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ABSTRACT

Military Intervention via Drone Strikes*

We study the 420 US drone strikes in Pakistan from 2006-2016, isolating causal effects on terrorism, anti-US sentiment, and radicalization via an instrumental variable strategy based on wind. Drone strikes are suggested to encourage terrorism in Pakistan, bearing responsibility for 16 percent of all attacks or 2,964 terror deaths. Exploring mechanisms, we distinguish between *insiders* (members of terrorist organizations) and *outsiders* (the Pakistani populace). Analyzing data from a leading Pakistani newspaper, anti-US protests, and Google searches, drone strikes appear to increase anti-US sentiment and radicalization: *Outsiders* seem to sympathize with *insiders* because of drone strikes.

JEL Classification: C26, D74, F51, F52, H56, O53

Keywords: military intervention, drone strikes, terrorism, counter-terrorism, anti-US sentiment, radicalization

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"The program is not perfect. No military program is. But here is the bottom line: It works."

MICHAEL V. HAYDEN (Hayden, 2016), former Air Force four-star general and CIA Director on drone strikes

1 Introduction

The US war on terror is not restricted to active war zones alone. In weakly institutionalized states that oppose terrorists but are not considered capable enough to combat them, the US intervenes remotely through unmanned aerial vehicles (UAVs) or drones. Drone strikes have become a hallmark of US military policy. Seeking $6.97 billion for its drone program in 2018, the Department of Defense increased its request for UAVs threefold in 2019 (Gettinger, 2017, 2018). Drones are advocated as a military technology that avoids most of the hazards associated with conventional air strikes, promising precision and limiting unintended consequences (Obama, 2013). However, in practice, the consequences of drone strikes remain difficult to isolate.

In the following pages, we introduce an identification strategy based on weather conditions (specifically wind) to explore potential effects of drone strikes in Pakistan related to terrorism, attitudes towards the US, and radicalization.[1] Since 2004, Pakistan has experienced 63 percent of all drone strikes directed at countries that are not at war with the US (TBIJ, 2017b). The fact that no other US military intervention is possible in Pakistan (no troops on the ground or other aerial strikes are permitted) allows us to isolate the effect of drone strikes from other military operations, conditional on operations by the Pakistani military, preceding terror attacks, and time-specific observables.

Of course, the US employed strategic aerial bombings in the past and researchers have studied the associated consequences related to insurgencies, as well as political preferences and beliefs. Nevertheless, identifying causality remains problematic, impeding our understanding of whether and how such military operations affect insurgents and local populations. Put simply, bombings are not exogenous to enemy activity and local conditions, i.e., endogeneity abounds. As one of the few studies able to address endogeneity, Dell and Querubin (2017) employ a regression discontinuity design based on the algorithm used

[1] By radicalization, we mean political radicalization, described by McCauley and Moskalenko (2008) as "increasing extremity of beliefs, feelings, and behaviors in support of intergroup conflict and violence".

to decide over the implementation of air strikes in the Vietnam War. They find substantial repercussions, such as rising support for the Vietcong and reduced civic engagement (also see Kalyvas and Kocher, 2009, Kocher et al., 2011, and Miguel and Roland, 2011). However, contrary to military technologies that are largely unable to discriminate between targets and civilians, unmanned drones have been lauded for being able to surgically hit militants and their associates with improved precision. Thus, in theory, drone strikes may carry few (if any) negative consequences for the local population. Nevertheless, some commentators and scholars argue drone strikes can produce trauma in the civilian population (Cavallaro et al., 2012), provoke anger and hatred against the US (Hudson et al., 2011), and facilitate recruitment efforts by terrorist organizations (Kilcullen and Exum, 2009; Jordan, 2014).

To date, empirical evidence on the consequences of drone strikes remains correlational (Smith and Walsh, 2013; Johnston and Sarbahi, 2016; Jaeger and Siddique, 2018). First, reverse causality remains difficult to address, especially when the majority of both parties' (the US military's and the terrorists') operations remain unobserved. For example, the US may launch a drone strike *because* terror attacks are imminent, which would introduce an upward bias into estimates predicting subsequent terrorism with drone strikes. And second, omitted variables can affect the timing and frequency of drone strikes and terror attacks alike. For instance, assume militants are reorganizing and thus frequently moving locations (e.g., see Buncombe, 2013, Kugel, 2016, and Yusufzai, 2017). Such movements may make them easier targets for a drone strike – but at the same time we would expect fewer attacks in the immediate future *because of* their reorganization efforts. This would introduce a downward bias into the coefficient associated with the number of drone strikes in predicting subsequent terror attacks.

Our main approach employs wind as an instrumental variable (IV): We hypothesize that the likelihood of drone strikes decreases on days with stronger wind gusts, conditional on observables. This hypothesis is derived from the scientific literature suggesting UAVs to be sensitive to prevailing weather conditions and especially wind (Glade, 2000; DeGarmo, 2004; Fowler, 2014). Accessing daily data in Pakistan from 2006-2016, we indeed find fewer drone strikes on windy days. In turn, it is difficult to imagine how wind gusts could systematically affect subsequent terrorist activity through other channels, conditional on observable factors related to (i) preceding terror attacks, (ii) Pakistani military actions, (iii) fixed effects for days of the week and months of the year, (iv) time trends, and (v) Ramadan days.

Empirically, wind gusts remain orthogonal to terror attacks and Pakistani military operations on the same day.

Following this IV strategy, we identify a local average treatment effect (LATE) that suggests drone strikes *increase* the number of terror attacks in the upcoming days and weeks. This result emerges consistently in a range of empirical specifications, employing alternative (i) IVs (e.g., wind speed and wind speed combined with cloud coverage and precipitation – factors that are also suggested to affect drone flights), (ii) definitions of terrorism, (iii) econometric methods, (iv) timeframes (e.g., weekly instead of daily data), as well as (v) additional control variables. The IV results contrast those from conventional regression analyses that are unable to account for endogeneity, where we identify a precisely estimated null relationship. Thus, ignoring endogeneity introduces a systematic downward bias – and therefore potentially misleading policy conclusions – when regressing subsequent terror attacks on drone strikes, even when controlling for a comprehensive list of observable characteristics. Our benchmark IV estimation implies one drone strike causes more than four terror attacks per day in the subsequent week. Back-of-the-envelope calculations suggest drone strikes to be responsible for 16 percent of all terror attacks in Pakistan from 2006-2016, leading to 2,964 deaths.

We then explore mechanisms to better understand whether reactions to drone strikes are restricted to members of terrorist organizations (*insiders*) or whether the general Pakistani populace (*outsiders*) also responds. We focus on this distinction because respective policy recommendations differ substantially: If drone strikes provoke *insiders* exclusively, a hawkish military argument would suggest targeting all terrorists to eradicate terrorism; however, if *outsiders* are radicalized and harbor anti-US sentiments, drone strikes are likely to extend the pool of militants. Evidence for the latter would be consistent with the *blowback hypothesis* (Kilcullen and Exum, 2009; Hudson et al., 2011; Cavallaro et al., 2012; Cronin, 2013; Jordan, 2014), whereby military intervention can facilitate recruitment efforts of and financial support for terrorist organizations (Hudson et al., 2011).

To distinguish between *insiders* and *outsiders* being affected, we first explore unclaimed attacks as an indicator of missions that are less likely to be orchestrated by established terror groups. Second, we analyze the frequency, negative emotions, and anger of drone- and US-related articles in the leading English-language newspaper in Pakistan, *The News International*. Third, we study whether drone strikes predict anti-US protests. Fourth, *Google* searches for the terms *jihad*, *Taliban video*, and *Zarb-e-Momin/Zarb-i-Momin* (a weekly Pakistani magazine expressing radical beliefs and religious extremism) provide day-to-day proxies of radicalization.[2] The results from IV regressions consistently suggest positive effects, i.e., drone strikes appear to raise support for terrorist organizations among the *general* Pakistani population.

Overall, this paper aims to contribute to three strands of research. First, it informs the literature on the consequences of foreign military intervention by providing what we believe to be the first causal evidence on the effects of drone strikes on terrorism, anti-US sentiment, and radicalization. Given the increasing importance of drone operations in US military strategy, we hope these results are of interest to policymakers and researchers alike. For example, Michael V. Hayden, the former Air Force general and CIA director quoted at the beginning of our paper, argues that "in my firm opinion, the death toll from terrorist attacks would have been much higher if we had not taken action [via drone strikes]" (Hayden, 2016). Our results suggest the opposite and are in line with those related to adverse consequences of indiscriminate bombings, such as those identified in the Vietnam War.

Second, our empirical methodology and results may enrich the literature on counterterrorism efforts (Sandler et al., 2005; Jaeger and Paserman, 2006, 2008; Bueno de Mesquita and Dickson, 2007; Mueller and Stewart, 2014; Jensen, 2016). Although Jaeger and Paserman (2008) find no Granger causality from Israeli anti-terror missions to Palestinian attacks, our results imply that terrorism can increase significantly after a military strike. An important aspect of the setting we study is the fact that military interventions occur from abroad, which may further contribute toward a negative perception of drone strikes. If national sovereignty is continuously violated, locals may respond more profoundly to drone strikes than if military operations were conducted by national governments. These and other avenues forward are discussed in our conclusions.

Third, we speak to the literature on the factors explaining anti-US sentiment and radicalization (Gentzkow and Shapiro, 2004; McCauley and Moskalenko, 2008; Goldsmith and Horiuchi, 2009; Schatz and Levine, 2010; Blaydes and Linzer, 2012; Rink and Sharma, 2018). While Gentzkow and Shapiro

[2]Naturally, not all searches for *jihad* or *Taliban video* may symbolize a desire to radicalize. Nevertheless, we hypothesize that a systematic trend in these online interests would be indicative of radicalization, especially when induced by our identification strategy based on wind (see Section 5.4).

(2004) argue that the source of information matters for tilting the opinion of the Muslim world in favor of or against the US, we find that particular US military actions in foreign lands influence the portrayal of the US in the local media. Our results suggest these dynamics are not driven by reporting on drones alone as articles that mention the US but not drones also become more negative and angry in tone because of drone strikes.

The paper proceeds with a short background of drone strikes and their relationship with terrorism. Section 3 documents our empirical strategy and data, laying out the empirical difficulties in isolating causal effects. Section 4 describes our main findings. In Section 5, we explore mechanisms related to *insiders* and *outsiders*. Section 6 offers conclusions.

2 Background

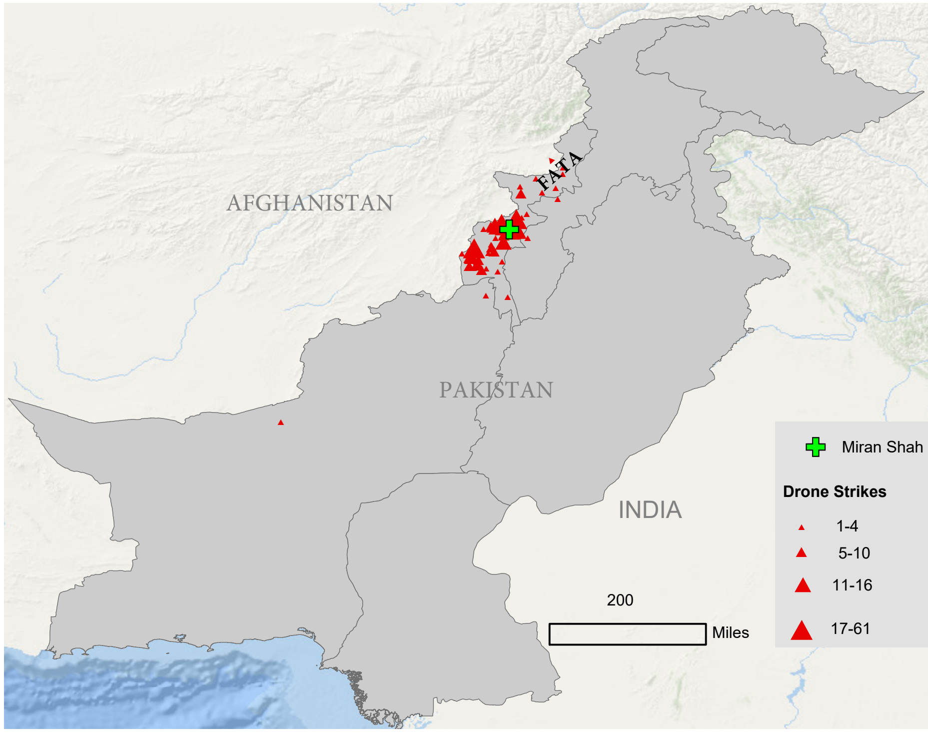
2.1 Drone Strikes in Pakistan

In 2004, the US began to employ drone strikes in Pakistan, first sporadically with 11 strikes conducted until 2007, and then more frequently with 38 strikes in 2008 alone (TBIJ, 2017b).[3] Since then, the US has conducted 'signature strikes' in addition to 'personality strikes', where the former do not require specific intelligence on terrorists but identify terrorists on the basis of certain behavioral patterns alone (Fair et al., 2014). Thus, military-aged men who appear to be members of terrorist organizations are targeted, increasing the risk of civilian casualties (Zenko, 2013).

