Efficacy of Third-Party Airstrikes in Counterinsurgencies: Evidence from Yemen

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Abstract

A Saudi-led coalition has launched more than 20,000 air raids since 2015 in Yemen's ongoing civil war against the Houthis. What effect does this counterinsurgency strategy have on subsequent insurgent attacks? While there is a general consensus that indiscriminate violence is often counter-productive in such conflicts, the effects in Yemen have yet to be analyzed empirically. Following similar studies, I first use geospatial matching and difference-in-differences estimation on event-level conflict data in Yemen to test whether insurgent attacks increase within varying spatial and temporal windows after an airstrike. Since I observe that the majority of airstrikes do not experience *any* insurgent attacks within the geographic and temporal vicinity after a strike, I also conduct a second test to investigate whether the Houthis increase their attacks in Saudi Arabia, particularly in response to fatal airstrikes. I argue that the relationship between the Houthis and Saudi Arabia plays a role in shaping conflict dynamics within the context of this third-party counterinsurgency strategy. Results suggest that insurgent attacks increase both in the geographic vicinity of airstrikes and in Saudi territory. While the effects are small, these findings illuminate the unique impact fatal airstrikes have on rebel activity. Despite a number of limitations in these two analyses, this study adds further support to the general consensus that indiscriminate violence is not an effective strategy towards reducing insurgent attacks.

Introduction

Are airstrike campaigns an effective counterinsurgency strategy? Do aerial bombings on populated areas achieve the coercive political goals of the bombers? Saudi Arabia and its allies confront these questions daily. In March 2015, a coalition of nine Arab states, led by Saudi Arabia, launched Operation Decisive Storm, a military intervention in Yemen. At the request of Yemen's president, Abdrabbuh Mansur Hadi, this intervention aimed to "defend the legitimate government of Yemen" against the Houthi insurgency ("President Hadi Leaves Yemen" 2015). Despite an announcement by the Saudi Defense Ministry claiming success the following month, aerial bombing by the Saudi-led coalition has remained relentless (Hamid 2015). Four years later, the civil war in Yemen continues.

While Saudi Arabia and others may seek to gauge the effectiveness of this strategy through a political lens, conflict researchers may prefer to simply look at the numbers. What can we say empirically about the utility of airstrikes against insurgents within the context of an intrastate conflict? Does this strategy of coercion foster the desired behavior from rebels?

The literature on counterinsurgency offers evidence supporting the argument that violence which does not discriminate between targets is generally less effective than discriminate, selective violence (Kocher, Pepinsky, and Kalyvas 2011; Schutte 2017; Condra et al. 2012; Toft and Zhukov 2015; Wood 2010; Lyall 2017). Others, however, find evidence to the contrary (Downes 2007; Lyall 2009). Airstrikes are relevant in this debate as they are a form indiscriminate violence due to their range of impact. Some early studies sought to better understand the use of air power in an interstate context more generally (Pape 2004; Horowitz and Reiter 2001; Allen 2007), but few studies, if any, have examined aerial bombings within the environment of a third-party civil war intervention. As a modern conflict infamous for the deployment of more than 20,000 coalition airstrikes, the war in Yemen offers a data-rich case in which to analyze this particular counterinsurgency strategy.

Determining causal inference in unstable conflict zones is an extremely difficult endeavor. Though challenging, the increasing collection and use of event-level conflict data offers exciting opportunities to apply quasi-experimental methods. Previous studies have leveraged these data and methods, such as using geospatial matching on conflict event data and difference-in-differences estimation, to investigate the impact of airstrikes and indiscriminate violence on insurgent and civilian behavior in Afghanistan (Schutte 2017; Lyall 2017). Results from these studies are not only fascinating but also critical for policymakers in areas of foreign affairs and international security.

In the case of Yemen, states offering support to the current military intervention may be keen to know whether or not their finite resources are going towards an effective counterinsurgency operation. To date, this conflict has yet to be analyzed empirically in the academic conflict literature.

I offer such an analysis in two parts using conflict event data in Yemen from January 2016 to July 2019 in order to assess the impact these Saudi-led coalition airstrikes have on subsequent insurgent attacks.

The first analysis employs Matched Wake Analysis, a method that harnesses the power of spatial matching and difference-in-differences estimation, in order to calculate the treatment effect of airstrikes on the number of Houthi attacks post-airstrike within varying temporal and spatial windows. Results indicate a moderate increase of 6 to 40 additional insurgent attacks for every 100 airstrikes launched. However, in 71% of actual cases, airstrike locations experience zero Houthi attacks up to 25 days and within a 5 km radius post-airstrike. This generates a follow-up question: If we observe so few cases where Houthis respond in the geographic and temporal vicinity of an airstrike, where *do* they respond?

Airstrikes launched in Yemen largely target insurgent strongholds, therefore it makes sense theoretically that insurgents would not respond within their own territory where they enjoy a hold on power. I argue that the rebels will respond where it hurts their primary opponent – in this case, Saudi territory. Additionally, I suspect that airstrikes resulting in fatalities will more likely motivate a response from the Houthis. In the second analysis, I convert event-level data to a time-series format and run multiple negative binomial models to test whether fatal airstrikes lead to an increase in the number of Houthi attacks in Saudi Arabia. Results suggest they do, although to a very small degree (1.5 additional attacks for every 100 fatal airstrikes). To account for the multitude of zeros within the data, I also run a hurdle model that models, first, the binary occurrence of attacks in Saudi Arabia and, second, the number of attacks given that an attack occurrence is likely. Results from this model suggest a more conservative interpretation: we can say that fatal airstrikes may increase the *likelihood* of Saudi Arabia experiencing a Houthi attack on their soil, however, we cannot speak with confidence to the number of expected attacks.

Altogether, this analysis offers additional evidence to the growing literature that finds indiscriminate violence via airstrikes is generally counterproductive. The next section will provide an overview of this literature, followed by a brief description of the ongoing civil war in Yemen. The theory motivating this paper's research question and hypotheses will then be outlined in detail. The empirical analysis will be structured in two parts, each addressing a separate hypothesis using a different method. The paper concludes with a discussion about the overall findings, limitations, and implications for future research.

The Use of Airstrikes in Counterinsurgencies

Why Airstrikes?

The use of air power in war is not a new phenomenon. As John Buckley so clearly highlights in *Air Power in the Age of Total War*, "in the space of a little over 40 years, aircraft progressed from the Wrights' first faltering flights in the Kill Devil Hills in 1903 to the mass destruction of Dresden, Tokyo and, most poignantly, Hiroshima and Nagasaki in 1945" (1998, 1). Since then, weaponized aircraft have become a standard part of modern warfare, with the technology behind them becoming more sophisticated with time.

There are many explanations offered as to why aerial bombings have become such a popular strategy over the last century. Buckley argues air power added a "third dimension" to war, allowing direct attacks on enemy rear zones, cities, economies, and civilian populations (1998, 2). Robert Pape in *Bombing to Win: Air Power and Coercion in War* outlines the advantages of air power over those of land and sea:

> Unlike land power, [air power] can reach deep into the enemy's homeland from the outset of a conflict, and it promises to achieve its effects at sharply lower cost in lives than land power. Unlike sea power, bombing can focus on specific categories of targets, attacking either political, economic, population, or military targets in isolation or combination. (1996, 45)

The strategic advantages of air power from a state's foreign policy perspective seem rather clear: airstrikes allow for more control at a lower cost with fewer risks to their own soldiers (Allen 2007; Byman, Waxman, and Larson 1999; Cohen 1994). Not only are the material costs lower but so too are the political costs. A strategy of remote violence via air power may be easier for governments to "sell" to their constituents under the constraints of certain domestic or international institutions. For these reasons, airstrikes are an attractive tool for states when seeking to coerce and alter the behavior of their opponents (Allen 2007).

Indeed, aircraft and missile exports worldwide have increased since World War II. At the end of the Cold War, export levels dropped, but have since been steadily increasing (see Figure 1). While the use of aerial campaigns might be an attractive strategy, what do we know about their effectiveness in practice?

The first attempt to scientifically assess the utility of air power was Robert Pape's *Bombing to Win* in 1996, followed by a more rigorous statistical analysis by Horowitz and Reiter (2001). Pape's (1996) initial examination consisted of five in-depth case studies with a large-n analysis of 40 others, categorized according to the air power strategy used and whether or not is was successful. The large-n analysis relied on basic statistics. Horowitz and Reiter (2001) largely followed

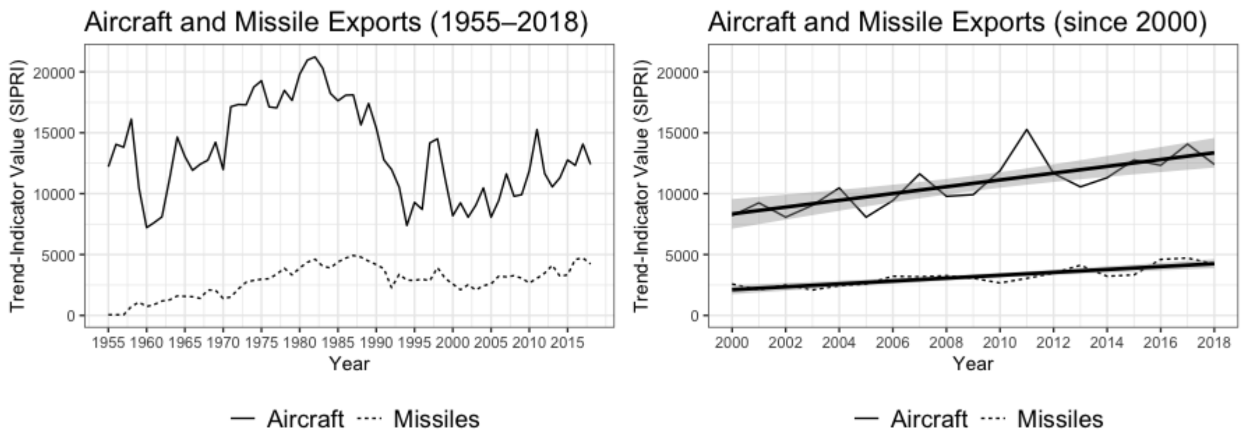

Figure 1: Increasing aircraft and missile exports since WWII and over the past two decades. Data is from the Stockholm International Peace Research Institute (SIPRI), https://www.sipri.org/databases/armstransfers.

Pape's example but sought to improve upon this work by applying a multivariate probit regression analysis.

In categorizing air campaigns, Pape (1996) defines two strategies: punishment and denial. A punishment strategy aims to harm civilians "in order to lower their morale and motivate them to force their governments to end the war" while a denial strategy aims to "[damage] the opponent's war economy to the point that sufficient production cannot be maintained to continue the war successfully" (Pape 1996, 45). Horowitz and Reiter (2001) include these strategies in their work as well.

Both found that targeting military positions over civilians (i.e. using a denial strategy) was more likely to result in a successful air campaign (Pape 1996, Horowitz and Reiter 2001). Horowitz and Reiter (2001) defined a "successful" air campaign as one that coerces the target to comply with the demands of the aggressor before an "utter conquest" occurs (150). Bombing to the point of total and utter destruction or terminating the campaign before the target concedes are both outcomes considered to be coercion failures (Horowitz and Reiter 2001). Under these definitions, aerial strategies that target military vulnerabilities, as opposed to civilian vulnerabilities, are found to be more effective (Horowitz and Reiter 2001).

Indiscriminate Violence in Counterinsurgencies

The distinction between targets among punishment and denial air power strategies follows a similar distinction between targets of indiscriminate and selective violence. A strategy of punishment could be considered employing indiscriminate violence (civilians and noncombatants as targets) whereas a strategy of denial (industry, military, etc. as targets) could be considered employing selective violence.

If we consider the targeting of military positions as a strategy of selective violence, these early findings of Pape (1996) and Horowitz and Reiter (2001) on air power effectiveness are supported by the broader literature on violence in the context of counterinsurgencies (Kocher, Pepinsky, and Kalyvas 2011; Schutte 2017; Lyall 2017; Condra et al. 2012; Toft and Zhukov 2015). In looking at the use of US aerial strikes in the Vietnam War, Kocher, Pepinsky, and Kalyvas (2011) found that this strategy of indiscriminate violence against civilians actually shifted control on the ground in favor of the insurgents. Using georeferenced data in an ordered-logit model supported by a quasi-experimental matching method, they write, "the results consistently show that bombing was counterproductive as a counterinsurgency practice. Higher frequencies of bombing correspond unambiguously to higher levels of downstream control by the Viet Cong" (202). The main argument presented here is that indiscriminate violence removes the deterrence effect. If selective violence is used specifically against insurgents or other non-civilian targets, civilians are deterred from participating in the insurgency; however, if everyone is a potential target of violence regardless of participation, this deterrence effect no longer applies and indiscriminate violence becomes counterproductive, instead increasing the participation of civilians in insurgencies (Kocher, Pepinsky, and Kalyvas 2011, 203).

