The War On Error: Air Strike Efficacy and Boomerang Effects[*]

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The United States has spent over a trillion dollars battling terror organizations in the Middle East. The weapon of choice: air strikes and missiles launched from remotely piloted drones. These precision weapons strike individual terrorists or assets without the cost, complexity, or risk of deploying ground forces. The expansion, persistence, and lethality of the Islamic State movement highlights the need for terrorism policy backed by empirical evidence. I combine data from Yemen, where nearly all air strikes target Al Qaeda in the Arabian Peninsula (AQAP), with a time series of AQAP attacks to determine whether or not aerial attacks are an effective tool for battling terrorism. Multiple VAR specifications fail to show a decline in terror activity after an air strike, and, in fact, some support the notion that the strikes are increasing the local prevalence of the targeted groups.

JEL: H56, C30, D2

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1. *Introduction*

Since the events of September 11, 2001, the United States and its NATO allies have battled a multitude of terror organizations in the Middle East. The weapon of choice is the aerial attack: fighter jets and unmanned aerial vehicles (UAV) armed with missiles. The UAVs carry out precision attacks without the complexity or risk of deploying ground forces. Instead, the risk is transferred to communities on the ground. Fang (2015) reports that nearly 90% of individuals killed in drone strikes were not those originally targeted.[1]

The efficacy of deterrence methods has been well studied since Schelling (1960). Ganor (2011) argues forceful military policies that combat terrorism are often effective. More recently, there is a growing literature that explores whether there are rebound or boomerang effects (potential for an intervention to have the opposite of the intended effect) to methods of indiscriminate violence.

Poorly targeted violent interventions may induce empathy for the terror orga-

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[1] Data used in this study does not parse fatalities by those originally targeted and those hit accidentally, and therefore cannot corroborate this statistic.

nization within proximate communities. This could reduce the terror group's cost of operations through a positive labor supply shift due to growth in hostility, hatred, and desire for revenge against the United States and other Western powers. Benmelech, Berrebi and Klor (2015) offer the most thorough empirical analysis of the boomerang effect.[2]

The debate about drone strikes has also raged on in popular media. The C.I.A. director from 2006-2009, Hayden (2016) calls drones "the most precise and effective application of firepower in the history of armed conflict." On the other hand, in an article title "How Drones Create More Terrorist," Abbas (2013) claims "Terrorists and their misguided sympathizers often expose and market civilian casualties – particularly women and children – quite effectively." This article brings empirical rigor to that debate by employing advanced econometric techniques designed to tease out causal policy effects.

Although predator drones are accurate, it is often very difficult to locate and isolate the targeted individual. As a result, unintended targets, such as nearby civilians, are frequently casualties or so called "collateral damage." Stories like the one reported by Almasmari (2013) where 14 civilians were killed in a December 2013 aerial attack on a wedding convoy in Yemen, have become commonplace in popular media and sparked a debate about the morality of drone strikes. Strikes like these have led Amnesty International and Human Rights Watch to criticize the transparency of the United States drone program in particular (Rawlings, 2013).

From an economic perspective, the cost effectiveness of the air strikes is a function of deterrence benefits, financial cost, and human life cost. Because it is empirically challenging to estimate how many lives were saved as a result of a specific drone strike that eliminates a dangerous terrorist (due to the lack of a counterfactual), alternative measures must be used to gauge effectiveness. This thesis evaluates whether the U.S. drone program in Yemen, which mainly targets Al Qaeda in the Arabian Peninsula (AQAP), is a useful tool to weaken AQAP's output of terror attacks.

Multiple VAR specifications fail to show a decline in terror activity after a drone strike, and, in fact, some support the notion that the drone strikes are increasing the prevalence of the targeted groups.

Section 2 reviews the existing literature on terrorism and deterrence. Section 3 offers a theoretical framework that shows how methods of indiscriminate violence can feed into the cost function of a terrorist group. A dynamic empirical analysis of the effectiveness of United States' air strikes in Yemen is given in section 4. Concluding remarks are offered in section 5.

2. *Previous Literature*

Following Schelling (1960), debate ensued about which policies were effective at achieving deterrence, and which had the potential to cause escalation. Scholarly work in this realm was done mostly with Action-Reaction models, but the results were often contradictory. Lichbach (1987) summarizes this literature and instead uses a Rational Actor model to find that inconsistent accommodation or repression can lead to a violent escalation.

The interaction between government and terror organizations investigated by Lichbach (1987) illustrates which deterrence policies are likely to be most ef-

[2] A description of their study and method is given in section 2.

fective.[3] Cost effective anti-terror policy is difficult to achieve because of rent seeking politicians' incentives to provide counter-terrorism measures in excess of the public optimum in response to voter pressure (Bueno de Mesquita, 2007).

Game theoretic models of this interaction have shown how poorly targeted anti-terror policies can end up having the reverse of the desired effect. Bueno De Mesquita (2005) uses a dynamic model of a government, a terrorist organization, and a population of potential terrorist volunteers, and allows for decisions to be endogenous to economic conditions. Not surprisingly, he finds that the precision with which a crackdown is targeted has a direct effect on the labor supply to the terror group. Precisely targeted operations decrease mobilization of terror movements, whereas indiscriminate deterrence methods have the opposite effect.

Instead of endogenizing economic conditions, Rosendorff and Sandler (2004) endogenize the target that the terrorist chooses and the event type, normal or spectacular, that the terrorist pursues. Their model shows that the boomerang effect is salient: the overspending on counter-terrorism measures mentioned by Bueno de Mesquita (2007) can contribute to higher labor supply to the organization which can ultimately lead to more spectacular terror attacks and a larger number of fatalities. Their findings support the idea of a feedback loop between governments and terrorist organizations.

Methods of violence that are deemed fair are less likely to result in retaliatory responses or generate positive labor supply shocks to terror organizations (Kalyvas, 2006).[4] Unfair punishments that involve forms of indiscriminate violence can induce a collective action problem and spark reverse effects. Kalyvas and Kocher (2007) claim that the war in Iraq is an example of such an occupation. Iraq is now home to the rapidly growing Islamic State movement (which we are currently battling with air strikes, drones, and small special forces units) just three years after the withdrawal of United States troops. Case studies such as Tishkov (2004) in Chechnya and Wood (2003) in El Salvador have also illuminated the harmful effects of indiscriminate violence.

The above models and case studies show the potential increase in support for terror, insurgency, or rebel groups when governments use methods of indiscriminate violence. This concept is salient to the terror organizations themselves, and distorts incentives to the point where perpetrators disguise themselves in highly populated civilian areas in hopes of generating outrage from counter-terrorism measures (Berlow, 1996).

The estimated relation between economic conditions and terrorism described by Bueno De Mesquita (2005) is a mere correlation. Lack of education and opportunity tend to be associated with high levels of terrorism, but terrorists themselves are often educated and not poor. Benmelech and Berrebi (2007) shows that not only are terrorist volunteers educated, but education is positively correlated with probability of a successful attack and number of fatalities, and negatively correlated with the probability that the perpetrator is captured. Contrary to previous beliefs, using data from Afghanistan, Iraq, and the

[3] For an analysis of how this interaction is altered when the state sponsors terrorism see Siqueira and Sandler (2006).

[4] A "fair" punishment is one that punishes only those directly responsible for terrorism

Philippines, Berman et al. (2011), find no positive correlation between unemployment and attacks against the government.

Until recently, empirical work on indiscriminate deterrence methods has been sparse due to the lack of natural experiments and readily available data. Benmelech, Berrebi and Klor (2015) take advantage of data from the Second Palestinian Infitada (2000-2005) where the Israeli government used home demolitions as a means of combating suicide terrorism. Two types of home demolitions were used. Punitive home demolitions were used to discourage potential suicide bombers by assuring that their home would be demolished after the attack and their family would have no place to live. Precautionary home demolitions are done because of where the home is located, independent of who owns the home.

The punitive home demolitions are a form of discriminate deterrence, and the precautionary home demolitions are indiscriminate with respect to the owner of the home. Benmelech, Berrebi and Klor (2015) found significant and robust results indicating that the punitive home demolitions were an effective tool to deter suicide terrorism, but the precautionary home demolitions had the reverse effect. The number of suicide bombings increased after a large number of precautionary home demolitions were done.[5]

Instead of just looking at the Second Palestinian Intifada, Dugan and Chenoweth (2012) look at Palestinian-Israeli conflict data from 1987-2004 and analyze the deterrence effects of repressive vs. conciliatory actions. Repressive actions were those which attempted to raise the cost of committing an act of terrorism (punitive home demolitions are an example of this). Conciliatory actions instead attempt to increase the benefits of abstaining from terrorism. They find that actions by the Israeli government that are classified as repressive either had no effect on terror or resulted in increases in terror activity. Conciliatory actions, however, were correlated with decreases in terror activity.

Using data from Iraq between 2004 and 2009, Condra and Shapiro (2012) obtain a similar result to Benmelech, Berrebi and Klor (2015) and Dugan and Chenoweth (2012). They find that accidental coalition killings of civilians predict high levels of insurgency in the following month (the effect dies out after a month). On the other hand, killing insurgents is associated with lower levels of insurgency in the following month. Azam and Thelen (2012) find that military interventions become a point of attraction for recruits to terrorist organizations. They instead recommend conciliatory actions such as targeting foreign aid at the country that is the source (not the host) of the terrorism.

Israel and Iraq are both arenas in which it is difficult to carry out strikes without collateral damage because the terrorists live and work amongst the civilian population. In 2008-2010 an international naval mission in the Gulf of Aden attempted to combat Somalian piracy and terrorism. This was a unique natural experiment as the mission had no risk of collateral damage (no civilians live in the Gulf). Shortland and Vothknecht (2011) find that the mission was a success. Not only did it help to decrease piracy, but it also halted pirates from joining radical Islamic movements and further threatening international security.

The feedback loop of counter-terrorism

[5] Another method used by the Israelis is targeted killings of opposition leaders. Byman (2006) speaks to the randomness with which Palestinian factions retaliate to the killing of their leaders.

measures and terrorist attacks alluded to by Bueno de Mesquita (2007) is a corollary to the earlier empirical work in Enders and Sandler (1993). Using a vector autoregression to allow for dynamic feedback, Enders and Sandler (1993) find that there is a degree of complementarity and substitutability between types of terror attacks. A policy may very well deter one type of attack, but terror organizations can respond by using a different type. For example, Enders and Sandler (1993) find that putting metal detectors in airports decreased instances of hijackings, but increased other types of hostage attacks and assassinations.[6]

Schneider, Brück and Meierrieks (2015) provide a full review of the theoretic and empirical literature on counter-terrorism methods. It supports the notion that rational choice models are useful for cost-benefit analysis of deterence methods. Further, they argue that the main limitation of the rational choice models is that they fail to account for the dynamics between terror organizations and governments, and ignore second order effects. This article seeks to fill that gap in the literature by using a VAR that allows for dynamics and endogeneity.