Panel A of Figure 1 visualizes the fact that 418 of the 420 strikes between January 1, 2006, and December 31, 2016, targeted the Federally Administered Tribal Areas (FATA), located in Western Pakistan and bordering Afghanistan (TBIJ, 2017b). In appendix A, we provide additional background information on FATA. 93 percent of all strikes occurred in North and South Waziristan, two of the seven tribal agencies of FATA, primarily targeting Al-Qaeda, Tehrik-e-Taliban Pakistan (TTP), the Afghan Taliban, the Haqqani network, the Islamic movement of Uzbekistan (IMU), and recently the Islamic State of Iraq and Syria (ISIS; see Berge and Sterman, 2018).

[3]The US primarily uses MQ-1 Predator drones manufactured by General Atomics (Williams, 2010). Recently, MQ-9 Reaper drones have also been used (Enemark, 2011; Wall and Monahan, 2011).

Panel A: Drone strikes



Panel B: Terror attacks

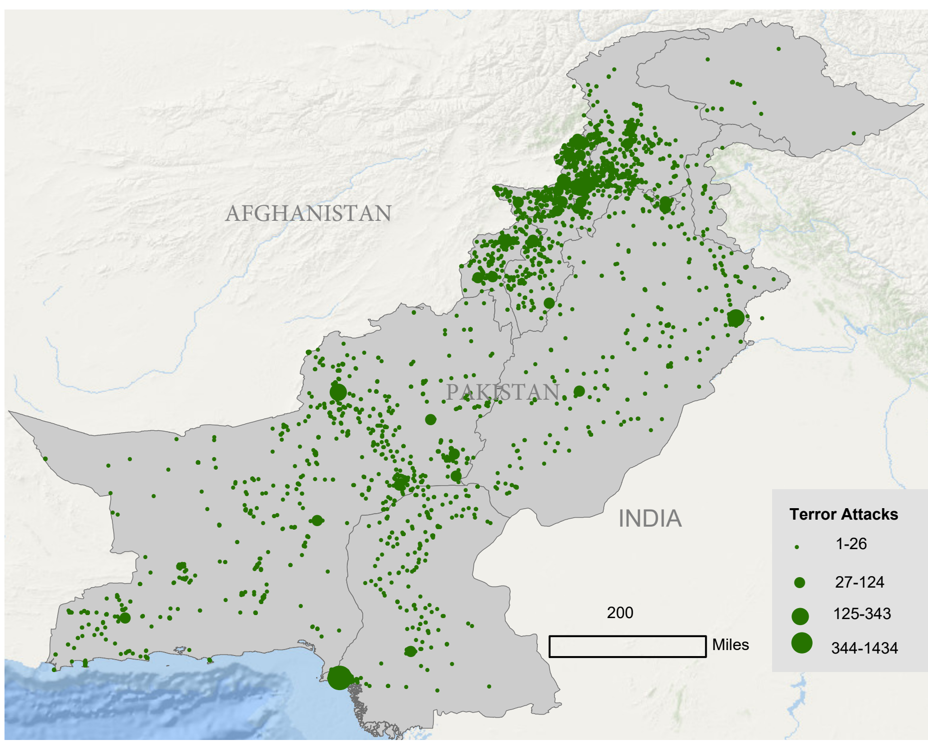


Figure 1: Visualizing the location of drone strikes and terror attacks in Pakistan from 2006 to 2016. The green cross marks Miran Shah, where wind gusts are measured.

Although the Pakistani government never officially admitted to an agreement with the US, it is widely believed that Pervez Musharraf (president from 2001-2008) tacitly approved of drone operations (Singh, 2012). As their frequency increased, the Pakistani government began to acknowledge US involvement, both because people found US markings on the missile pieces after attacks and because of the transition to a democratically elected, more transparent government (Fair et al., 2014). Since then, the government publicly condemns almost every drone strike as a breach of state sovereignty. The National Assembly and the Senate passed resolutions against drone strikes (National Assembly of Pakistan, 2013; Senate of Pakistan, 2017b) and demanded the government's full disclosure of any treaties signed with international organizations in this respect (Senate of Pakistan, 2017a).

2.2 Arguments in Favor of Drone Strikes

The US drone program has earned praise for killing key terrorist leaders, destroying their communication channels, and instilling fear into terrorists' minds (Williams, 2010; Byman, 2013; Burke, 2016). Downfalls of traditional bombings rooted in the difficulty to distinguish between targets and civilians are substantially diminished with the precision promised by drones. Thus, many military leaders believe that unintended consequences in the form of local resistance are also alleviated. For example, Michael V. Hayden labels the US drone program "the most precise and effective application of firepower in the history of armed conflict" (Hayden, 2016). Surveys suggest that, while many US Americans oppose the use of drone strikes on US citizens abroad, "by a wide six-to-one margin (75%-13%) voters approve of the U.S. military using drones to carry out attacks abroad on people and other targets deemed a threat to the U.S." (Woolley and Jenkins, 2013.

Theoretical justifications for targeted killings can be found in pre-drone, game theory-based models as helping to diminish the power of terrorist organizations and containing their activities (e.g., see, Sandler, 2003, Arce and Sandler, 2005, Sandler and Siqueira, 2006, and Bandyopadhyay and Sandler, 2011). Naturally, killing militants may directly weaken terrorist groups by diminishing their manpower, intimidating their members, and deterring those who consider joining. In their correlational analysis, Johnston and Sarbahi (2016) find drone strikes to be associated with a lower frequency and lethality of terror attacks in FATA and neighbouring areas. Studying data from 2007-2011, Jaeger and Siddique

(2018) employ a vector autoregressive model to find Taliban attacks increase in the first week after a drone strike but decrease in the second week.

2.3 Arguments Opposing Drone Strikes

Nevertheless, the hypothesis that drone strikes curb terrorism has been challenged. A majority of the associated arguments hinges on the *blowback hypothesis*: The violation of state sovereignty along with civilian casualties could fan grievances in the *general* populace, i.e., not just within terrorist groups. The resulting sentiments could translate to physical, financial, or ideological support for terrorists (Kilcullen and Exum, 2009; Hudson et al., 2011; Cavallaro et al., 2012; Cronin, 2013; Jordan, 2014).

In fact, drone strikes feature heavily in the propaganda of several terrorist groups. For example, *Al-Sahab*, the propaganda wing of Al-Qaeda, used video footage of drone strikes to portray the US as a heartless oppressor that indiscriminately targets Muslims (Cronin, 2013). In their English-language magazine *Inspire*, Al-Qaeda in the Arabian Peninsula describes drone strikes as resulting in the death of innocent people and oppressing Muslims (Ludvigsen, 2018). In the magazines published by the Tehrik-e-Taliban Pakistan, drones are projected as weapons against Islam; the Pakistani government and military are repeatedly blamed for letting the US wreak havoc with Muslims in Pakistan. In one of the magazines, *Sunnat e Khauwla*, the story of a six-year old 'mujahid' is published who vows to avenge his family and friends who were killed via drones.[4]

Numerous public figures and politicians have expressed concerns about drone strikes, arguing they weaken democracy, push people towards extremist groups, and threaten peace in the region, such as Pakistan's former High Commissioner to Britain (Woods, 2012), then-Army chief Ashfaq Pervaiz Kayani (BBC, 2011), and Pakistan's interior minister (Peralta, 2013). All major political parties publicly condemn drone strikes. Imran Khan, the current Prime Minister, participated in a public protest against drone strikes in 2012 (Doble, 2012). The former prime minister, Nawaz Sharif, called for an end to

[4]The magazine uses sentimental language to gain sympathy and support among readers, in addition to stressing the need to take revenge. For instance, Tehrik-e-Taliban Pakistan (2017) write: "I thought what kind of people kuffar [non-believers] are that they drop bombs on little children. Pakistan is my country but then why Pakistan army allow kuffar to bring in drones and bomb their own children? I then prayed to Allah to give me strength to fight those who bombed my little Maryam. I hate this scary plane, it killed my brother Osama and now my friend Maryam. I and all my friends will inshAllah [by the will of God] do jihad to finish bad people who drop bombs on children."

US drone strikes in his first address after coming into power (BBC, 2013). The Pakistan People's Party (PPP), who lost their chairperson Benazir Bhutto in a *terror* attack in 2009, terms drone strikes a violation of international laws and national sovereignty (Tribune, 2013a). The Awami National Party (ANP) condemns drone strikes (Dawn, 2012) and the more religiously oriented Jammat-e-Islami (JI) and Jamiat Ulema-e-Islam (JUI) organize protests against drone strikes (Tribune, 2013b; Dawn, 2013).

A poll by the New America Foundation and Terror Free Tomorrow reveals that US drone strikes are highly unpopular in the FATA region (NAF and TFT, 2010). According to a Pew survey in 2012, 97 percent of the surveyed Pakistanis who heard about drone strikes hold an unfavorable opinion about them (Pew Research Center, 2013) and 94 percent think drone strikes kill too many innocent people (Afzal, 2018). In sum, this narrative stands in stark contrast to that proposed by US military leaders and it remains an empirical question to understand which forces dominate.

3 Data and Empirical Methodology

3.1 Data

We access daily data on drone strikes from the Bureau of Investigative Journalism, an independent, not-for-profit organization from January 1, 2006, until December 31, 2016 (TBIJ, 2017a,b). All results are virtually identical when employing data from the New America Foundation (Berge and Sterman, 2018; see appendix Table B1). We opt for the *TBIJ* database in our main estimations because it offers active links to sources, images, and video clips for the majority of drone strikes. Both organizations derive their data from news reports and press releases; they show an almost perfect overlap on the number of drone strikes (correlation coefficient of 0.95; see appendix Figure B1). However, reports on the number of casualties, as well as their affiliations and classification as terrorists, are not consistently available and often differ across both sources.

We study national data in Pakistan, rather than region-level data. Since almost all drone strikes occurred in the FATA region, we observe little to no statistical variation in the number of drone strikes in the rest of Pakistan. However, Panel B of Figure 1 visualizes the fact that terror attacks are not restricted to the FATA region alone, i.e., terrorist groups can usually strike throughout the country. Nevertheless, results are consistent if we split the data into FATA and non-FATA regions (see appendix Table B7).

Table 1 documents summary statistics of our main variables. On average, one drone strike occurs every tenth day and three days experienced as many as four strikes. Data on terror attacks are derived from the Global Terrorism Database (GTD, 2017; START (2017)). Pakistan experienced 2.85 terror attacks *on an average day* during our sample period, which ranks the country second worldwide during the 2006-2016 period (behind Iraq). On October 29, 2013, alone, Pakistan suffered 38 terror attacks and only 23 percent of all days in our sample passed without any attack.

Table 1: Summary Statistics of main variables for all 4,018 days from January 1, 2006, until December 31, 2016.

Variable	Mean	(Std. Dev.)	Min	(Max.)	Description	Source
Panel A: Main variables						
Drone strikes	0.10	(0.38)	0	(4)	# of drone strikes	TBIJ (2017b)
Terror attacks	2.85	(2.98)	0	(38)	# of terror attacks	GTD (2017)
Wind gusts	23.92	(8.68)	6.84	(92.16)	Maximum wind gusts (km/h) in Miran Shah	Meteoblue (2018)
Panel B: Control variables						
Pakistani military actions	1.01	(1.40)	0	(10)	Pakistani military actions against terrorists	PICSS (2018)
Ramadan	0.08	(0.27)	0	(1)	Ramadan days	Moonsighting.com (2017)

Weather data for Miran Shah come from Meteoblue (2018) and Section 3.2.3 will discuss our identification strategy based on wind and weather in detail. Maximum wind gusts average almost 24 km/h throughout and reach values as high as 92 km/h. Data and results for employing alternative weather-related IVs are discussed in Section 4.2 with summary statistics available from Table B2. Data on Pakistani military operations against terrorists – a potentially meaningful factor when predicting terror attacks – come from the Pakistan Institute of Conflict and Security Studies that gathers data from publicly available sources (PICSS, 2018). Finally, we consult the Islamic lunar calendar to create a binary variable for Ramadan days.

To get an overall idea of long-term timelines, Figure 2 plots the number of drone strikes and terror attacks. Both variables rise until early 2009, before drone strikes intensify with the beginning of the first

Obama administration. Drone strikes peak in mid-2010 and the frequency of terror attacks increases until reaching its height in early 2013 with almost seven per day.

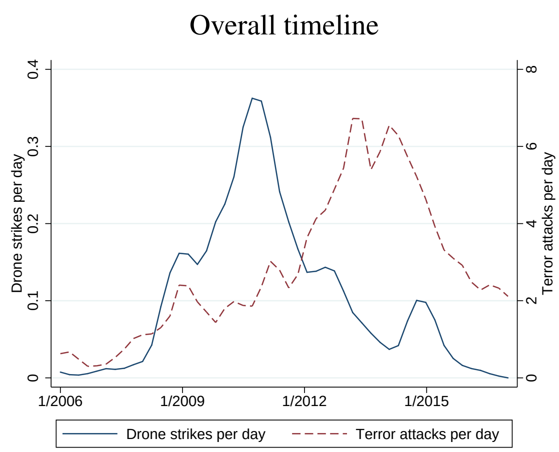


Figure 2: Drone strikes and terror attacks in Pakistan over time, employing a kernel-weighted local polynomial smoothing method of daily observations.