Using a similar quasi-experimental matching method on event-level data in Afghanistan, Schutte (2017) found support that, rather than deter civilians, indiscriminate airstrikes actually result in "reactive mobilization" and increases collaboration of citizens with the insurgents. Civilians are motivated by a sense of revenge and retaliation against indiscriminate attacks against their loved ones (Schutte 2017, 1602). Likewise, Lyall (2017) found that airstrikes in Afghanistan increased the number subsequent insurgent attacks for at least 90 days after a strike. Departing from the use of airstrikes in particular, Condra and Shapiro (2012) found that state-based indiscriminate violence, measured as civilian killings, predicts higher levels of insurgent violence. In another quasi-experimental event analysis, Toft and Zhukov (2015) found that, with regard to nationalist rebels specifically, selective counterinsurgency tactics are more effective than indiscriminate violence in suppressing insurgent violence. Taken together, these studies lend support to the argument that indiscriminate violence is a counterproductive strategy.

Others, however, find different results. Using the British counterinsurgency strategy in the Second Anglo-Boer War as a case study, Downes (Downes 2007) found there may be certain conditions under which indiscriminate violence can be an effective counterinsurgency strategy. "When the population from which the guerrillas draw support is relatively small, the land area in which the insurgents operate is similarly constricted, and external sanctuary and supply is not available, governments have been able to strangle rebel movements with indiscriminate violence"

(2007, 440). Downes (2007) argues that indiscriminate violence may be effective in such cases where populations are small and the potential for defection can essentially be eradicated through violence against civilians (438). This conclusion is naturally limited in scope; however, returning to the impact of air power specifically, as well as a quasi-experimental research design, Lyall (2009) found evidence in the case of Chechnya that indiscriminate aerial shellings may reduce insurgent attacks due to the destruction of rebel infrastructure, resources, and material goods as well as feelings of resentment by locals towards insurgents. In the context of counterterrorism efforts by US forces in Pakistan, Johnston and Sarhabi (2016) found that drone strikes are associated with a reduced incidence of terrorist violence. Similar to Lyall (2009), they theorized this effect is due to the "disruption" of militant operations.

A further complication in the study of counterinsurgency strategies with regard to the use of indiscriminate violence is the role of third-party actors in civil war contexts. As far as I am aware, no empirical study has examined the nexus between third-party civil war intervention and counterinsurgency strategy and, further, how third-party intervention strategies impact rebel activities in response. Only Amegashie (2014) examines theoretically how third-party interventions might affect the behavior and response of rebels. Using a game-theoretic model, rebels are shown to behave more aggressively and over-invest in arms in order to illustrate bravado and discourage actual third-party involvement. However, the actual strategy employed by the third-party is largely overlooked when studying rebel or civilian responses in a civil war.

The advantages of air power in counterinsurgencies are fairly clear; the strategic, theoretical, and empirical debate, however, remains as to which strategy is most effective: indiscriminate or selective violence (or, using Pape's conception, punishment or denial). The literature has generally found consensus that indiscriminate violence is counterproductive, although others have produced evidence to the contrary. Moreover, quantitative research on strategies employed by third-party interveners in the context of civil war counterinsurgencies is lacking. This paper aims to contribute to this literature by examining whether the general consensus towards indiscriminate violence holds in the case of Yemen's civil war and what role a third-party actor might have within this environment.

The Case of Yemen

Yemen's ongoing civil war is a data-rich case in which to study air power as a counterinsurgency strategy. A coalition of nine Arab states, led by Saudi Arabia, has been engaged in an airstrike campaign against the Houthis since March 2015. This intervention came at the request of Yemen's president, Abdrabbuh Mansur Hadi, in order to "protect Yemen and its great people from the aggression of the Houthi militias" (United Nations Security Council 2015).

The politics, rivalries, and power-grabs at work in Yemen, Saudi Arabia, and the region are beyond the scope of this paper. However, the relationship between the Houthis and the Yemeni and Saudi states offers important context for this study's theoretical expectations. Therefore, a brief historical and political background is provided with regard to the Houthis and the current civil war.

The Houthis are Zaydis, a small sect of Shi'a Islam that exists almost entirely in Yemen, especially in the north. A Zaydi imamate was established in 893 and ruled most of present-day Yemen for over 1,000 years (Winter 2011, 105). Shortly after the succession of the next imam in 1962, an army coup d'etat took place that established the Yemen Arab Republic, finally ending centuries of Zaydi imamate rule.

With the victory of the Yemen Arab Republic after an eight-year civil war, Saudi Arabia wanted to ensure this new republic in Yemen, backed by its rival, Egypt, would not be a security threat. Through Saudi influence and encouragement, Zaydiyyah lost its religious prominence as Salafism[1] spread and became more popular, especially among Yemen's youth (Winter 2011, 106). The rise of Salafi ideology and the marginalization of Zaydiyyah, however, corresponded with a Zaydi "resurgence" movement in the late 1980s and early 1990s, led by the none other than the al-Houthi family (Bruck 2010, 190; Winter 2011).

Throughout this period, a rivalry became more entrenched between Salafis and Zaydis as they competed for legitimacy and popularity, both religiously and politically. Tensions between the Houthi movement and the Yemeni state heightened after 9/11 due to President Saleh's friendly alignment with the United States, culminating in 2004 with the start of what would be years of armed clashes between the Houthis and the Yemeni government (Hamidi 2009; Winter 2011).

The first instance of Saudi intervention occurred in 2008 when Saudi Arabia gave the Yemeni government $3 billion in order to "put down 'the insurgents'"(Hamidi 2009, 171). In response to a Saudi border guard being killed by the Houthis in November 2009, Saudi Arabia launched an offensive against Houthi positions near the border as well as a naval blockade to prevent the import of Houthi weapons ("Saudi Forces Keep Up Houthi Assault" 2009).

A ceasefire was agreed to in 2010 between the Yemeni government and the Houthis. With the exception of a few sporadic clashes, the agreement generally held (Winter 2011, 113). A year later in 2011, however, a new political development arose: a popular uprising against President Saleh, i.e. Yemen's Arab Spring. Many protested and demonstrated in the streets, calling for an end to corruption, the delivery of jobs, a more equitable distribution of wealth, and governmental reform ("Yemen: Conflicting Opinions from the Street" 2011). Both the Houthis and the Islah party, a Salafi political party, supported the protests and the resignation of President Saleh.

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1. Broadly, Salafism is a traditionalist branch of Sunni Islam calling for a return to an "uncorrupted" version of the faith and emulating the earliest Islamic period at the time of the Prophet (Turner 2014).

Initiated by the Gulf Cooperation Council and supported by the UN Security Council, a peaceful political transition occurred with President Saleh handing over the keys to power to his vice-president, Abdrabbuh Mansur Hadi. A ten-month-long National Dialogue Conference (NDC) took place that involved "all of Yemen's main political actors and civil society representatives, including the Houthis" (Nußberger 2017). The NDC concluded in January 2014 with plans for sweeping democratic reforms. However, it was followed by months of political inaction and escalating tensions, including armed clashes and territorial gains by the Houthis in addition to major public demonstrations against the government (Al-Sakkaf 2014b, 2014a; Al-Yarisi 2014; Al-Moshki 2014a, 2014b)

The infamous Houthi takeover of the Sana'a capital a year later in January 2015 was the result of their distrust of and dissatisfaction with Hadi and the Yemen government in implementing the NDC outcomes (Saeed 2014; Al-Sakkaf 2014b). Conflict ensued, accompanied by government resignations and a dissolved parliament, leading President Hadi to eventually flee to Saudi Arabia where his request for military assistance materialized in March 2015. Operation Decisive Storm, followed closely by Operation Restoring Hope, commenced in the form of airstrikes against Houthi positions by a Saudi-led coalition of various states. What was intended to be a relatively quick operation is still active today, having transformed into a full-fledged civil war. After four years of failed agreements and disputed political legitimacy and territorial control, Yemen finds itself in a dire humanitarian crisis – far from where it was headed in 2014.

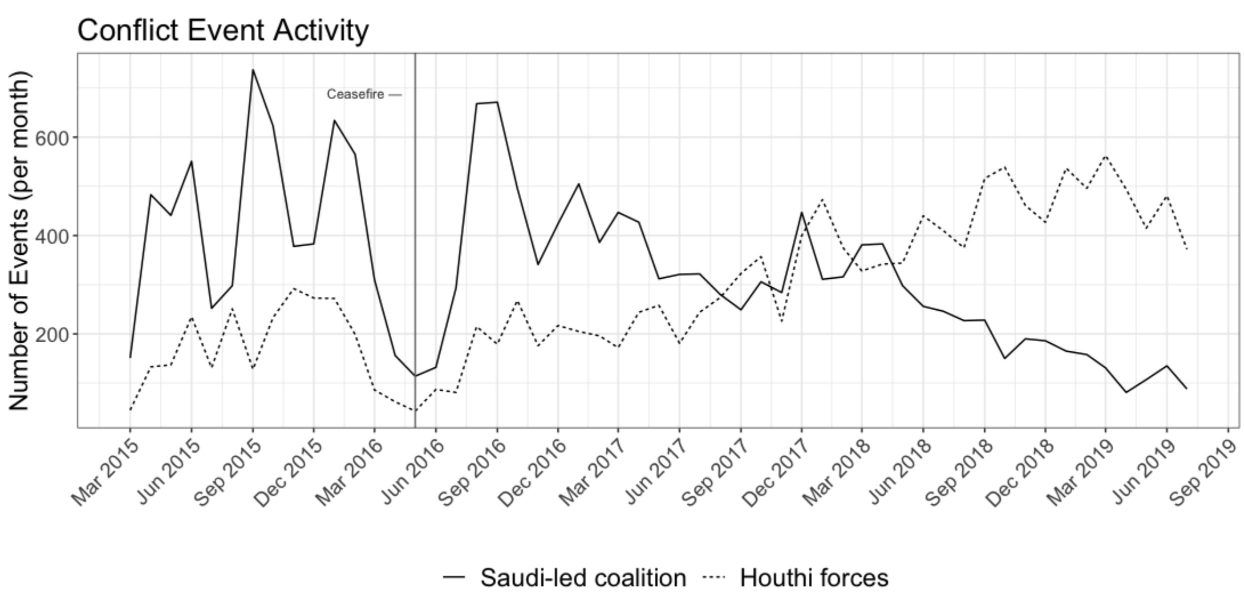

Figure 2: Saudi-led coalition airstrikes (solid line) in Yemen and Houthi activity (dotted line) in Yemen and Saudi Arabia since March 2015. Data sourced from the Armed Conflict Location Event Data Project (ACLED).

The Yemen Data Project, an independent data collection project, has been collecting data on the conduct of the war since airstrikes began in 2015. They have documented 20,025 coalition air raids as of this writing, with more than 8,000 civilians killed and over 9,000 injured. In cooperation with the Armed Conflict Location Event Database (ACLED), Houthi activities and attacks are also documented, with both airstrikes and rebel events being temporally and geographically tagged. Leveraging such data offers the potential for new insights based on an ongoing case of third-party counterinsurgency.

As a contemporary conflict that has been given relatively little attention until recently, Yemen's civil war now appears at the center of debate in many important government chambers, including the United States, United Kingdom, France, Germany, and Spain.[2] Allies of Saudi Arabia, these Western countries have had to wrestle with their own involvement in this aerial strategy and the humanitarian crisis that has evolved as a result. As the situation worsens for millions of Yemenis, coalition members and their allies ought to be asking themselves, "is this airstrike campaign effective?" That is the central question this paper seeks to answer empirically.

Theory on Rebel Responses in Geographic Space

Beyond the discussion surrounding the utility of airstrikes and indiscriminate violence, I argue that the relationship between insurgents and the third-party airstrike actor matters greatly in theorizing expectations of outcomes. There is support for both of the following arguments: 1) Indiscriminate violence removes the deterrence effect and increases insurgent activity and 2) Air power reduces such activity by destroying and disrupting insurgent operations and infrastructure. I propose that gauging the effectiveness of the Saudi-led coalition's air power strategy in Yemen among these two arguments is intimately tied to the historical and political relationship between the Houthi rebels and Saudi Arabia.

Due to varying loyalties and tribal tensions, the Yemeni state does not have a strong, independent security apparatus to employ against the Houthi insurgency (Gaub 2015). Since the start of the

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2. In light of the assassination of Jamal Khashoggi in October 2008, politicians in many Western countries allied with Saudi Arabia challenged their respective country's support for the military intervention in Yemen. U.S. members of Congress debated a resolution to halt American military support in the air campaign, which ultimately failed to pass the Senate (Schmitt and Gibbons-Neff 2018). Campaigns in the UK have brought about a legal court ruling that arms sales to Saudi Arabia are unlawful given the risks of international humanitarian law violations ("UK Arms Sales to Saudi Arabia Unlawful, Court Rules" 2019). France has also come under pressure for its arms sales to Saudi Arabia, forcing the government to defend its position against heavy criticism ("France Under Pressure to Come Clean Over Arms Exports in Yemen War" 2019). Meanwhile, states like Germany and Spain have passed measures to halt arms exports ("Germany Extends Ban on Arms Sales to Saudi Arabia" 2019; "Spain Confirms it has Halted Sale of Bombs to Saudi Arabia" 2018)

current conflict, the Houthis have enjoyed a substantial amount of territorial control, including that of the capital city and critical port cities in the west. With the relative strength of the insurgents and the power of Yemen's ideologically-motivated ally along its northern border, the Saudi-led coalition military intervention comes as no surprise (Kathman 2011, Findley and Teo 2006, Gent 2008, Aydin and Regan 2011). As third-party interventions have been found to increase the likelihood of the supported group achieving military victory (Balch-Lindsay, Enterline, and Joyce 2008), the strategy was to, in the words of Adel al-Jubair, Saudi ambassador to the US, "defend and support the legitimate government of Yemen and prevent the radical Houthi movement from taking over the country." ("Saudi and Arab Allies Bomb Houthi Positions in Yemen" 2015).

