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# Strategic Drones *

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**Abstract**

US drone strikes are popular with the electorate and overseen by the President. This paper investigates whether the US President uses drone strikes strategically for political gain. We document that US drone strikes in Afghanistan, Pakistan, Somalia, and Yemen are significantly more likely before US elections, when popularity has high payoffs. We find no changes for unpopular, piloted airstrikes. Consistent with unusually high drone approvals, abnormally cloudy skies before US elections lead to a postponement or redirection of strikes to other target countries. To examine whether drone strikes are used strategically to divert attention from damaging media coverage, we gather closed captions from all cable TV coverage of the President and analyze their tone using natural language processing. Drone strikes are more likely in weeks when news anchors cover the President more negatively, a relation that holds both during and outside of election periods. We find no such relationship for piloted airstrikes or during weeks of high news pressure.

**Keywords:** drone strikes, strategic timing, conflict, political economy.

**JEL Codes:** D72, D74, H56, L82.

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# 1. Introduction

The Diversionary Theory of War argues that political leaders may use foreign conflict as a tool to boost their popularity and to divert attention from domestic problems (e.g. Simmel, 1955; Coser, 1956; Levy, 1989).[1] For example, it is alleged that rising domestic unpopularity in 1982 drove Argentina to invade the Falkland islands. In 1998, President Clinton ordered airstrikes in Afghanistan and Sudan, shortly after his affair with Monica Lewinsky was made public. However, since then, technological developments have radically changed warfare. The use of unmanned aerial vehicles, or drones, has increased significantly and is expected to become the major means of warfare of the future (The Economist, 2023). Since drones are remotely operated, there is no danger to the aggressor. This technological development drastically reduces the political costs of conflict thus potentially changing the strategies adopted by political leaders.

This paper investigates whether the US president uses drone strikes strategically for political advantage. Drone strikes are popular with the US electorate with support between 48% and 83% (Kreps, 2014). Moreover, the 'Authorization for Use of Military Force' (US Congress, 2001) gives the President control over drone strikes. To detect the strategic deployment of drone strikes, we examine whether their timing systematically aligns with periods that are politically advantageous for the US president. A key element of the Diversionary Theory of War is that political leaders start conflicts to stay in office. To assess whether drone strikes are used to sway the electorate, we estimate whether strike patterns change in the run-up to elections. We also investigate whether drone strikes carried out before elections feature more prominently in presidential speeches in the following week. Consistent with another aspect of the Diversionary Theory, we explore whether the President uses drone strikes to detract the media away from damaging news. To this end, we collect closed captions of cable TV news covering the President, analyze their tone using natural processing algorithms and relate these to drone strikes.

To assess whether the US President uses drone strikes strategically to influence electoral

[1] The use of conflict as a political diversion has also been fictionalized in Wag the Dog (1997).

outcomes, we examine whether the US electoral cycle affects the weekly incidence of drone strikes in Afghanistan, Pakistan, Somalia, and Yemen (drawn from the Bureau of Investigative Journalism, TBIJ, as used by Mahmood and Jetter, 2022; among others). After demonstrating their popularity in social and the printed media, we show that the weekly incidence of drone strikes increased by 35 percentage points (on a mean of 76 percent) in the five weeks preceding presidential and mid-term elections between 2009 and 2016 – during the Obama administration. The effect size is comparable to retaliations for US casualties, a plausibly important determinant of drone strikes.[2] After elections, drone strikes revert to their long-term mean.

We do not find a similar pattern under President Trump, suggesting that the strategic use of drone strikes around elections was specific to Obama's presidency. Consistent with this, President Obama is more vocal about these military actions. We find that a week after being carried out, drone strikes are more likely to feature in presidential speeches in the run-up to elections, suggesting that the President purposefully publicizes strikes. By contrast, President Trump delegated much of his authority over the drone program to the military. In line with previous research (Lewandowsky et al., 2020; Marques-Pereira, 2023), we find that President Trump chose alternative means to influence electoral outcomes. We document that both the frequency and the tone of Trump's social media activity changed significantly before elections. In the run-up to elections, social media posts by Trump on Twitter (now $X$) increase by around 30 percent. Trump's social media posts before elections are significantly less negative.

For causal identification, we leverage plausibly exogenous variation in the feasibility of drone strikes arising from aerial cloud cover anomalies. We find that when abnormally cloudy skies hinder the execution of drone strikes in the pre-election period, these strikes are systematically deferred in accordance with military protocol or redirected to alternative target countries. Leaked confidential military guidelines stipulate that once approved, a drone strike must be carried out within 60 days, corresponding to 8 weeks (The Intercept, 2015).

[2] https://www.defense.gov/News/News-Stories/Article/Article/3665734/us-strikes-targets-in-iraq-and-syria-in-response-to-deadly-drone-attack/, accessed April 2025

This 60-day window implies that any drone strikes that cannot be carried out immediately following approval will be postponed, but never by more than 60 days. In line with these rules, we show that unusually cloudy skies in the run-up to elections lead to a postponement of drone strikes towards the end of the approval window followed by a reversion to the mean after expiry of authorization.

We also find evidence that – before elections – drone strikes that cannot be carried out in one target country are re-directed to the other three. During most of the year, drone strikes in country $i$ (e.g. Afghanistan) are not affected by cloud anomalies in the other three countries (Pakistan, Somalia, and Yemen, in this example). However, in the five weeks leading up to elections, we find that drone strikes in country $i$ are significantly increased by cloud anomalies in the three other countries. These findings suggest strategic substitution across theaters of operation in the lead-up to elections, as constraints in one location lead to increased activity elsewhere.

We carry out a number of additional identification checks, including i) studying whether terrorists in target countries synchronize their attacks with US elections, ii) using piloted airstrikes and unconfirmed drone strikes as placebo treatments, and iii) investigating the randomness of US election dates.

After documenting an increase in drone strike frequency before US elections, we investigate whether the President also uses drone strikes to divert media attention away from negative presidential coverage. To this end, we employ a comprehensive dataset of television transcripts from the three main cable television stations CNN, Fox News, and MSNBC, covering nearly all programming aired between 2010 and 2020. These data allow us to track both mentions of drone strikes and news coverage of the US President. To quantify negative news coverage of the President, we apply natural language processing to classify the tone of President-related news segments. We then examine whether drone strike frequency changes in together with negative media coverage of the President.

We begin by showing that drone strikes are routinely covered in the media – but only when these occur. Using cloud cover as an exogenous shifter in drone strike feasibility, we show that a one standard-deviation increase in cloud cover anomalies in Afghanistan, Pakistan, Somalia, and Yemen decreases television mentions of drone strikes by nearly 20 percent in the same week, particularly on Fox News and MSNBC. By contrast, cloud anomalies in the weeks before or after have no such effect, suggesting that coverage is tied to real-time drone events. These effects are strongest during weeks of low media pressure — when the news agenda is not dominated by major natural or industrial disasters — suggesting that strike visibility depends on available news space.

Next, we test whether drone strikes improve media sentiment toward the President. Consistent with prior qualitative research (e.g. Pew Research Center, 2015), we find that a one-standard-deviation increase in cloud anomalies — which reduces drone strikes — leads to a 0.1 standard deviation decline in presidential coverage tone the following week, with the strongest effects again observed on Fox News.

Finally, we examine whether Presidents respond to negative coverage with increased drone strike activity. We find that drone strikes are significantly more likely in weeks when the tone of cable news coverage toward the President is more negative. Importantly, this relationship holds throughout the presidential term and is not limited to the run-up to elections, suggesting that media-driven diversion can occur even outside of clear electoral incentives. There is no such relationship for piloted airstrikes or drone strikes not recognized by the US. Moreover, the effect disappears in weeks when the US experiences major disasters, consistent with the idea that drone strikes are more likely to be used as a diversionary tactic when media attention is not already occupied by more salient news. Taken together, these findings point to the President's strategic use of drone strikes to manage the news cycle, particularly when media attention is most susceptible to being redirected.

By linking research strands from various fields, our analysis contributes to several disciplines. First, our novel finding of presidential approval's relation to drone strikes speaks to the long-standing literature in the political sciences that studies the political use of forces to divert the public attention away from domestic issues (Ostrom and Job, 1986; Meernik, 1994; Fordham, 2005). More recently, Amarasinghe (2022) shows that governments employ diversionary strategies, often manifesting as verbally aggressive foreign interactions. Our analysis demonstrates that such diversionary strategies go beyond verbal threats to translate into violent actions.

A nascent literature investigates the effectiveness of drone strikes for military or counter-terrorism purposes (Johnston and Sarbahi, 2016; Jaeger and Siddique, 2018; Rigterink, 2021). However, little is known about the strategic use of drones – as a new, popular, and relatively cheap technology – for political purposes. Since traditional military interventions tend to take time and resources, presidents are likely to adopt this strategy when unpopular. By contrast, drone technology allows for short-term, one-off interventions. Consequently, drone strikes are potentially more responsive to small changes in popularity.

Furthermore, we shed light on the strategic behavior of one particular actor: the U.S. President in the context of media bias. Our paper is closely related to Djourelova and Durante (2022), who find that the U.S. President tends to sign unpopular presidential executive orders on the eve of days when the news is dominated by other important stories. We show that the U.S. President can also strategically time popular drone strikes for political purposes. Interestingly, Lewandowsky et al. (2020) demonstrate how President Trump uses social media to divert traditional media from potentially harmful news. Marques-Pereira (2023) further shows that Trump's tweets are rapidly amplified to offline audiences by cable television networks, and that this coverage shifts the opinions of these networks' viewers. The alternative use of social media as a diversionary tactic by President Trump constitutes a possible explanation for the diverging results with those found under the Obama administrations.

Finally, we also contribute to an emerging literature assessing how news, through traditional or social media, mediate the propagation of violence around the world. It has been established that news affect political approval and voting behaviours (Adena et al., 2015; DellaVigna and Kaplan, 2007; Enikolopov et al., 2011; Zhuravskaya et al., 2020). Media in conflict-prone areas has also been found to play a key role in explaining organised violence (Armand et al., 2020; Manacorda and Tesei, 2020; Yanagizawa-Drott, 2014), coordinating protests (Gagliarducci et al., 2020; Enikolopov et al., 2020; Fergusson and Molina, 2021) and inter-group antagonism (Adena et al., 2015; DellaVigna et al., 2014). However, little is known on how news and the resulting political consequences in one country like the US may affect the propensity to use forces in conflict-prone areas on the other side of the world. The study by Durante and Zhuravskaya (2018) constitutes an exception documenting that Israeli attacks are more likely when US news media are dominated by predictable events. We also shed light on the strategic use of forces but for political purposes.

By providing –to the best of our knowledge– the first causal evidence on the strategic use of drone strikes, our study has wide ranging policy implications. Article 2(4) of the United Nations Charter prohibits *'the threat or use of force against the territorial integrity'* of another state. Since drone strikes are included in this definition, the US is required to and has frequently obtained permission to carry out strikes in countries such as Afghanistan or Pakistan. Our finding that at least part of the motivation for drone strikes is to further the President's political agenda is likely to feature in decisions regarding the approval of US drone strikes overseas.

Section 2. provides background. Section 3. delineates our identification strategies and presents our main results for the effect of US elections on drone strikes. We discuss the role of media in shaping the strategic use of drones in Section 4.. Section 5. concludes.

## 2. US drone strikes - Background and data

Drones – also known as unmanned aerial vehicles – are remotely operated aircrafts without human pilots on board. Military strikes using drones increased drastically under the Obama administration[3] and are expected to become the major means of warfare of the future (The Economist, 2023). Appendix A. provides a detailed history.

[3] https://www.thebureauinvestigates.com/stories/2017-01-17/obamas-covert-drone-war-in-numbers-ten-times-more-strikes-than-bush/ accessed Feb 2025.

## 2.1. Popularity of US drone strikes

Drone strikes are broadly popular with the US electorate, despite experts' criticism.[4] An overview by Kreps (2014) shows high support for drone strikes ranging from 83% for and 11% against (Washington Post and ABC News, 2012) to 48% for and 19% against (Economist/YouGov, 2013). A Pew poll (Pew Research Center, 2015) further reports that 58% of respondents approve of the US utilizing drone strikes to target extremists in nations such as Pakistan, Yemen, and Somalia. Republicans (74%) demonstrate greater support compared to independents (56%) and Democrats (52%). Still, drone strikes appear popular across the political spectrum. Drone strike are considerably more popular than piloted airstrikes (which we use as an identification check later on) with a survey by the Bulletin of the Atomic Scientists (2016) finding that respondents were on average twice as likely to support the former to the latter. The Center for a New American Security (CNAS, 2016), further reports that respondents preferred piloted to drone airstrikes only in 1 out of 10 scenarios. We confirm the popularity of drone strikes in section 4.4..

## 2.2. Rules for US drone strikes

The US President wields significant control over US drone strikes, as confirmed by Obama's statement that *"ultimately I'm responsible for the* [drone] *process"* (CNN, 2012).

**Presidential control over US drone strikes.** After the 9/11 attacks, US Congress passed the Authorization for Use of Military Force against Terrorists (AUMF) Act, expanding the President's military authority allowing the use of *"all necessary and appropriate force against those nations, organizations, or persons he determines planned, authorized, committed, or aided in the Sept. 11 attacks."* (Pub.L. 107-40, 115 Stat. 224, 2001). The AUMF grants the President the ability to target emerging adversaries without the customary approval from Congress (BBC News, 2017; Burns and Stravers, 2020) thus giving the

[4] Critics argue that the vaguely defined legal basis for the use of AUMF, the lack of accountability and possible civilian casualties lead an endless "forever-war." (Jaffer, 2016)

decision-making power over the drone program exclusively to the President. Since its introduction, the AUMF has been employed to rationalize strikes against targets, such as al-Qaeda in the Arabian Peninsula in Yemen or al-Shabaab in Somalia.

Whilst during the Obama administration, drone strikes required explicit White House approval (see Appendix B.), President Trump loosed drone strike guidelines delegating much of his authority to the military.[5] In March 2017, for instance, President Trump declared Somalia and parts of three provinces of Yemen areas of active hostility, thereby removing the requirement for White House approval.

**Military rules for carrying out drone strikes.** Confidential military documents leaked by Daniel Hale (The Intercept 2015) outline a two-stage authorization process. Joint Special Operations intelligence personnel (JSOC's Task Force 48-4) create a comprehensive profile of a targeted individual. This dossier moves up the chain of command to the operational Commander (Centcom for Afghanistan, Pakistan, and Yemen, and Africom for Somalia), the Chairman of the Joint Chiefs of Staff and the Secretary of Defense, finally reaching the President for approval. Once approved, US forces have a 60-day window to execute the strike. If this 60-day authorization expires without the strike being carried out, analysts must begin the time-consuming process of gathering intelligence from the beginning to build a new case. We use this 60-day window as a causality check in section 3.2.. The Drone Papers provide some suggestive evidence on the time frames involved for carrying out drone strikes in Afghanistan, where around 22 percent of strikes were carried out the same day as the authorization. The median and mean days for execution were 11 and 30, respectively.

**The role of the military.** The military is expected to focus on execution of drone strikes whilst remaining neutral and apolitical. For instance, the main military representative informing the President is the Chairman of the Joint Chiefs of Staff (CJCS) and their political affiliation is not publicly stated. The only two cases of political post-retirement stance have

[5] In active war zones, such as Afghanistan, the military has greater authority over the strikes. In Section 3.2., we assess the robustness of our main results by removing drone strikes in Afghanistan where the President has a softer decision-making power.

been the declared opposition to President Trump on domestic issues by General Martin Dempsey (2011-2015 CJCS) and General Mark Milley (2019-2023 CJCS). Moreover, the influential Centcom or Africom Commanders, who are in charge of operations in the Middle East and Africa, have remained apolitical with strong bipartisan support. See Appendix B. for more details.

## 2.3. Data

**Drone strikes.** Data on drone strikes are drawn from The Bureau of Investigative Journalism (TBIJ), which collects information on US strikes in Afghanistan, Pakistan, Somalia, and Yemen from military personnel, governments, intelligence officials, and credible academic and media sources. The data contain information on piloted and unpiloted strikes, casualties, including civilian casualties, and whether the US acknowledged the strike between 2002 and 2020. The TBIJ data have been used by previous work on drone strikes (e.g. Mahmood and Jetter, 2022). We complement these data with information from Airwars.[6] Using these data, we construct a weekly time series from 2009 to 2020.

**Presidential speeches and statements.** We collect official communications from the White House archives for President Obama and Trump using the *BeautifulSoup* web-scraping library. Our dataset includes transcripts of public statements, speeches and press briefings published on the White House's official website.[7]

**Televison.** We collect a comprehensive dataset of television transcripts covering nearly all programming aired between 2010 and 2020 from the three main US cable news channels: CNN, Fox News, and MSNBC from the Internet Archive's Television News Archive and include closed captioning text for each broadcast. We process the transcripts to identify mentions of 'drone strikes' as well as news segments referring to the US President. To assess tone, we apply standard natural language processing techniques (more details on Section

[6] We use this data to perform robustness checks for the Trump mandate but do not use it for the Obama years as it is incomplete during that period.

[7] See https://trumpwhitehouse.archives.gov/ and https://obamawhitehouse.archives.gov/.

Table 1: US Drone Strikes and Casualties 2009 to 2020

| | Strikes | Casualties | Civilians |
|---|---|---|---|
| **Afghanistan** | 315 | 2411 - 3176 | 52 - 166 |
| **Pakistan** | 381 | 2111 - 3440 | 257 - 637 |
| **Somalia** | 44 | 422 - 564 | 5 - 21 |
| **Yemen** | 249 | 1033 - 1487 | 102 - 191 |
| **Total** | **989** | **5977 - 8667** | **416 - 1015** |

**Notes:** The table reports the number of drone incidents, overall casualties, and civilian casualties by country from 2009 to 2020. Columns 2 and 3 report lower and upper estimates of casualties. Source: TBIJ

4.1.). This allows us to construct a weekly time series capturing both the salience and sentiment of television news coverage related to drone strikes and the President.

**Social media.** We collect Twitter (now *X*) posts (i.e. tweets) in English, containing the words 'drone strikes' between 2009 to 2020 using the *snscrape* (social networking services) web-scraping algorithms. Only a small percentage of tweets are geo-coded. To ensure that we are capturing only tweets from the US, we restrict our sample to tweets posted during daylight hours in the US and corresponding to nighttime hours in the target countries.

**Newspapers.** We collect news articles using the Factiva database covering drone strikes from the printed versions of The New York Times (NYT), USA Today (USAT), The Wall Street Journal (WSJ) and the New York Post (NYP) between 2009 and 2020.