3. *Theory*

Terrorist organizations, not unlike multinational corporations, tend to have hierarchical structures (Gerwehr and Daly, 2006). Although there may be a decision maker (or group of decision makers) who determines an optimal quantity of output (attacks), the objective function of the group is likely a deviation from profit maximization. For a theoretical discussion of utility maximization in place of profit maximization see Haring and Smith (1959), Ng (1974), Formby and Millner (1985), and Northrop (2013).[7]

The terrorist leader gets utility from attacking targets (A) and purchasing security measures (S). The security measures increase the likelihood the terrorist leader remains alive.

$$U = f(A, S)$$

In the short run, the weaponry and tools available to the group are fixed, so the group produces attacks with a univariate production function in labor (F for followers).

$$A = g(F)$$

At the same time, the followers choose to supply their labor according to some exogenous vector of market and cultural conditions ($\boldsymbol{x}$), compensation offered by the terrorist group (w), and the number of fatalities from drone strikes (δ). The market and cultural conditions include other wage earning opportunities. Members of a terrorist group are often compensated with living accommodations or payments made to families of those who elect to be suicide bombers. All forms of compensation are considered in w.

$$F = h(\boldsymbol{x}, w, \delta)$$

There is strong evidence suggesting that occupying forces are the main motive behind suicide terrorism (Pape, 2005).[8] Drone strikes may be considered a type of occupation. Groups are attacked by an unidentifiable opponent without a chance to confront the occu-

[6] Baliga and Sjöström (2012) and Berman (2011) explore this interaction further.

[7] Empirical applications include Fellner (1966), Lin, Dean and Moore (1974), Lopez (1986), and Brammer and Millington (2005).

[8] For a further discussion on the determinants of suicide terrorism see Santiford-Jordan and Sandler (2014)

pying force, perhaps leading to a perception of unfair war tactics.

The drone strikes can either weaken the group's ability to produce attacks or strengthen it. So long as the utility function is increasing in attacks ($\frac{\partial U}{\partial A} > 0$) and the marginal product of labor is positive ($\frac{\partial A}{\partial F} > 0$), the effect of the drone strikes on labor supply will determine the feedback into the group's productivity.

The drone strikes increase the perceived risk of joining the terrorist group, but may also induce a preference for terrorism. If a drone strike causes empathy or united hatred of the opponent after family and friends have been killed or businesses and homes have been destroyed, then labor supply could increase (Bueno De Mesquita, 2005). The relative strength of these effects will determine the sign of $\frac{\partial F}{\partial \delta}$ and ultimately $\frac{\partial A}{\partial \delta}$.

To illustrate the optimization process, imagine the leader of the terrorist group is endowed with a Cobb-Douglas utility function.

$$U = f(A, S) = \vartheta A^{\theta} S^{1-\theta} \tag{3.1}$$

Consider utility, U, to be static and path independent, determined solely by the contemporaneous values of attacks and security measures. In this framework, utility can also be thought of as expected utility over an arbitrary time horizon.

$$A = g(F) = \varphi F^{\phi} \tag{3.2}$$

The production function has scale parameter φ and rate parameter ϕ.

$$F = h(\boldsymbol{x}, w, \delta) \tag{3.3}$$

It is reasonable to expect the utility function to be increasing in both attacks and security measures.

$$\frac{\partial U}{\partial A} > 0 \qquad \frac{\partial U}{\partial S} > 0$$

Under the assumption of a competitive labor market, the value of the marginal product of labor should equate the real wage.

$$\text{MPL} = \frac{\partial A}{\partial F} = \phi\varphi F^{\phi-1} \tag{3.4}$$

The static utility framework forces the terrorist leader to maximize utility subject to spending all of the group's available money on producing attacks and security measures. That leaves the following budget constraint where I is the group's available income and P_S is the average cost of a unit of security.

$$I = wF + P_S S = \phi\varphi F^{\phi} + P_S S \tag{3.5}$$

The terrorist leader is then concerned with the following optimization problem.

$$\max_{A,S,\lambda} \ \psi = U - \lambda(\phi\varphi F^{\phi} + P_S S - I)$$

The first order conditions are

$$\frac{\partial \psi}{\partial A} = \theta\vartheta A^{\theta-1} S^{1-\theta} = \phi\lambda \tag{3.6}$$

$$\frac{\partial \psi}{\partial S} = (1-\theta)\vartheta A^{\theta} S^{-\theta} = P_S\lambda \tag{3.7}$$

$$\frac{\partial \psi}{\partial \lambda} = \phi\varphi F^{\phi} + P_S S = I \tag{3.8}$$

Equation 3.6 and 3.7 simply mandate that the marginal utility ratio equate the cost ratio, while 3.8 imposes the budget constraint. Dividing 3.6 and 3.7 by one another and simplifying leaves the following expression.

$$\phi\lambda / P_S\lambda = \frac{\theta\vartheta A^{\theta-1}S^{1-\theta}}{(1-\theta)\vartheta A^{\theta}S^{-\theta}} \tag{3.9}$$

$$\frac{\phi}{P_S} = \frac{\theta S}{(1-\theta)A} \tag{3.10}$$

$$P_S S = \frac{A\phi(1-\theta)}{\theta} \tag{3.11}$$

Imposing the budget constraint leaves the following simplified expression for attacks (see [A1] for simplification process).

$$A = \frac{\theta I}{\phi} \tag{3.12}$$

The response of attacks to drone strikes, $\frac{\partial A}{\partial \delta}$, is implicit in 3.12. The budget constraint, I, can be written as its own function.

$$I = b(F, S) \tag{3.13}$$

The optimal quantity of attacks can then be expressed as a function of the budget constraint.

$$A = \frac{\theta}{\phi} b(F, S) \tag{3.14}$$

$$A = \frac{\theta}{\phi} b\Big(h(\boldsymbol{x}, w, \delta), S\Big) \tag{3.15}$$

Attacks can now be differentiated with respect to δ.

$$\frac{\partial A}{\partial \delta} = \frac{\theta}{\phi}\frac{\partial I}{\partial F}\frac{\partial F}{\partial \delta} \tag{3.16}$$

The sign on $\frac{\partial A}{\partial \delta}$ determines whether or not air strikes increase or decrease instances of terror attacks. So long as attacks are a "good" in the utility function (more is better) and the number of attacks are increasing in labor, then the sign of $\frac{\partial F}{\partial \delta}$ will directly drive the direction of $\frac{\partial A}{\partial \delta}$. Ultimately, the effect of the drone strikes on the marginal recruit will dictate the response of the terror group to air strikes.

Because the production of attacks is expected to be increasing in followers and the budget constraint, $b(F, S)$, is increasing in followers, the sign on $\frac{\partial F}{\partial \delta}$ should ultimately drive the terror group's response to drone strikes. In short, if drone strikes lower the group's cost of operating through an increase in labor supply, then it is reasonable to expect that the strikes may also increase production in-line with the above methodology.

4. Data

4.I. Description

The data on terrorist attacks comes from the Global Terorrism Database (hereto referred to as the GTD).[9] The GTD, housed under the Start initiative at the University of Maryland, is a thorough dataset that logs terror activity worldwide from 1970 to the present. The GTD attempts to collect data not only on the location, date, and outcome of the attacks (casualties, fatalities, etc.), but also on the motivation behind the attack, the group responsible, and the weapons used.

In order for an attack to be logged in the GTD, the act must be intentional, violent or contain the threat of violence, and be carried out by a non-governmental actor. According to the GTD manual, the incident must exhibit at least two of the following three characteristics (University of Maryland, 2015).

1) The act must be aimed at attaining a political, economic, religious, or social goal.

[9] For a full decomposition and descriptive analysis of the GTD see Enders, Sandler and Gaibulloev (2011)

2) There must be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims.

3) The action must be outside the context of legitimate warfare activities.

Note that the above criteria fail to exclude events that may not be traditionally associated with terrorism. For example, many social movements and threats to destroy infrastructure are logged in the GTD. As a result, the data can be noisy. Between the years 2009 and 2014, the GTD has record of 52,914 terrorist attacks. To illustrate the expanse of the data, Pakistan had multiple attacks on over 80% of days in the same time period. Enders, Sandler and Gaibulloev (2011) suggest that the GTD may over report some of these recent minor incidents.

It can become difficult to identify the efficacy of US aerial attacks on terror groups in such an expansive framework. Many of the attacks are unclaimed or the motives are unclear, and determining which incidents were in response to or motivated by US aerial attacks is difficult. Considering only the activity of one group or country allows for a cleaner estimation.

A unique natural experiment, in which nearly all drone strikes in Yemen target one group, allows for a more direct identification. Al Qaeda in the Arabian Peninsula (AQAP) is the most active and powerful arm of Al Qaeda. Nearly all drone strikes launched in Yemen were aimed at leaders or members of AQAP. In fact, the first known combat use of a predator drone was a US strike launched from Djibouti into the Marib province of Yemen on September 19, 2002. The attack killed Al Qaeda leader Abu Mi, the man behind the USS Cole bombing, and naturalized US citizen Kamal Darwish, accused of leading a terror support cell in Buffalo, New York.[10]

The 2002 strike, however, was an outlier. Yemen banned drone strikes and the next documented military intervention in Yemen was not until 2009. As seen in Figure 1, 2012 was the year with the most fatalities from air and drone strikes. Potential reasons for this include the fact that it was an election year in the United States and a civil war broke out in Yemen. There are strong incentives for politicians to appear strong on terrorism, especially in election years (Bueno de Mesquita, 2007).

AQAP does not need to travel far to retaliate against the US. Saudi Arabia is a de facto ally of the US and the Yemen government is the entity that allows the drone strikes to take place (from 2009 onwards). As a result, it is easy for AQAP to express their displeasure with the US domestically or immediately across the border.

The air strike data is from the Bureau of Investigative Journalism (hereto referred to as the BIJ). Based at the City University in London, the BIJ has won numerous awards for its work, including Thomson Reuters' Reporting Europe Award, and has been featured in nearly 50 front page stories. Due to the break in the data mentioned in the previous paragraph, I use the BIJ data from 2009-2014. The six provinces with the largest number of drone strikes are shown with their respective number of AQAP attacks in Table 1.

