

Fear the Reaper: How drone and air strikes impact terrorist attacks

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Abstract

Prior studies concluding that drone strikes are an effective counterterrorism strategy frequently limit their analyses to US drone strikes conducted within a geographically constrained region of Pakistan. However, this limitation leads to an overestimation of the effect of drone and air strikes and prevents an accurate assessment of potential displacement effects. Our study aims to overcome these challenges by using a larger dataset that includes terrorist attacks in each of Pakistan's provinces, as well as both US drone and Pakistani air strikes deployed against terrorist groups across the country. We use Bayesian Causal Forests (BCF) to measure the conditional average treatment effect of strikes on two outcomes: civilian casualties and the geographic distance between consecutive terrorist attacks. We find no evidence that strikes substantively decrease the number of civilians killed in terrorist attacks. Interestingly, strikes appear to substantially increase the distance from one terrorist attack to the next, particularly for attacks occurring in Sindh province, suggesting that terrorist groups may relocate after being targeted. These findings contradict prior studies and indicate that drone and air strikes do not effectively degrade terrorist groups.

1. Introduction

The US “War on Terror” introduced a new military capability to modern conflict: drones. Drones, also referred to as Unmanned or Uncrewed Aerial Vehicles (UAV) or Systems (UAS), enabled the US military to wage counterterrorism campaigns across the Middle East and Africa while minimizing the number of US soldiers exposed to combat. However, drones are no longer limited to counterterrorism contexts: both Ukraine and Russia have demonstrated that drones convey significant advantages in conventional warfare, such as enabling increased access to hostile territory.¹ However, long-range drones also increasingly endanger brigades far from the front lines and render expensive Western defense technology useless.² Furthermore, while drones can limit the number of soldiers killed in conflict, they may also lower the threshold of war, meaning more states can and will pay the cost of conflict.³ Many countries, including the United States, have already begun shifting defense production towards more attritable drone technology; for example, the US Department of Defense’s Replicator Initiative aimed to deliver thousands of self-piloting ships and uncrewed aircraft by 2025.⁴

The rapid transition of drones from a counterterrorism tool to a standard component of modern military arsenals raises a critical question: How effective are drones when operating within broader military campaigns? Most previous studies examine drones in isolation and only in counterterrorism contexts, arriving at competing “pessimistic” or “optimistic” conclusions about whether drone strikes effectively degrade terrorist organizations.⁵ “Pessimists” find that drone strikes increase terrorist attack prevalence and lethality by exacerbating principal-agent problems, encouraging civilian backlash against the counterterrorist state, or inciting

¹Mariano Zafra et al, “How drone combat in Ukraine is changing warfare,” *Reuters*, (2024), <https://www.reuters.com/graphics/UKRAINE-CRISIS/DRONES/dwpkeyjwkpm/>.

²Zafra et al, “How drone combat in Ukraine is changing warfare,” *Reuters*, (March 2024), <https://www.reuters.com/graphics/UKRAINE-CRISIS/DRONES/dwpkeyjwkpm/>, Zafra et al, “How drone combat in Ukraine is changing warfare.”

³For discussions of how drones lowered the threshold of conflict under the Obama and Trump administrations, see Eric Bonds, “Humanitized violence: Targeted killings and civilian deaths in the US war against the Islamic State,” *Current Sociology*, 67, no. 3 (2019): 438–455; Rachel Stohl and Shannon Dick, *A New Agenda for US Drone Policy and the Use of Lethal Force*, (Stimson 2021); and Chris Woods, *Sudden justice: America’s secret drone wars*, (Oxford University Press 2015).

⁴The Replicator Initiative, <https://www.diu.mil/replicator>, accessed November 25, 2025.

⁵Schwartz et al, “Do armed drones counter terrorism, or are they counterproductive? Evidence from eighteen countries,” *International Studies Quarterly*, 66, no. 3 (August 2022), p. 3-4.

terrorist revenge; in contrast, “optimists” argue that drone strikes disrupt terrorist operations or degrade terrorist capabilities.⁶ These studies tend to focus on US drone operations in the Federally Administered Tribal Area (FATA), a geographically constrained region of Pakistan and major focus of the US counterterrorism campaign. While this focused analysis facilitates an understanding of whether drone strikes alone effectively degrade terrorist groups, Schwartz et al rightfully point out that it overlooks the broader impact of drones on political violence.⁷ Schwartz et al make a significant contribution to the literature by expanding analysis of drones beyond Pakistan and assessing the impact of aggregate drone *programs* on terrorism in eighteen countries.⁸

However, isolating the effect of drones may miss the bigger picture, since drones are rarely the only tool states deploy, even in a counterterrorism context. For example, while the United States utilized drones for an explicitly counterterrorist purpose in Pakistan, the wider campaign consisted of both US drone strikes and Pakistani conventional air strikes. The United States primarily conducted drone strikes in FATA and Khyber Pakhtunkhwa, tribal regions of Pakistan along Pakistan’s border with Afghanistan, but Pakistan’s military also deployed conventional airpower in the form of jets and helicopters to fight terrorist threats in Balochistan and Punjab.

While prior studies further our understanding of the immediate effects of drone strikes, widening the scope of analysis to include the fully integrated air campaign in Pakistan offers several opportunities to build on prior research. First, studies focusing on one province cannot wholistically evaluate the success of the counterterrorism campaign in Pakistan, only that of US operations, and potentially only that of US operations in FATA. Several “optimist” studies find that US drone strikes decrease terrorist attack lethality in FATA, but it remains understudied whether the counterterrorism campaign decreased terrorist attack lethality in other provinces of Pakistan as well. Second, previous studies fail to adequately measure displacement effects, since drone operations in Pakistan were constrained to FATA and terrorist activities are no longer observed if a group relocates to a province outside of the study area. Several studies acknowledge this limitation and note the existence of qualitative evidence suggesting that the

⁶Schwartz et al, p. 3-4.

⁷Schwartz et al, p. 2.

⁸Schwartz et al.

Tehrik-i-Taliban (TTP), the primary terrorist threat in Pakistan, relocated to Sindh province following US operations in FATA.⁹ If groups such as the TTP relocate and continue conducting terrorist attacks, then the decrease in terrorist attack prevalence and lethality observed in the literature does not indicate successful degradation, but rather displacement.

To overcome this challenge, we focus on all terrorist attacks in Pakistan, not just in FATA or its neighboring provinces. This wider geographic analysis allows us to evaluate how counterterrorism efforts impact terrorist lethality overall, as well as to measure heterogeneity in these effects across the various provinces. Examining the entire country also enables us to address questions about whether terrorist groups shift their operations and continue conducting attacks, or whether counterterrorism efforts truly degrade terrorist capabilities.

As in other studies, identifying a causal relationship is difficult because the effect of strikes on terrorist violence is often small and confounded by other factors, such as ongoing conflict. To overcome this challenge, we employ Bayesian Causal Forests (BCF) to measure the conditional average treatment effect of strikes on two outcomes: the number of civilians killed in terrorist attacks and the distance between consecutive attacks. BCF excels at isolating treatment effects in the presence of strong confounding by modeling the baseline outcome separately from the treatment effect. For each outcome, BCF captures baseline attack patterns (lethality or geographic spacing) as a function of controls (province, time, and terrorist characteristics), while separately estimating how drone and air strikes alter these patterns. This approach also addresses selection bias; certain terrorist groups are more likely to be targeted than others, so we estimate each group’s propensity for being targeted using Bayesian Additive Regression Trees (BART) and include this propensity score in the BCF model to reduce confounding bias.

We estimate 70 BCF models across varying temporal specifications of the treatment window. To capture the full effect of counterterrorism efforts in Pakistan, we consider a group “treated” if they are targeted by US drone strikes or Pakistani air strikes in varying windows of time prior to conducting an attack. We extend the treatment window from 2 weeks to 52 weeks, skipping every 2 weeks, and from 1 to 10 years, skipping every year, and estimate a model for each temporal specification. We find no evidence that strikes substantively decrease

⁹Zia Ur Rehman, “The Pakistani Taliban’s Karachi Network,” *CTC Sentinel*, no. 6.5 (2013): p. 1.; Asfandyar Mir and Dylan Moore, “Drones, surveillance, and violence: Theory and evidence from a US drone program,” *International Studies Quarterly*, no. 63, 4 (2019), p. 846.

the number of civilians killed in terrorist attacks but do find evidence that strikes have an initial displacement effect that decays over time. This assessment provides a more nuanced understanding of the counterterrorism campaign in Pakistan and the limited efficacy of airpower. In addition, we contribute to ongoing debates about the “whack-a-mole” effect and suggest that, although strikes displace terrorist groups, they quickly regain capacity to continue attacking civilians. Finally, these results are immediately relevant to current and future conflicts, which are likely to feature drones alongside conventional airpower in integrated campaigns that require a better understanding of how drones operate as part of a broader military strategy.