3.2 Empirical Methodology

3.2.1 Conventional Regression Analysis

We begin by regressing a measure of the average daily number of terror attacks from days $t+1$ to $t+7$ on the number of drone strikes on day t. Section 4.3 explores alternative timeframes of the outcome variable since, a priori, it is not clear how many days and weeks, if any, potential effects of drone strikes may last. In all estimations, we predict the *average* daily number of attacks, which allows for a comparable interpretation of the derived coefficients when extending the time horizon of the outcome variable. Formally, we estimate:

$$\frac{(Attacks)_{(t+1),\ldots,(t+7)}}{7} = \beta_0 + \beta_1 \big(Drone\ strikes\big)_{(t)} + \boldsymbol{X'_{(t)}}\beta_2 + \epsilon_{(t)}, \tag{1}$$

where β_1 constitutes the coefficient of interest, $\boldsymbol{X'_{(t)}}$ contains control variables, and $\epsilon_{(t)}$ denotes the conventional error term. Standard errors are estimated robust to arbitrary heteroscedasticity and autocorrelation (HAC SEs) throughout our analysis. To isolate the effect of drone strikes from other military interventions, $\boldsymbol{X}'_{(t)}$ includes a measure for actions by the Pakistani military. For example, military interventions may themselves produce collateral damage or spark grievances and thus retaliation from terrorists. $\boldsymbol{X}'_{(t)}$ also incorporates fixed effects for each day of the week and month of the year. For instance, in the Islamic tradition Friday holds a special sanctity and congregational prayers (Jumuah) are offered on Friday afternoon. Sunday is important for Christians with church attendance being more common. The probability of terror attacks may be affected by such routines. Similarly, the likelihood of terror attacks may vary across months of the year. $\boldsymbol{X}'_{(t)}$ also includes a binary indicator to control for Ramadan, a sacred month for Muslims in which terrorists may conduct more or fewer attacks.[5] Finally, we account for (i) terror attacks on day t, (ii) the sum of terror attacks in the preceding seven days, and (iii) a time trend to control for patterns of terrorism (e.g., see Berrebi and Lakdawalla, 2007).

3.2.2 Endogeneity Concerns

Although equation 1 will provide correlational insights about the link between drone strikes and subsequent terror attacks, one should be careful in interpreting β_1 as causal. A range of unobservable factors can bias β_1 in either direction. We briefly discuss some examples of the two main concerns: Reverse causality and omitted variables.

With respect to reverse casuality, the US may employ drone strikes when attacks are imminent, introducing an upward bias in the estimation of β_1. Alternatively, gathering intelligence to plan drone strikes may be affected by group movements right before attacks (e.g., see BBC, 2015, TBIJ, 2015, and Mir, 2017). Thus, equation 1 cannot exclude the possibility that upcoming terror attacks influence the likelihood of the US conducting drone strikes.

With respect to omitted variables, the fact that both the US military and terrorist organizations share as little as possible about their plans and operational dynamics greatly hinders an empirical analysis of causality. To illustrate these concerns, we briefly discuss four examples. First, terrorists hunt spies and give them exemplary punishment (Dawn, 2008, 2009; SATP, 2009; Sunday Morning Herald, 2010; START, 2017). Now consider the case in which a terrorist group gains in strength, perhaps in the form

[5] Hodler et al. (2018) analyze the effect of Ramadan on terrorism. Al-Baghdadi (2014) presents an example of how terrorists can appeal to the masses during Ramadan.

of additional members or a more efficient organizational structure: The likelihood to expose spies (i.e., prevent drone strikes) *and* to conduct more attacks rises. In this case, unobservable factors related to group strength could introduce a downward bias into β_1.

Second, it has been suggested that Pakistani intelligence agencies share information about terrorists with the US (Khan and Brummitt, 2010; Ali, 2018; Mir, 2018). Now imagine the Pakistani military arrests a key militant: The possibility of subsequent leads to other terrorists increases (Chaudhry, 2018; Ali, 2018; Indian Express, 2018; The News, 2018), which could facilitate drone strikes. At the same time, the group's activities are disrupted because a key militant has been arrested. Again, β_1 could be biased downwards as the arrest remains unobservable for the researcher.

Third, consider a case in which terrorists are re-organizing – perhaps debating over merging with another group or choosing a new leader – and are therefore conducting a series of meetings. In this case, terrorists are both easier to target for drone strikes (because of their movements) *and* less likely to conduct missions during the reorganization. Fourth, and following a similar logic, assume an intra-group conflict within a terrorist organization. Such infighting may both increase the chances of the US military receiving tip-offs on the location of terrorists *and* affect the planning of attacks.

In sum, equation 1 is unlikely to provide us with insights on causal effects from drone strikes, as endogeneity can affect the sign, statistical precision, and magnitude of β_1.

3.2.3 Identification Strategy

To address endogeneity, we instrument the number of drone strikes with weather conditions on the same day. This choice is based on substantial evidence showing that weather, and in particular wind, matters for drone flights (Government Accountability Office, 2009, 2017; Whitlock, 2014). As drones are much lighter than manned aircrafts, a range of reports document the crucial role of weather in military decisions to launch a drone.[6] In fact, 20 percent of all Predator B flights between 2013 and 2016 were cancelled because of weather conditions (Government Accountability Office, 2017). Potential monetary losses contribute to the delicate nature of an unsuccessful drone operation. A standard Predator drone cost

[6] An empty Predator drone weighs 4,900 pounds (U.S. Airforce, 2015a), while an F-16 jet without fuel weighs 19,700 pounds (U.S. Airforce, 2015b).

US$4.03 million in 2010 and is designed for numerous flights (U.S. Airforce, 2010).[7] Further, a drone crash behind enemy lines may give away the most up-to-date military technology.[8] All these factors motivate our hypothesis that the US military, wary of a potentially unsuccessful operation, is less likely to employ drone strikes under crash-prone weather conditions in the target area, everything else equal.

Among the weather conditions that are particularly challenging, wind stands out as a key factor. In one tactical guide issued by the US Joint Forces Command, a typical drone does not have operational capabilities of flying in cross-winds greater than 15 knots or 27.78 km/h (USJFCOM, 2010; Whitlock, 2014). This would correspond to 989 of the 4,018 days in our sample or almost every fourth day. In addition, icing, precipitation, and low cloud covers can be detrimental to a successful drone operation (USJFCOM, 2010). Consistent conclusions are reached by the UK armed forces (Brooke-Holland, 2015) and risk assessments of Predator or Reaper drones (AFSOC, 2008).

To be clear, we are suggesting that the US military uses weather (and in particular wind) conditions in areas close to potential targets as *one* factor to decide over the use of a drone strike. We are not arguing for wind to be the *only* factor; rather, taking into account all other factors, we hypothesize that weather and wind particularly is taken as one determinant to decide over the use of a drone strike. Thus, in our main estimations, we use an index of maximum wind gusts on day t to predict drone strikes on day t in the first stage of a 2SLS approach. Formally, our first stage takes on the following form:

$$\left(Drone\ strikes\right)_{(t)} = \alpha_0 + \alpha_1 \left(Wind\ gusts\ \right)_{(t)} + \boldsymbol{X}'_{\boldsymbol{(t)}} \alpha_2 + \delta_{(t)}. \tag{2}$$

The predicted drone strikes on day t are then used in the second stage to predict subsequent terrorism, following equation 1. In Section 5, we follow this econometric framework in analyzing alternative outcome variables related to anti-US sentiment and radicalization.

[7]For instance, the first Predator drone that carried a hellfire missile completed 196 combat missions before its retirement (Connor, 2018).

[8]For example, this appeared to be a significant problem when a US drone crashed in Iran in 2011. General Norton Schwartz, then-US Air Force Chief, stated that "[t]here is the potential for reverse engineering, clearly" (Erdbrink, 2011). Iran's national security committee claimed not only to decode hard drives of the crashed drone but also to access its sensitive databases (The Telegraph, 2012).

3.2.4 Validity of IV

We employ weather data from Miran Shah, the capital of FATA located in the North Waziristan agency, where 71 percent of all drone strikes occurred (see Panel A of Figure 1). In fact, 93 percent of all drone strikes targeted the North and South Waziristan agencies. Wind gusts in Miran Shah are strongly correlated with those from Wana, the regional capital of South Waziristan, located approximately 154 km to the Southwest (see appendix Table B3).

To test for the validity of our IV, Table 2 presents regression results from predicting the number of drone strikes on day t with wind gusts on day t, accessing all 4,018 days from January 1, 2006, until December 31, 2016. Column (1) displays results from a basic univariate regression, showing that wind emerges as a negative and statistically powerful predictor of drone strikes. This relationship prevails when incorporating the respective control variables introduced in equation 1 in columns (2) and (3). Thus, wind gusts measured in Miran Shah, which lies at the center of the main target area for drone strikes, are a negative and statistically powerful predictor of drone strikes, even when accounting for a comprehensive list of potentially confounding factors. The fact that the coefficient remains virtually unaffected in magnitude and statistical precision once we control for terror attacks, Pakistani military actions, and time-specific characteristics underlines the importance of wind for the implementation of drone strikes.

3.2.5 Excludability of IV

With respect to the excludability of the IV, there is no evidence to suggest drone flights can affect wind. However, one may argue that wind could affect terrorism or actions by the Pakistani military via channels other than drone strikes. For instance, in windy conditions, when drones may not be able to fly, the US could share intelligence with the Pakistani armed forces who may conduct an operation. If that were the case, we should observe a positive correlation between wind gusts and actions against terrorists by the Pakistani military. Another possibility is that terror attacks themselves are sensitive to weather conditions. For example, if terrorists anticipated fewer drone strikes in windy conditions, they may attack more. If that were true, we should observe a positive and statistically significant correlation between terror attacks and wind gusts on the same day, conditional on observables.

Table 2: Predicting the number of drone strikes on day t with wind gusts on day t.

Dependent variable: # of drone strikes$_{(t)}$	(1)	(2)	(3)
Wind gusts$_{(t)}$	-0.0025***	-0.0021***	-0.0021***
	(0.0006)	(0.0006)	(0.0006)
Control set I^{a}		yes	yes
Control set II^{b}			yes
N	4,018	4,018	4,018

*Notes:*Newey-West standard errors for autocorrelation of order one are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.^{a}Control set I includes terror attacks on day t, the sum of terror attacks on days $t-1$ until $t-7$, a time trend, as well as fixed effects for each day of the week and each month of the year. ^{b}Control set II includes Pakistani military actions and a binary indicator for Ramadan.

Table 3 explores both these possibilities, displaying results from predicting terror attacks (column 1) and actions by the Pakistani military (column 2) with contemporaneous wind gusts, conditional on the lagged dependent variable. However, neither variable appears systematically affected by wind gusts on the same day, supporting the exclusion restriction. In fact, if anything, both variables display a *negative* correlation with wind gusts on the same day. Nevertheless, the derived coefficients remain far from statistically relevant in conventional terms.

4 Empirical Findings: Terrorism

4.1 Benchmark Results

Table 4 reports our main empirical findings, where columns (1)-(3) consider linear regression results and columns (4)-(6) turn to IV estimates. Column (1) documents findings from a univariate regression, predicting the number of terror attacks per day in the subsequent seven days solely with the number of drone strikes today. The corresponding coefficient is negative but statistically indistinguishable from zero. Column (2) adds control variables pertaining to terror attacks on day t and on the preceding

Table 3: Are wind gusts correlated with contemporaneous terror attacks or Pakistani military actions?

	(1)	(2)
Dependent variable:	*Terror attacks*$_{(t)}$	*Pakistani military actions*$_{(t)}$
Wind gusts$_{(t)}$	-0.005	-0.001
	(0.005)	(0.002)
Terror attacks$_{(t-1),...,(t-7)}$	0.119***	
	(0.005)	
Pakistani military actions$_{(t-1),...,(t-7)}$		0.111***
		(0.004)
N	4,018	4,011

Notes: Newey-West standard errors for autocorrelation of order one are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

seven days, a linear time trend, as well as fixed effects for each day of the week and month of the year. However, the corresponding results remain largely unchanged, although standard errors decrease by one third compared to column (1), which indicates that the corresponding control variables contribute towards a more precisely estimated correlation. Column (3) incorporates actions by the Pakistani military and the binary indicator measuring Ramadan, but conclusions with respect to the role of drone strikes remain unchanged. Panel C shows that even if the estimation were statistically precise, the corresponding magnitude would be minimal: One drone strike would be able to explain a decrease of only 0.052 attacks per day in the following week.

Columns (4)-(6) repeat the same sequence of regressions but employ wind gusts in the first stage to predict the number of drone strikes. Panel B shows wind gusts to be a negative and statistically powerful predictor of drone strikes in all estimations, and Panel C displays the corresponding F-statistics. The respective values range from 12 to 18.5, i.e., above the often-employed rule-of-thumb threshold value of ten (Stock and Yogo, 2005; Stock and Watson, 2015). The second-stage results related to the role of drone strikes are now substantially different when it comes to sign, magnitude, and statistical precision. Drone strikes become a positive and statistically precise predictor of subsequent terrorism. Without

Table 4: Main regression results from predicting the average daily number of terror attacks on days *t+1* to *t+7*.

