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GONE WITH THE WIND: THE CONSEQUENCES OF US DRONE STRIKES IN PAKISTAN*

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Employing day-to-day wind conditions as an identification strategy, we explore the consequences of the 420 US drone strikes in Pakistan between 2006 and 2016. Results suggest that drone strikes encourage terrorism over the upcoming days and weeks, causing up to 19% of all terror attacks with more than 3,000 terror deaths in Pakistan during that period. Studying a leading Pakistani newspaper, we identify a polarised response to drone strikes as negative emotions and anger, but also positive emotions, in drone-related articles increase. Finally, anti-US protests and online searches exhibiting radical Islamist concepts increase as a consequence of drone strikes.

'The program is not perfect. No military program is. But here is the bottom line: It works.'
Michael V. Hayden, 'To keep America safe, embrace drone warfare', *New York Times* (2021), former Air Force 4-star General and CIA Director on drone strikes.

The US War on Terror is not restricted to active war zones alone. In weakly institutionalised states that are not considered capable enough to combat terrorism, the United States intervenes remotely through unmanned aerial vehicles (UAVs), commonly known as drones. Labelled '*the* defining

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weapon of the War on Terror' (Hessen Schei, 2014; Woods, 2015), armed drones have become a hallmark of US military policy with applications in Afghanistan, Libya, Pakistan, Somalia and Yemen (Hazelton, 2016; TBIJ, 2017b; New York Times, 2021). In 2019, the Department of Defense tripled its funding request for UAVs from the previous year to \$21 billion (Gettinger, 2017; 2018). Advocates argue drone strikes curb terrorism by surgically decimating terrorist networks while overcoming the risks associated with ground invasions and conventional air strikes (Bergen, 2013; Byman, 2013; McGreal, 2013; Obama, 2013; Hayden, 2016; ProCon.org, 2017). However, sceptics fear such missions can traumatise the civilian population (Cavallaro *et al.*, 2012), provoke anger towards the United States (Hudson *et al.*, 2011) and facilitate recruitment efforts of terrorist organisations (Kilcullen and Exum, 2009; Jordan, 2014). The anecdotal evidence on local reactions remains mixed, ranging from appreciation to anti-US protests (see Online Appendix B).

To date, empirical studies have remained correlational (Smith and Walsh, 2013; Johnston and Sarbahi, 2016; Jaeger and Siddique, 2018; Mir and Moore, 2018), largely for two reasons. First, reverse causality complicates identification, primarily because operational developments (by the US military and terrorist groups) remain secretive. For example, the United States may strike *because* terror attacks are imminent, which would introduce an upward bias into estimates predicting subsequent terrorism with drone strikes. Second, unobservable developments can simultaneously affect the occurrence of drone strikes and terror attacks. For instance, while reorganising and therefore frequently changing locations (see, e.g., Buncombe, 2013, Kugel, 2016 and Yusufzai, 2017), groups may become easier targets for drone strikes; however, we would expect fewer attacks *because of* these reorganisation efforts. Similarly, if the Pakistani military arrested a terror leader, we may observe both fewer subsequent attacks and more drone strikes, potentially because of the intelligence obtained from the arrest. Both of these narratives would suggest a downward bias associated with the coefficient measuring the number of drone strikes in predicting subsequent terror attacks. In general, several potential confounders are conceivable and supported by anecdotal evidence (see Subsection 2.3).

In the following pages, we introduce an identification strategy to explore the effects of drone strikes in Pakistan on (*i*) terrorism and (*ii*) attitudes towards the US and major terrorist organisations. Since 2004, Pakistan has experienced 63% of all drone strikes directed at countries not at war with the United States (TBIJ, 2017b). The fact that no other US military intervention is possible in Pakistan (such as ground troops or manned aircrafts) allows us to isolate the effect of drone strikes from other military operations.[1]

Our empirical specifications leverage exogenous variation from wind conditions. We hypothesise that the likelihood of drone strikes decreases on days with stronger winds, everything else equal. This hypothesis is built on the scientific literature suggesting UAVs to be sensitive to windy conditions (Glade, 2000; DeGarmo, 2004; Fowler, 2014). Accessing daily data from 2006 to 2016, we indeed find fewer drone strikes on windy days. This is particularly the case when predicting strikes that are *not* aimed at prominent terror leaders (which corresponds to 84% of all drone strikes; see Online Appendix Table F1), which informs the local average treatment effect (LATE) in our identification strategy. In turn, it is difficult to imagine how wind conditions could systematically affect subsequent terrorist activity through other channels, conditional on (*i*) preceding terror attacks, (*ii*) Pakistani military actions, (*iii*) fixed effects for days of the

[1] The only recorded non-drone military intervention by the United States remains the CIA-led operation against Osama bin Laden in 2011, which employed helicopters (Sherwell, 2011).

week and months of the year, (*iv*) temperature and precipitation levels and (*v*) Ramadan days.[2] Empirically, wind conditions remain orthogonal to immediately preceding terror attacks and Pakistani military operations.

Contrary to correlational results (that produce a null relationship), our instrumental variable (IV) regressions imply that drone strikes increase the number of terror attacks in the upcoming days and weeks. This result emerges consistently in a range of specifications, employing alternative (*i*) IV definitions (i.e., wind gusts or wind speed; continuous variables or binary indicators above particular threshold levels), (*ii*) econometric methods, (*iii*) definitions of terrorism, (*iv*) data sources on drone strikes, (*v*) accounting for a host of control variables as well as (*vi*) considering alternative time dimensions when averaging observations over three, six or 14 days. Investigating subsequent attacks for up to 70 days, drone strikes seem to not only affect the timing, but rather the total number of terror attacks and terror deaths. This is even though the number of deaths per terror attack declines. Finally, we conduct reduced-form regressions to predict subsequent terrorism with wind gusts in a cross-country panel database, studying Pakistan along with the most terrorism-ridden countries that have not experienced any drone strikes. Indeed, wind has been particularly predictive of subsequent terrorism in Pakistan ever since the first drone strike occurred in 2004, but is not a statistically significant predictor by itself.

Next, we aim to understand whether and, if so, how the general Pakistani populace responds to drone strikes. While terror attacks in the subsequent days and weeks are more likely to be conducted by existing members of terror groups, understanding the general population's reaction matters for potential policy recommendations. If drone strikes exclusively provoke existing terror group members, a hawkish military argument would suggest targeting all terrorists to eradicate terrorism; however, if non-members are affected, drone strikes may affect popular opinion and potentially widen the public's acceptance of militants. For example, the *blowback hypothesis* suggests that military intervention can facilitate recruitment efforts of and financial support for terrorist organisations (Kilcullen and Exum, 2009; Hudson *et al.*, 2011; Cavallaro *et al.*, 2012; Cronin, 2013; Jordan, 2014).

First, we analyse the emotional content of articles discussing drones, the United States and major terror organisations in the leading English-language newspaper in Pakistan, *The News International*.[3] Our regressions show that negative emotions and anger towards the United States increase because of drone strikes, but these conclusions only emerge for articles that also discuss drone strikes. These results prevail when studying sentiment in the exact sentences that mention the United States and when analysing *top stories* only. However, we also find evidence to suggest *positive* emotions become more frequent in articles mentioning drone strikes. In turn, both negative and positive emotions associated with coverage about major terror organisations become less frequent, i.e., the emotional tone becomes more neutral.

Second, we explore anti-US and anti-terror-group protests documented in the *Global Data on Events, Location and Tone* database. Both OLS and IV estimates indicate a rise in anti-US protests, while the number of anti-terror-group protests remains statistically unchanged or, if anything, decreases marginally because of drone strikes. Third, to explore the day-to-day prominence of radical concepts and groups, we study *Google* searches for the terms *jihad*, *Taliban video*, *Zarb-e-Momin*/*Zarb-i-Momin* (a weekly Pakistani magazine expressing radical

[2] We also explore the possibility that extreme wind conditions could affect terror activities independently, but find no evidence to support this hypothesis. The actual wind conditions are not strong enough to constitute storms, for example.

[3] If anything, this newspaper is seen to be more open to the United States than non-English-language outlets in Pakistan (Shah, 2010; Fair *et al.*, 2014).

beliefs) and *Ghazwa e Hind* (the battle for the Indian subcontinent, mentioned frequently in terrorist propaganda literature). Our analysis consistently identifies elevated search frequencies because of drone strikes. In contrast, US-related topics are not searched more frequently, studying the terms *USAID* (US Agency for International Development), US immigration and *USEFP* (US Educational Foundation in Pakistan). Taken together, these results suggest an increase in anti-US sentiment among the general Pakistani populace. It is important to point out that our identification strategy is not well positioned to directly explore links between civilian attitudes and terror attacks.