2. Literature Review

Studies concerned with drone strike effectiveness typically examine terrorist attack frequency and lethality, measured by changes in the number of terrorist attacks committed or in the number of people killed or injured in those attacks, to determine factors associated with terrorist capacity.¹⁰ Johnston and Sarbahi (2016) analyze the effects of US drone strikes on the incidence and lethality of terrorist attacks in FATA and determine that they decreases both, particularly against tribal elders.¹¹ Jaeger and Siddique (2018) also examine the effects of US drone strikes in FATA, but their findings are mixed: their analysis suggests a week-long “vengeance period” immediately after a drone strike in which a terrorist attack is 9.7% *more* likely to occur, while strikes appear to have a “deterrent” effect the following week, with an attack becoming 8.7% *less* likely.¹² In “Drones, Surveillance, and Violence: Theory and Evidence from a US Drone Program,” Mir and Moore specifically focus on North Waziristan, the only district in FATA the CIA was legally allowed to operate in, and compare the frequency

¹⁰Alternatively, studies concerned with decapitation strikes utilize group duration as the outcome variable. For examples of studies examining duration, see Jenna Jordan, “Attacking the Leader, Missing the Mark: Why Terrorist Groups Survive Decapitation Strikes,” *International Security*, 38, no. 4 (April 2014): 7–38, and Bryan C. Price, “Targeting top terrorists: How leadership decapitation contributes to counterterrorism,” *International Security*, 36, no. 4, (2014): 9-46.

¹¹Patrick B. Johnston and Anoop K. Sarbahi, “The Impact of US Drone Strikes on Terrorism in Pakistan,” *International Studies Quarterly*, 60, no. 2 (June 2016): 203–19, <https://doi.org/10.1093/isq/sqv004>.

¹²David A. Jaeger and Zahra Siddique, “Are drone strikes effective in Afghanistan and Pakistan? On the dynamics of violence between the United States and the Taliban,” *CESifo Economic Studies*, no. 64, 4 (2018): p. 695.

and lethality of terrorist attacks in North Waziristan to nearby districts. They find that North Waziristan experienced 9 to 13 fewer attacks and 51 to 86 fewer casualties than other districts as a result of the US drone program.¹³ However, these studies limit their analyses to drone strikes conducted by the United States within FATA, a relatively small region of Pakistan.¹⁴ By only inspecting FATA, prior studies constrain their analyses to the US counterterrorism campaign along the Afghanistan-Pakistan border and fail to capture how strikes affect terrorist activities across a broader region.

3. Dataset

We create a dataset of attacks against civilians in Pakistan from 2010-2024¹⁵ using the Armed Conflict Location and Event Database (ACLED), which records the date, perpetrator, target, location, and fatalities of reported violence and protest events worldwide.¹⁶ ACLED surveys various media to create a comprehensive database of political violence, including traditional media at the subnational level, reports from international organizations, and verified social media accounts. ACLED also frequently corroborates and updates its databases. Previous studies of civilian victimization frequently use ACLED data, although drone research has typically relied on the New America Foundation and the Bureau of Investigative Journalism, both of which restrict their coverage to US drone strikes in limited regions of Pakistan.¹⁷

To create the dataset for this study, we used two datasets on Pakistan from ACLED: violence against civilians and air and drone strikes from 2010-2024. Since we are only interested in terrorist violence against civilians, we removed all instances of state military, tribal militia,

¹³Asfandyar Mir and Dylan Moore, p. 846.

¹⁴FATA was merged with the Khyber Pakhtunkhwa province in 2018, but the majority of scholars continue to distinguish between the two provinces even after the merger.

¹⁵Our study begins in 2010 because ACLED began covering Pakistan in 2010.

¹⁶C. Raleigh, R. Kishi, and A. Linke, “Political instability patterns are obscured by conflict dataset scope conditions, sources, and coding choices,” *Humanit Soc Sci Commun* no. 10, 74 (2023), <https://doi.org/10.1057/s41599-023-01559-4>.

¹⁷For examples of civilian victimization studies utilizing ACLED, see Nathaniel DF Allen, “Assessing a decade of US military strategy in Africa,” *Orbis*, no. 62, 4 (2018): pp. 655–669; John O’Loughlin, Frank DW Witmer, and Andrew M Linke, “The Afghanistan–Pakistan wars, 2008–2009: Micro-geographies, conflict diffusion, and clusters of violence,” *Eurasian Geography and Economics*, no. 51, 4 (2010): pp. 437–471; and Reed M Wood, “From loss to looting? Battlefield costs and rebel incentives for violence,” *International Organization*, no. 68, 4 (2014): pp. 979–999.

and communal militia violence against civilians, leaving 22 unique terrorist groups in the dataset (Table 2). We also filtered the air and drone strikes data to include only instances in which the actor deploying the drone strike was a state military to isolate the effect of counterterrorism campaigns and eliminate any instances of intra-terrorist group violence.

Each observation in our dataset is therefore a terrorist attack against civilians. The treatment variable, *targeted*, equals 1 if the terrorist group was targeted by air and drone strikes and 0 otherwise.¹⁸ In addition to the date, location, and terrorist group data provided by ACLED, we created additional predictor variables using ACLED’s data on air and drone strikes. The *strikes* variable aggregates the number of strikes deployed against a terrorist group prior to each attack they conducted, and the *strike_fatalities* variable calculates the number of terrorists killed in these strikes. The *type_rel* variables categorizes each terrorist group in the dataset according to its organizational type. We agree with Jenna Jordan’s assessment that identifying organizational type also encapsulates group goals, so we follow her system and code each group as religious, separatist, or ideological.¹⁹ However, only religious and separatist groups are present in the dataset. The *age* variable records the age of each terrorist group in years since its formation until 2024. Each province variable denotes whether an attack occurred in *Balochistan*, *FATA*, the *Federal Capital Territory*, *Punjab*, or *Sindh*, with *Khyber Pakhtunkhwa* reserved as the reference category.

We test two different outcome variables: the number of civilians killed in terrorist attacks and distance between one terrorist attack and the next. ACLED’s *fatalities* count records the number of civilians killed in each terrorist attack. Using the date and location information from ACLED’s data on air and drone strikes, we measure the the distance between consecutive terrorist attacks by calculating the distance between a terrorist group’s $n - 1$ and n attack.

For our treatment variable, *targeted*, we create lagged measures to evaluate how drone and air strikes impact the outcome variables when the treatment occurs at varying lengths of time prior to the attack. We extend the temporal window of the treatment biweekly from 2 to 52 weeks, as well as annually from 1 to 10 years. For example, *targeted_2weeks* measures whether

¹⁸There were eight terrorist groups in the original datasets that were targeted by strikes but never attacked civilians. Because they did not attack civilians, they are excluded from our analysis, but future research should consider whether drone strikes can prevent terrorist groups from ever attacking civilians.

¹⁹Jordan, “When heads roll,” p. 737.

a terrorist group was targeted by drone or air strikes in the two weeks before they committed n attack. We also include lagged covariates for the number of strikes deployed against a terrorist group and the number of terrorists killed in these strikes, both of which measure strike intensity in the temporal window.

3.1. Summary Statistics

Numeric Variables						
Variable	Min	Max	Median	Mean	SD	Description
fatalities	0.00	141.00	1.00	2.16	6.91	Civilian fatalities per attack
distance_km	0.00	1235.88	168.19	273.62	285.11	Distance between consecutive attacks (km)
mon_yr	2010.00	2024.33	2020.75	2018.50	5.26	Time variable at the monthly frequency
age	6.00	77.00	17.00	29.91	23.44	Group age (years since founding)

Categorical Variables				
Variable	Category	Count	Proportion	Description
Province	Balochistan	243	0.35	Balochistan province
	Khyber Pakhtunkhwa	289	0.41	Khyber Pakhtunkhwa province
	FATA	94	0.13	Federally Administered Tribal Area
	Sindh	51	0.07	Sindh province
	Punjab	22	0.03	Punjab province
	Federal Capital Territory	4	0.01	Islamabad
Group Type	Religious	494	0.70	Religious (Islamist) militant groups
	Separatist	209	0.30	Separatist groups

Table 1: Summary Statistics of Variables

The final dataset has 703 observations. On average, each terrorist attack kills 2.16 civilians, although this number varies widely from 0 to 141, since some terrorist attacks are exceptionally

violent. The distance between one terrorist attack and the next also varies widely, with an average distance of 273.62 kilometers and a range of 0 to 1235.88 kilometers. Religious groups committed the majority of terrorist attacks in Pakistan from 2010-2024, which is not surprising given that the Tehrik-i-Taliban (TTP), an extremist Islamist group based in FATA, has represented the primary terrorist threat in Pakistan for the past several decades.²⁰ Terrorist attacks were most common in Khyber Pakhtunkhwa, Balochistan, and FATA, with 41.11, 35.69, and 13.37 percent of attacks occurring in each of these provinces, respectively. Most of the attacks committed by separatist groups were concentrated in Balochistan, where violent movements advocating for a separate Baloch state have been active since Pakistan’s independence.²¹ The vast majority of attacks in Khyber Pakhtunkhwa and FATA, in contrast, were committed by religious groups, at 99.65 and 97.87 percent, respectively. Because counterterrorism operations in Pakistan have tended to focus on extremist Islamist groups, almost all “treated” groups in the dataset are religious, making any comparison of the treatment effects on religious and separatist groups challenging.