Estimation method:	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Predicting the average daily number of terror attacks on days $t+1$ to $t+7$						
Drone strikes$_{(t)}$	-0.036	-0.051	-0.052	7.516***	4.454***	4.377***
	(0.070)	(0.047)	(0.047)	(2.282)	(1.637)	(1.602)
Control set I^{a}		yes	yes		yes	yes
Control set II^{b}			yes			yes
Panel B: First stage results, predicting the number of drone strikes on day t						
Wind gusts$_{(t)}$				-0.003 ***	-0.002***	-0.002***
				(0.001)	(0.001)	(0.001)
Control set I^{a}		yes	yes		yes	yes
Control set II^{b}			yes			yes
Panel C: Statistics						
F-test insignificance of IV				18.530***	12.033***	12.313***
Endogeneity test				25.223***	17.992***	17.902***
Terror attacks explained by drone strikes	0%	0%	0%	28%	16%	16%
N	4,011	4,011	4,011	4,011	4,011	4,011

Notes: Newey-West standard errors for autocorrelation of order one are displayed in parentheses for the OLS regressions, while heteroscedasticity and autocorrelation consistent (HAC) standard errors are displayed for the IV regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ^{a}Control set I includes measures for the dependent variable on days t and days $t-1$ until $t-7$, a time trend, as well as fixed effects for each day of the week and each month of the year. ^{b}Control set II includes Pakistani military actions and a binary indicator for Ramadan.

control variables, drone strikes at their mean (0.1 per day) would lead to more than 0.75 terror attacks per day in the following week, which would be equivalent to 28 percent of all terror attacks (see Panel C). Once we account for the familiar set of covariates in columns (5) and (6), that magnitude decreases to 16 percent ($4.377 * 0.10 = 0.44$, which translates to 16 percent of the 2.85 terror attacks per average day). Assuming these to be average attacks, a back-of-the-envelope calculation suggests that Pakistan would have suffered 2,964 fewer deaths from terrorism if there were no drone strikes at all (taking into account all 18,524 deaths from the 11,461 terror attacks in our sample).

4.2 Robustness Checks and Placebo Tests

These results from column (6) remain robust to (i) alternative IVs that are suggested to influence the success of drone flights (including wind speed instead of wind gusts, cloud coverage, and precipitation), (ii) alternative definitions of terrorism, (iii) studying deaths from terror attacks (as opposed to attacks), (iv) employing various additional control variables (also pertaining to weather), and (v) using alternative estimation techniques. The corresponding results are referred to the appendix Tables B4, B5, and B6.

In particular, we use three alternative definitions of terrorism based on the three *GTD* criteria (START, 2017). Additional control variables include a binary indicator for the period after Osama bin Laden's (OBL) death, temperature, seasonal indicators (see Meier et al., 2007, Hsiang et al., 2013, and Burke et al., 2015, for environmental effects on conflict), attacks in Afghanistan, and bi-monthly fixed effects. We also estimate the main specification via Poisson and negative binomial regression methods since our dependent variable is a count variable. To minimize concerns about double-counting attacks in overlapping time windows of the outcome variable, we aggregated all data over three- and seven-day periods, producing consistent results (see Table B7). Further, studying regional subsamples, we find that drone strikes result in additional terror attacks not only in the FATA region but also in the rest of the country (see Table B7).

We also conduct a placebo test, exploring whether terrorism in Afghanistan is predicted by drone strikes in Pakistan, which could indicate that unobservable developments are driving terrorism in both countries. However, we find no statistically discernible relationship (see appendix Figure B2).

Finally, using wind gusts in a reduced form to predict subsequent terror attacks produces consistent results: When wind gusts are stronger, we observe significantly fewer terror attacks in the subsequent days (see Section B.6). We now turn to alternative timeframes of the outcome variable before distinguishing between attack types and targets.

4.3 Alternative Timeframes

Figure 3 displays second-stage coefficients from alternative 2SLS regressions, where we adjust the timeframe of subsequent terror attacks, following column (6) of Table 4 as the benchmark specification. Throughout the remainder of the paper, we will display 2SLS regression results graphically. Figure 3 serves two purposes. First, we explore whether the results from Table 4 are specific to the seven-day period after a drone strike (and perhaps spurious) or whether alternative time windows produce consistent findings.

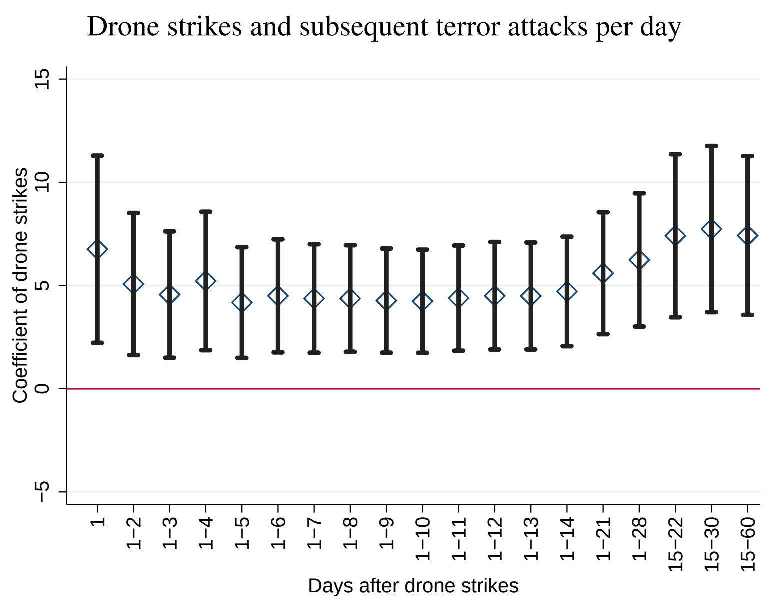


Figure 3: Predicting additional terror attacks per day after drone strikes, employing alternative time windows for the dependent variable. Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.

Second, we investigate how long the effect lasts. If attacks only increase immediately after drone strikes but *decrease* thereafter, terrorists may simply conduct attacks earlier than planned, perhaps because they want to retaliate or fear further drone strikes. If that were the case, the results from Table 4 would speak to the *timing* but not the total number of attacks. One way to explore this possibility is to extend the time window of the outcome variable – if the results affected timing only, we should see a *negative* effect for attacks further in the future, i.e., planned attacks are conducted sooner after drone strikes and the number of attacks decreases later on.

However, Figure 3 shows that subsequent terror attacks per day remain relatively consistent for time windows of up to 60 days after the initial drone strikes. The fact that the coefficient remains far from turning negative and, if anything, marginally increases indicates drone strikes do not merely affect the timing but rather the total number of terror attacks.

4.4 Attack Types and Targets

Figures 4 and 5 display regression coefficients when distinguishing between terror types and targets. If attacks indeed increase because of drone strikes, can we say more about their characteristics? Our benchmark results suggest attacks are conducted that would not have occurred if there were no drone strikes. If that was the case within days or a couple of weeks, we would expect those attacks to increase that are relatively easy to plan, as opposed to those that are difficult to orchestrate. The *GTD* provides information on eight types of terror attacks (START, 2017) and we group these into four categories: Bombings (approximately 57 percent of all attacks), assaults (29 percent), kidnappings (seven percent), and assassinations (six percent).

Intuitively, bombings and assaults appear easier to plan and conduct than assassinations and kidnappings, as the latter two categories likely require strategic planning with respect to the target. For a discussion on the relative complexities of different terror operations, we refer to Oots (1986), Drake et al. (1998), and Jackson and Frelinger (2009). The corresponding results displayed in Figure 4 suggest exactly that: Following our familiar 2SLS estimation strategy, bombings and assaults increase significantly after drone strikes, but we identify little activity (if any) related to assassinations and kidnappings. One

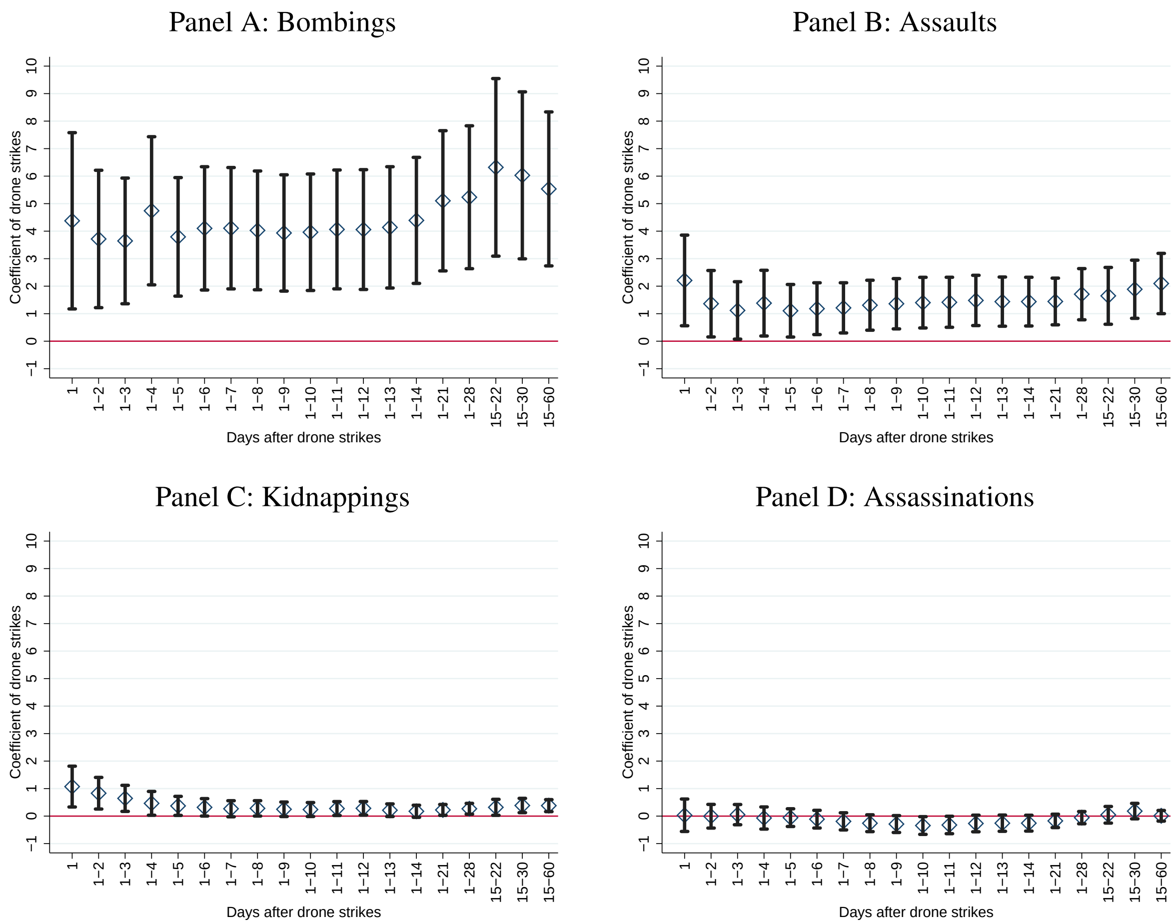


Figure 4: Predicting additional terror attacks per day after drone strikes, distinguishing by terror types. Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.

drone strike leads to approximately four additional bombings and one additional assault per day in the subsequent days and weeks.[9]

Figure 5 distinguishes by terror targets, predicting attacks on government (53 percent of all attacks), private citizens and property (22 percent), as well as businesses (eight percent).[10] We find that attacks on all three target types increase after drone strikes. However, the impact is largest for government targets, where a drone strike results in three to four additional attacks per day in the subsequent days and weeks, whereas the corresponding magnitude suggests two (one) additional attacks per day on private property or citizens (on business). These results are consistent with a retaliatory narrative of terrorists who perceive the Pakistani government as a US collaborator and the Pakistani military and government as apostates (Tehrik-i-Taliban Pakistan, 2019).

5 Mechanism: *Insiders* vs. *Outsiders*

An important question emerging from our results relates to whether drone strikes exclusively affect those who are already affiliated with terrorist groups (*insiders*) or also ordinary Pakistanis (*outsiders*). The respective policy conclusions would differ substantially. If the former were true, one could argue for targeting all current terrorists as a solution. However, if the latter were true, drone strikes may increase support for terrorist groups and facilitate their recruitment efforts. We pursue several strategies to explore whether *outsiders* are affected by drone strikes, using data from (i) unclaimed terror attacks, (ii) the main English-language Pakistani newspaper, (iii) protests against the US, and (iv) online search behavior indicative of radicalization. Summary statistics of all additional variables are referred to the appendix Table C1.

Throughout these analyses, we follow the same 2SLS methodology outlined in Section 3.2.3. Similar to the endogeneity concerns pertaining to drone strikes and subsequent terror attacks, unobservable

[9] The bombings/explosion category in the *GTD* also includes suicide bombings, which are highlighted via the variable *suicide*. Four percent of all attacks in our sample are classified as suicide attacks. Analyzing these separately, we do not find any significant increase in the number of suicide attacks after drone strikes. One possibility is that the time required to prepare a suicide bomber is longer than two months, the maximum time for which we conduct our analysis (Lakhani, 2010).