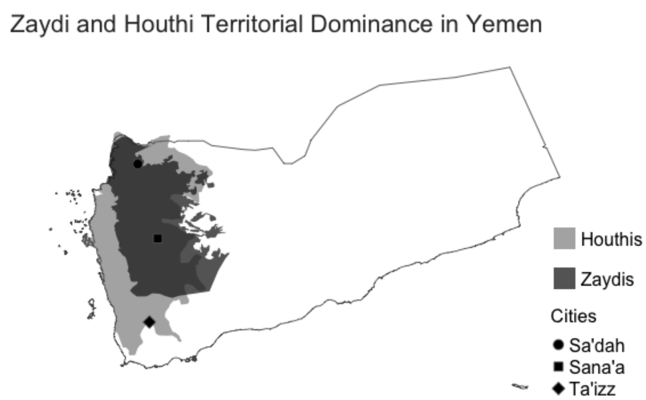

Figure 3: Territorial regions where Zaydis are dominant and Houthis maintain control.

Based on Horowitz and Reiter's (2001) conception of effectiveness, air campaigns are a form of coercion that ought to alter the behavior of the insurgents to the attacker's preferred outcome. Saudi Arabia and its coalition members ideally would like to see the Houthis concede power and demilitarize. Failure of their strategy, then, would be observing Houthi behavior to be the exact opposite of their preferred outcome – not conceding, thus, continuing the fight. If Houthi attacks increase in response to these airstrikes, this would indicate that the air power campaign is an ineffective strategy. However, if Houthi attacks decrease, this would lend support to the argument that such airstrike strategies are effective in altering insurgent behavior.

I now refer to the Zaydi-Salafi divide discussed in the background section. Religious and political competition between Zaydi and Salafi influences has been fought by the Houthis for decades. While the Houthis claim they do not seek total political domination over the Yemeni state, they would nevertheless be enraged by a predominantly Saudi-backed Yemen government and leadership (Shaker and Edroos 2018). In this sense, their fight against the Saudi-led coalition is an existential one. Showcasing resolve to their fellow Yemenis is crucial to the Houthis' long-term strategy. They seek to make a permanent stake in the future government of Yemen, which requires a show of force against coalition strikes. Thus, my general expectation is that airstrikes, especially those launched by an insurgents' existential opposition, increase insurgent attacks.

However, this theoretical expectation is conditioned by spatial and temporal factors. Previous methods have often looked at the dependent variable (i.e. insurgent attacks, territorial control, civilian collaboration) within a defined geographic radius surrounding the initial airstrike (Lyall 2009; Kocher, Pepinsky, and Kalyvas 2011; Schutte 2017; Lyall 2017). The assumption here is that the reaction to an airstrike is likely to be observed in the same spatial vicinity, such as the same village or within a 5 km radius. However, I emphatically reject this assumption, at least as it relates to rebel responses. The nature of airstrikes, and what makes them so appealing to their users, is their remote execution. Rather than place military vulnerabilities on the ground in enemy territory, air power strategists can simply fly above their target and drop a missile from relative safety. If such a missile is dropped on an insurgent base or stronghold, what incentive is there for insurgents to respond with attacks in their own territory? I argue, then, that their response is likely to be elsewhere. Consequently, I aim to test the following hypothesis:

H1: Airstrikes do not increase insurgent attacks in the same geographic vicinity

If I do not expect insurgents to respond in the vicinity of airstrikes, where should I expect them to respond? I theorize that insurgents respond by attacking their opposition where it hurts. Although the Saudi-led coalition is made up of nine states, Saudi Arabia is at the forefront of the military intervention and clearly has political and strategic interests in Yemen, interests that come at the expense of the Houthis. Therefore, I expect Saudi territory to experience an increase in the number of Houthi attacks as a result of airstrikes. I also suspect that fatal airstrikes are more likely to motivate such a response. Coalition airstrikes with large death tolls receive more international press coverage and create stronger feelings of resentment among locals and rebels, encouraging a greater urgency to retaliate and show resolve against the party responsible. Therefore:

H2: Fatal airstrikes increase insurgent attacks in territories belonging to the third-party launching airstrikes

Overall, these hypotheses aim to better understand the relationship between airstrikes and insurgent activity, specifically in the unique case of Yemen and the Saudi-led coalition's military intervention. Where, when, and how many Houthi attacks we observe in response to airstrikes will help to illuminate whether such a counterinsurgency strategy is useful or effective for third-party interveners in civil wars.

Part I: Do Insurgent Attacks Increase in the Vicinity of Airstrikes? Georeferenced Data with Matched Wake Analysis

This section will test the first hypothesis using a matching and difference-in-differences method that has been used before in previous similar studies (Schutte 2017; Kocher, Pepinsky, and Kalyvas 2011; Lyall 2009, 2017). These studies employed such a method in order to determine the impact of airstrikes and bombings on some dependent variable. They identify geographic areas (e.g. villages) that are virtually similar in every way except for the fact that one experienced an airstrike and the other did not. By creating these sets of "control" and "treatment" units, they can compare the mean differences between outcome variables and assess, to some reasonable extent, the causal effect of airstrikes on some dependent variable. The major drawback of this approach, however, is that it only tests whether the effect occurs in the same geographic vicinity as the initial airstrike. Nevertheless, I will apply this method and evaluate how the results of Yemen's case compare with those of Chechnya, Afghanistan, and Vietnam (Lyall 2009, 2017; Schutte 2017; Kocher, Pepinsky, and Kalyvas 2011). As explained in the previous section, I hypothesize that airstrikes will not necessarily increase rebel attacks within the same geographic vicinity of the initial strike.

Research Design

An issue with matching techniques using georeferenced event data is the selection of appropriate spatial units and the aggregation of data within them. The scale and aggregation of spatial data can drastically impact the analysis. This problem, coined as the modifiable aerial unit problem (MAUP), often arises in the analysis of census data where individual-level data is aggregated at some county or regional unit for privacy reasons (Charlton 2008). Past studies looking at airstrikes and conflict use villages, hamlets, or fixed grid-cell rasters to aggregate and analyze their data – units which are all affected by the modifiable aerial unit problem. Regression and correlation coefficients, as well as the number of observations under study, can vary depending on the spatial unit selected (Charlton 2008; Schutte and Donnay 2014).

Schutte and Donnay (2014) offer a methodological solution to this problem for inferential analysis in conflict event data. Matched Wake Analysis (MWA) combines "sliding spatio-temporal windows to overcome MAUP and statistical matching to allow for clean causal inference" (Schutte and Donnay 2014, 2). The basic premise of MWA can be described in three general steps. First, events are associated with geographic variables relevant for matching control and treatment events (for example, population density, area of government or rebel control, distance from capital, etc.). Second, based on these geographic covariates, Coarsened Exact Matching (CEM) is implemented to prune those events that do not have an appropriately matched treated and control pair, leaving behind a sample where every "treatment" event has a coarsely matched "control" event[3] (Iacus, King, and Porro 2012). Finally, a difference-in-differences OLS regression is applied on the final matched database to assess the treatment's effect on the dependent variable (Schutte and Donnay 2014). Using sliding windows in both time and space, this process is repeated over a range of spatial and temporal units, creating spatial-temporal "cylinders" for both treatment and control events where pre- and post-treatment dependent events are counted and compared. Figure 4 provides an illustration of the method created by Schutte and Donnay (2014).

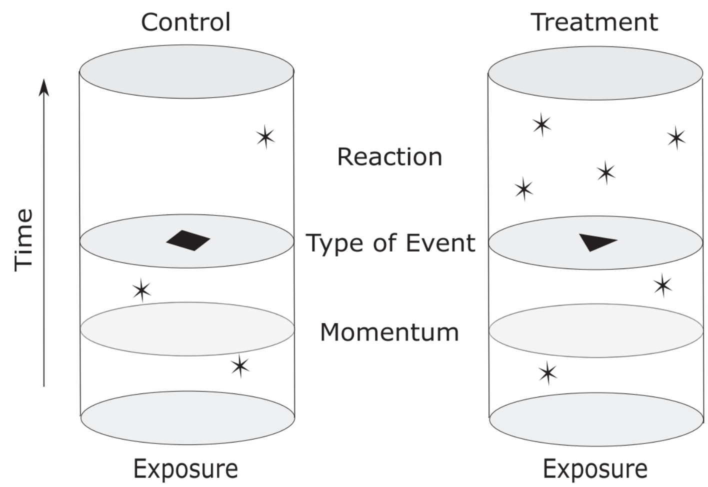

Figure 4: Visual representation of Matched Wake Analysis, taken from Schutte and Donnay (2014). The cylinder's radius refers to the spatial unit while the cylinder's height refers to the temporal unit. The square and triangle shapes inside refer to the control and treatment event type, with pre-treatment dependent events counted before ("momentum") and post-treatment dependent events counted after ("reaction"). The two cylinders are then compared with one another to extract a treatment effect.

Employing Matched Wake Analysis requires event data that is both timestamped and geographically referenced with latitude and longitude. For this, I utilize data from the Armed Conflict Location Event Data Project (Raleigh et al. 2010). ACLED codes "reported information on the exact location, date, and other characteristics of politically violent events in unstable and warring states" (ACLED 2017). For event data in Yemen, the Yemen Data Project contributes their data collection of Saudi-led coalition airstrikes to the ACLED dataset.

3. The MWA R package has an option to implement k-to-k matching within CEM; this option was used in the analysis (Schutte and Donnay 2017).

For this study, ACLED data is limited to Houthi and Saudi-led coalition events occurring in Yemen and Saudi Arabia between March 2015 and July 2019.[4] MWA further requires events to be categorized as a dependent event, treatment event, or control event. Houthi attack events are thus assigned as dependent events while Saudi-led coalition events are assigned as treatment events.

In order to include control events, similar geographic areas must be selected where an airstrike could have occurred but did not. In this way, MWA can assess the impact of airstrikes by comparing the difference between areas that experienced an airstrike and areas that did not, holding all other characteristics the same (or very similar).

To create this synthetic risk-set, a point-process model is used to randomize points around Yemen, excluding areas where an airstrike occurred within a 5 km radius.[5] In order to reduce the risk-set to only those points that are reasonably likely to experience an airstrike, an initial run of Coarsened Exact Matching is applied on the latitude and longitude of treatment and control events in order to retain randomized spatial points that are more likely at risk (e.g. Only Western Yemen experiences Saudi-led coalition airstrikes, so points not in this region can largely be dropped). Figure 5 illustrates this process. The surviving "control" events are then combined with the outcome and treatment events to create the full dataset necessary to run the MWA analysis.

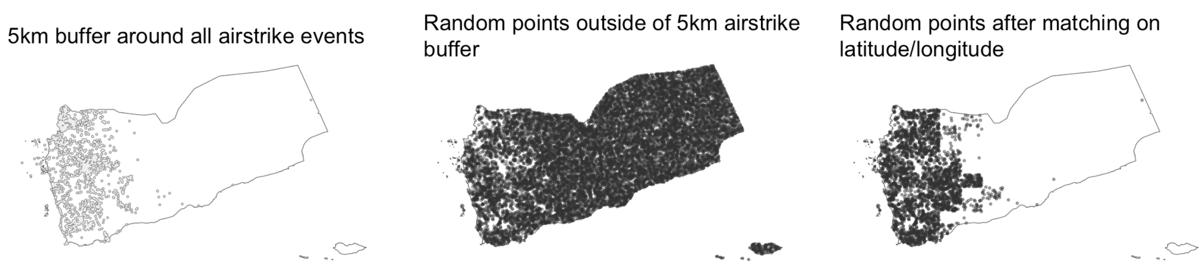

Figure 5: Illustration of step-by-step process in creating control events for MWA.

The geographic variables associated with each event used for matching within MWA include the following: population density, strategic location (number of roads and populated centers within

4. Saudi-led coalition events are those with the actor labelled as "Operation Decisive Storm" and "Operation Restoring Hope". Houthi events are those with the actor labelled as "Military Forces of Yemen (2016-) Supreme Political Council" and "Military Forces of Yemen (2015-2016) Supreme Revolutionary Committee."

