Spend 'Em If You Got 'Em: The Timing of Terrorist Attacks as a Function of Funding Consistency

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Abstract

Given the short time horizons faced by terrorist groups, inflows in funding should correlate with spikes in the number of attacks. This pattern, moreover, should be the most prominent for groups whose sources of funding are less consistent and predictable, as uncertainty further shortens the group's time horizons and imposes additional organizational pressures. I test these predictions on a subset of terrorist organizations whose funding is likely linked to drug-trafficking by proxying variation in drug production with the data on weather during the month of harvest. The statistical tests support the predictions. For groups whose funding is tied to narco-trafficking, the timing and number of attacks closely follow the drug-harvesting cycle. Favorable weather conditions during the month of drug harvest correspond to spikes in the number of terrorist attacks in the current and subsequent months, whereas unfavorable weather conditions during drug harvest are associated with the reverse pattern.

Introduction

Terrorist organizations are inherently weak actors. Powerful terrorist groups with ready access to resources and large territorial control, such as pre-9/11 al-Qaeda, are more of an exception that the rule.[1] Despite the popular images of vast training grounds and Swiss bank accounts, most terrorist groups are small in size, strapped for resources, and operating with rather short-horizons, due to the fear of detection. Meticulous planning and strategic timing of attacks are luxuries that most terrorist groups cannot afford. Instead, I argue that terrorist activity, and specifically the timing of attacks, is largely a function of the availability and consistency of groups' funding inflows.

I draw on the organizational theory (Asal and Rethemeyer 2008; Horowitz 2010; Shapiro 2013) to argue that, given the short time horizons and other related pressures faced by terrorist groups, inflows in funding will correlate with spikes in the number of attacks. This pattern, moreover, will be the most prominent for groups whose sources of funding are less consistent and predictable, as uncertainty further shortens the group's time horizons and imposes additional organizational pressures. I test these predictions on a subset of terrorist organizations whose funding may be linked to drug-trafficking by proxying the variation in drug production with data on weather during the month of harvest. In other words, if the number of attacks is a function of the resources available to a terrorist organization, then the number of attacks should increase following periods of plentiful crops, and subside during periods of low drug yields.[2]

This study's reliance on an instrumental variable approach for measuring the central causal variable has a number of advantages (Ritter and Conrad 2016;

[1] For example, according to the BAAD dataset on terrorist organizations between 1998–2005, only about 8 percent of such organizations are coded as having territorial control, and less than 5 percent of terrorist organizations are coded as large in size (Asal, Rethemeyer, and Anderson 2011).

[2] No individual group produces enough supply to, on its own, impact price, so low yield corresponds to reduced income for any individual terrorist organization. A study of the heroine market in 1980-1983 London shows, for instance, that at the consumer level, the market was never entirely dominated by a single source. Instead, local sellers had to compete with imports from Southeast Asia, as well as Turkey, India, Pakistan, Iran, and a number of other sources. A failure to form a monopoly is explained as a result of continued fluctuation in production, delivery, and consumption (Lewis et al. 1985, 282).

Potoski, Urbatsch, and Yu 2015). The quasi-random variation in temperature during the month of drug harvest helps rule out reverse causality, i.e. an alternative expectation that terrorist groups raise funding in proportion to the number/complexity of planned attacks. Even assuming that all terrorist groups, including narco-terrorists, seek additional funding in preparation for costly attacks, weather-related fluctuation and the associated uncertainty allows for modeling the effect of unanticipated, and hence, impossible to plan for, variation in funding inflows. The instrumental variable approach also helps produce a more systematic measure that covers a wider temporal and spatial domain—an advantage that would hold even if there existed some direct data on drug production.

The paper elucidates the link between the consistency of funding and the timing of terrorist attacks by conducting one of the first systematic evaluations of the relationship between timing of attacks and drug trafficking (also see Piazza 2011, 2012; Piazza and Piazza 2017). I show that, for groups whose funding is tied to narco-trafficking, the timing and number of attacks closely follow the drug-harvesting cycle. Favorable weather conditions during the month of drug harvest correspond to spikes in the number of terrorist attacks in the current and subsequent months, whereas unfavorable weather conditions during drug harvest are associated with the reverse pattern.