Overall, this paper informs four areas of research and policy-making. First, we speak to the literature on identifying causal effects of foreign military operations. Previous studies found detrimental consequences from foreign military interventions in (*i*) Afghanistan (but not Iraq), where civilian casualties sparked insurgent violence (Condra *et al.*, 2010); (*ii*) Colombia, where US military assistance increased paramilitary attacks, but not guerrilla attacks (Dube and Naidu, 2015; also see Acemoglu *et al.*, 2016) and (*iii*) Vietnam, where US bombings deepened military and political opposition (Dell and Querubin, 2017; see also Kalyvas and Kocher, 2009, Kocher *et al.*, 2011 and Miguel and Roland, 2011). In contrast, Russian artillery fire has been identified as *reducing* insurgent attacks in Chechnya (Lyall, 2009), highlighting the context-specific dimensions of military interventions. To our knowledge, we are the first to present an identification strategy to explore the effects of drone strikes. Although focusing on Pakistan, our identification strategy based on wind conditions may prove useful in isolating causal effects from drone operations in other settings.

Second, our study informs the literature on counterterrorism efforts (Arce and Sandler, 2005; De Mesquita, 2005; Jaeger and Paserman, 2006; 2008; Bueno de Mesquita and Dickson, 2007; Mueller and Stewart, 2014; Jensen, 2016). Even locally targeted drone strikes appear to exacerbate terrorism and can influence the public's attitudes towards conflict parties. Importantly, drone strikes may breed anti-US sentiment in a country where the average citizen is already hostile towards the United States (Bursztyn *et al.*, 2020).[4]

Third, a major area of research is concerned with understanding the reasons for terrorism, especially the surge in Islamist groups since the turn of the millennium (see Gaibulloev and Sandler, 2019 for a recent overview). Our results support the idea that, in general, foreign military interventions may backfire when it comes to Islamist extremism (see Azam and Thelen, 2010).

Fourth, this paper informs our understanding of drivers of anti-US sentiment and radicalisation (Gentzkow and Shapiro, 2004; McCauley and Moskalenko, 2008; Goldsmith and Horiuchi, 2009; Schatz and Levine, 2010; Blaydes and Linzer, 2012; Rink and Sharma, 2018). We show that US military actions can influence how the United States is portrayed in local media. Finally, online interest in extremist material rises because of drone strikes—a warning sign that ordinary Pakistanis could be more likely to become radicalised as a consequence of drone strikes.

1. Background: Drone Strikes in Pakistan

In 2004, the United States started to employ drone strikes in Pakistan—first sporadically, with only 11 strikes conducted until 2007, and then more frequently with 38 strikes in 2008 alone

[4] It is possible that locals respond more severely to *foreign* interventions than they would to domestic interventions—a hypothesis that lies beyond the scope of this paper. Our setting and research design are also unable to explore how an alternative 'hearts-and-minds-type' intervention would fare (see, e.g., Berman *et al.*, 2011 and Child, 2019).

(TBIJ, 2017b).[5] Figure 1(a) visualises 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 (TBIJ, 2017b). Ninety-three per cent of all strikes occurred in North and South Waziristan (two of the seven tribal agencies of FATA)—an area sometimes referred to as the 'kill box' because of US drone operations (Hessen Schei, 2014). Counting approximately five million inhabitants (similar to Alabama or Ireland), FATA covers an area comparable to Massachusetts or Albania. Online Appendix A provides additional background information on the region.

Figure 1(b) locates all terror attacks from 2006 to 2016, illustrating that terror groups are capable of operating countrywide even though drone strikes exclusively target the FATA region. Substantial anecdotal evidence suggests that the groups targeted by drone strikes are well connected throughout the country. For instance, claims of retaliation to drone strikes are associated with attacks all across Pakistan, including Peshawar, Rawalpindi, Attock, Lahore, Karachi and even Sukkur (START, 2017). Furthermore, retaliation does not always come from the organisation that was targeted in the respective drone strike. For example, the Abdullah Azam Brigades claimed attacks in retaliation to drone strikes against the Tehrik-e-Taliban Pakistan (TTP) group and against Al-Qaeda (START, 2017). Similarly, the Mujahideen Ansar group, affiliated with the TTP, claimed retaliation to drone strikes on the Turkistan Islamic Party, among others. These instances highlight cooperation between terrorist organisations that, combined with their common ideological motivations, can blur the dividing lines between organisations (Puri, 2010; Abdullah, 2014; SATP, 2017b; Stanford University, 2017).

Consistent with that background, our main analysis focuses on time-series national data, rather than distinguishing between particular Pakistani regions or groups in a panel setting.[6] Nevertheless, we identify consistent results when exclusively focusing on terror attacks in the FATA or non-FATA regions (see Online Appendix Table F4). Online Appendix B summarises the commonly perceived advantages and disadvantages of drone strikes from the Pakistani perspective.

2. Data and Empirical Strategy

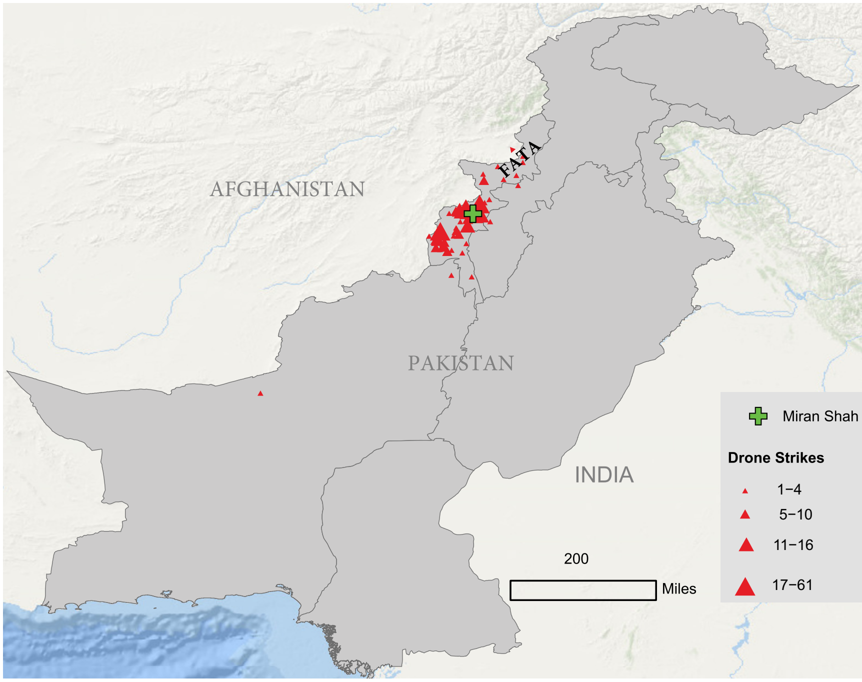
2.1. *Data*

We derive daily data on drone strikes from January 1, 2006 until December 31, 2016 from the Bureau of Investigative Journalism, an independent, not-for-profit organisation (TBIJ, 2017a,b). Data on the number of drone strikes from the New America Foundation (Berge and Sterman, 2018) are strongly correlated with the TBIJ's numbers and produce virtually identical conclusions (see Online Appendix Table F3). We prefer the TBIJ database in our main regressions because it offers active links to sources, images and video clips for the majority of strikes. In both databases, casualty numbers, demographics and terrorist definitions are not consistently available (and, if so, they are provided in wide ranges), and such data often differ substantially across both sources. Table 1 documents summary statistics, showing that one drone strike occurs every tenth day, on average. Three days saw as many as four strikes.

[5] The United States 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).

[6] In practical terms, it also remains impossible to identify the exact group targeted by a particular drone strike. Similarly, attributing each terror attack to a group remains difficult as the Global Terrorism Database is unable to assign a group name to 76% of all attacks in Pakistan between 2006 and 2016.

(a) Drone strikes



(b) Terror attacks

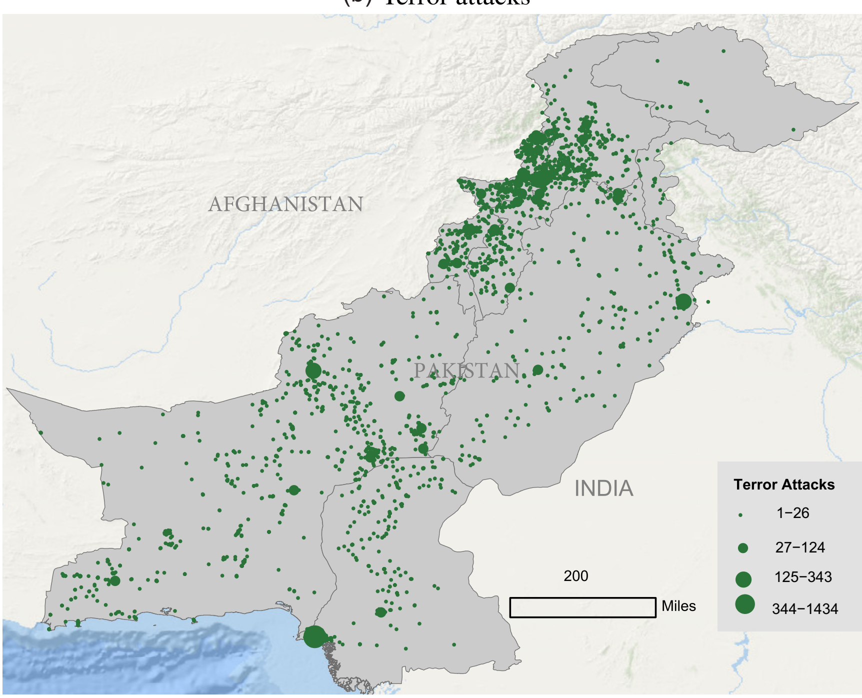


Fig. 1. *The Locations of Drone Strikes and Terror Attacks in Pakistan between 2006 and 2016.*
Notes: The cross marks Miran Shah, where wind conditions are measured.