Air strikes and terror attacks are strongly correlated at the provincial level. Geographic variation in drone strikes is unique to Yemen. In Pakistan, for example, all drone strikes except for two took place in the Federal Tribal Ar-

[10]See Gordon (2002).

Table 1—Provincial Activity

Province	Air strikes	Attacks
Abyan	70	158
Shabwa	44	85
Hadhramout	25	149
Bayda	22	65
Marib	21	23
Jawf	8	5

Table 2—Summary Statistics

Variable	Mean	St. Dev.	Min.	Max.
Air Strike Data: Monthly				
Min. Strikes	3.12	5.29	0	30
Max. Strikes	3.65	6.13	0	30
Min. Total Fatalities	13.86	25.25	0	110
Max. Total Fatalities	19.72	33.86	0	171
Min. Civilian Fatalities	2.25	6.70	0	44
Max. Civilian Fatalities	3.53	8.18	0	44
Min. Child Fatalities	0.56	2.57	0	21
Max. Child Fatalities	0.61	2.73	0	22
Min. Total Injuries	3.54	8.70	0	55
Max. Total Injuries	5.82	14.48	0	88
Terror Data: Monthly				
Attempted Attacks	12.05	10.44	1	49
Successful Attacks	10.83	9.60	0	44
Multi-pronged Attacks	1.63	3.26	0	15
Suicide Bombings	1.56	1.86	0	7
Total Fatalities	45.31	54.77	0	303
Total Injuries	38.69	57.86	0	327
Total Perpetrators	18.83	75.50	0	600
Total Terrorists Killed	9.54	15.41	0	62

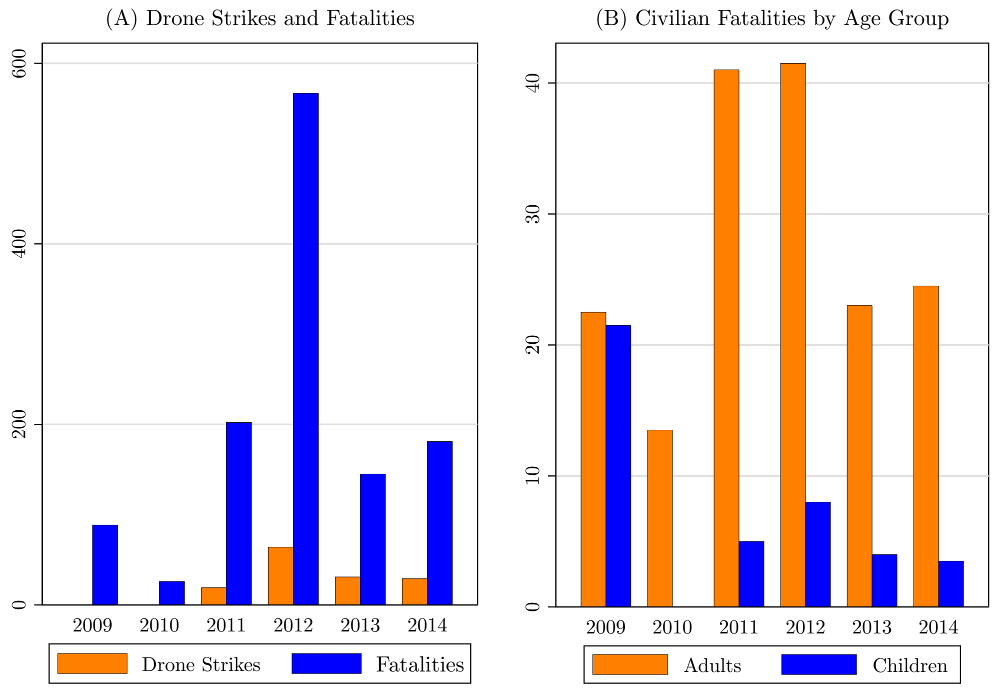
Note: The minimum and maximum bounds for the drone data are recorded by taking the lower and upper bound estimates from strike reports. The drone data and terror data are monthly from 2009-2014.

eas where the Taliban tends to congregate. AQAP attacked 157 different cities in five different countries. AQAP logged 759 attempted attacks between 2009 and 2014 with 747 in Yemen, nine in Saudi Arabia, and one in the US[11], UK, and UAE. The number of strikes, attacks, and the time duration considered are comparable to those found in Benmelech, Berrebi and Klor (2015).

Descriptive statistics for the variables of interest are given in Table 2. The BIJ collects the drone data by mining for ground reports as well as local and inter-

[11]See O'Connor and Schmitt (2009).

FIGURE 1. DRONE STRIKES IN YEMEN



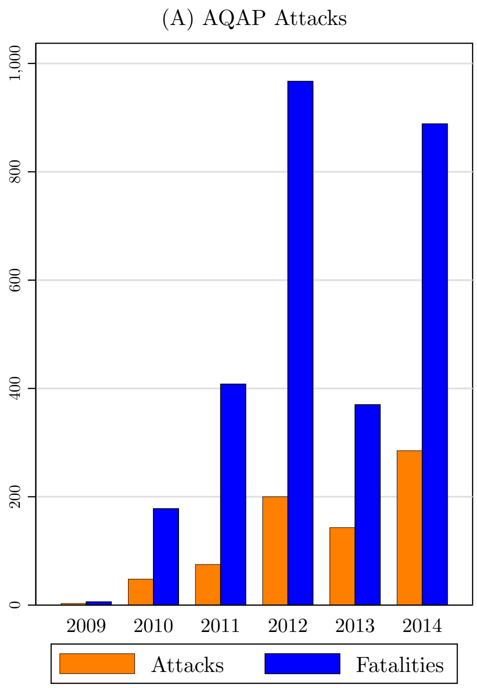
national media reports about the strikes. As a result, all of the variables in the BIJ are expressed as ranges where the minimum is the smallest incidence reported and the maximum is the largest.[12] An average of the gap between the two is given in Figure A1.

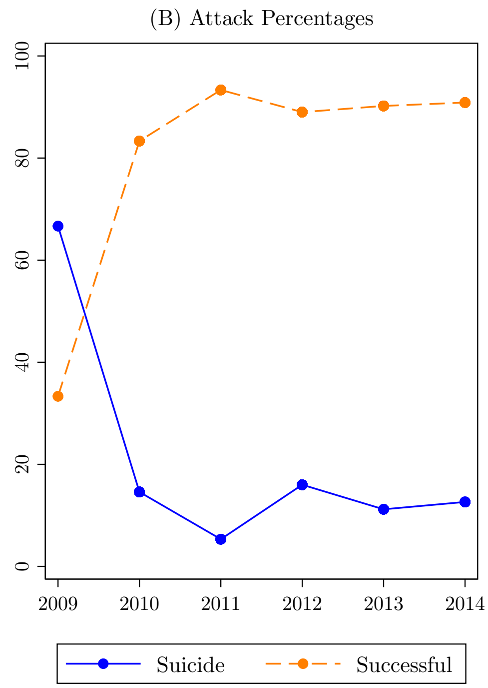
There were at least 225 drone strikes in the six year period of interest with the most occuring in 2012 (94 strikes). Similarly, 2012 was the deadliest year to be an AQAP terrorist or to live near AQAP operational areas, as there were a total of 468 fatalities from drone strikes in 2012. The lethality of each strike declined from a global peak in 2009 and remained fairly flat for the remaining years. There were only three strikes in 2009, two of which killed more than 30 people. The total fatalities figure reported by the BIJ is not the sum of civilian and militant deaths, it is actually the sum of civilian and unidentified fatalities. The remaining people could have been militants or civilians.

A further exploration of the terror attacks is given in Figure 2. Although 2014 was AQAP's most active year with around 300 attacks, 2012 was AQAP's deadliest year with nearly 1000 fatalities. In 2009 less than 40% of AQAP's attacks succeeded, but by 2010 their success rate was above 80% and it would stay there through 2014. There is no discernible time trend (see Figure A2) in fatalities per attack, but 2011 was the peak with over five deaths per AQAP attack.

[12]For all analyses, the average of the minimum and the maximum is reported.

Figure 2. AQAP Terrorist Attacks





The raw series of the fatalities from drone strikes and terror attack are shown in Figure 3.[13] There are no discernible time trends or seasonality, but there are multiple instances of shocks to air strikes preceding increases in terror attacks and terror attacks preceding air strikes. This hints at a potential simultaneity problem that will be remedied using orthogonal identification techniques.

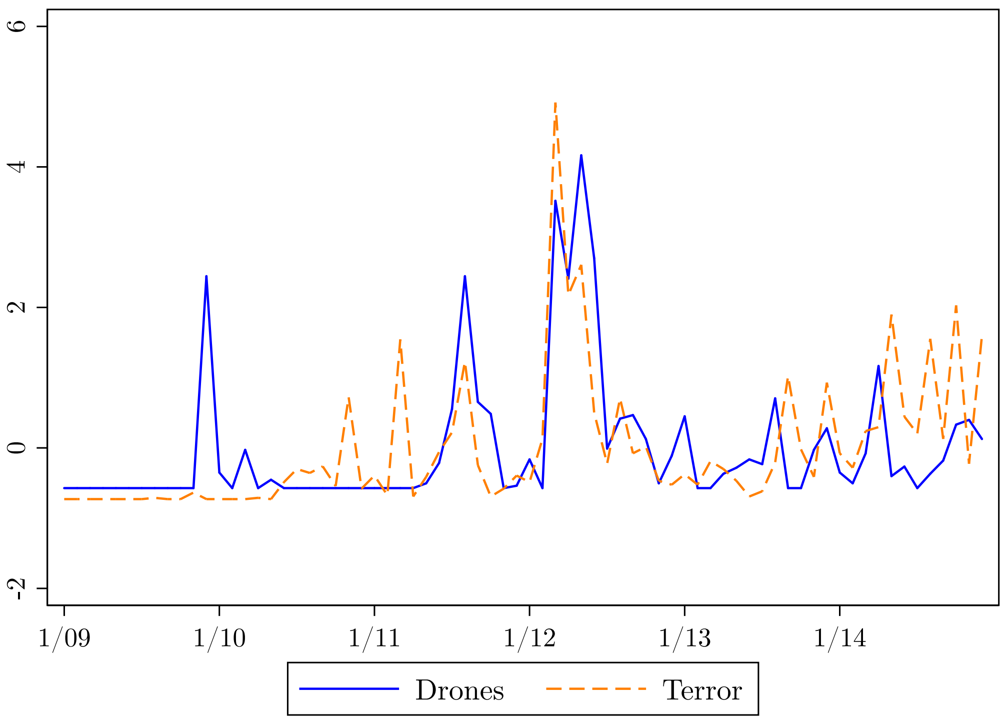
4.II. Model

A vector autoregression (VAR) allows for both terror attacks and drone strikes to endogenously feed off of each other. The parameters take into account the cross equation correlations of the error terms. The error derivations for the VAR involve a normality assumption, which is likely not appropriate for this application (fatalities and quantity of attacks form discrete count data). Instead, I report bootstrapped error bands for the impulse response functions and forecast error variance decompositions.