5. I argue a 5 km radius is large enough to reasonably separate geographic points impacted by airstrikes while also not being too large to exacerbate the modifiable aerial unit problem or to exclude geographically similar areas for control events.

a 5 km radius),[6] Zaydi religious dominance, Houthi control, and distance from Sa'dah, Taizz, Sana'a, and the Saudi border. These variables were chosen based on similarly selected variables used in previous studies (Lyall 2009; Schutte 2017; Lyall 2017). Further, they distinguish important characteristics that ought to be matched for a feasible comparison between geographic areas. Two urban areas are more similar to each other than an urban and rural area. While Zaydi- and Houthi-dominant areas largely overlap, there exist some regions where they do not. Yemen's two largest cities, Sana'a and Taizz, as well as the Houthis' stronghold in the northern city of Sa'dah, are heavily targeted by the Saudi-led airstrikes, making the distance from these locations critical. Additionally, much of the Houthi conflict activity occurs along the Yemeni-Saudi border, again making the distance from this border an important characteristic to match on. Unfortunately, disaggregated geographic data for other important measures, such as poverty, were inaccessible; however, used together, the other variables should result in geographic "control" areas that are very similar to targeted areas with the exception that these areas did not experience an airstrike.

Data measuring population density comes from the NASA Socioeconomic Data and Applications Center (SEDAC) hosted by Columbia University. It is a 2015 global raster measuring population density at a 5 km resolution (Center for International Earth Science Information Network - CIESIN - Columbia University 2016). Data on roads and population centers in Yemen are available from OpenStreetMaps (OpenStreetMap contributors 2015).[7] The religious dominance of Zaydiyya (binary variable) comes from the Geo-referencing Ethnic Power Relations (GeoEPR) dataset which geo-codes all politically relevant ethnic groups (Wucherpfennig et al. 2011). Time-varying data on Houthi vs. government territorial control from the period under study was inaccessible; however, a static polygon of Houthi-controlled territory from 2017 was extracted from the Live Universal Awareness Map (Live Universal Awareness Map 2017). This was used to create a dummy variable for Houthi governance. Finally, distances from cities Sa'dah, Taizz, and Sana'a were calculated using the raster R package (Hijmans 2019). Distance from the Saudi border was calculated using the geosphere R package (Hijmans 2017). Together, these data form the foundation on which MWA can be run (Schutte and Donnay 2017). The final difference-in-differneces model specification is the following:

6. This inclusion of 'strategic location' is inspired by Jesse Hammond's "Maps of Mayhem: Strategic Location and Deadly Violence in Civil War" (2017), though the operationalization I use is a much more simplified version of his.

7. Only primary and secondary highways are included. Likewise, population centers were restricted to cities, suburbs, and towns.

$$nRebelAttacks_{post} = \beta_0 + \beta_1 nRebelAttacks_{pre} + \beta_2 AirstrikeTreatment + u$$

The number of Houthi attacks are counted before and after the timestamp of matched control and treatment events.[8] The quantity of interest from this model is β_2, the regression coefficient of the treatment effect. A positive coefficient that is statistically significant will indicate that areas "treated" by an airstrike experience subsequently more rebel attacks than those areas that do not receive the treatment.

Results

The effect of airstrikes on subsequent rebel activity in the geographic vicinity of the strike appears to be positive. Difference-in-differences estimation results show a statistically significant treatment effect between 0.06 and 0.4, depending on the spatial and temporal range in question. Figure 6 plots the output on spatial and temporal axes. The treatment effect is smallest within a 2.5 km radius up to 5 days post-strike, but grows as the number of days increases. At 25 days within a 3 km radius post-strike (near the center of the plot), Houthi attacks are expected to increase by 0.207, or 20.7 for every 100 airstrikes. Estimates for each spatial-temporal cylinder can be found in Table 1 in the Appendix.

These results run contrary to my first hypothesis; there does, in fact, appear to be a statistically significant increase in subsequent rebel responses after an airstrike attack in the same geographic vicinity. This finding falls in line with the work of Lyall (2017), Schutte (2017), and Kocher, Pepinsky, and Kalyvas (2011). These studies find that, overall, indiscriminate violence (by which airstrikes are considered) leads to increased levels of insurgent violence (or, in the case of Schutte (2017), leads to uncooperative civilian behavior). Lyall (2009) is the lone exception. A side-by-side comparison of my results with these studies can be seen in Table 2 in the Appendix.

Results should be considered cautiously, however, as there are a number of issues with this analysis. First, the selection of treatment and control events is not a representative sample of actual events. Saudi-led coalition airstrikes are highly concentrated in major city locations (see Figure 7). Due to this density, many airstrike events in cities were ignored when matched with control events. There are no control events that could be reasonably matched with one of these city center treatment events, as virtually every city has been struck heavily; thus, the resulting control and treatment pairs do not accurately represent the effects of airstrikes in city centers, which likely biases the MWA output. Nonetheless, these results may still speak to the effects of airstrikes in less urban areas where more comparable control and treatment pairs exist. Figure 8 shows the

8. With k-to-k matching, each control event was assigned the timestamp of its matched treatment event.

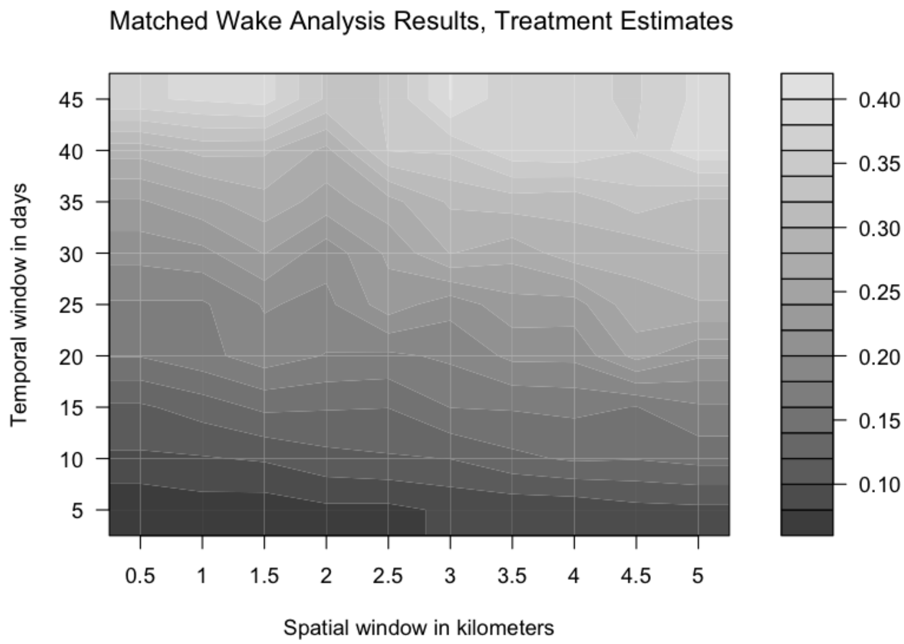

Figure 6: Plot showing estimates of treatment effects at different spatial and temporal windows.

mean differences between the MWA control and treatment samples by their matched covariates. On average, the samples' covariates are similar, although some particular matched pairs differ greatly (e.g. distances from the major cities and population density).

Another concern is the fact that, in an overwhelming majority of both control and treatment cases, there were no Houthi attacks within the specified spatial and temporal window. For example, when looking specifically at the "cylinder" that calculated counts based on a 25-day and 5 km window, 98.9% of control cases and 78.9% of treatment cases experienced zero Houthi attacks both *before and after* the treatment date. Such a frequent occurrence of zeros likely drives the statistical significance behind the results. However, this distribution of zeros is actually quite representative of actual airstrike events. Figure 9 illustrates the subsequent number of Houthi attacks that occur in the geographic and temporal vicinity of an airstrike in both the MWA sample and original data. We see here that 71% of airstrikes do not experience any subsequent rebel attacks in its geographic vicinity. This makes sense theoretically: if an airstrike is dropped on an insurgent base or stronghold,[9] what incentive is there for the Houthis to respond with attacks in their own territory of control? While the MWA results do not statistically support my first

9. In Yemen, the majority of airstrikes are dropped in the major cities where Houthis hold most of the control. Compare Figure 3 and Figure 7.

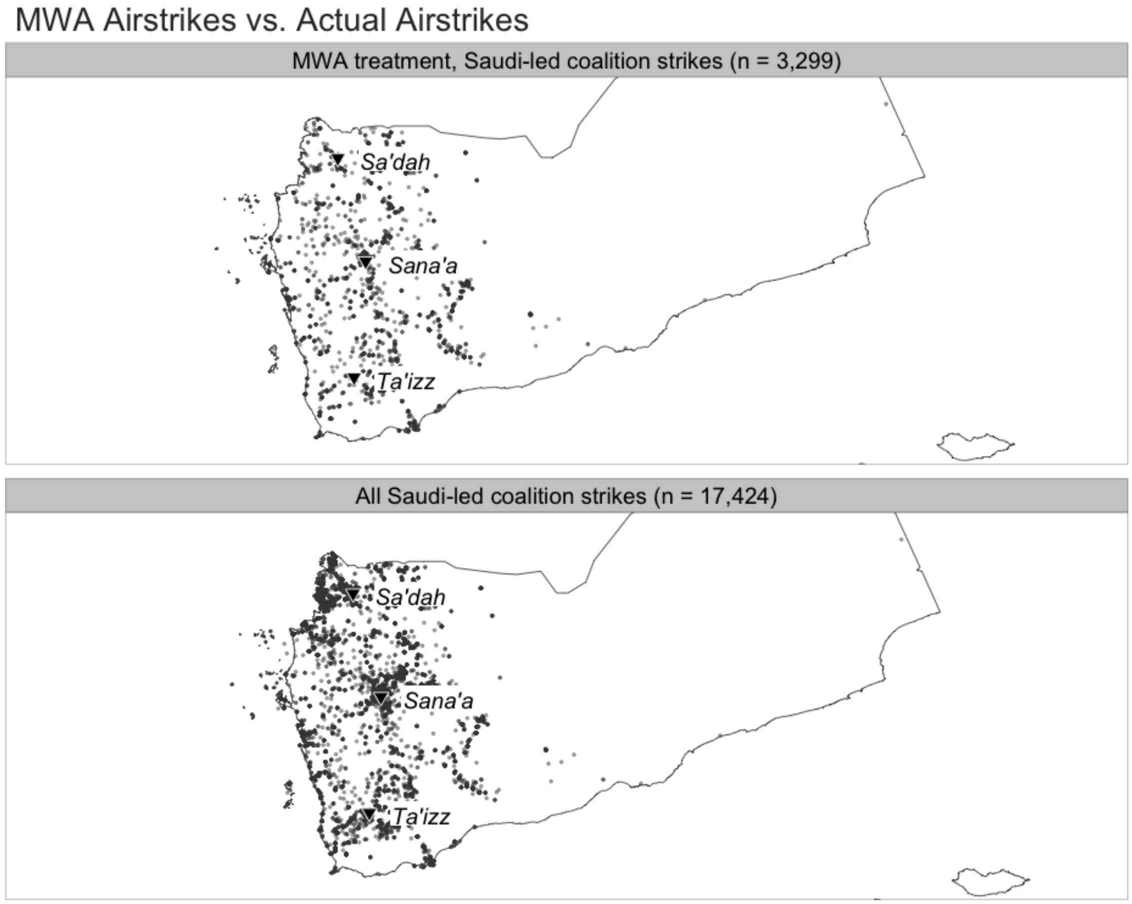

Figure 7: Map illustrating airstrike locations from the MWA sample versus in reality. There is an extremely high density of airstrikes in the cities that is not accurately captured in the MWA sample.

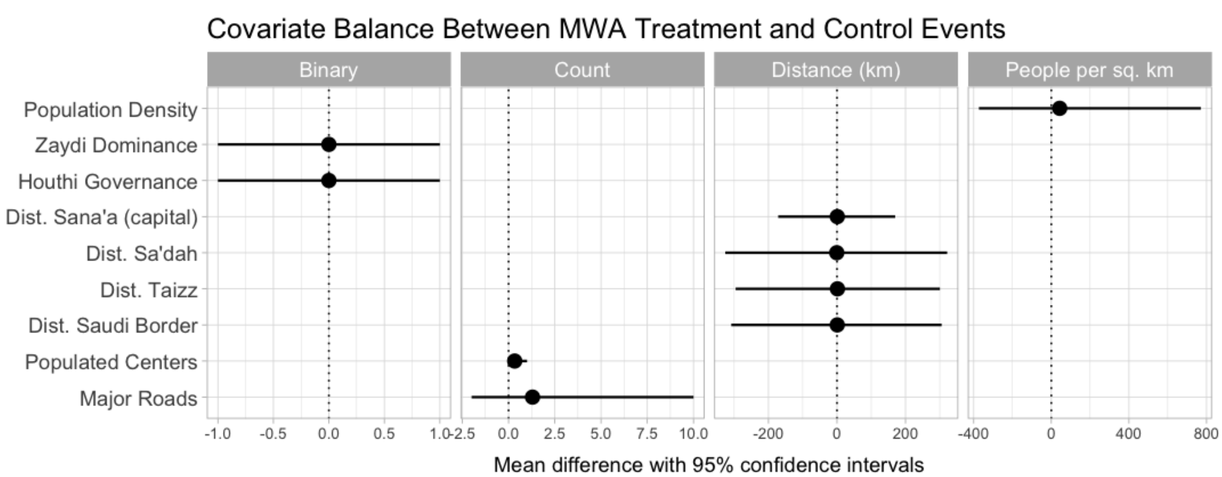

Figure 8: Difference between MWA treatment and control covariates used to match pairs (treatment values minus control values). Means of these differences are shown with their 95% confidence intervals.

hypothesis that airstrikes do not necessarily increase insurgent attacks in the same geographic vicinity, the observation illustrated by Figure 9 offers a point of contention that would benefit from further investigation, motivating the second analysis of this paper.