Table 1. *Summary Statistics of Main Variables for all 4,018 Days from January 1, 2006 until December 31, 2016. All Variables are Measured at the Daily Level.*

Variable	Mean	(SD)	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	START (2017)
Panel B: instrumental variables						
Wind gusts	23.92	(8.68)	6.84	(92.16)	Maximum wind gusts (km/h) in Miran Shah	Meteoblue (2018)
Wind speed	11.77	(3.41)	3.68	(43.87)	Average wind speed (km/h) in Miran Shah	Meteoblue (2018)
Panel C: main 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)
Temperature	22.15	(8.63)	−4.40	(36.85)	Average temperature (°C) in Miran Shah	Meteoblue (2018)
Precipitation	1.52	(3.79)	0	(59.60)	Total precipitation (in mm) in Miran Shah	Meteoblue (2018)

Data on terror attacks are derived from the Global Terrorism Database (GTD; START, 2017). Pakistan experienced 2.85 attacks on an average day during our sample period, ranking the country second worldwide behind Iraq. Only 23% of all days passed without any attack. On average, 4.61 people per day die from terror attacks in Pakistan, which translates to 18,523 deaths throughout our sample period. Online Appendix Figure E1 visualises the long-term development of drone strikes and terror attacks.

We employ wind data from Miran Shah, the FATA capital located in North Waziristan, where 71% of all drone strikes occurred. All but two drone strikes occurred in FATA, and the FATA agency located farthest from Miran Shah, Bajaur, lies approximately 239 km to the northeast. Wind gusts in Miran Shah are strongly correlated with those from Wana, the regional capital of South Waziristan that hosts the only other station to provide daily data on wind conditions within FATA, located approximately 154 km to the southwest (correlation coefficient of 0.729). Thus, wind conditions in Miran Shah constitute a reasonable proxy for wind conditions in the area where drone strikes usually occur. If anything, imprecise measures of the relevant wind conditions would introduce statistical noise in our empirical applications, which would complicate the derivation of statistically precise estimates.

2.2. *Correlational Analysis*

We begin by regressing the number of terror attacks per day from days $t+1$ to $t+7$ on the number of drone strikes on day t.[7] Formally, we estimate

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

[7] Results are consistent when employing negative binomial or Poisson regressions to predict the total number of attacks in the upcoming seven days, thereby acknowledging the count nature of the dependent variable (see Online Appendix Table F3).

where β_1 constitutes the coefficient of interest, X_t' captures observable control variables and ϵ_t denotes the conventional error term. To account for autocorrelation in the dependent variable (see Online Appendix Table F2), X_t' includes 14 lagged values of terror attacks. We estimate standard errors robust to arbitrary heteroscedasticity and autocorrelation of order one, but results are consistent, although less precisely estimated, with a lag structure of 15 days or when employing an automatic bandwidth selection procedure (following Newey and West, 1994; see Online Appendix Table F3).[8]

Variable X_t' accounts for 14 lags of Pakistani military actions in the previous 14 days, because such operations may produce collateral damage or spark retaliation from terrorists. Results are consistent when including further lagged values (available upon request). Variable X_t' also incorporates fixed effects for each day of the week and month of the year. For instance, Friday carries a special sanctity in the Islamic tradition with congregational prayers being offered. Terror attacks may also vary by month, e.g., because of seasonal particularities. Furthermore, X_t' includes a binary indicator for Ramadan, as studies have shown Islamist terror groups alter their actions during that time (Al-Baghdadi, 2014; Hodler *et al.*, 2018). In addition, we account for a linear time trend to control for general terror-related developments (see, e.g., Berrebi and Lakdawalla, 2007). Finally, in anticipation of our identification strategy related to wind, we control for temperature and precipitation levels in Miran Shah—factors that may independently correlate with wind conditions and affect the execution of terror attacks. Nevertheless, our estimations show that these factors remain inconsequential for the derived conclusions.

In addition to daily data, we also derive three-, six- and 14-day periods where we average all variables over three, six or 14 days. These estimations employ non-overlapping time periods to predict terror attacks in a period (e.g., averaging over days t, $t+1$ and $t+2$) with independent variables averaged over the previous period (averaging over days $t-3$, $t-2$ and $t-1$).

2.3. *Endogeneity*

Although (1) can provide correlational insights, one should be careful in interpreting β_1 as causal, because a range of unobservable factors can bias β_1 in either direction. First, the estimated coefficient may be biased upwards for a number of reasons. For example, the United States may employ drone strikes just as attacks are imminent, potentially because gathering intelligence is facilitated when terror groups are organising attacks (see, e.g., BBC, 2015; TBIJ, 2015 and Mir, 2017). Alternatively, the US military may conduct strikes precisely to try and prevent imminent attacks.

Second, a downward bias remains equally plausible. For instance, as terrorists are meeting to re-organise (e.g., to elect new leaders or debate merging), they may become easier targets for drone strikes and be less prone to conducting attacks because of their re-organisation. Similarly, intra-group conflicts may raise the chances of the US military receiving tip-offs on the location of terrorists, while simultaneously disrupting attack plans. Furthermore, if a group gains in strength, members may simultaneously be more likely to expose spies who are essential in providing information to the United States (Dawn, 2008; 2009; SATP, 2009; Sunday Morning Herald, 2010; START, 2017) and conduct more attacks.

[8] We select a bandwidth structure of 15 days because Baum (2005) writes: ‘the bandwidth is one greater than the number of lags (thus bw(1) specifies that no lagged values of the residuals are to be included; bw(2) = lag(1), etc.).’ Regarding the role of autocorrelation and the use of lagged-dependent variables in time-series data, we also refer the reader to the discussion provided by Beck and Katz (2011) and the references therein.

Finally, Pakistani intelligence agencies occasionally share information with the United States (Khan and Brummitt, 2010; Ali, 2018; Mir, 2018). Thus, arrests of prominent militants may raise the probability of providing the intelligence to facilitate drone strikes (Ali, 2018; Chaudhry, 2018; Indian Express, 2018; The News, 2018). At the same time, the arrest may disrupt the group's activities and in itself signal weakening of the group. In fact, using data from the South Asia Terrorism Portal (SATP, 2021) on the arrests of terrorists shows that drone strikes are particularly likely to be conducted in the week after such arrests (see Online Appendix Table F5). In sum, (1) is unable to provide causal insights as endogeneity can affect the sign, statistical precision and magnitude of β_1.

2.4. *Identification Strategy*

To address these concerns, we instrument the number of drone strikes with contemporaneous wind conditions in Miran Shah. Substantial scientific evidence shows that wind matters for a drone flight's feasibility and chances of success, largely because drones are much lighter than manned aircrafts (Government Accountability Office, 2009; 2017; Whitlock, 2014).[9] Tactical guides by the US Joint Forces Command highlight that 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; see also AFSOC, 2008 and Brooke-Holland, 2015). Looming monetary losses contribute to the delicate nature of a potentially unsuccessful drone operation: designed for numerous flights, a standard Predator drone cost US$4.03 million in 2010 (U.S. Airforce, 2010).[10] Furthermore, a drone crash behind enemy lines may expose precious military technology.[11] Thus, the US military, wary of a potentially unsuccessful operation, may be less likely to employ drone strikes in windy conditions in the target area, everything else equal.

Our main specifications employ wind *gusts*, defined as '[a] rapid fluctuation of wind speed with variations of 10 knots [18.52 km/h] or more between peaks and lulls' (National Weather Service, 2019). Results are virtually identical when using wind *speed* or employing a binary indicator for wind gusts exceeding the 27.78km/h threshold (see Online Appendix Table F3).[12] Drawing on data from Meteoblue (2018), a meteorological service created at the University of Basel in cooperation with the US National Oceanic and Atmospheric Administration, maximum wind gusts in Miran Shah average almost 24 km/h throughout our sample days and reach values as high as 92 km/h (see panel C of Table 1).

Our main estimations employ an index of maximum wind gusts on day t to predict drone strikes on day t in the first stage of a two-stage-least-squares (2SLS) estimation:

$$(\mathit{Drone\ strikes})_t = \alpha_0 + \alpha_1(\mathit{Wind\ gusts})_t + \boldsymbol{X}_t'\alpha_2 + \delta_t.$$

[9] 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).

[10] The first Predator drone that carried a hellfire missile completed 196 combat missions before its retirement (Connor, 2018).

[11] For example, this appeared to be a significant problem when a US drone crashed in Iran in 2011. Then-US Air Force chief, General Norton Schwartz, feared that '[t]here is the potential for reverse engineering, clearly' (Erdbrink, 2011). Iran's national security committee claimed to have decoded the crashed drone's hard drives and accessed its sensitive databases (The Telegraph, 2012).