**Aerial cloud cover.** We obtain daily aerial cloud cover and wind-speed data from Visual Crossing, that integrates observations from over 100,000 global weather stations with satellite and radar inputs.[8] Historical values are derived using weighted averages of nearby station readings. All data undergo systematic quality control procedures to correct anomalies and ensure reliability for empirical research.[9]

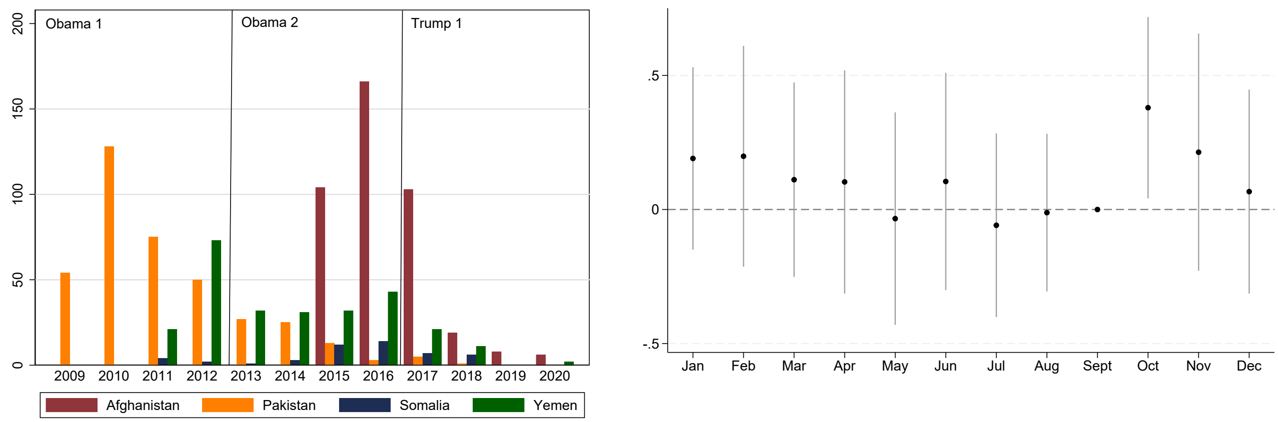
[8] https://www.visualcrossing.com/weather-api/

[9] https://www.visualcrossing.com/resources/documentation/weather-data/weather-data-sources-and-attribution/

Figure 1: Incidence of drone strikes

(a) Incidence of drone strikes

(b) Drone strikes (even vs odd years)




**Notes:** The figure reports the yearly number of drone incidents per country (panel a) from 2009 to 2020. Panel b reports the monthly differences in the frequency of drone strikes between even and odd years during Obama's presidency. Source: TBIJ.

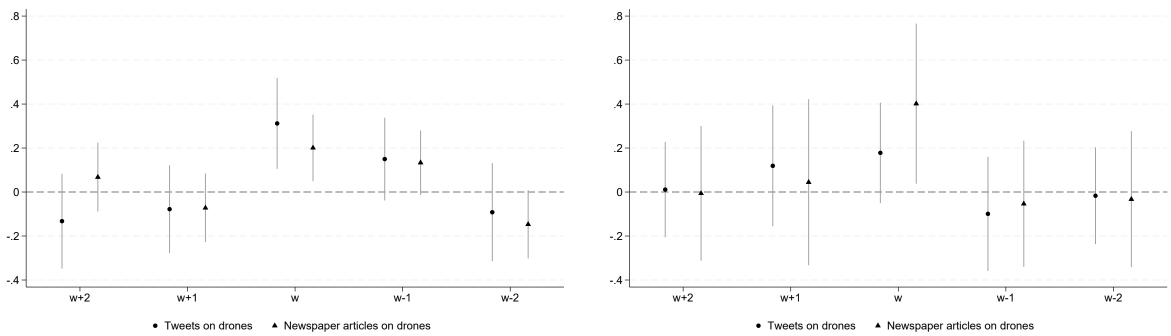
## 2.4. Descriptive evidence

**Prevalence of drone strikes.** Between 2009 and 2020, the TBIJ recorded 989 separate incidences of drone strikes in Afghanistan, Pakistan, Somalia, and Yemen (Table 1). The total fatalities from these strikes are estimated to be between 5,977 and 8,667 of which between 416 and 1,015 are thought to be civilians. Pakistan experienced the highest number of drone strikes with 381 incidents, resulting in 2,111 to 3,440 casualties (257 to 637 civilians). Afghanistan and Yemen followed with respectively 315 and 249 drone strikes. Appendix Table E.1 reports disaggregated statistics. Figure 1a) plots the temporal evolution of drone strikes by country. The number of drone strikes were particularly high under the Obama administrations, in particular during his second mandate. The temporal patterns suggest a shift from Pakistan to Afghanistan and to some extent, Somalia and Yemen.[10]

[10] Our estimates tally with evidence provided by the Financial Times https://www.ft.com/content/6346dd78-322d-11ea-9703-eea0cae3f0de, accessed in March 2025.

Figure 2: Drone strikes, tweets and news articles

(a) 2009 to 2016 (b) 2017 to 2020




**Notes:** The figure reports the coverage of drone strikes on Twitter and in four major newspapers for the years 2009 to 2016 (panel a) and 2017 to 2020 (panel b). Estimates are based on analogues of equation (1); point estimates are reported as shapes and 95% confidence intervals as vertical lines; standard errors are Newey-West standard errors with 4 lags. Dependent variables are log number of tweets containing the words 'drone strikes' and of newspaper articles on drone strikes. Key explanatory variable is a dummy = 1 if the US carried out at least one drone strike in year $t$ and week $w$ and its two lags and leads.

**Is the US public aware of drone strikes?** To gauge the public's awareness of drone strikes, we assess whether strikes are echoed in the media. We start by regressing the weekly log number of tweets in English published during hours of US daytime containing the words 'drone strikes' on an indicator variable taking the value 1 if the US carried out at least one drone strike that week (controlling for year and week fixed effects and including two weeks leads and lags).[11] Figure 2a) shows that in a week when the US carried out at least one drone strike, tweets discussing drones increase by more than 35 percent during the Obama administrations. Figure 2b) indicates a similar, albeit weaker, pattern for the Trump years. We replicate this exercise using the log number of weekly newspaper articles covering drone strikes in the New York Post, the New York Times, USA Today, and the Wall Street Journal and find similar results.[12]

[11] We follow standard practice (such as Jaeger and Siddique, 2018) and carry out a number of time series tests. We are able to reject the hypothesis of unit root for our main variables.

[12] Tables E.2 and E.3 provide more detailed results behind Figure 2. Table E.4 shows the robustness of these results to alternative US daytime definitions. Using Airwars data for the Trump years does not change our results (see Table E.5).

**Communication about drone strikes.** Drone strikes feature frequently in official communications from the White House, such as press briefings, presidential statements, and speeches, and President Obama's speech at the National Defense University in May 2013 discussing various aspects of drone strikes. Appendix Figure D.2 shows the temporal evolution of presidential statements to the press and not to the press. As discussed in Appendix B., President Obama is communicating more frequently and voluntarily (as shown by the contrast between Presidential statements and responses to the press) about drone strikes.[13]

**Drone strikes and elections.** Figure 1b) provides descriptive evidence suggesting that drone strike frequency increases before US elections. US presidential and mid-term elections are held in early November of even years. Figure 1b) displays differences in the probability of drone strikes between even and odd years for each month (with September as the base category). During the two Obama terms, the only month during which drone strikes are significantly more likely in even years is October, which coincides with the weeks leading up to elections.[14]

# 3. Drone strikes and the US electoral cycle

## 3.1. Empirical strategy

To investigate whether drone strikes are more likely to occur before US elections, we construct a weekly time series and estimate the following regression:

$$drone_{tw} = \alpha \ election_{tw} + \beta \mathbf{X}_{tw} + \tau_t + \omega_w + \epsilon_{tw} \tag{1}$$

[13] The spike in President Trump's statements 2018-19 is due to mentions of surveillance drones along the US/Mexico border and the rising tensions with Iran.

[14] To capture the week of elections, we recode the first week of November as October. When repeating the same exercise for Trump with both TBIJ and Airwars data, we find no significant differences. See Figures D.3 in Appendix D..

where $drone_{tw} = 1$ if at least one US drone strike occurred in Afghanistan, Pakistan, Somalia, and Yemen in week $w$ and year $t$ and $election_{tw} = 1$ in the five weeks before (and including) a presidential or mid-term election. In practice, $election_{tw} = 1$ for the entire October and the first week of November in election (even) years.

The vector $\mathbf{X}_{tw}$ consists of macroeconomic indicators including (monthly) unemployment, inflation, balance of payments, and oil price, which have been highlighted as important determinants of presidential popularity (Nannestad and Paldam, 1994; Lewis-Beck and Stegmaier, 2000, 2013). Including such economic variables allows us to control for global economic downturns which may suppress the US economy (thus decreasing popularity) and fuel terrorist activity in Afghanistan, Pakistan, Somalia, and Yemen (thus increasing the need for drone strikes). We also include five lags of the dependent variable and second third order polynomial time trends; $\tau_t$ and $\omega_w$ are year and week fixed effects.

The vector $\mathbf{X}_{tw}$ also includes the number of terrorist attacks in Afghanistan, Pakistan, Somalia, and Yemen in week $w$ and year $t$ and its five lags (drawn from the Global Terrorism Database). Controlling for terrorist activity in these four countries addresses the possibility that insurgents strategically time attacks to coincide with US elections; a possibility we address in more detail in section 3.2.. To account for serial correlation, we use Newey-West standard errors with up to 5 lags, corresponding to approximately the number of time periods raised to the power of 0.25, as recommended by Green (2003).[15]

**Identification.** We investigate the causal interpretation of our coefficients in several ways. Our two main identification checks exploit plausibly exogenous variation in drone strike feasibility resulting from anomalies in aerial cloud cover. We find that when abnormally cloudy skies impede the execution of drone strikes before elections, strikes are systematically postponed towards the end of the 60-day authorization window or redirected to other countries. These patterns do not hold outside the pre-election period, suggesting an elevated approval rate of drone strikes specifically in the run-up to elections. Further identification checks

[15] This is the number of lags when considering the overall period of interest 2009-2020. When focusing on either the Obama or Trump presidency, the recommended number of lags goes down to 4.

include: estimating how drone strikes evolve in the weeks after elections, when presidential popularity is less important, investigating whether terrorists strategically time their attacks to coincide with US elections, using unpopular piloted airstrikes and drone strikes unrecognized by the US in the same regions as placebo treatments, and carrying out balancing tests to check whether US elections are quasi-random with respect to current economic conditions.

## 3.2. Do US elections increase US drone strikes?

**Incidence of drone strikes.** Column (1) of Table 2 shows that between 2009 and 2020 the weekly incidence of drone strikes is 19.7 percentage points higher in the five weeks leading up to presidential or mid-term elections (compared to a mean of around 63 percent). Columns (2) and (3) further highlight that this effect is entirely driven by elections taking place during the Obama administrations with an increase of around 35 percentage points (and no effect during the Trump administration).[16] In line with previous work (Lewandowsky et al., 2020; Marques-Pereira, 2023), we show that President Trump's Twitter activity changes significantly before elections suggesting he uses social media to sway the electorate (see section 3.5.).

To interpret the magnitude of the pre-election increase in drone strikes, we compare it to US retaliations to its own casualties, highlighted as an important determinant of drone strikes by the US Ministry of Defense.[17] Using the Global Terrorism Database, we calculate the number of fatalities of US citizens from terrorist attacks in Afghanistan, Pakistan, Somalia, and Yemen in the three weeks prior to week $w$ and year $t$. Column (4) of Table 2 shows that the standardized effect of US elections is larger, yet comparable to the standardized effect of retaliations to US fatalities. In Appendix Table E.6, we test the robustness of our results by using different samples, different covariates, and by excluding drone strikes in Afghanistan.

To illustrate the temporal evolution of drone strikes on either side of US elections, we group

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[16] Using data from Airwars does not change the conclusion that we find no effect during the Trump administration.

[17] https://www.defense.gov/News/News-Stories/Article/Article/3665734/us-strikes-targets-in-iraq-and-syria-in-response-to-deadly-drone-attack/, accessed April 2025.

weeks into monthly intervals and re-estimate equation (1) as an event study, substituting these intervals for the dummy $election_{tw}$. The estimates reported in Figure 3a) show that during the Obama administration the probability of drone strikes increases in the month before elections (October and first week of November in even years, denoted as 'Election'). After elections (November, December, and January), when presidential popularity has very low payoffs, the probability of drone strikes reverts back to its long-run average. In Appendix Figure D.4a), we find a similar pattern using either weekly or bi-weekly dummies.

**Mentions of drone strikes in presidential speeches.** A strategic use of drone strikes is expected to go hand in hand with such strikes being publicized by the President. Column (5) of Table 2 provides evidence that drone strikes carried out before elections are more likely to feature in presidential speeches in the following week. We regress an indicator variable equal to one if the words 'drone strike' occur in at least one presidential speech in week $w$ on whether or not a drone strike occurred in the previous week. For most of the year, drone strikes are not discussed the week after they have been carried out (coefficient on *Drone strike* $(w-1)$). However, in the weeks leading up to elections, drone strikes are significantly more likely to be mentioned a week later in presidential speeches (coefficient on *Drone strike* $(w-1)$ $\times$ *Election*). Taken together, these results show that not only do drone strikes increase in the weeks leading up to elections, President Obama is also more likely to discuss these in the following week.

## 3.3. Causal identification

### 3.3..1 Postponement and redirection of drone strikes before elections

Our two main identification checks leverage plausibly exogenous variation in the feasibility of drone strikes resulting from aerial cloud cover anomalies together with military operational guidelines and cross-country variation in strike activity. We document that before US elections abnormally cloudy skies (which limit strike feasibility) significantly increase

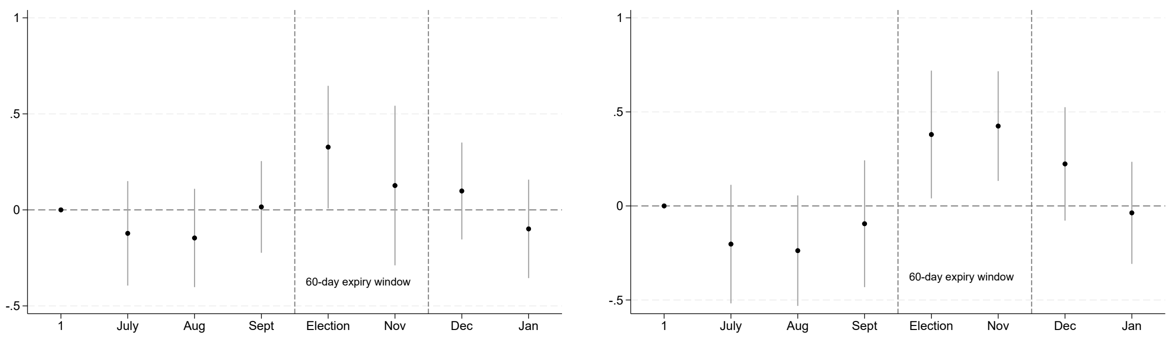
Table 2: Effect of US elections on US drone strikes

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Dependent variable** = 1 if | | | | |
| | Drone strike | Drone strike | Drone strike | Drone strike | Speech mention | Drone strike | Drone strike | Uncon-firmed | Air strike |
| **Mean:** | 0.625 | 0.760 | 0.354 | 0.760 | 0.083 | 0.760 | 0.760 | 0.288 | 0.190 |
| | **A:** Main results | | | | | **B:** Identification | | | |
| **Election** | 0.197 | 0.349 | 0.077 | 0.082 | -0.359 | 0.329 | 0.333 | -0.074 | -0.030 |
| | (0.093) | (0.131) | (0.117) | (0.029) | (0.177) | (0.202) | (0.136) | (0.122) | (0.140) |
| **US fatalities** | | | | 0.049 | | | | | |
| | | | | (0.036) | | | | | |
| **Drone strike (w-1)** | | | | | 0.001 | | | | |
| | | | | | (0.031) | | | | |
| **Drone strike (w-1) × Election** | | | | | 0.336 | | | | |
| | | | | | (0.164) | | | | |
| **Election × past cloud** | | | | | | 0.118 | | | |
| | | | | | | (0.193) | | | |
| **Post-election** | | | | | | -0.078 | | | |
| | | | | | | (0.269) | | | |
| **Post-election × past cloud** | | | | | | 0.586 | | | |
| | | | | | | (0.234) | | | |
| **Presidency** | Ob & Tr | Obama | Trump | Obama | Obama | Obama | Obama | Obama | Obama |
| **Observations** | 628 | 420 | 208 | 420 | 420 | 420 | 420 | 420 | 420 |
| **Covariates, $\tau_t$, $\omega_w$** | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| **z-scores** | | | | yes | | | | | |
| **Attacks (12 leads)** | | | | | | | yes | | |

**Notes:** The table reports effect of US elections on weekly incidence of US drone strikes 2009 to 2020. Estimates are OLS and based on equation (1). Dependent variable =1 if US carried out at least one drone strike in week $w$ and year $t$ in columns 1, 2, 3, 4, 6 and 7 and at least one piloted airstrike in column 9; in column 5 the dependent variable is the number of drone-related mentions in speeches and other official communication (excluding those to the press) made by the President in week $w$ and year $t$; in column 8 the dependent variable = 1 if US carried out at least one drone strike in week $w$ and year $t$ but it was not confirmed by the US. *Election=1* during the week of a US presidential or mid-term election and the 4 weeks before; *US fatalities* is z-score of US fatalities from terrorist attacks in four target countries in the past three weeks; *Post-election=1* during the four weeks following US presidential or mid-term elections; Covariates are unemployment, inflation, balance of payments and oil price, 5 lags of drone strikes, 5 lags of terrorist attacks and second and third polynomial time trends; column 7 also controls for 12 leads of terrorist activity in target countries; $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors (with 5 lags for column 1 and 4 lags for columns 2-9 ) reported in parentheses.