[10] Attacks on government include attacks on armed forces, government-owned infrastructure, public transport systems, etc. The variable includes categories 2, 3, 4, 6, 7, 8, 9, 11, 16, 18, 19, and 21 of the *GTD* variable *targtype1*. As a robustness check, we considered only the general attacks on government (category 2) and find consistent results, albeit smaller in magnitude.

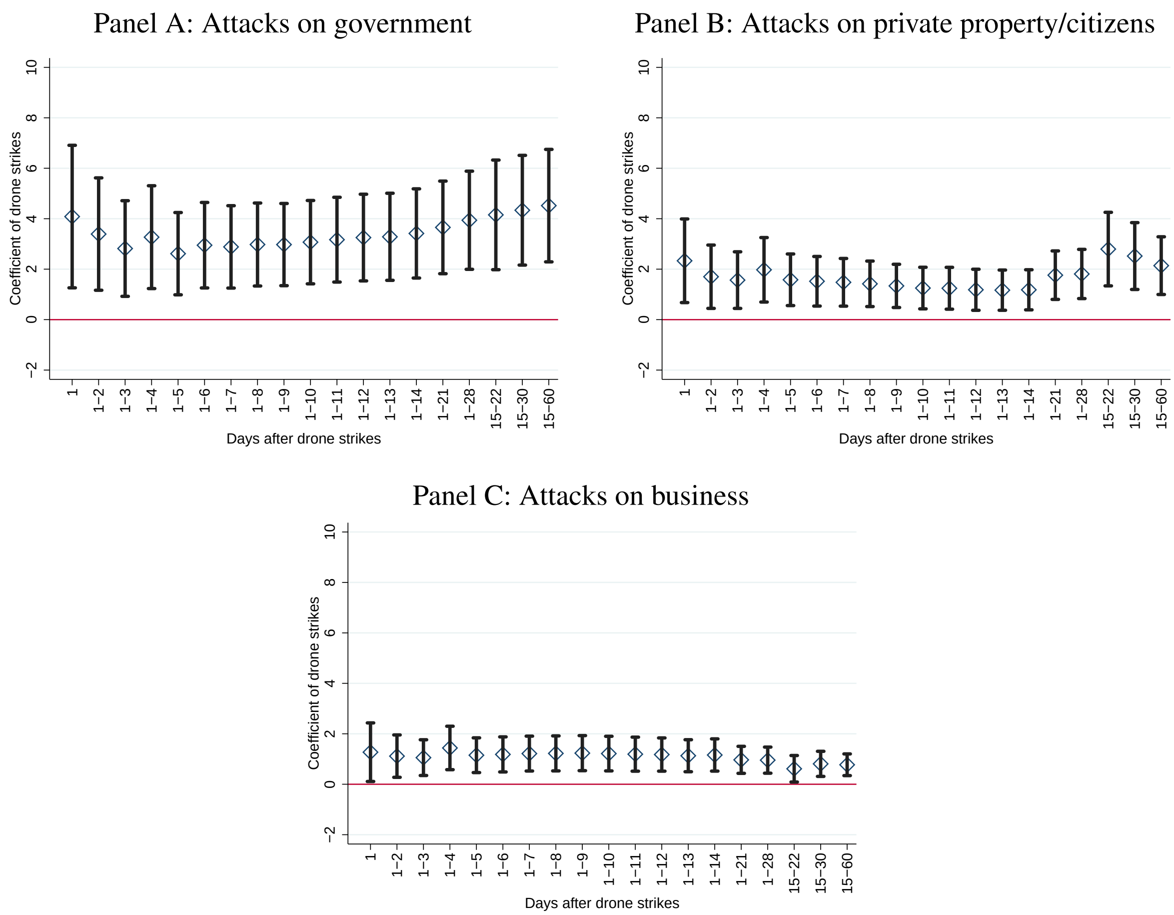


Figure 5: Predicting additional terror attacks per day after drone strikes, distinguishing by terror targets. Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.

characteristics can also affect attitudes and beliefs in the Pakistani population. In particular, economic, political, and societal developments at home and abroad may affect drone strikes and Pakistanis' attitudes alike. For example, if terrorist groups are gaining strength in society and become more visible, this may affect both the likelihood of drone strikes and public sentiment toward the US.

5.1 Unclaimed Attacks

For the first indication of whether *outsiders* could be affected, we turn to those terror attacks that are listed as unclaimed by the *GTD*. Intuitively, if *insiders* were to conduct attacks, we would assume they like everybody to know who it was, perhaps as a signal of retaliation for the preceding drone strikes. However, if *outsiders*, who are not part of a particular terrorist organization at this point, were angered, an attack is more likely to remain unclaimed.

Figure 6 displays regression coefficients when predicting unclaimed attacks only. Indeed, we derive positive coefficients throughout. We can think of two possible explanations for this result. First, radicalized individuals or small groups may respond by becoming violent to express their discontent with drone strikes. This narrative would be consistent with *outsiders* turning to violent extremism in response to drone strikes. Second, if more conservative leaders are killed, those subordinates who favor extensive violence are freer to act and do so without claiming them (e.g., see Rigterink, 2018). Such an explanation would still be consistent with *insiders* perpetrating more attacks. We now move beyond the *GTD* to explore developments that are more representative of the general Pakistani population.

5.2 Anti-US Sentiment in Newspaper Articles

To measure political attitudes prevalent in the Pakistani media, we first explore newspaper articles published in *The News International* (*TNI*), the largest circulating English-language newspaper in Pakistan.[11] To capture the potentially relevant news, we focus on articles in the categories *Top Story* and *National*. Although reaching fewer people than the major daily circulations published in Urdu, several character-

[11] The respective archive can be accessed via www.thenews.com.pk. We restrict our analysis to an English-language newspapers because text analysis programs generally do not allow analyses of Urdu texts. In additional estimations, we also explored the *Dawn* newspaper, the oldest English-language newspaper in Pakistan, but their online archive exhibits numerous missing days for the time period when drone strikes were highest in number, i.e., in 2009 and 2010.

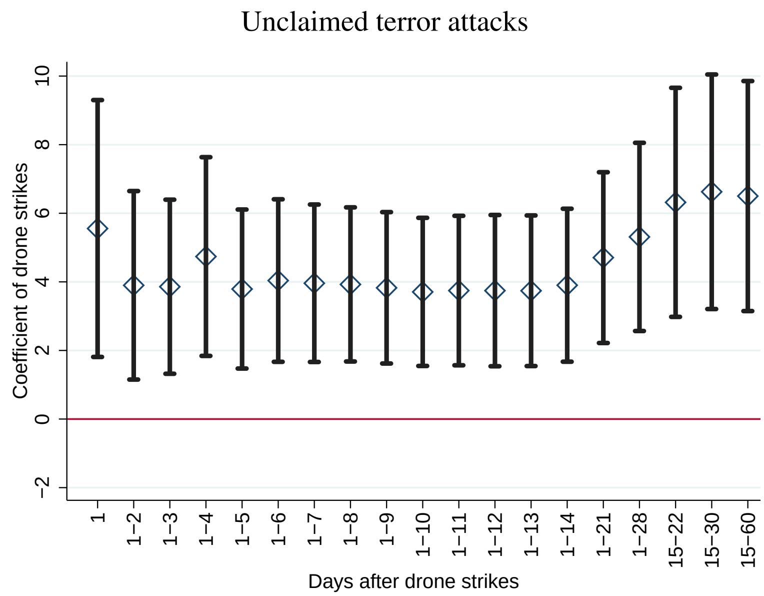


Figure 6: Predicting unclaimed terror attacks per day after drone strikes. Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.

istics make *TNI* a useful case study. First, *TNI* is owned by the Jang group whose Urdu daily (*Jang*) enjoys the widest circulation in Pakistan. Thus, although management of the two dailies differs, they likely reflect comparable attitudes toward political topics.[12] Second, if anything, prior research suggests newspapers published in Urdu to be more anti-drone and anti-US than newspapers published in English, employing "highly emotive vocabulary" to describe casualties from drone strikes (Shah, 2010; Fair et al., 2014). Thus, any effects identified in *TNI* may constitute a lower bound estimate of the general effects in other newspapers.

We begin by exploring how many articles include the word *drone* (upper- or lower-case spellings), with the respective results displayed in Figure 7. Naturally, the media plays an important role in informing Pakistanis about drone strikes. If the media were unfree to report or chose not to report on drone strikes, the general populace were less likely to learn about drone strikes. This, in turn, would make it less likely that *outsiders* become radicalized.

[12]The Jang group also owns a private television network (the *Geo TV* network) with their *Geo News* channel capturing the largest viewership in the country (Gallup Pakistan, 2019).

Panel A displays descriptive statistics illustrating the number of articles mentioning *drone* to be significantly larger on days after a drone strike. Panel B predicts the number of articles mentioning *drone* using the familiar 2SLS approach and finds a statistically significant increase from the second day onwards. On average, two to four additional articles per day mention *drone* in the subsequent days and weeks. In additional estimations analyzing *Google Trends*, we find searches for *drone* increase by approximately 50 percent in the week following drone strikes (see appendix Table C1). This further illustrates that drone strikes in Pakistan do not go unnoticed; people tend to learn about them and try to get more information.

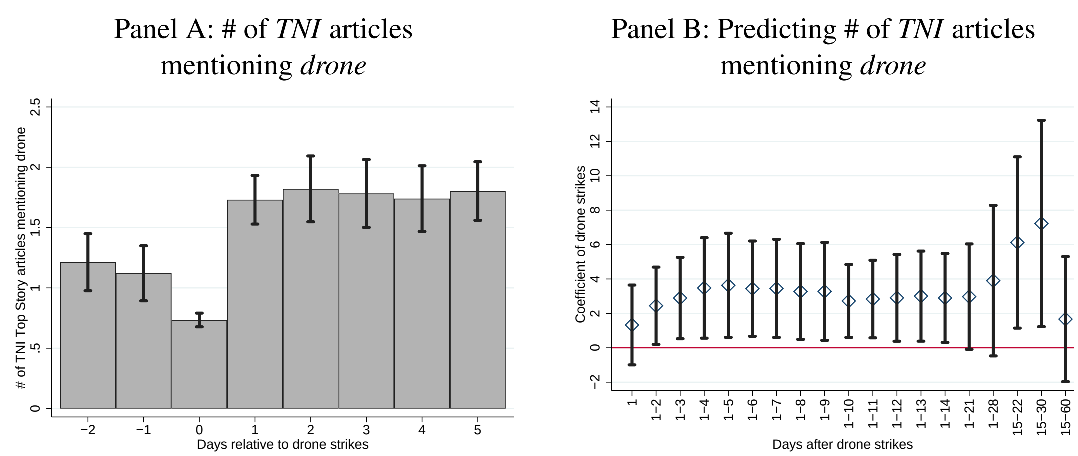


Figure 7: Panel A: Number of *TNI* articles mentioning *drone* on the respective days relative to drone strikes. Panel B: Predicting additional *TNI* articles mentioning *drone* (including upper- and lower-case spellings), after drone strikes. Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.

However, the respective *TNI* coverage may not necessarily paint a negative image of the US if the media presented drone strikes in a positive light, perhaps in assisting Pakistan to curb terrorism. To explore *TNI* sentiment towards drone strikes, we apply the *Linguistic Inquiry and Word Count* program (*LIWC*; Pennebaker et al., 2001) to derive each article's degree of (i) negative emotions and (ii) anger.[13]

[13]For details about the LIWC program, we refer to the LIWC website and Pennebaker et al. (2015). The LIWC program matches each word of an article with a built-in dictionary designed to identify certain psychological traits, such as negative emotions. Because the program employs probabilistic models of language use, the analysis is reliable in the event of multiple and opposite uses of the same word and may capture the general vein of the article in case of ironic or sarcastic expressions, though not as perfectly as a human reader. For example, to measure negative emotions, the dictionary includes 744 words and

We then calculate the average negative emotional content and average anger expressed in *TNI* articles mentioning *drone* on the respective day.

Panels A and B of Figure 8 present results from the corresponding 2SLS estimations. The results suggest that articles mentioning *drone* systematically feature more negative emotions and anger after drone strikes. In terms of magnitude, one drone strike increases negative emotions and anger by approximately three standard deviations in the following week. These sentiments persist for weeks.

Next, we ask whether negative sentiments are restricted to articles about drones. To explore *TNI* attitudes toward the US, Panels C and D of Figure 8 display results from considering the average sentiment in articles mentioning the US.[14] Here again, both negative emotions and anger appear to rise because of drone strikes. Finally, to isolate reporting about the US that is *not* related to drones, Panels E and F display results from 2SLS regressions predicting the emotional content of *TNI* articles mentioning the US but not including the word *drone*. Here again, negative emotional content and anger increase, suggesting that general reporting about the US changes after drone strikes. Quantitatively, one drone strike is predicted to raise negative emotions (anger) by a magnitude equivalent to up to three (two) standard deviations in the following week.

