	0.0716	0.275**
	(0.102)	(2.189)	(0.197)	(0.0639)	(0.110)	(0.128)	(0.129)
t+5	-0.178*	-1.716	0.115	-0.0373	0.0189	0.0624	0.0544
	(0.0999)	(2.163)	(0.192)	(0.0627)	(0.108)	(0.125)	(0.126)
t+6	0.0588	-3.004	0.532***	-0.0283	0.102	-0.0478	0.388***
	(0.103)	(2.237)	(0.194)	(0.0642)	(0.111)	(0.126)	(0.127)
Observations	1,577	1,577	1,577	1,577	1,577	1,577	1,577
R-squared	0.676	0.186	0.741	0.355	0.818	0.893	0.797
Group FE	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES
Prob > F lags hit	0.5758	0.4155	0.0003	0.5433	0.0284	0.9266	0.0004
Prob > F leads hit	0.8584	0.3023	0.2727	0.0448	0.9328	0.0604	0.0889
Prob > F lags targeted	0.1070	0.1762	0.6854	0.5041	0.3375	0.2017	0.1575
Prob > F leads targeted	0.3795	0.9912	0.0390	0.0000	0.2110	0.1234	0.8604
Control mean	0.7582	3.9494	1.0786	0.0629	0.9475	0.2520	0.8349

Newey-West standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

7.3 Signaling

There is some evidence that a drone hit on a terrorist leader induces terrorist groups to signal their strength and resolve by committing an increasing number of attacks (H3.1).

Attacks that send a strong signal may include attacks that quickly follow the drone strike, are claimed, and hit high-profile targets. From the main results, the timing of the increase in terrorist attacks is not obviously consistent with the signaling mechanism: statistically significant increases in the number of terrorist attacks are only observed from two months after the drone hit onward (Figure 1). Table 8 furthermore shows no increase in terrorist attacks on US citizens, which would be a high-profile target.

Consistent with the signaling mechanism however, Column 6 of Table 6 does show a statistically significant increase in the number of claimed terrorist attacks in month one and three after a drone hit compared to after a drone miss. Coefficients are jointly statistically significant. Furthermore, Table 8 column 3 also shows a significant increase in attacks on military targets, also high-profile, after a drone hit.

Lastly, the incentive to signal strength may be greater after the death of more prominent leaders (H3.2). The final columns of Table 7 explore this hypothesis. Results in these columns provide some tentative support in favour of this hypothesis. Terrorist attacks are significantly higher in the second month after a drone hit on a leader who is designated 'first in command' according to the Stanford project (column 6), or for whom the US Department of Justice ever offered a reward (column 5). However, lags on neither set of interaction terms are jointly statistically significant.

In sum, there is evidence in favour of some hypotheses following from the signaling mechanism. Alternatively, we might think that patterns observed arise out of terrorist group's desire for revenge. However, not all hypotheses are supported with evidence and this mechanism cannot explain the results on unclaimed attacks, group splintering or infighting.

7.4 Backlash

There is no evidence that drones strikes killing civilians are associated with an increase in terrorist attacks, as *backlash* would suggest (H4.1).

Even if drone strikes cause backlash, this effect does not necessarily coincide with the effect of targeted leader killing. Backlash would affect the analysis only if drone hits on a leader killed more civilians than drone misses, and Table 2 does not provide any evidence for this. There is also no evidence that terrorist organizations specifically use drone strikes on terrorist leaders in their recruitment propaganda: propaganda refers to drone strikes as a 'failing' policy and does not emphasize hits on terrorist leaders (Ludvigsen, 2018).

Nevertheless, I test whether drone strikes killing civilians are associated with an increase in terrorist attacks. To do so, I estimate two variations on equation 1. The first variation replaces hit_{it} with the number of civilian casualties from drone strikes targeting group i in month t and $targeted_{it}$ with the total number of casualties from drone strikes in month t on group i. The second variation replaces hit_{it} with an indicator that equals one if some drone strike in month t targeting terrorist group i instead killed only civilians[23], and $targeted_{it}$ with an indicator for any drone strike in month t on group i. These specifications do not control for the total number of drone strikes to avoid multicolinearity. BIJ provides maximum and minimum casualty estimates. Table 9 shows results from maximum casualty estimates, but similar results are obtained when using minimum casualty estimates (not shown).

Table 9 provides no evidence that drone strikes hitting only civilians, or done strikes hitting many civilians, are associated with an increase in terrorist attacks, compared to other drone strikes (H4.1). If anything, it shows a *decrease* in the number of terrorist attacks, by the terrorist group itself and by an aggregation of all terrorist groups in the study[24]. The sign on virtually all coefficients is negative, although coefficients on the lags of the dependent variable of interest are not jointly statistically significant in each instance.

[23] If the maximum number of civilian casualties is larger than or equal to the minimum total number of casualties from a drone strike (for maximum civilian casualty estimates), or if the maximum number of civilian casualties is equal to the maximum total number of casualties (for minimum civilian casualty estimates).

[24] Using specification: $Y_t = \sum_{k=-6}^{6} \beta_{t-k} hit_{t-k} + \sum_{k=-6}^{6} \delta_{t-k} targeted_{t-k} + \lambda t + \epsilon_t$, where λ captures a linear time trend

Table 9: Drone strikes with civilian casualties

VARIABLES	(1) Terr. att.	(2) Terr. att.	(3) Terr. att.	(4) Terr. att.
t	-0.0140***	-0.0381	-0.0147*	0.667***
	(0.00435)	(0.0760)	(0.00844)	(0.248)
t+1	-0.0160***	-0.149*	-0.00875	-0.0192
	(0.00436)	(0.0762)	(0.00864)	(0.315)
t+2	-0.0166***	-0.0828	-0.0136**	-0.749**
	(0.00435)	(0.0780)	(0.00682)	(0.334)
t+3	-0.0127***	-0.0617	0.00120	0.322
	(0.00434)	(0.0770)	(0.00490)	(0.243)
t+4	-0.0102**	-0.00751	-0.00694	-0.278
	(0.00446)	(0.0760)	(0.00905)	(0.270)
t+5	-0.00602	-0.101	-0.00550	-0.382
	(0.00450)	(0.0767)	(0.0116)	(0.256)
t+6	-0.00353	-0.0583	0.00458	-0.435
	(0.00440)	(0.0809)	(0.00747)	(0.301)
Observations	1,577	1,577	132	132
R-squared	0.858	0.848		
Indep. var.	# civ	only civ	# civ	only civ
Control	# cas	strike	# cas	strike
Model	Gr-mnth	Gr-mnth	Month	Month
Group FE	YES	YES	NO	NO
Period FE	YES	YES	NO	NO
Time trend	NO	NO	YES	YES
Affiliate FE	NO	NO	NO	NO
Prob > F lags	0.0026	0.4792	0.1866	0.0007
Prob > F leads	0.0000	0.0001	0.1546	0.7323

Newey-West standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

This study by no means convincingly shows that drone strikes causing civilian casualties decrease terrorist violence. In two of the specifications shown, the leads of the dependent variable are jointly statistically significant. As this provides evidence that the parallel trends assumption is violated, these results should be interpreted with due caution. The sole purpose of this exercise is to show the lack of evidence in favour backlash.

8 Conclusion

Exploiting a natural experiment provided by drone strikes hitting and missing terrorist leaders in FATA, Pakistan, this paper investigates how drone strikes killing terrorist leaders – and undermining control within terrorist organizations – affect terrorist attacks. It suggests that such counterterrorism policies can backfire, and that terrorist groups whose leader is killed increase the number of attacks they commit in three out of six months after the drone hit by between 47.7% and 70.3%.

This paper suggests that the most likely explanation for this result is that the new leader is less able or willing to exert control over the group's operatives, following theoretical models by Shapiro (2013) and Abrahms and Potter (2015). Although unable to measure control within terrorist organizations directly, this paper provides evidence in favour of six hypotheses indirectly testing whether drone strikes undermine control. We have theoretical reasons and empirical reasons to expect that leaders exert control to limit indiscriminate violence against civilians, and that leaders strategically leave attacks they did not sanction unclaimed. This paper provides evidence that drone strikes killing terrorist leaders lead to more terrorist attacks targeting civilians (echoing results obtained by Abrahms and Mierau (2017)) and more unclaimed terrorist attacks. Less control of terrorist leaders over operatives might also translate into changes in the organizational structure of terrorist groups. This paper finds drone hits to be related to terrorist group splintering and infighting. Finally, the effect of a decrease in control is predicted to be larger for those groups and leaders that relied more strongly on central control to begin with.

Some evidence is also found in favour of signaling (or revenge) as a theoretical explanation. In some of the six months after a drone hit on a terrorist leader, the number of terrorist attacks on military targets, and claimed terrorist attacks increases.

Two caveats to these results are in order. First, this paper is only able to capture the medium-term effect (six to fifteen months) of targeted leader killing. It has been suggested that terrorist organizations, specifically Al-Qaida, are in the process of disintegration partially because their leaders have been consistently killed or captured, and that increased violence may be the organization's "death throws" (Cronin 2006). Although I cannot exclude the possibility that this may happen in the future, the number of attacks by the terrorist organizations studied in this paper currently shows no sign of decreasing. In fact, the number of attacks has increased over eight-fold between 2004 and 2015. Secondly, this paper investigates the effect of drone hits relative to drone misses. It cannot comment on the effect of the *threat* of drone strikes, i.e. the number of terrorist attacks in the current state of the world, relative to a counterfactual world in which terrorist leaders were never targeted by drone. Similarly, it cannot comment on individuals' willingness to join terrorist groups in a world with and without drone strikes risking civilian casualties. Hence results do not directly translate into an assessment of the overall impact of the use of drone technology.

The conclusion that drone strikes may undermine control within terrorist groups has important policy implications beyond counterterrorism, in the arenas of law and diplomacy. Legal scholars suggest that the lawfulness of drone strikes under International Humanitarian Law (IHL) depends on an armed group's level of internal organization (Heyns et al., 2016). For IHL to apply to drone strikes, they must take place in the context of a Non-International Armed Conflict. The level of organization of parties to the conflict, including the existence of a command structure, is one of two criteria used to determine whether a situation is thus classified (Heyns et al., 2016). The results presented in this paper suggest that drone strikes, by virtue of their own 'success' in killing leaders and undermining terrorist command structure, may contribute to making themselves unlawful.

Undermining leaders' control over a terrorist organization may furthermore undermine the prospect of peace talks. Peace agreements between the Pakistani government and terrorist groups are common: Staniland et al. (2018) document 24 individual peace deals. However, anecdotal evidence suggests that leader killing by drone may impede such agreements. For example, TTP leader Hakimullah Mehsud was reportedly ready to participate in peace talks, but following his death by drone, TTP splintered over the question of whether to engage in such talks and TTP attacks spiked (Crenshaw (2012)). Future research may investigate the impact of drone strikes, or other counterterrorism policies, on terrorist group splintering and peace agreements in greater detail.

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Online Appendix

A Data

A.1 Terrorist groups included in dataset (as classified by BIJ)

Table A.1

Group	Subgroups[25]	Start month[26]
Al-Qaida	AQ in Iraq	
	AQ in the Arab Peninsula	
	AQ Indian Subcontinent	
	Abu Kasha's group	
	Islamic Army of Great Britain	
	Lashkar al Zil	
Al-Badr		
East Turkestan Islamic Movement		
Haqqani Network	Maulvi Ihsanullah's faction	
Harkat-ul-Jihad al-Islami		
Islamic Movement of Uzbekistan (IMU)		
Islamic Jihad Union		
Jund al Khilafah		September 2011
Lashkar-e-Islam		
Punjabi Taliban		
Taliban	Hezb-i-Islami	
	Maulvi Nazir's faction	
	SWAT Taliban	
Taliban (Pakistan)		
Tehrik-e-Taliban Pakistani (TTP)	Khan Said's faction	December 2007
	Hafiz Gul Bahadur's faction	
	Jamaat e Islami Azad Kashmir	
	Sajna faction	

[25]This table does not give a comprehensive overview of subgroups of these terrorist groups, merely of those subgroups that are named in the BIJ data.
[26]If after January 2014.