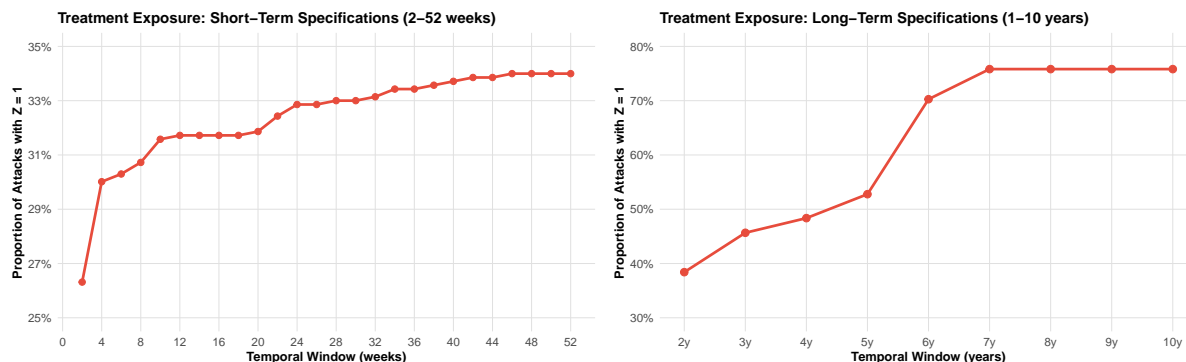


Figure 1: Proportion of observations falling into the treatment group over the biweekly specified temporal window (left) and the annually specified temporal window (right). Note the different scales.

²⁰Stanford University, “Tehrik-i-Taliban Pakistan,” *Mapping Militant Organizations*, July 2018, <https://cisac.fsi.stanford.edu/mappingmilitants/profiles/tehr-i-taliban-pakistan>.

²¹Stanford University, “Balochistan Liberation Front,” *Mapping Militant Organizations*, August 2015, <https://web.stanford.edu/group/mappingmilitants/cgi-bin/groups/view/457>.

4. Method

We use Bayesian Causal Forests (BCF) to measure the conditional average treatment effect of drone and air strikes on the number of civilians killed in terrorist attacks and the distance between consecutive terrorist attacks. BCF is a nonlinear regression model that is especially useful in situations with small effect sizes, heterogenous effects, and strong confounding factors.²² Attempting to isolate the effect of strikes on terrorist violence often encounters these challenges, since ongoing conflict makes it difficult to separate the effect of strikes from existing patterns of violence. Previous studies examining drone strikes often utilize panel methods with fixed effects and rely on parallel trends assumptions (that treated and control units would have followed similar violence trajectories absent drone strikes).²³ However, these assumptions may not hold, which undermines the credibility of prior findings that drones strikes effectively degrade terrorist groups. For example, Mir and Moore (2019) acknowledge that their pre-program parallel trends test suggests significant differential trends between North Waziristan and control districts before the US drone program began in 2008.²⁴

BCF addresses this limitation by flexibly modeling baseline violence patterns through a non-parametric prognostic function $\mu(X)$, which can capture non-linear, unit-specific trajectories without imposing functional form restrictions. When we replicate Mir and Moore’s analysis using BCF, we find no evidence that the US drone program reduced casualties in North Waziristan. Our estimated treatment effects consistently range from -0.08 to +0.35 casualties per tehsil-month (95% credible intervals include zero), contradicting Mir and Moore’s difference-in-differences estimate of -9.53 casualties (95% confidence interval: [-13.79, -5.27]). These results suggest that flexible modeling of pre-existing differential trends yields substantially different conclusions about drone strike effectiveness (see Table 3).

BCF also enables the inclusion of control variables in the model and reveals at which levels the treatment has the strongest effects. This advantage of BCF enables a broader survey of

²²P. Richard Hahn, Jared S. Murray, Carlos M. Carvalho, "Bayesian Regression Tree Models for Causal Inference: Regularization, Confounding, and Heterogenous Effects (with Discussion)" *International Society for Bayesian Analysis*, no. 3, 15 (2020): pp. 965–1056.

²³Johnston and Sarbahi, "The impact of US drone strikes on terrorism in Pakistan"; Mir and Moore, "Drones, surveillance, and violence".

²⁴Mir and Moore, "Drones, surveillance, and violence," p. 852, 856.

drone and air strikes and facilitates analysis of factors not considered in earlier studies, such as how violence levels change across different provinces in Pakistan in response to counterterrorism efforts.

The BCF specifications conform to the following structure:

$$E(Y_i | x_i, Z_i = z_i) = \mu(x_i, \hat{\pi}(x_i)) + \tau(x_i)z_i \tag{1}$$

where the functions μ and τ are given independent BART priors and $\hat{\pi}(x_i)$ is an estimate of the propensity score $\pi(x_i) = \Pr(Z_i = 1 | x_i)$.²⁵ The propensity function measures the probability that treatment will be applied given the control variables, meaning the probability that drone or air strikes will be conducted against a terrorist group with the specified control variable characteristics. We estimate the propensity function using logit BART for dichotomous outcomes. Y_i represents our outcome variables, the number of civilians killed in terrorist attacks or the distance between consecutive attacks, z_i is the treatment variable and is coded as a 1 if the terrorist group was targeted in the specified temporal window, and x_i is the vector of control variables. x_i includes the number of strikes and strike fatalities occurring in the temporal window, the date and location of an attack, and terrorist group age and type.

5. Main Results

5.1. Model 1: Civilian Fatalities

Figure 2 shows the results of BCF models estimated using the number of civilians killed in terrorist attacks as the dependent variable. The relationship between strikes and terrorist lethality is insignificant for every temporal specification, with 95% credible intervals consistently overlapping zero across treatment windows. This null finding contradicts prior studies' conclusions that drone strikes degrade terrorist capabilities. According to Figure 2, this null result is robust to alternative specifications of treatment timing, meaning that we find no evidence that drone and air strikes reduce terrorist attack lethality when groups are targeted

²⁵P. Richard Hahn, Jared S. Murray, Carlos M. Carvalho, "Bayesian Regression Tree Models for Causal Inference," p. 969

anywhere from 2 to 52 weeks prior to an attack. Figure 8 extends the treatment window from one to 10 years prior to the attack and similarly finds no significant relationship between strikes and terrorist lethality.