5.3 Anti-US Protests

Beyond newspapers, we now turn to protests against the US, accessing data from the *Global Database of Events, Language, and Tone* (*GDELT*; Leetaru and Schrodt, 2013) database, the largest open platform gathering information on geo-located events from print, broadcast, and web news in more than 100 languages. We extract data on events where Pakistan is listed as *Actor 1*, whereas the US is listed as *Actor 2*, focusing on event code 14 (protests). During our sample period from 2006 to 2016, *GDELT* reports 3,745 protests in Pakistan against the US.

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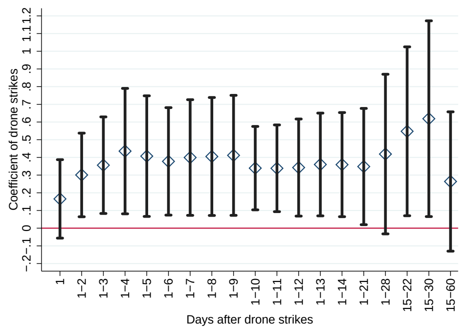
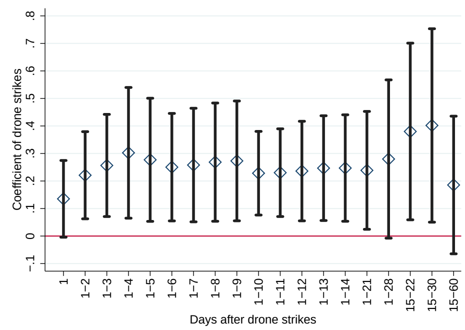
expressions, while for identifying anger (a sub-category of negative emotions) the dictionary uses 230 words and expressions. The number of matched words and expressions is then converted to a percentage of the total words in the text. Higher percentages indicate more negative emotional content and anger, respectively. As an example application of the *LIWC* program, we refer to Borowiecki (2017) who measures the emotional content of letters by famous composers.

[14] We identify those *TNI* articles that mention the words *America* (excluding articles on *South America*), *United States*, *US* (in capital letters), or *U.S.* (in capital letters).

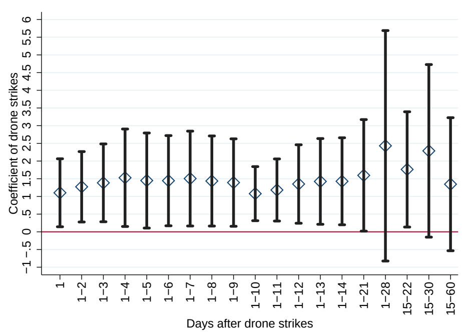
Panel A: Predicting average negative emotions in *TNI* articles mentioning *drone*



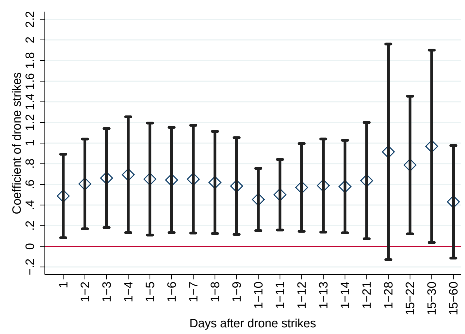
Panel B: Predicting average anger in *TNI* articles mentioning *drone*



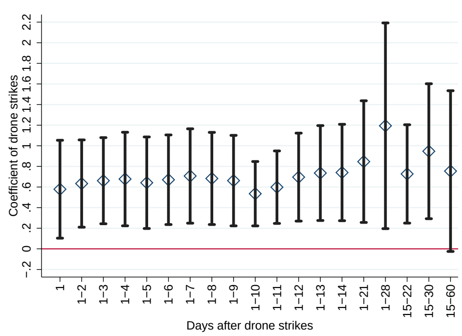
Panel C: Predicting average negative emotions in *TNI* articles mentioning *US* (*America, US, United States, U.S.*)



Panel D: Predicting average anger in *TNI* articles mentioning *US* (*America, US, United States, U.S.*)



Panel E: Predicting average negative emotions in *TNI* articles mentioning *US* but not drone



Panel F: Predicting average anger in *TNI* articles mentioning *US* but not drone

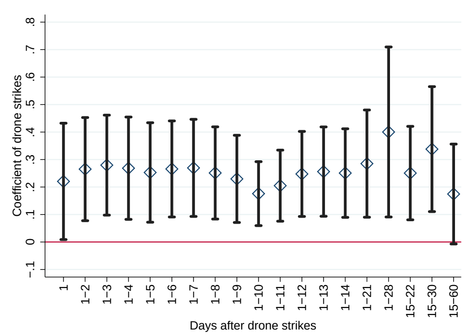


Figure 8: Predicting additional average negative emotional content and anger in *TNI* articles. Each point in each graph represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed. Note: scales of the corresponding y-axes differ to illustrate underlying effects.

Figure 9 presents the corresponding results from 2SLS regressions to predict anti-US protests, revealing a substantial rise after drone strikes. As before, our IV strategy allows us to free the relationship between drone strikes and protests from unobserved developments. In terms of magnitude, one drone strike results in two to four additional protests against the US per day in the following days and weeks. These results are consistent with the hypothesis that anti-US sentiment rises in the general Pakistani population after drone strikes.

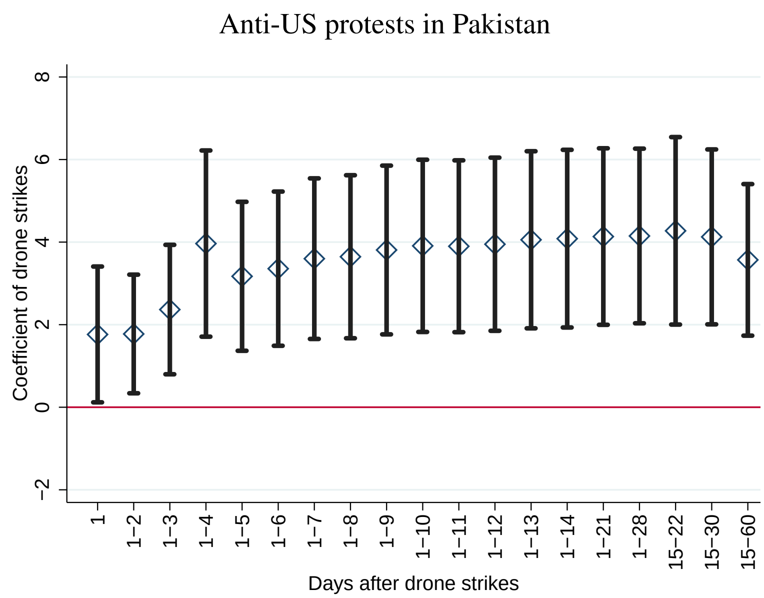


Figure 9: Predicting additional anti-US protests in Pakistan per day. Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.

5.4 Signs of Radicalization

In our final set of estimations, we turn to *Google Trends*. A growing body of research suggests Google searches as meaningful measures of social developments because of the large number of data points and an absence of social censoring (e.g., see Conti and Sobiesk, 2007, Kreuter et al., 2008, Stephens-Davidowitz, 2014, and Stephens-Davidowitz and Pabon, 2017). To proxy for radicalization, we study three search terms: (i) *Jihad*, which literally means 'struggle' and has become synonymous with the armed struggle against enemies of Islam, (ii) *Taliban video*, and (iii) *Zarb-e-Momin/Zarb-i-Momin*, which translates to ‘strike of a devout Muslim’ and constitutes a weekly magazine published in Pakistan, expressing radical beliefs and religious extremism.

With respect to *jihad*, it is important to highlight that the term is not only used to describe terrorism in Pakistan. For example, the war against the Pakistani military is also termed *jihad* and the official school curriculum contains information on *jihad* as one of the four pillars of Islam. Nevertheless, terrorists use this term solely to refer to their cause and to justify their acts in the eyes of a common citizen of Pakistan. For instance, the top five queries related to *jihad* include *al jihad*, which produces *Egyptian Islamic jihad* as the first search result on *Google* in Pakistan. Other prominent related queries include *jihad in islam*, *jihad Pakistan*, *jihad videos*, and *jihad nasheed*, where the final two terms are typically used to describe the motivational resources used by terrorist organizations.[15] Our identification strategy via wind is likely orthogonal to other uses of the term *jihad*. Thus, a significant increase in *Google* searches for *jihad* may be able to tell us something about trends in radicalization.

Our second term, *Taliban video* shows among the top ten queries information about the Taliban and killings by the Taliban. Everything else equal, we posit that more searches for *Taliban video* signal an increased interest in Taliban activities, one of the most powerful terrorist groups in Pakistan (as opposed to, for example, only searching for *Taliban* alone). Such interest may be indicative of an intent to join or support the Taliban (financially or otherwise).

The third search term *Zarb-e-Momin*/*Zarb-i-Momin* returns the *Facebook* pages of the weekly newspaper ‘Zarb-e-Momin (*ZeM*)’ and urdu texts of this newspaper among the top five results on *Google* in Pakistan. *ZeM* started as a weekly newspaper published by Al-Rashid Trust, a charity known to support terrorist activities (Stanford University, 2012). According to a report by Stanford University, “Zarb-e-Momin was originally founded in the 1990s by ART [Al-Rashid Trust], and served as JeM’s [Jaish-e-Muhammad’s] official newspaper and later emerged as a Taliban mouthpiece” (Stanford University, 2012). Despite the proscription of Jaish-e-Muhammad, the magazine can still be accessed online and in print, although it does not bear the name of its publisher, editor, or printing press (Hassan, 2011). Such publications are known to disseminate their views on political developments in Pakistan and abroad and

[15]Further, the search term *jihad videos* produces Islamic jihad training videos on *YouTube* as the first result, while *jihad nasheed* yields links to various jihadi songs uploaded by radical organizations and individuals.

are allegedly relatively successful in driving youth to their cause, in addition to raising funds for terrorist organizations (Kakar and Siddique, 2015).

Figure 10 shows the corresponding results from 2SLS estimations. For all the three search terms, we identify a significant rise in *Google* searches after drone strikes. Quantitatively, one drone strike increases the corresponding *jihad* searches by 37 percentage points (equivalent to approximately two standard deviations), *Taliban video* searches by 33 percentage points (1.6 standard deviations), and *ZeM* searches by 22 percentage points (one standard deviation) per day in the subsequent week. Interestingly, searches for *jihad* return to their average three weeks after the respective drone strikes, whereas searches for the other two terms are slower in returning to their base level.

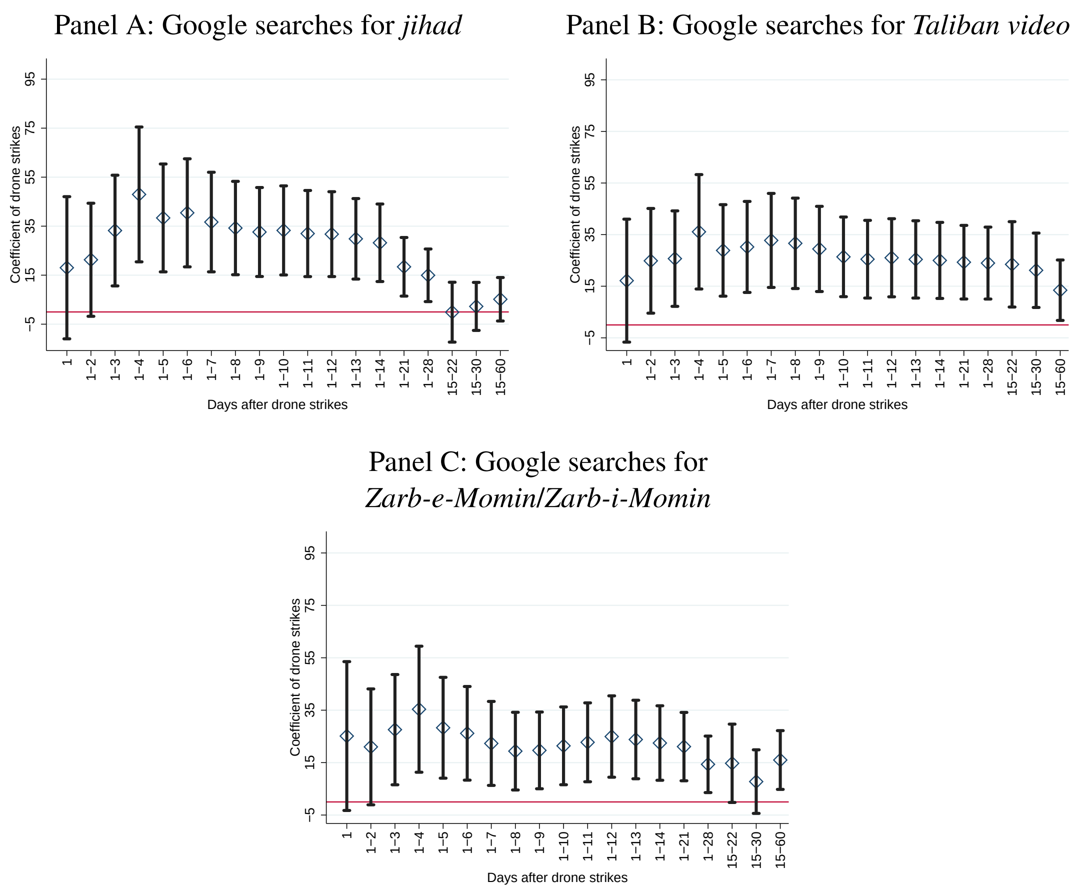


Figure 10: Predicting additional *Google* searches for *jihad*, *Taliban video*, and *Zarb-e-Momin/Zarb-i-Momin* per day. Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.