A.2 Codebook targeted leader killing

Coding Instructions

targettype

1=vehicle
2=building
3=both a vehicle and a building
9=unknown/other

Record the physical object hit by the strike, according to BIJ.

targetnamed

0=no
1=yes

Code 1 if AT LEAST ONE of the following is satisfied:

1. Report includes a NAMED individual classified by BIJ as "leader", "commander", "senior figure" or similar of a militant group, who, or a location associated with whom, is named by BIJ as "target" of a drone strike, potential or otherwise, or is mentioned as (falsely) claimed to have died in or as a result of the strike by any source.
2. BIJ identifies as a target of the strike, potential or otherwise, OR as having died in or as a result of the strike
   a. Individuals (allegedly) associated with a NAMED militant group, OR
   b. (alleged) militants (allegedly) associated with a NAMED individual, identified implicitly or explicitly as leader or similar of a militant group, OR
   c. a location associated with a NAMED militant group.

Code 0 otherwise.

IF 0: leave all remaining fields blank
IF 1: for EACH UNIQUE NAMED militant group under (2.) or associated with individual(s) under (1.) AND EACH UNIQUE NAMED individual NOT associated with a named militant group under (1.) or (2.) fill in the remaining fields.

NOTE: see page 2 for known named militant groups

group?HVTtarget

0=no
1=yes

FOR EACH UNIQUE named militant group or named individual not associated with a militant group
Code 1 if ALL of the following are satisfied

1. A named individual OR a gathering of more than two unnamed individuals,
2. Classified by BIJ as "leader(s)", "commander(s)", "senior figure(s) or similar of a militant group
3. Was either
   a. Named by BIJ as "target" of the drone strike, potential or otherwise
   b. Mentioned as (falsely) claimed to have died in or as a result of the strike by any source.

Code 0 otherwise

group?HVTdied

0=no
1=yes
9=unknown

Blank if group?HVTtarget=0

FOR EACH UNIQUE named militant group or named individual not associated with a militant group

Code 1 if ANY of the individuals recorded under group?HVTname have died in, or as a result of injuries incurred during, the drone strike.
Code 9 if BIJ mentions the death of ALL individuals recorded under group?HVTname is uncertain and/or if the BIJ cites conflicting reports on the death of ALL individuals recorded under group?HVTname.
Code 0 if otherwise.

group?HVTname

Text field (codes available)

Blank if group?HVTtarget=0 AND group?militant is EITHER 2, 3, OR 4 not involving a location associated with a named leader.

FOR EACH UNIQUE militant group or named individual not associated with a militant group

Record name(s) of HVT(s) under group?HVTtarget and group?militant IF group?militant=1 OR group?militant=4 and it involves a location associated with a named leader, separated by ; and including any aliases in brackets ( ).

Record ‘gathering’ if group?HVTtarget=1 because the report involved a gathering of more than two unnamed individuals.

group?militant

1=Militants associated with HVT
2=Named militants
3=Unnamed militants
4=Location associated with militants

Blank if group?HVTtarget=1

FOR EACH UNIQUE named militant group or named individual not associated with a militant group
record the LOWEST code applicable. Code:

1. If BIJ identifies as a target of the strike, potential or otherwise, OR as having died in or as a result of the strike, one or more individuals identified as (alleged) militant(s) AND associated with, or alleged to be associated with, a NAMED individual (or “Named individual’s group”) identified implicitly or explicitly as leader or similar of a militant group.
2. If BIJ identifies as a target of the strike, potential or otherwise, OR as having died in or as a result of the strike, one or more individual(s) BY NAME AND as militant(s) or alleged militant(s) associated with the named group.
3. If BIJ identifies as a target of the strike, potential or otherwise, OR as having died in or as a result of the strike, one or more UNNAMED individual(s) as (alleged) militant(s) associated with the named group.
4. If BIJ records that the location that was struck is (allegedly) associated with the named militant group or a named individual classified as “leader”, “commander” “senior figure” or similar.

group?name

Text field, see spelling below

FOR EACH UNIQUE militant group, record name of:

1. the militant group the HVT is associated with if group?HVTtarget=1, OR group?militant=1 OR group?militant=4 and this involves a location associated with an HVT.
2. the militant group militants are associated with if group?militant=2 OR group?militant=3
3. the militant group the location struck is associated with if group?militant=4 AND this does NOT involve a location associated with a an HVT.

Record ‘unknown’ if group?HVTtarget=1 OR group?militant=1 AND the HVT is NOT associated with a militant group.

AQ: Al Qaeda
Haqqani: Haqqani network
LeI: Lashkar-e-Islam
IMU: Islamic Movement of Uzbekistan
Afghan Taliban: Afghan Taliban
TTP: Pakistani Taliban, Tehrik-e-Taliban Pakistani, Local Taliban
Taliban: Taliban, unspecified

Foreigner: including “Arab”, “non-local” or individuals of a specific nationality not Pakistani, Afghani, Uzbek or Punjabi.
NOT TO BE CODED SIMULTANESOULY WITH AQ
Punjabi: Punjabi militants
Uzbeks: Uzbeks, Uzbek militants.
NOT TO BE CODED SIMULTANEOUSLY WITH IMU

A.3 Terrorist leaders included in dataset

Table A.2

Leader name	Group	Subgroup	# times targeted	hit
Abu Mus'ab al-Zarqawi	Al-Qaida	AQI	0	0
Abu Yahya al-Libi	Al-Qaida		2	1
Ahmad Farouq	Al-Qaida	AQIS	3	1
Amran Ali Siddiqi	Al-Qaida	AQIS	1	1
Atiyah adb al-Rahman	Al-Qaida		3	1
Ayman al-Zawahiri	Al-Qaida		2	0
Badruddin Haqqani	Haqqani network		2	1
Baitullah Mehsud	TTP		3	1
Hafiz Gul Bahadur	TTP		2	0
Hakimullah Mehsud	TTP		5	1
Jalaluddin Haqqani	Haqqani network		0	0
Maulana Faqir Muhammed	TTP		1	0
Maulvi Ahmad Jan	Haqqani network		1	1
Maulvi Nazir[27]	Taliban	Maulvi Nazir group	2	1
Muhammad Ilywas Kashmiri	Harkat-ul-Jihad		5	1
Mustafa Abu al-Yazid	AQ		1	1
Nasser al-Wuhayshi	AQ	AQAP	1	0
Qari Hussain	TTP		6	1
Qarri Imran	AQ	AQIS	1	1
Sangeen Sadran	Haqqani network		3	1
Sirajuddin Haqqani	Haqqani network		1	0
Wali ur Rehman Mehsud	TTP		1	1
TOTAL			46[28]	15

[27] Note that major attacks by the Maulvi Nazir faction as identified by the Stanford project are all coded as having been perpetrated by the 'Taliban' by the GTD. Hence, this faction is classified as Taliban, even though it was briefly merged with the TTP (Crenshaw, 2012)

[28] Note that the unit of analysis for this Table is the leader, whereas the unit of analysis in Table 2 of the main text is the group. As one drone strike targeted (and missed) two leaders from the same group simultaneously, the number of individual leaders targeted equals 46, but the number of times a drone strike targeted a group's leader equals 45.

A.4 Splinter groups included in dataset

Table A.3

Affiliate name	Parent group name	Source
Abdullah Azzam Brigades	AQ	https://www.trackingterrorism.org/group/abdullah-azzam-brigades-aab
Abu Hafs Katibatul al-Ghurba al-Mujah	AQ	https://www.trackingterrorism.org/group/katibat-al-ghuraba-al-turkistan-kgt-al-qaeda-aqc
Ahle Sunnat Wal Jamaat	AQ	http://www.bbc.co.uk/news/world-asia-17322095
Al-Fatah	None	https://www.trackingterrorism.org/group/al-fatah
Al-Jihad (Pakistan)	Not found	
Al-Mansoorian	AQ	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/79
Al-Qaida	AQ	
Al-Qaida in the Indian Subcontinent	AQIS	
Amr Bil Maroof Wa Nahi Anil Munkir	AQ	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/445
Ansar Al-Mujahideen (Pakistan)	TTP	http://www.thefridaytimes.com/tft/ptis-peace-paradox/
Ansar Wa Mohajir (Pakistan)	TTP	https://speekout.wordpress.com/category/ansar-wa-mohajir/
Ansarul Islam (Pakistan)	None	https://www.rferl.org/a/pakistan-ansar-ul-islam-taliban-ttp/24886662.html
Baba Ladla Gang	None	https://www.dawn.com/news/1312260
Baloch Liberation Army (BLA)	None	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/297
Baloch Liberation Front (BLF)	None	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/297
Baloch Liberation Tigers (BLT)	None	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/297
Baloch Militant Defense Army	Not found	

Continuation of Table A.3		
Affiliate name	Parent group name	Source
Baloch Mussalah Diffah Tanzim (BMDT)	TTP	https://www.trackingterrorism.org/group/balochistan-musalla-difa-tanzeem-bmdt-haq-na-tawar
Baloch National Liberation Front	None	
Baloch Nationalists	Not found	
Baloch Republican Army (BRA)	None	
Baloch Republican Guards (BRG)	None	https://www.app.com.pk/14-activists-of-banned-outfit-in-balochistan-surrender/
Baloch Waja Liberation Army (BWLA)	None	
Baloch Young Tigers (BYT)	Not found	
Balochistan Liberation United Front	None	
Balochistan National Army	None	https://www.trackingterrorism.org/group/baluchistan-national-army
Bhittani tribe	Not found	
Free Balochistan Army (FBA)	Not found	
Gholam Yahya Akbar	Taliban	https://www.longwarjournal.org/archives/2009/02/coalition_strike_kil.php
Gunmen	Not found	
Hafiz Gul Bahadur Group	TTP	
Haji Fateh	None	http://www.xactrisk.com/international-security-update.html
Halqa-e-Mehsud	TTP	
Haqqani Network	Haqqani	
Harkatul Jihad-e-Islami	Harkat-Ul-Jihad	
Hizb al-Tahrir al-Islami (HT)	None	https://www.globalsecurity.org/military/world/para/hizb-ut-tahrir.htm
Hizb-I-Islami	Taliban; AQ	http://www.understandingwar.org/hizb-i-islami-gulbuddin-hig
Imam al-Bukhari Brigade	Taliban	https://www.longwarjournal.org/archives/2016/07/foreign-jihadists-advertise-role-in-latakia-fighting.php

Continuation of Table A.3		
Affiliate name	Parent group name	Source
Islambouli Brigades of al-Qaida	AQ	https://www.trackingterrorism.org/group/al-islambouli-brigades-al-qaeda
Islami Jamiat-e-Talaba (IJT)	AQ; TTP	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/101?highlight=IJT
Islamic Movement of Uzbekistan (IMU)	IMU	
Jaish al-Muslimin	Taliban	https://reliefweb.int/report/afghanistan/baag-afghanistan-monthly-review-oct-2004
Jaish al-Umar (JaU)	Not found	
Jaish as-Saiyouf (Army of Swords)	Not found	
Jaish Usama	TTP	https://nation.com.pk/05-Mar-2014/not-bound-to-follow-ceasefire-jaish-e-usama
Jaish-e-Islam	None	https://jamestown.org/program/a-profile-of-militant-groups-in-bajaur-tribal-agency/
Jaish-e-Khorasan (JeK)	AQ	https://www.linkedin.com/pulse/rise-islamic-state-terror-its-climax-september-2014-hassan-ali/
Jaish-e-Mohammad	AQ; Taliban	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/95
Jamaat Tauhid Wal Jihad (Pakistan)	AQ	https://ctc.usma.edu/militant-imagery-project/0068/
Jamaat-E-Islami (India/Pakistan)	None	
Jamaat-ul-Ahrar	TTP	Dawn
Jeay Sindh Qaumi Mahaz (JSQM)	None	https://tribune.com.pk/story/354308/pakistan-day-jsqm-leader-demands-freedom-for-sindh-and-balochistan/
Jundallah (Pakistan)	TTP	Dawn
Khatm-e-Nabuwat (KeN)	None	https://www.rabwah.net/ahrar-khatmenabuwat-terrorist-organizations/
Khorasan Chapter of the Islamic State	TTP; Taliban	https://thediplomat.com/2015/05/islamic-state-and-jihadi-realignments-in-khorasan/
Khorasan jihadi group	AQ	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/21?highlight=khorasan
Lashkar-e-Balochistan	None	https://www.trackingterrorism.org/group/lashkar-e-balochistan
Lashkar-e-Islam (Pakistan)	Lashkar-e-Islam	
Lashkar-e-Jarrar	Not found	