[12] We also explored additional polynomials in wind gusts in the first stage, but such specifications do not improve statistical precision to predict drone strikes. Nevertheless, the second-stage results remain consistent (results available on request).

The predicted drone strikes on day t are then used in the second stage to predict subsequent terrorism, following (1).[13] In additional estimation, we apply this identification strategy to analyse alternative outcome variables related to terror deaths, the emotional sentiment of relevant news coverage, protests and online search behaviour in Pakistan. For the specifications employing three-, six- or 14-day averages, we also average the corresponding wind gusts over the same time period.

A particular threat to identification relates to the feasibility of terror attacks in windy conditions: in severe winds (e.g., in a storm), terror attacks may become difficult to execute. In our setting, however, maximum wind conditions in Miran Shah remain far from the lowest hurricane definition, which corresponds to category one on the Saffir-Simpson scale with 119 km/h (see National Oceanic and Atmospheric Administration, 2019). Tropical storms are defined by winds above 63 km/h, and only nine days in our sample period fall into that category. That number drops to zero days if we use wind speed, which constitutes the defining measure for tropical storms. Nevertheless, excluding these nine days leaves conclusions virtually unchanged (results available upon request).

3. Empirical Findings: Terrorism

3.1. *First Stage, Reduced Form and Placebos*

Beginning with the first stage, Figure 2(a) visualises a binned scatterplot of drone strikes on day t against wind gusts in Miran Shah on the same day, controlling for the full set of covariates introduced in (1). As expected, we observe a negative and statistically significant relationship (p-value of 0.000). Figure 2(b) provides a placebo check using wind conditions in Karachi—the largest Pakistani city, located 900 km away from Miran Shah. Wind gusts between both cities are only marginally correlated (coefficient of 0.08), i.e., we would not expect wind in Karachi to predict drone strikes that almost exclusively take place in the FATA region. Indeed, no statistically meaningful link emerges (p-value of 0.489).[14]

Figure 2(c) turns to the reduced-form estimation, plotting subsequent terror attacks against wind gusts in Miran Shah. The relationship is negative and statistically significant at the 1% level (p-value of 0.001). However, Figure 2(d) illustrates the null relationship between wind gusts in Karachi and subsequent terror attacks throughout Pakistan (p-value of 0.314). In additional placebo estimations, we also find wind gusts in Baghdad and Jerusalem to be statistically meaningless predictors of terror attacks in Iraq and Israel, respectively (p-values of 0.896 and 0.361; see Online Appendix Figure E2).

Figures 2(e) and 2(f) graph results from two additional placebo estimations, predicting terror attacks and Pakistani military actions on day $t-1$ with wind gusts on day t. Logically, there should be no discernible relationship between today's wind conditions and yesterday's terror-related activities. Indeed, we derive precisely estimated null relationships (p-values of 0.336 and 0.286).

[13] Notably, the first-stage coefficient associated with wind gusts loses statistical significance at conventional levels when also incorporating a squared time trend. However, most importantly, whenever we derive a statistically significant coefficient related to wind gusts or wind speed in the respective first stage, second-stage results pertaining to drone strikes remain consistent. Furthermore, reduced-form estimations that directly regress terror attacks on preceding wind gusts in the larger time series and panel samples introduced in Subsection 3.1, are robust to additionally accounting for a squared time trend (see Online Appendix Table C2).

[14] Excluding control variables also produces a statistically irrelevant coefficient (p-value of 0.261; not displayed).

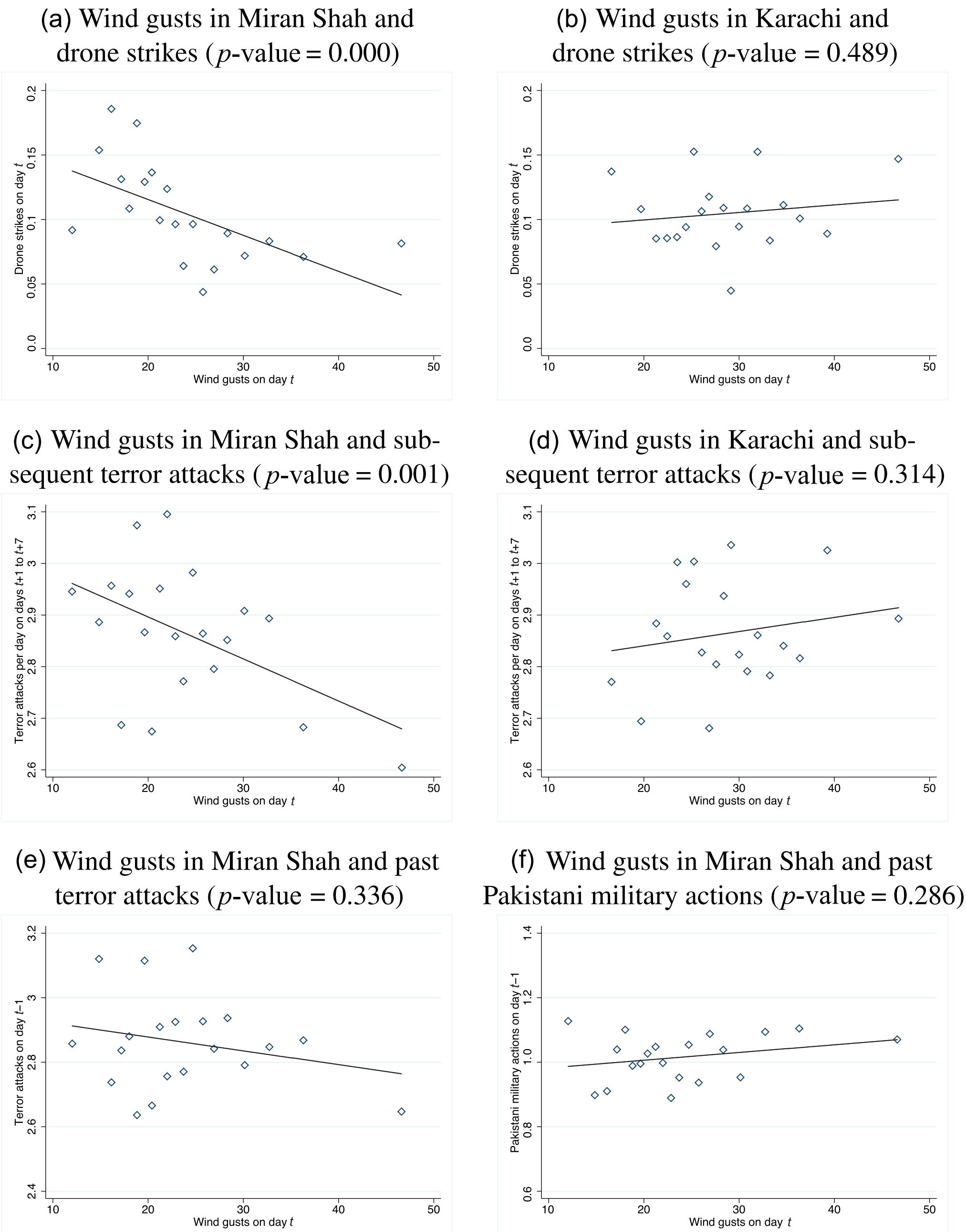


Fig. 2. *Binned Scatterplots of Wind Conditions (x Axis) against the Number of Contemporary Drone Strikes and Terror Attacks in the Subsequent Seven Days at Various Locations.*
Notes: Control variables for all graphs include those listed in (1). Panels (e) and (f) predict terror attacks and Pakistani military actions on day $t-1$, excluding the respective dependent variable in the list of control variables.

To further explore the reduced-form relationship between wind gusts and subsequent terror attacks, we run additional regressions, all of which are referred to Online Appendix Section C with Tables C1 and C2. Specifically, we find that wind gusts are not predictive of drone strikes in Pakistan before June 16, 2004 (when the first-ever drone strike occurred), as expected. Furthermore, we generate a panel database to examine the relationship between wind gusts and subsequent terror attacks in those countries of the ten most terror-ridden nations that never experienced drone strikes, in addition to Pakistan.[15] Intuitively, we should identify a statistically meaningful coefficient for wind gusts to predict subsequent terrorism in Pakistan after drone strikes became an option, but not in these other nations. That is indeed what we find, and the corresponding results are robust to including the usual set of covariates, as well as country-fixed effects. In sum, wind gusts by themselves are not predictive of subsequent terror attacks when drone strikes are not an option.

3.2. *Regression Results*

Table 2 reports our main findings, where all regressions account for the full set of covariates. Panel A reports the second-stage coefficients associated with drone strikes, while panel B documents first-stage estimates. Panel C lists various statistical characteristics and panel D shows the corresponding coefficients from OLS regressions. Columns (1) and (2) consider daily data to predict terror attacks on days $t + 1$ until $t + 7$, whereas the remaining columns consider three-, six- and 14-day averages. We report HAC standard errors accounting for bandwidth one in parentheses and standard errors accounting for bandwidth 15 in brackets.