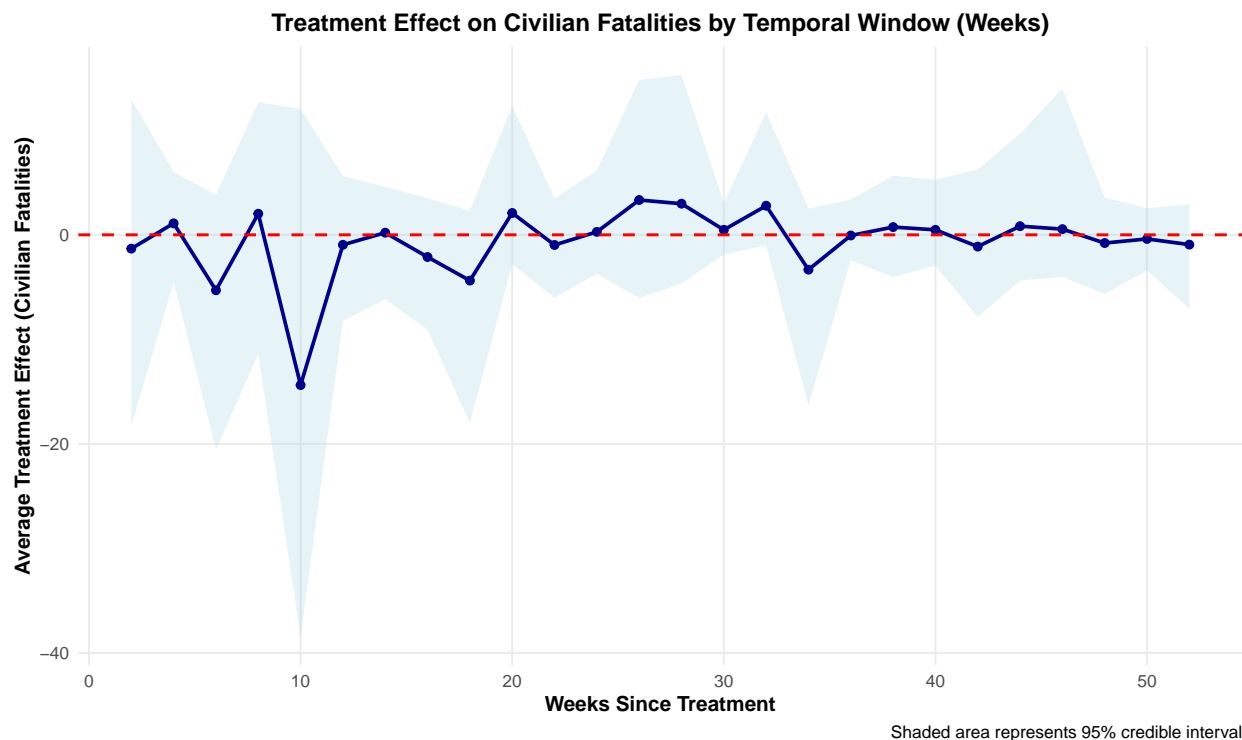


Figure 2: Average treatment effect of strikes on terrorist lethality. The outcome modeled is civilian fatalities. z is equal to one if strikes targeted the terrorist group committing the attack within the temporal window (specified by the x-axis).

One of the advantages of BCF is that it allows for analysis of the heterogeneity of treatment effects and supports better understanding of how the impact of strikes vary depending on the province, month and year, and characteristics of the targeted group. Figure 3, for example, presents the distribution of posterior mean treatment effects across individual attacks for the four-week temporal specification. Although the distribution is centered near zero, consistent with our null aggregate finding, it exhibits substantial spread ranging from approximately -5 to +10 civilian deaths per terrorist attack. This variation reflects both genuine heterogeneity in treatment effects across contexts and posterior uncertainty in unit-level estimates. To identify which, if any, of our covariates influence the treatment effects, we examine recursive partitioning summaries.

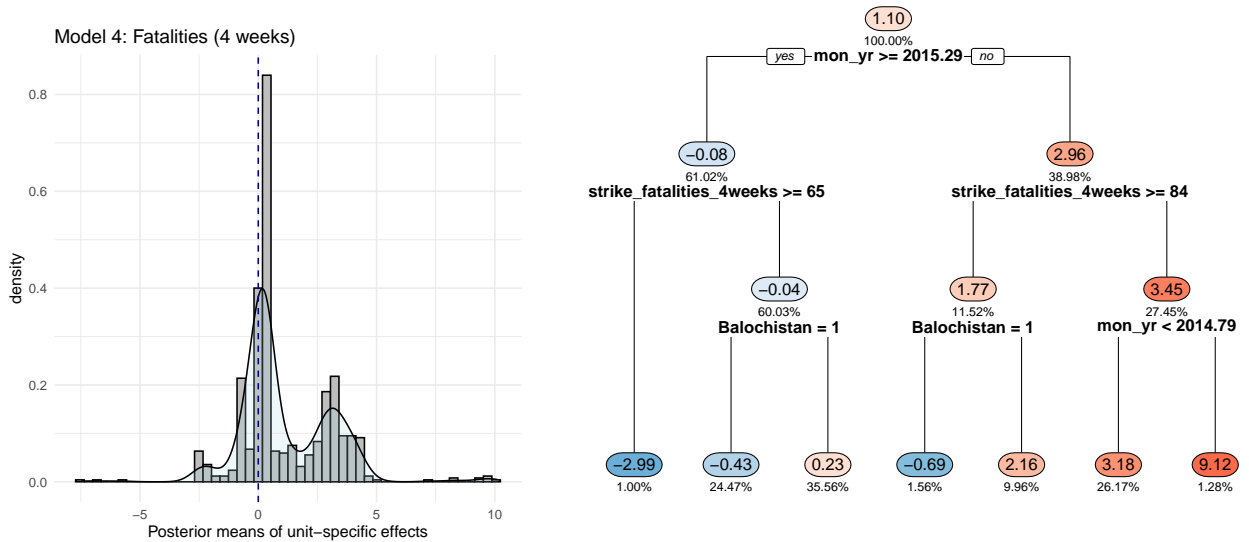


Figure 3: Distribution of posterior mean individual treatment effects (left) and regression tree summary of treatment effect heterogeneity (right). Numbers within nodes represent the subgroup’s average treatment effect (τ), and numbers below nodes show the subgroup’s percentage of the total sample. Node colors indicate effect direction: red for positive effects, blue for negative effects, and white for effects near zero.

One concern is that the observed null treatment effect is the result of heterogeneous subgroup effects averaging to zero. For example, if conventional airstrikes in provinces like Balochistan increase terrorist activity, this positive treatment effect could mask a negative treatment effect in FATA, where previous studies find that drone strikes decrease terrorist lethality. To test this possibility, we analyzed the regression tree summaries, such as the right-hand figure in Figure 3, from all 35 BCF models estimated using civilian fatalities as the dependent variable.

Tree analysis reveals that temporal variation dominates heterogeneity in the treatment effects: 17 of 35 models (49%) split on month/year at the root node, suggesting that the effect of drone and airstrikes vary primarily across time periods rather than geographic regions. In contrast, province indicators rarely appear as the primary split variable. When FATA does appear as a moderator, it emerges at tertiary tree levels and only affects small subsamples.

To further ensure the null finding was not driven by offsetting provincial effects, we directly tested the difference between the conditional average treatment effect for attacks occurring in FATA and those occurring in other provinces using the BCF model estimated with the 2-week temporal window. There is actually suggestive evidence that air and drone strikes

are associated with *more* civilian deaths in FATA compared to other provinces (posterior probability = 0.87), but this difference is negligible and not credible at the 95% interval (-0.04, 2.00).

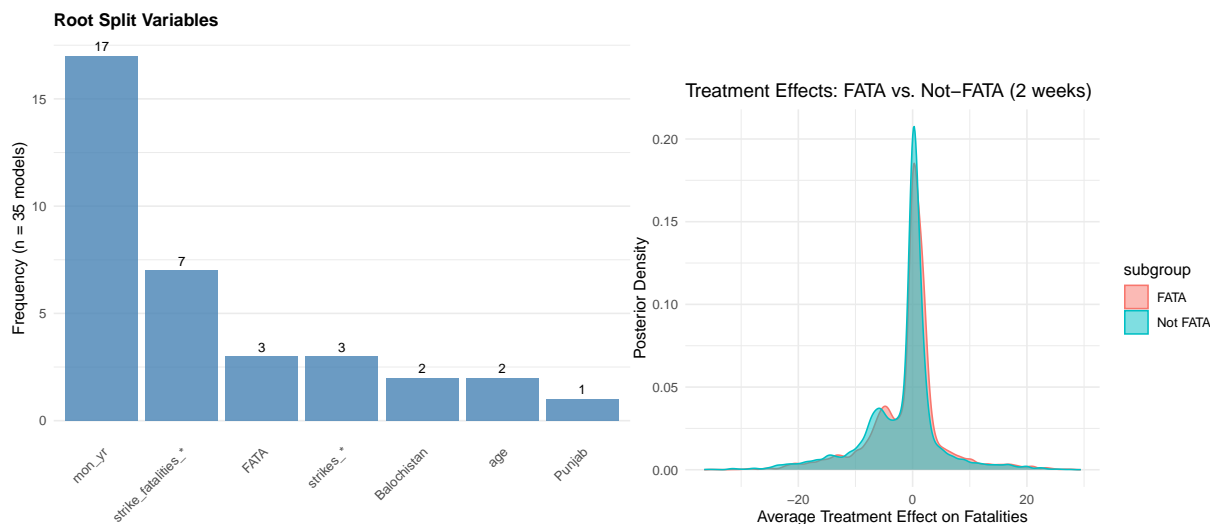


Figure 4: Distribution of the root node splits in the regression trees (left) and comparison of the conditional average treatment effects for attacks in FATA and outside of FATA (right).