Continuation of Table A.3

Affiliate name	Parent group name	Source
Lashkar-e-Jhangvi	None	
Lashkar-e-Taiba (LeT)	AQ	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/79
Mahaz Fedai Tahrik Islami Afghanistan	Taliban	Dawn
Mahsud Tribe	Not found	
Majlis-e-Askari	TTP	https://therearenosunglasses.wordpress.com/2017/05/25/us-drone-strike-in-khost-kills-3-ttpisis-taliban-while-pak-army-hangs-2-more-same-group/
Majlis-e-Lashkari	TTP	https://therearenosunglasses.wordpress.com/2017/05/25/us-drone-strike-in-khost-kills-3-ttpisis-taliban-while-pak-army-hangs-2-more-same-group/
Militants	Not found	
Mujahideen Ansar	TTP	http://www.thefridaytimes.com/tft/ptis-peace-paradox/
Mullah Dadullah Front	Taliban	https://www.trackingterrorism.org/group/dadullah-front
Muslim extremists	Not found	
Muslim Fundamentalists	Not found	
Mutahida Majlis-e-Amal	None	https://www.geo.tv/latest/166882-muttahida-majlis-e-amal-restored
Muttahida Qami Movement (MQM)	None	
New People's Army (NPA)	None	
Orakzai Freedom Movement	TTP	https://books.google.co.uk/books/about/Countering_New_est_Terrorism.html?id=8TZDDwAAQBAJ&redir_esc=y
Pakistani People's Party (PPP)	None	
People's Amn Committee	None	
Punjabi Taliban	Punjabi Taliban	
Qari Kamran Group	TTP	https://www.trackingterrorism.org/group/qari-kamran-group
Separatists	Not found	
Sindh Liberation Front	None	

Continuation of Table A.3		
Affiliate name	Parent group name	Source
Sindh Revolutionary Army	None	
Sindhu Desh Liberation Army (SDLA)	None	
Sindhudesh Revolutionary Army (SRA)	None	
Sipah-e-Sahaba/Pakistan (SSP)	None	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/147
Sipah-I-Mohammed	None	http://www.satp.org/satporgtp/countries/pakistan /terroristoutfits/SMP.htm
Sirri Powz	Not found	
Sunni Muslim extremists	Not found	
Taliban	Taliban	
Taliban (Pakistan)	Local Taliban	
Tanzeem al-Islami al-Furqan	None	https://www.trackingterrorism.org/group/tanzeem-ul-islami-ul-furqan-tif
Tawheedul Islam	Not found	
Tehrik-e-Khilafat	TTP	http://www.dailymail.co.uk/news/article-2686009/Pakistani-terror-group-jihadi-group-defect-ISIS-outside-Middle-East-leader-al-Baghdadis-influence-grows.html
Tehrik-e-Nafaz-e-Shariat-e-Mohammadi	TTP	http://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/411
Tehrik-e-Nifaz-e-Aman Balochistan	None	http://thebalochistanpoint.com/taliban-in-balochistan/
Tehrik-e-Taliban Islami (TTI)	TTP	https://in.reuters.com/article/idINIndia-58032520110701
Tehrik-e-Tuhafaz (Pakistan)	None	https://www.catholicforlife.com/tag/tehreek-e-tuhafaz/
Tehrik-i-Taliban Pakistan (TTP)	TTP	
Tela Mohammed	Not found	
Tribesmen	Not found	
United Baloch Army (UBA)	None	http://www.dopel.org/UBA.htm
Unknown	Not found	

Continuation of Table A.3		
Affiliate name	Parent group name	Source
Uzair Baloch Gang	None	https://www.dawn.com/news/1326325
Zehri Youth Force (ZYF)	Not found	

B Further results and robustness checks

B.1 Graphs of terrorist attacks and drone hits and misses

Graphs B.1-B.5 depict raw data on (unlogged) terrorist attacks, and drone hits and misses on terrorist leaders, for those terrorist groups that experienced at least one hit and one miss. The number of terrorist attacks by group fluctuates strongly over time, in periods after drone hits or misses and in periods without drone attempts on a group's leader. From these graphs alone, it is difficult to discern any definitive pattern in the number of terrorist attacks after a drone hit, versus after a drone miss.

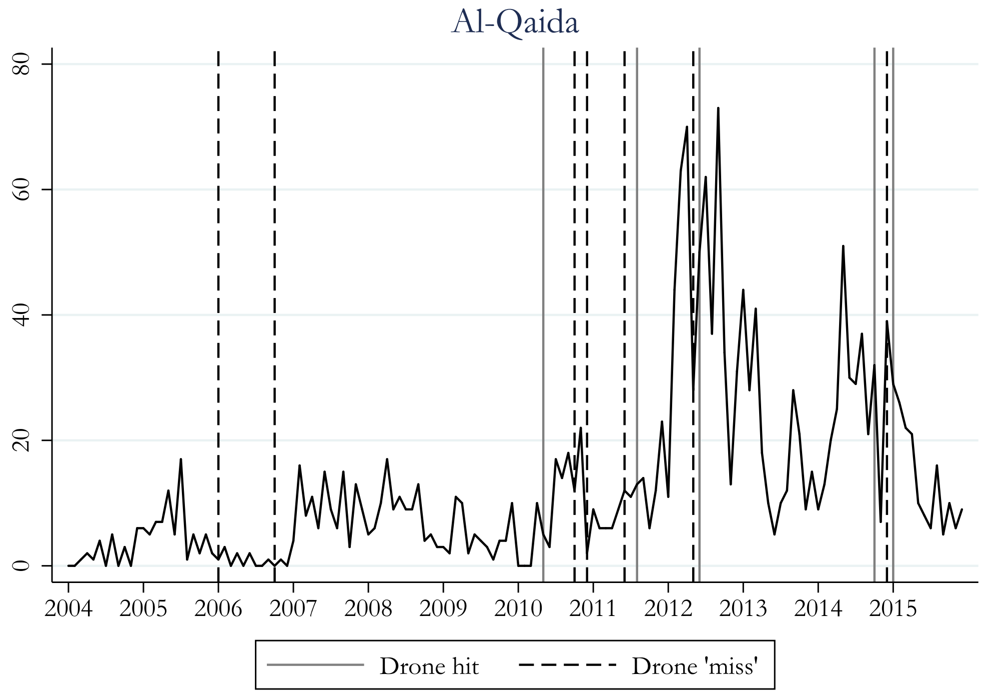
B.2 Bias due to misreporting and measurement error

Two kinds of biases could affect the main results. First, media may be more likely to report on terrorist attacks by a group in the six months after its leader was hit by a drone, compared to when he was missed. Second, there may a time trend in the likelihood that GTD attributes a terrorist attack to a particular group, which could correlate with the group-specific probability that a drone strike targeting its leader succeeds in killing him. Simulations show that either type of reporting bias would have to be substantial in size for it to fully account for the main results.

B.2.1 Differential probability of media reporting of terrorist attacks after a drone hit or miss

Media may be more likely to report terrorist attacks by a terrorist group after a drone strike hit its leader, compared to after a drone miss. This could arise if a drone hit on a group's leader puts

Figure B.1: Descriptive relationship: Al-Qaida

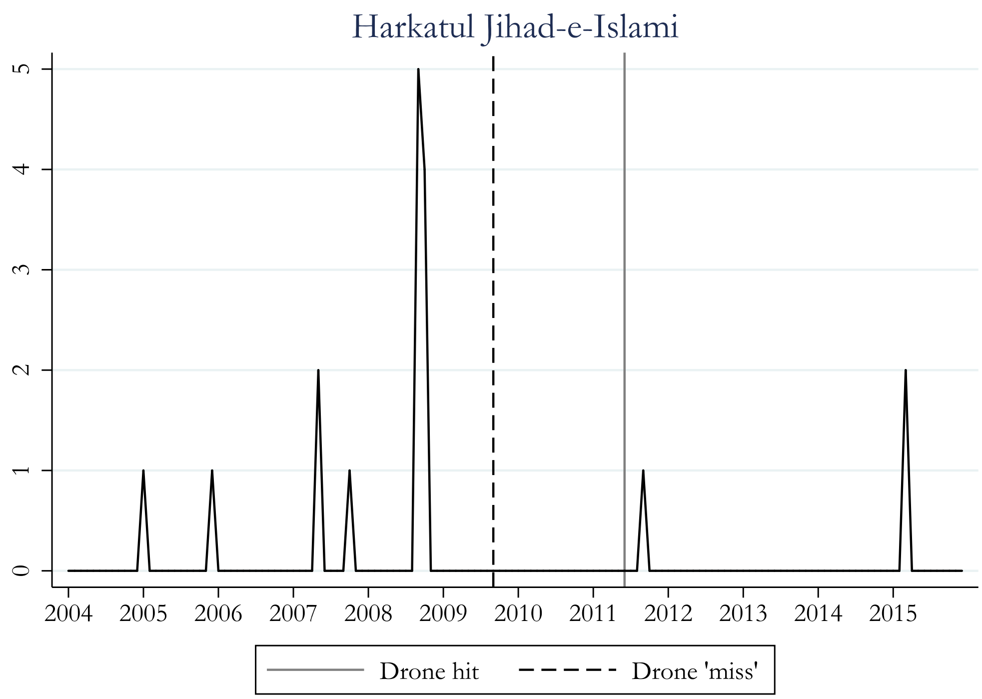


a group at the center of the news cycle, whereas a drone miss does so to a lesser degree. This may be somewhat plausible, although a news item along the lines of "leader runs free and orders attacks" might be equally news-worthy as "group takes revenge after drone strike kills its leader". In addition, recall that the main analysis finds the strongest effect on terrorist attacks only in two to six months after a drone hit. This time-frame is much longer than we can expect any news cycle to be.

A look at news sources cited by GTD[29] further undermines the idea that reporting of terrorist attacks is strongly influenced by the success or failure of US drone strikes. Out of the top 20 media sources cited, over half are non-Western media, mainly from Afghanistan and Pakistan, but also from China and the Philippines. Reporting on terrorist attacks by these sources is plausibly driven

[29] Analysis of the number of times a particular media source is cited is somewhat hampered because GTD naming of these sources is not always consistent across events

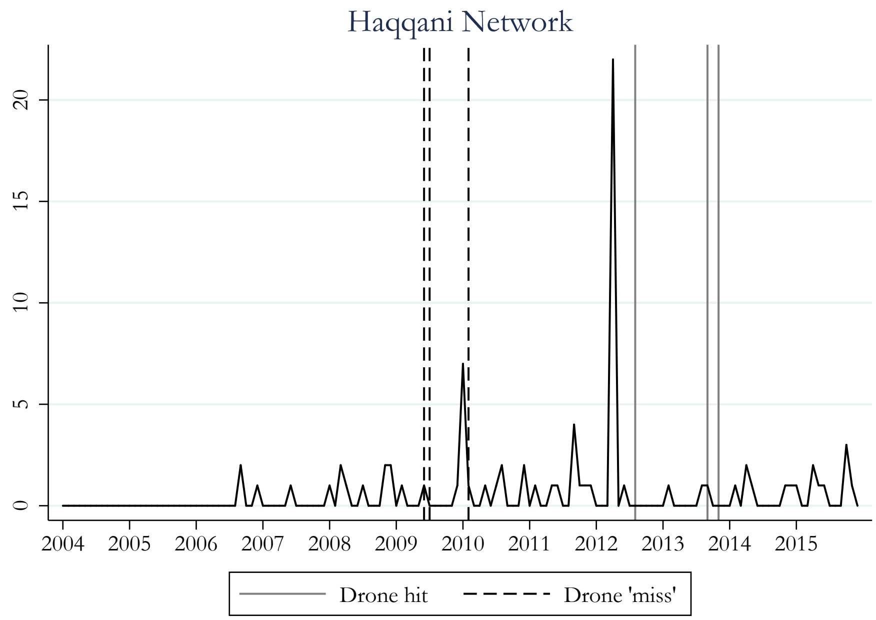
Figure B.2: Descriptive relationship: Harkatul Jihad-e-Islami



by national dynamics rather than US counterterrorism.