Figure 3: Timing of US drone strikes around US elections

(a) Whole sample (b) When cloudy




**Notes:** The figure reports event study for drone strikes three months before and after US presidential or mid-term elections during the Obama administration; *Election*=1 in week of election and in the previous month (October); *Jul*=1, *Aug*=1, and *Sept*=1 in July, August, and September before US presidential or mid-term elections, respectively, *Nov*=1, *Dec*=1, and *Jan*=1 in November, December, and January after US presidential or mid-term elections, respectively. Same notes as Table 2 apply. Circles denote point estimates and vertical lines 95% confidence intervals. Panel a: selects whole sample. panel b: selects only years when cloud anomalies 8 weeks before week $w$ were above the median.

the likelihood that drone strikes are either postponed towards the end of the operational window set by military guidelines or redirected to other target countries. We do not observe these patterns during the remainder of the year, consistent with an elevated rate of strike approvals in pre-election periods.

**Importance of aerial cloud cover for drone strikes.** Drone strikes are susceptible to weather fluctuations (Glade, 2000; DeGarmo, 2004; Fowler, 2014) and aerial cloud cover makes it particularly hard to carry out strikes (Saeed and Spagat, 2021).[18] We confirm this negative relation by regressing drone strikes in Afghanistan, Pakistan, Somalia, and Yemen on various measures for cloud anomalies (in the same countries). Our results show strong negative effects throughout – see Appendix Table E.7.[19] Further, to test the exogeneity of

[18] According to the Air Force doctrine publication 3-59 on weather operations, persistent heavy cloud cover can hamper intelligence collection effort, possibly creating major changes to a campaign plan. See https://www.doctrine.af.mil/Doctrine-Publications/AFDP-3-59-Weather-Ops/. According to the US Government Accountability Office, cloud cover impacts the take off and landing of Predator B drones. In the context of the Predator B operations for border control, adverse weather, including cloud cover and storms, contributed to 20% of mission cancellations from 2013 to 2016.

[19] We define cloud cover anomalies as follows: for each week of the year (1 to 52) we calculate the mean cloud cover and subtract it from realized cloud cover in ever year in that week. Note that since we include week fixed effects, this average is subtracted mechanically.

cloud cover anomalies we show that these are unrelated to macroeconomic variables such as US unemployment, CPI, balance of payments, and the oil price – see Appendix Table E.8. Following Mahmood and Jetter (2022), we also estimate the effect of wind speed and find similar results, albeit less precisely estimated. The most likely reason for this slight difference in results to Mahmood and Jetter (2022) is that we consider a distinct set of countries and a time period that only partially overlaps.

**Postponement of drone strikes after abnormally cloudy skies.** For our first major identification check, we combine the random variation in drone strike feasibility resulting from aerial cloud cover anomalies outlined above with confidential military guidelines stipulating that presidential drone strike authorization expires after 60 days (see Section 2.). As a result of these rules, any strike that cannot be carried out immediately after approval can be postponed but never by more than 60 days.

This 60-day approval window generates the following prediction for the timing of drone strikes before and after elections. If a disproportionately high number of strikes are approved in October ahead of US elections, abnormally cloudy skies during this period will lead to a postponement of strikes towards late November, coinciding with the expiry of the 60-day authorization window. After expiry in early December, by contrast, drone strike activity will revert back to its long-term average. Appendix Figure D.5 provides a graphical illustration of the postponement mechanism.

To test the postponement of strikes empirically, we estimate whether cloud cover anomalies before elections (i.e. in October) increase drone strikes in November after elections. To this end, we define a dummy *past cloud* $= 1$ if cloud cover anomalies 8 weeks in the past were above the sample median. Under normal circumstances, abnormally high cloud cover two months in the past (i.e. in week $w-8$) should be unrelated to drone strikes in week $w$. However, if the President approved an exceptionally high number of drone strikes in October before elections (i.e. week $w-8$), the postponement mechanism outlined above implies that abnormally high cloud cover will increase drone strikes in November (towards the end of the 60-day window in week $w$). This increase should be followed by reversion to the long-run mean, after expiry of authorization. Appendix Figure D.6 provides a graphical illustration of how we use past cloud cover to detect the postponement mechanism.

Column (6) of Table 2 illustrates how abnormally cloudy skies before elections cause a postponement in drone strikes. Interacting the dummy *past cloud* with an indicator for the four weeks after elections shows that cloudy skies before elections increase drone strikes after elections (coefficient on *Post election* × *past cloud*). By contrast, when the weeks leading up to elections are not cloudy, drone strikes revert back to their long-run average in November (coefficient on *Post election*). As mentioned above, under normal circumstances past cloud cover should not matter for drone strikes. We investigate this by interacting the *past cloud* dummy with our election indicator and find no effect. We replicate the same exercise in a more temporally disaggregated form in panel b) of Figure 3 and find the same pattern. Appendix Figure D.7 reports the same event study in bi-weekly intervals. This temporally disaggregated event study highlights the drop after expiry of presidential authorization. Appendix Table E.9 contains variations of this estimation where we vary the thresholds and time span of cloud anomalies. The results remain robust.

**Cross-country re-routing of drone strikes before elections** Exploiting cross-country variation, we show that—before elections—adverse flight conditions in one target country lead to drone strikes being redirected to the other three. This finding points to a deliberate effort to ensure drone strikes are carried out in the run-up to elections irrespective of their geographical location.

As preliminary evidence, we regress an indicator for drone strikes in country $i$ on an indicator for at least one drone strike being carried out in the other three countries (in the same week). Column (1) of Table 3 shows that drone strikes in country $i$ are significantly higher in weeks when no drone strikes are carried out in the other three countries. This finding is possibly explained by the US military only having limited capacity and thus focusing its resources on one country per week. However, column (2) shows that the re-routing of drone strikes highlighted in column (1) is significantly stronger in weeks leading up to elections, pointing towards an effort to increase drone strikes anywhere before elections.

Table 3: Cross-country substitution of drone strikes

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Dependent variable:** | = 1 if at least one drone strike in country | | | | | |
| | $i$ | $i$ | $i$ | $\neq i$ | $i$ | $i$ |
| **Mean:** | 0.255 | 0.255 | 0.255 | 0.629 | 0.255 | 0.255 |
| **No drone in other 3 countries** | 0.076 | 0.068 | | | | |
| | (0.021) | (0.022) | | | | |
| **No drone in other × Election** | | 0.224 | | | | |
| | | (0.094) | | | | |
| **Cloudy in $i$ (z-score)** | | | -0.051 | | -0.051 | -0.049 |
| | | | (0.019) | | (0.019) | (0.019) |
| **Cloudy in $\neq i$ (z-score)** | | | | -0.066 | -0.004 | -0.011 |
| | | | | (0.021) | (0.019) | (0.019) |
| **Cloudy in $\neq i$ × Election** | | | | | | 0.185 |
| | | | | | | (0.066) |
| **Country, year, week** | yes | yes | yes | yes | yes | yes |
| **Obama & Trump** | yes | yes | yes | yes | yes | yes |
| **Observations** | 1,680 | 1,680 | 1,680 | 1,680 | 1,680 | 1,680 |
| $R^2$ | 0.384 | 0.387 | 0.382 | 0.269 | 0.382 | 0.384 |

**Notes:** The table reports US drone strikes across Afghanistan, Pakistan, Somalia, and Yemen during Obama administration (2009-2016). Estimates are OLS. Dependent variable =1 if US carried out at least one drone strike in week $w$ and year $t$ and country $i$ in columns 1, 2, 3, 5, and 6; Dependent variable =1 if US carried out at least one drone strike in week $w$ and year $t$ and in a country that is not $i$ in column 4; *No drone in other 3 countries*=1 if the US did not carry out a drone strike in 3 countries other than country $i$; *Election*=1 if presidential or mid-term election is held within the next 4 weeks; *Cloud anomalies in i (z-score)* denotes the z-score of cloud anomalies in year $t$, week $w$, and country $i$, *Cloud anomalies in $\neq$ i (z-score)* denotes the z-score of median cloud anomalies in year $t$, week $w$, and the 3 countries excluding country $i$, Bootstrapped standard errors with 400 replications are reported in parentheses.

For causality, we exploit random variation in the viability of drone strikes resulting from cloud anomalies across the four target countries and show that –before elections– abnormally cloudy skies in one country increase drone strikes in the other three. Column (3) of Table 3 shows that cloud anomalies being above the median in country $i$ decreases drone strikes in the same country by 5.1 percentage points. These estimates are the panel data equivalent of the ones presented in Appendix Table E.7. Similarly, above median cloud anomalies in the three other countries decrease drone strikes in these three other countries by 6.6 percentage points (column 4). As expected, column (5) shows that drone strikes in country $i$ remain unaffected by cloud anomalies in the three countries excluding country $i$.

Our key finding in column (6) shows that –before US elections– cloud anomalies in the three other countries *increase* drone strikes in country $i$ by a statistically significant 18.5 percentage points. This finding implies that in weeks leading up to US elections cloudy skies in three countries (Afghanistan, Pakistan and Somalia, for instance) significantly increase drone strikes in the remaining target country (Yemen in this example). For the remainder of the year, by contrast, there is no effect.

#### 3.3..2 Additional identification checks

**Do terrorists time their attacks to coincide with US pre-elections periods?** A possible concern is that terrorist groups in Afghanistan, Pakistan, Somalia, and Yemen strategically change their activities to coincide with US elections. To address this concern, we re-estimate equation (1) including 12 leads of terrorist attacks in the four target countries. Any anticipation effect by terrorists will be picked up by these leads. As column (7) of Table 2 shows, the results remain stable.

**Exogeneity of election dates.** In contrast to many other countries, the US government has no power to change the date of elections. Since 1845, "the Electors [...] shall be appointed in each state on the Tuesday next after the first Monday in the month of November of the year in which they are to be appointed." (U.S. Congress, 1845). In other words, the period leading up to the elections comprises the month of October and the first week of November in *even* years. This rule was set in the US more than 150 years ago and is thus plausibly unrelated to current terrorism in Eastern Africa and the Middle East. We test this assumption using standard balancing tests by re-estimating equation (1) using economic indicators (monthly unemployment, inflation, oil price, and balance of payments) as dependent variables.[20] Appendix Table E.8 shows that in the month before and during elections, macroeconomic variables are not significantly different to the rest of the year.

**Unconfirmed drone and piloted airstrikes as placebo treatments.** To further rule out any spurious correlations between elections and drone strikes, we carry out two placebo checks. First, we isolate drone strikes that have not been confirmed by a US source in column (8) of Table 2. Since these strikes have only been confirmed by local sources, we use them as proxies for covert strikes, which are strikes the US does not want to be associated with. As expected, US elections have no effect on these types of strike. Second, we estimate the effect of US elections on US *piloted* airstrikes in the same four countries. Both drone and piloted airstrikes are plausibly determined by similar military or strategic considerations. Crucially, however, the latter are not popular with the US electorate (see Section 2. for details on the low popularity of piloted airstrikes). Accordingly, column (9) of Table 2 shows no effect of US elections on piloted airstrikes.

## 3.4. Are strategic drone strikes different?

The strike patterns we find suggest no evidence of intertemporal substitution of drone strikes. Moreover, drone strikes before elections are, on average, carried out in a way that minimizes expected civilian casualties.

**Inter-temporal substitution of drone strikes?** One possible mechanism behind the increase in drone strikes before elections is that strikes scheduled later in the year are antici-

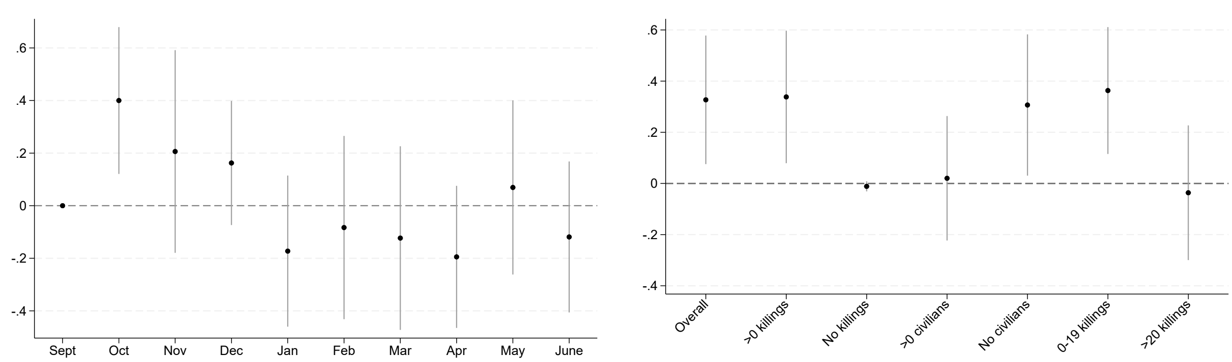
[20] Since these variables are reported at a monthly frequency, we collapse the data at the year-month level.

pated. We find no evidence for this inter-temporal substitution. To that end, we re-estimate an event study with a longer time horizon. Figure 4a) shows the usual increase in drone strikes before elections. In the months following an election (i.e. February, March, and April of the following year), the probability of drone strikes reverts back to the long run average. This finding –rather than that of drone strikes decreasing after elections– suggests that inter-temporal substitution is not the reason behind the increase in drone strikes.

**Characteristics of drone strikes.** We find that US elections increase one particular type of drone strikes. In Figure 4b), we re-estimate equation (1) for different types of drone strikes. The figure shows that elections do not increase drone strikes leading to civilian casualties. Given that civilian deaths are unpopular with the US electorate (Ron et al., 2019; Pew Research Center, 2015), one possible explanation is that the military aims to minimize these before elections. This is consistent with the last two estimates, which show that drone strikes with a low casualty count increase significantly before elections. Larger strikes, which are more likely to hurt civilians, by contrast, remain unchanged before elections.

Figure 4: Strategic drone strikes

(a) Intertemporal substitution of drone strikes (b) Elections and drone strikes - by type




**Notes:** Panel a reports event study for drone strikes before and after US presidential or mid-term elections during the Obama administration. Same notes as Table 2 apply. Panel b reports the effect of election on different types of drone strikes. Estimates are based on analogues of equation (1). Circles denote point estimates and vertical lines 95% confidence intervals. Covariates are unemployment, inflation, balance of payments and oil price, 5 lags of drone strikes, 5 lags of terrorist attacks and second and third polynomial time trends. Source: TBIJ

## 3.5. President Trump's social media use before elections

The lack of a significant increase in drone strikes in the weeks leading up to US elections under President Trump (column (3) of Table 2) is in line with his delegation of authority to the military. In this section, we show that President Trump instead changed his social media activity significantly before elections. Together with the finding that drone strikes did not change before elections during the Trump presidency, this finding suggests that Presidents Obama and Trump employed distinct strategies to influence electoral outcomes. The finding that President Trump focuses on social media use is in line with previous studies (Lewandowsky et al., 2020; Marques-Pereira, 2023).

Table 4: Strategies employed by President Trump

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | **Dependent variable** | | | |
| | =1 if drone strike | log nr of tweets | neg. VADER senti. | pos. VADER senti. |
| **Election** | 0.077 | 0.302 | -0.634 | 0.063 |
| | (0.117) | (0.135) | (0.319) | (0.285) |
| **Years** | 2017-20 | 2016-20 | 2016-20 | 2016-20 |
| **Covariates, $\tau_t$, $\omega_w$** | yes | yes | yes | yes |
| **Observations** | 208 | 261 | 261 | 261 |

**Notes:** Table reports effect of US elections on drone strikes and tweets by President Trump. Estimates are OLS and based on equation (1). Dependent variable =1 if US carried out at least one drone strike in week $w$ and year $t$ in column 1, the log number of tweets in column 2, the z-score of the negative VADER sentiment of tweets in column 3, and the z-score of the positive VADER sentiment of tweets in column 4, *Election=1* during the week of a US presidential or mid-term election and the 4 weeks before; covariates are unemployment, inflation, balance of payments and oil price, 5 lags of drone strikes, 5 lags of terrorist attacks and second and third polynomial time trends; columns 2, 3, and 4 also control for the lag of log number of tweets, negative, and positive VADER sentiment scores; $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors (with 4 lags) reported in parentheses.

To document changes in President Trump's social media activity, we leverage a comprehensive dataset of all tweets posted from his personal account, @realDonaldTrump, before and during his first presidency. The data, collected by the Trump Twitter Archive (Trump Twitter Archive, Link), comprises 26,237 tweets, including 9,655 retweets and 1,094 posts that were later deleted either by Trump or by Twitter. For each tweet, we observe the timestamp, text, and engagement metrics such as retweets and likes. This dataset enables a granular analysis of both the volume and tone of Trump's social media presence over time.

Estimating equation (1) using the log number of social media posts on Twitter as dependent variable, we find an increase of around 30 percent in the five weeks leading up to elections – see column (2) of Table 4.[21] Appendix Figure D.8a) shows the distribution of weekly number of social media posts by Trump before elections (in blue) and for the remainder of the year (in red). The figure confirms the higher number of social media posts before elections. Both of these pieces of evidence stand in contrast with column (1), which replicates the effect of elections on drone strikes during the Trump Presidency.

We also investigate whether the tone of Trump's social media posts changes before elections. To this end, we analyze the content of Trump's social media posts using the Valence Aware Dictionary and sEntiment Reasoner (VADER) rule-based sentiment analysis tool. VADER is designed to detect sentiment in social media text and uses a lexicon of words with associated sentiment scores and heuristics that account for punctuation, capitalization, degree modifiers, and negations to produce scores indicating sentiment of social media posts.

Column (3) of Table 4 shows that social media posts are significantly less negative before US presidential or mid-term elections compared to the remainder of the year. The parameter estimates indicate that before elections social media posts are 0.6 of a standard deviation less negative. Positive tone, by contrast, does not change – see column (4). The distributions for the z-score of negative VADER sentiment reported in Appendix Figure D.8b) confirm this by showing a leftward shift in the negative distribution.

[21] We include the year 2016 in these estimates since Trump was running for office and because, in contrast to drone strikes, social media use is not conditional on being President.

# 4. Drone strikes and US Media

An important aspect of the Diversionary Theory of War is that political leaders use conflict as a means of diverting attention away from negative news. This section examines whether the timing of drone strikes correlates with negative television tone toward the President.

## 4.1. Data and summary statistics

We use a comprehensive dataset of television transcripts from CNN, Fox News, and MSNBC, covering nearly all shows aired between January 2010 and December 2020.[22] This dataset is provided by the TV News Archive (Link). From these transcripts, we construct two key variables: volume and tone of media coverage.