The paper proceeds in the following way. I start the next section with a broad review of the existing literature that links political violence to resource availability. I build on this literature to develop a theoretical model of timing of terrorist attacks as a function of resource availability, and derive testable hypotheses. Next, I describe the data and research design, provide the results of the statistical estimation, and conclude.

Previous Literature

Resource scarcity falls within the "greed" part of the "greed vs. grievance" theories of intra-state political violence (Abadie 2006; Buhaug and Gates 2002; Collier and Hoeffler 2004; Doyle and Sambanis 2000; Fearon 2004; Fearon and Laitin 2003; De Soysa 2002). Developed by scholars of civil war, these theories explain political violence as driven by competition for resources between the government and other domestic actors, such as the political opposition, insurgents, or terrorist groups. Access to resources helps fund insurgencies or a state's response to them: for instance, rebel access to resources, such as gemstones and narcotics, may prolong civil wars (Fearon 2004). If control of the resources lies with the state, then insurgency may also be motivated by the expectation of concessions (Thomas 2014). More recently, scholars have shown that these resource-related patterns of insurgency also apply to terrorist groups (Asal et al. 2016; Bapat and Zeigler 2016; Carter 2016; Koga 2011). I build on this research by exploring the effect of resources on the *timing* of terrorist attacks—an outcome that has received less attention in scholarly research.

Existing theoretical literature suggests that, if the goal is to maximize the terror, there should be no discernible patterns in the timing of terrorist attacks (Sandler and Enders 2007).[3] Appearance of randomness in the timing of attacks will induce anxiety and panic in the widest possible audience as well as thwart the state's counter-terrorism efforts. In practice, the timing of terrorist attacks has been shown to depend on a host of factors, such as counter-terrorism, government concessions, electoral cycles, religious holidays, and even seasonal changes.

Theoretical research also suggests that the timing of terrorist attacks should depend on the level of counter-terrorism (Powell 2007). Enders and Sandler (1993) and Brandt and Sandler (2010) find empirical support for this expectation by revealing patterns of substitution among complementary types of terrorist attacks. Installation of metal detectors in airports, for example, was associated with a decrease in a number of skyjackings, but increases in other types of attacks, such as crimes against protected persons. The theoretical logic behind this finding is that, as counter-terrorism efforts increase the costs of attacking certain types of targets, terrorist organizations switch to targeting less defended targets.

[3] In theory, terrorist groups could employ more sophisticated timing strategies, such as randomizing over the location while announcing the timing before the attack, but in practice, terrorist attacks rarely exhibit this level of sophistication in planning.

A related line of research links the timing of attacks to the cycle in the terrorist–government interaction (Bueno de Mesquita 2005; Berrebi and Klor 2006; Rasler 1996). Bueno de Mesquita (2005) argues that spikes in terrorist violence are observed in the immediate aftermath of government concessions, because, as the moderates accept the concessions, the terrorist organization is effectively left in the hands of the extremists. Importantly, this result is only possible if the resources available to the terrorists are not substantially diminished as a result of the negotiations.

Aksoy (2014) argues that domestic terrorist groups are particularly likely to engage in attacks during the time immediately preceding elections, especially in regimes that do not provide an institutional mechanism for political representation of small and marginal groups (also see Bali and Park 2014; Staniland 2015). Berrebi and Klor (2006) contend that, if the goal of terrorism is to extract concessions, then we should observe more attacks during the periods when a moderate political party is in power than during a period ruled by hardliners. They find evidence for this argument using data on the Israeli-Palestinian conflict.

Other studies have argued that the timing of terrorist attacks may depend on seasonal changes (Winters 2001). In a study on ETA terrorist attacks between 1968–2002, Barros, Passos, and Gil-Alana (2006) find that terrorist violence spikes during summers, compared to other seasons. Toft and Zhukov (2015) find that religious terrorist violence may coincide with religious holidays (also see Reese, Ruby, and Pape 2017). The link between violence and the labor calendar has been explained in terms of increases in leisure due to time off work (Becker 1968; Durkheim 1951 [1897]).