In placebo estimations, we also analyze the effect of drone strikes in Pakistan on *jihad* searches in the US and Afghanistan. The corresponding results show no statistically meaningful effects (see Figure C2), indicating that unobservable international factors are not driving the results from Figure 10.

6 Conclusion

This paper introduces an empirical strategy to isolate the causal effects of drone strikes in Pakistan on subsequent terrorism, anti-US sentiment, and radicalization, employing wind as the key IV. We hypothesize that wind decreases the likelihood of the US military employing a drone strike, conditional on observable characteristics, whereas wind is otherwise orthogonal to terrorist activities. Both assumptions receive support in our sample of 4,018 days from 2006 to 2016. Results from 2SLS estimations suggest drone strikes increase the number of terror attacks in Pakistan in the upcoming days and weeks. This finding prevails in a host of alternative estimations and robustness checks.

Extending the timeframe of subsequent terrorism, we find evidence indicating drone strikes do not just affect the timing of attacks (e.g., by moving forward planned attacks) but rather increase the total number of attacks. In terms of magnitude, one drone strike today causes over four additional terror attacks per day in the next seven days which implies drone strikes are responsible for 16 percent of all terror attacks in Pakistan. A back-of-the-envelope calculation suggests 2,964 people died from terror attacks because of drone strikes.

We then explore mechanisms, distinguishing between *insiders*, i.e., those who already belong to terrorist organizations, and *outsiders*, i.e., regular Pakistanis. Specifically, we study anti-US sentiment in the major English-language newspaper in Pakistan, anti-US protests, and online searches for terms that may be indicative of radicalization (*jihad*, *Taliban video*, and *Zarb-e-Momin*). In line with the blowback hypothesis, results from 2SLS estimations suggest the general populace increasingly turns to anti-US and radical expressions after drone strikes as all these measures rise substantially because of drone strikes.

It is important to put the results pertaining to Pakistani news and *Google* search behavior in context. We are not suggesting *Google Trends* as the perfect yardstick to measure radical attitudes – an online search for a radical term does not make a terrorist. Further, identifying more negative emotions and anger in US-related articles does not necessarily prove anti-US attitudes. For instance, articles mentioning the US may systematically apply negative language to their enemies. However, the persistency with which we identify signs of radicalization and anti-US sentiment because of drone strikes in the general Pakistani populace is consistent with the hypothesis that drone strikes systematically turn Pakistanis toward radical groups and against the US. In fact, given a literacy rate of 58 percent (Government of Pakistan, 2017) and the hypothesis that the tendency to radicalize usually decreases with education in Pakistan (Fair et al., 2014), studying an English-language newspaper and online search behavior (requiring literacy and internet access) may actually present a lower bound estimate of anti-US sentiment.

To our knowledge, this is the first empirical analysis that is able to isolate causal effects of drone strikes. Contrary to the current opinion in the US military which suggests drone strikes curb terrorism, we find evidence to the contrary: Drone strikes (i) lead to more terrorism, (ii) make the US more unpopular in Pakistan, and (iii) steer Pakistanis toward radical ideas. In other words, not only are *insiders* retaliating against the US but *outsiders* appear to change their attitudes. As a consequence, the pool of militants may grow, if anything. As the US military continues to build and expand its drone program (e.g., in Yemen), we hope our research provides useful insights into the underlying consequences.

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Appendices

A The Federally Administered Tribal Areas (FATA) in Pakistan

FATA borders the Khyber Pakhtunkhwa (KPK) and Balochistan provinces to the east and south, while five Afghani provinces lie to the north and west (Kunar, Nangarhar, Paktia, Khost, and Paktika). Until 2018, FATA was a semi-autonomous region which was not governed by the Pakistani Constitution but rather by a set of laws called the Frontier Crimes Regulation (FCR) 1901. Tribal affairs were generally regulated by the tribes themselves according to their unwritten customary rules (Ullah, 2016). Nevertheless, the region fell under direct executive authority of the President of Pakistan who could introduce special regulations to promote peace and good governance in the region (Shad and Ahmed, 2018). On May 31, 2018, after our sample period investigated in this paper, the 31^{st} Constitutional Amendment made FATA a part of the Khyber Pakhtunkhua (KPK) province and the region has been governed under the Constitution of Pakistan since then (Kiani, 2018).

Perhaps the lack of formal governance served as one of the most important factors, in addition to its geographical location, in making FATA an attractive organizing hub for a variety of terrorist organizations (Nawaz, 2009). The same reasons also made FATA a preferred target for US drone strikes. Owing to the FCR, access to FATA was limited, both for foreign journalists and Pakistanis, hindering the acquisition of accurate information (Fair et al., 2014) and encouraging covert activities by militants and the state. This, in addition to the FCR provisions, make the execution of drone strikes and the associated risk of collateral damage relatively easier in FATA than in the rest of the country.

B Additional Data and Estimation Results

B.1 Using Data from the New America Foundation

Table B1: Predicting the average daily number of terror attacks on days *t+1* to *t+7*, using data on drone strikes from the New America Foundation.

Estimation method:	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Predicting the average daily number of terror attacks on days $t+1$ to $t+7$						
Drone strikes$_{(t)}$	-0.036	-0.037	-0.038	8.039***	4.558***	4.499***
	(0.075)	(0.051)	(0.051)	(2.432)	(1.631)	(1.607)
Control set I^{a}		yes	yes		yes	yes
Control set II^{b}			yes			yes
Panel B: First stage results, predicting the number of drone strikes on day t						
Wind gusts$_{(t)}$				-0.002 ***	-0.002***	-0.002***
				(0.001)	(0.001)	(0.001)
Control set I^{a}					yes	yes
Control set II^{b}						yes
Panel C: Statistics						
F-test insignificance of IV				18.687***	13.088***	13.287***
Endogeneity test				25.200***	17.992***	17.902***
Terror attacks explained by drone strikes	0%	0%	0%	29.4%	16.7%	16.5%
N	4,011	4,011	4,011	4,011	4,011	4,011

Notes: Newey-West standard errors for autocorrelation of order one are displayed in parentheses for the OLS regressions, while heteroscedasticity and autocorrelation consistent (HAC) standard errors are displayed for the IV regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ^{a}Control set I includes measures for the dependent variable on days t and days $t-1$ until $t-7$, a time trend, as well as fixed effects for each day of the week and each month of the year. ^{b}Control set II includes Pakistani military actions and a binary indicator for Ramadan.

B.2 A Comparison of Data Sources for Drone Strikes

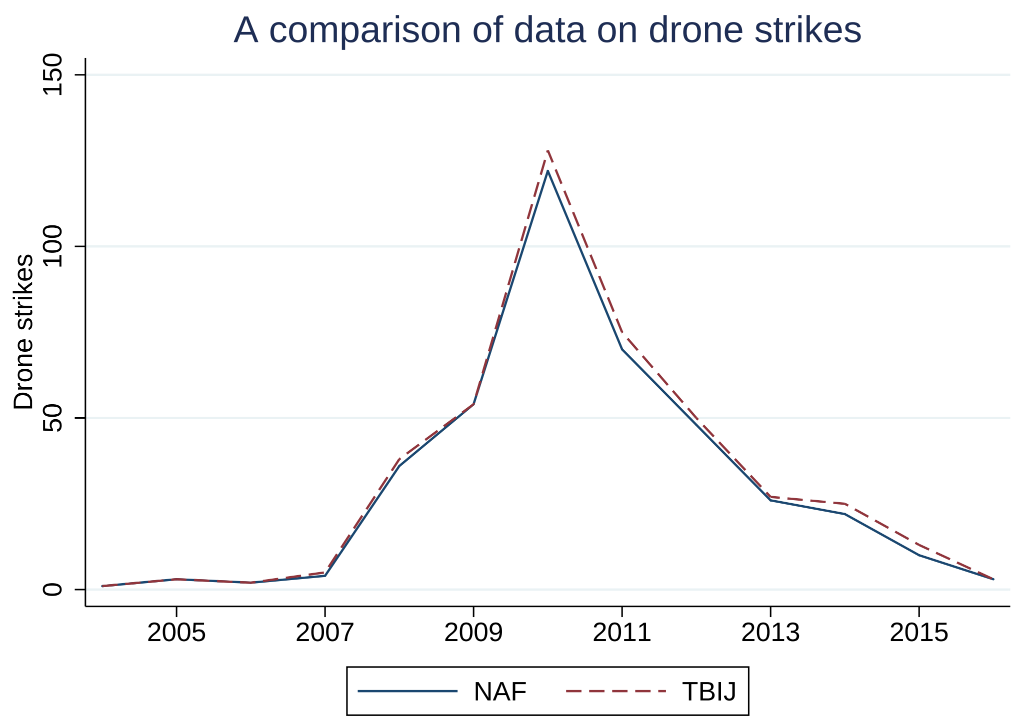

Figure B1: Comparing data on drone strikes from the New America Foundation (*NAF*) and the Bureau of Investigative Journalism (*TBIJ*).

Table B2: Summary Statistics of additional weather variables and controls, for all 4,018 days from January 1, 2006, until December 31, 2016.

Variable	Mean	(Std. Dev.)	Min	(Max.)	Description	Source
Wind speed	11.77	(3.41)	3.68	(43.87)	Average wind speed (km/h) 80m above ground in Miran Shah	Meteoblue (2018)
Index	0	(0.53)	-1.01	(4.03)	Average of standardized values of wind speed, wind gusts, precipitation, and cloud coverage in Miran Shah	Meteoblue (2018), Own calculation
Temperature	22.15	(8.63)	-4.40	(36.85)	Average temperature (C) 2m above ground in Miran Shah	Meteoblue (2018)
Binay Indicator for post-OBL era	0.52	(0.50)	0	(1)	Days after death of Osama bin Laden	
Attacks in Afghanistan	2.68	(3.13)	0	(57)	# of terror attacks in Afghanistan	GTD (2017)

Table B3: Correlation between weather variables of Miran Shah (North Waziristan) and Wana (South Waziristan).

		(Miran Shah)			
		Wind gusts	Wind speed	Cloud cover	Precipitation
	Wind gusts	0.729***			
(Wana)	Wind speed		0.214***		
	Cloud cover			0.883***	
	Precipitation				0.615 ***
N		4,018	4,018	4,018	4,018

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wind gusts measure the maximum wind gusts in km/h in a day, wind speed constitutes the average daily wind speed 80m above ground in km/h, cloud cover is the average daily total cloud cover, while precipitation refers to total precipitaion in a day.

B.3 Instrumental Variables

Table B4: Predicting the average daily number of terror attacks on days *t+1* to *t+7*, employing different instruments.

Instruments:	(1) Wind speed	(2) Wind gusts & wind speed	(3) Index[a]
Panel A: Predicting the average daily number of terror attacks on days $t+1$ to $t+7$			
Drone strikes$_{(t)}$	5.813**	4.663***	1.659***
	(2.710)	(1.605)	(0.498)
Standard controls[b]	yes	yes	yes
Panel B: First stage results, predicting the number of drone strikes on day t			
Instruments$_{(t)}$	-0.003 ***	-0.002 ***	-0.084***
	(0.001)	(0.001)	(0.001)
		-0.002	
		(0.001)	
Standard controls[b]	yes	yes	yes
Panel C: Statistics			
F-test insignificance of IV	6.64**	6.55 ***	60.64***
Endogeneity test	15.208***	22.518***	14.444***
Hansen J-Statistic		0.441	
N	4,011	4,011	4,011

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]The variable $Index$ averages standardized values of wind speed, wind gusts, precipitation, and cloud coverage in Miran Shah. [b]Standard controls include measures for the dependent variable on days t and days $t-1$ until $t-7$, Pakistani military actions, a binary variable for Ramadan, a time trend, as well as fixed effects for each day of the week and each month of the year.

B.4 Robustness Checks

Table B5: Predicting terrorism per day on days *t+1* to *t+7*, employing a 2SLS regression approach.