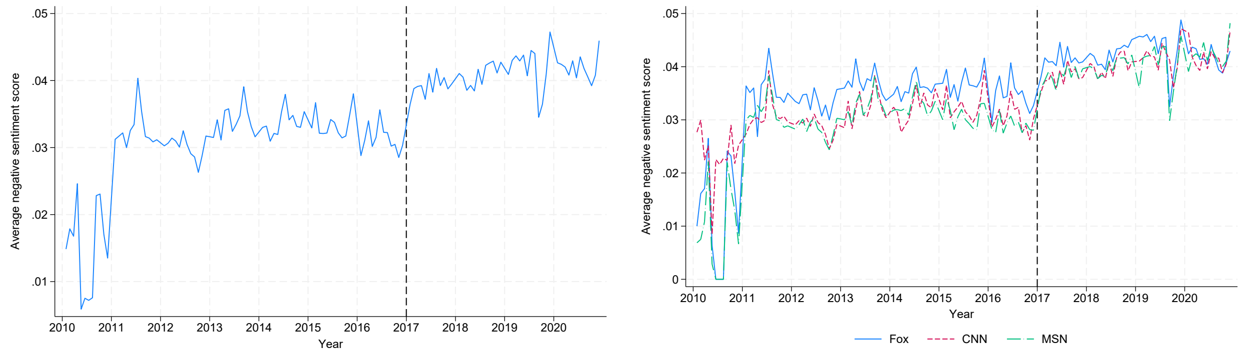
The volume measure captures topic salience, defined as the daily count of specific keywords (e.g., "Trump", "Obama") across all shows. Our tone measure quantifies the sentiment surrounding mentions of the President, with a focus on negativity. For each mention of "Obama" or "Trump," we extract nearby words and assign scores using the valence norms from Warriner et al. (2013), a widely used dictionary of affective ratings. This lexicon is designed for general-purpose text and better suits broadcast content than social-media-specific tools such as VADER (Hutto and Gilbert, 2014). We focus on negatively valenced words within a fixed word neighborhood of each mention, applying minimal text preprocessing and a "hard" dictionary matching. Details on the construction, alternative specifications, and validation checks of this measure are provided in Appendix C.2..

Figure 5a) reports our negative sentiment score over time, averaged at a monthly frequency to enhance clarity. Whilst 2010 exhibits some measurement error, values stabilize from 2011 onward at approximately 0.032. At the beginning of the Trump presidency (indicated by the

[22] Although transcripts are available from mid-2009 onward, primetime broadcasts only start to be consistently covered from 2010 onward. Full coverage across all three networks begins at the end of 2011 or at the start of 2012. Figure C.1 shows network coverage over time; Table C.1 reports average yearly coverage by time of day and network. From the end of 2011 onward, we capture transcripts for approximately 90% of all broadcasts.

Figure 5: Negative sentiment score over time

(a) All network (b) By network




**Notes:** Figure reports monthly average negative sentiment score from 2010 to 2020. Higher values denote more negative tone. The vertical dashed line indicates the start of the Trump presidency.

vertical line), negativity increases sharply to around 0.041—a rise of roughly 23%. Figure 5b) breaks down sentiment by network. Although Fox News anchors are consistently the most negative, the increase in our negative sentiment score at the start of the Trump presidency is least pronounced for Fox News and most stark for MSNBC. This fits with the political orientation of the two networks on the right and left of the political spectrum, respectively (Martin and Yurukoglu, 2017; Kim et al., 2022). Fox News sentiment increased from 0.036 in the second Obama term to 0.042 in the first Trump term. For MSNBC, the respective figures are 0.031 and 0.040. In absolute terms, MSNBC's increase (0.009) is approximately 50% larger than that of Fox News (0.006).

## 4.2. Media coverage of drone strikes

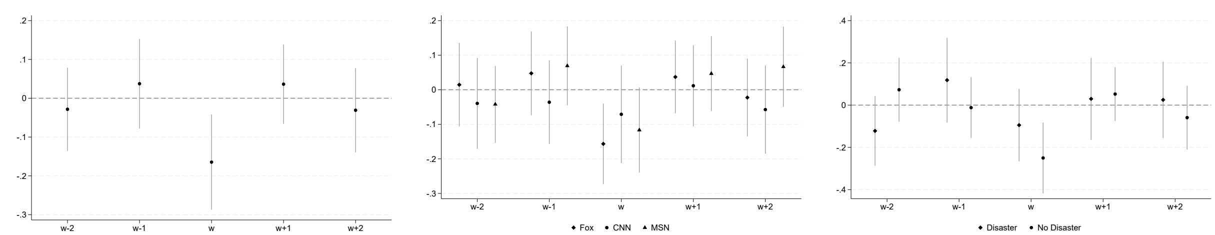
We first investigate whether cable news outlets report on drone strikes. Without such coverage, drone operations would fail as tools for diverting public attention.

Causal interpretation is challenging due to reverse causality: drone strikes might be ordered in response to negative media coverage, which could simultaneously reduce strike coverage due to congested news cycles. A simple regression of drone coverage on strike incidence might therefore obscure meaningful relationships. To address this challenge, we leverage aerial cloud cover anomalies in drone-targeted countries as an exogenous shifter for drone strikes that is unrelated to US news dynamics (see Section 3.3..1 for details). If weather-driven variation in drone activity predicts news coverage variation, we can infer that media responds to drone strikes, supporting the strategic diversion hypothesis.

We implement an event-study specification to track how drone strike coverage in cable news evolves before and after cloud cover anomalies in target regions. This approach also tests for pre-trends – assessing whether coverage increases only during or after favorable strike conditions emerge.

Figure 6: Drone strike coverage in television

(a) All networks (b) By network (c) All networks - by disaster




**Notes:** The figure reports effect of cloud anomalies in Afghanistan, Pakistan, Somalia, and Yemen on log number of drone mentions in cable TV. Circles, squares, and diamonds report parameter estimates from regression of log mentions of drones on two week leads and lags of the z-score of cloud anomalies. Vertical lines denote 95% confidence intervals based on Newey-West standard errors with 4 weeks lag. Covariates are unemployment, inflation, balance of payments and oil price, 5 lags of drone strikes, 5 lags of terrorist attacks and second and third polynomial time trends. Panel a: dependent variable is log mentions of drones in all three cable TV networks aggregated (Fox News, CNN, and MSNBC). Panel b: three dependent variables are log mentions of drones in Fox News, CNN, and MSNBC. Panel c: distinguishes weeks during which a natural or industrial disaster occurred in the US (diamonds) to weeks in which it did not (circles).

Our findings show that drone strike coverage on cable news significantly decreases in weeks with unusually high cloud cover in drone-targeted countries. As shown in Panel a) of Figure 6, a one standard deviation increase in cloud anomalies in Afghanistan, Pakistan, Somalia, and Yemen reduces drone mentions by nearly 20 percent in the same week. Importantly, we detect no comparable shifts in the weeks before or after these anomalies, strengthening our interpretation that the effect is exclusively driven by the timing of drone strikes rather than broader news dynamics. Panel b) of Figure 6 breaks down this effect by network. The coverage decline concentrates on Fox News and to some extent, MSNBC – the two outlets furthest from the political center (Martin and Yurukoglu, 2017; Kim et al., 2022). This aligns with polls showing partisan differences in support for drone use (Pew Research Center, 2015). CNN devotes less attention to drone strikes, suggesting that drone coverage becomes more salient in ideologically polarized media environments.

### 4.3. Drone strikes and shifts in media sentiment

Consistent with the qualitative evidence presented in Section 2.1., we show that drone strikes improve media sentiment towards the President. A simple regression of sentiment on past drone strikes would likely be biased: if the President deploys drone strikes in response to negative media coverage, such regressions would confound the effect of strikes with the persistence of prior negativity or heightened editorial focus.

To address this, we use cloud cover anomalies in countries targeted by drone strikes (Afghanistan, Pakistan, Somalia, and Yemen) as plausibly exogenous constraints on strike feasibility. We focus on the week after anomalies occur: if drone strikes are less likely during abnormally cloudy weeks, and if strikes improve sentiment, then sentiment should be less positive than expected the week after an unusually cloudy week. To capture deviations from expected news sentiment, we predict news sentiment in week $w$ using its ten lags and subtract this prediction from observed news sentiment.[23] This difference captures the deviation in news sentiment from its trend (as predicted by the past 10 weeks).

Column (1) of Table 5 shows that in weeks after cloud cover anomalies increase by one standard deviation news sentiment is around 0.12 of a standard deviation more negative than expected based on past trends. Columns (2) to (4) further indicate that this effect holds across all three cable networks.

One possible concern with this strategy is that if the President intends to use strikes in response to negative coverage, then a cloudy week may simply delay – rather than cancel

[23] We also control for the log number of mentions of the US President in week $w$ to account for the focus of the media on the president.

– a strategically timed strike. In such cases, any observed relationship between past cloud anomalies and current sentiment could simply reflect the underlying temporal persistence of earlier negative sentiment. To address this concern, we interact past cloud anomalies with the one week lag of the sentiment score. This interaction term allows us to distinguish between periods of negative sentiment that were already unfolding and those in which the absence of drone strikes independently contributed to continued negative sentiment.

Table 5: Positive effect of lagged cloud anomalies on presidential popularity

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Dependent variable** | Negative news sentiment minus linear prediction (z-score) | | | | | | | |
| **Network** | All | Fox | CNN | MSN | All | Fox | CNN | MSN |
| **Cloud anomalies** | 0.117 | 0.093 | 0.081 | 0.089 | 0.089 | 0.078 | 0.106 | 0.041 |
| **in week $w-1$** | (0.048) | (0.041) | (0.043) | (0.043) | (0.042) | (0.038) | (0.054) | (0.041) |
| **Cloud ano (w-1)** | | | | | -0.026 | -0.036 | -0.080 | 0.011 |
| **× lag senti** | | | | | (0.045) | (0.046) | (0.059) | (0.048) |
| **Covariates, $\tau_t$, $\omega_w$** | yes | yes | yes | yes | yes | yes | yes | yes |
| **Observations** | 575 | 575 | 575 | 575 | 575 | 575 | 575 | 575 |

**Notes:** Table reports effect of lagged cloud anomalies on the difference between observed and predicted negative news sentiment score. Estimates are OLS and based on equation (1). Dependent variable is the z-score of observed negative news sentiment minus its linear prediction (derived from its five lags). *Cloud anomalies in week $w-1$* is the z-score of the lag of aerial cloud cover anomalies for Afghanistan, Pakistan, Somalia, and Yemen, *Cloud ano (w-1) × lag senti* is the z-score of the lag of aerial cloud cover anomalies times the lag of the sentiment score. Covariates are unemployment, inflation, balance of payments and oil price, 5 lags of drone strikes, 5 lags of terrorist attacks, lagged dependent variable, log mentions of president in week $w$, and second and third polynomial time trends; estimates are reported for the years 2010 to 2020; $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors (with 5 lags) reported in parentheses.

In columns (5) through (8) of Table 5 we include an interaction between lagged cloud anomalies and lagged sentiment, which allows us to test whether the effect of strike delays depends on the prior state of media sentiment. Across multiple networks, we find that lagged cloud anomalies are positively associated with residual negativity in news sentiment, supporting the hypothesis that drone strikes improve media tone—and that their absence, when exogenously constrained, worsens it.

## 4.4. Presidential news coverage and drone strikes

Consistent with the US President using drone strikes to divert media attention away from damaging news, we find that drone strikes are significantly more likely when media coverage of the US President is negative. Table 6 shows that a one-standard deviation increase in weekly negative tone is associated with a 9.6 percentage point increase in drone strikes in targeted countries (column 1 of panel A). This correlation remains robust across different networks (columns 2–4). The relation also persists when weighting sentiment by volume of presidential mentions, allowing weeks with greater media focus to have greater impact (columns 5–8). In line with the findings in Figure 6b), Fox News and MSNBC show the strongest relation to drone strikes.

The mechanism we investigate implies that drone strikes are different to other types of conflict in as far as their political costs are low. Thus, to rule out any spurious correlations between media coverage and drone strikes, we carry out two placebo checks by estimating the relation between negative media coverage and unrecognized drone strikes and piloted airstrikes. In Panels B and C of Table 6, we regress piloted airstrikes and unconfirmed drone strikes on negative sentiment. The estimates reveal no statistically significant relation to drone strikes for these alternative military actions. This reinforces our argument that drone strikes – due to their relatively low political cost and high domestic acceptability compared to piloted operations – may be uniquely deployed for diversionary purposes.

Next, we investigate whether this effect varies during politically sensitive periods by interacting negative tone with an indicator for the five weeks leading up to US Presidential or Mid-term elections. Results in Appendix Table E.10 demonstrate that the tone–strike link persists even outside electoral periods. A one standard deviation increase in negative coverage is still associated with around a 9 percentage point increase in drone strikes (column 1). This suggests a routinized form of media management extending beyond moments of heightened political scrutiny, which carries significant policy implications.

**News pressure weakens the relationship between sentiment and drone strikes.** Crucially, we provide evidence that news pressure attenuates the relationship between negative presidential coverage and drone strikes. We define news pressure as the saturation of media cycles by high-salience, exogenous events—such as natural or industrial disasters—that reduce available bandwidth for other stories. We follow Eisensee and Strömberg (2007) by testing whether the effect of negative coverage weakens during periods with natural or industrial disasters in the US (using these as instruments for news pressure). Panel (c) of Figure 6 corroborates our use of natural / industrial disasters as proxies for news pressure – cable news coverage of drone strikes only responds to cloud anomalies in weeks without major disasters. In other words, when disasters saturate the news cycle, the media does not respond to an exogenous shift in drone strike activity, likely due to competing coverage priorities.

Panel D of Table 6 estimates the relation between negative coverage and drone strikes separately for weeks during which a natural or industrial disaster occurred in the US and for weeks when this was not the case. The results show that the predictive effect of negative presidential coverage on drone strikes vanishes during weeks of elevated news pressure—in the context of this exercise, periods when a disaster took place. This finding further supports our diversionary hypothesis: drone strikes are used as reactions to negative presidential coverage only when media bandwidth allows these to efficiently redirect media attention away from unfavorable coverage.

**Alternative sentiment scores.** Our results are robust to different ways of constructing our negative sentiment score. Column (1) in Panel A of Table 6 uses a sentiment measure that leverages pre-processed text extensively, 12 words before and after an "Obama" mention, "hard" matches words to our sentiment dictionaries, and employs valence (scaled) to weight words. In Appendix Table E.11, we vary these four components of our sentiment score (see Appendix C.2. for details on each of these dimensions). Column (2) uses "soft" matching, columns (3), (4), and (5) use word neighborhoods with a radius of 3, 6, and 24 words respectively, column (6) does not use pre-processed text, column (7) weights words by valence

Table 6: News sentiment and drone strikes

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | **Panel A:** Dependent variable = 1 if drone strike | | | | | | | |
| **Negative Sentiment** | 0.096 | 0.086 | 0.046 | 0.093 | 0.116 | 0.093 | 0.071 | 0.099 |
| | (0.034) | (0.034) | (0.024) | (0.042) | (0.039) | (0.037) | (0.032) | (0.043) |
| | **Panel B:** Dependent variable = 1 if manned airstrike | | | | | | | |
| **Negative Sentiment** | -0.042 | -0.041 | -0.021 | -0.038 | -0.025 | -0.017 | -0.020 | -0.012 |
| | (0.035) | (0.035) | (0.021) | (0.034) | (0.038) | (0.036) | (0.028) | (0.037) |
| | **Panel C:** Dependent variable = 1 if unconfirmed drone strike | | | | | | | |
| **Negative Sentiment** | 0.024 | 0.019 | 0.026 | 0.002 | 0.014 | 0.005 | 0.028 | -0.010 |
| | (0.030) | (0.028) | (0.018) | (0.035) | (0.035) | (0.029) | (0.028) | (0.037) |
| | **Panel D:** Dependent variable = 1 if drone strike | | | | | | | |
| **Negative Sentiment** | 0.029 | 0.025 | 0.011 | 0.008 | 0.064 | 0.052 | 0.034 | 0.036 |
| **(Disaster in week $w$)** | (0.045) | (0.045) | (0.034) | (0.052) | (0.051) | (0.046) | (0.046) | (0.051) |
| **Negative Sentiment** | 0.123 | 0.110 | 0.066 | 0.125 | 0.135 | 0.108 | 0.092 | 0.121 |
| **(No disaster in week $w$)** | (0.032) | (0.032) | (0.027) | (0.040) | (0.039) | (0.036) | (0.034) | (0.044) |
| **Network** | All | Fox | CNN | MSN | All | Fox | CNN | MSN |
| **Wghtd by log vol** | | | | | yes | yes | yes | yes |
| **Covariates, $\tau_t$, $\omega_w$** | yes | yes | yes | yes | yes | yes | yes | yes |
| **Observations** | 367 | 367 | 367 | 367 | 367 | 367 | 367 | 367 |

**Notes:** The table reports correlations between negative sentiment score in cable TV news covering the president and drone strikes. *Negative sentiment* is the negative sentiment expressed toward the President, where higher values denote more negative coverage. *Negative sentiment* $\times$ *disaster* is the negative sentiment during a week in which a natural or industrial disaster occurred, *Negative sentiment* $\times$ *no disaster* is the negative sentiment during a week in which no natural or industrial disaster occurred. Columns 1 to 4 report negative sentiment score, columns 5 to 8 report negative sentiment score multiplied by the log number of mentions of the President in cable TV news. Dependent variable =1 if US carried out at least one drone strike in week $w$ and year $t$ in panels a and d, Dependent variable =1 if US carried out at least one manned airstrike in week $w$ and year $t$ in panel b, Dependent variable =1 if US carried out at least one unconfirmed drone strike in week $w$ and year $t$ in panel c, covariates are unemployment, inflation, balance of payments and oil price, 5 lags of drone strikes, 5 lags of terrorist attacks and second and third polynomial time trends; $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors with 4 lags reported in parentheses.

times log of arousal, column (8) weights words by valence times min-max normalized arousal, and column (9) weights words by valence times squared min-max normalized arousal. Results remain robust throughout.

## 5. Conclusion

This paper has presented several pieces of evidence suggesting that the US President uses popular drone strikes strategically to further his own political aims. Drone strikes are significantly more frequent in the run-up to US presidential or mid-term elections, pointing towards a deliberate effort to sway the electorate. We find no such effects for unpopular piloted airstrikes. Consistent with an unusually high number of drone strikes being approved by the President, we find that cloudy skies before elections lead to a postponement and a rerouting in drone strikes. Moreover, we document a strong and consistent relation between drone strikes and presidential popularity in the media. Analyzing closed captions from cable news programs shows that drone strikes are significantly more likely during weeks when news portray the President more negatively. We find no such relation when the media are distracted by natural or industrial disasters or for unpopular piloted airstrikes.