Importantly, the existing theoretical explanations have not explicitly modeled the timing of an attack as a strategic decision made under the resource constraints and given the organizational pressures faced by terrorist groups. In what follows, I build and expand upon the existing research to develop a theoretical model of the effect of resource availability of the strategic timing of terrorist attacks.

Resources and the Timing of Attacks

In line with recent research, I start with a premise that, at their core, terrorist organizations function according to some of the same principles as other bureaucracies, albeit with specific types of constraints, such as the need for secrecy (Asal and Rethemeyer 2008; Shapiro 2013). Similar to other bureaucracies, terrorist groups vary in terms of their organizational structure, communication and reporting, recruitment strategies, remuneration and monitoring of members, and other characteristics. As highlighted by Shapiro (2013), in the case of terrorist organizations, the key trade-off that determines the organizational structure is that between control and safety. On one hand, a rigid hierarchical structure, transparency, and reliable communication among members help maximize efficiency and tighten the leadership's control over their operatives in the field, yet may jeopardize members' safety by creating a paper trail or increasing the probability of leaks, intercepted communications, infiltration, or detection. In contrast, decentralized organizational structure, secrecy of membership and limited communication help minimize the risk of detection, but also create a disconnect between the leadership and the operatives, which may decrease the organization's ability/efficiency to work towards its political goals. Evidence of inefficient and counter-productive feuds related to such mundane issues as travel reimbursements, accounting, and reporting, have been found in records of even such well-organized and tightly-run groups like al-Qaeda (Shapiro 2013, 39). Unauthorized attacks by the group's more radical low-level operatives are also not uncommon and may lead to unraveling of important ceasefire agreements, such as that between the more moderate leadership of Hamas and the state of Israel in 2004 (Shapiro 2013, 20).

While terrorist organizations may prefer to prioritize control, most are unable to do so due to an even more pressing need for secrecy. The few prominent examples, in which an organization is able to tilt the balance in favor of control are more of exceptions that the rule. For example, the pre-9/11 al-Qaeda was able to minimize its concerns with detection, due to vast training grounds, the ability to openly raise and transfer funds, and other freedoms that granted by the Taliban. It is these very special circumstances (along with a number of grave mistakes by US intelligence) that enabled al-Qaeda to engage in the substantial planning that culminated in the 9/11 attacks—a plot that by all accounts was much better planned and required much greater support infrastructure than the majority of terrorist attacks (Shapiro 2013, 21).

Most terrorist organizations, however, do not operate in such favorable circumstances. In most cases, therefore, the need for secrecy and fear of government detection forces terrorist organizations closer to the other organizational extreme, in which the leaders have to sacrifice their control over the operatives. De-centralized organizational structure, in turn, reduces organization's efficiency in both the use of resources, as well as planning and executing the attacks, necessarily allowing greater discretion to the lower-level operatives in the field. In the absence of tight top-down control and monitoring, low-level operatives may misappropriate or squander resources or even engage in unauthorized attacks that may prove counter-productive for the group's political cause.

Another key factor that affects the groups' activity is its access to resources. It is now well-established in the terrorism literature that, almost by definition, terrorist groups are weak actors, both in absolute terms and also compared to the state actors that confront them. While access to funding is important to survival and operation of organizations of all types, it is an even more crucial factor for terrorist organizations. Marginalized from the rest of the population by their radical beliefs and means, terrorist groups struggle to survive, let alone make progress towards achieving their political goals, without a relatively consistent inflow of funding.

Terrorist groups obtain their funding from a variety of sources. Some groups' funding is closely connected to criminal activities, such as kidnappings and extortion, drug and human trafficking, and trade in other illicit and counterfeit substances (Avdan 2012; Conrad et al. 2018; Piazza 2012). Other groups rely on more "traditional" sources of revenue, such as donations, trade in natural resources, or even banking and finance, agriculture, and industrial production (Brisard and Martinez 2014; Swanson 2015).