Our results contradict prior research and provide no evidence that drone or air strikes either reduce or escalate the number of civilians killed in terrorist attacks. Mir’s theory of Legibility and Speed-of-Exploitation (L & S), developed in “What explains counterterrorism effectiveness? Evidence from the US drone war in Pakistan,” may help explain our null result. Mir proposes that L & S capture a state’s counterterrorism capabilities, which he argues can account for mixed campaign results that variations in terrorist group type fail to explain.²⁶ Legibility refers to the counterterrorism state’s knowledge of the target’s environment, including social, economic, and political factors, while speed refers to the counterterrorism state’s ability to act on this knowledge to target identified terrorists quickly. According to Mir’s theory, a stalemate occurs when the counterterrorism state has a high capability in one category and a low capability in the other.²⁷

²⁶Mir, “What explains counterterrorism effectiveness?.”

²⁷Mir, “What explains counterterrorism effectiveness?,” pp. 47, 51.

1. The Legibility and Speed-of-Exploitation (L&S) System and Counterterrorism Effectiveness

		speed of exploitation	
		low	high
legibility	low	low L&S outcome: ineffective	intermediate L&S outcome: stalemate
	high	intermediate L&S outcome: stalemate	high L&S outcome: effective

Figure 5: The Legibility and Speed-of-Exploitation (L&S) System and Counterterrorism Effectiveness.

Mir considers a campaign to have reached a stalemate once certain conditions are met, such as when the terrorist organization is neither gaining nor losing operational capacity.²⁸ Although Mir does not define operational capacity, prior studies evaluate terrorist capacity by measuring the number of civilians killed in terrorist attacks, since stronger groups are capable of conducting more lethal attacks.²⁹ We argue that the counterterrorism campaign in Pakistan was in a stalemate because the model shows that US drone and Pakistani air strikes failed to reduce the number of civilians killed in terrorist attacks. Although there appears to be heterogeneity in the treatment effects across different time periods, the estimate of the treatment effect remains near 0 across temporal specifications, even up to 10 years, so we assess the state of stalemate as persisting from 2010 to 2024.

Mir may be correct that the United States possessed high L & S at periods during the “War on Terror,” especially in North Waziristan.³⁰ However, the United States operated under unique conditions in North Waziristan; according to Mir, the drone program “was enabled by continuous aerial surveillance, wide-ranging communication interception, an abundance of an-

²⁸Asfandiyar Mir, “What explains counterterrorism effectiveness?,” pp. 50.

²⁹Byman, “Do targeted killings work,” p. 95; David A Jaeger, M Daniele Paserman, et al, “The shape of things to come? On the dynamics of suicide attacks and targeted killings,” *Quarterly Journal of Political Science*, no. 4, 4 (2009): pp. 315–342; Jaeger and Siddique, “Are drone strikes effective in Afghanistan and Pakistan?”; Johnston and Sarbahi, “The impact of US drone strikes on terrorism in Pakistan,” pp. 203–219; and Max Abrahms and Jochen Mierau, “Leadership matters: The effects of targeted killings on militant group tactics,” *Terrorism and Political Violence*, no. 29, 5 (2017): pp. 830–851.

³⁰Asfandiyar Mir, “What explains counterterrorism effectiveness?,” pp. 48.

alysts for processing technical/ human intelligence gains, and unilateral targeting authority.”³¹ However, these conditions break down outside North Waziristan, and the L & S environment moves toward stalemate. Even though the United States likely maintained high legibility in much of Pakistan, thanks to US intelligence agencies, Pakistan only granted the United States permission to operate without restriction in North Waziristan, meaning its speed-of-exploitation would have been lower in other districts and provinces.³² Over time, resistance to US intervention in Pakistan increased, forcing the Pakistani government to constrain US operations and further lowering the United States’ ability to strike targets in any location quickly.³³

Mir’s discussion of L & S focuses on the United States’ capabilities in Pakistan as the counterterrorism state, which overlooks Pakistan’s role as the “local partner.”³⁴ Pakistan conducted significant air strikes in multiple provinces against various terrorist threats; these operations comprise approximately half of the dataset in our analysis. If we consider Pakistan’s L & S over the course of the US campaign, it is likely that Pakistan would have faced similar problems of either legibility or speed as the United States. Pakistan’s military is historically highly ineffective, which would contribute to both low legibility and low speed. Additionally, Pakistan’s government lacks authority over significant regions of the country, further undermining its ability to “see” the terrain being targeted.³⁵

An environment in which strikes consistently fail to hit their intended target, either because they are deployed too slowly or with poor targeting information, could explain why the counterterrorism campaign was ineffective at reducing the number of civilians killed in terrorist attacks. Only in an environment where the counterterrorism state and its local partner possesses the information and the capability to respond rapidly would we witness significant reductions in civilian casualties.

Terrorist group type may also partially explain our null result. In our dataset, the majority of groups targeted by either drones or air strikes were religious groups, especially for

³¹Mir and Moore, “Drones, surveillance, and violence,” p. 846.

³²Mir and Moore, “Drones, surveillance, and violence,” p. 846.

³³James Cavallaro, Sarah Knuckey, and Stephan Sonnenberg, *Living under drones: Death, injury, and trauma to civilians from US drone practices in Pakistan*, International Human Rights and Conflict Resolution Clinic, (2012), pp. 132, 138.

³⁴Asfandiyar Mir, “What explains counterterrorism effectiveness?,” pp. 55.

³⁵*Need sources here. SATP?*

shorter time windows. Religious groups tend to be decentralized, making them more difficult to degrade since there is no true leader to decapitate, in contrast to a hierarchical group.³⁶ Additionally, even when drone strikes eliminate a pivotal leader of a religious group, there may be little to no impact on the group, whereas removing a leader from a hierarchical group tends to leave a power vacuum.³⁷ Separatist groups are similarly decentralized, since they rally around a common cause, so their capabilities may be just as challenging to degrade as religious groups.³⁸

However, this explanation still begs the question: why would deploying *more* strikes not decrease terrorist lethality? We find no evidence that the treatment effects vary by strike intensity, measured by the number of strikes deployed against a terrorist group and the number of terrorists killed in those strikes (Figure 10, Figure 11). This null finding may be explained by the principal-agent problem, which occurs in terrorist organizations when lower-level members want to engage in indiscriminate violence, which the leader restrains due to an understanding that senseless violence undermines the terrorist group’s message. If drone and air strikes in Pakistan’s counterterrorism campaign elevated low-level terrorist members to leadership positions, allowing them to target civilians more frequently than their superiors, this leadership turnover could explain why we do not observe reductions in terrorist lethality, even when strike intensity increases.³⁹

5.2. Model 2: Distance Between Attacks

Figure 6 shows the results of BCF models estimated using the distance between consecutive terrorist attacks as the dependent variable. The relationship between strikes and distance is significant across most of the temporal windows, when groups are targeted anywhere from 2 to 36 weeks prior to an attack. Figure 6 demonstrates a clear negative trend, suggesting that

³⁶Abrahms and Potter, “Explaining terrorism: Leadership deficits and militant group tactics,” *International Organization*, no. 69, 2 (2015), p. 318; Byman, “Do targeted killings work,” p. 100; Cronin, “Behind the curve,” p. 44.

³⁷Carley, Lee, and Krackhardt, “Destabilizing Networks,” p. 88.

³⁸Cronin, “Behind the curve,” p. 40.