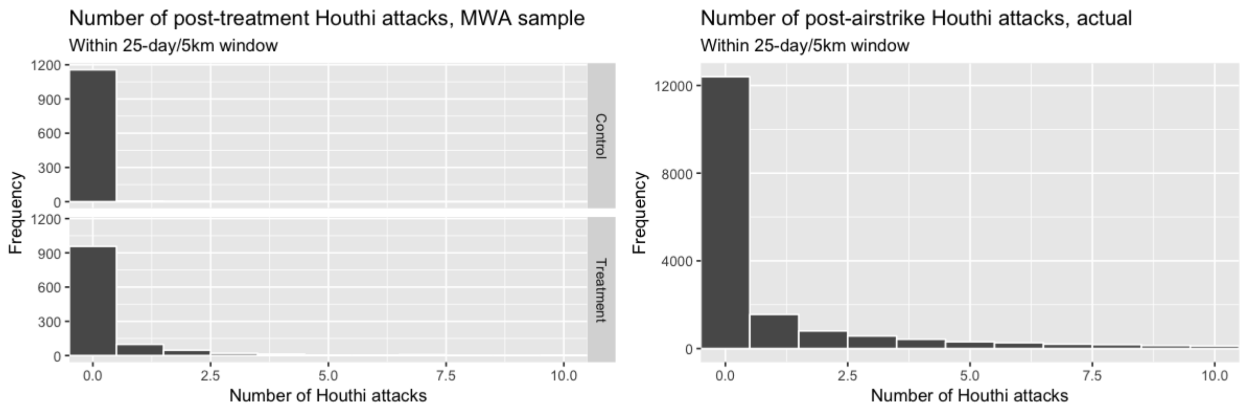

Figure 9: Histogram of post-airstrike Houthi attack event counts calculated in MWA sample vs. the actual counts.

Robustness

With regard to the modelling technique itself, three different robustness checks were implemented in order to establish internal validity. First, I tested a naive model without matching control and treatment events. MWA without matching means that all control and treatment events from the original dataset are included in the difference-in-differences estimation.[10] The results were not drastically different; treatment coefficients over all temporal and spatial windows without matching were, on average, only 0.07 more than the original model's estimates. In other words, the model without matching estimates 7 more additional Houthi attacks for every 100 airstrikes. The consistency in terms of direction and relative magnitude of the treatment effect is reassuring that the analysis is not driven purely by the matched sample.

Second, in order to assess whether the analysis is sensitive to the buffer size around airstrikes in creating control events, I recalculated control events using a 2.5 km and 10 km buffer radius. The airstrike buffer means that the randomized points used to create control events will not exist within a 2.5 km or 10 km radius of any airstrike. Results indicate very little difference between

10. Recall that the original MWA dataset already includes matched treatment and control events based purely on latitude and longitude in order to ignore randomized control points that are geographically irrelevant.

buffer variations. Since all analyses include a 2.5 km spatial window for calculating pre- and post-treatment dependent events, I compared all temporal windows at this radius among the three buffer specifications. There is only a coefficient difference range of 0.014 to 0.028. Substantively, this is very small. All results remain positive and statistically significant, adding further evidence to the resilience of the main analysis.

Finally, I tested whether the timestamps assigned to the control events are driving the results. In the main analysis, I assigned every control event with the identical timestamp of its matched treatment event (e.g. the timestamp of the actual airstrike event). Here, I instead randomize the timestamps with replacement and run the same analysis. Results remain positive and statistically significant; however, the estimates are lower, ranging from 0.06 to 0.22 instead of 0.06 to 0.40. Despite slightly more conservative estimates, these results indicate that the timing of airstrikes is largely independent from the overall effect on subsequent Houthi attacks.

Between a non-matched analysis, varied buffer sizes for control event creation, and randomized control event timestamps, these robustness checks produce results that remain notably consistent with the main analysis. Coefficient direction and magnitude are resilient against these different specifications.

Part II: Do Insurgent Attacks Increase Elsewhere after Fatal Airstrikes? Time-Series Analysis of Conflict Events

This section tests the second hypothesis using a time-series analysis to assess whether or not fatal airstrikes increase the number of rebel attacks in Saudi Arabia. Since we observed from the previous analysis that 71% of Saudi-led airstrikes do not experience Houthi attacks within a 5 km radius up to 25 days after the strike, it is fruitful to look for rebel responses elsewhere. Amongst the noise of so many airstrikes and conflict events on the ground, one way to tease out a potential causal relationship in such a setting is looking at the number of attacks that occur directly against the third-party actor launching the airstrikes. These attacks are the most likely to be in direct response to previous airstrikes since they are targeting the airstrike actor. In the context of Yemen's civil war, the main retaliatory target of the insurgents would be Saudi Arabia. Although the Saudi-led coalition is made up of eight other states, Yemen shares a border with Saudi Arabia and the Houthis have a longstanding rivalry with them, making this targeting strategy against Saudi Arabia very likely.

We can further fine-tune this relationship between airstrikes and insurgent responses in third-party territories by distinguishing fatal airstrikes from nonfatal airstrikes. I argue that fatal airstrikes are more likely to induce a response from the insurgents. Rebels will seek to show more resolve and retaliation against such indiscriminate violence where perhaps tens or hundreds of civilians were killed. Therefore, I expect that fatal airstrikes will increase the number of Houthi attacks in Saudi Arabia, more so than nonfatal airstrikes.

Research Design

Rather than use conflict events as the unit of observation, I used days and instead counted the number of Houthi attacks per day as the outcome variable. My main independent variable is the number of airstrikes that occurred within a 21-day range prior to the day of observation.[11] These data again come from ACLED (Raleigh et al. 2010).

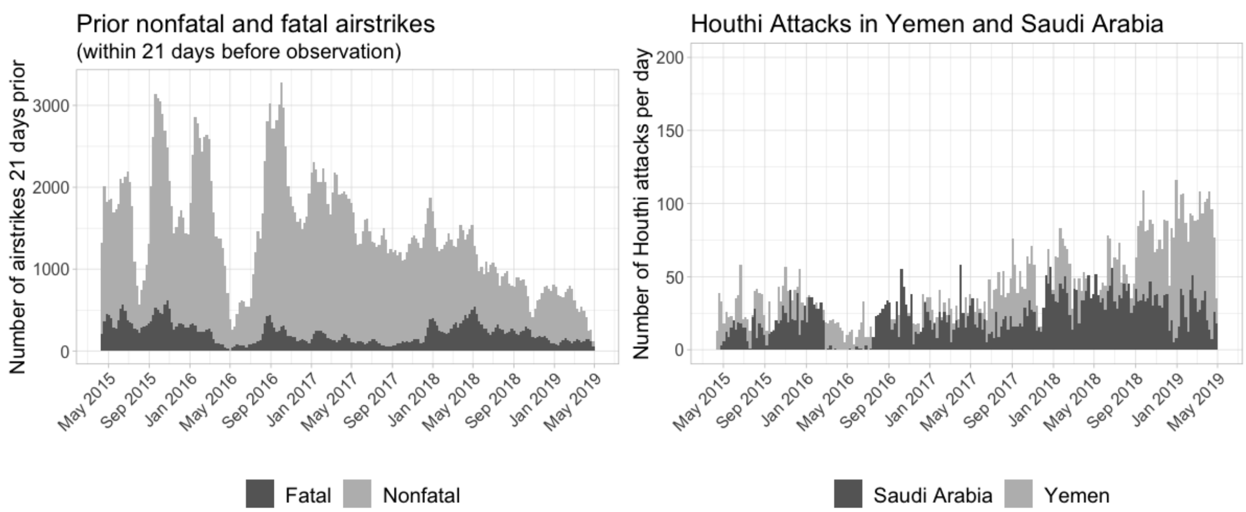

Figure 10: Time-serial distributions of main independent and dependent variables.

I ran two different models to test whether the type of airstrike (fatal and nonfatal) has an effect on the number of Houthi attacks in Yemen and Saudi Arabia. My theoretic expectation is that airstrikes resulting in fatalities will motivate increased rebel responses in the territory of the actor responsible for the airstrike. Thus, I regressed prior fatal and nonfatal airstrikes on daily Houthi activity in both Saudi Arabia and Yemen to test whether this is, in fact, the case.

In order to control for other factors that may explain changes in Houthi activity, variables that vary by day are included in the model, such as food prices and whether or not Houthi forces are allied with ex-president Saleh. Food prices serve as a proxy measure for the blockade of Yemen and overall daily economic situation for both Yemeni civilians and Houthi insurgents. Restricted access to resources may hinder Houthi capabilities or sow resentment among the people supporting them. Median food price data comes from the World Food Programme. Additionally, between

11. This selection is discussed and checked for robustness in the next section.

July 28, 2016 and December 2, 2017, the Houthis were aligned with ex-president Saleh and his forces. Both of these factors may have an independent effect on Houthi activity with regard to their material capabilities in carrying out attacks (Aronson et al. 2015).

Since the outcome variable is a count of Houthi attacks per day, a negative binomial model is implemented using the following general specification:

$$nRebelAttacks_t = \beta_0 + \beta_1 FatalAirstrikes_{[t-21,\, t-1]} + \beta_2 NonfatalAirstrikes_{[t-21,\, t-1]} + \beta_3 FoodPrices + \beta_4 SalehAlliance + u$$

The number of rebel attacks at time t is modeled in Yemen and Saudi Arabia separately. Fatal and nonfatal airstrikes are counted over a 3-week period (21 days) prior to time t, expressed as an interval, $[t-21,\, t-1]$.

Results

Negative binomial results[12] presented in Table 3 in the Appendix show that for every 100 fatal airstrikes launched within a 3-week period, Houthis increase their number of attacks in Saudi Arabia by 1.5. Since the average number of fatal airstrikes in a 3-week period is about 30, the overall increase of Houthi attacks in Saudi Arabia is less than 1. While this effect is statistically significant, it is substantively negligible.

Though the expected effect is small, it is nevertheless important to note that we do not see a significant decrease in Houthi activity as a result of airstrikes, fatal or not. This lends support to the notion that indiscriminate violence does not achieve its primary objective in altering insurgent behavior; if anything, it may only increase rebel attacks. In looking at the results where Houthi attacks are modeled in Yemen, the direction of the effect of fatal airstrikes is positive whereas the direction of the effect of nonfatal airstrikes is negative (both are statistically significant). This result suggests that fatal airstrikes are not effective whereas nonfatal airstrikes may be somewhat effective, at least with regard to insurgent attacks in Yemen. However, in looking at these effects in Saudi Arabia, both fatal and nonfatal airstrikes lead to an increase in subsequent Houthi attacks. This change in direction of the effect of nonfatal airstrikes between Yemen and Saudi Arabia is fascinating; one theoretical explanation could be that after a nonfatal airstrike, the Houthis focus their energy towards the fight in Saudi territory, thus decreasing their overall activity in Yemen. It also points to a theoretically interesting difference between airstrike types and offers support for making such a distinction in similar analyses.