Our findings have wide-ranging implications for both policy and research. In October 2013, the United Nations General Assembly held its first formal debate on armed drones, where several member states condemned the US program as illegal and harmful to sovereignty.[24] The finding that at least part of the reason behind drone strike approvals is to increase re-election chances of the President, in particular, provides a novel reason for increased oversight of the US drone program. This analysis is also likely to be of interest to territories where the US carries out drone strikes. By highlighting a novel application of the Diversionary Theory of War, our paper also furthers the literature on the political economy of conflict.

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[24] https://www.theguardian.com/world/2013/oct/25/un-drones-us-policy-debate?utm_source=chatgpt.com accessed May 2025.

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# Online Appendix for 'Strategic Drones'

# Online Appendix

## Appendix A. A history of drone strikes

**A warfare revolution.** According to TBIJ, the first drones used in warfare date back to the 19th century, when Austrians deployed pilotless hot-air balloons to bomb Venice. [1] Following the Wright brothers' breakthrough in powered flight, modern unmanned aircraft began to develop, leading to the first remote-controlled planes during World War I. The technology then continued to evolve throughout the interwar period, when the term 'drone' appeared. While early models were mostly used as guided bombs, the late 1950s marked a shift as the US began employing radio-controlled, camera-equipped unmanned aircraft as spy planes over China and Vietnam.

Since then, several technological advancements accelerated the development of the modern drone technology and its increased use. The first technological advancement is due to the work of Abraham Karem, an Israeli-educated engineer considered 'the father of drones' and a key figure in modern warfare. His work in the 1970s created aircraft that could stay aloft for over 24 hours. He designed the Predator drone, which has evolved into the Raptor and Avenger UAVs, produced by General Atomics for the US military (The Economist, 2012). A second pivotal advancement in drone technology occurred with the advent of the global positioning system (GPS) and improved data relay capabilities through satellites. These developments enabled the Predator to be piloted remotely from a distance of up to a thousand miles.

These advancements have tremendously decreased the financial and human costs of warfare (Byman, 2013). Originally developed as reconnaissance aircraft, drones became tools for targeted killings and serve now this dual purpose. This has transpired over the course of Washington's ongoing 15-year war on terror during which drones have adeptly gathered intelligence, and effectively located and eliminated terrorists and insurgents.

[1] https://www.thebureauinvestigates.com/explainers/history-of-drone-warfare

**US use of drones** The US Army first deployed modern drones during the conflict in the former Yugoslavia, providing real-time intelligence and extended airborne monitoring capabilities to military commanders. In 2001, a shift occurred when a drone was equipped with a Hellfire missile during the conflict in Afghanistan, marking the start of the regular use of armed drones during the 'war on terror'. Drones have now become an integral part of the US military's strategy in combating terrorism and conducting military operations worldwide. Their use significantly transformed warfare. The distinct characteristic of drone operations, namely their limited on-the-ground presence, rendered it politically more feasible for the United States to conduct operations in nations where formal declarations of war were absent. Numerous strikes have been executed in countries such as Yemen, Pakistan, and Somalia. These operations were carried out covertly by the Central Intelligence Agency and the Joint Special Operations Command under the Pentagon.

**US drone strikes in the Middle East and Africa** The scope of the US drone campaign experienced a substantial surge during President Barack Obama's mandates. In response to shifting threats posed by militants and advancements in remote piloting technology, Obama authorized counter-terrorism strikes at a rate ten times higher than his predecessor, George W. Bush, during his time in office.[2] President Trump continued the use of drones.

**US Drone strikes in Afghanistan** The US drone campaign in Afghanistan began in 2001 and ended in 2021. Throughout this period, Afghanistan was considered as a zone of active hostility by the US. Prior to 2015, the strikes were delegated to the joint authority of the NATO-led International Security Assistance Force.[3] Once this mission came to an end, the US continued strikes in Afghanistan. Strikes were high during the last three years of Obama's mandate and the first year of Trump's mandate. They decreased from 2018 onward. Strikes conducted in Afghanistan are under the command of the military and more precisely under the control of the US Air Force central command, which is part of the unified

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[2] https://www.thebureauinvestigates.com/explainers/history-of-drone-warfare accessed Aug 2023.

[3] https://www.thebureauinvestigates.com/drone-war/data/afghanistan-reported-us-covert-actions-2018/p11/

central command (Centcom). Operations were mainly concentrated in the South and East of the country. The groups targeted by theses operations include : al Qaeda, the Haqqani Network, Islamic State's Afghan franchise Islamic State – Khorasan, the Pakistan Taliban, and the Afghan Taliban.[4]

**US drone strikes in Pakistan** The drone campaign in Pakistan started in 2004 under the Bush administration and lasted until 2018. Initially, the campaign was relatively limited and it was only during the final year of Bush's presidency that the frequency of strikes increased. Obama accelerated the campaign until 2016, with only three strikes that year. In March 2017, after a nine month pause, a strike was conducted under Trump's administration. However, Trump did not restart a drone campaign and after launching 6 strikes in the first two years of his mandate, no further strikes were recorded. Until 2016, only the Central Intelligence Agency (CIA) was responsible for carrying strikes. However, in May 2016 the US Special forces also began to conduct strikes through Centcom. Throughout the drone campaign in Pakistan, the strikes were mainly located along Pakistan's Northern border with Afghanistan. The only exception was the last strike of the Obama administration which occurred in the West of the country. The groups targeted by these operations included al Qaeda, the Pakistan Taliban and the Haqqani Network.[5]

**US Drone strikes in Somalia** The US has a long standing military presence in Somalia that can be traced back to the beginning of the 2000s. The drone campaign started in 2011 under the Obama administration, when the US military shifted from ground operations to a strategy more centered on drone warfare. The campaign continued throughout his mandate. In March 2017, Trump declared some regions in Somalia "areas of active hostilities", which increased the autonomy of the military in conducting the drone campaign (for more explanation, see Appendix B.). The drone campaign in Somalia continued during Biden's presidency and is still ongoing.

[4] This information is given by TBIJ in the presentation of their data for Afghanistan https://www.thebureauinvestigates.com/stories/2017-01-01/drone-wars-the-full-data

[5] https://www.newamerica.org/future-security/reports/americas-counterterrorism-wars/the-drone-war-in-pakistan/

Most of the strikes in Somalia are led by the US Military through the Joint Special Operations Command (JSOC) operating under Africom. However, the CIA has a strong presence in the Horn of Africa and operates a secret base at the Mogadishu airport. The strikes have mainly targeted Southern and Central Somalia. The groups targeted were mainly al Shabaab and since 2017, ISIS.[6]

**US Drone strikes in Yemen** The first drone strike in Yemen took place in 2002. After a 7-years halt, the drone campaign resumed in 2009 and accelerated from 2012 onward. Strikes continued during Trump's mandate and according to Airwars, increased sharply during the first year of its mandate. The campaign slowed down from 2018 onward and no strike has been reported since 2023. Both the CIA and the JSOC (operating under Centcom) have carried operations in Yemen, from Camp Lemonnier in Djibouti and a base in Saudi Arabia. The strikes have been located mainly in Southern and Central Yemen, primarily in Shabwa, Abyan, Marib, Al-Bayda, Hadramout, Lahij, and Al-Jawf provinces. The strikes have mainly targeted al Qaeda.[7]

[6] https://www.newamerica.org/future-security/reports/americas-counterterrorism-wars/the-war-in-somalia/

[7] https://www.newamerica.org/future-security/reports/americas-counterterrorism-wars/the-war-in-yemen/

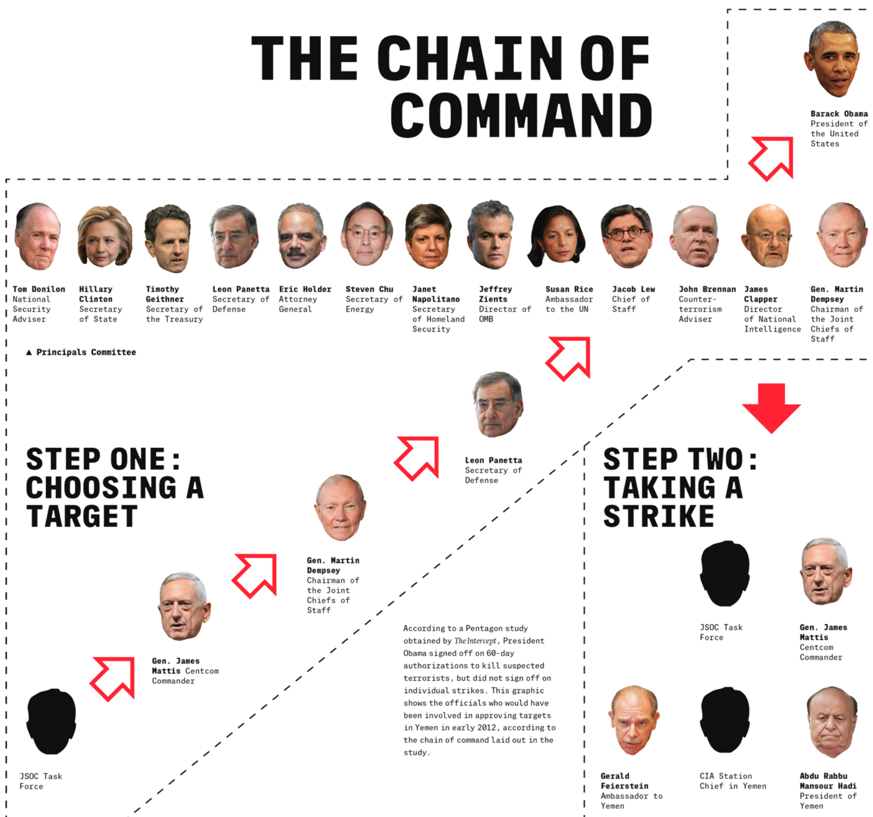
# Appendix B. More details about drone strikes

In February 2014, Daniel Hale, who had previously served in the Air Force and later worked as a contractor at the National Geospatial-Intelligence Agency, disclosed 17 classified documents to The Intercept, called 'The Drone Papers' (2015). This collection of classified slides sheds light on the US military's kill/capture operations during a crucial period in the development of drone warfare, specifically between 2011 and 2013. These confidential documents not only reveal insights into the drone program's inner workings but also disclose military guidelines used during the operations in Somalia and Yemen carried out by the Joint Special Operations Command (JSOC).

These leaked slides reveal a two stage process for carrying an attack. In the first step, intelligence personnel from the JSOC collaborates with other intelligence agencies to build a case for taking action against a specific individual, creating a comprehensive profile, often referred to as a "baseball card". The targeted individual's intelligence dossier then moves up the chain of command to the Joint Chiefs of Staff and the Secretary of Defense. The information is subjected to scrutiny by the Principals Committee of the National Security Council, a group of top advisors, and their deputies and finally reaching the US President, who approves each target. Once a target is approved by the President, the second step begins and the US forces have a 60 day window to execute the strike. Figure B.1 identifies the individuals involved in the decision making process. As mentioned above, the Chairman of the Joint Chiefs of Staff (CJCS) is the main military representative involved in informing the President. Their official political orientation is not publicly stated, as military leaders are expected to remain apolitical. The 4 CJCS serving between 2009 and 2020 have stressed the importance to remain apolitical even after retirement. As far as we know, the only two cases of political post-retirement stance have been the declared opposition to President Trump by General Martin Dempsey (2011-2015 CJCS) and General Mark Milley (2019-2023 CJCS) regarding the use of military force in domestic protests. The Centcom or Africom Commanders - in charge of operations in the Middle East and Africa, respectively - plays a role in identifying possible targets but only influence the President's decision through the

Chairman of the Joint Chief of Staff (CJCS). Although General James Mattis (2010-2013, Centcom) and General Lloyd Austin (2013-2016 Centcom) have been appointed Secretary of Defense by President Trump and Secretary of Defense by President Biden, respectively, they remain apolitical and have received strong bipartisan support at the times of confirmation by the US Senate.[1]

Figure B.1: The Chain of Command




**Notes:** The image illustrates the chain of command for drone authorization and identifies the individuals involved in the decision-making process. It is based on a U.S. military slide from May 2013, leaked as part of The Drone Papers. Source: The Intercept.

**Presidential authority over the strikes** Although it is explained on the slides that the President approves each target, it is not explicitly stated that the President approves each strike. However, it has been reported in the press on a few occasions that the President

[1] General James Mattis received an overwhelmed support with a 98-1 vote, while General Lloyd Austing received 93 favorable votes against 2, reflecting in both cases strong backing from both Republicans and Democrats.

personally approves strikes outside of active war zone. An article from the New York Times reports that "Obama signs off on every strike in Somalia and Yemen and also on the more complex and risky strikes in Pakistan".[2] That information from the press is consistent with Obama's comment in 2012 who when asked about the drone program said '*ultimately I am responsible*' (CNN, 2012).[3]

The degree of presidential authority over drone strikes depends on whether the strike occurs in an active war zone or not. In active war zones, such as Afghanistan, the military has greater authority over the strikes. In non active war zone, the presidential authority is more important. In May 2013, the Obama administration published the Presidential Policy guidance, which details specific procedures for approving direct action against terrorist targets located outside the United States and areas of active hostilities. This was accompanied by a speech at the National Defense University discussing drone strikes and announcing the plan to limit drone usage. According to the press, these guidelines where intended to constrain the military autonomy over the strikes. Where previously the military maintained some flexibility in the decision to launch strikes, the new policy would now require explicit White House approval for operations in non-combat zones.[4]These guidelines also included rules to prevent civilians casualties, stating that a strike could happen if there is a near certainty that non combatants will not be injured or killed. Under the Trump administration, those guidelines were loosened. In March 2017, he declared Somalia and parts of three provinces of Yemen areas of active hostility, thereby removing the requirement for White House approval and granting the military greater discretion in conducting drone strikes.[5]

**Presidential communication on drone strikes** Drone strikes also featured in official White House communications. As shown in Figure D.2, President Obama communicated

[2] https://www.nytimes.com/2012/05/29/world/obamas-leadership-in-war-on-al-qaeda.html?_r=0

[3] https://www.thebureauinvestigates.com/stories/2012-09-06/obamas-five-rules-for-covert-drone-strikes/ accessed June 2024.

[4] https://www.nbcnews.com/news/other/why-white-house-blessed-recent-yemen-drone-strikes-f6C10936036

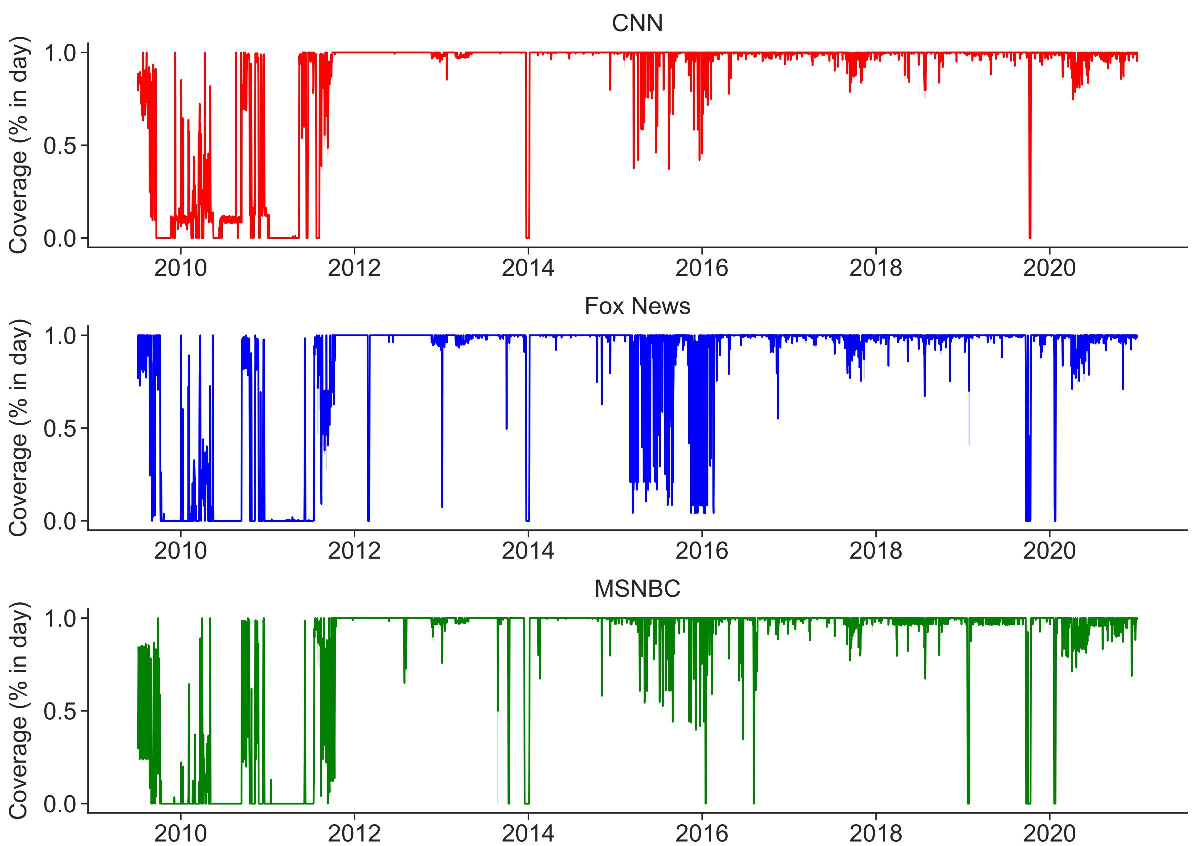
[5] https://www.newamerica.org/future-security/reports/americas-counterterrorism-wars/the-war-in-yemen/ and https://www.nytimes.com/2017/03/30/world/africa/trump-is-said-to-ease-combat-rules-in-somalia-designed-to-protect-civilians.html

a lot about drone strikes during his second mandate. That is not surprising since it is the period when drone strikes were more frequent. But President Obama seems to have voluntarily communicated about drone strikes, as illustrated by the May 2013 speech. Figure D.2 further illustrates that Obama addressed drone strikes more frequently in presidential statements than in responses to the press. In contrast, a spike in drone-related mentions under President Trump occurred during the 2018-2019 federal government shutdown, mostly as reactions to the press concerning border surveillance drones. A further rise in mentions during Trump's later term relates to escalating US-Iran tensions, including Iran's downing of a US drone in June 2019 and the January 2020 US drone strike that killed Iranian General Qasem Soleimani.