³⁹Macartan Humphreys and Jeremy M. Weinstein, “Handling and Manhandling Civilians in Civil War,” *American Political Science Review*, 100, no. 3 (August 2006): 429–47, <https://doi.org/10.1017/S0003055406062289>; Max Abrahms and Philip B.K. Potter, “Explaining Terrorism: Leadership Deficits and Militant Group Tactics,” *International Organization*, 69, no. 2 (2015): 311–42, <https://doi.org/10.1017/S0020818314000411>; Abrahms and Mierau, “Leadership Matters,” September 3, 2017.

air and drone strikes have an initial displacement effect that decays over time. Beyond a year, the average treatment effect remains insignificant and is centered at zero. (Figure 9)

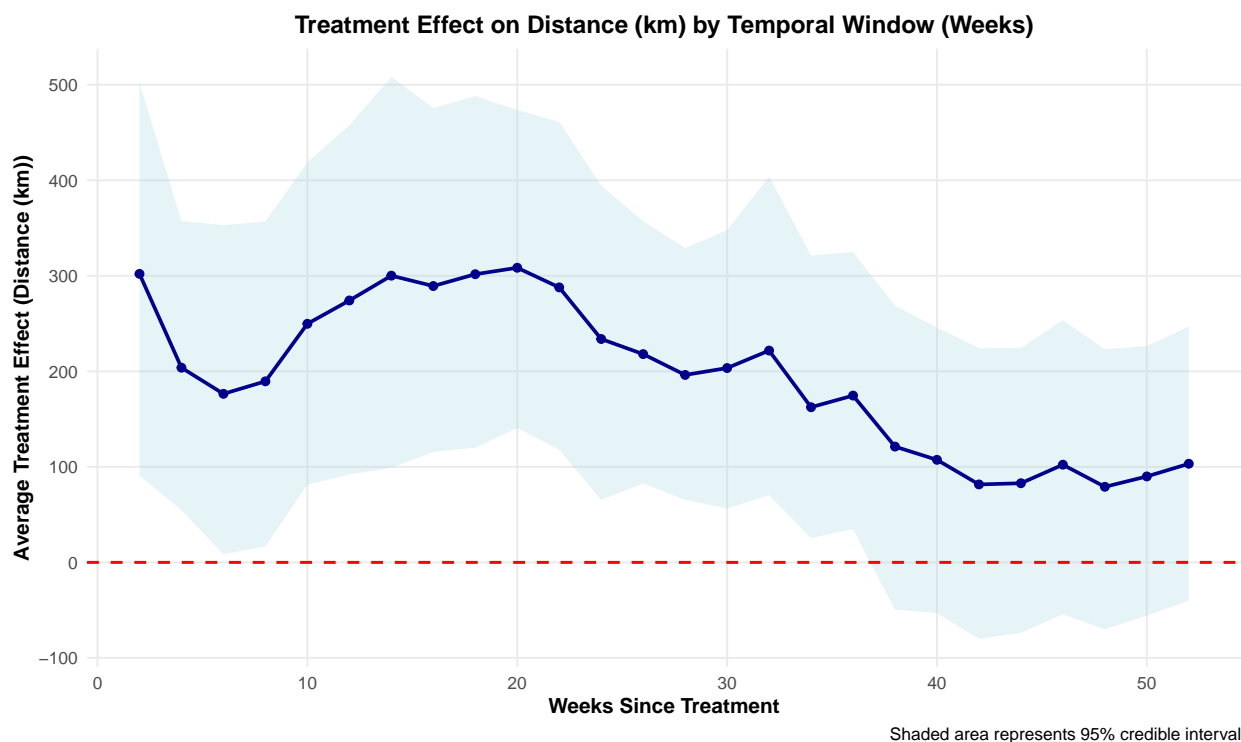


Figure 6: Average treatment effect of strikes on terrorist displacement. The outcome modeled is distance between consecutive terrorist attacks. z is equal to one if strikes targeted the terrorist group committing the attack within the temporal window (specified by the x-axis).

Heterogeneity analysis of the treatment effects for these BCF models reveals that province is a more dominant driver of heterogeneity in the treatment effects than previously, suggesting that air and drone strikes impact terrorist displacement differently across varying geographic regions. Month/year is still an important component of the heterogeneity in the treatment effects, with 10/35 (29%) of the models splitting on the time control variable at the root node. Interestingly, where the regression trees split on province, including initial, secondary, and tertiary splits, the majority of splits are on Sindh province. This pattern is surprising, because it indicates that displacement effects may differ in Sindh compared to other provinces in Pakistan. Sindh contains Karachi, which is where terrorist groups reportedly relocated following US targeting in FATA and Khyber Pakhtunkhwa and where they frequently concentrate

attacks against both civilian and military targets.⁴⁰ Testing the difference between the conditional average treatment effect for attacks occurring in Sindh and those occurring in other provinces provides suggestive evidence (posterior probability = 0.83) that treatment effects are larger in Sindh, though the difference is not credible at the 95% level.

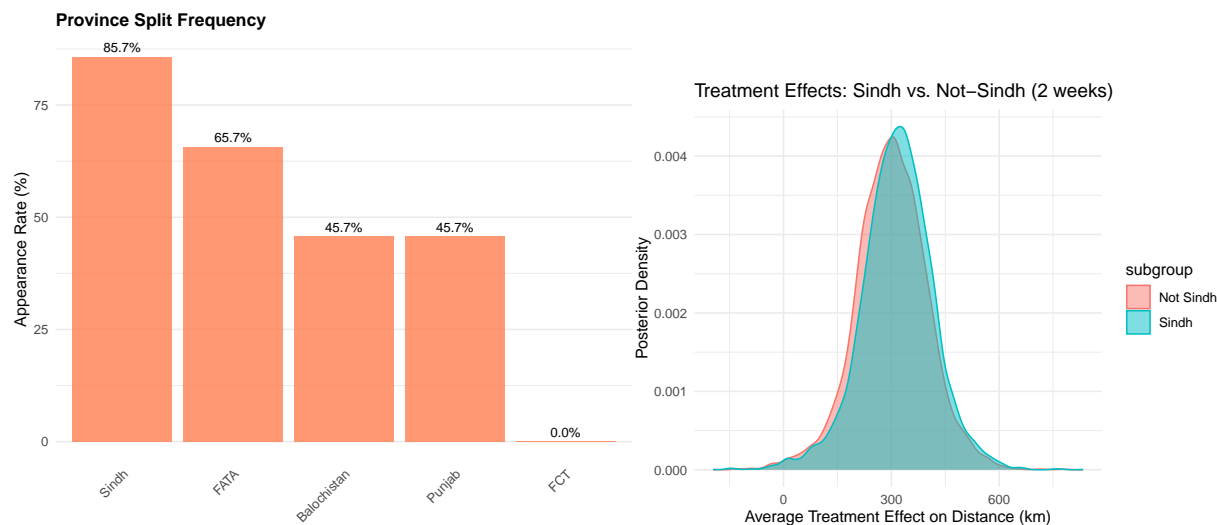


Figure 7: Distribution of the root node splits in the regression trees (left) and comparison of the conditional average treatment effects for attacks in Sindh and outside of Sindh.

While our analysis provides evidence for displacement effects in Pakistan, it remains unclear whether our results mean that the counterterrorist state has succeeded or failed. Little research to this point has examined displacement effects, although the concern that terrorist groups may relocate after being targeted is acknowledged both in previous studies and by policymakers. Several of the explanations proposed by the “optimist” camp in favor of drone strike effectiveness may be applied to understanding whether terrorist displacement is a positive effect. First, more geographically widespread attacks, as indicated by an increased distance from one attack to the next, could suggest that strikes successfully eliminated several terrorist cells, forcing the remaining cells to work in isolation and ultimately degrading the entire network. Eliminating even a few cells may prevent a terrorist group, even a decentralized one, from coordinating and executing attacks since it becomes harder for cells across the network to communicate.⁴¹ Even

⁴⁰Zia Ur Rehman, “The Pakistani Taliban’s Karachi Network,” *CTC Sentinel*, no. 6.5 (2013): p. 1.

⁴¹Marc Sageman, *Understanding Terror Networks* (Philadelphia: University of Pennsylvania Press, 2004), 140; See also Ami Pedahzur and Arie Perliger, “The Changing Nature of Suicide Attacks: A Social Network Perspective,” *Social Forces* 84, no. 4 (2006): 1987–2008.

though we do not find evidence that drone and air strikes decrease terrorist attack lethality, strikes may still reduce a terrorist group’s capacity and weaken its influence in a region. Second, if anticipatory effects following a strike cause a cell to “go dark” for fear of being targeted, and another cell within the same group hundreds of kilometers away conducts an attack, our model captures this shift as an increase in the distance from one attack to the next. Thus, anticipatory effects may temporarily degrade some cells’ capacity to conduct attacks, during which time other cells carry out more operations. Although it may appear that the terrorist group has successfully relocated, in reality its capacity has been degraded, which is a positive outcome for the counterterrorist state.

However, more widespread attacks could also indicate that strikes failed to degrade a terrorist group and instead encouraged them to relocate and extend their operations across more territory. Mir and Moore argue that there is little evidence for this “displacement hypothesis,” but in interviews conducted with the Pakistani Taliban, they find that members of the group did relocate to South Waziristan, another district in FATA, and Karachi, in the Sindh province; neither region is included in Mir and Moore’s study.⁴² Local reporting confirms that entire neighborhoods within Karachi came under TTP control after the group relocated to the city following intense US drone strikes against the group’s stronghold in North and South Waziristan.⁴³ If terrorist groups are capable of moving from one province to another, then drone and air strikes are not degrading them sufficiently to prevent them from relocating and continuing to attack civilians.