Figure 11 simulates the expected number of Houthi attacks over a range of both fatal and nonfatal airstrike events. The direction is clearly positive in the case of fatal airstrikes in Saudi

12. Negative binomial model is run using glm.nb from the MASS package (Venables and Ripley 2002).

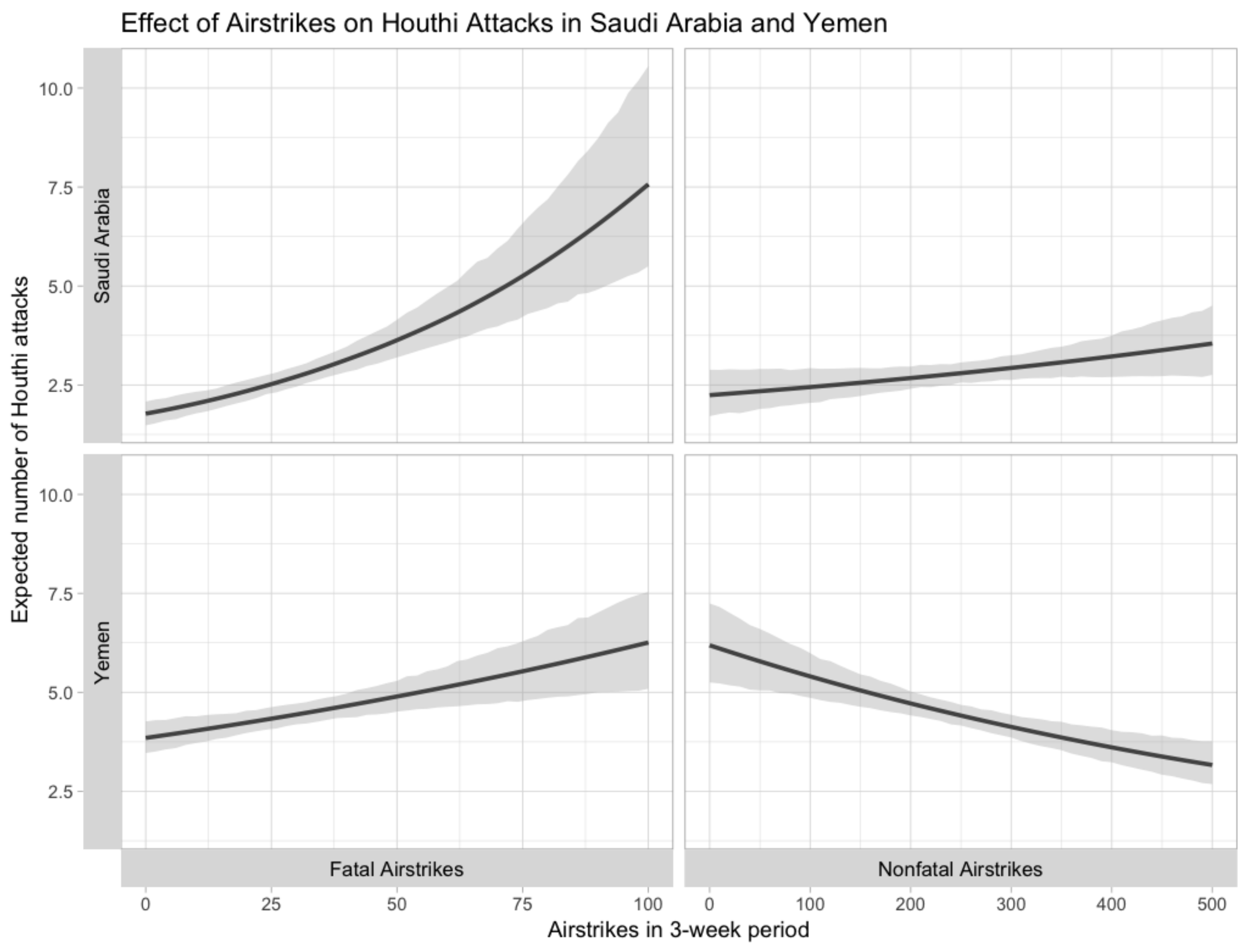

Figure 11: Simulated expected counts of Houthi attacks over a range of airstrike counts, both fatal and nonfatal. An observed-value approach is used, meaning that every observed case is simulated over a range of airstrike values. Calculations are based on negative binomial models (model 2 for Yemen and model 4 for Saudi Arabia, see Table 3 in the Appendix).

Arabia; however, the expected number of attacks remains well under 10. A change from zero to 30 fatal airstrikes, the average number of fatal airstrikes in a 3-week period, results in just 1 additional Houthi attack in Saudi Arabia. Though this change is statistically significant, it is not a substantively drastic effect.

The simulated effects in Figure 11 further show a contrast between the effects of fatal and nonfatal airstrikes as well as the impact on Houthi attacks in Yemen versus Saudi Arabia. In Saudi Arabia, the effect of nonfatal airstrikes on Houthi attacks is positive but less so compared to fatal airstrikes. In Yemen, nonfatal airstrikes actually have a negative effect on Houthi attacks, as discussed earlier. Although the overall magnitude of these effects are quite small, these simulations visually illustrate the distinct impact fatal airstrikes have on Houthi attacks in Saudi territory.

An issue with the selected negative binomial model, however, is the distribution of the outcome variable. Out of 1,447 days under observation, 417 of these days, 28%, experienced zero Houthi attacks in Saudi Arabia. A better approach may be to implement a hurdle model that assumes two different data-generating processes: one that models the binary probability of a day experiencing a Houthi attack in Saudi Arabia or not (binomial logit) and another that models the count of attacks once the non-zero "hurdle" has been crossed (truncated negative binomial). The results from this hurdle analysis (see Table 4 in the Appendix) indicate that fatal airstrikes may play a role in whether or not Houthi attacks in Saudi Arabia occur, however, they are not statistically significant in explaining the numerical count of such attacks.

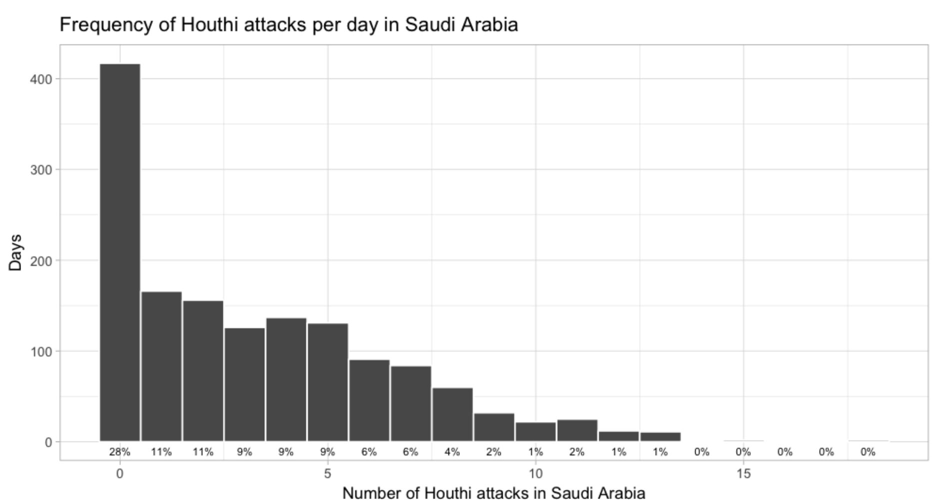

Figure 12: Distribution of the number of Houthi attacks in Saudi Arabia.

A Vuong likelihood-ratio test suggests this hurdle model is an improvement over the single negative binomial model (Vuong 1989). The hurdle model offers a more conservative interpretation of the results: while we cannot argue a clear relationship between the *number* of Houthi attacks in

Saudi Arabia and prior fatal airstrikes, there does appear to be a statistically significant relationship between the likelihood of Houthi attacks in Saudi Arabia and prior fatal airstrikes. When simulating the effect of nonfatal airstrikes from this hurdle model, the direction is only weakly positive and statistically insignificant, suggesting there must be something unique about fatal airstrikes to produce such a different result (see Figure 13). Predicted probabilities of a Houthi attack occurring in Saudi Arabia over a range of fatal and nonfatal airstrikes can also be seen in Figure 13. The predicted probability of Houthis attacking in Saudi Arabia increases from 46% to 96% moving from zero fatal airstrikes to 100 fatal airstrikes, a change of 50 percentage-points. In moving from zero to 500 nonfatal airstrikes, the increase in the predicted probability of a Houthi attack in Saudi territory is only 10 percentage-points.

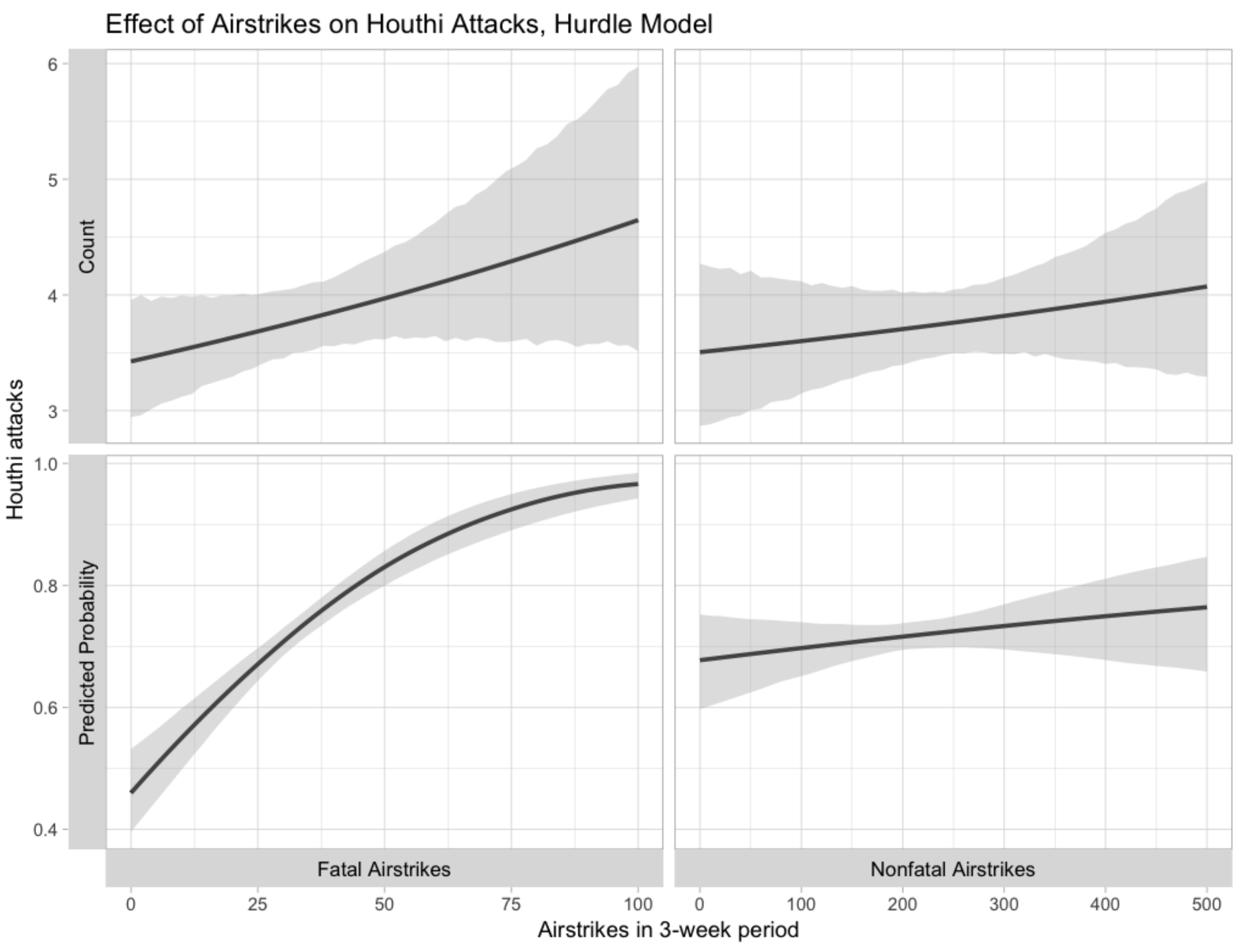

Figure 13: Simulated expected counts and predicted probabilities of Houthi attacks over a range of airstrike counts, both fatal and nonfatal. An observed-value approach is used, meaning that every observed case is simulated over a range of airstrike values. Calculations are based on the hurdle model (see Table 4 in the Appendix) that employs two separate components: a binomial logit to model the abundance of zeros and a truncated negative binomial to model the non-zero counts.

In order to more clearly see the shifts that occur when the number of Saudi-led coalition airstrikes increase, Figure 14 displays simulated first difference calculations between zero and 30 fatal airstrikes and zero and 210 nonfatal airstrikes (the averaged observed value for each). These differences are calculated using model 2 (negative binomial on Houthi attacks in Yemen), model 4 (negative bionomial on Houthi attacks in Saudi Arabia), and the hurdle model (two-compontent model on Houthi attacks in Saudi Arabia). A positive shift of 30 fatal airstrikes is significant in both Yemen and Saudi Arabia; however, the increase in Houthi attacks is incredibly small at under 1 attack. Meanwhile, an increase in 210 nonfatal airstrikes appears to decrease the number of Houthi attacks in Yemen by about 1.5. This same shift does not seem to make a difference in Houthi attacks in Saudi Arabia. The hurdle model shows an increase in Houthi attacks in Saudi Arabia as a result of both types of airstrikes; however, this increase is both statistically and substantively insignificant.