	(1) Terror Attacks (Criterion 1)	(2) Terror Attacks (Criterion 2)	(3) Terror Attacks (Criterion 3)	(4) Deaths in terror attacks	(5) Terror Attacks (ivpoisson)	(6) Terror Attacks (ivnbreg)
Panel A: Predicting the average daily number of terror attacks on days $t+1$ to $t+7$						
Drone strikes$_{(t)}$	4.341***	4.249***	5.001***	11.359**	1.355***	0.811*
	(1.587)	(1.551)	(1.778)	(4.680)	(0.258)	(0.416)
Standard controls^{a}	yes	yes	yes	yes	yes	yes
Time trend^{b}	yes	yes	yes	yes	yes	
Panel B: First stage results, predicting the number of drone strikes on day t						
Wind gusts$_{(t)}$	-0.002 ***	-0.002 ***	-0.002***	-0.002 ***		-0.027***
	(0.001)	(0.001)	(0.001)	(0.001)		(0.008)
Standard controls^{a}	yes	yes	yes	yes	yes	yes
Time trend^{b}	yes	yes	yes	yes	yes	
Panel C: Statistics						
F-test insignificance of IV	12.389 ***	12.651 ***	11.503 ***	13.013 ***		
Endogeneity test	17.928***	17.389***	23.714***	10.573***		
N	4,004	4,004	4,004	4,011	4,011	4,011

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ^{a}Standard controls include measures for the dependent variable on days t and days $t-1$ until $t-7$, Pakistani military actions, a binary variable for Ramadan, as well as fixed effects for each day of the week and each month of the year. ^{b} Convergence is not achieved in the negative binomial regressions if a trend is included as an additional control.

Table B6: Predicting the average daily number of terror attacks on days *t+1* to *t+7*, employing a 2SLS regression approach.

	(1)	(2)	(3)	(4)	(5)
Panel A: Predicting the average daily number of terror attacks on days $t+1$ to $t+7$					
Drone strikes$_{(t)}$	2.740***	3.571**	4.181***	6.083**	3.888***
	(1.063)	(1.394)	(1.545)	(2.404)	(1.408)
Additional controls	Binary indicator for post-OBL era	Temperature	Binary indicators for seasons	Attacks in Afghanistan^{b}	Bi-monthly FE
Standard controls^{a}	yes	yes	yes	yes	yes
Fixed effects for each weekday	yes	yes	yes	yes	yes
Month-fixed effects	yes	yes		yes	
Panel B: First stage results, predicting the number of drone strikes on day t					
Wind gusts$_{(t)}$	-0.003 ***	-0.002***	-0.002 ***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Additional controls	Binary indicator for post-OBL era	Temperature	Binary indicators for seasons	Attacks in Afghanistan	Bi-monthly FE
Standard controls^{a}	yes	yes	yes	yes	yes
Fixed effects for each weekday	yes	yes	yes	yes	yes
Month-fixed effects	yes	yes		yes	
Panel C: Statistics					
F-test insignificance of IV	16.47***	12.88***	12.69 ***	8.60***	13.85***
Endogeneity test	10.338***	12.891***	16.852***	23.310***	16.020***
N	4,011	4,011	4,011	4,004	4,011

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ^{a}Standard controls include measures for the dependent variable on days t and days $t-1$ until $t-7$, Pakistani military actions, a binary indicator for Ramadan and a time trend. ^{b}Attacks in Afghanistan are controlled for by introducing two variables; attacks in Afghanistan on day t and days $t-1$ until $t-7$ and attacks in Afghanistan on days $t+1$ to $t+7$.

Table B7: Predicting the average number of terror attacks for different levels of aggregation, regions, and time, employing a 2SLS regression approach.

	Aggregated Data		Regional Data	
	(1)	(2)	(3)	(4)
Dependent variable:	Terror attacks in next 3 days	Terror attacks in next 7 days	Terror attacks per day in next 7 days in FATA	Terror attacks per day in next 7 days outside FATA
Panel A: Predicting terror attacks				
Drone strikes	4.043**	4.081**	1.654***	3.584***
	(1.979)	(1.736)	(0.567)	(1.344)
Standard controls^{a}	yes	yes	yes	yes
Fixed effects for each weekday			yes	yes
Month-fixed effects	yes	yes	yes	yes
Panel B: First stage results, predicting the number of drone strikes on day t				
Wind gusts	-0.01 ***	-0.04 ***	-0.002***	-0.002 ***
	(0.002)	(0.01)	(0.001)	(0.001)
Standard controls^{a}	yes	yes	yes	yes
Fixed effects for each weekday			yes	yes
Month-fixed effects	yes	yes	yes	yes
Panel C: Statistics				
F-test insignificance of IV	18.257***	23.326***	11.551***	13.060***
Endogeneity test	4.772**	6.110**	17.405***	17.474***
N	1,339	574	4,004	4,004

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ^{a}Standard controls in estimations on aggregated data include lag of dependent variable, Pakistani military actions, a binary indicator for Ramadan and a time trend. Standard controls for regional estimations include measures for the dependent variable on days t and days $t-1$ until $t-7$, Pakistani military actions, a binary indicator for Ramadan and a time trend.

B.5 Placebo Test for Terrorism

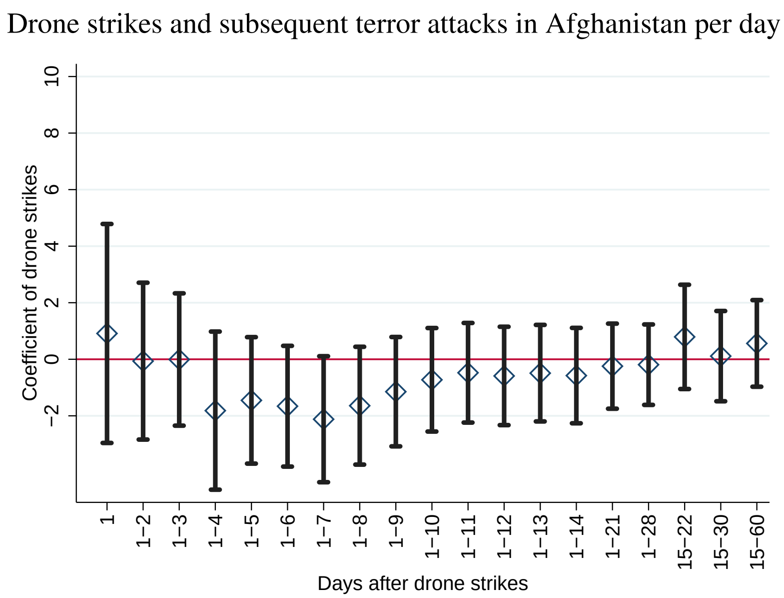

Figure B2: Predicting additional terror attacks per day in Afghanistan, after drone strikes in Pakistan, employing alternative time windows for the dependent variable. Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.

B.6 Reduced Form Estimations

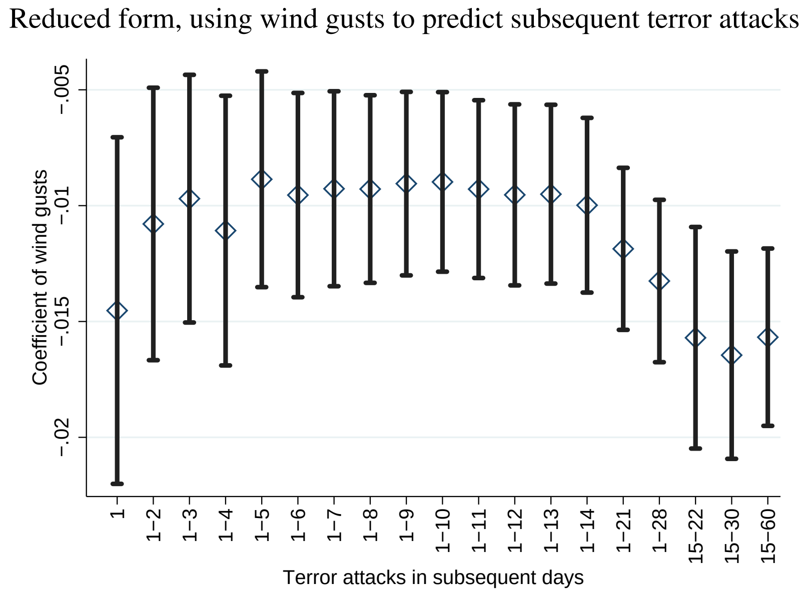

Figure B3: Displaying results from reduced form estimations, where wind gusts are used to predict subsequent terrorism. Each point represents the coefficient related to wind gusts in an OLS regression where Newyey-West standard errors are computed for autocorrelation of order one, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.

C Mechanisms: Data and Additional Estimation Results

C.1 Summary Statistics for Variables Measuring Anti-US Sentiment and Radicalization

Table C1: Summary Statistics of key variables for exploring mechanisms.

Variable	*N*	Mean	(Std. Dev.)	Min	(Max.)	Description	Source
# of articles about drones	3,859	1.13	(1.73)	0	(20)	# of articles about drones	*TNI*
Negative emotions about drones	3,859	0.09	(0.14)	0	(1.46)	Average negative emotional content in articles about drones	*TNI*
Anger about drones	3,859	0.05	(0.09)	0	(0.85)	Average anger in articles about drones	*TNI*
Negative emotions about the US	3,859	0.47	(0.25)	0	(2.56)	Average negative emotional content in articles about the US	*TNI*
Anger about the US	3,859	0.22	(0.14)	0	(1.69)	Average anger in articles about the US	*TNI*
Negative emotions about the US excluding drones	3,859	0.39	(0.23)	0	(2.56)	Average negative emotional content in articles about the US that do not mention drones	*TNI*
Anger about the US excluding drones	3,859	0.17	(0.12)	0	(1.69)	Average anger in articles about the US that do not mention drones	*TNI*
Anti-US protests	4,018	0.31	(1.24)	0	(26)	# of protests against the US	*GDELT*
Google searches for *jihad*	4,018	23.29	(24.21)	0	(100)	*Google* searches for *jihad*	*Google trends*
Google searches for *Taliban video*	4,018	15.17	(20.23)	0	(100)	*Google* searches for *Taliban video*	Google trends
Google searches for *Zarb-e-Momin/Zarb-i-Momin*	4,018	9.58	(22.82)	0	(174)	*Google* searches for *Zarb-e-Momin/ Zarb-i-Momin*	*Google trends*

C.2 Google Searches for *Drone*

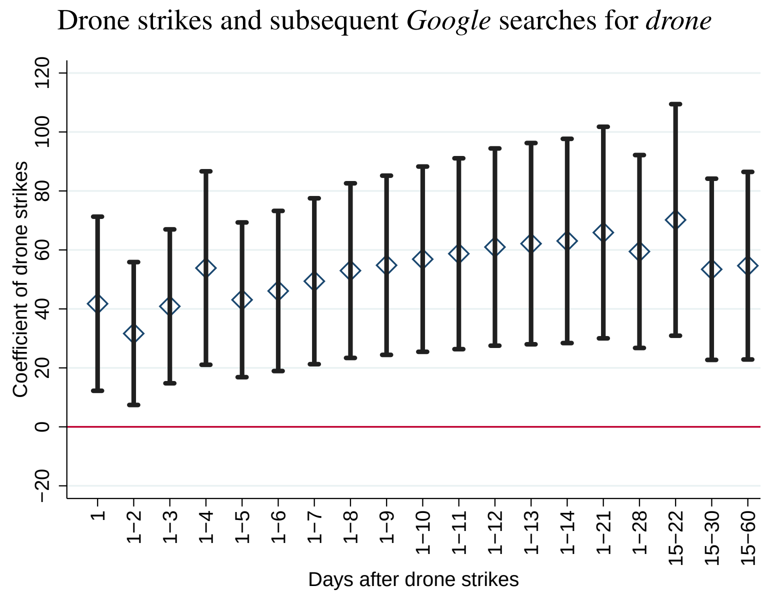

Figure C1: Predicting additional *Google* searches for *drone* per day after drone strikes. Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.

C.3 Placebo Tests for Radicalization

Panel A: Drone strikes and subsequent *Google* searches for *jihad* in Afghanistan

Panel B: Drone strikes and subsequent *Google* searches for *jihad* in the US

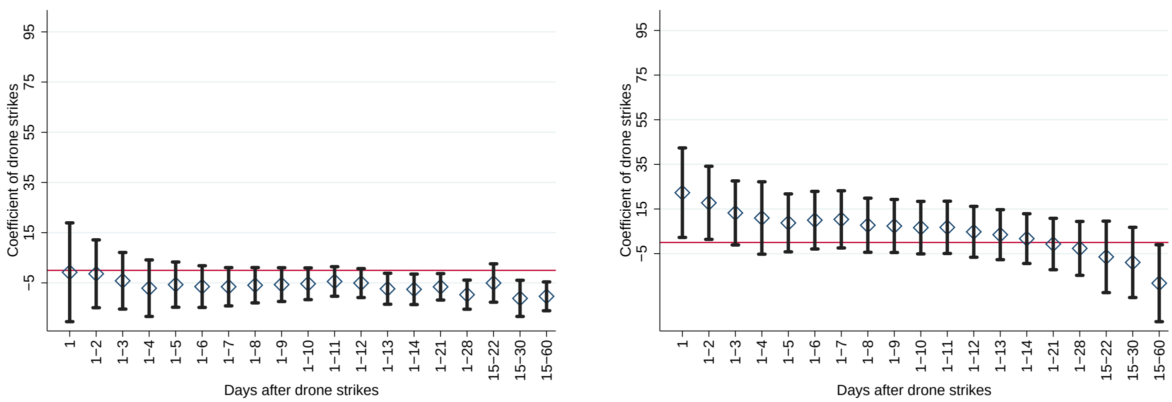

Figure C2: Predicting additional *Google* searches for *jihad* in Afghanistan and the US per day after drone strikes. Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (6) of Table 4. Two-sided 95 percent confidence intervals are displayed.