6. Conclusion

Prior studies examining drone strike efficacy have primarily focused on how US drone strikes in FATA impact terrorist lethality. This paper provides two main contributions to the literature. First, we utilize a dataset that includes terrorist attacks in all of Pakistan’s provinces and the Federal Capital Territory, as well as both US drone strikes and Pakistani air strikes conducted against these terrorist threats. This broader context enables us to evaluate

⁴²Mir and Moore, “Drones, surveillance, and violence,” p. 854. Mir and Moore exclude South Waziristan because the nature of the U.S. drone program in that district remains unclear.

⁴³Rehman, “The Pakistani Taliban’s Karachi Network,” p. 1.

the efficacy of the entire counterterrorism campaign in Pakistan, while also gaining a better understanding of how drones function within an integrated military campaign. Second, our research design allows us to estimate displacement effects, a concern that is acknowledged by previous studies but still contested. We make both of these contributions by fitting a Bayesian Causal Forest (BCF), a method uniquely suited to estimating treatment effects in contexts with strong confounding and small effects.

We find no evidence that US drone and Pakistani air strikes reduce civilian deaths in terrorist attacks, a finding which undermines previous results indicating that drone strikes effectively degrade terrorist groups. Furthermore, our results suggest that aerial strikes increase the distance between one terrorist attack and the next, possibly because terrorist groups relocate after being targeted. As a result, policymakers should be skeptical about deploying drone and air strikes when their goal is to degrade a terrorist group, especially if there are nearby territories in which the terrorist group can seek refuge. Constraining drone strikes to limited geographies may compound this problem, since it creates safe havens to which terrorist groups can escape and re-establish operations. Additionally, focusing on a specific region precludes strikes from targeting terrorist cells throughout the entire terrorist network. In a decentralized terrorist group, eliminating cells across the network is especially critical since it makes it harder for isolated cells to communicate and coordinate attacks.⁴⁴ However, we caution against concluding that counterterrorism states should necessarily conduct strikes across a wider geographic area, since they are usually constrained by partner states, international humanitarian law, and public opinion. Rather, policymakers should acknowledge that terrorist groups are rarely geographically constrained, and targeting their base of operations may only result in the group shifting their operations elsewhere.

Future research should further explore the validity of the “displacement” hypothesis: both whether displacement actually occurs, and, if so, what it means for the success of the counterterrorism operation. To better identify whether counterterrorism operations displace terrorist groups, future qualitative research may seek to trace how terrorist groups move over time in response to targeting. Additional quantitative work may also seek to replicate our findings with different methods of operationalizing displacement, such as the distance from a drone or

⁴⁴Sageman, *Understanding Terror Networks*, p. 140.

air strike to a terrorist group's next attack. Future studies may also explore questions related to the conditions under which terrorists relocate. For example, how does geography influence when and where terrorists relocate? Is terrorist displacement always driven by counterterrorism efforts—in other words, are terrorists always “forced out”—or, do terrorists also move in anticipation of future military operations? Finally, does displacement equate to degradation and operational success within the targeted environment, or does it indicate terrorist resiliency and failure of the counterterrorism campaign?

A. Tables

Group	Type	Year Formed	Strikes	N
ASP: Ansar ul-Sharia Pakistan	Religious	2017	No	2
ASWJ: Ahle Sunnat Wal Jamaat	Religious	1985	No	2
Baloch Separatists (Pakistan)	Separatist	1947	Yes	116
BLA: Baloch Liberation Army	Separatist	2000	No	40
BLF: Baloch Liberation Front	Separatist	1964	No	31
BLT: Baloch Liberation Tigers	Separatist	1996	No	4
BRA: Baloch Republican Army	Separatist	2006	No	4
BRAS: Baloch Raaji Ajoi e Sangar	Separatist	2018	No	2
Hizbul Ahrar	Religious	2017	No	2
IJT: Islami Jamiat-e-Talaba	Religious	1947	No	3
IMK: Ittehad-e-Mujahideen-e-Khorasan	Religious	2011	No	2
Islamic State (Pakistan)	Religious	2015	Yes	24
JuA: Jamaat-ul-Ahrar	Separatist	2014	Yes	4
Jundallah	Religious	2003	No	6
LeI: Lashkar-e-Islam	Religious	2004	Yes	15
LeJ: Lashkar-e-Jabbar	Religious	2001	Yes	17
LeJ: Lashkar-e-Jhangvi	Religious	1996	No	3
MQM: Muttahida Qaumi Movement	Religious	1986	No	6
SRA: Sindhudesh Revolutionary Army	Separatist	1972	No	6
TLP: Tehreek-e-Labbaik Pakistan	Religious	2015	No	2
TTP-HGB: Tehreek-i-Taliban Pakistan-Hafiz Gul Bahadur	Religious	2009	Yes	2
TTP: Tehreek-i-Taliban Pakistan	Religious	2007	Yes	410

Table 2: List of perpetrator groups, types, years formed, strike information, and number of observations.

B. Additional Model Estimates

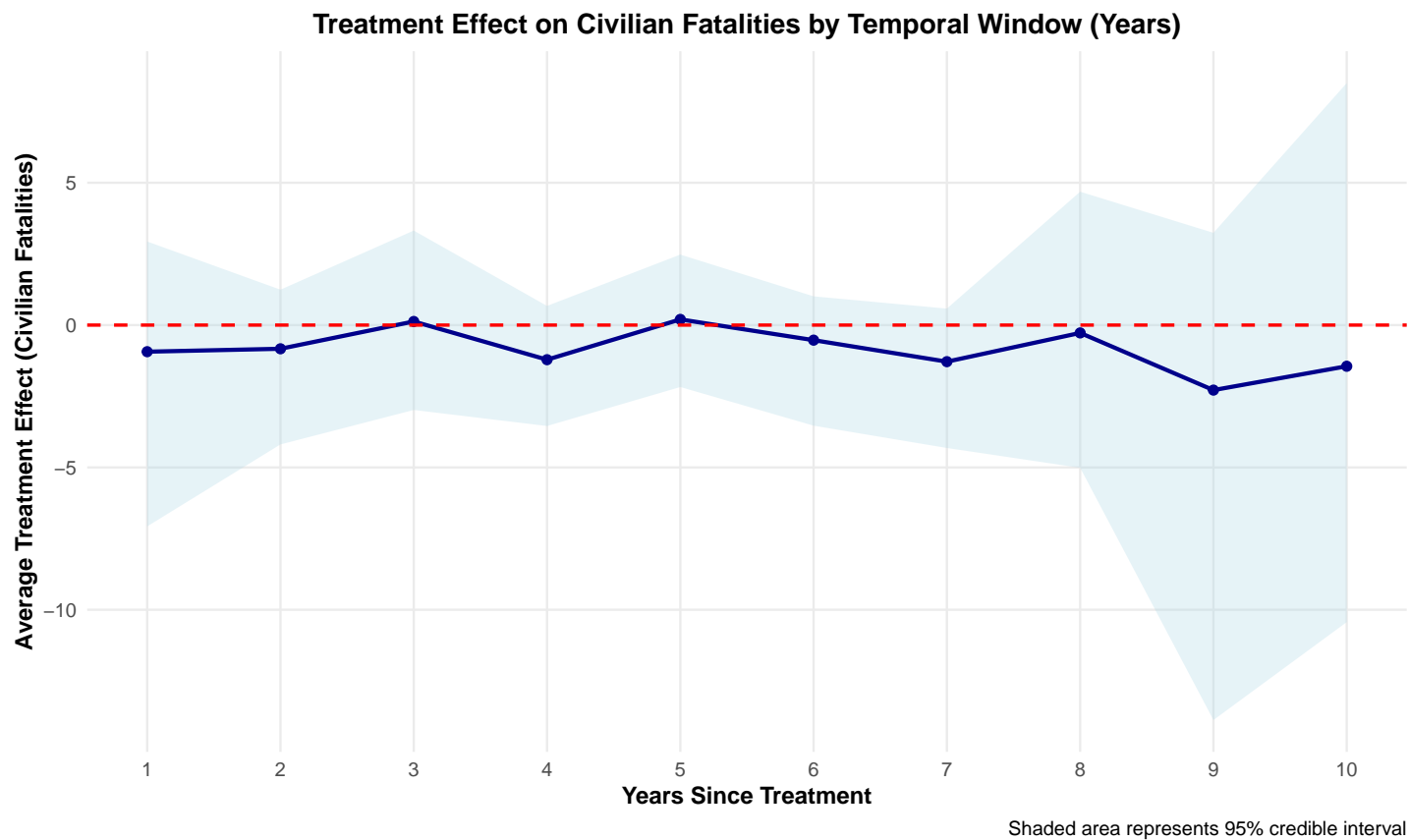


Figure 8: Average treatment effect of strikes on terrorist lethality. The outcome modeled is civilian fatalities. z is equal to one if strikes targeted the terrorist group committing the attack within the temporal window (specified by the x-axis).