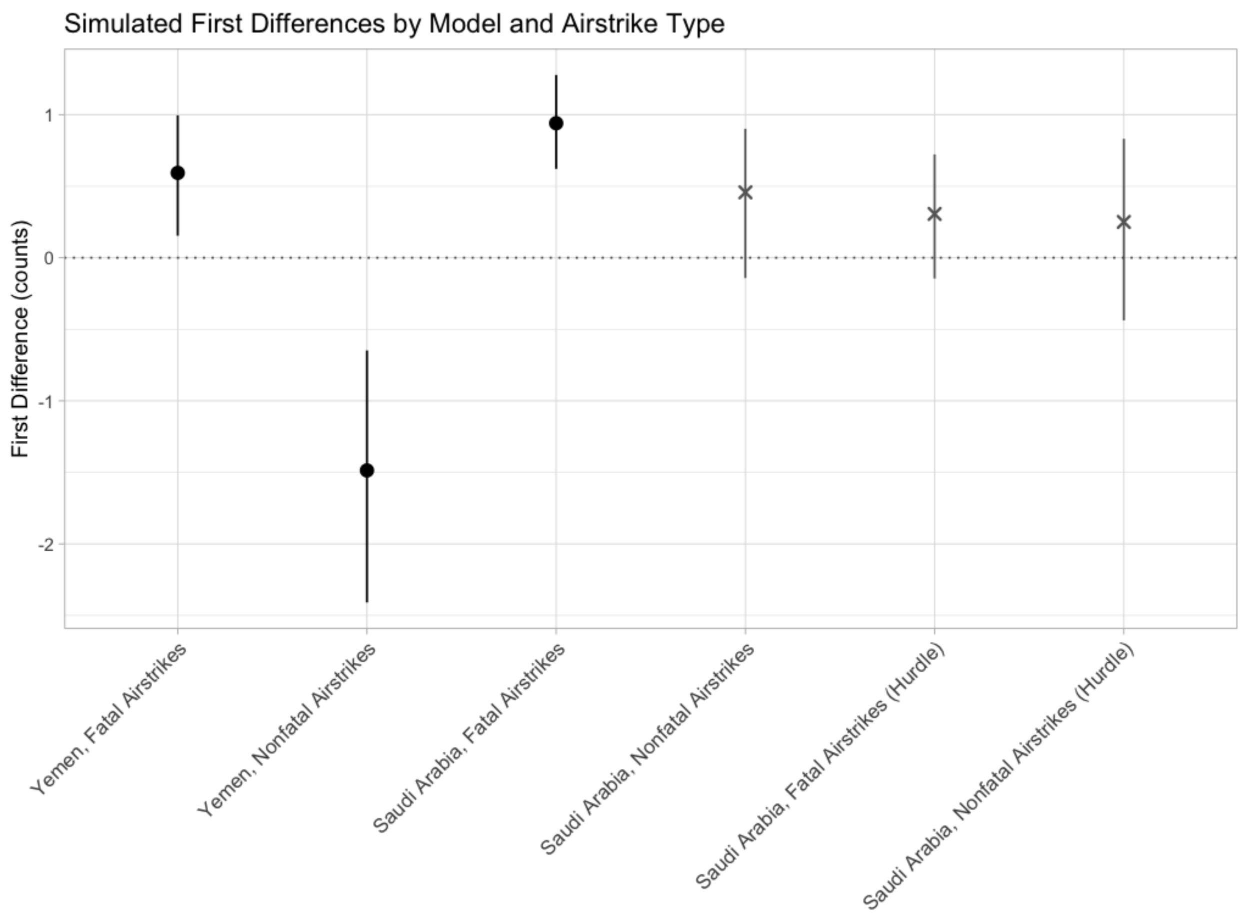

Figure 14: Simulated first differences between zero and 30 fatal airstrikes and zero and 210 nonfatal airstrikes across all models. Mean differences that are statistically significant from zero are marked by a circle while differences that are not statistically significant from zero are marked by an X. Lines denote 95% confidence intervals.

Combined, these results technically support my second hypothesis that fatal airstrikes increase insurgent attacks in territories belonging to the third-party responsible for the strike, as this effect is stronger in Saudi Arabia than it is in Yemen. However, the magnitude is very small and it may be more justified to argue, instead, that fatal airstrikes simply increase the *likelihood* of insurgent attacks in these third-party territories.

Robustness

The selection of 21 days, or 3 weeks, as the range in which to count prior airstrikes is rather arbitrary. Without internal day on rebel operations, there is no way to know how long it takes insurgent groups to launch an attack in response to an airstrike. Attacks could be spontaneous or planned well in advance. I argue that a range of three weeks offers enough time to plan a response while still being close enough in time to assume a connection between the strike and insurgent attack. In order to show resolve to local populations, it is in the interest of the rebels to respond rather quickly.

To test the robustness of the 21 day selection, I ran three of the models again using three alternative temporal ranges: 3 days, 7 days and 35 days. Similar results between these different ranges will ensure that the models are resilient to changes in the temporal measurement of our main independent variables, the number of fatal and nonfatal airstrikes.

Figure 15 illustrates the coefficients, standards errors, and statistical significance of the "fatal airstrikes" variable resulting from this sensitivity analysis. The negative binomial model investigating the outcome variable in Yemen as well as the count-component of the hurdle model both remain stable across these different temporal specifications. The magnitude remains very low and mostly statistically insignificant. Slightly more variation can be seen in the negative binomial model investigating the outcome variable in Saudi Arabia. There is a coefficient jump at 7 days, increasing from 0.015 at 21 days to 0.031. While statistically significant, the magnitude remains very low. In substantive terms, there may be a difference of 1.6 Houthi attacks for every 100 fatal airstrikes launched, depending on whether this airstrike count is measured over a one week period or a three week period.

Despite this small coefficient change, the results remain very similar to one another. Though not visually represented here, estimates of the other variables also remained fairly stable. Overall, the results of the main models using a 21-day range do not appear to be driven by this selection in counting the number of prior airstrikes.

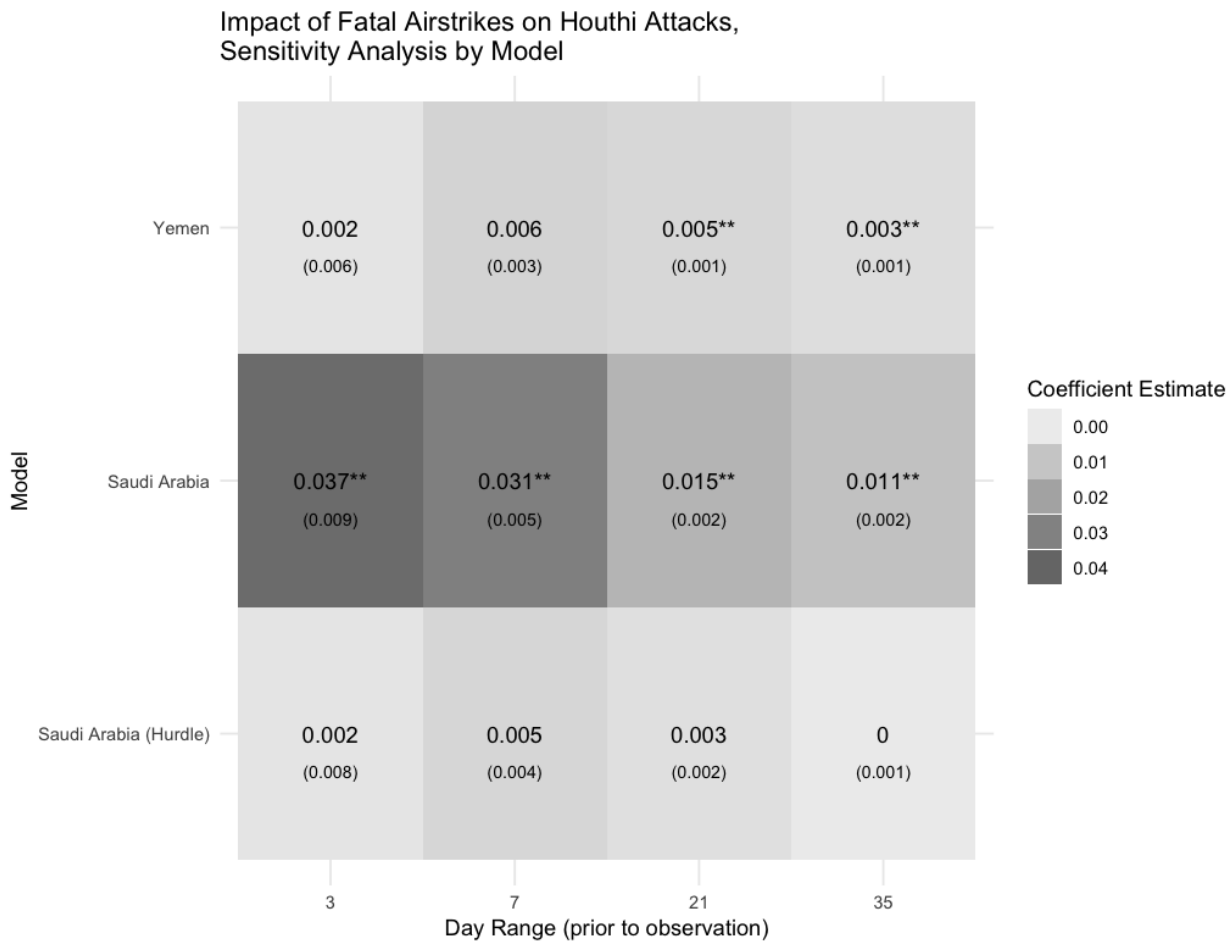

Figure 15: Testing model sensitivity to a change in the temporal aggregation of airstrike counts prior to an observed day. For fatal airstrikes, the main independent variable of interest, estimates remain consistently low and vary little within the same model. Other variables experience similar patterns.

Conclusion

In answering the question as to whether the Saudi-led coalition's aerial campaign in Yemen's civil war is an effective counterinsurgency strategy, the empirical evidence suggests no, it is not. A liberal interpretation of the results would be that airstrikes lead to an increase in insurgent attacks, however small, both in the geographic vicinity of the airstrike location as well as in the territory of the third-party airstrike actor (i.e. Saudi Arabia). A more conservative interpretation of the results would be that, at the very least, fatal airstrikes increase the *likelihood* of subsequent insurgent attacks in third-party airstrike-actor territories. As we do not see a *decrease* in subsequent insurgent attacks (except for perhaps in Yemen after nonfatal airstrike), both interpretations offer support for the general argument that indiscriminate violence via airstrikes, particularly fatal airstrikes, are ineffective in coercing insurgents to the incumbent's preferred behavior.

In previous studies, arguments have been made that air power strategies in counterinsurgency contexts reduce insurgent activity by destroying and disrupting rebel operations and infrastructure (Lyall 2009; Johnston and Sarbahi 2016). However, other empirical studies support the argument that such aerial campaigns remove the deterrence effect and thereby increase insurgent activity (Kocher, Pepinsky, and Kalyvas 2011). If everyone is a potential target of an airstrike regardless of participation, civilians are no longer deterred from supporting the insurgency. They may be more induced to collaborate and aid insurgents out of a sense of revenge and retaliation against those responsible for the indiscriminate attacks (Schutte 2017). The present study adds further evidence to this line of argument, with the added contribution that the relationship between insurgents and the third-party actor launching airstrikes is relevant in forming theoretical expectations.

The Houthis are not a new insurgent group in Yemen; they have been fighting the influence of Saudi Arabia and Salafism since the 1980s, officially picking up arms in 2004. After the popular uprising in 2011 of Yemeni citizens, the Houthis hoped to carve a more legitimate role for themselves during the democratic transition process. Dissatisfied and distrustful of the interim Yemeni government, the Houthis took matters into their own hands by taking over the capital in 2015, leading President Hadi to request military assistance from Saudi Arabia. With an understanding of the historical and political ties between the Houthis and Saudi Arabia, it comes as no surprise that the Houthis would prefer to show strength and resolve against, rather than concede to, a power they have long seen as an existential threat.

The first hypothesis challenged the assumption from previous studies that we should expect to see insurgent responses in (or around) the same location as the initial airstrike. I expected that the number of Houthi attacks would not necessarily increase in a proximate spatial-temporal window post-airstrike. Using Matched Wake Analysis that utilized a Coarsened Exact Matching method with difference-in-differences estimation, I found support that, indeed, Houthi attacks increase by a count of 6 to 40 attacks (per 100 airstrikes) up to 45 days after the airstrike within a 5 km radius. This finding is statistically significant and consistent with evidence from Afghanistan (Lyall 2017; Schutte 2017), though the estimates here are more conservative. However, is it important to note that most airstrike locations do not experience insurgent attacks within a 5 km radius up to 45 days before or after the airstrike. This observation partially supports my general argument that we are more likely to see rebel responses occur elsewhere, which is the primary motivation of exploring this question further in my second analysis.

The second hypothesis tested a more direct causal link between airstrikes and rebel responses by looking at airstrikes resulting in fatalities and subsequent Houthi responses in Saudi territory. If the Houthis want to show resolve and retaliation against particularly violent airstrikes, it is expected they would target Saudi vulnerabilities. I implemented a time-series model by calculating the number of Houthi attacks per day as well as the number of fatal and nonfatal airstrikes occurring within 21 days prior to the day of observation. Negative binomial model results indicated an increase of 1.5 attacks in Saudi Arabia for every 100 fatal airstrikes, while 100 nonfatal airstrikes only increased attacks by 0.1, suggesting there is a real difference in rebel responses towards fatal versus nonfatal airstrikes. The magnitude is very small, but nevertheless offers interesting insights.

To account for the large number of observations (days) that experienced zero Houthi attacks, I also implemented a hurdle model that runs both a binomial logit model on the zeros and a negative binomial model on the counts. These results suggest fatal airstrikes have a statistically significant and positive impact on the likelihood that a day will experience a Houthi attack in Saudi Arabia; however, airstrikes of either type (fatal or nonfatal) do not appear to affect the actual number of Houthi attacks. This finding suggests that fatal airstrikes may simply increase the *likelihood* of insurgent attacks in Saudi Arabia, not necessarily the number of insurgent attacks.

Between both parts of this study, empirical evidence is on the side of airstrikes being ineffective in the context of counterinsurgency efforts in Yemen. However, there are important limitations to these findings. First, in reference to the Matched Wake Analysis, results are based on a sample of treatment and control events that ignore urban effects. Most airstrikes occur within these city and urban centers, so finding a similar urban location that did *not* experience an airstrike is virtually impossible. Thus, the final treatment sample is not wholly representative of real events, likely causing biased MWA results.