The VAR is appropriate for this application because it attempts to alleviate omitted variable bias by lagging each dependent variable. There is no declassified information on who each drawn strike targets, the relative importance of that individual in the structure of Al Qaeda, and who else was killed in the strike. Further, it is unknown which of Al Qaeda's attacks are in direct retaliation for a drone strike and which are

[13]Variables standardized to have mean 0 and standard deviation 1.

Figure 3. Fatalities



due to unobserved religious or geopolitical motivations.

Terror attacks and drone strikes occur on a scale of varying severity. Information about the event scale is retained by using fatality variables as opposed to the quantity of incidents, which would force a small and large attack to be treated the same.

Following from Hamilton (1994), the VAR will take the form

$$\mathbf{y_t} = \mathbf{A}\mathbf{y}_{t-1} + \mathbf{B}\mathbf{x}_{jt} + \boldsymbol{\mu}_t \tag{4.1}$$

$$\mathbf{y}_t = \begin{bmatrix} D_t \\ T_t \end{bmatrix} \tag{4.2}$$

where $\mathbf{y_t}$ is a vector of dependent variables, D_t for drone fatalities in time t and T_t for terror fatalities in time t, $\mathbf{A}$ is a matrix of parameters applied to the endogenous lags, $\mathbf{B}$ is a vector of coefficients, $\mathbf{x}_{jt}$ is a vector of exogenous variables at time t, and $\boldsymbol{\mu}_t$ is the error vector. For the case with one lag and no exogenous variables:

$$\mathbf{A} = \begin{bmatrix} \pi_1 & \pi_2 \\ \theta_1 & \theta_2 \end{bmatrix} \tag{4.3}$$

$$\mathbf{y}_{t-1} = \begin{bmatrix} D_{t-1} \\ T_{t-1} \end{bmatrix} \tag{4.4}$$

$$\boldsymbol{\mu}_t = \begin{bmatrix} \mu_{D1} \\ \mu_{T1} \end{bmatrix} \tag{4.5}$$

In order for the impulse response functions to have a causal interpretation the exogenous variables must be truly exogenous. That is

$$\mathbb{E}(\mathbf{x}_{jt}\boldsymbol{\mu}_{jt}^{\top}) = 0$$

and the residuals are pure noise such that the following holds.

$$\mathbb{E}(\boldsymbol{\mu}_t\boldsymbol{\mu}_m^{\top}) = 0,\ t \neq m$$
$$\mathbb{E}(\boldsymbol{\mu}_t^{\top}) = 0$$

We would like to study how changes affect the variables in $\mathbf{y}$. If we let $\bar{\mathbf{y}}$ equal the constant mean of the variables in $\mathbf{y}$ then the model (without any exogenous variables) can be rewritten using a moving average.

$$\mathbf{y}_t = \bar{\mathbf{y}} + \sum_{i=0}^{\infty} \boldsymbol{\xi}_i \boldsymbol{\mu}_{t-i} \tag{4.6}$$

As Hamilton (1994) points out, this is only appropriate when the VAR is stable, otherwise $\bar{\mathbf{y}}$ would be time variant.[14]

$$\boldsymbol{\xi}_i = \begin{cases} \mathbf{I}_2 & \text{if } i = 0 \\ \sum_{m=1}^{i} \boldsymbol{\xi}_{i-m}\mathbf{A}_m & \forall\ i \neq 0 \end{cases}$$

The j, k element of $\boldsymbol{\xi}_i$ will show what happens to the jth element of $\mathbf{y}_t$ after i periods for a time unit increase in the kth element of $\boldsymbol{\mu}_t$.

The $\boldsymbol{\xi}_i$ cannot be causally interpreted due to the contemporaneous correlation in the $\boldsymbol{\mu}_t$. Mainly,

$$\mathbb{E}(\boldsymbol{\mu}_{Dt}\boldsymbol{\mu}_{Tt}^{\top}) \neq 0$$

and it then becomes impossible to parse out the effect of the drones on the terror attacks because the variables tend to move together. A simple impulse response function like that of $\boldsymbol{\xi}_i$ cannot be used. This applicatin requires orthogonal impulse response functions.

Hamilton (1994) suggests we define

$$\boldsymbol{\Sigma} = \mathbb{E}(\boldsymbol{\mu}_t\boldsymbol{\mu}_t^{\top})$$

and find a $\mathbf{P}$ such that[15]

$$\boldsymbol{\Sigma} = \mathbf{P}\mathbf{P}^{\top}$$
$$\mathbf{P}^{-1}\boldsymbol{\Sigma}(\mathbf{P}^{\top})^{-1} = \mathbf{I}_2$$

Now we can begin to rewrite (4.6).

$$\mathbf{y}_t = \bar{\mathbf{y}} + \sum_{i=0}^{\infty} \boldsymbol{\xi}_i \mathbf{P}\mathbf{P}^{-1}\boldsymbol{\mu}_{t-i}$$

Then the two components below are orthogonal

$$(\boldsymbol{\xi}_i\mathbf{P})(\mathbf{P}^{-1}\boldsymbol{\mu}_t)^{\top} = 0$$

and the $\boldsymbol{\xi}_i\mathbf{P}$ can be causally interpreted.

The caveat of course, is that we must find a reasonable estimate of $\mathbf{P}$. Sims (1980) suggests using the Cholesky decomposition of $\boldsymbol{\Sigma}$ after estimating the VAR. The impulse response functions and forecast error variance decompositions will then be a function of the ordering of the variables in the Cholesky decomposition.

Our VAR is only two dimensional and so there are only two ways of doing the Cholesky decomposition. I do both in the following section. The model with the drone data first in the Cholesky decomposition is emphasized due to the drones being arguably relatively more exogenous then the terror strikes. Drones tend to respond to intelligence shocks and less so to changes in the geopolitical landscape.

[14] All VARs used here are indeed stable. The roots of the companion matrix all lie within the unit circle (see Figure A7).

[15] Notation used here matches that of StataCorp. (2013). The same results follow from Hamilton (1994).

TABLE 3—GRANGER CAUSALITY TESTS

Aggregation:	Monthly		Weekly	
Granger causing $\rightarrow$	Terror Drones	Drones Terror	Terror Drones	Drones Terror
χ^2	6.06	0.14	26.47	7.42
Degrees of Freedom	1	1	5	5
P(χ^2)	0.01**	0.71	0.00***	0.19

*** p<0.01, ** p<0.05, * p<0.1

4.III. Monthly Results

Both data series are event counts where the date of each drone strike or terror attack is known. I aggregate by month as in Table 2 to form a time series.

Before estimating the VAR, both variables need to be tested for stationarity. To avoid a functional imposition assumption, I use three variants of the augmented Dickey-Fuller of lag length p (Dickey and Fuller, 1979).

$$\Delta y_t = d + \beta t + \gamma y_{t-1} + \boldsymbol{\delta}\boldsymbol{\Delta}\mathbf{y} + \varepsilon_t$$
$$\boldsymbol{\delta} = [\delta_1 \quad \ldots \quad \delta_{p-1}]$$
$$\boldsymbol{\Delta}\mathbf{y} = \begin{bmatrix} \Delta y_{t-1} \\ \vdots \\ \Delta y_{t-p+1} \end{bmatrix}$$

The first variant restricts $d = 0$ and $\beta = 0$ (allowing for no drift or trend), the second and third simply restrict either β or d to zero (allowing for either a drift or a trend). For lag lengths one to four the Dickey-Fuller statistic is given by

$$DF = \frac{\hat{\gamma}}{SE(\hat{\gamma})}.$$

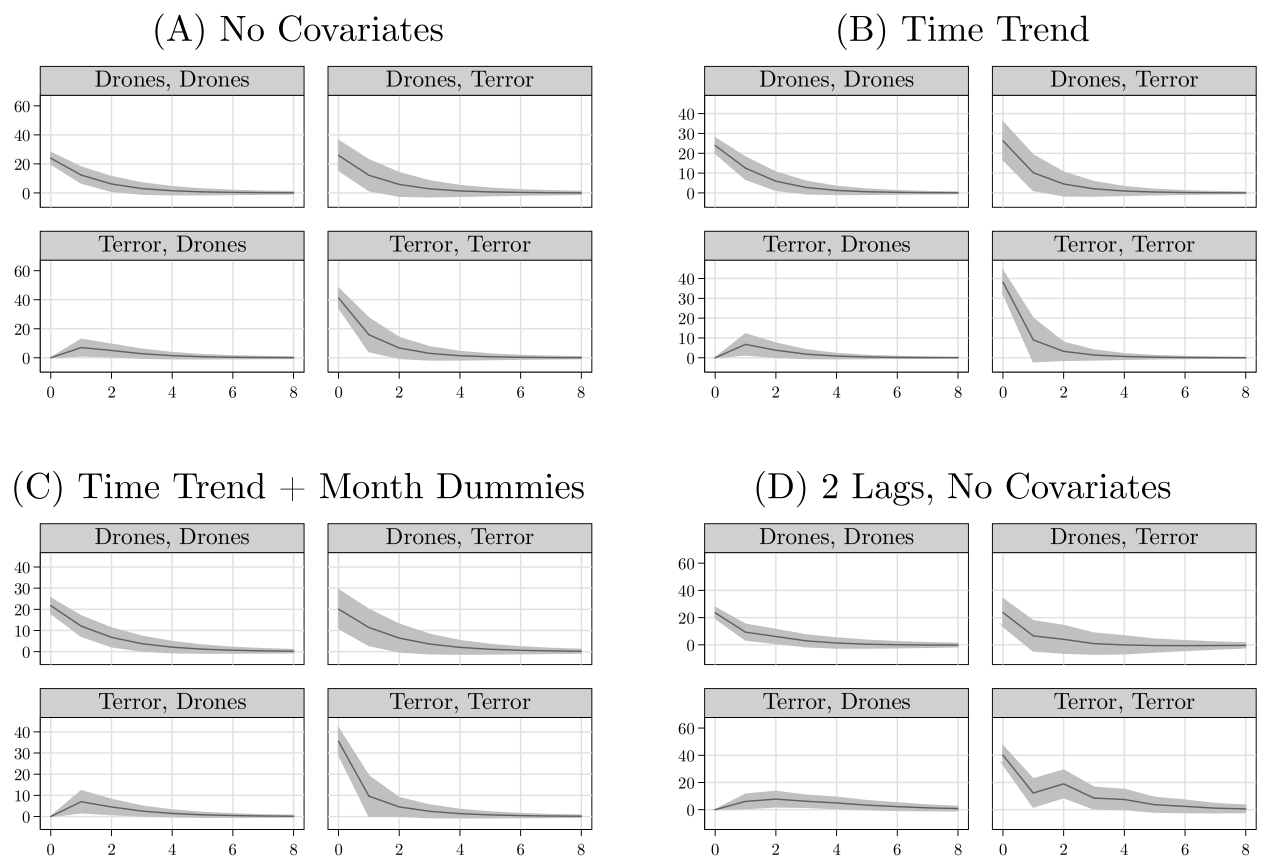
For each test both drone fatalities and terror fatalities reject the null hypothesis at the 95% confidence level that they contain a unit root. This leads to an acceptance of the alternate hypothesis that both are generated by a stationary process.