Sources of funding, in turn, have important implications for the consistency of the funding flow, as well as the flow's potential to replenish (Bellemare 2015). Terrorist organizations, who finance some of their activities through drug trafficking or agriculture-based products, in particular, will face larger amount of variation in the consistency of funding flows than groups that obtain their funding from mineral resources, industrial production, or government-like activities (extortion/taxation, or banking and finance). Lewis et al. (1985, 282), for instance, point out that inclement weather in areas of opium cultivation corresponded to "a marked decline" in the supply of Southeast Asian heroin in 1978-79. Groups that rely on donations, kidnappings, and robberies are also likely to experience fluctuation in funding. For instance, inflows in donations may increase following an attack, while income from kidnappings and robberies may fluctuate with the government's emphasis on law enforcement.

Groups with less consistent sources of funding face difficulty quickly replenishing any lost or seized funding. Especially if the funding source is tied to agricultural production, such as drug trafficking, any funding lost due to a seizure/destruction of this year's crop is unlikely to be replenished until the next crop cycle. Similarly, groups whose funding comes from donations may be unable to quickly elicit additional donations in the immediate aftermath of a major bust and seizure of funds, as donations tend to increase in the aftermath of attacks, but not arrests or failures. I argue that this variation in the consistency of financing supply and the group's ability to replenish any lost/seized funding has important implications for the groups' activities, such as recruitment, operations, planning, or timing of attacks. Groups with consistent funding are able to maintain relative stability in terms of their size and operations, and have longer horizons for planning, timing and executing attacks. Inconsistency of funding, in contrast, creates uncertainty regarding the groups' future; groups whose funding inflows fluctuate over time in an unpredictable manner are forced to operate with shorter time horizons (Bellemare 2015). Although funding consistency will affect all aspects of groups' operations, for the purposes of empirical testing, I focus on deriving prediction related to the *timing* of attacks.

In the absence of funding constraints, the terrorists' aim of maximizing the amount of terror is best achieved by randomizing the timing of attacks. Uncertainty and unpredictability in the timing of attacks amplifies the public's fear and panic. Carrying out attacks with no discernible time pattern also minimizes counter-terrorist groups' ability to anticipate and prevent attacks. The few groups that face few funding (or operations) constraints, such as pre-9/11 al-Qaeda, will be able to time their attacks in the way that maximizes its chances of achieving its political goals; attacks by such groups may coincide in timing with religious holidays, elections, or peace negotiations (Bali and Park 2014; Staniland 2015; Toft and Zhukov 2015). Importantly—and the focus of the current study—in actuality, a large number of terrorist groups operate under substantial funding constraints, which in turn may limit their ability to strategically time attacks.

This study zeroes in on one type of terrorist group that may face significant fluctuation in the inflows of funding—those whose funding flows are tied to agricultural production, and especially drug trafficking. Such groups, by definition, experience temporal fluctuation in the amounts of funding that they are able to use for recruitment and planning of attacks. During and immediately following cash inflows, such groups have to decide whether to spend money as soon as possible through carrying out attacks or to save/stockpile funds for use towards a future attack. Acting quickly reduces the risk of losing the funds, yet prevents the group from deriving any additional benefits associated with strategic timing. A planned attack allows the group to maximize the benefit associated with strategic timing, yet stockpiling funds carries an increasing risk that counter-terrorist groups will trace and seize the funding or the funding is lost through bureaucratic inefficiency. If additional funding and recruitment is conditional on carrying out successful attacks (e.g., funding from donations), and the group's funding is not quickly replenishable, then groups with inconsistent funding have a strong incentive to spend any inflows in funding as soon as possible. Attacks by such groups should therefore increase during the periods of funding inflows and decrease as the amount of funding decreases. Another implication is that the fear of losing funds will force groups with inconsistent funding to value the "quantity of terror" over its quality: short horizons may entice such groups to execute a larger number of less sophisticated attacks rather than a smaller number of more sophisticated ones.