# Appendix C. Media coverage

## Appendix C.1. Data

Figure C.1: Average TV News Transcripts Coverage by Date and Network




**Notes:** Each panel shows the estimated share of each 24-hour day occupied by televised news programming for CNN, Fox News, and MSNBC, respectively. Coverage is based on closed captioning data and represents the proportion of time with identifiable programming per calendar day. Gaps may reflect missing caption data, unaired segments, or collection issues from TV News Archive (Link). Averages are computed at a daily level across the full observed period.

Table C.1: Average TV News Coverage by Time of Day, Network, and Presidential Mandate

| | 2009-2012 (Obama #1) | | | 2013-2016 (Obama #2) | | | 2017-2020 (Trump #1) | | |
|---|---|---|---|---|---|---|---|---|---|
| | CNN | FNC | MSN | CNN | FNC | MSN | CNN | FNC | MSN |
| Time-of-Day | | | | | | | | | |
| Daily | 0.56 | 0.51 | 0.47 | 0.97 | 0.93 | 0.96 | 0.98 | 0.97 | 0.97 |
| Overnight (12AM-5AM) | 0.57 | 0.49 | 0.44 | 0.96 | 0.92 | 0.95 | 0.97 | 0.96 | 0.96 |
| Early Morning (5AM-9AM) | 0.55 | 0.52 | 0.49 | 0.95 | 0.94 | 0.96 | 0.99 | 0.97 | 0.97 |
| Daytime (9AM-4PM) | 0.55 | 0.51 | 0.48 | 0.97 | 0.88 | 0.92 | 0.98 | 0.93 | 0.95 |
| Late Afternoon (4PM-7PM) | 0.51 | 0.49 | 0.45 | 0.96 | 0.90 | 0.92 | 0.97 | 0.96 | 0.95 |
| Prime Time (7PM-11PM) | 0.60 | 0.51 | 0.46 | 0.96 | 0.93 | 0.95 | 0.98 | 0.96 | 0.95 |
| Late Night (11PM-12AM) | 0.41 | 0.53 | 0.44 | 0.91 | 0.92 | 0.94 | 0.92 | 0.96 | 0.93 |

Notes: Coverage is measured as the share of each time block occupied by news programming for each network. "Daily" represents the average over a full 24-hour day. Values are averages across years within each 4-year period. Data derived from closed captioning where available; gaps may exist due to missing airings or data collection issues.

# Appendix C.2. Measures

### Appendix C.2.1. Definition

To identify coverage specifically referring to the U.S. president, we extract all instances in which the surnames Obama or Trump are mentioned. To avoid capturing mentions of family members (e.g., "Michelle Obama," "Ivanka Trump"), we exclude any snippet where these surnames are preceded by a known first name of an Obama or Trump family member. Afterwards, we compute sentiment as follows:

1. **Neighborhood radius:** For each mention of the president, we define a neighborhood – a contiguous window of words around the mention (e.g., $\pm 15$ words). This allows us to vary the textual context used to compute sentiment.

2. **Text preprocessing:** We compute sentiment using both minimally processed and more extensively preprocessed versions of each snippet. The minimum preprocessing removes non-letter characters, URLs, and words with two or fewer characters; normalizes whitespace; tokenizes text into whitespace-separated words; and strips leading/trailing spaces. The full preprocessing converts text to lowercase, removes non-letter characters and URLs, deletes English stopwords (excluding negation terms), removes short tokens, and tokenizes the text.

3. **Dictionary mapping:** Each word in a snippet is mapped to its valence score from our WARR dictionary. This mapping can be performed in two ways. Under a "hard" match, a word is assigned a valence score only if it appears exactly in our WARR dictionary. Under a "soft" match, a word is assigned a score equal to the average valence of all WARR dictionary words that appear as substrings within it. For example, if the word being matched is "misleading", and our WARR dictionary includes only "mislead", our final score will be based on "mislead".

   The WARR dictionary maps 13,915 English words to 3 affective dimensions – valence, arousal and dominance. Valence reflects how pleasant or unpleasant a word is; it is scaled from 1 (very unpleasant) to 9 (very pleasant) – e.g., "death" (low valence), "happiness" (high valence). Arousal measures how exciting or calming a word is; it is scaled from 1 (very calming) to 9 (very exciting/stimulating) – e.g., "explosion" (high arousal), "sleep" (low arousal). Dominance captures the sense of control or submissiveness evoked by the word; it is scaled from 1 (feeling very controlled/submissive) to 9 (feeling very in control/dominant) – e.g., "slave" (low dominance), "leader" (high dominance).

We rely on valence and arousal to construct different sentiment measures:

(a) *valence scaled* [`main sentiment measure, used in our main results and for which we provide descriptive statistics`], which rescales valence by subtracting 5 to center the scale at zero (zero stands for neutral; negative valence indicates negativeness and positive valence indicates positiveness);

(b) *valence* $\times$ *log arousal*, which multiplies the rescaled valence by the logarithm of the arousal score to give greater weight to emotionally intense words while compressing extreme arousal values, thus reducing the influence of outliers;

(c) *valence* $\times$ *normalized arousal*, which uses min-max normalization on the arousal score before multiplying by the valence;

(d) *valence* $\times$ *squared normalized arousal*, which amplifies high-arousal words by squaring the normalized arousal prior to multiplication.

4. **Negation handling:** Following Hutto and Gilbert (2014), we account for local negation. If a negation term (from the LIWC-15 and LIWC-22 dictionary) appears within the trigram preceding a sentiment word, we invert the word's score.

5. **Aggregation:** We focus exclusively on negative sentiment. For each snippet, we sum the rescaled valence scores of all words with negative valence (after any negation adjustment). This sum forms our measure of a snippet's negative tone.

Table C.2: Examples of WARR Words and Negation Terms

**A: Top 5 Words with Most Positive Valence**

| Word | VS | VS × log(A) | VS × A | VS × A² |
|---|---|---|---|---|
| vacation | 0.88 | 1.61 | 0.47 | 0.25 |
| happiness | 0.87 | 1.75 | 0.60 | 0.41 |
| happy | 0.87 | 1.69 | 0.55 | 0.35 |
| enjoyment | 0.84 | 1.57 | 0.47 | 0.26 |
| fun | 0.84 | 1.68 | 0.56 | 0.37 |

**B: Top 5 Words with Most Negative Valence**

| Word | VS | VS × log(A) | VS × A | VS × A² |
|---|---|---|---|---|
| pedophile | -0.94 | -1.68 | -0.47 | -0.24 |
| rapist | -0.93 | -1.84 | -0.62 | -0.41 |
| AIDS | -0.92 | -1.64 | -0.46 | -0.23 |
| torture | -0.90 | -1.63 | -0.46 | -0.24 |
| leukemia | -0.88 | -1.69 | -0.52 | -0.31 |

**C: Random Sample of Words from Dictionary**

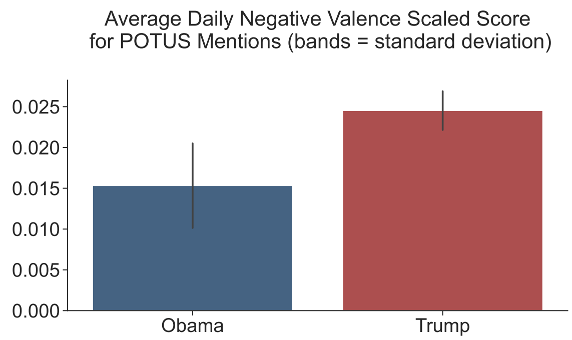
| Word | VS | VS × log(A) | VS × A | VS × A² |
|---|---|---|---|---|
| joke | 0.72 | 1.37 | 0.43 | 0.25 |
| witless | -0.50 | -0.84 | -0.21 | -0.09 |
| bottom | -0.35 | -0.50 | -0.10 | -0.03 |
| khaki | 0.01 | 0.02 | 0.00 | 0.00 |
| adrenalin | 0.33 | 0.60 | 0.17 | 0.09 |

**D: Random Sample of Negation Phrases**

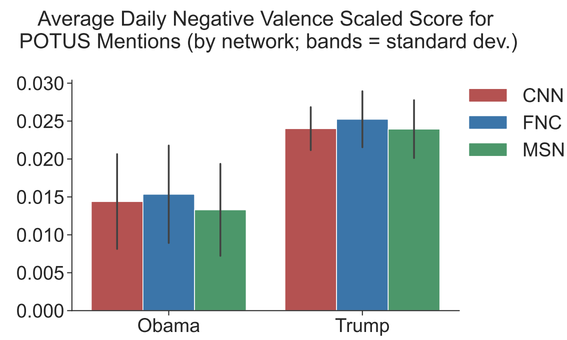
| Negation |
|---|
| by no means |
| couldnt |
| didnt have |
| do not have |
| idk |
| never |
| no idea |
| noones |
| not have any |
| not really |
| not so much |
| nowhere |
| nt enough |
| nt even sure |
| nt one |
| nt precise |
| nt quite |
| nt the case |
| uhuh |
| wouldnt |

Notes: Panel A displays top 5 words from Warriner et al. (2013) dictionary with highest (most positive) valence scores. Panel B shows top 5 words with lowest (most negative) valence scores. Panel C includes a random sample of 5 words from full dictionary. Panel D (right column) presents a random sample of negation phrases (of 3 words or fewer) drawn from LIWC's negation dictionary.

## Appendix C.2.2. Descriptive statistics



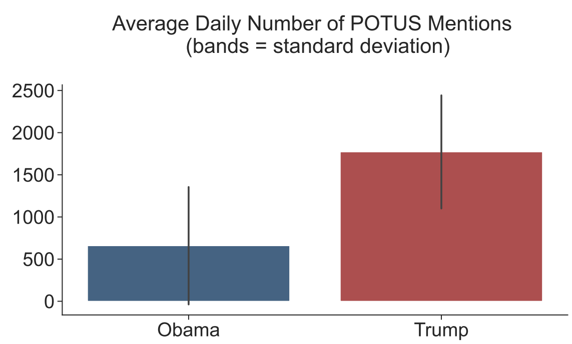

(a) Daily Average



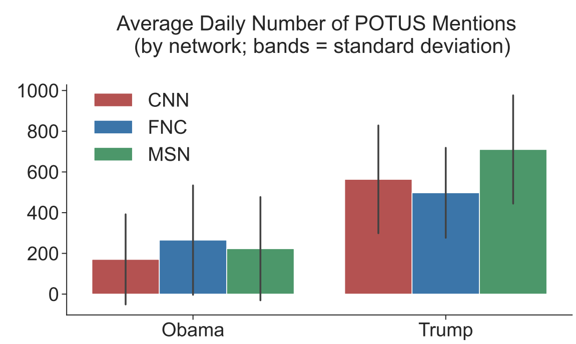

(b) Daily Average, by Network

Figure C.2: Average of WARR Sentiment Score

Notes: Average daily values of local WARR negative sentiment scores for presidential mentions. Valence scaled scores constructed with ±12-word neighborhoods, words within neighborhood are "hard" matched to WARR, neighborhoods are minimally preprocessed. Confidence bands show standard deviation.




(a) Daily Average




(b) Daily Average, by Network

Figure C.3: Average of POTUS Coverage

Notes: Average daily mentions of U.S. president, based on closed captioning.

Table C.3: Examples of Top WARR Snippets, Random Obama Selection

| year | example | CNN | FNC | MSN |
|---|---|---|---|---|
| 2009 | random_1 | whether his opponents are racist today nancy pelosi warning the angry anti obama rhetoric is getting frightening and could lead to violence also our exclusive | and tell me what it means bill this whole interrogation torture situation barack obama may allow a phony unnecessary show trial driven by the far left | an american issue not a left/right issue are you disappointed with president obama for not leading the charge against assault this ban on assault weapons |
| | random_2 | right thanks very much bill schneider thanks bill okay ¿¿¿ well president obama today called the terrorist bombing of two hotels in indonesia an outrage | but each with a potentially fatal political disease if you will only barack obama overcame his disease a smart candidate bill what was barack obama | actual alaska republican who is serving in office went further joining mr obama in calling the death panel lie a lie a lie now owned |
| 2010 | random_1 | unpopular war hanging over their head especially a war that is considered obama s war it s not a very good thing to try to | attack from the president on former vice president dick cheney cheney said president obama reversal of the bush administration policies on guantanamo bay and terror suspect | bush tax cuts you re adopting the hostage taking garbage too barack obama didn t even fight he didn t even fight i mean arianna |
| | random_2 | on national debt the election results we saw were not good for president obama and not good for democrats but at the same time my republican | a chemical attack biological attack or some type of crippling cyber attack president obama has taken our nuclear option off the table you work in homeland | a terrorist attack this comment suggested alarming fatalism on the part of president obama and his administration once again the president seems eerpgt unwilling or unable |

Notes: Table presents example statements about President Obama that received lowest local sentiment scores using WARR valence-scaled negative sentiment measure. "Local sentiment" refers to a score computed using words contained in a fixed-length window surrounding president-related mentions (radius $r = 12$; words "hard" matched to WARR). For each network (CNN, Fox News, MSNBC), two random statements were selected from ten most negative-scored examples for each year. A minimum amount of preprocessing was applied to remove or standardize formatting artifacts.

Table C.4: Examples of Top WARR Snippets, Random Trump Selection

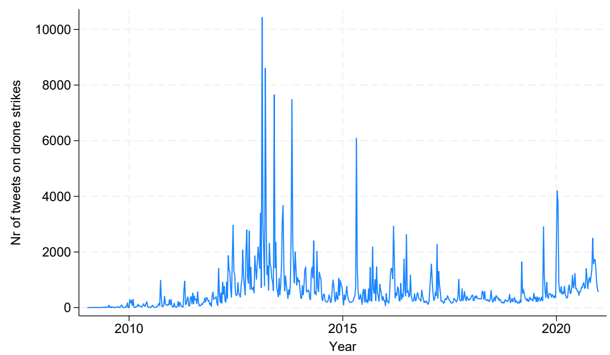
| year | example | CNN | FNC | MSN |
|---|---|---|---|---|
| 2019 | random_1 | on the scene of that attack thank you ¿¿¿ frustration anger uncertainty president trump simmering in palm beach as he awaits the senate impeachment trial we | you hate trump rage against melania infuriating sean the hate rage trump media mob it flows laura want to put that want to | a violent racist scum bag all the violent racist scum bags are donald trump supporters and all the guys writing manifestos are donald trump supporters and |
| | random_2 | can blame donald trump for this attack i think you can blame donald trump for really trafficking in bigotry and islamophobia wanting to ban all muslims | a bigot and racist this isn t subjective this is who donald trump is old racist a racist who make ever more outrageous racist | this country he has spewed hate racism anti semitism and inspired more donald trump did not create hate and racism and anti semitism what he has |
| 2020 | random_1 | on the scene of that attack thank you ¿¿¿ frustration anger uncertainty president trump simmering in palm beach as he awaits the senate impeachment trial we | both have surgery after the shooting and both were shot multiple times president trump tweeted if they die fast trial death penalty for the killer only | from tax fraud insurance fraud money laundering you mentioned e jean carroll trump organization tax fraud inauguration funds misuse c aign finance laws racketeering it |
| | random_2 | the virus the cancer that is killing us are these poisonous things trump shows a cheat against any real integrity and argument on the facts | write books virus flu the swine flu under biden the virus how trump is handling it sean it turned out interestingly swine flu impacting younger | candidate x candidate trump will you condemn men who abuse women and trump had said well what kind of abuse sexual abuse physical abuse what |

Notes: Table presents example statements about President Trump, during his first mandate, that received lowest local sentiment scores using WARR valence-scaled negative sentiment measure. "Local sentiment" refers to a score computed using words contained in a fixed-length window surrounding president-related mentions (radius $r = 12$; words "hard" matched to WARR). For each network (CNN, Fox News, MSNBC), two random statements were selected from ten most negative-scored examples for each year. A minimum amount of preprocessing was applied to remove or standardize formatting artifacts.

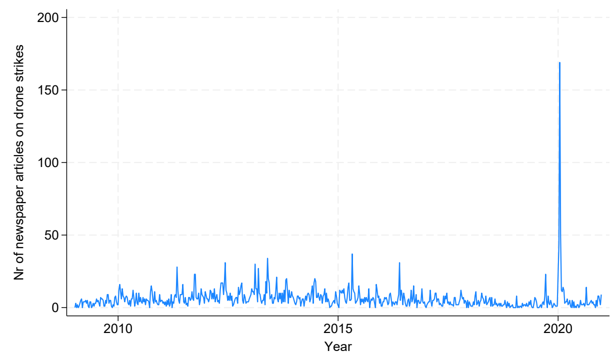
# Appendix D. Additional Figures

Figure D.1: Social media posts and newspaper articles about drones strikes

(a) Weekly tweets on drone strikes

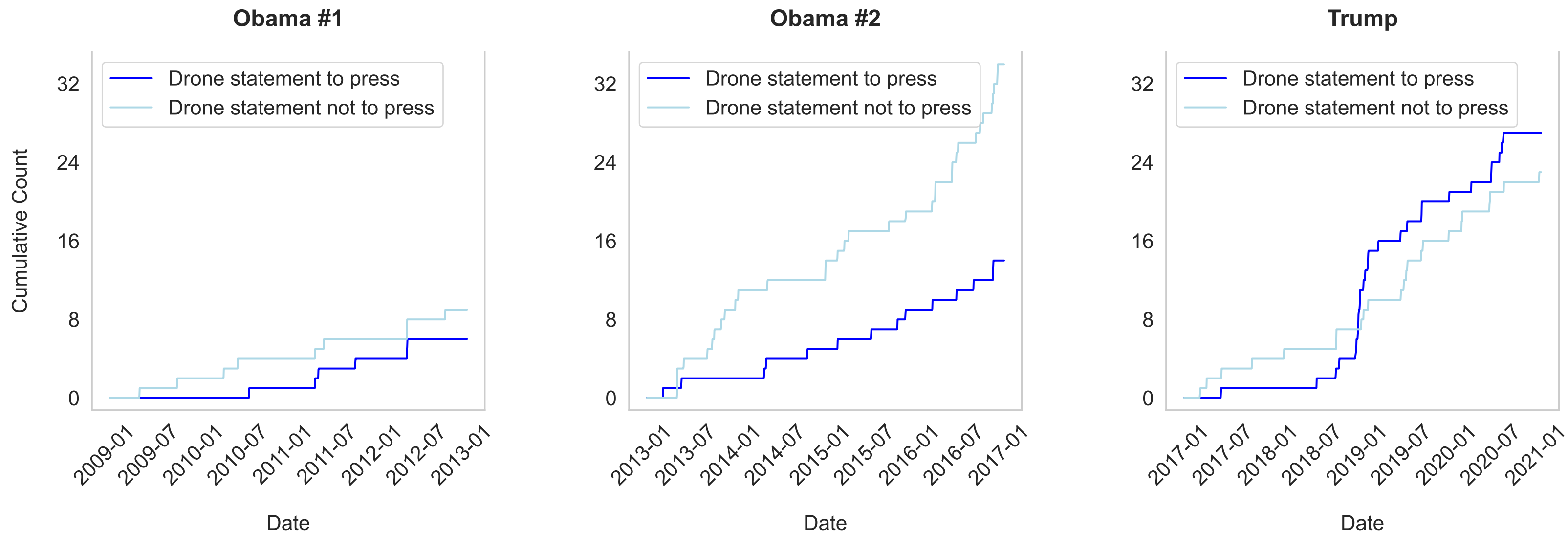



(b) Weekly newspaper articles on drone strikes




**Notes:** Figure reports the total weekly number of media mentions of drone strikes. Panel a reports the total weekly number of social media posts on Twitter containing the words 'drone strikes'. Panel b reports the total weekly number of newspaper articles in the New York Post, New York Times, USA Today, and Wall Street Journal covering drone strikes.