Nevertheless, I formally investigate the degree of reporting bias necessary to produce the main results. To do so, I start from the assumption that the number of terrorist attacks is completely unaffected by drone strikes: that the actual probability of a terrorist attack by some group is the same for the six months after a drone hit, the six months after a drone miss and in absence of prior drone strikes targeting its leader. However, the probability that the media will report the terrorist attack may differ across these periods. Specifically, I benchmark the likelihood of the media reporting a terrorist attack by a group in the six months after a drone hit on its leader at 1: $P(report|hit = 1)$. The probability of media reporting a terrorist attack by a group in the six months after a miss on its leader is $P(report|miss) < 1$, and the probability of the media reporting a terrorist attack by a group at any other time (including in periods after a drone strike not aimed at the group's leader) is $P(report|none) < 1$. I assume $P(report|miss) > P(report|none)$: a group

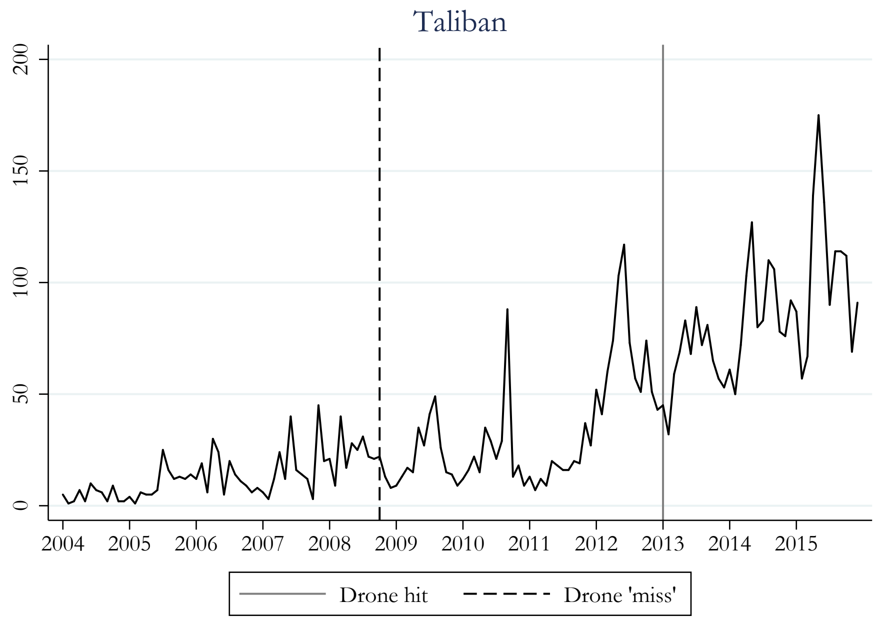
Figure B.3: Descriptive relationship: Haqqani Network



is more newsworthy after a drone miss on its leader than after no drone strike targeting its leader at all.

To reflect this situation, I create 100 simulated datasets of terrorist attacks, in which the number of terrorist attacks by a group in a particular month is drawn randomly from a negative binomial distribution. The negative binomial distribution is chosen because it outperforms the Poisson distribution in a likelihood-ratio test for ten of the thirteen groups, and because there is no evidence that a zero-inflated negative binomial distribution outperforms the negative binomial distribution for any of the groups. For groups with at least one drone hit, parameters of the negative binomial distribution are estimated from the number of terrorist attacks reported in GTD for the six months after a drone hit on its leader. For groups with no drone hits, these parameters are estimated from all terrorist attacks by the group reported in GTD. Note that because parameters are estimated for each group individually, no group and period fixed effects are included, and negative binomial regression can be consistently estimated. As expected, the simulated datasets contain substantially

Figure B.4: Descriptive relationship: Taliban



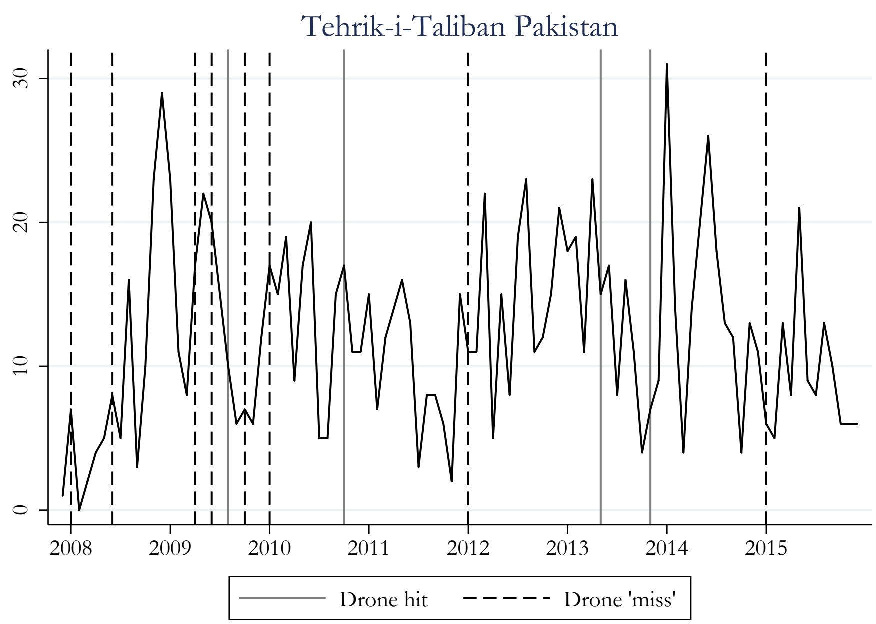
more terrorist attacks than GTD.

Assume that media only report terrorist attacks with some probability. For each of the 100 simulated datasets of terrorist attacks, I simulate the number of *reported* terrorist attacks for each group in each month. The number of reported terrorist attacks is randomly drawn from a binomial distribution, where n equals the simulated number of terrorist attacks and p equals 1 for the six months after a drone hit, $P(report|miss) = [0.05, 0.1, 0.15...0.95, 1]$ for the six months after a miss, and $P(report|none) = [0.1, 0.2...0.9, 1]$ for all other group-months. For each of the 84 combinations of probabilities allowed by the assumption $P(report|miss) > P(report|none)$, I simulate the number of reported terrorist attacks 10 times, resulting in a total of 84.000 iterations.

I run specification 1 in the main text for each iteration. The test statistic is the share of regressions that give a statistically significant coefficient estimate on at least one lag of hit. Recall that the analysis in the main paper gives three such significant coefficients.

Table B.1 reports the results from the simulation. It displays all combinations of $P(report|miss)$

Figure B.5: Descriptive relationship: TTP



and $P(report|none)$ for which $P(report|miss) > P(report|none)$, and the corresponding share of simulated regressions that result in a statistically significant coefficients on at least one of the six lags of *hit*. To obtain a single statistically significant coefficient with 95% certainty, media would have to report all terrorist attacks by a group after a drone strike hit its leader and only approximately 65% of terrorist attacks by the group after a drone strike missed its leader. The share of terrorist attacks reported by the media reported in the period not following either a hit or a miss does not strongly affect this conclusion. This seems a high level of reporting bias, especially over a six-month time frame and considering that the analysis in the main paper obtains three statistically significant coefficients.

B.2.2 Terrorist attacks with an unknown perpetrator

A second type of bias might arise because GTD records the perpetrator of a terrorist attack with error, and often cannot attribute terrorist attacks to a particular terrorist group. If there is a

Table B.1: Simulation of reporting bias

P(report — none)	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
P(report — miss)									
0.95	.49	.496	.5	.489	.486	.471	.427	.386	.304
0.90	.58	.588	.585	.568	.554	.535	.503	.452	.374
0.85		.683	.682	.677	.658	.637	.59	.527	.439
0.80		.774	.78	.771	.77	.726	.703	.633	.545
0.75			.863	.863	.859	.851	.823	.765	.646
0.70			.91	.918	.905	.913	.888	.864	.782
0.65				.956	.954	.951	.944	.93	.888
0.60					.985	.989	.986	.963	.943
0.55					.999	.999	.998	.994	.975
0.50						1	1	1	.996
0.45						1	1	1	1
0.40							1	1	1
0.35							1	1	1
0.30								1	1
0.25								1	1
0.20									1
0.15									1

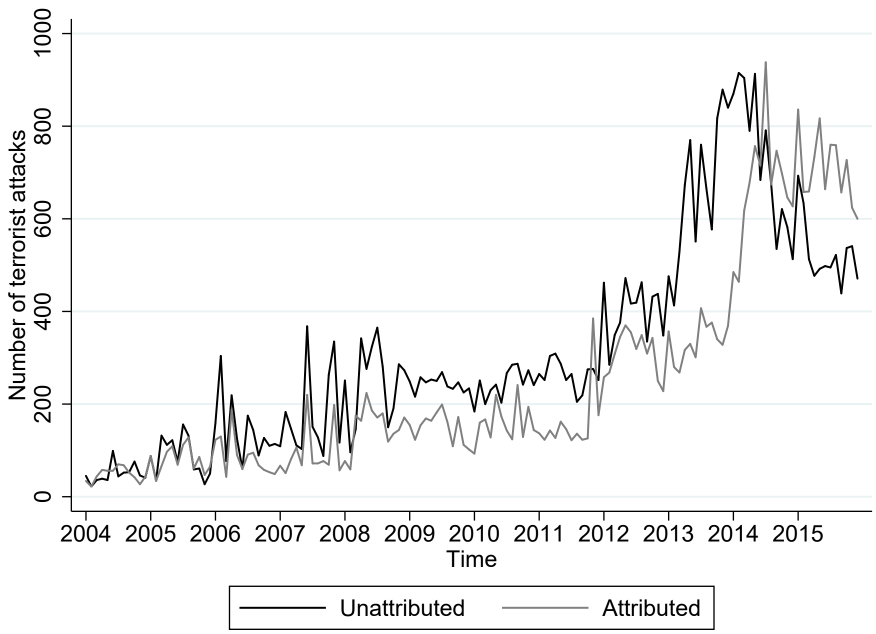
This table displays the share of simulated regressions with at least one coefficient statistically significant at the 5% level at the given probability that media report an attack by a terrorist group in the six months after a drone miss on its leader, and given no drone attempt on its leader respectively. Probability of media reporting an attack by a terrorist group in the six months after a drone hit on its leader is set to 1.

group-specific time trend in whether the media, and thus GTD, attribute terrorist attacks to a terrorist group, this could bias the analysis. For it to do so, this trend would have to be correlated with the probability that a drone strike targeting the group's leader succeeds in killing him.

Figure B.6 shows the number of terrorist attacks in GTD over time that are and are not attributed to a known perpetrator. The numbers of attributed and unattributed attacks track each other fairly closely for the nine years of the research period. However, they diverge for the last three years, after 2013, which could introduce bias if trends in the probability that GTD attributes a terrorist attack to a group in the main dataset correlate to trends in the probability that a drone attempt on those groups' leaders' lives succeeds.

Figure B.7 investigates whether drone hits on the leaders of the thirteen terrorist groups in the main dataset correlate to the number of unattributed terrorist attacks worldwide. For this purpose, I aggregate the main dataset to the month level, for each month taking the maximum of

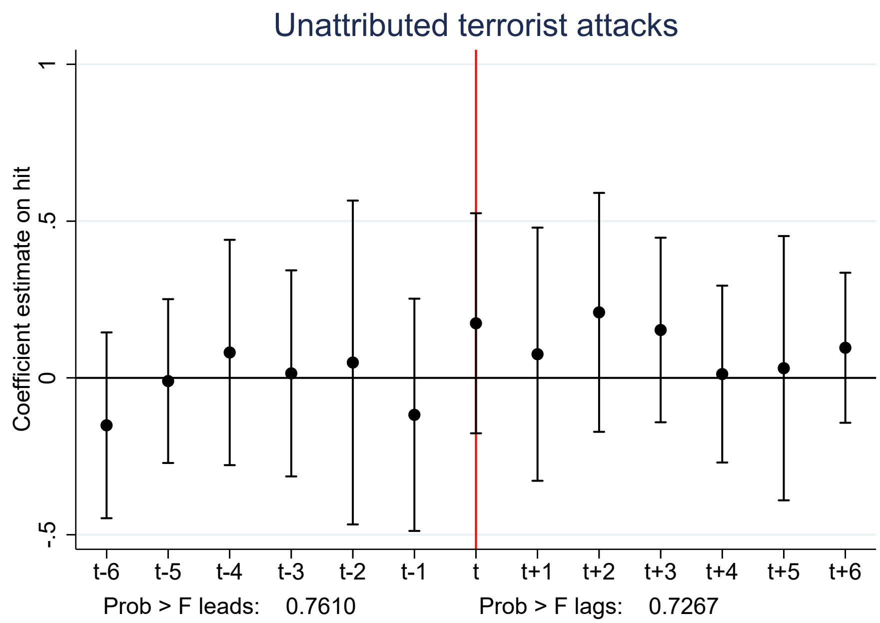
Figure B.6: Terrorist attacks attributed and unattributed to a terrorist group in GTD over time



the indicators *hit* and *targeted* and sum of the number of all drone strikes, regardless of whether they target a leader, which functions as a control variable. The dependent variable is the logged number of terrorist attacks with an unknown perpetrator in GTD. As is evident from Figure B.7, the number of unattributed terrorist attacks is unrelated to drone hits. Coefficients on all leads and lags of *hit* are individually and jointly insignificant.