Although there exists little systematic information about the sources of funding for most terrorist groups, it is rather straightforward to assume that groups that operate in areas with high production of narcotics will derive a significant portion of their funding from either taxing local drug production or even directly participating in drug-trafficking activities. Even if these groups supplement their funding with other sources during the non-growth season, they should still experience significant but inconsistent spikes in cash flows that correspond to the variation in drug production.

More precisely, these groups may expect the largest spikes in funding during the time of harvest, as long as the weather conditions throughout the growth cycle, but especially during the time close to harvest, were favorable to the growth of the specific plant. The time of harvest is particularly important, as this is the time when the plants are the most susceptible to weather damage, and also the part of the growth cycle when farmers have the least control over the effect of weather conditions. If adverse weather happens during the planting time, for instance, farmers may postpone planting or cover the plants. Adverse weather conditions during harvest, however, will almost inevitably reduce the amount, quality, and size of the harvest. For instance, cannabis plants, whose development virtually stops without sufficient sunlight, is harvested early in bad weather years (Cervantes 2015, 110). Unfavorable weather conditions during the time of harvest will therefore result in an (unanticipated) dip in funding. Favorable weather conditions, in contrast, will result in an influx of funding, either in the form of direct revenues or the ability to borrow against plentiful crops (e.g., if the drug requires processing).

Research Hypothesis: *For groups whose funding may be linked to drug trafficking, the number of terrorist attacks will spike immediately following a favorable harvest of drug crops.*

There are two auxiliary mechanisms that reinforce the same expectation, especially for narco-trafficking groups. First, since narco-trafficking is criminalized in most countries, such groups have an additional incentive to opt for de-centralized organizational structures that helps prioritize safety over control. Such groups then will be the most likely to suffer from the principal-agent problem, i.e. under less tight control from the leadership, local operatives may be more likely to misappropriate or misuse funds, increasing the pressure on the leadership to quickly spend funds lest they are lost.[4]

Second, this particular source of funding removes the leaders' ability to provide funds on a need-to-have basis, which is one of the key mechanisms that the leaders use to prevent local operatives from freelancing and engaging in unauthorized attacks. Unlike with other sources of funding, in the case of narco-trafficking, it is the field operatives who are likely to help raise the drug-related revenue for the group, either through collecting dues from the local farmers, participating in drug transportation, or even farming, producing, or processing the drugs themselves. As the raised funds pass through the hands of the local operatives, there is a greater probability that some of the operatives who may disagree with the leaders' attack plans and timelines will take it upon themselves to spend some of the funds on attacks.[5]

Finally, smaller and weaker terrorist groups are more likely to experience all the pressures described above. Large groups are more likely to have multiple and more diverse sources of funding, which may help offset some of the uncertainty or fluctuation of drug-related revenues. State-sponsored terrorist groups are also less subject to harvest-related variation in drug production, as their main source of income comes from their state sponsors. This logic suggests an auxiliary prediction that the effect of weather fluctuation will be the strongest for weaker groups that are smaller in size and do not have a state sponsor.

[4]For a detailed argument that links secrecy to inefficiency, see Shapiro (2013).

[5]See Shapiro (2013) for a formal argument on why local operatives may want to engage in attacks independent of the leaders' orders.

Research Design

I test the research hypothesis using monthly data on terrorist attacks between 1970-2014, obtained from the Global Terrorism Database. The unit of analysis is the group-month. The dependent variable is measured as monthly count of terrorist attacks perpetrated by a terrorist organization. The number of attacks is the most direct measure of the amount of terrorist activity or the "quantity of terror," which is the theoretical concept it intends to measure. Measuring the "quantity of terror" using, say, the number of casualties, would conflate activity with successful attacks, whereas attacks' success depends on other factors, such as counterterrorism. Measuring the "quantity of terror" using some measure of attack's sophistication (e.g., the type of attack) is also inappropriate, as sophistication requires planning, and planning takes time—a luxury that groups with short horizons cannot afford.