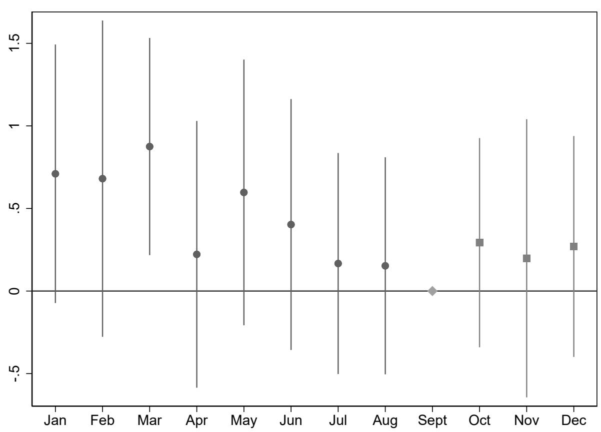
Figure D.2: Presidential statements and press briefing mentioning drone strikes



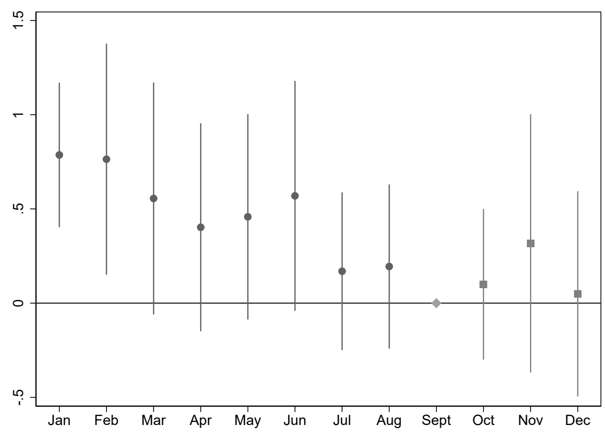

**Notes:** Each subplot displays the cumulative count of statements referencing drones across three presidential mandates: Obama's first term (2009–2013), Obama's second term (2013–2017), and Trump's term (2017–2021). As discussed in Section 2.3., we collect official communications from the White House archives for Presidents Obama and Trump using the BeautifulSoup web-scraping library. This dataset includes transcripts of public statements, speeches, and press briefings published on the official White House websites. Drone-related mentions are identified using keyword matching for the terms "drone", "unmanned aircraft system", and "unmanned aerial vehicle". The blue line in each panel represents statements made to the press, defined as either explicitly designated press communications (e.g., press releases) or public events featuring Q&A sessions with the press, where only the answers given by the President or the White House press secretary are analyzed. The light blue line represents drone-related statements made not to the press, which primarily include speeches and other forms of public communication not structured as press engagements.

Figure D.3: Drone strikes even vs odd years - Trump

(a) TBIJ data



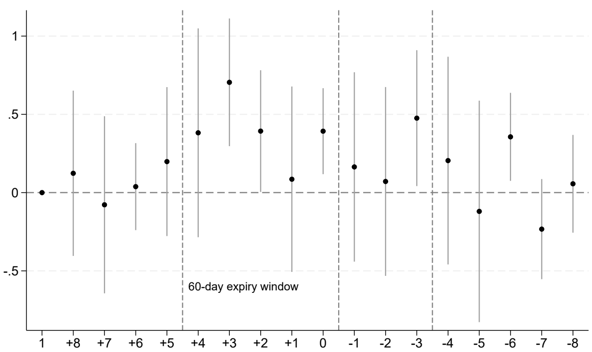

(b) Airwars data



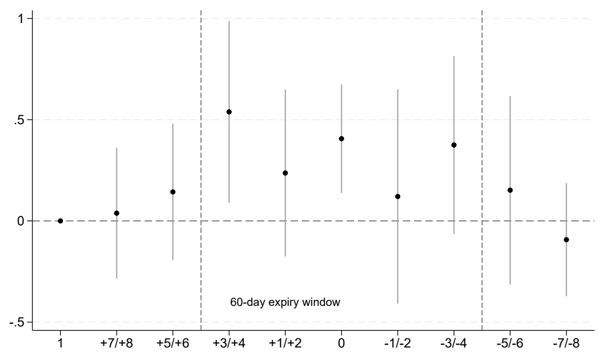

**Notes:** The figure reports the monthly differences in the frequency of drone strikes between even and odd years during Trump's presidency. Panel a uses TBIJ data, panel b uses Airwars data.

Figure D.4: Timing of drone strikes around elections

(a) Weekly event study



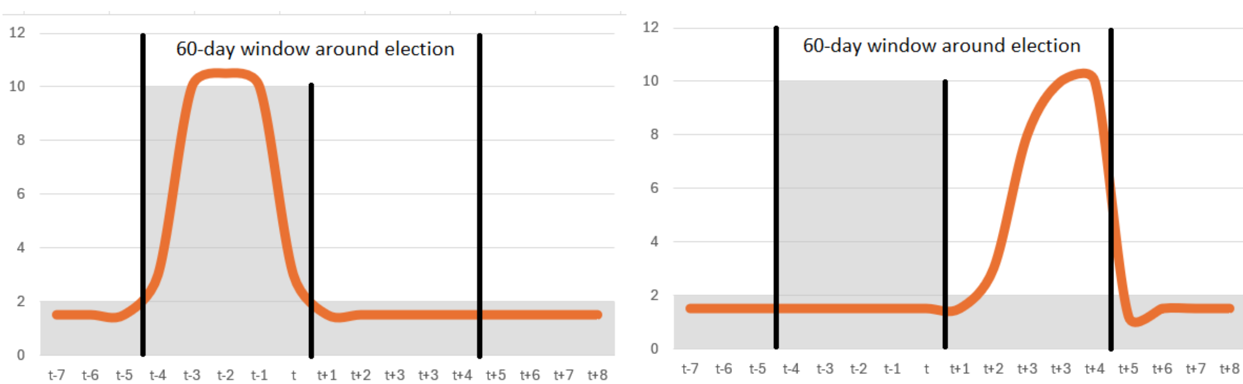

(b) Bi-weekly event study




**Notes:** Panel a reports an event study for drone strikes three months before and after US presidential or mid-term elections during the Obama administration with weekly dummies; Panel b reports an event study for drone strikes three months before and after US presidential or mid-term elections during the Obama administration with bi-weekly dummies (i.e. two weeks grouped together); Same notes as Table 2 apply. Circles denote point estimates and vertical lines 95% confidence intervals.

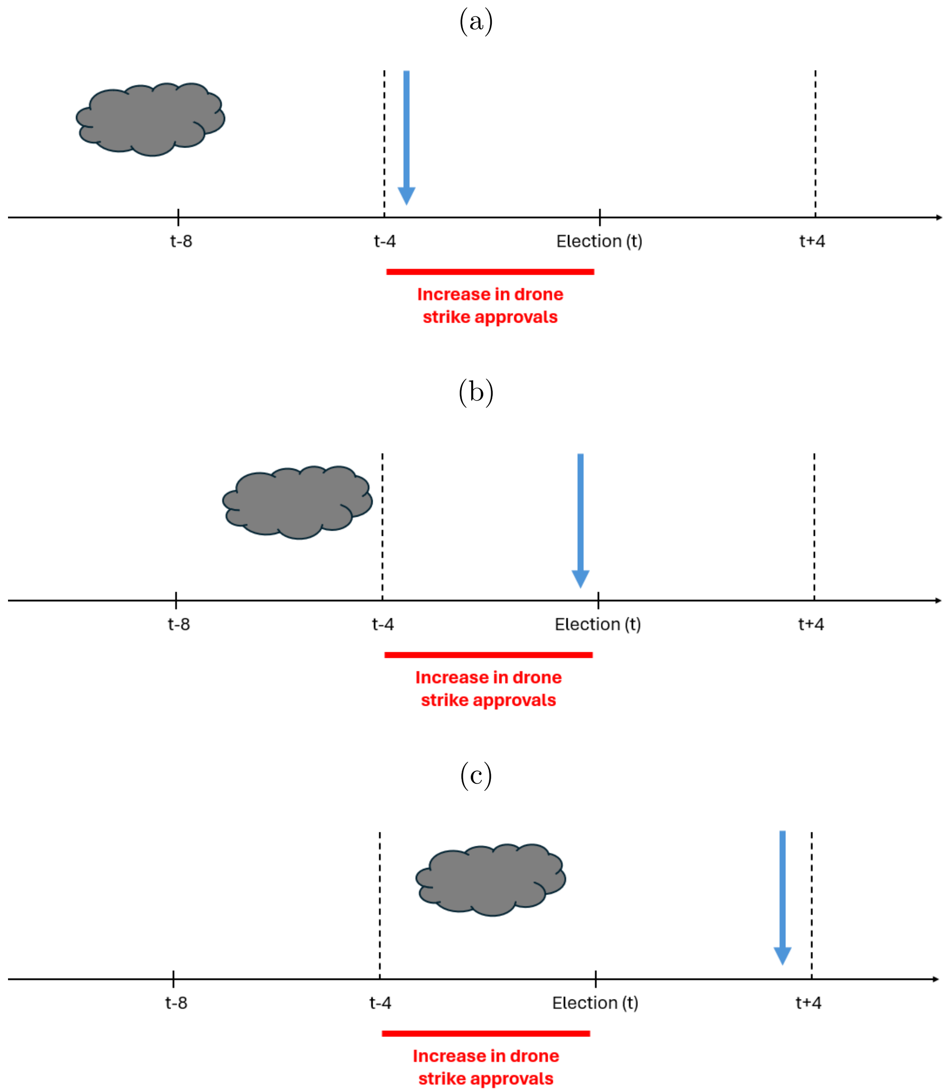
Figure D.5: Graphical illustration of postponement due to 60-day rule

(a) Not cloudy (b) Cloudy




**Notes:** Figure reports a graphical illustration of the postponement in drone strikes arising from the 60-day expiry of presidential authorization. Panel a illustrates drone strike pattern when weeks leading up to elections are not cloudy. Panel b illustrates drone strike pattern when weeks leading up to elections are abnormally cloudy.

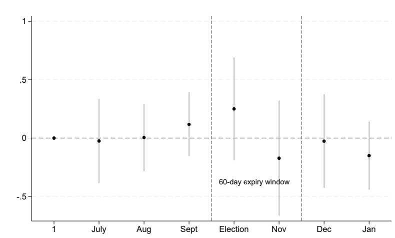
Figure D.6: Graphical illustration of postponement due to 60-day rule



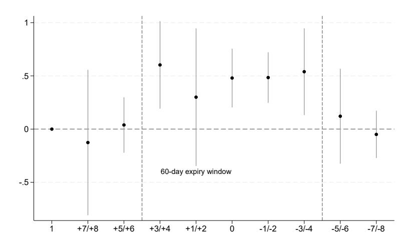

**Notes:** Figure reports a graphical illustration of the effect of cloud cover 8 weeks in the past (week $w - 8$) on drone strikes if the president approved an unusually high number of drone strikes in the weeks leading up to elections. Panels a and b: past cloud cover does not coincide with period of unusually high drone approval and past cloud should have no effects on done strikes. Panel c: past cloud cover does coincide with period of unusually high drone approval (i.e. the weeks leading up to elections) and thus past cloud should have a sigificant effects on done strikes.

Figure D.7: Timing of drone strikes around elections - cloudy and not cloudy

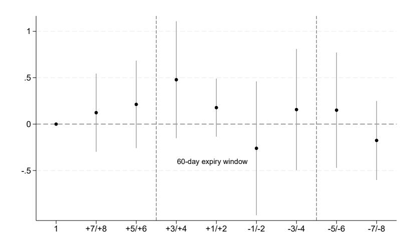
(a) Monthly event study - not cloudy




(b) Bi-weekly event study - cloudy



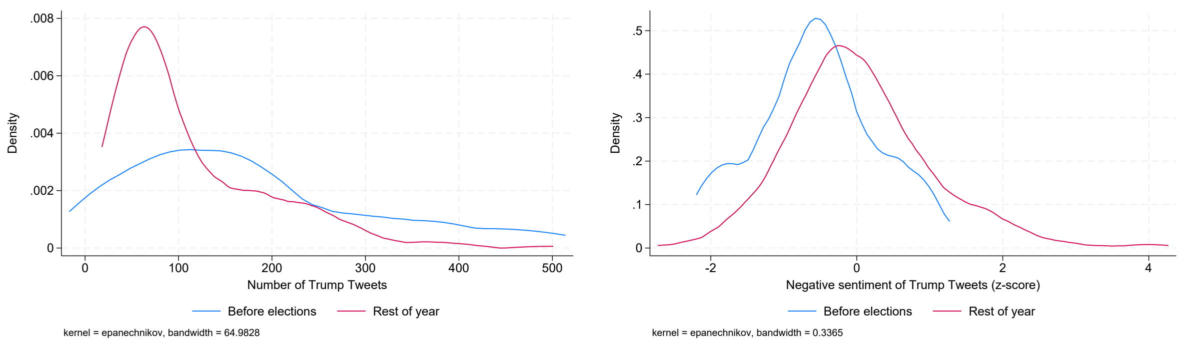

(c) Bi-weekly event study - not cloudy




**Notes:** Panel a reports an event study for drone strikes three months before and after US presidential or mid-term elections during the Obama administration; *Election*=1 in week of election and in the 4 weeks before; we look at drone strikes in the twelve weeks before this election period and the twelve weeks after. Same notes as Table 2 apply. Circles denote point estimates and vertical lines 95% confidence intervals.

Figure D.8: Tweets by Trump and US elections

(a) Number of tweets | (b) Negative sentiment of tweets




**Notes:** The figure reports social media postings by President Trump on Twitter (now X). Panel a: reports the kernel density estimates for the number of tweets by Trump from 2016 to 2020. Blue line denotes tweets during in the five weeks prior to and including US presidential and mid-term elections. Red line denotes tweets during the remainder of the year. Panel b: reports the kernel density estimates for the negative sentiment VADER sentiment score of tweets by Trump from 2016 to 2020. Blue line denotes tweets during in the five weeks prior to and including US presidential and mid-term elections. Red line denotes tweets during the remainder of the year.

# Appendix E. Additional Tables

Table E.1: US Drone Strikes and Casualties by Presidential Term

| | Strikes | Casualties | Civilians |
|---|---|---|---|
| **Obama 1** | | | |
| Afghanistan | 0 | 0 - 0 | 0 - 0 |
| Pakistan | 307 | 1800 - 2937 | 254 - 622 |
| Somalia | 6 | 6 - 12 | 0 - 1 |
| Yemen | 83 | 482 - 691 | 66 - 87 |
| **Total** | **396** | **2288 - 3640** | **320 - 710** |
| **Obama 2** | | | |
| Afghanistan | 218 | 1822 - 2295 | 44 - 95 |
| Pakistan | 68 | 295 - 478 | 3 - 12 |
| Somalia | 25 | 276 - 406 | 3 - 11 |
| Yemen | 132 | 463 - 674 | 25 - 75 |
| **Total** | **443** | **2856 - 3853** | **75 - 193** |
| **Trump 1** | | | |
| Afghanistan | 97 | 589 - 881 | 8 - 71 |
| Pakistan | 6 | 16 - 25 | 0 - 3 |
| Somalia | 13 | 140 - 146 | 2 - 9 |
| Yemen | 34 | 88 - 122 | 11 - 29 |
| **Total** | **150** | **833 - 1174** | **21 - 112** |

**Notes:** The table reports the number of drone incidents, overall casualties, and civilian casualties by country for each presidential term. Columns 2 and 3 report lower and upper estimates of casualties. Data covers 2009-2020. Source: TBIJ

Table E.2: Drone Strikes and Twitter coverage

| | **Dependent variable:** log(1+tweets) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Both Presidents** | | **Obama** | | **Trump** | |
| Drone ($t$) | 0.312*** | 0.296*** | 0.316*** | 0.312*** | 0.238* | 0.178 |
| | (0.087) | (0.084) | (0.107) | (0.105) | (0.124) | (0.115) |
| Drone ($t+2$) | | -0.071 | | -0.132 | | 0.011 |
| | | (0.078) | | (0.110) | | (0.109) |
| Drone ($t+1$) | | -0.019 | | -0.078 | | 0.119 |
| | | (0.079) | | (0.102) | | (0.139) |
| Drone ($t-1$) | | 0.089 | | 0.150 | | -0.010 |
| | | (0.076) | | (0.096) | | (0.131) |
| Drone ($t-2$) | | -0.094 | | -0.092 | | -0.017 |
| | | (0.081) | | (0.114) | | (0.111) |
| Observations | 628 | 627 | 420 | 420 | 208 | 207 |
| Covariates, $\tau_t$, $\omega_w$ | Yes | Yes | Yes | Yes | Yes | Yes |
| 5 lags terrorist attacks | No | Yes | No | Yes | No | Yes |

**Notes:** The table reports estimates for the effects of US drone strikes on the number of tweets mentioning drone strikes posted between 9 AM and 9 PM EST which corresponds to 5 PM to 5 AM in Somalia and Yemen, 7 PM to 7 AM in Pakistan, and 6:30 PM to 6:30 AM in Afghanistan. Estimates are derived from OLS regressions and based on analogues of equation (1). Dependent variables are log number of tweets containing the words 'drone strikes'. Key explanatory variable is a dummy = 1 if the US carried out at least one drone strike in year $t$ and week $w$ and its two lags and leads. Covariates are unemployment, inflation, balance of payments and oil price, 5 lags of terrorist attacks and second and third polynomial time trends; $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors (with 5 lags for column 1 and 2 lags for columns 3 to 6) reported in parentheses.