I use a simulation to further investigate the sensitivity of the main results to bias resulting from unattributed terrorist attacks. For this simulation, I attribute a share of terrorist attacks GTD classifies as committed by an "unknown" perpetrator to each of the thirteen groups in the main dataset. This is done using random draws from a binomial distribution, where n equals the total number of unattributed terrorist attacks worldwide and p equals the three-month rolling average of the share of worldwide terrorist attacks with a known perpetrator that GTD attributes to each group. This introduces a flexible, group-specific time trend in the probability that an unattributed terrorist attack should in reality have been attributed to one of the thirteen terrorist groups. Draws

Figure B.7: Relationship between a drone hit and unattributed terrorist attacks



are repeated 1000 times. The number of attacks newly attributed to the terrorist group is added to the number of terrorist attacks by the group in GTD and this sum is logged. Specification 1 in the main text is run on each simulated dataset.

Table B.2 contains the results of this simulation. It displays the 2^{nd} and 98^{th} percentile of the distribution of coefficients for each of the six lags of *hit*, which constitutes the upper and lower bound of a simulated 96% confidence interval. Implied confidence intervals for 5 out of 6 coefficients are positive and exclude zero. In 88% of simulated regressions, the coefficient on at least one of the lags of *hit* is statistically significant.

This simulation constitutes a fairly strict test of the impact of reporting bias resulting from unattributed terrorist attacks. Several of the thirteen terrorist groups in the main dataset are high-profile organizations, and we might expect that the share of terrorist attacks with a known perpetrator attributed to them by GTD exceeds the share of terrorist attacks with an unknown perpetrator mistakenly *not* attributed to them. Given simulated confidence intervals and statistical

Table B.2: Simulation of bias in allocating attacks by unknown perpetrator

Lag of hit	Lower bound implied 96% CI	Upper bound implied 96% CI
t+1	.1366357	.4089971
t+2	.2682199	.5916294
t+3	.3482034	.5850728
t+4	.0417288	.382581
t+5	-.0357263	.2542275
t+6	.1377445	.4724822

This table displays 2th and 98th percentile of simulated coefficients obtained when allocating terrorist attacks with an unknown perpetrator to terrorist groups included in this study based on the 3-month rolling share of worldwide terrorist attacks with a known perpetrator that these groups committed

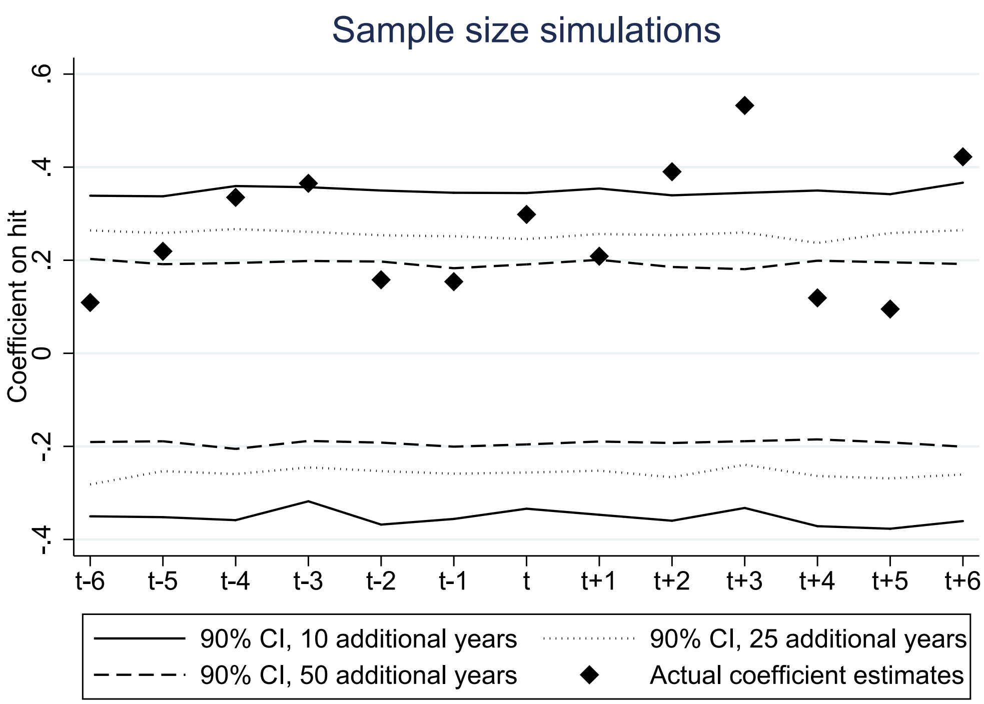
significance of simulated individual coefficients, we can conclude that results obtained in the main paper largely hold in this strict test.

B.3 Simulations of expanded sample size

By expanding the sample using simulated data, this section explores whether the lack of statistical significance of the coefficients on individual lags (or leads) of *hit* is due to a small sample size. The main results, in which three lags and none of the leads carry statistically significant coefficients, are based on 12 years of data, and 45 hits and misses on terrorist leaders.

To expand the dataset, I add additional years to the end of the dataset, in five-year increments. Data on terrorist attacks, drone hits and misses on terrorist leaders, and number of drone strikes for all additional periods is drawn randomly based on the actual group-specific distribution of these variables. Data on terrorist attacks (drone strikes) is drawn from a negative binomial distribution, where parameters r and p differ by terrorist group and are estimated using the actual data. The negative binomial distribution is chosen because it outperforms the Poisson distribution in a likelihood-ratio test for ten (five in the case of drone strikes) of the thirteen groups, and because there is no evidence that a zero-inflated negative binomial distribution outperforms the negative binomial distribution for any of the groups. Note that because parameters are estimated for each group individually, no group and period fixed effects are included, and negative binomial regression can be consistently estimated. Data on drone hits and misses is drawn from a binomial distribution,

Figure B.8: Sample size simulations



where n equals one and p equals the actual group-specific probability of a drone hit or miss on a terrorist leader respectively.

Draws are repeated one thousand times for each sample size, and specification 1 in the main text is run on each simulated dataset. The 5th and 95th percentile of the resulting thousand coefficients demarcate the simulated 90% confidence interval for a given sample size. Figure 8 displays these 90% confidence intervals, together with the main results, the actual coefficient estimates obtained when running specification 1 in the main text on the original sample.

Simulations suggest that the sample size would have to be radically expanded to make a meaningful difference to the statistical significance of individual coefficients. Only after expanding the sample with fifty additional simulated years, more than quintupling the original dataset in size, do more coefficients on lags of *hit* gain statistical significance at the 10% level. This suggests that the first, fourth and fifth lag of *hit* are null. A similar observation holds for the leads of *hit*, although a single lead gains statistical significance after adding ten additional simulated years to the dataset, and one gains statistical significance after adding 25 additional years of data. Even when radically expanding the dataset, simulations never indicate an immediate (i.e. in the same month, or the month immediately following) effect of a drone hit on a terrorist leader compared to a drone miss. Nor do results of any of the simulations indicate a divergence in trends between a hit and a miss in the two months immediately preceding the drone strike.

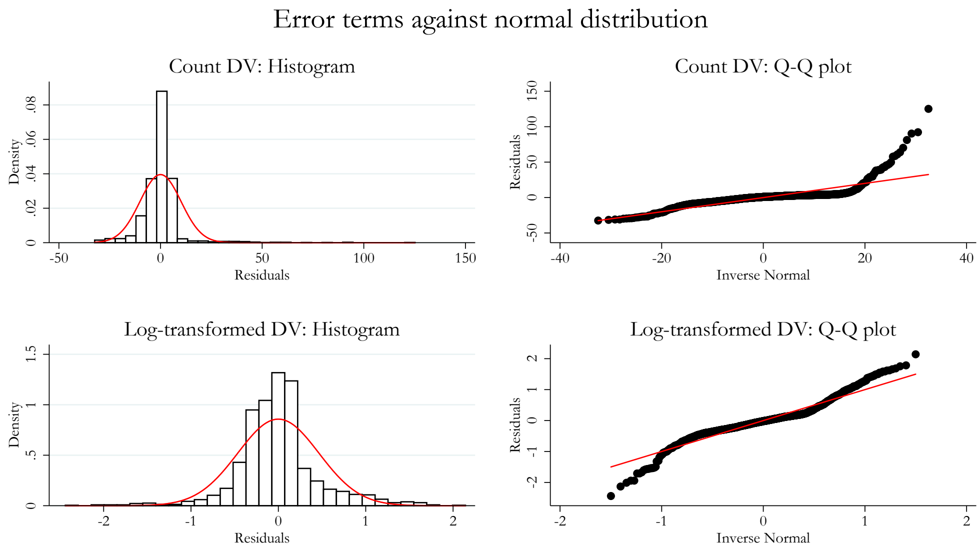
B.4 Choice of econometric specifications

The preferred specification in the main paper is OLS, using a logged count of terrorist attacks as a dependent variable. For the particular specification presented in the main paper, using OLS has several advantages over using negative binomial regression, a commonly used alternative.

To estimate p-values for the statistical significance of individual coefficients, OLS relies on the assumption that residuals are normally distributed. Figure B.9 suggests that residuals of an OLS regression on a logged count of terrorist affects are indeed approximately normally distributed (bottom panel). This assuages concerns that standard errors from the OLS regressions in the main paper are biased downward due to non-normal distribution of residuals. The same cannot be said for the distribution of residuals from an OLS regression using the raw count of terrorist attacks as a dependent variable, which in places deviates from the normal distribution (top panel). This provides a clear argument for taking the log of terrorist attacks ($ln(attacks + 1)$) as a dependent variable.

The main argument against using negative binomial regression to analyze the raw count of terrorist attacks, is that unconditional fixed effects negative binomial regression has been shown to give inconsistent and biased results in the presence of many fixed effects (Hilbe, 2011; Allison, 2012). Specification 1 in the main text contains 145 fixed effects, well above the threshold of 20 that Hilbe (2011) gives as a rule of thumb for what constitutes 'many'. Simulations show that potential bias is small in size in particular cases (e.g. Allison and Waterman (2002)). However, these simulations investigate a case markedly different from the one presented in the main paper: simulations investigate cases with many cross-sectional and no time-fixed effects, whereas specification 1 in the

Figure B.9: Distribution of error terms from OLS



main text has few cross-sectional and many time-fixed effects. As such, the extent of bias that using unconditional fixed effects negative binomial regression would introduce to the present analysis is not known. Alternatively, one might use conditional fixed effects negative binomial regression. Although this does give consistent results this has long been shown to not be a true fixed effects estimator and it has fallen into disuse (Allison and Waterman, 2002). Hence, although results from both specifications are presented in section B.5, these should be treated with caution.

Other count models, notably Poisson regression, can be consistently estimated in the presence of fixed effects. However, Poisson regression and zero-inflated Poisson regression suffer from overdispersion. A likelihood ratio test rejects the hypothesis that the overdispersion parameter is zero ($p < 0.0000$), implying that Poisson-estimated standard errors are biased downward. Zero-inflated negative binomial regression is subject to the same problems as negative binomial regression.