Akaike's information criterion (Akaike, 1998) test for lag selection recommends $p = 1$ for both Cholesky orderings. Estimation in Figure 4 uses drone strikes as the first variable in the Cholesky decomposition. This is arguably the most valid as the United States has a predetermined "disposition matrix," and individuals on the list are then killed upon the realization of an exogenous information shock (for example, intelligence sources may report that an individual will be in a certain home at a certain time).[16]

The orthogonalized impulse response functions from four different VAR specifications are given in Figure 4. Panels

[16]For more on this process see Cobain (2013).

Figure 4. Monthly VAR IRF: Drones First in Cholesky Ordering



Orthogonalized IRFs. Graphs by impulse variable, response variable. Bootstrapped error bands.

(A), (B), and (C) use a lag length of one as recommended by both Akaike's information criterion and the Hannan and Quinn information criterion. Panel (D) is estimated with two lags and no covariates. Panel (A) does not use any exogenous variables, panel (B) uses a linear time trend, and panel (C) uses a linear time trend and monthly dummies to allow for seasonality.

The specification of the Cholesky ordering is a type of structural decomposition. Figure 4 allows for drones to contemporaneously respond to terror attacks, but not the other way around. The structural decomposition and orthogonal impulse response functions allow for a causal interpretation.

The orthogonal impulse response functions in Figure 4 can be interpreted as the time path of the response variable for a positive one standard deviation shock to the impulse variable. In a stationary and stable system like this one, it is standard for the shock to dissipate as time goes on. The impulses labeled "Drones, Terror" are showing the response of fatalities from AQAP attacks for a one standard deviation increase in fatalities from drone strikes. On the other hand, "Terror, Drones" show the response of drone fatalities for a one standard deviation increase in fatalities from AQAP attacks.

A Lagrange multiplier test for autocorrelation in the error terms, as first presented by Johansen (1995), returns a failure to reject the null hypothesis of no autocorrelation for all four specifications presented in Figure 4. The error bands are bootstrapped using the residuals. A parametric bootstrap is not necessary due to the linearity of the VAR.

Across all four models each variable responds significantly to a shock in its own value. Most notable, however, is the strong response of AQAP to the drone strikes, and the weak response of the drones to AQAP attacks.

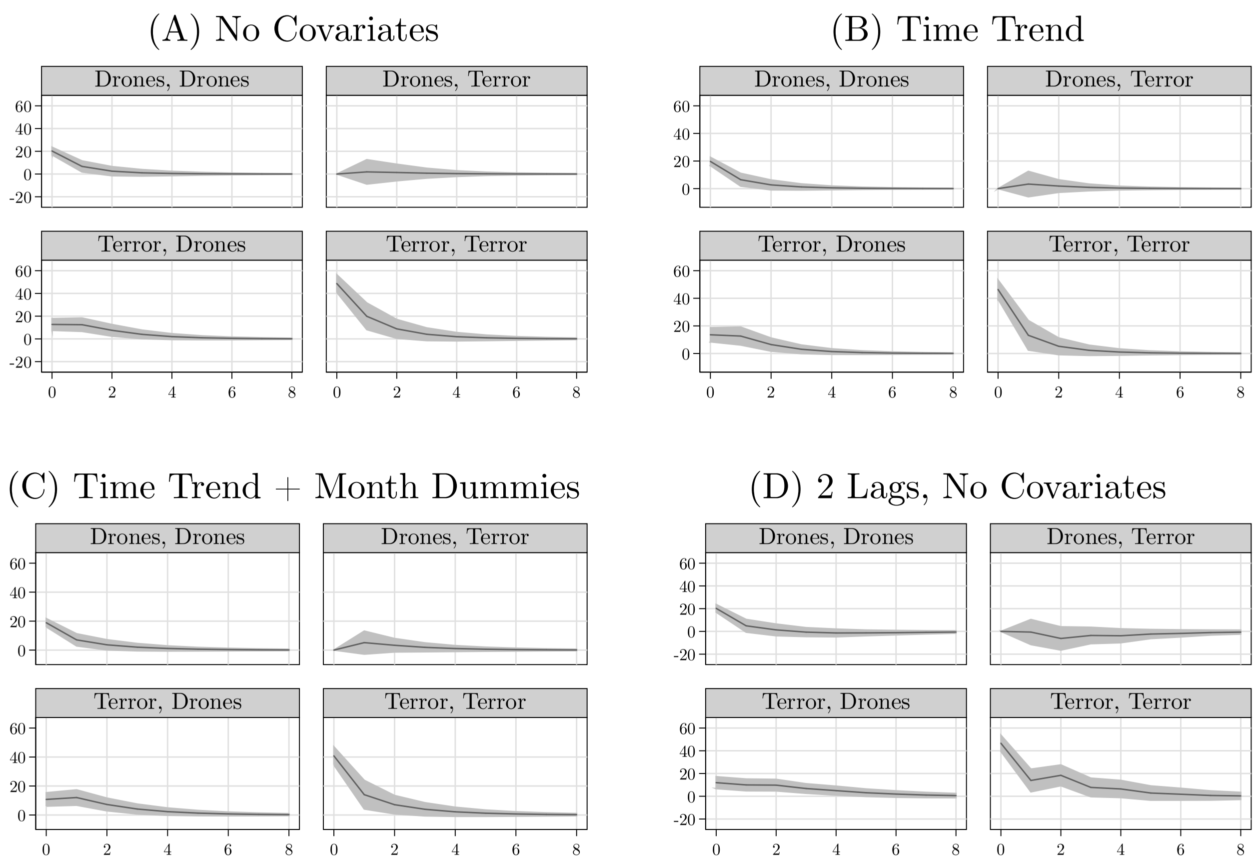
The Granger (1969) causality test in Table 3 suggests that the terror attacks are Granger causing the drones, but the drones do not Granger cause the terror attacks. The forecast error variance decompositions in Figure A3 tell a similar story. The variables are almost exclusively explained by innovations in their own values and not by each other. Although, as time expires from the date of a positive shock in drone strikes, there appears to be a small increase in the explanatory power of the drone strikes to predict the terror attacks and the other way around. This could be the realization of a delayed labor supply shock alluded to in the theory section.

According to the orthogonalized impulse response functions, AQAP appears to be responding within a two month window to drone attacks by increasing terror operations to the tune of 15 – 35 fatalities (depending on the model and confidence intervals) for a one standard deviation increase in drone fatalities. The result is statistically significant and persistent for approximately two months, but not supported by the Granger causality tests.

On the other hand, the drones respond slightly to the AQAP attacks, but the shock dies out quickly and lacks significance across a few specifications. These results support the notion that the US does not immediately respond to terror attacks with drones. Rather, the US implements the drone strikes when they receive intelligence about the terrorist's location.

Figure 5 has the same four vector autoregressions as Figure 4, but the ordering of the Cholesky decomposition is reversed. Because our $\mathbf{\Sigma}$ remains positive definite we can still find a lower

Figure 5. Monthly VAR IRF: Terror First in Cholesky Ordering



Orthogonalized IRFs. Graphs by impulse variable, response variable. Bootstrapped error bands.

triangular $\mathbf{P}$ such that

$$\boldsymbol{\Sigma} = \mathbf{P}\mathbf{P}^{\top}.$$

The orthogonalized impulse response functions look similar to those in Figure 4, except the positive response of AQAP to the drone strikes dies out to zero and statistically insignificant. Also, there appears to be a small, positive, and statistically significant drone response when for a one standard deviation increase in the fatalities due to AQAP attacks. The forecast error variance decompositions for the VARs in Figure 5 are given in Figure A4. This specification leads to the same qualitative conclusions as the Granger causality tests in Table 3.

The forecast error variance decomposition is sensitive to the Cholesky ordering. When terror fatalities are decomposed first, the AQAP attacks are able to explain a larger share of the drone strikes. The terror fatalities, however, are still mainly explained by their own lags and appear independent of the drone strikes.

Across both the impulse response functions and the forecast error variance decompositions there is no evidence that the drone strikes are doing anything to deter AQAP terror attacks. The Granger causality results are the same for both Cholesky orderings.

4.IV. Weekly Results

The VARs run on the monthly aggregated data could be biased due to the contemporaneous correlation of the two series. When aggregating to a low frequency it is possible that the impulse response functions could show AQAP retaliating or being deterred by a drone strike later in the month that has yet to occur. The following VARs are run on weekly aggregated data to eliminate those concerns.

The same variants of the Dickey-Fuller are implemented for the weekly aggregated data, and both series are stationary over a thorough range of Dickey-Fuller specifications with lags, trends, and drift terms.

Akaike's information criterion (Akaike, 1998) test for lag selection recommends $p = 5$. All log likelihood tests recommend a lag length between three and five. Specifications of both three and five lags will be included. Each will be estimated with and without a linear time trend.