The time-series analysis also suffers from omitted variable bias as relevant data varying by day is hard to come by. Consequently, trying to measure and test alternative explanations or theoretically relevant controls was extremely limited. While showcasing a level of internal validity, the external validity of this analysis should be strongly questioned. Issues of reverse causality and autocorrelation likely impact the integrity of this analysis and its results.

Despite these limitations, this study offers interesting insights for future research. The distinction between fatal and nonfatal airstrikes appears to be important and deserves further investigation. For example, research could look more closely at the actual targets of airstrikes (i.e. military, civilian, etc.) as well as the fatality count to understand how rebels respond to these different types of airstrikes. Likewise, targets of insurgent attacks could also be looked at in more detail to improve our understanding of insurgent strategy. In order to really test whether the relationship between insurgents and third-party interveners shapes conflict dynamics, researchers could explore counterinsurgency strategies and rebel responses in other cases where a more "neutral" third-party is engaging in indiscriminate violence.

This study contributes to the conflict literature by examining whether the general consensus towards indiscriminate violence holds in the case of Yemen, and indeed, it does. According to the definition of aerial bombing success or failure put forward by Horowitz and Reiter (2001), bombing to the point of total and utter destruction is a clear coercion failure. The Saudi-led coalition and its allies would be wise to reconsider their aerial strategy if an end to the conflict is truly their primary aim.

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Appendix

Table 1: MWA results listing the time and spatial windows used to count the number of Houthi events before and after a control and treatment (airstrike) event. Treatment effects are calculated using a linear model and range from 0.063 to 0.401. All p-values fall under the 0.01 level. The L1 metric measures the dissimilarity between the joint distributions of the covariates in treatment and control groups (0 = similar, 1 = dissimilar). The %SO and %MO measure possible violations of the Stable Unit Treatment Value Assumption (SUTVA). %SO is fraction of cases where two or more of the same event type overlap in time and space (same overlap) and %MO is the fraction of cases where two different event types overlap in time and space (mixed overlap).

Matched Wake Analysis Results							
Time (days)	Space (km)	Treatment Effect Size	p-value	Adj. R^2	L1 metric	%SO	%MO
5	0.5	0.063	$<$0.01	0.194	0.874	15.8	0.0
5	1.0	0.070	$<$0.01	0.162	0.877	16.5	0.0
5	1.5	0.068	$<$0.01	0.165	0.876	17.5	0.0
5	2.0	0.075	$<$0.01	0.140	0.875	18.5	0.0
5	2.5	0.075	$<$0.01	0.109	0.879	20.0	0.0
5	3.0	0.083	$<$0.01	0.135	0.879	21.3	0.0
5	3.5	0.084	$<$0.01	0.149	0.889	22.4	0.0
5	4.0	0.085	$<$0.01	0.151	0.884	23.6	0.0
5	4.5	0.093	$<$0.01	0.140	0.885	24.6	1.8
5	5.0	0.095	$<$0.01	0.134	0.893	25.7	4.1
10	0.5	0.097	$<$0.01	0.233	0.849	20.9	0.0
10	1.0	0.098	$<$0.01	0.307	0.873	21.7	0.0
10	1.5	0.102	$<$0.01	0.266	0.871	23.0	0.0
10	2.0	0.114	$<$0.01	0.274	0.881	24.5	0.0
10	2.5	0.118	$<$0.01	0.334	0.878	26.6	0.0
10	3.0	0.120	$<$0.01	0.285	0.875	28.4	0.0
10	3.5	0.135	$<$0.01	0.250	0.889	30.0	0.0
10	4.0	0.143	$<$0.01	0.323	0.896	31.6	0.0
10	4.5	0.141	$<$0.01	0.279	0.885	33.2	1.9
10	5.0	0.147	$<$0.01	0.327	0.893	35.1	4.3
15	0.5	0.117	$<$0.01	0.165	0.867	23.8	0.0
15	1.0	0.129	$<$0.01	0.116	0.871	24.7	0.0
15	1.5	0.144	$<$0.01	0.130	0.880	26.3	0.0
15	2.0	0.142	$<$0.01	0.161	0.883	28.3	0.0
15	2.5	0.140	$<$0.01	0.353	0.888	30.9	0.0
15	3.0	0.160	$<$0.01	0.367	0.896	33.2	0.0
15	3.5	0.162	$<$0.01	0.216	0.888	35.0	0.0
15	4.0	0.165	$<$0.01	0.177	0.881	36.9	0.0
15	4.5	0.159	$<$0.01	0.269	0.889	38.8	2.0
15	5.0	0.177	$<$0.01	0.223	0.879	41.0	4.4
20	0.5	0.161	$<$0.01	0.228	0.853	26.0	0.0
20	1.0	0.173	$<$0.01	0.155	0.853	27.0	0.0

20	1.5	0.191	<0.01	0.150	0.858	28.8	0.0
20	2.0	0.179	<0.01	0.313	0.883	30.9	0.0
20	2.5	0.176	<0.01	0.283	0.887	33.9	0.0
20	3.0	0.184	<0.01	0.266	0.878	36.4	0.0
20	3.5	0.205	<0.01	0.341	0.885	38.5	0.0
20	4.0	0.205	<0.01	0.263	0.869	40.6	0.0
20	4.5	0.247	<0.01	0.223	0.874	42.9	2.1
20	5.0	0.222	<0.01	0.344	0.883	45.2	4.7
25	0.5	0.178	<0.01	0.076	0.846	27.4	0.0
25	1.0	0.177	<0.01	0.273	0.855	28.5	0.0
25	1.5	0.202	<0.01	0.314	0.851	30.6	0.0
25	2.0	0.195	<0.01	0.194	0.856	32.9	0.0
25	2.5	0.231	<0.01	0.304	0.881	36.2	0.0
25	3.0	0.207	<0.01	0.275	0.860	39.0	0.0
25	3.5	0.233	<0.01	0.290	0.863	41.3	0.0
25	4.0	0.231	<0.01	0.326	0.868	43.7	0.0
25	4.5	0.275	<0.01	0.272	0.893	46.2	2.2
25	5.0	0.278	<0.01	0.362	0.883	48.7	4.9
30	0.5	0.207	<0.01	0.351	0.891	28.9	0.0
30	1.0	0.214	<0.01	0.293	0.885	30.2	0.0
30	1.5	0.241	<0.01	0.307	0.871	32.3	0.0
30	2.0	0.208	<0.01	0.399	0.894	35.0	0.0
30	2.5	0.244	<0.01	0.419	0.895	38.4	0.0
30	3.0	0.281	<0.01	0.310	0.899	41.5	0.0
30	3.5	0.267	<0.01	0.443	0.871	44.0	0.0
30	4.0	0.292	<0.01	0.301	0.900	46.4	0.0
30	4.5	0.285	<0.01	0.349	0.873	49.0	2.3
30	5.0	0.299	<0.01	0.311	0.891	51.6	5.1
35	0.5	0.238	<0.01	0.491	0.893	30.0	0.0
35	1.0	0.254	<0.01	0.340	0.888	31.3	0.0
35	1.5	0.273	<0.01	0.375	0.869	33.6	0.0
35	2.0	0.251	<0.01	0.499	0.893	36.4	0.0
35	2.5	0.273	<0.01	0.310	0.876	40.0	0.0
35	3.0	0.303	<0.01	0.340	0.881	43.2	0.0
35	3.5	0.310	<0.01	0.352	0.900	45.9	0.0
35	4.0	0.306	<0.01	0.392	0.869	48.5	0.0
35	4.5	0.331	<0.01	0.344	0.877	51.3	2.3
35	5.0	0.315	<0.01	0.425	0.890	54.1	5.3
40	0.5	0.288	<0.01	0.327	0.865	31.1	0.0
40	1.0	0.306	<0.01	0.316	0.864	32.4	0.0
40	1.5	0.303	<0.01	0.319	0.863	34.9	0.0
40	2.0	0.274	<0.01	0.443	0.876	37.8	0.0
40	2.5	0.341	<0.01	0.379	0.898	41.6	0.0

40	3.0	0.343	<0.01	0.321	0.895	45.0	0.0
40	3.5	0.373	<0.01	0.304	0.876	47.7	0.0
40	4.0	0.377	<0.01	0.425	0.882	50.3	0.0
40	4.5	0.361	<0.01	0.427	0.884	53.1	2.5
40	5.0	0.396	<0.01	0.440	0.900	56.0	5.4
45	0.5	0.377	<0.01	0.162	0.878	31.8	0.0
45	1.0	0.383	<0.01	0.294	0.869	33.2	0.0
45	1.5	0.390	<0.01	0.170	0.877	35.7	0.0
45	2.0	0.337	<0.01	0.298	0.871	38.8	0.0
45	2.5	0.341	<0.01	0.312	0.873	42.9	0.0
45	3.0	0.401	<0.01	0.302	0.881	46.2	0.0
45	3.5	0.365	<0.01	0.428	0.887	49.1	0.0
45	4.0	0.364	<0.01	0.480	0.883	51.7	0.0
45	4.5	0.358	<0.01	0.501	0.885	54.5	2.6
45	5.0	0.385	<0.01	0.477	0.904	57.4	5.6

	Similar Studies Comparison				
	Draper 2019	Schutte 2017	Lyall 2017	Kocher, Pepinsky, and Kalyvas 2011	Lyall 2009
CASE	Yemen	Afghanistan	Afghanistan	Vietnam	Chechnya
DEPENDENT VARIABLE	Insurgent attacks	Civilian collaboration (with incumbent)	Insurgent attacks	Insurgent control (territory)	Insurgent attacks
INDEPENDENT VARIABLE	Airstrikes	Airstrikes	Airstrikes	Bombings	Artillery shelling
SPATIAL UNITS	Sliding spatial windows	Sliding spatial windows	Villages	Hamlets	Villages
DIRECTION	+	–	+	+	–
TREATMENT EFFECT	Range: 0.06 to 0.4	Range: 0 to -0.10	7 days: .371 45 days: 1.288 90 days: 2.339	0.536	90 days: -0.506

Table 2: Comparison of this paper's first analysis (MWA) against previous studies looking at the effect of airstrikes on conflict dynamics. All studies employ a form of matching to assess treatment effects of airstrikes.

	Negative Binomial Results			
	Houthi Attacks in Yemen		Houthi Attacks in Saudi Arabia	
	(1)	(2)	(3)	(4)
All airstrikes	-0.0005^{**}		0.003^{***}	
	(0.0002)		(0.0003)	
Fatal airstrikes $[t-21,\, t-1]$		0.005^{***}		0.015^{***}
		(0.001)		(0.002)
Nonfatal airstrikes $[t-21,\, t-1]$		-0.001^{***}		0.001^{*}
		(0.0003)		(0.0005)
Food prices	0.008^{***}	0.008^{***}	0.009^{***}	0.009^{***}
	(0.0004)	(0.0004)	(0.001)	(0.001)
Saleh alliance	0.108^{**}	0.231^{***}	0.266^{***}	0.537^{***}
	(0.044)	(0.054)	(0.069)	(0.086)
Constant	-0.724^{***}	-0.688^{***}	-2.631^{***}	-2.579^{***}
	(0.172)	(0.174)	(0.285)	(0.286)
Observations	1,477	1,477	1,477	1,477
Log Likelihood	−3,912.258	−3,906.010	−3,368.835	−3,355.539
θ	3.583^{***} (0.236)	3.610^{***} (0.237)	1.161^{***} (0.069)	1.194^{***} (0.072)
Akaike Inf. Crit.	7,832.516	7,822.021	6,745.670	6,721.079
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 3: Time-series analysis using a negative binomial count model. Observations (1477) are days between April 15, 2015 and July 28, 2019. Models 1 and 2 estimate the number of Houthi attacks in Yemen and models 3 and 4 estimate the number of Houthi attacks in Saudi Arabia. The variable "all airstrikes" drops the fatal and nonfatal distinction and combines both. Fatal airstrikes include airstrikes with at least 1 reported death. Airstrike variables are counted over a 3-week period prior to the day of observation. Table created using stargazer R package (Hlavac 2018).

	Hurdle Model Results (Saudi Arabia)	
	Count (Negative Binomial)	Zeros (Binomial Logit)
FATAL AIRSTRIKES	0.003	0.040***
$[t-21,\ t-1]$	(0.002)	(0.005)
NONFATAL AIRSTRIKES	0.0003	0.001
$[t-21,\ t-1]$	(0.0004)	(0.001)
FOOD PRICES	0.004***	0.016***
	(0.001)	(0.002)
SALEH ALLIANCE	0.007	1.528***
	(0.076)	(0.179)
CONSTANT	0.071	-6.139***
	(0.292)	(0.649)
Observations	1,477	1,477
	(1,060 counts)	(417 zeros)
Log Likelihood	−3,242.923	−3,242.923
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4: Time-series analysis examining impact of airstrikes on Houthi attacks in Saudi Arabia using the "hurdle" function from pscl R package (Zeileis, Kleiber, and Jackman 2008) to model two components: the data-generating process for zeros and the data-generating process for non-zero counts. Table created using stargazer R package (Hlavac 2018).