Using OLS as the main specification is also advantageous because it allows the use of Newey-West standard errors robust to autocorrelation. As the present analysis involves a long time series, autocorrelation is a serious concern. Newey-West standard errors cannot be readily estimated for count models.

B.5 Alternative econometric specifications

Table B.3 investigates the robustness of the main results (reproduced in column 1) to the use of alternative econometric specifications.

To investigate whether the joint statistical significance of the coefficients on the lags *hit* is an artefact of the inclusion of the leads of *hit*, column 2 presents the main results excluding all lead variables. Main results are unaffected. Similarly, the lack of joint statistical significance of the coefficients on the leads of *hit* does not depend on the inclusion of the lags of *hit* (column 3). Column 4 restricts the analysis to periods within 6 months of a drone strike targeting a leader of some terrorist group. Again, results are unaffected. The model in column 5 includes linear group-time trends instead of period-fixed effects, giving results very similar to the main results. As column 6 shows, results are somewhat sensitive to using HAC instead of Newey-West standard errors: although the third lag of *hit* is still statistically significant at the 5% level, the coefficients on lags are no longer jointly statistically significant at conventional levels ($p = 0.1150$). Main results are robust to using Driscoll-Kraay standard errors (column 7).

Columns 8 and 9 estimate specification 1 in the main text using negative binomial regression instead of OLS, taking the raw count of terrorist attacks as a dependent variable. As highlighted in section B.4, these results should be taken with caution: unconditional negative binomial regression has been shown to give inconsistent results in the presence of many fixed effects, and conditional negative binomial regression is not a true fixed effects estimator. Keeping these caveats in mind, results are weakened when using either estimator. None of the resulting individual coefficients on lags of *hit* are statistically significant in column 8, and only one coefficient is statistically significant at the 10% level in column 9. However, in both regressions, coefficients on *hit* are jointly statistically significant at the 5% level. For both regressions, the p-value for joint significance is obtained using a likelihood ratio test, not an Wald test as is the case for linear models.

Table B.3: Alternative econometric specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				<7 mnths				Uncond.	Cond.
	Baseline	Only lags	Only leads	from targeted	Baseline	Baseline	Baseline	Neg. bin.	Neg. bin.
VARIABLES	Terr.att.	Terr.att.	Terr.att.	Terr.att.	Terr.att.	Terr.att.	Terr.att.	Terr.att.	Terr.att.
t	0.298	0.233		0.289	0.147	0.298	0.298	0.0127	-0.0991
	(0.191)	(0.186)		(0.185)	(0.152)	(0.227)	(0.256)	(0.222)	(0.255)
t+1	0.209	0.120		0.187	-0.00636	0.209	0.209	0.0368	0.0671
	(0.193)	(0.192)		(0.187)	(0.152)	(0.230)	(0.198)	(0.347)	(0.263)
t+2	0.390**	0.374*		0.363*	0.195	0.390	0.390	0.0853	0.0994
	(0.191)	(0.194)		(0.185)	(0.152)	(0.266)	(0.255)	(0.225)	(0.248)
t+3	0.533***	0.537***		0.517***	0.291*	0.533***	0.533***	0.534	0.453*
	(0.191)	(0.190)		(0.185)	(0.151)	(0.198)	(0.185)	(0.478)	(0.257)
t+4	0.119	0.130		0.104	-0.0455	0.119	0.119	-0.126	-0.238
	(0.194)	(0.194)		(0.188)	(0.152)	(0.260)	(0.269)	(0.111)	(0.262)
t+5	0.0951	0.0363		0.0785	-0.0517	0.0951	0.0951	-0.170	-0.105
	(0.189)	(0.191)		(0.183)	(0.149)	(0.191)	(0.142)	(0.171)	(0.271)
t+6	0.422**	0.300		0.394**	0.198	0.422	0.422**	0.400	0.364
	(0.192)	(0.184)		(0.186)	(0.152)	(0.275)	(0.210)	(0.341)	(0.269)
Constant								1.136	-0.0531
								(1.039)	(0.605)
Observations	1,577	1,655	1,655	1,368	1,577	1,577	1,577	1,577	1,577
R-squared	0.850	0.847	0.836	0.869	0.891	0.850	0.850		
Includes 6 leads	YES	NO	YES	YES	YES	YES	YES	YES	YES
Group FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	NO	YES	YES	YES	YES
Group-Month trend	NO	NO	NO	NO	YES	NO	NO	NO	NO
Standard errors	N. West	N. West	N. West	N. West	N. West	HAC	Drisc.-Kr.	Clustered	IOM
p-val lags hit	0.0236	0.0292		0.0273	0.1760	0.1150	0.0228	0.0431	0.0179
p-val leads hit	0.6137		0.3193	0.6125	0.7345	0.9258	0.9609	0.3023	0.1920
p-val lags targeted	0.8760	0.7974		0.8983	0.6576	0.9707	0.9493	0.1194	0.1140
p-val leads targeted	0.2688		0.4640	0.2853	0.0937	0.6053	0.0489	0.2745	0.0622
Control mean	1.9450	1.9450	1.9450	1.9450	1.9450	1.9450	1.9450	11.0792	11.0792
Number of groupid									13

Standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

Table B.4: Alternative counterfactuals and further robustness

VARIABLES	(1) Baseline Terr.att.	(2) Cntrfac: drone strike Terr.att.	(3) Cntrfac: leader named Terr.att.	(4) Only < Sept. 2015 Terr.att.	(5) Drop 2 small gr. Terr.att.	(6) Region- Gr.-mnth Terr.att.	(7) Region- Gr.-mnth Terr.att.	(8) Region- Gr.-mnth Terr.att.	(9) Exp. sample Terr.att.
t	0.298	0.209	0.385**	0.298	0.459*	0.124	0.124***	0.124	0.396*
	(0.191)	(0.141)	(0.156)	(0.191)	(0.235)	(0.101)	(0.0469)	(0.103)	(0.222)
t+1	0.209	0.120	0.204	0.209	0.381	0.0308	0.0308	0.0308	0.255
	(0.193)	(0.143)	(0.158)	(0.193)	(0.239)	(0.102)	(0.0471)	(0.104)	(0.219)
t+2	0.390**	0.299**	0.448***	0.390**	0.760***	0.109	0.109**	0.109	0.472*
	(0.191)	(0.142)	(0.158)	(0.191)	(0.236)	(0.0980)	(0.0463)	(0.100)	(0.280)
t+3	0.533***	0.480***	0.530***	0.533***	0.778***	0.135	0.135***	0.135	0.585***
	(0.191)	(0.142)	(0.158)	(0.191)	(0.237)	(0.100)	(0.0472)	(0.103)	(0.185)
t+4	0.119	0.214	0.174	0.119	0.433*	0.0688	0.0688	0.0688	0.233
	(0.194)	(0.144)	(0.159)	(0.194)	(0.242)	(0.107)	(0.0486)	(0.110)	(0.276)
t+5	0.0951	0.130	0.0885	0.0951	0.297	0.0162	0.0162	0.0162	0.202
	(0.189)	(0.146)	(0.161)	(0.189)	(0.230)	(0.106)	(0.0481)	(0.109)	(0.172)
t+6	0.422**	0.512***	0.456***	0.422**	0.980***	0.0871	0.0871*	0.0871	0.454*
	(0.192)	(0.147)	(0.162)	(0.192)	(0.229)	(0.111)	(0.0525)	(0.113)	(0.264)
Observations	1,577	1,577	1,577	1,577	1,313	6,308	6,308	6,308	10,421
R-squared	0.850	0.849	0.852	0.850	0.869	0.276	0.842	0.290	0.753
Group FE	YES	YES	YES	YES	YES	YES	NO	YES	YES
Period FE	YES	YES	YES	YES	YES	YES	YES	NO	YES
Region FE	NO	NO	NO	NO	NO	YES	NO	NO	NO
Region-group FE	NO	NO	NO	NO	NO	NO	YES	NO	NO
Region-period FE	NO	NO	NO	NO	NO	NO	NO	YES	NO
Prob > F lags hit	0.0236	0.0009	0.0020	0.0236	0.0000	0.438	0.0294	0.460	0.0365
Prob > F leads hit	0.6137	0.1203	0.0571	0.614	0.0701	0.523	0.0201	0.544	0.8714
Prob > F lags targeted	0.8760			0.876	0.7061	0.953	0.823	0.956	0.9542
Prob > F leads targeted	0.2688			0.269	0.8737	0.704	0.335	0.717	0.5762
Control mean	1.9450	1.9450	1.9450	1.945	1.9450	0.574	0.574	0.574	1.9450

Newey-West standard errors in parentheses, column (9) displays HAC standard errors
* p<0.1 ** p<0.05 *** p<0.01

Table B.4 presents a final set of robustness checks. Drone misses are measured with error: a leader may have been targeted by a particular drone strike, but this may be unobserved by the media or the BIJ. Hence one may be concerned that the main results are an artefact of this measurement error. Therefore, columns 2 and 3 investigate alternative counterfactuals for a drone hit that may be more easily observed. In column 2 any drone strike not killing a terrorist leader is taken as a counterfactual. In column 3, any drone strike in which a leader is named, but not necessarily targeted is considered a counterfactual. These include drone strikes targeting militants closely associated with the leader, locations associated with the terrorist leader – commonly a known residence – or family members of the terrorist leader. Coefficient estimates on *hit* are similar to those obtained in the baseline model (column 1), and they are strongly jointly statistically significant (1% level). These are not the preferred specifications however, as it becomes more difficult to substantiate the parallel trends assumption. In column 3 leads of *hit* are jointly statistically significant, albeit only at the 10% level. Perhaps unsurprisingly, groups that have their militants but not their leaders (or individuals or locations associated with their leaders rather than their leaders themselves) targeted may already commit an increasing number of terrorist attacks prior to a drone strike.

Results are unaffected when excluding periods after September 2015, the month in which the Pakistani military acquired its own weaponized drones (Column 4).

Some may be concerned that the probability of a hit on a terrorist leader conditional on a leader being targeted is different for the leaders of large compared to small terrorist groups and that these small groups would somehow drive the main results. However, main results are robust to excluding two groups which commit substantially fewer attacks, the Haqqani network and Harkat-ul-Jihad-al-Islami (column 5).

Up to this point, the dependent variable in all regressions is an aggregation of all terrorist attacks committed by a group globally. One might worry about the existence of region-time specific factors (for instance holidays or other occasions which may be a target of terrorist groups) that could be correlated to level of effort to hit leaders of groups active in these regions. One might have similar worries about group-region specific factors, such as differential ability of groups to commit terrorist attacks in different regions. Therefore, the final three columns of Table B.4 re-estimates the baseline model at the group-region-month level, distinguishing four regions (Western Europe, the US and Australia, Asia, Middle East and North Africa). Models include region-fixed effects (column 6), region-time fixed effects (column 7) and region-group fixed effects (column 8) respectively. Estimates for these three models are extremely similar, as there is limited variation across regions between groups (many groups commit terrorist attacks only in a single region) and limited variation over time across regions (two regions do not experience any terrorist attacks in most time periods). In all three models, the size of the coefficients decreases, as these now represent the impact of a drone hit per month, group and region, and they are not individually statistically significant in columns 6 and 8. This loss in statistical significance follows exclusively from an increase in the size of the standard errors, not from a decrease in coefficient size. As such, the loss of significance in those columns is likely a result of introducing substantial noise into the dataset, rather than the fixed effects capturing some omitted variable. Coefficients on lags of *hit* are individually and jointly statistically significant in column 7.

Column 9 displays the results obtained when running specification 1 in the main text on an expanded sample, adding all terrorist organizations that committed more than one terrorist attack in Afghanistan or Pakistan over the research period. This specification employs HAC standard errors, as adding these observations introduces strong heteroskedasticity. Results are very similar to those presented in the main text.

B.6 Randomization inference

The empirical strategy in the main paper can be considered a quasi-experiment with a small number of clusters (i.e. terrorist groups) and several treatment coefficients (i.e. lags of *hit*). Under these circumstances, we may worry that either outliers or multiple testing can lead to false conclusions regarding the statistical significance of the main results (Young, 2017). Furthermore, even though the distribution of residuals from an OLS regression on the logged number of terrorist attacks resembles the normal distribution (see Figure B.9), there may be lingering concerns about the OLS assumption that residuals are normally distributed.