Columns (1) and (2) show that drone strikes become a positive and statistically significant predictor of subsequent terror attacks once we instrument that variable with wind gusts or wind speed. The derived coefficients are able to explain 10.7% or 12.4% of all terror attacks throughout our sample period (see the penultimate row).[16] These estimates are remarkably similar in magnitude, even though the alternative variables capturing wind conditions are only modestly correlated with a correlation coefficient of 0.4. The derived coefficients differ notably from the respective OLS estimates that would imply a marginally negative coefficient that nevertheless remains statistically indistinguishable from zero with p-values of 0.326 and 0.378. Subsection 3.3 provides a detailed comparison of the OLS and IV estimates.

Column (1) constitutes our benchmark specification throughout the rest of the paper. This result is robust to a host of alternative specifications (see Online Appendix Table F3). In particular, we (*i*) employ alternative estimation methods with a negative binomial regression, and a Poisson estimation to predict a count variable of the number of subsequent terror attacks; (*ii*) control for lagged drone strikes and terror attacks in Afghanistan; (*iii*) instrument drone strikes with a binary indicator for gusts exceeding the 27.78 km/h threshold discussed in Subsection 2.4, while independently controlling for wind speed as a potential confounder; (*iv*) use an alternative data source for drone strikes (Berge and Sterman, 2018) and (*v*) employ alternative definitions of terrorism provided by the GTD.

[15] This list includes India (10,684 terror attacks), the Philippines (5,889 attacks), Thailand (3,588 attacks) and Nigeria (3,414 attacks).

[16] We calculate magnitudes by multiplying the derived coefficient with the mean number of drone strikes (0.1045) before dividing the result by the mean number of terror attacks per day (2.8551). For example, in column (1), we derive $(2.9268 \times 0.1045)/2.8551 = 0.1071$, i.e., 10.7%.

Table 2. *Main Results. All Regressions Account for the Full Set of Control Variables.*[a]

Data dimensions of dependent variable: terror attacks	Days $t+1$ until $t+7$		Three-day averages[b]	Six-day averages[b]	14-day averages[b]
	(1)	(2)	(3)	(4)	(5)
Panel A: second-stage results, predicting subsequent terror attacks					
Drone strikes	2.9268	3.3847	3.0358	3.4046	2.5263
	(1.0159)***	(1.3543)**	(1.4397)**	(1.5034)**	(1.4517)*
	[1.5113]*	[1.9144]*	[1.4907]**	[1.5045]**	[1.3493]*
Panel B: first-stage results, predicting drone strikes on day t					
Wind gusts	−0.0028		−0.0043	−0.0061	−0.0094
	(0.0006)***		(0.0009)***	(0.0012)***	(0.0021)***
	[0.0008]***		[0.0011]***	[0.0014]***	[0.0023]***
Wind speed		−0.0054			
		(0.0015)***			
		[0.0020]***			
Panel C: statistical properties					
F-test insignificance of IV	19.388***	13.494***	21.767***	25.772***	19.188***
Stock-Wright S statistics (p-value)[c]	0.000***	0.000***	0.015**	0.006***	0.044**
Weak IV test (Wald, p-value)[d]	0.004***	0.012**	0.035**	0.024**	0.082*
Kleibergen-Paap rk LM statistic (p-value)[e]	0.000***	0.000***	0.000***	0.000***	0.000***
Endogeneity test (p-value)[f]	0.000***	0.001***	0.012**	0.010***	0.105
Panel D: OLS results					
Drone strikes$_t$	−0.0439	−0.0439	0.0480	−0.0697	0.2718
	(0.0447)	(0.0447)	(0.1735)	(0.2205)	(0.3717)
	[0.0498]	[0.0498]	[0.1647]	[0.2100]	[0.3820]
Mean of dep. var.	2.8551	2.8551	2.8535	2.8547	2.8584
Mean of main indep. var.	0.1045	0.1045	0.1046	0.1047	0.1049
% of dep. var. explained by drone strikes in IV	10.7%	12.4%	11.1%	12.5%	9.3%
N	3,997	3,997	1,333	666	285

Notes: All IV estimations are conducted using the *ivreg*2 command in Stata with robust, heteroskedastic and autocorrelation consistent (HAC) standard errors (option $r\ bw(1)$ in Stata) displayed in parentheses. HAC standard errors accounting for bandwidth 15 are displayed in brackets (five, three and two lags in columns (3), (4) and (5), respectively). OLS (panel D): Newey–West standard errors calculated assuming a lag of one day are displayed in parentheses, while Newey–West standard errors calculated assuming a lag of 15 days are displayed in brackets. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$ indicate statistical significance at the 10%, 5% and 1% levels. [a]Includes 14 measures of terror attacks in the preceding 14 days, 14 measures of Pakistani military actions in the preceding 14 days, a binary indicator for Ramadan, a linear time trend, measures for temperature and precipitation in Miran Shah as well as fixed effects for each day of the week and month of the year. In columns (3)–(5), we account for lagged values of Pakistani military actions and terror attacks for five, two and two periods, respectively. Day-of-the-week fixed effects are excluded in column (5). [b]Dependent variables are measured over the following three, six and 14 days, respectively. For example, we predict the average numbers of terror attacks on days t, $t+1$ and $t+2$ with independent variables averaged over days $t-3$, $t-2$ and $t-1$. Similarly, wind gusts are averaged over days $t-3$, $t-2$ and $t-1$ in the first stage. [c]Following Stock and Wright (2000). [d]Following Magnusson (2010), we apply the *weakiv* command in Stata to test for weak instruments. [e]Following Kleibergen and Paap (2006). [f]Following Hayashi (2000) and Wooldridge (2015), we test whether endogenous regressors are in fact exogenous. Statistical significance indicates variables must be treated as endogenous.

Online Appendix Table F4 reports several additional results, delineating between attack and target types, by region, and between perpetrator identity (if available). First, especially bombings increase in frequency after drone strikes, whereas assassinations remain unaffected.[17] Second,

[17] The bombings/explosion category includes suicide bombings (variable *suicide*) that constitute 4% of all attacks. Analysing these separately, we do not find any statistically significant increase. It is possible that the time to prepare a suicide bomber takes much longer, as this has been suggested to take several months (Lakhani, 2010).

we identify positive and statistically significant estimates across all three target types of government, private and business locations.[18] Third, delineating by location shows consistent results when predicting attacks in the FATA region or the rest of the country. Finally, attacks in which perpetrators have been identified as Islamist groups spike after drone strikes, while those associated with separatist groups do not.

Columns (3)–(5) of Table 2 show that employing three-, six- or 14-day periods as the unit of observation produces consistent findings, addressing concerns about double counting of terror attacks. While the associated OLS regressions again produce null relationships, the IV estimates associated with drone strikes are positive and statistically significant at conventional levels. This is the case even when we use 14-day periods, which decreases the sample to 285 observations (p-values of 0.082 and 0.061, depending on the consideration of autocorrelation in calculating standard errors). Quantitatively, we derive magnitudes that are closely comparable to those from columns (1) and (2), ranging between 9% and 12.5%. Placebo tests predicting terror attacks in the days *preceding* drone strikes produce statistically insignificant estimates (see Online Appendix Table F7).

Panels B and C display first-stage coefficients and statistics relevant for IV performance and suitability. To put the implied magnitudes in context, the coefficient of wind gusts in column (1) suggests that a one-SD increase in wind gusts (equivalent to 8.68 km/h) would decrease the number of drone strikes by 0.024 units, i.e., approximately 23% of the mean ($8.68 \times -0.0028 = 0.0243$, which constitutes 23% of the mean number of drone strikes of 0.1). Wind gusts and wind speed assume the expected negative signs when predicting contemporaneous drone strikes in all estimations. The econometric test results in panel C support the IV's statistical power (Stock and Yogo, 2005; Magnusson, 2010; Stock and Watson, 2015), as well as our hypothesis of endogeneity constituting a major concern if not accounted for.

3.3. *Comparing IV and OLS Results*

How can we explain the discrepancy between the derived IV and OLS estimates? To better understand these differences, we pursue three complementary avenues. First, we apply the omitted variable bias test of Cinelli and Hazlett (2020) to estimate how powerful unobservable confounders would have to be to bring the OLS coefficient of interest to a value that would be statistically indistinguishable from the IV coefficient of 2.9. In our case, unobservable confounders would need to explain 57% of the residual variance. While that magnitude appears large, it is certainly not impossible, given the ample evidence of potential confounders discussed above and the inherent secrecy of the operations conducted by the involved parties.

Second, to explore such unobservable confounders, we assess a potentially testable narrative from Subsection 2.3, if only descriptively. We were able to obtain a database featuring arrests of terrorist leaders (SATP, 2017a), which allowed us to test whether such arrests correlate with subsequent drone strikes, presumably because of the provided intelligence (Ali, 2018; Chaudhry, 2018; Indian Express, 2018; The News, 2018). Regression results from predicting subsequent drone strikes indeed reveal arrests as a positive predictor with coefficients that are statistically significant at the 1% level, even when incorporating the usual set of covariates and contemporaneous terror attacks (see Online Appendix Table F5). These findings are consistent

[18] 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 also consider only the general attacks on government (category 2) and find consistent results.

with a narrative suggesting that OLS coefficients may be biased downwards because of largely unobservable confounders.