Data on the origin and characteristics of terrorist organizations are obtained from the BAAD Lethality Data (Asal, Rethemeyer, and Anderson 2011). Inconsistency of funding is operationalized as a group's reliance on drug trafficking for a substantial part of its funding, proxied with the group's country of operation. Thus, groups operating in countries that are known as major sources of opium, cannabis, and cocaine are treated as groups with inconsistent funding. For such groups, the binary variable *Narcotics* equals 1; *Narcotics* equals 0 for groups that operate in coutries that are not known as major producers of the above-mentioned drugs. In the secondary analysis, I restrict the sample just to groups from drug-producing countries and explore the effects of specific drugs using variables *Opium*, *Cannabis*, and *Cocaine* that equal 1 if the country is a major producer of the corresponding drug and 0 otherwise. Data on narcotics production are obtained from Lujala (2017) and Buhaug and Lujala (2005).

Our dataset includes ten countries known for cultivating opium poppy (Afghanistan, China, India, Iran, Laos, Lebanon, Myanmar, Pakistan, Thailand, and Turkey), eight countries known for cultivating cannabis (Colombia, Ethiopia, Lebanon, Morocco, Russia, South Africa, Swaziland, and Thailand) and three countries known for cultivating cocaine (Bo-

Table 1: Optimal Temperature at Harvest

	Temperature, Celsius
Opiates	5.6–23.5
Cannabis	6–27
Coca plants	18–25

Sources: Duke (1983); Acock et al. (1996).

livia, Colombia, and Peru). Including groups from countries that are not known as major producers of the above mentioned drugs, the resulting sample contains 3,825 non-missing observations from 206 terrorist organizations in 51 countries. The subsample of just the drug-producing countries includes 1,562 observations of groups from 21 countries. Table 7 of Appendix displays the full list of groups included in the analysis along with whether each is coded as linked to drug-trafficking of a specific drug. Any coding errors, of course, will introduce a conservative bias in the statistical analysis by adding additional uncertainty to the model, i.e. will make it more difficult to find support for the research hypothesis.

Since the data on the independent variable—the (time-varying) amount of narcotics production—are not directly available in a systematic manner, I measure this variable by linking the production of each drug to the range of temperatures that are known to be favorable to harvesting of the specific plant. To do so, I collected additional data on the optimum temperature for harvesting each of the drugs, and the typical harvesting months in each of the countries in the sample. As shown in Table 1, the optimal temperature for harvesting *papaver somniferum* (opium poppy) is between 5.6–23.5 degrees Celsius (Duke 1983), the best temperature for harvesting cannabis plants is between 6–27 degrees Celsius, and the best temperature for harvesting coca plants is around 18-25 degrees Celsius (Acock et al. 1996).

I measure the independent variable—the amount of narcotics production—using an indicator variable that equals 1 if the average monthly temperature during the typical harvesting months fell within the range of optimal temperatures for the plant produced in that country, and 0 otherwise. The average monthly temperature data for each country were collected by the Climatic Research Unit of the University of East Anglia (World Bank 2016).[6] Some previous research that employed weather data as instruments for variables of interest has used *deviations* from the norm rather than monthly averages (e.g., Hansford and Gomez 2010, Hendrix and Salehyan 2012; although see Ritter and Conrad 2016). Unfortunately, the amounts of missingness in the data for the countries in the sample, especially at the daily level, prevented us from using a deviations-related measure, such as a monthly count of days, in which the temperature deviated from that optimal for harvesting specific plants.

The resulting variable, *Favorable Temperature*, is not a direct measure of the production volume, but is certainly a strong correlate of the increase in funding the group may expect in a given month.[7] After all, narcotics crops depend on weather conditions just like any other crops. Moreover, the exogenous nature of this variable provides an important statistical advantage of helping identify the model and rule out reverse causality (i.e. the natural growth cycle prevents terrorists groups from strategically increasing their drug-trafficking revenues to fund attacks during the off-season).