Since the model now has multiple lags there are multiple $\mathbf{A}_i$.

$$\begin{aligned}\mathbf{y}_{\boldsymbol{t}} &= \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-1} + \dots \\ &\quad + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{B}\mathbf{x}_{jt} + \boldsymbol{\mu}_t\end{aligned}$$

For a general p lag VAR the companion matrix is

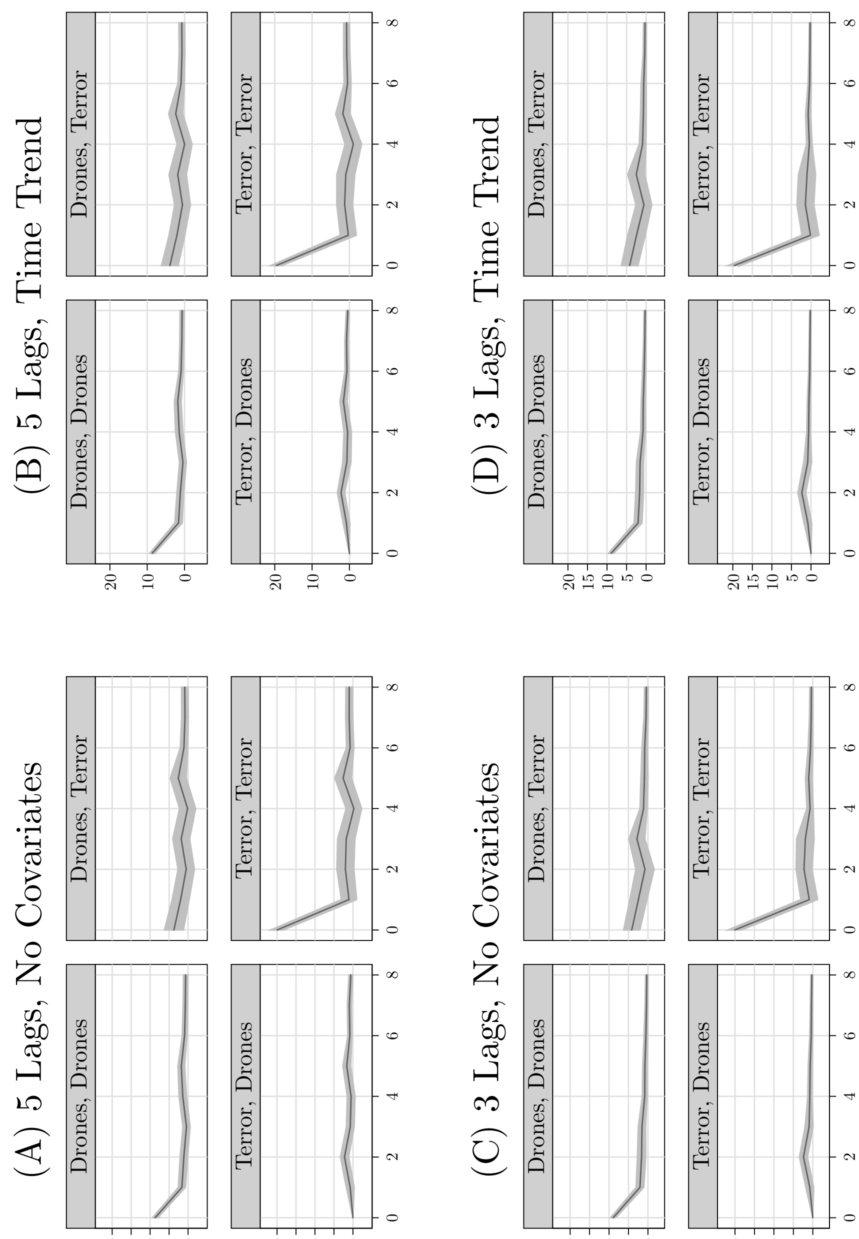
$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_2 & \dots & \mathbf{A}_{p-1} & \mathbf{A}_p \\ \mathbf{I} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} & \dots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{I} & \mathbf{0} \end{bmatrix}.$$

Hamilton (1994) and Lütkepohl (2005) show that so long as the eigenvalues (roots) of $\mathbf{A}$ have modulus less than one, the VAR is stable.

Like the monthly results, all VARs are stable. The eigenvalues of the companion matrix look similar for each. A VAR on the weekly data with drones first in the Cholesky decomposition is shown in Figure 6. As an example, Figure A7 graphs each eigenvalue on the unit circle for the VAR in panel (A) of Figure 6. All have a two-norm smaller than one.

The Granger (1969) causality test (Table 3) looks similar to the monthly data. The terror fatalities Granger cause the drones, but the drones do not Granger

Figure 6. Weekly VAR IRF: Drones First in Cholesky Ordering



Orthogonalized IRFs. Graphs by impulse variable, response variable. Bootstrapped error bands.

cause the terror fatalities. That being said, the $P(\chi^2)$ is much smaller for the weekly data. At an 80% significance level, the drones are Granger causing the terror fatalities.

The impulse response functions in Figure 6 show a small and statistically significant bump in fatalities from AQAP terror fatalities following a positive shock to drone fatalities. The drones appear to be increasing, not decreasing, fatalities from terror attacks. Again, both variables react strongly and positively to positive shocks in their own values, and the response dies out between two and four weeks. On the other hand, there appears to be little to no drone reaction to the terrorist fatalities. There is a small increase in drone activity two weeks after an AQAP terrorism incident.

The forecast error variance decomposition for the VARs in Figure 6 are given in Figure A5. The error decompositions look nearly identical to those of the monthly aggregated VAR with drones first in the Cholesky decomposition. There is a tiny positive uptick in the ability of the drone fatalities to explain the terror fatalities and vice versa a few weeks after an incident, but the variance in both series are better explained by their own values.

Switching the order of the Cholesky decomposition in Figure 7 has a symmetrical effect to the monthly data. When ordering terror fatalities first, the increase in terror fatalities after a shock to drones dies out to zero and statistically insignificant. The largest difference between these impulses and those from the monthly data are that the drone response to terror dies out as well.

Looking at the forecast error variance decompositions in Figure A6 we get qualitatitively identical results to Figure A5. The variables have little ability to explain each other and nearly all explanatory power comes from their own lags. Again, there is no evidence from this approach to suggest that the drones are even marginally deterring terror fatalities.

4.V. Seemingly Unrelated Estimation

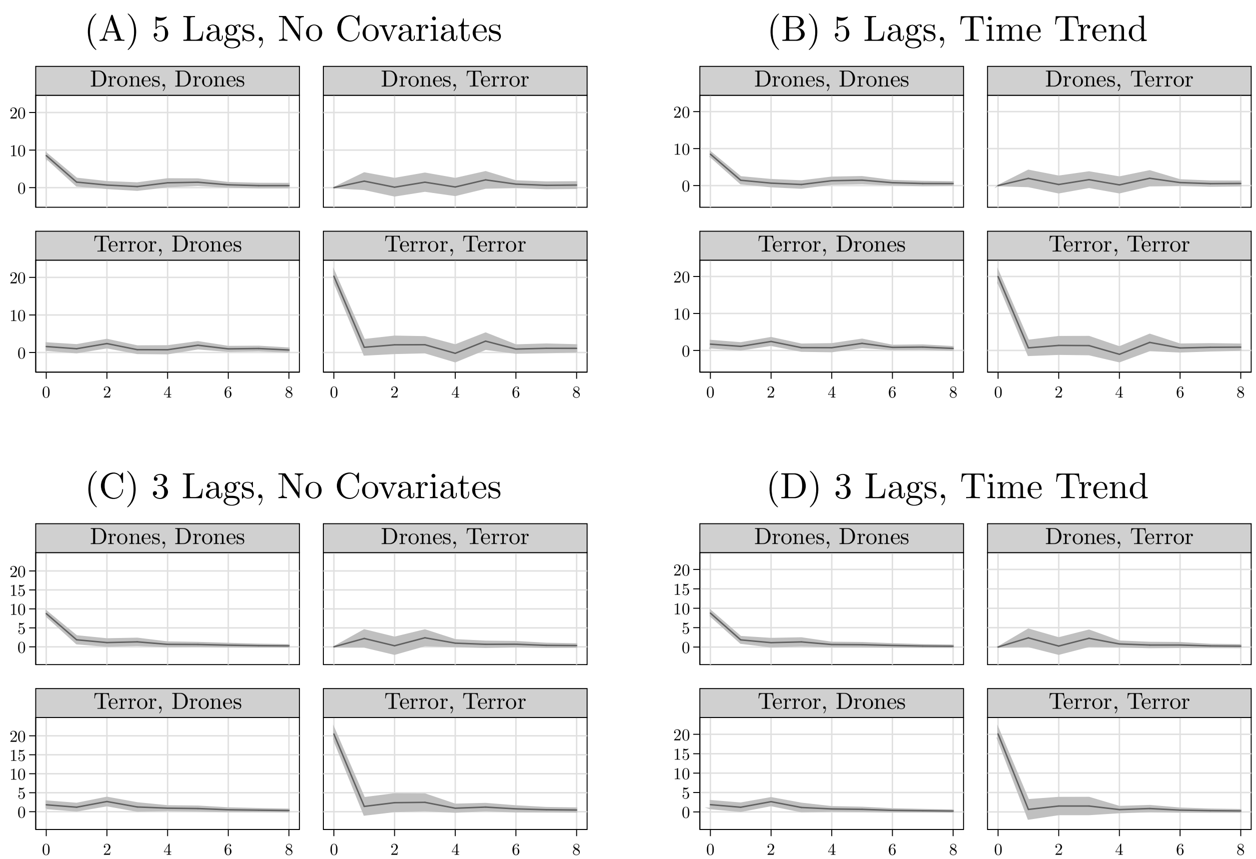
A potential issue with the Granger causality tests in Table 3 is that they are estimated with ordinary least squares using data that are naturally discrete. Using the monthly data, a univariate lag structure, and a linear time trend, the Granger causality tests are redone in Table 4 using poisson and negative binomial regression as comparison points.

Table 4 uses seemingly unrelated estimation to estimate consistent standard errors as in White (1982), White (1996), and Hausman (1978). Although the error estimates are improved, the coefficients are no longer consistent as the dynamics of the model have been removed. Each regression is estimated separately and then the error covariance matrices are combined to obtain robust standard errors.

The estimates in Table 4 offer the same qualitative conclusions as the VAR models. The null hypothesis on the coefficients can be interpreted as the Granger test statistic because there is only one lag. If there were more than one, an F-test would be required.

The drone fatalities have a positive and statistically insignificant effect on the terror fatalities in all three specifications. This can be interpreted as a lack of Granger causality, which is the same result as Table 3. The drones do appear to be Granger causing the terror fatalities at a 10% confidence level in the poisson specification. On the other hand, the terror fatalities do appear to be Granger causing the drone fatalities.

Figure 7. Weekly VAR IRF: Terror First in Cholesky Ordering



Orthogonalized IRFs. Graphs by impulse variable, response variable. Bootstrapped error bands.

5. *Conclusion*

Scholarly work on the effectiveness of counter-terrorism methods has been concentrated with rational choice models that do not allow for dynamics. This article seeks to follow in the path of Enders and Sandler (1993) and test whether or not the United States' drone program in Yemen has been an effective tool for countering AQAP. By employing a vector autoregression, second and third order effects are captured by allowing AQAP and the United States to dynamically react to one another.