Third, an important attribute of any IV regression concerns the LATE, i.e., we need to distinguish compliers (intended drone strikes sensitive to wind conditions) from never and always takers. For example, strikes on prominent and elusive leaders likely constitute always takers, as these operations are unlikely to be affected by wind. Indeed, wind conditions are predictive of strikes *without* an explicit target description and *not* targeting leaders (see Online Appendix Table F1) that make up 73% and 84% of all drone strikes, respectively. However, wind gusts are not predictive of strikes targeting leaders. Thus, it is possible that the population would be particularly upset with what happen to be the complier drone strikes because the 'benefits' of the strike may not be immediately visible. In that case, it is easier to conceive of a narrative that suggests that the population would perceive the drone strike as an unwarranted violent act. In sum, we may be picking up a LATE that constitutes an upper bound of the unobserved mean effect of drone strikes.

Overall, however, we are not able to fully delineate the exact reasons behind the discrepancy in the IV and OLS estimates from Table 2. In general, our results indicate a severe downward bias in correlational regressions predicting subsequent terror attacks with drone strikes. Thus, narratives of omitted variables that simultaneously increase the number of drone strikes, but decrease the number of subsequent terror attacks, or vice versa, appear to dominate (see Subsection 2.3).

3.4. *Time Frame of Subsequent Terrorism*

We now turn to the time frame of the dependent variable. Our main specification of seven days for subsequent attacks may well appear arbitrary, as there is no theoretical framework or meaningful body of anecdotal evidence implying how long it would take to plan and conduct a terror attack. In addition, it is important to understand whether the results from Table 2 affect the *timing* of terror attacks or whether drone strikes affect their overall number. For example, attacks that are planned for in, say, two weeks may simply be moved forward as a response to drone strikes, perhaps because perpetrators expect further drone strikes. This would change the interpretation of our results.

To explore the consistency of our findings, we re-estimate IV regressions for a range of alternative time dimensions of the outcome variable. Figure 3(a) displays the resulting second-stage coefficients. Results are consistent when moving the time frame of subsequent terror attacks between one and 28 days. The final three estimates in Figure 3(a) come from regressions that consider days 15–21, 15–28 and then 15–70 after the initial drone strikes. We conduct these regressions to check whether the sign of the derived coefficient switches at some point, which would indicate that, eventually, drone strikes may lead to a decrease in attacks. This could be the case if, for example, drone strikes are able to severely affect the operational capabilities of terror groups. However, we still derive a positive and statistically significant coefficient that remains stable in magnitude: up to five attacks per day are suggested to happen solely because of a drone strike.

Second, Figure 3(b) displays the same structure of regression coefficients, but this time we predict terror *deaths*. Interestingly, coefficients are less precisely estimated for shorter time horizons, and we only identify a statistically meaningful relationship for six days after the initial drone strikes (p-value of 0.035). In additional results, we find that the severity of attacks (i.e., deaths per attack) decreases as a consequence of drone strikes, while we find no evidence for

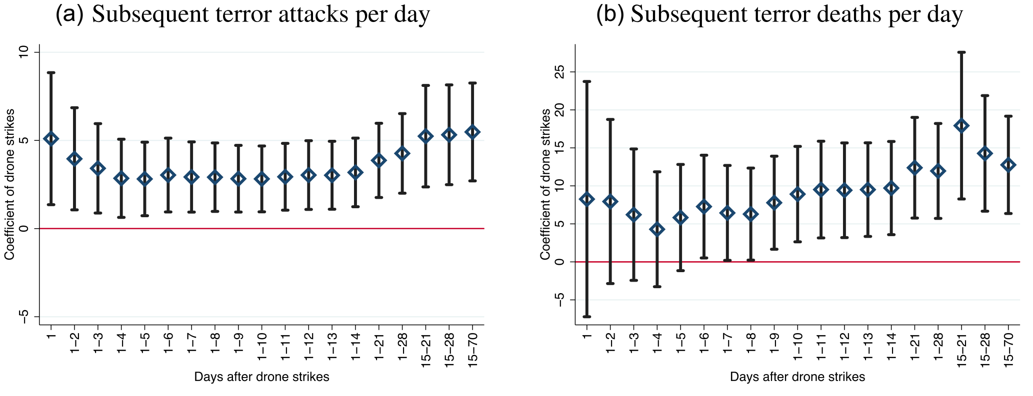


Fig. 3. *Predicting Additional Terror Attacks (Left) and Deaths from Terror Attacks (Right) per Day after Drone Strikes, Employing Alternative Time Windows for the Dependent Variable.*
Notes: Each point represents the coefficient related to drone strikes in a 2SLS regression, including the covariates from column (1) of Table 2. Two-sided 95% confidence intervals are displayed.

weapon diversity used in terror attacks to decrease as an indicator of group strength (see Online Appendix Table F3). Several hypotheses may explain this finding, although our data are not able to fully delineate these. First, terror groups may react emotionally with more attacks that are less planned out and therefore less deadly. Second, attacking more to eventually achieve more deaths in total may be a deliberate attempt to convey group strength. Third, the groups' operational capabilities may be diminished because of drone strikes, which could affect attack efficiency, but perhaps less so attack incidence. Other explanations are of course possible.

4. Empirical Findings: Beliefs and Attitudes

4.1. *Overview*

An important question relates to whether and, if so, how drone strikes affect the general Pakistani populace. We pursue three strategies to explore that question, employing data from (*i*) the main English-language Pakistani newspaper, (*ii*) protests and (*iii*) online search behaviour. Online Appendix Table F8 documents summary statistics of all additional variables. Throughout these analyses, we follow the familiar identification strategy based on wind gusts, while reporting the corresponding OLS estimates in Online Appendix Figures E3, E4, E8 and E9. As with the endogeneity concerns pertaining to drone strikes and subsequent terror attacks, unobservable characteristics likely affect attitudes and beliefs in the Pakistani population.[19]

4.2. *News Sentiment*

We first study coverage in the largest English-language newspaper in Pakistan, *The News International* (*TNI*).[20] Although reaching fewer people than the major Urdu-language dailies, the *TNI*

[19] 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 towards the United States.

[20] The *TNI* archive can be accessed via www.thenews.com.pk. We focus on an English-language newspaper because text analysis programs generally do not allow analyses of Urdu texts yet. We also explored the *Dawn* newspaper, the oldest English-language newspaper in Pakistan, but its online archive does not feature near-comprehensive data coverage.

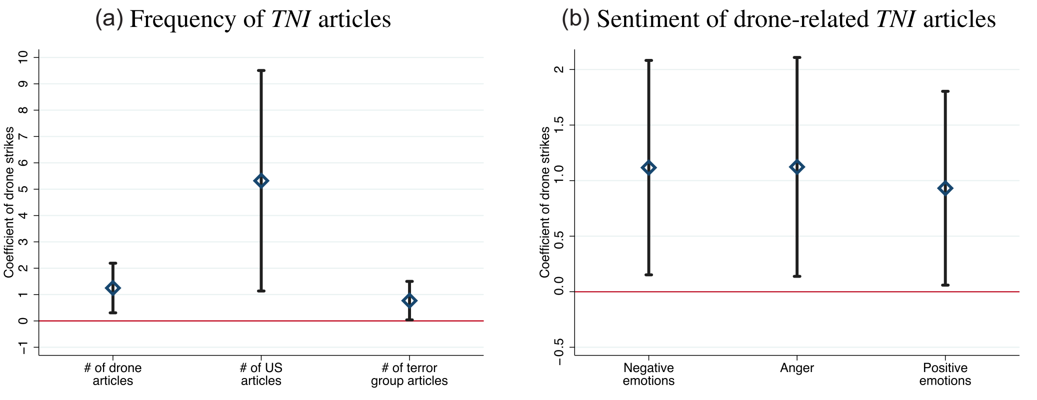


Fig. 4. *Left: IV Results from Predicting the Number of TNI Articles Mentioning Drone, a US-Related Keyword or a Terror-Group-Related Keyword on Days $t+1$ until $t+7$. Right: IV Results from Predicting Emotional Content of Drone-Related Articles on Days $t+1$ until $t+7$.*
Notes: All regressions include the full set of covariates from column (1) of Table 2, as well as measures for terror attacks on day t and days $t+1$ until $t+7$. Two-sided 95% confidence intervals are displayed.

owners (the Jang group) also publish the most popular Urdu-language daily (*Jang*) and private television network (*Geo TV*; see Gallup Pakistan, 2019) in Pakistan. Thus, *TNI* likely reflects political attitudes that are comparable to some of the most popular news outlets in the country.