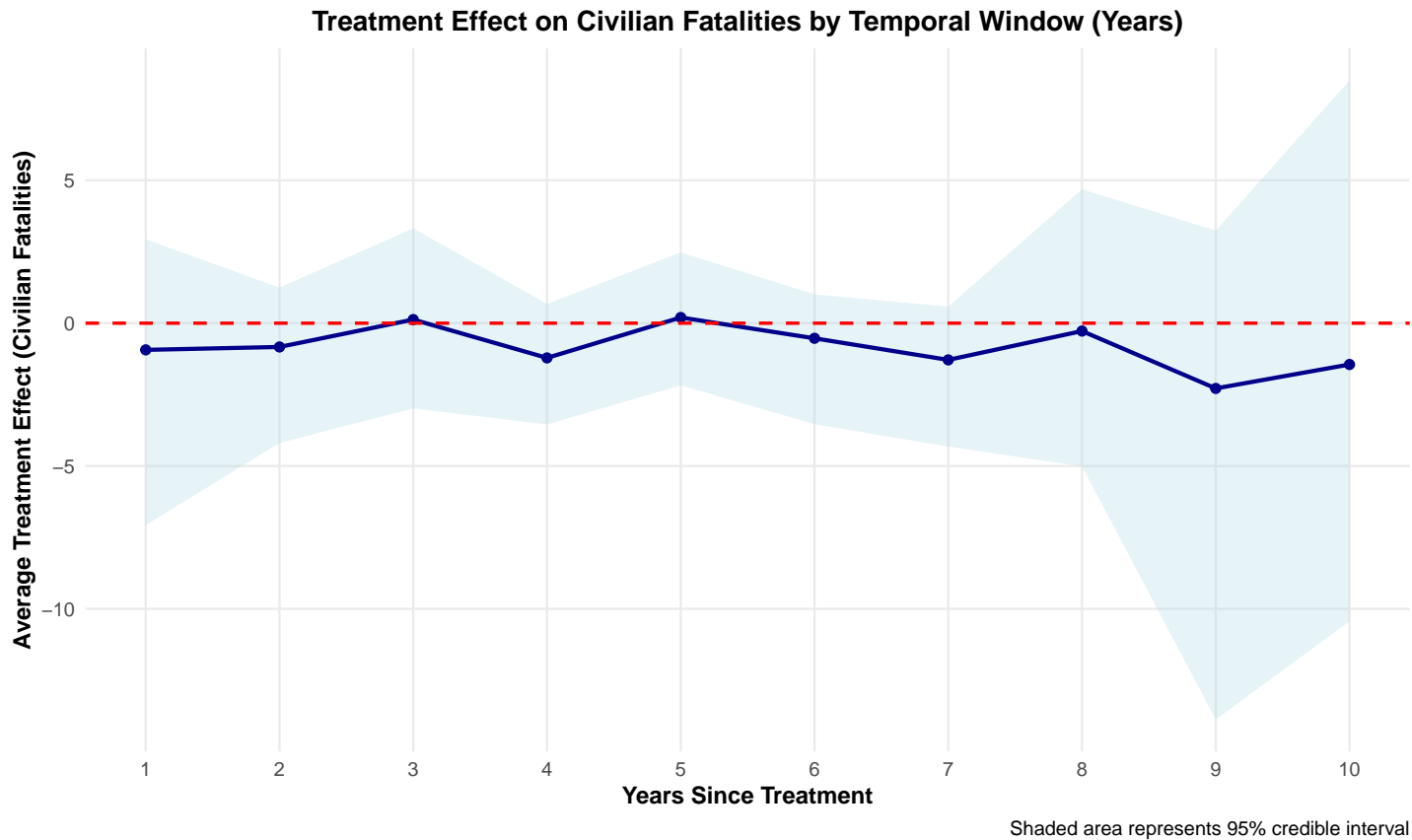


Figure 9: Average treatment effect of strikes on terrorist lethality. The outcome modeled is distance between consecutive terrorist attacks. z is equal to one if strikes targeted the terrorist group committing the attack within the temporal window (specified by the x-axis).

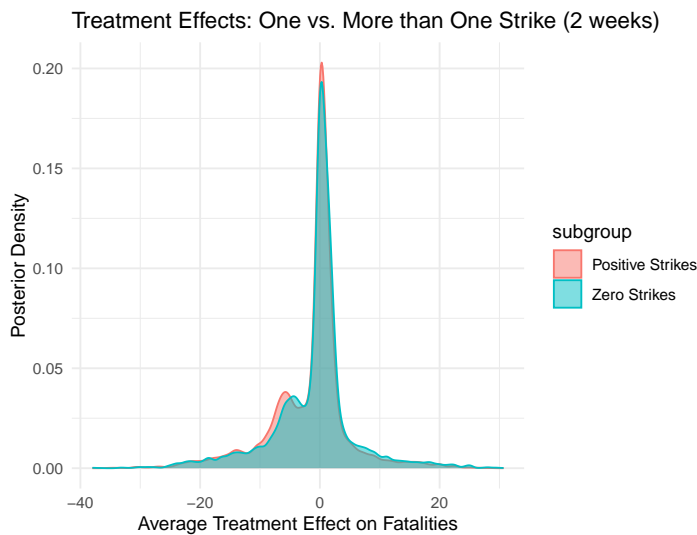


Figure 10: Heterogeneity analysis comparing the conditional average treatment effect on civilian fatalities when one vs. more than one strike was deployed.

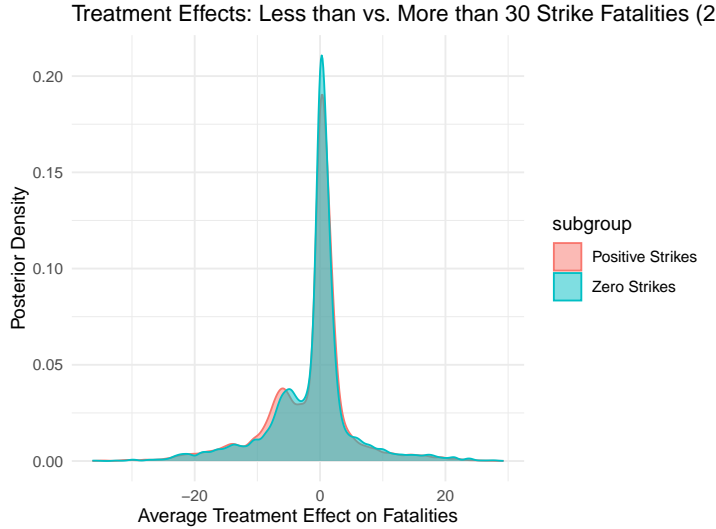


Figure 11: Heterogeneity analysis comparing the conditional average treatment effect on civilian fatalities when less than vs. more than 30 terrorists were killed by drone and strikes.

C. Replication

Table 3: Comparison of BCF and Difference-in-Differences Estimates: Replication of Mir & Moore (2019)

Model	ATE	95% CI		$P(\tau > 0)$
		Lower	Upper	
BCF: Near-Deterministic π (0.95, 0.05)	-0.079	-2.334	1.281	0.592
BCF: BART-Learned π (Tehsils)	0.346	-0.948	1.723	0.710
BCF: Uniform π (0.5)	0.038	-0.877	1.537	0.406
Mir & Moore: DiD Regression 4	-9.532**	-13.790	-5.270	—

Notes: ATE = Average Treatment Effect (casualties per tehsil-month). BCF models use covariates from Mir & Moore (2019) Table 3 regression 4 (p. 853): month-year fixed effects, tehsil fixed effects, linear time trends, tehsil-specific time trends, and heterogeneous controls for military operations and peace deals. Near-deterministic propensity assigns $\pi = 0.95$ to North Waziristan Agency tehsils and $\pi = 0.05$ to others. BART-learned propensity is estimated from tehsil indicators using BART. Uniform propensity assigns $\pi = 0.5$ to all observations. All BCF models estimated with 2,000 burn-in iterations and 2,000 MCMC samples. Mir & Moore estimates from Table 3, regression 4. ** indicates statistical significance at $p < 0.05$ level in original study. $P(\tau > 0)$ is the posterior probability that the treatment effect is positive.

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