To mitigate these concerns, I estimate standard errors by randomization inference. Within each terrorist group, I re-allocate the logged number of terrorist attacks randomly to some other time period and run specification 1 in the main text on the resulting dataset. Doing this repeatedly gives an indication of how exceptional the coefficients making up the main results are in a universe of 10,000 possible random assignments of the outcome variable. Note that this determination can be made on the basis of simulated coefficients alone, and does not require any assumption regarding the distribution of standard errors.

Figure B.10 gives the distribution of simulated coefficients for each lag of *hit*, and the actual coefficients from the main paper. The percentages in the white boxes reflect the percentage of simulated coefficients that are larger than the actual coefficient, providing a simulated p-value. The third and sixth lag of *hit* are statistically significant by this metric, albeit at a lower level of significance for the sixth lag. The second lag of *hit* is narrowly no longer statistically significant at conventional levels. Overall, results from estimating standard errors using randomization inference are qualitatively similar to the main results.

B.7 Alternative numbers of leads and lags

Table B.5 illustrates that main results are not an artefact of choosing six as the particular number of leads and lags of the variables of interest to include. The table gives the p-value for each lag of *hit* in specification 1 in the main text, varying the number of leads and lags of all variables included between four and fifteen. Coefficient estimates on most lags of *hit* are similar across the nine models. The second and third lag of *hit* is statistically significant at the 5% level in each of the twelve cases. The significance of the sixth lag of *hit* is somewhat sensitive to the number of leads and lags included, but still statistically significant in six out of ten regressions in which it is included. No coefficient on any lag of *hit* beyond the seventh is ever statistically significant.

B.8 Graph of results on infighting

Figure B.11 shows graphically the results on infighting presented in section 6.1 of the main text. It shows that the leads of *hit* are strongly jointly statistically significant, but that this is driven

Table B.5: p-values on lags of hit when varying number of leads and lags (L&L) included

# L&L	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12	t+13	t+14	t+15
4	.576	.048	.001	.353											
5	.552	.032	.003	.415	.626										
6	.277	.041	.005	.537	.614	.029									
7	.299	.028	.006	.495	.449	.066	.32								
8	.327	.023	.004	.272	.533	.125	.341	.253							
9	.285	.017	.003	.24	.378	.137	.237	.335	.926						
10	.242	.016	.004	.16	.418	.161	.215	.529	.957	.185					
11	.541	.005	.005	.599	.343	.128	.195	.577	.911	.249	.282				
12	.406	.008	.023	.543	.211	.09	.188	.577	.966	.271	.256	.434			
13	.402	.019	.036	.657	.14	.045	.112	.582	.921	.335	.37	.424	.483		
14	.576	.011	.023	.786	.138	.019	.031	.593	.973	.313	.346	.263	.378	.75	
15	.756	.013	.017	.709	.153	.008	.03	.667	.796	.3	.67	.306	.381	.878	.567

This table displays the p-value for each lag of hit when varying the number of leads and lags of hit, target and control variables between 4 and 15

by the first lead of *hit*. Closer examination reveals that this is not an artefact of a single outlier. Therefore, results on infighting should be treated with some caution. However, there is no evidence that trends in infighting differ between a hit and a miss prior to a drone strike for any other time period.

C Affiliate groups

The effect of a drone strike killing the leader of a terrorist group may extend beyond the group itself, to its affiliates[30]. With a few notable exceptions (i.e. Enders and Jindapon (2010) and Siqueira and Sandler (2006)), few theoretical models cover the effect of counterterrorism against a group on the group's affiliates. Both existing models suggest that the effect on affiliates is ambiguous. As such, this paper hopes to contribute to future theory development by providing empirical results for the case of drone strikes.

[30] An affiliate is defined as a terrorist organization that has either (a) pledged fealty to the parent group and relies on it for support or guidance; or (b) shares a similar ideology or goals and coordinates operations with the parent group; (c) once operated under the same banner as the parent group and consolidated resources with the parent (Crenshaw, 2012).

C.1 Drone hits on parent groups and affiliate attacks

To investigate the impact of the death of a group's leader on affiliated terrorist groups, I record all affiliations, alliances and mergers involving the thirteen terrorist groups identified by Crenshaw (2012), and locate the terrorist groups involved in the GTD. For the purpose of this paper, any terrorist group that was ever affiliated, allied or merged with one of the thirteen groups is considered an affiliate. Figure C.12 shows the distribution of affiliates for those terrorist organizations coded as having any. Al-Qaida has the most affiliations, both in terms of the number of affiliates and the number of attacks they commit, although most other terrorist organizations included in the dataset have substantial affiliations as well.

To estimate the effect of killing a group's leader on attacks by affiliated terrorist groups, I employ the following specification:

$$Y_{jit} = \sum_{k=-6}^{6} \beta_{i,t-k} hit_{i,t-k} + \sum_{k=-6}^{6} \delta_{i,t-k} targeted_{i,t-k} + \sum_{k=-6}^{6} \rho_{j,t-k} hit_{j,t-k} + \sum_{k=-6}^{6} \phi_{j,t-k} targeted_{j,t-k}$$
$$\gamma_{i,t-k} X_{i,t-k} + \psi_{j,t-k} X_{j,t-k} + \mu_j + \theta_t + \epsilon_{jit} \tag{2}$$

where Y_{jit} represents the logged number of terrorist attacks perpetrated by group j affiliated to parent group i. The coefficients of interest are the coefficients on the lags of hit_i, which represent the effect of a drone hit (compared to a miss) on the parent group on violence perpetrated by the affiliate. As some groups are both parent group and affiliate, this specification controls for drone misses and hits on the leaders of the affiliate groups. Similarly, six leads and lags of the number of drone strikes targeted at both parent and affiliate (regardless of whether these targeted a leader) are included as control variables. Inclusion of affiliate-group fixed effects (μ_j), makes including parent-group fixed effects redundant.

Affiliates of a terrorist group commit an increasing number of terrorist attacks after a drone strike that hit, compared to missed, the parent group's leader. Table C.1 investigates the impact of a drone hit on a terrorist group leader on terrorist attacks committed by other terrorist groups affiliated with the group struck. I present results at the group-month level (specification 1 in the main text), and at the affiliate-month level, following specification 2 in this Appendix.

Table C.1: Effect of drone strikes on attacks by affiliates

VARIABLES	(1) Affil. att.	(2) Affil. att. excl. AQ	(3) Affil. att.	(4) Affil. att. excl. ISIS
t	0.487*	0.283	0.151	0.0978
	(0.272)	(0.340)	(0.103)	(0.0913)
t+1	0.106	-0.194	0.0338	-0.0155
	(0.279)	(0.354)	(0.104)	(0.0920)
t+2	0.498*	0.370	0.0186	-0.0423
	(0.274)	(0.346)	(0.104)	(0.0921)
t+3	0.327	0.0105	0.213**	0.139
	(0.273)	(0.340)	(0.106)	(0.0937)
t+4	0.465*	0.250	0.189*	0.120
	(0.280)	(0.342)	(0.108)	(0.0956)
t+5	0.342	0.280	0.0138	-0.0548
	(0.272)	(0.336)	(0.106)	(0.0942)
t+6	0.608**	0.661*	0.163	0.0707
	(0.273)	(0.353)	(0.102)	(0.0906)
Observations	1,577	1,445	3,312	3,168
R-squared	0.857	0.830	0.657	0.706
Model	Gr.-mnth	Gr.-mnth	Affil.-mnth	Affil.-mnth
Group FE	YES	YES	NO	NO
Period FE	YES	YES	YES	YES
Affiliate FE	NO	NO	YES	YES
Prob > F lags hit	0.1798	0.1980		
Prob > F leads hit	0.4739	0.6705		
Prob > F lags targeted	0.6953	0.3656		
Prob > F leads targeted	0.3860	0.4844		
Control mean	3.1340	3.1340	0.5760	0.5497
Prob > F lags parent hit			0.0450	0.0903
Prob > F leads parent hit			0.7786	0.4320
Prob > F lags parent targeted			0.8416	0.9638
Prob > F leads parent targeted			0.9658	0.7308
Prob > F lags affil. hit			0.1297	0.0823
Prob > F leads affil. hit			0.2087	0.1173

Newey-West standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

Column 1 and 3 show that a drone hit on a parent group is associated with an increase in terrorist attacks by affiliates of that group. For the regression at the group-month level (column 1), three coefficients on the lags of *hit* are individually statistically significant, although coefficients are not jointly statistically significant. This effect is substantial in size: estimates in column 1 suggest an increase in terrorist attacks by affiliates of between 59.2% and 83.7% for the months in which it is significant. For reference, the mean number of terrorist attacks by affiliates per month in the six months after a drone miss on the parent's leader is approximately 23. There is no evidence that drone strikes targeting but missing the parent group's leader affect affiliates: coefficients on leads and lags of *targeted* are jointly statistically insignificant.

These results at the group-month level are strongly influenced, but not exclusively driven, by Al-Qaida, the terrorist group with the most affiliates. Column 2 of Table C.1 presents results excluding Al-Qaida. Coefficients on *hit* are no longer jointly statistically significant and only the coefficient on the sixth lag retains statistical significance, and that only at the 10% level.

Evidence at the affiliate-month level are somewhat stronger compared to those at the group-month level. Estimates suggest that a drone hit on the parent group is associated with an increase in terrorist attacks by affiliate groups in month three and four after the drone strike, and these coefficients are jointly statistically significant (column 3). Results at the affiliate-month level are markedly weakened by excluding Islamic State (ISIS) from the analysis (column 4), although coefficients retain joint statistical significance at the 10% level.

C.2 Analysis by attack type

I proceed to analyze which type(s) of terrorist attacks drive the increase in affiliate group violence after a drone hit on their parent group. The increase in terrorist attacks by affiliates, following a drone strike killing the leader of their parent group, is driven by an increase in attack types across the board.

Table C.2, showing results at the group-month level, and Table C.3, showing results at the affiliate-month level, suggest that a drone hit is associate with an increase in terrorist attacks on military, private, and civilian targets, and terrorist attacks with a US citizen killed our wounded.

I find some limited evidence that a drone hit on the parent group's leader negatively affects affiliate capacity. Measuring capacity as the mean number of victims per terrorist attack, results at the group-month level appear to suggest that affiliate capacity decreases in the fifth and sixth month after a drone hit on the parent group's leader (Table C.2, column 2). Coefficients are not jointly statistically significant however, and the result is not reproduced at the affiliate-month level (Table C.3, column 1). At the affiliate-month level, the percentage of 'successful' terrorist attacks by affiliates appears to decrease following a drone hit on the parent group's leader (Table C.3, column 1). This result is not reproduced at the group-month level, although coefficients are consistently negative (Table C.2, column 1).