The *TNI* online archive contains all available articles for 3,928 of the 4,018 sample days with only the first three months missing. To capture relevant news, we focus on *TNI*'s top story and national categories. Figure 4(a) visualises second-stage coefficients for drone strikes when predicting the number of articles that mention (*i*) the word *drone* (lower- and upper-case spellings; 4,346 articles overall), (*ii*) the United States (24,817 articles) or (*iii*) one of the major terror groups (5,329 articles). For the United States, we identify articles containing the words *America* (excluding *South America*), *United States*, *US* (capital letters) or *U.S.* (capital letters). For the major terror groups, we select the groups targeted in drone strikes (TBIJ, 2017b) and use the keywords *TTP*, *Tehrik-e-Taliban Pakistan*, *Tehrik-i-Taliban Pakistan*, *Al-Qaeda*, *Al Qaeda*, *Al-Qaida*, *Al Qaida*, *Haqqani network*, *Haqqani Network*, *ISIS* and *Islamic Movement of Uzbekistan*. All regressions include the familiar set of control variables, as well as measures for terror attacks on day t and days $t+1$ until $t+7$ to filter out variation owed to contemporaneous terror attacks. Figure 4(a) documents increased coverage after drone strikes for all three sets of keywords, and particularly articles mentioning the United States increase substantially because of drone strikes.

To explore news sentiment, we apply the *Linguistic Inquiry and Word Count* program (*LIWC* program; Pennebaker *et al.*, 2001; 2015) to derive each article's degree of negative emotions, anger and positive emotions.[21] We then average that score across articles mentioning *drone*, for

[21] 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 the case of ironic or sarcastic expressions, though not as perfectly as a human reader. For example, the dictionary includes 744 words and expressions to measure negative emotions, while it uses 230 words and expressions for identifying anger (a sub-category of negative emotions). The number of matched words and expressions is then converted to a percentage of the total words in the text. As an example application, we refer the reader to Borowiecki (2017), who measured the emotional content of letters by famous composers.

example, for every day and standardise each variable to facilitate quantitative comparisons.[22] Figure 4(b) displays IV results for drone-related articles, showing that all three types of emotions rise after drone strikes. This result also emerges from the corresponding OLS coefficients (see Online Appendix Figure E3(b)).

Next, Figure 5 explores US- and terror-group-related articles. To properly delineate between keywords, we also present results measuring emotions in articles that mention the United States, but not any of the respective terror groups and vice versa, as well as articles that exclude the word *drone*.[23] All results from Figure 5 are generally consistent if we (*i*) predict sentiment over the subsequent 14 days (Online Appendix Figure E5), (*ii*) analyse sentiment of individual sentences that mention the respective keywords (Online Appendix Figure E6) and (*iii*) study top stories only (Online Appendix Figure E7).

For US-related news, Figure 5(a) illustrates that negative emotions and anger, but not positive emotions, rise systematically after drone strikes. This result is driven by articles that also mention the word *drone*; however, once we exclude drone-related articles in the final regressions of Figure 5(a), the derived coefficients lose statistical and quantitative significance.

Figure 5(b) turns to terror-group-related news segments. In this case, we derive negative estimates throughout, most of which differ statistically from zero. Thus, *TNI* articles that discuss any of the major terror groups become less emotional—a result that is independent of drone- or US-related coverage. This is even though the number of terror-group-related articles increases, as seen in Figure 4(a).

4.3. *Anti-US Protests*

We now turn to anti-US and anti-terror-group protests, accessing the *Global Database of Events, Language, and Tone* (*GDELT*; Leetaru and Schrodt, 2013), the largest open platform gathering information on geo-located events from print, broadcast and web news in more than 100 languages. For protests against the United States, we focus on event root code 14 (protests), listing Pakistan as *Actor 1* and the United States as *Actor 2*. Concerning the major terror groups, we identify events listing Pakistan as *Actor 1* and rebels, separatists or insurgents as *Actor 2*. During our sample period, *GDELT* reports 3,745 protests against the United States and 824 protests against the major terror groups. To ensure that we are not double counting the same protests (see Ward *et al.*, 2013), we also generate binary indicators for these protest variables.

Figure 6 presents the corresponding results from 2SLS regressions, revealing a substantial rise in anti-US protests as a result of drone strikes. The same conclusions emerge when considering OLS regressions instead (see Online Appendix Figure E8). In terms of magnitude, one drone strike raises anti-US protests by 2–3 SDs in the following days and weeks, signalling a substantial increase in public expressions of disapproval with the United States.

However, protests against the major terror groups become less frequent, if anything, although the corresponding estimates are statistically insignificant at conventional levels when considering the subsequent seven days with p-values of 0.102 and 0.111. The respective coefficients are more precisely estimated, however, when predicting protests over the subsequent 14 days in Figure 6(b) with p-values of 0.101 and 0.077.

[22] We assign a value of zero to days without any articles mentioning the respective keywords.

[23] Overall, of the 24,817 articles mentioning a US-related keyword, 21,304 do not mention the word *drone*, while 22,360 do not mention any terror-group-related keyword. Of the 5,329 articles mentioning any of the terror groups, 4,351 do not mention the word *drone*, and 2,872 do not mention any US-related keyword.

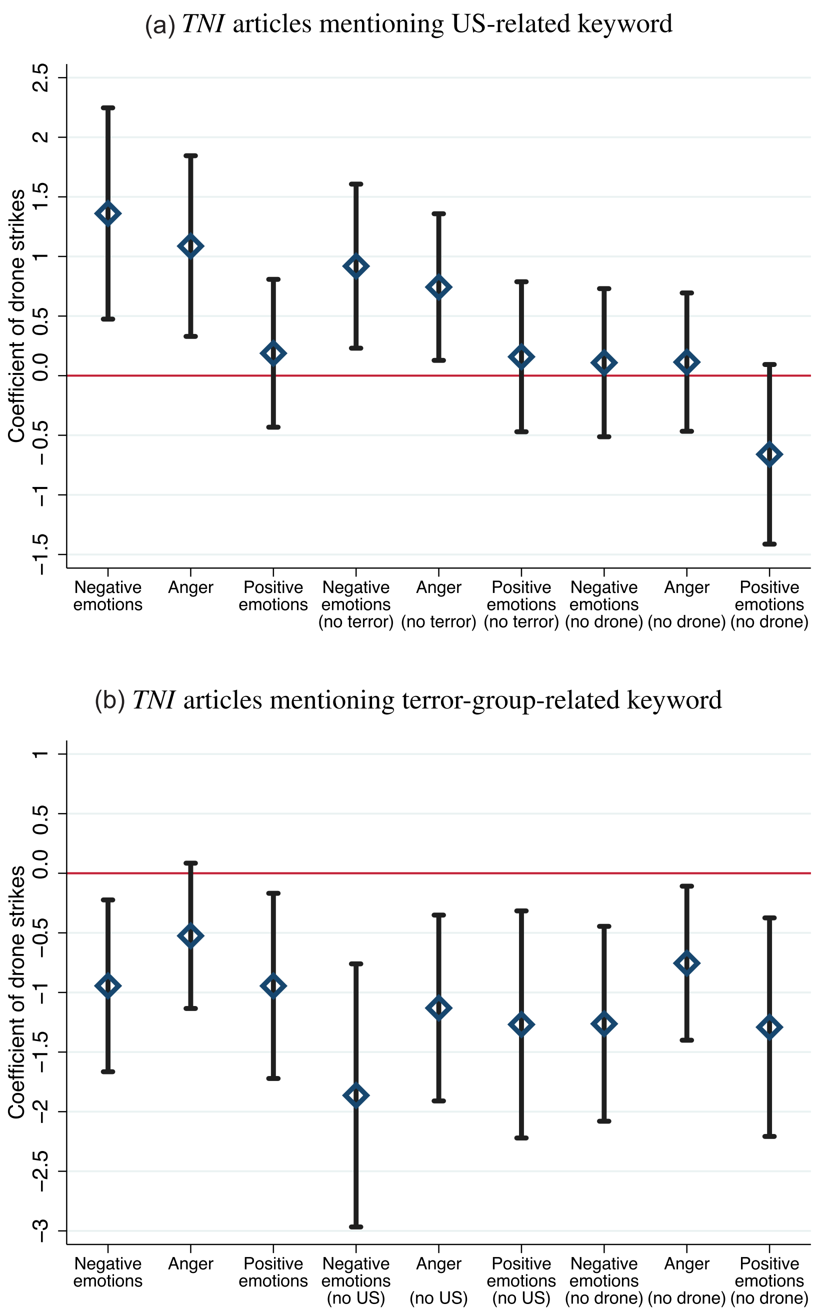


Fig. 5. *Top: IV Results from Predicting Emotional Content of Articles Mentioning a US-Related Keyword on Days* $t+1$ *until* $t+7$. *Bottom: IV Results from Predicting Emotional Content of Articles Mentioning a Terror-Group-Related Keyword on Days* $t+1$ *until* $t+7$.

Notes: All regressions include the full set of covariates from column (1) of Table 2, as well as measures for terror attacks on day t and days $t+1$ until $t+7$. Two-sided 95% confidence intervals are displayed, and outcome variables are standardised.