Aggregating data at both the weekly and monthly level, altering the order of the Cholesky decomposition, and multiple Granger causality tests fail to reject the hypothesis that United States drone strikes in Yemen are increasing or having no effect on the output of AQAP. Multiple specifications support the notion that AQAP is retaliating to the drone strikes and increasing the number of fatalities from terrorist attacks in the months and weeks following the strikes. This finding is in agreement with other empirical studies on methods of indiscriminate violence and has direct policy implications.

A potential shortcoming of this work is that the welfare function of the United States government is unknown. The drone strikes could be stopping attacks on the United States, but increasing the power of AQAP locally in Yemen. Further, it is possible that the drone strikes cause immediate violent outbursts, but may have long run positive effects that occur beyond the time scope of this study. If the United States' sole objective is to stop attacks on its homeland, then data used by this study have no ability to comment on the effectiveness of the drones. If the United States has any interest in defeating the terrorist group at large, the above analysis suggests that drone strikes are an ineffective tool for doing so in the short run.

Further, the structural parameters from the theoretical model are unidentifiable with the data used in this study. The causal mechanism in the impulse response functions may therefore be driven by something other than a labor supply shock (or lack thereof). Because Al Qaeda and ISIS are tactically different, these results may not have direct implications to the fight against ISIS, but further stress the questionable effectiveness of indiscriminate violence. The immediate implication of this article is that those with access to classified data should consider employing dynamic empirical techniques to ensure that the drone and air strikes are having the desired effect.

Table 4—Alternative Granger Causality Regressions

Estimator:	OLS		Poisson		Negative Binomial	
Variables	(Drone)	(Terror)	(Drone)	(Terror)	(Drone)	(Terror)
L.Drone Fatalities	0.374***	0.274	0.015***	0.007*	0.021*	0.002
	(0.114)	(0.176)	(0.005)	(0.004)	(0.012)	(0.009)
L.Terror Fatalities	0.197**	0.272**	0.006	0.006**	0.005	0.008*
	(0.078)	(0.126)	(0.005)	(0.003)	(0.007)	(0.005)
Time Trend	-0.065	0.774***	0.008	0.027***	0.049***	0.049***
	(0.144)	(0.238)	(0.012)	(0.007)	(0.018)	(0.010)
Observations	71	71	71	71	71	71
R-squared	0.45	0.42	-	-	-	-
Pseudo R-squared	-	-	0.44	0.50	0.07	0.07

Standard errors estimated via seemingly unrelated estimation and shown in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Appendix

A1. Imposition of the Budget Constraint

Plugging 3.11 into 3.8:

$$I = \phi\varphi F^{\phi} + P_S S = \phi\varphi F^{\phi} + \frac{A\phi(1-\theta)}{\theta} \tag{A1}$$

$$\theta I = \theta\phi\varphi F^{\phi} + A\phi - A\phi\theta \tag{A2}$$

Note that 3.2 imposes $A = \varphi F^{\phi}$.

$$\theta I = A\theta\phi + A\phi - A\phi\theta \tag{A3}$$

That leaves:

$$I = \frac{A\phi}{\theta} \tag{A4}$$

$$A = \frac{I\theta}{\phi} \tag{A5}$$

Figure A1. Fatality Reporting: Difference Between Min and Max

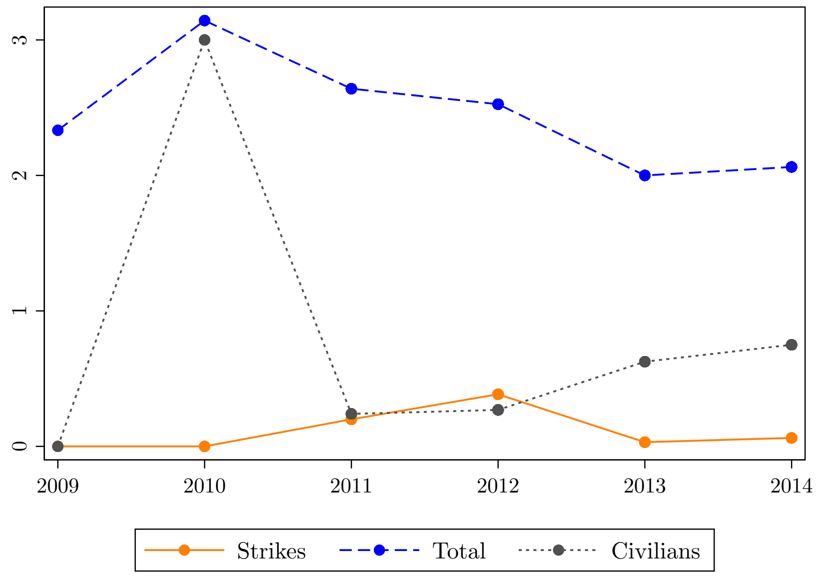


Figure A2. Fatalities Per AQAP Attack

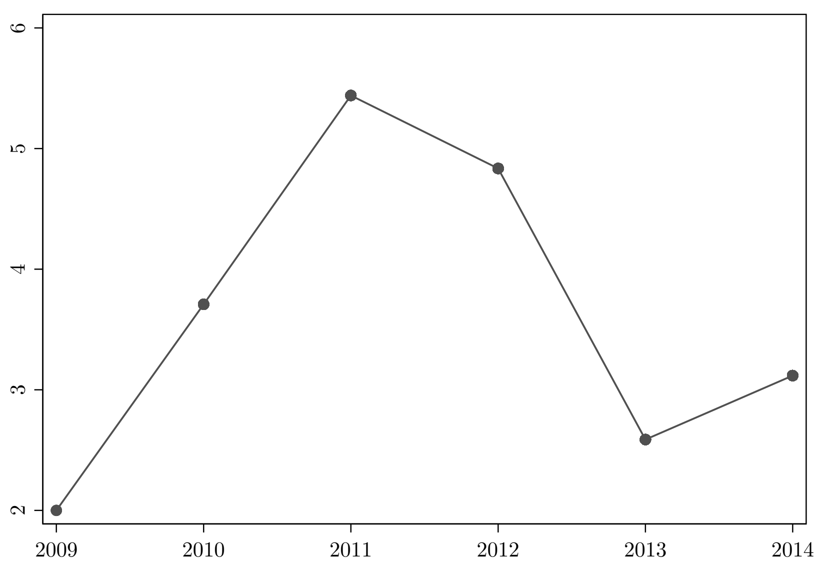
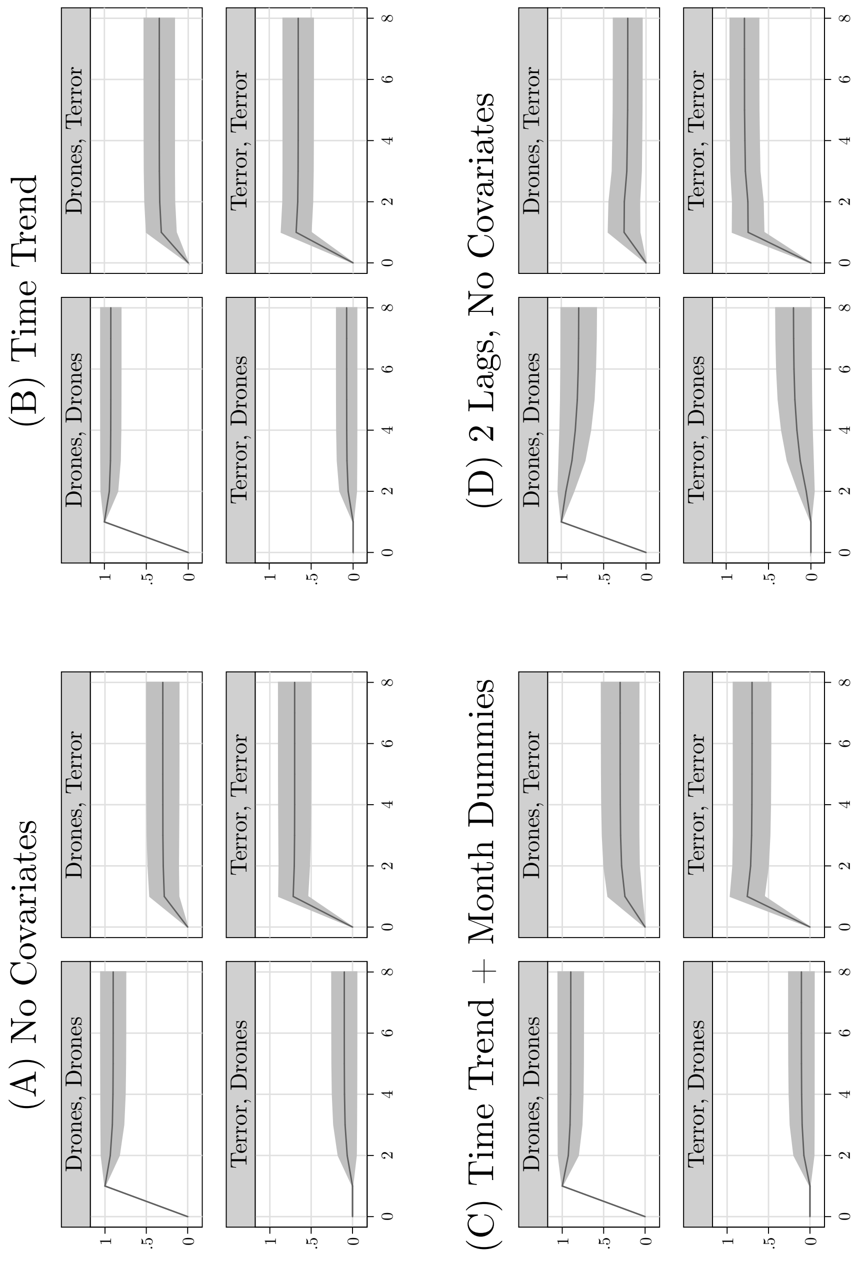
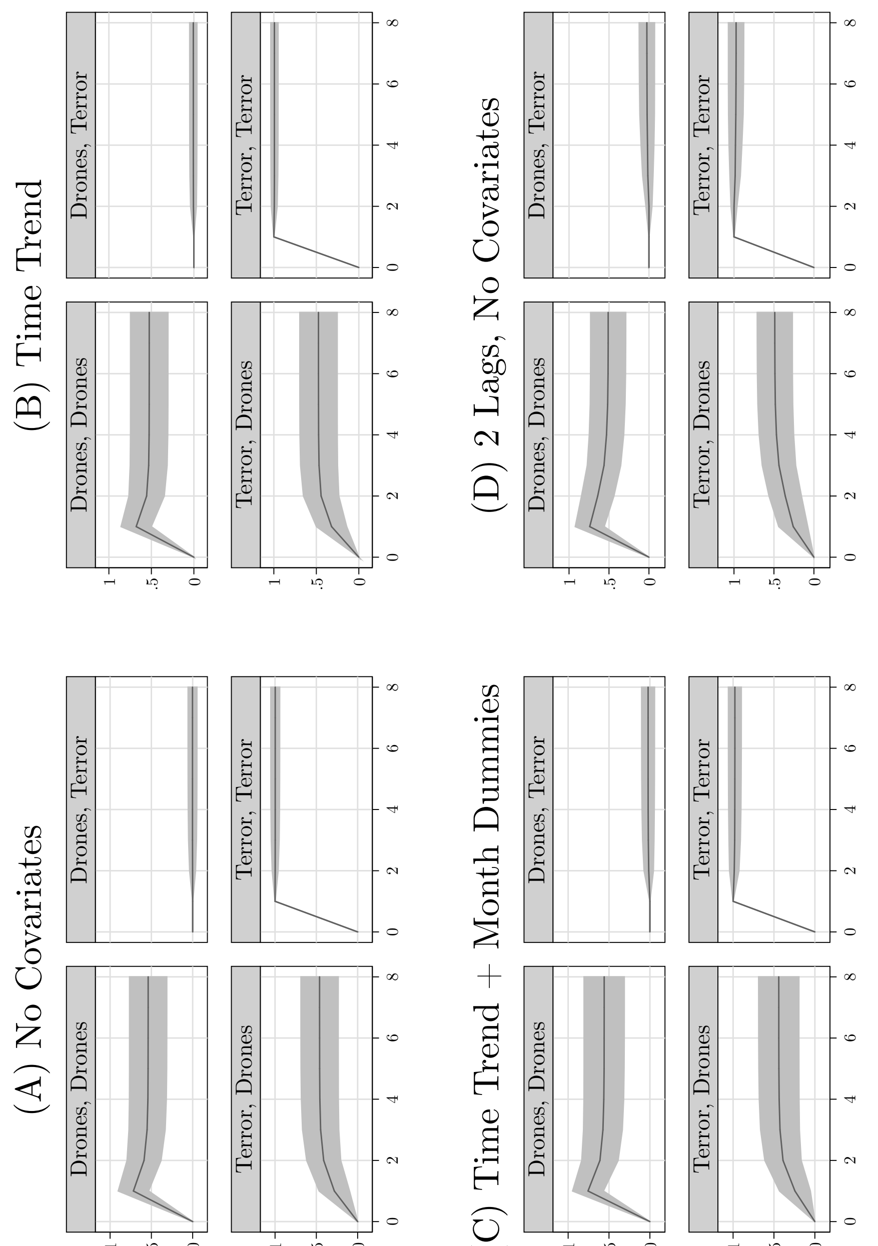