Table C.2: Type of affiliate attack (group-month level)

VARIABLES	(1) % success Affil.att.	(2) mean # vics. Affil.att.	(3) Civilian Affil.att.	(4) Private Affil.att.	(5) Military Affil.att.	(6) US vic. Affil.att.
t	-0.0418	0.470**	0.484*	0.361	0.700***	0.116
	(0.0923)	(0.206)	(0.273)	(0.255)	(0.261)	(0.0956)
t+1	-0.00269	-0.184	0.104	0.440*	0.333	0.365***
	(0.0934)	(0.207)	(0.280)	(0.261)	(0.267)	(0.0963)
t+2	-0.0566	-0.0144	0.480*	0.450*	0.546**	0.0972
	(0.0924)	(0.206)	(0.275)	(0.257)	(0.263)	(0.0956)
t+3	-0.0645	-0.198	0.324	0.111	0.755***	0.258***
	(0.0924)	(0.206)	(0.274)	(0.256)	(0.262)	(0.0956)
t+4	0.00376	-0.260	0.550*	0.560**	0.919***	0.0507
	(0.0933)	(0.207)	(0.281)	(0.262)	(0.268)	(0.0963)
t+5	-0.0335	-0.502**	0.360	0.375	0.478*	0.281***
	(0.0914)	(0.203)	(0.273)	(0.255)	(0.261)	(0.0945)
t+6	-0.0695	-0.411**	0.571**	0.587**	0.678***	0.0210
	(0.0932)	(0.208)	(0.273)	(0.256)	(0.262)	(0.0968)
Observations	1,577	1,577	1,577	1,577	1,577	1,577
R-squared	0.770	0.682	0.853	0.788	0.788	0.510
Model	Gr.-mnth	Gr.-mnth	Gr.-mnth	Gr.-mnth	Gr.-mnth	Gr.-mnth
Group FE	YES	YES	YES	YES	YES	YES
Period FE	YES	YES	YES	YES	YES	YES
Prob > F lags hit	0.9589	0.1963	0.1961	0.0844	0.0184	0.0008
Prob > F leads hit	0.9534	0.7826	0.4140	0.7475	0.1441	0.0828
Prob > F lags targeted	0.9766	0.5147	0.8548	0.2920	0.3859	0.0406
Prob > F leads targeted	0.7522	0.8471	0.3792	0.5927	0.4531	0.1711
Control mean	0.8767	1.6992	3.0501	2.2180	1.8051	0.2608

Newey-West standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

Figure B.10: Results from randomization inference

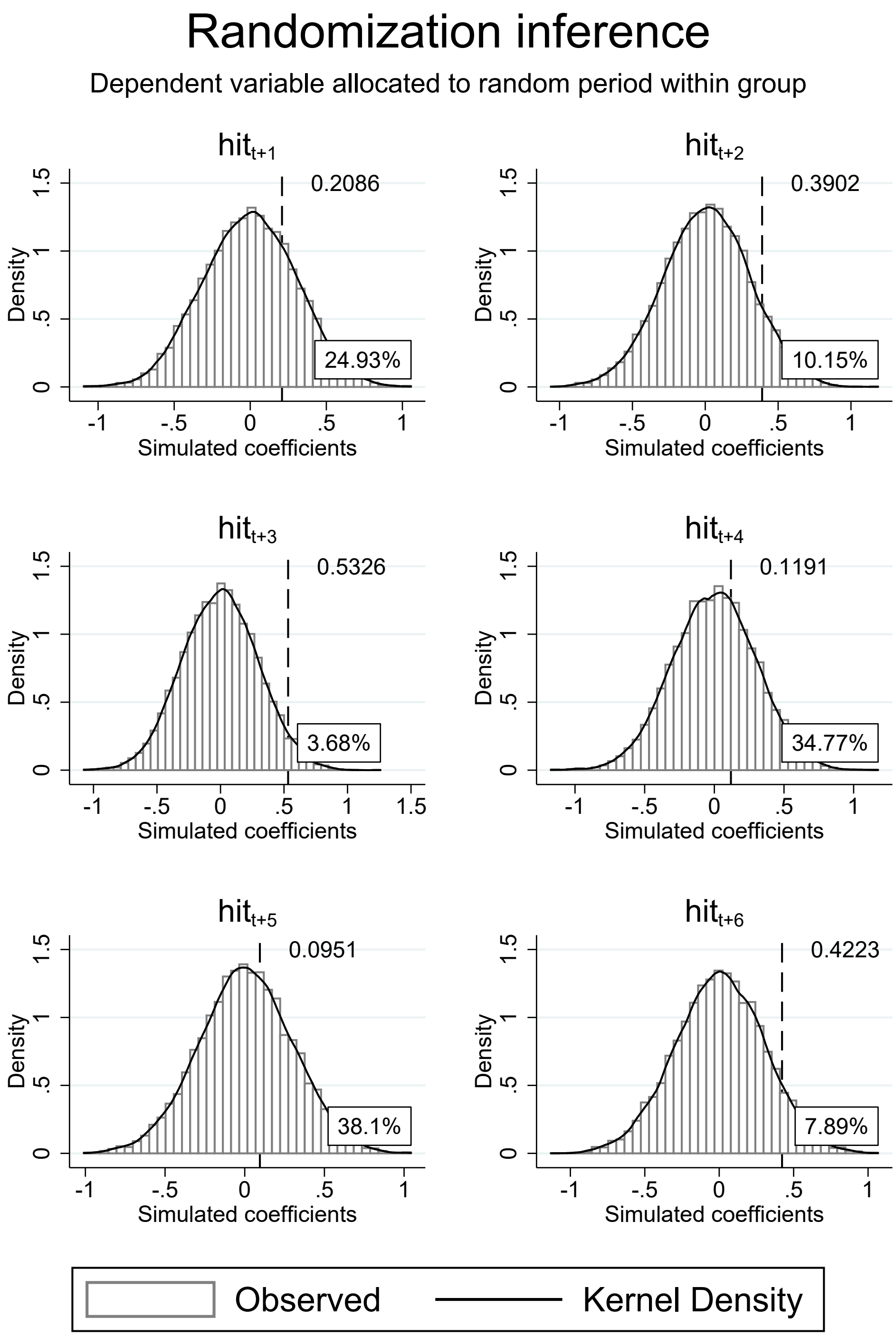


Figure B.11: Infighting

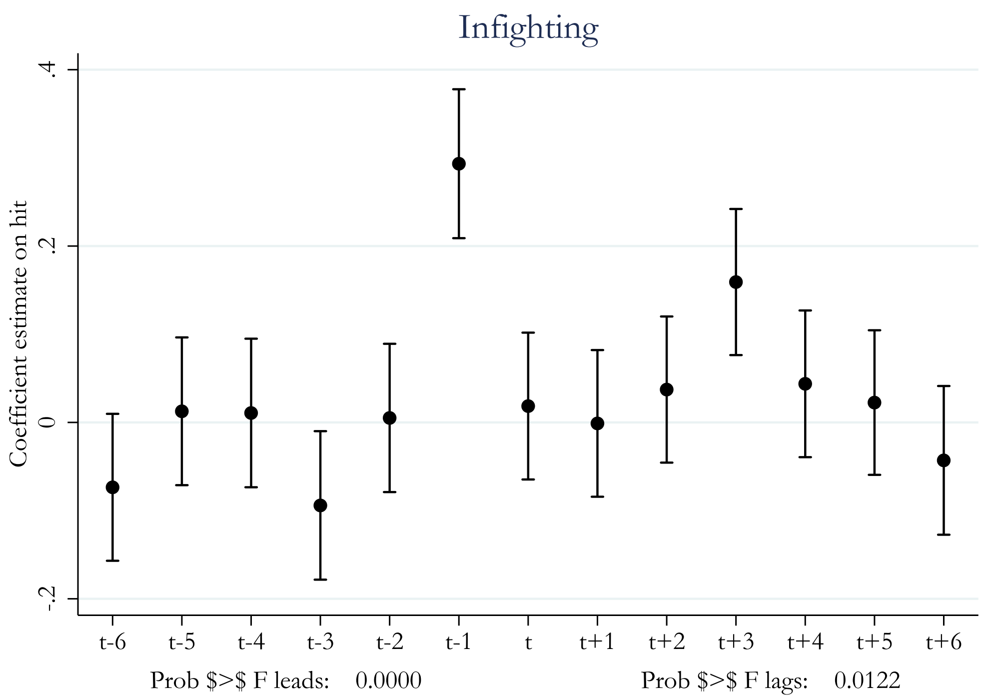


Figure C.12: Distribution of affiliates by terrorist organization

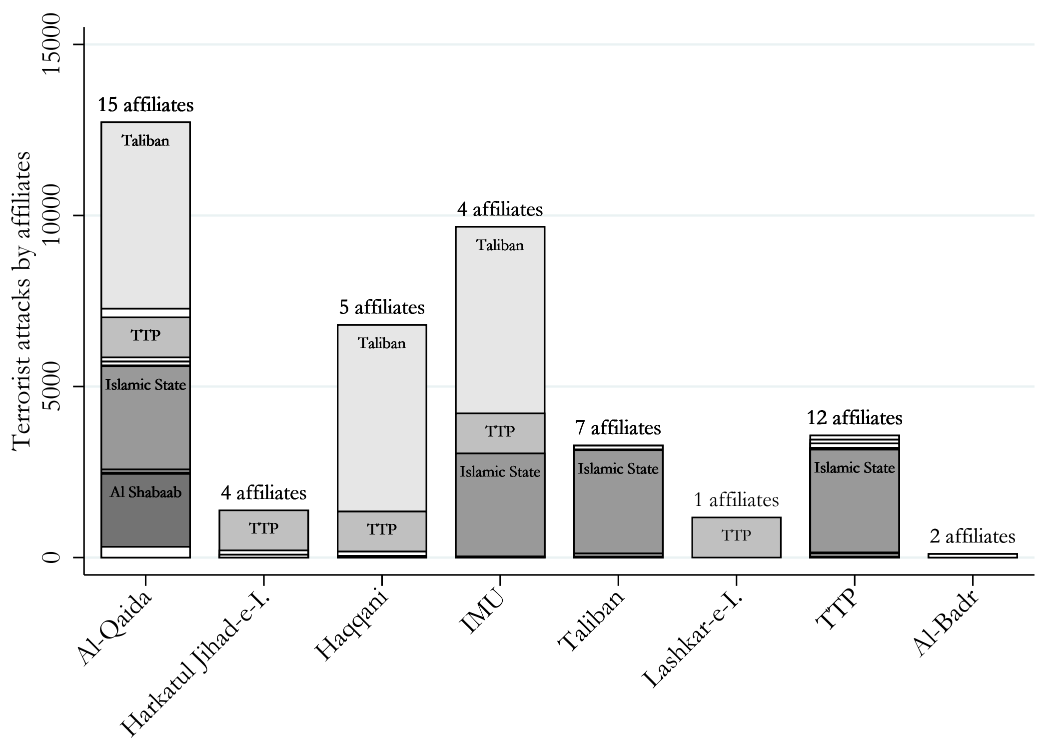


Table C.3: Type of affiliate attack (affiliate-month level)

VARIABLES	(1) % success Affil.att.	(2) mean # vics. Affil.att.	(3) Civilian Affil.att.	(4) Private Affil.att.	(5) Military Affil.att.	(6) US vic. Affil.att.
t	0.0410	0.920	0.151	0.144*	0.203**	0.0230
	(0.0523)	(0.858)	(0.103)	(0.0819)	(0.0865)	(0.0197)
t+1	0.0365	0.473	0.0324	0.107	0.0711	0.0576***
	(0.0524)	(0.857)	(0.104)	(0.0826)	(0.0873)	(0.0197)
t+2	-0.0956*	0.0176	0.0190	0.0693	0.101	0.0285
	(0.0523)	(0.854)	(0.104)	(0.0828)	(0.0876)	(0.0197)
t+3	0.0754	0.455	0.209**	0.0871	0.235***	0.0498**
	(0.0528)	(0.856)	(0.106)	(0.0842)	(0.0893)	(0.0198)
t+4	0.0291	0.668	0.191*	0.178**	0.249***	0.0172
	(0.0532)	(0.855)	(0.108)	(0.0860)	(0.0915)	(0.0199)
t+5	-0.0616	-1.185	0.0139	-0.0318	0.114	0.0392**
	(0.0527)	(0.852)	(0.106)	(0.0844)	(0.0896)	(0.0198)
t+6	0.0119	-1.011	0.163	0.0943	0.183**	-0.00361
	(0.0515)	(0.842)	(0.102)	(0.0811)	(0.0859)	(0.0195)
Observations	3,312	3,312	3,312	3,312	3,312	3,312
R-squared	0.467	0.139	0.657	0.577	0.577	0.319
Model	Affil.-mnth	Affil.-mnth	Affil.-mnth	Affil.-mnth	Affil.-mnth	Affil.-mnth
Group FE	NO	NO	NO	NO	NO	NO
Period FE	YES	YES	YES	YES	YES	YES
Affiliate FE	YES	YES	YES	YES	YES	YES
Prob > F lags parent hit	0.0413	0.5644	0.0481	0.0538	0.0460	0.0208
Prob > F leads parent hit	0.6253	0.2528	0.7850	0.6395	0.2475	0.5667
Prob > F lags parent targeted	0.5585	0.8313	0.8492	0.9861	0.8496	0.2144
Prob > F leads parent targeted	0.5551	0.1737	0.9660	0.6657	0.9356	0.9555
Prob > F lags affil. hit	0.9465	0.5066	0.1303	0.3564	0.0074	0.0010
Prob > F leads affil. hit	0.4157	0.9228	0.2097	0.1745	0.1357	0.0084
Control mean	0.2890	1.8059	0.5755	0.3452	0.3066	0.0219

Newey-West standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01