Table E.3: Drone Strikes and Newspaper coverage

| **Dependent variable:** log(1+newspapers) | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Both Presidents** | | **Obama** | | **Trump** | |
| Drone ($t$) | 0.268*** | 0.259*** | 0.202** | 0.201** | 0.444** | 0.402** |
| | (0.076) | (0.072) | (0.078) | (0.077) | (0.196) | (0.184) |
| Drone ($t+2$) | | 0.066 | | 0.068 | | -0.006 |
| | | (0.068) | | (0.080) | | (0.155) |
| Drone ($t+1$) | | -0.073 | | -0.072 | | 0.044 |
| | | (0.065) | | (0.079) | | (0.191) |
| Drone ($t-1$) | | 0.106* | | 0.133* | | -0.054 |
| | | (0.064) | | (0.075) | | (0.145) |
| Drone ($t-2$) | | -0.105 | | -0.147* | | -0.033 |
| | | (0.067) | | (0.079) | | (0.156) |
| Observations | 628 | 627 | 420 | 420 | 208 | 207 |
| Covariates, $\tau_t$, $\omega_w$ | Yes | Yes | Yes | Yes | Yes | Yes |
| 5 lags terrorist attacks | No | Yes | No | Yes | No | Yes |

**Notes:** The table reports estimates for the effects of US drone strikes on the number of newspaper articles in NYT, NYP, USAT, and WSJ covering drone strikes. Estimates are derived from OLS regressions and based on analogues of equation (1). Key dependent variable is the log number of newspaper articles on drone strikes. Key explanatory variable is a dummy = 1 if the US carried out at least one drone strike in year $t$ and week $w$ and its two lags and leads. Covariates are unemployment, inflation, balance of payments and oil price, 5 lags of terrorist attacks and second and third polynomial time trends; $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors (with 5 lags for column 1 and 2 lags for columns 3 to 6) reported in parentheses.

Table E.4: Drone Strikes and Twitter coverage - Different samples of tweets

| | **Dependent variable:** log(1+tweets) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Both Presidents** | | **Obama** | | **Trump** | |
| Drone ($t$) | 0.300*** | 0.289*** | 0.320*** | 0.286*** | 0.174 | 0.177 |
| | (0.084) | (0.082) | (0.104) | (0.099) | (0.115) | (0.120) |
| Drone ($t+2$) | -0.059 | -0.046 | -0.120 | -0.105 | 0.020 | 0.027 |
| | (0.078) | (0.080) | (0.110) | (0.112) | (0.110) | (0.112) |
| Drone ($t+1$) | -0.028 | -0.032 | -0.091 | -0.105 | 0.114 | 0.128 |
| | (0.079) | (0.083) | (0.101) | (0.105) | (0.140) | (0.151) |
| Drone ($t-1$) | 0.094 | 0.059 | 0.159* | 0.129 | -0.095 | -0.135 |
| | (0.076) | (0.077) | (0.095) | (0.096) | (0.136) | (0.132) |
| Drone ($t-2$) | -0.084 | -0.124 | -0.076 | -0.133 | -0.020 | -0.011 |
| | (0.079) | (0.078) | (0.111) | (0.107) | (0.113) | (0.114) |
| Observations | 627 | 627 | 420 | 420 | 207 | 207 |
| Covariates, $\tau_t$, $\omega_w$ | Yes | Yes | Yes | Yes | Yes | Yes |
| 5 lags terrorist attacks | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** The table reports estimates of the effects of US drone strikes on the number of tweets mentioning drone strikes. Columns 1, 3 and 5 include tweets posted between 10 AM and 10 PM EST, which corresponds to 6 PM to 6 AM in Somalia and Yemen, 8 PM to 8 AM in Pakistan, and 7:30 PM to 7:30 AM in Afghanistan. Columns 2, 4 and 6 include tweets posted between 3 PM and 9 PM EST, which corresponds to 11 PM to 5 AM in Somalia and Yemen, 1 AM to 7 AM in Pakistan, and 12:30 AM to 6:30 AM in Afghanistan. Estimates are derived from OLS regressions and based on analogues of equation (1). Dependent variables are log number of tweets containing the words 'drone strikes'. Key explanatory variable is a dummy = 1 if the US carried out at least one drone strike in year $t$ and week $w$ and its two lags and leads. Covariates are unemployment, inflation, balance of payments and oil price, 5 lags of terrorist attacks and second and third polynomial time trends; $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors (with 5 lags for column 1 and 2 lags for columns 3 to 6) reported in parentheses.

Table E.5: Robustness Checks Airwars Data

**Dependent variable:** log(1+newspapers)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **log(1+tweets)** | | **log(1+tweets)** | | **log(1+newspapers)** | |
| Drone ($t$) | 0.188** | 0.194** | 0.184* | 0.193** | 0.149 | 0.168 |
| | (0.087) | (0.093) | (0.093) | (0.095) | (0.128) | (0.128) |
| Drone ($t+2$) | | 0.099 | 0.096 | 0.124 | | 0.071 |
| | | (0.077) | (0.077) | (0.079) | | (0.114) |
| Drone ($t+1$) | | 0.054 | 0.055 | 0.079 | | 0.283 |
| | | (0.078) | (0.079) | (0.085) | | (0.153) |
| Drone ($t-1$) | | 0.003 | -0.006 | -0.014 | | 0.060 |
| | | (0.082) | (0.083) | (0.080) | | (0.127) |
| Drone ($t-2$) | | 0.016 | 0.136 | 0.011 | | 0.218 |
| | | (0.100) | (0.098) | (0.108) | | (0.138) |
| Observations | 208 | 207 | 207 | 207 | 208 | 207 |
| Covariates, $\tau_t$, $\omega_w$ | Yes | Yes | Yes | Yes | Yes | Yes |
| 5 lags terrorist attacks | No | Yes | Yes | Yes | No | Yes |

**Notes:** Columns 1 and 2 report estimates for the effects of US drone strikes on the number of tweets mentioning drone strikes posted between 9 AM and 9 PM EST which corresponds to 5 PM to 5 AM in Somalia and Yemen, 7 PM to 7 AM in Pakistan, and 6:30 PM to 6:30 AM in Afghanistan. Columns 3 and 4 report estimates for the effects of US drone strikes on the number of tweets mentioning drone strikes. Column 3 includes tweets posted between 10 AM and 10 PM EST, which corresponds to 6 PM to 6 AM in Somalia and Yemen, 8 PM to 8 AM in Pakistan, and 7:30 PM to 7:30 AM in Afghanistan. Column 4 includes tweets posted between 3 PM and 9 PM EST, which corresponds to 11 PM to 5 AM in Somalia and Yemen, 1 AM to 7 AM in Pakistan, and 12:30 AM to 6:30 AM in Afghanistan. Columns 5 and 6 report estimates for the effects of US drone strikes on the number of newspaper articles in NYT, NYP, USAT, and WSJ covering drone strikes. Dependent variables are log number of tweets containing the words 'drone strikes' for columns 1 to 4 and of newspaper articles on drone strike for columns 5 and 6. Key explanatory variable is a dummy = 1 if the US carried out at least one drone strike in year $t$ and week $w$ and its two lags and leads. Covariates are unemployment, inflation, balance of payments and oil price, 5 lags of terrorist attacks and second and third polynomial time trends; $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors with 4 lags reported in parentheses.

Table E.6: Main results - robustness

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **Dependent variable** = 1 if drone strike | | | | |
| **Election** | 0.285 | 0.317 | 0.271 | 0.598 | 0.338 |
| | (0.122) | (0.125) | (0.125) | (0.212) | (0.150) |
| **Sample** | 2009-16 | 2009-16 | 2009-12 | 2013-16 | 2009-16 |
| **Observations** | 420 | 420 | 210 | 210 | 420 |
| $\tau_t$, $\omega_w$ | yes | yes | yes | yes | yes |
| **Covariates** | | yes | yes | yes | yes |
| **No Afghanistan** | | | | | yes |

**Notes:** The table reports effect of US elections on US drone strikes in those countries. Estimates are OLS and based on equation (1). Dependent variable =1 if US carried out at least one drone strike in week $w$ and year $t$. All regressions control for $\tau_t$, $\omega_w$ (year and week fixed effects) and for second and third polynomial time trends. column 1 does not control for covariates, column 2 controls for unemployment, inflation, balance of payments and oil price, Column 3 uses weeks in first Obama term only, Column 4 uses weeks in the second Obama term only, Column 5 does not consider drone strikes carried out in Afghanistan, columns 3, 4, and 5 also control for 5 lags of drone strikes and 5 lags of terrorist attacks. Newey-West standard errors (with 4 lags) reported in parentheses.

Table E.7: Cloud cover anomalies and drone strikes - robustness

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Dependent variable** = 1 if US carried out at least one drone strike | | | | | | | | | |
| **Cloud cover** | -0.043 | -0.066 | -0.069 | -0.114 | -0.051 | -0.080 | -0.060 | -0.152 | | |
| | (0.016) | (0.032) | (0.033) | (0.038) | (0.020) | (0.043) | (0.044) | (0.054) | | |
| **Cloud cover lag 2** | | | | | | | | | -0.025 | |
| | | | | | | | | | (0.018) | |
| **Cloud cover lag 1** | | | | | | | | | 0.031 | |
| | | | | | | | | | (0.018) | |
| **Cloud cover lead 1** | | | | | | | | | 0.021 | |
| | | | | | | | | | (0.019) | |
| **Cloud cover lead 2** | | | | | | | | | 0.008 | |
| | | | | | | | | | (0.016) | |
| **Wind speed** | | | | | | | | | | -0.033 |
| | | | | | | | | | | (0.025) |
| **Measure** | z-score | =1 if above median | =1 if above mean | =1 if above 75th | z-score | =1 if above median | =1 if above mean | =1 if above 75h | z-score | z-score |
| **Presidency** | Ob & Tr | Ob & Tr | Ob & Tr | Obama | Obama | Obama | Obama | Ob & Tr | Ob & Tr | Ob & Tr |
| **Observations** | 628 | 628 | 628 | 628 | 420 | 420 | 420 | 420 | 628 | 628 |
| **Covariates, $\tau_t$, $\omega_w$** | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| **z-scores** | yes | | | yes | | | | | yes | yes |

**Notes:** The table reports effect of cloud anomalies in Afghanistan, Pakistan, Somalia, and Yemen on US drone strikes in those countries. Estimates are OLS and based on equation (1). Dependent variable =1 if US carried out at least one drone strike in week $w$ and year $t$. Cloud anomalies are defined as cloud cover in week $w$ and year $t$ minus average cloud cover in week $w$ for the years 2009 to 2020 and are measured as z-scores in columns 1, 5, 9, and 10, as dummies for being above the median in columns 2 and 6, as dummies for being above the mean in columns 3 and 7, and as dummies for being above the 75th percentiles in columns 4 and 8. Column 9 also controls for cloud anomalies in the two weeks before and after $w$. $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors (with 5 lags for column 1 and 4 lags for columns 2-9 ) reported in parentheses.

Table E.8: Exogeneity of election date and of cloud anomalies

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | **Dependent variable** | | | | | | | |
| | Unempl | CPI | Brent | BoP | Unempl | CPI | Brent | BoP |
| **October before elections** | -0.142 | 0.581 | -0.057 | 0.208 | | | | |
| | (0.088) | (0.354) | (0.167) | (0.372) | | | | |
| **November during elections** | -0.034 | -0.102 | -0.019 | 0.567 | | | | |
| | (0.081) | (0.657) | (0.175) | (0.450) | | | | |
| **Cloud anomalies** | | | | | -0.000 | 0.015 | -0.009 | -0.179 |
| | | | | | (0.015) | (0.139) | (0.031) | (0.100) |
| **Observations** | 96 | 96 | 96 | 96 | 96 | 96 | 96 | 96 |
| **Years** | 2009-16 | 2009-16 | 2009-16 | 2009-16 | 2009-16 | 2009-16 | 2009-16 | 2009-16 |
| **Covariates, $\tau_t$, $\omega_w$** | yes | yes | yes | yes | yes | yes | yes | yes |

**Notes:** The table reports effect of elections and cloud cover anomalies on macroeconomic variables. Dependent variables are the z-scores of unemployment in columns 1 and 5, inflation in columns 2 and 6, oil price in columns 3 and 7, and balance of payments in columns 4 and 8. Unit of observation is one month. All regressions control for $\tau_t$, $\omega_w$ (year and month fixed effects), for second and third polynomial time trends, and for 5 lags of drone strikes and 5 lags of terrorist attacks. *October before elections* =1 in the October before a presidential or mid-term election. *November during elections* =1 in the November during which a presidential or mid-term election takes place. *Cloud anomalies* is the z-score of the monthly average of cloud anomalies. Newey-West standard errors (with 4 lags) reported in parentheses.

Table E.9: Postponement of drone strikes and cloud anomalies - robustness

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **Dependent variable** = 1 if drone strike | | | | |
| **Election** | 0.333 | 0.334 | 0.421 | 0.334 | 0.342 |
| | (0.202) | (0.203) | (0.153) | (0.218) | (0.222) |
| **Election** | 0.113 | 0.111 | -0.129 | 0.066 | 0.073 |
| $\times$ **past cloud** | (0.192) | (0.192) | (0.285) | (0.206) | (0.211) |
| **Post-election** | -0.074 | -0.065 | 0.190 | 0.039 | 0.030 |
| | (0.248) | (0.245) | (0.179) | (0.211) | (0.219) |
| **Post-election** | 0.582 | 0.576 | 0.459 | 0.546 | 0.518 |
| $\times$ **past cloud** | (0.234) | (0.232) | (0.226) | (0.203) | (0.197) |
| **Past cloud =1 if** | > 0 | > mean | > 75h | > median | > median |
| **Lags (weeks)** | 8 | 8 | 8 | 7 | 6-8 |
| **Sample** | 2009-16 | 2009-16 | 2009-16 | 2009-16 | 2009-16 |
| **Observations** | 420 | 420 | 420 | 420 | 420 |
| **Covariates,** $\tau_t$, $\omega_w$ | yes | yes | yes | yes | yes |

**Notes:** The table reports effect of past cloud cover anomalies on drone strikes around time of elections. Dependent variable =1 if US carried out at least one drone strike in week $w$ and year $t$. All regressions control for $\tau_t$, $\omega_w$ (year and week fixed effects), for second and third polynomial time trends, for unemployment, inflation, balance of payments and oil price, and for 5 lags of drone strikes and 5 lags of terrorist attacks. *Past cloud* = 1 if 8 week lag of cloud cover anomalies is larger than zero in column 1, if 8 week lag of cloud cover anomalies is larger than the mean in column 2, if 8 week lag of cloud cover anomalies is larger than the 75th percentile in column 3, if 7 week lag of cloud cover anomalies is larger than the median in column 4, if the rolling avearage from 6 to 8 weeks lag of cloud cover anomalies is larger than the median in column 5. Newey-West standard errors (with 4 lags) reported in parentheses.

Table E.10: News sentiment and drone strikes

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | **Panel A:** Dependent variable = 1 if drone strike | | | | | | | |
| **Negative Sentiment** | 0.129 | 0.086 | 0.271 | 0.077 | 0.123 | 0.083 | 0.153 | 0.064 |
| **during Election** | (0.081) | (0.060) | (0.121) | (0.087) | (0.077) | (0.055) | (0.167) | (0.080) |
| **Negative Sentiment** | 0.095 | 0.084 | 0.043 | 0.096 | 0.120 | 0.094 | 0.076 | 0.108 |
| **not during Election** | (0.034) | (0.036) | (0.024) | (0.043) | (0.040) | (0.039) | (0.031) | (0.043) |
| **Network** | All | Fox | CNN | MSN | All | Fox | CNN | MSN |
| **Wghtd by log vol** | | | | | yes | yes | yes | yes |
| **Covariates, $\tau_t$, $\omega_w$** | yes | yes | yes | yes | yes | yes | yes | yes |
| **Observations** | 367 | 367 | 367 | 367 | 367 | 367 | 367 | 367 |

**Notes:** The table reports correlations between negative sentiment score in cable TV news covering the president and drone strikes. *Negative sentiment* $\times$ *election* is the negative sentiment during the five weeks leading up to and including a presidential or mid-term election, *Negative sentiment* $\times$ *no election* is the negative sentiment outside of the five weeks leading up to and including a Presidential or Mid-Term election, Columns 1 to 4 report negative sentiment score, columns 5 to 8 report negative sentiment score multiplied by the log number of mentions of the President in cable TV news. Dependent variable =1 if US carried out at least one drone strike in week $w$ and year $t$, covariates are unemployment, inflation, balance of payments and oil price, 5 lags of drone strikes, 5 lags of terrorist attacks and second and third polynomial time trends; $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors with 4 lags reported in parentheses.

Table E.11: Alternative measurements for sentiment

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | **Panel A:** Dependent variable = 1 if drone strike | | | | | | | | |
| **Negative Sentiment** | 0.096 | 0.082 | 0.095 | 0.101 | 0.095 | 0.091 | 0.091 | 0.085 | 0.065 |
| | (0.034) | (0.032) | (0.035) | (0.035) | (0.034) | (0.031) | (0.033) | (0.033) | (0.028) |
| **Matching** | hard | soft | hard | hard | hard | hard | hard | hard | hard |
| **Radius** | 12 | 12 | 3 | 6 | 24 | 12 | 12 | 12 | 12 |
| **Pre-proc** | yes | yes | yes | yes | yes | no | yes | yes | yes |
| **Score type** | vs | vs | vs | vs | vs | vs | vsla | vsam | vssam |

**Notes:** The table presents the results of panel A in column 1 in table 6 using different measures for the sentiment score. Dependent variable =1 if US carried out at least one drone strike in week $w$ and year $t$, *Negative Sentiment* is the z-score of the negative sentiment score as defined below, column 1 presents results in column 1 of panel A in table 6 (hard matching, 12 words radius, pre-processing and valence score, column 2 uses soft matching, columns 3, 4 and 5 use 3, 6, and 24 words either side respectively, column 6 does not pre-process the text, column 7 uses the valence scaled sentiment score times log(arousal), column 8 uses the valence times min-max normalized arousal sentiment score, column 9 uses the valence times squared min-max normalized arousal sentiment score, covariates are unemployment, inflation, balance of payments and oil price, 5 lags of drone strikes, 5 lags of terrorist attacks and second and third polynomial time trends; $\tau_t$, $\omega_w$ are year and week fixed effects. Newey-West standard errors with 4 lags reported in parentheses.