FIGURE A3. MONTHLY VAR FEVD: DRONES FIRST IN CHOLESKY ORDERING



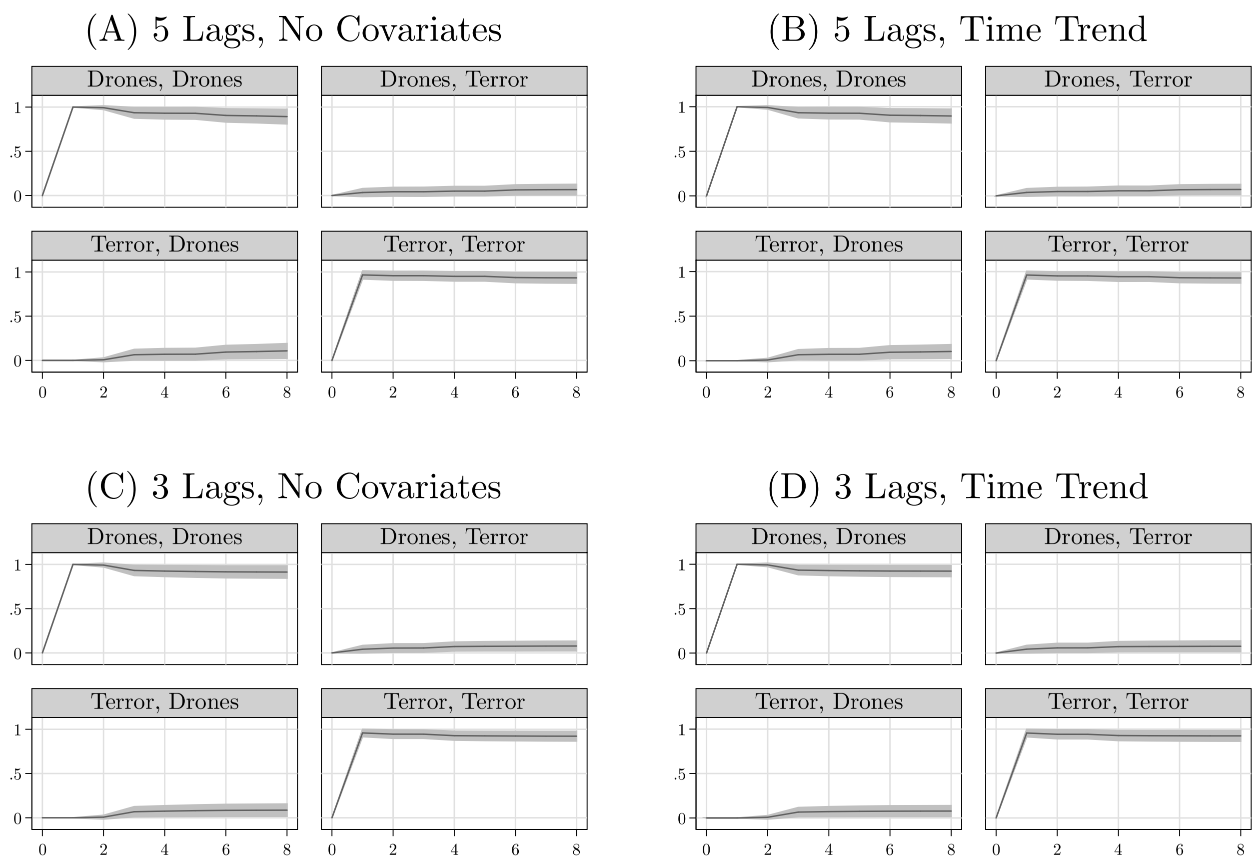
Graphs by impulse variable, response variable. Bootstrapped error bands.

Figure A4. Monthly VAR FEVD: Terror First in Cholesky Ordering



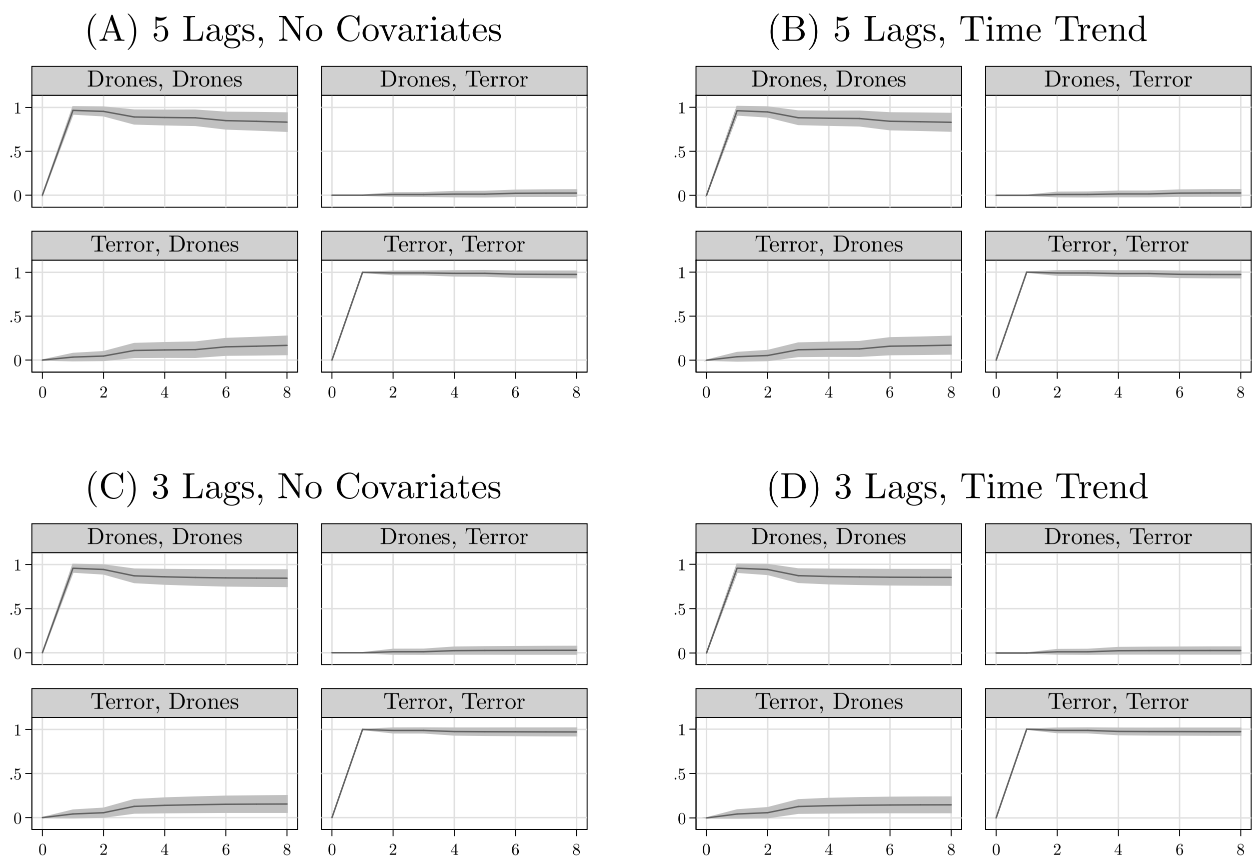
Graphs by impulse variable, response variable. Bootstrapped error bands.

FIGURE A5. WEEKLY VAR FEVD: DRONES FIRST IN CHOLESKY ORDERING



Graphs by impulse variable, response variable. Bootstrapped error bands.

Figure A6. Weekly VAR FEVD: Terror First in Cholesky Ordering



Graphs by impulse variable, response variable. Bootstrapped error bands.

Figure A7. Eigenvalues of the Companion Matrix