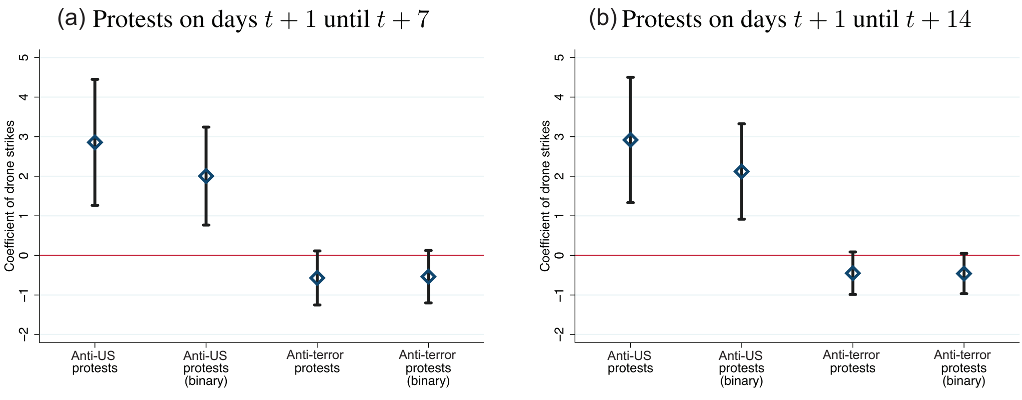


Fig. 6. *IV Results from Predicting Anti-US and Anti-Terror-Group Protests on Days* $t+1$ *until* $t+7$ *(until* $t+14$ *for the Graph on the Right).*

Notes: All regressions include the full set of covariates from column (1) of Table 2, as well as variables measuring terror attacks on day t and days $t+1$ until $t+7$ (until $t+14$ for the graph on the right). Two-sided 95% confidence intervals are displayed.

4.4. *Relevant Online Searches*

In our final set of specifications, we turn to *Google Trends* to get a glimpse into regular Pakistanis' reactions to drone strikes. A growing body of research employs *Google* searches as a powerful measure of attitudes and beliefs, largely because of the enormous number of data points and an absence of social censoring and social desirability biases.[24] *Google Trends* provides daily data that are both relative to searches of the same term in the surrounding six months and searches for other topics in the same location and day.

To proxy for interest in Islamist terrorism, we study day-to-day variation in four search terms: (*i*) *jihad*, which literally translates to 'struggle' and has become synonymous with the armed struggle against 'enemies of Islam'; (*ii*) *Taliban video*; (*iii*) *Zarb-e-Momin/Zarb-i-Momin*—which translates to 'strike of a devout Muslim'—a weekly magazine published in Pakistan, which expresses radical beliefs and religious extremism and (*iv*) *Ghazwa e Hind*, which means the 'Battle of the Indian subcontinent' and refers to the prophecy about Muslims' ultimate conquest of the sub-continent. We select these search terms to tease out the interest of Pakistanis in radical concepts and groups. Online Appendix D provides more detailed background information on why these terms are likely most relevant in that regard.

We also explore Pakistanis' frequency of searching for the most prominent US-related search terms as an indication of pro-US sentiment. To do so, we first identify those topics and queries related to the term *United States* that are generally receiving most online attention (see the list in Online Appendix Table D1 and a detailed discussion in Online Appendix D). This leads us to study online searches for (*i*) *USAID*, (*ii*) US immigration and (*iii*) *USEFP*.

Figure 7 shows the corresponding results from the IV estimations, where we again standardise all variables to facilitate comparability. Online Appendix Figure E9 displays the corresponding

[24] For example, Stephens-Davidowitz (2014) proxied racism in the United States through racially charged search terms (see also Stephens-Davidowitz and Pabon, 2017); Kearney and Levine (2015) consulted search data to understand the link between a popular television show and teenagers' fertility decisions; and Baker and Fradkin (2017) studied Google searches for employment purposes.

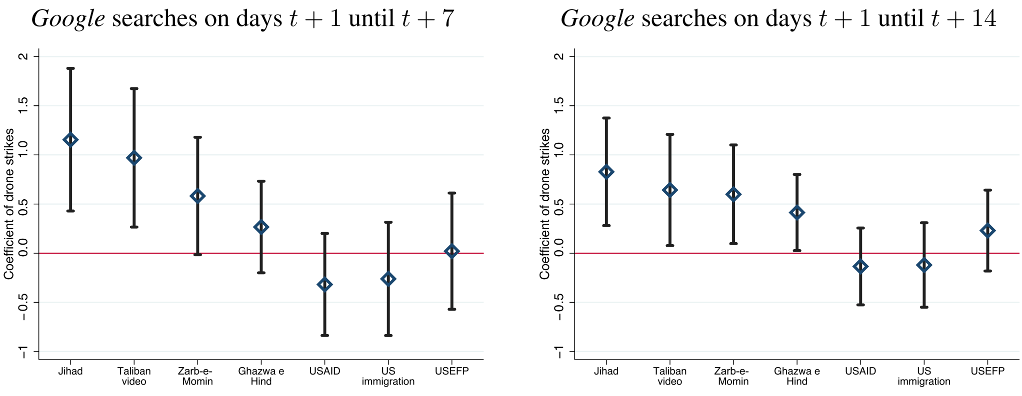


Fig. 7. *Left: IV Results from Predicting Google Searches for Various Topics on Days* $t + 1$ *until* $t + 7$. *Right: IV Results from Predicting Google Searches for Various Topics on Days* $t + 1$ *until* $t + 14$.
Notes: All regressions include the full set of covariates from column (1) of Table 2, including variables measuring terror attacks on day t and days $t + 1$ until $t + 7$ (or $t + 1$ until $t + 14$ in the bottom graph). Two-sided 95% confidence intervals are displayed.

OLS estimates. In the seven days after drone strikes, we identify a statistically significant increase in *Google* searches for *jihad* and *Taliban video*. Quantitatively, a drone strike increases the corresponding searches by approximately one SD. Searches for *Zarb-e-Momin* and *Ghazwa e Hind* show an increase after drone strikes when considering the subsequent 14 days in Figure 7(b) (*p*-values of 0.019 and 0.036). However, online interest in the terms capturing interest in US-related topics does not change, whether we consider the subsequent seven or 14 days. Interestingly, these IV results also differ from the corresponding OLS estimates (see Online Appendix Figure E9), indicating meaningful endogeneity concerns.

5. Conclusion

This paper aims to isolate the causal effects of drone strikes in Pakistan, employing exogenous variation from wind conditions as an identification strategy. We find that drone strikes encourage terrorist attacks, and a back-of-the-envelope calculation indicates that these missions are responsible for up to 19% of all terror attacks or more than 3,000 terror deaths in Pakistan from 2006 to 2016. These estimates stand in stark contrast to simple correlations that imply a null relationship. Thus, if endogeneity remains unaccounted for, the derived coefficient of drone strikes to predict subsequent terrorism suffers from a substantial downward bias.

We then explore whether and, if so, how regular Pakistanis respond to drone strikes. Because of drone strikes, the largest English-language newspaper in Pakistan reports more negatively and more angrily about the United States—but only in articles that do mention drones. In turn, language indicative of positive emotions also increases in drone-related articles, suggesting some form of polarisation in the popular discussion. Coverage about the major Pakistani terror groups, on the other hand, becomes generally less emotional. In addition, anti-US protests and online searches indicative of interest in extremist concepts become more frequent, while we find moderate evidence of *fewer* protests against the major terror organisations as a result of drone strikes.

Naturally, our analysis is not without caveats, and we want to briefly discuss what we believe to be the most pressing ones. First, our identification strategy relies on a local average treatment effect, i.e., we identify those cases where wind conditions played a decisive role in the decision to proceed with a drone strike or not. Additional analyses suggest that this would apply to up to 84% of all drone strikes, however (see Online Appendix Table F1). Second, an online search for a radical term does not make a terrorist, and the emotional content of US-related articles does not comprehensively prove anti-US attitudes. Nevertheless, the persistency with which we identify signs of anti-US sentiment as a consequence of drone strikes is consistent with the blowback hypothesis. In fact, given a literacy rate of 58% (Government of Pakistan, 2017) and a tendency to radicalise that usually decreases with education in Pakistan (Fair *et al.*, 2014), studying an English-language newspaper and online search behaviour (requiring literacy and internet access) may actually present lower bound estimates of the feelings that drone strikes provoke in the Pakistani population. Third and finally, our identification strategy based on wind conditions is naturally more suitable to identifying short-term variation in drone strikes, i.e., we should be cautious in drawing long-term conclusions, such as those related to the long-run strength of terror organisations.

To our knowledge, this is the first analysis that is able to identify causal effects of drone strikes. Taken together, the empirical results imply that drone strikes cause terror attacks in Pakistan and growing anti-US sentiment in the Pakistani population—attributes that stand in stark contrast to the goals advocated by the War on Terror. As the US military continues to expand its drone program, we hope that our research provides useful insights into the underlying consequences, as well as starting points for further research.

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Additional Supporting Information may be found in the online version of this article:

Online Appendix
Replication Package

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