To model the time-varying aspect of the increase in resources, I interact *Favorable Temperature* with the *Month Since Harvest*, which is measured as the number of months since the month of harvesting the plant. Thus, the month(s) of harvesting are coded as 1, the next month after harvest is coded as 2, and so on. If a drug is harvested multiple times in a year in a given country, then the counter restarts at the time of the next harvest. Table 2 shows the data I collected on the typical months of harvest for each drug and country of production. Note that in many but not all countries, the months of harvest are in the spring or summer, which may explain the previous finding that terrorist attacks tend to spike during the warm

[6]Alternative meteorological data sources, such as the NOAA National Climatic Data Center, contained too many missing values for countries of primary interest. For example, NOAA has no temperature data on Bolivia until 1982, Lebanon until 1993, Pakistan until 1981, and Peru until 1975.

[7]Harvesting opiates, in particular, is also known to be affected by the amount of rain (McGlade, Henkel, and Cerveny 1994). While the growers of opiates cannot control the temperature, they are able to alleviate the effect of extreme rain by planting the seeds in well-draining areas, e.g. mountains. In regions of tropical monsoon climate, opium farmers cultivate opiates at high altitudes and on well-drained slopes protected from rain by mountains, forestry, or drainage canals (Chouvy 2010, 126). As described below, the results are robust to measuring the production volume by combining the data on temperature and rainfall.

Table 2: Months of Harvest

Country	Type of Narcotics	Months
Afghanistan	Opium	April – August
Bolivia	Cocaine	March, June, November
China	Opium	April – August
Colombia	Cannabis	July, August
Colombia	Cocaine	March, June, November
Ethiopia	Cannabis	July, August
India	Opium	April – August
Iran	Opium	April – August
Laos	Opium	April – August
Lebanon	Opium	April – August
Lebanon	Cannabis	July, August
Morocco	Cannabis	July, August
Myanmar	Opium	April – August
Pakistan	Opium	April – August
Peru	Cocaine	March, June, November
Russia	Cannabis	July, August
South Africa	Cannabis	July, August
Swaziland	Cannabis	July, August
Thailand	Opium	April – August
Thailand	Cannabis	December, January, April, May
Turkey	Opium	April – August

Sources: Opium – Chouvy (2010); coca plant – Gay et al. (1976); cannabis – Duke (1983), and Daly (1996).

periods of the year (Barros, Passos, and Gil-Alana 2006).

The analysis also includes a number of control variables. I account for other factors associated with seasonality that may affect terrorist activity, such as snow or rain, by controlling for the monthly amount of rainfall.[8] Data on precipitation are obtained from the World Bank (2016). Previous research has shown a relationship between terrorist attacks and regime type (Aksoy, Carter, and Wright 2012). I model this relationship by including a binary indicator of *Democracy* of the primary target country, which equals to 1 if country scores above 7 on the *Polity2* variable, and 0 otherwise (Marshall and Jaggers 2014).[9] To

[8]As noted in fn. 8, while precipitation does affect plant growth, drug producers often take steps to address extreme values, such as setting up irrigation systems or drainage canals. Unfavorable temperatures, however, are more difficult to counteract.

[9]Primary target country is defined as the country that is most frequently attacked by the group.

account for counter-terrorism effectiveness, I include a measure of energy consumption of the country that is the primary target of each group.[10] Data on energy consumption were obtained from the Correlates of War Project (Singer 1987). In addition, I include controls for a number of variables related to the terrorist organizations, such organizational size, the size of the territory it controls, state sponsorship, number of alliances with other terrorist organizations, and whether an organization has a stated religious or nationalist goal. Data for these variables are obtained from Asal, Rethemeyer, and Anderson (2011). The *Size* of an organization is coded as 0 for organizations with up to 100 members, 1 for organizations between 101-1,000 members, 2 for 1,001-10,000 to ten thousand members, and 3 for organizations with more than 10,000 members. The variable *Territory* is coded as 1 if an organization has control of a territory and 0 otherwise. If an organization is known to be supported by one or more governments, the *State Sponsorship* variable is coded as 1, and 0 otherwise. Finally, the variable *Alliances* records the number of an organization's alliances with other groups (Asal, Rethemeyer, and Anderson 2011).

Since the dependent variable is a count variable, I model the relationship between funding and terrorist attacks using a negative binomial regression.

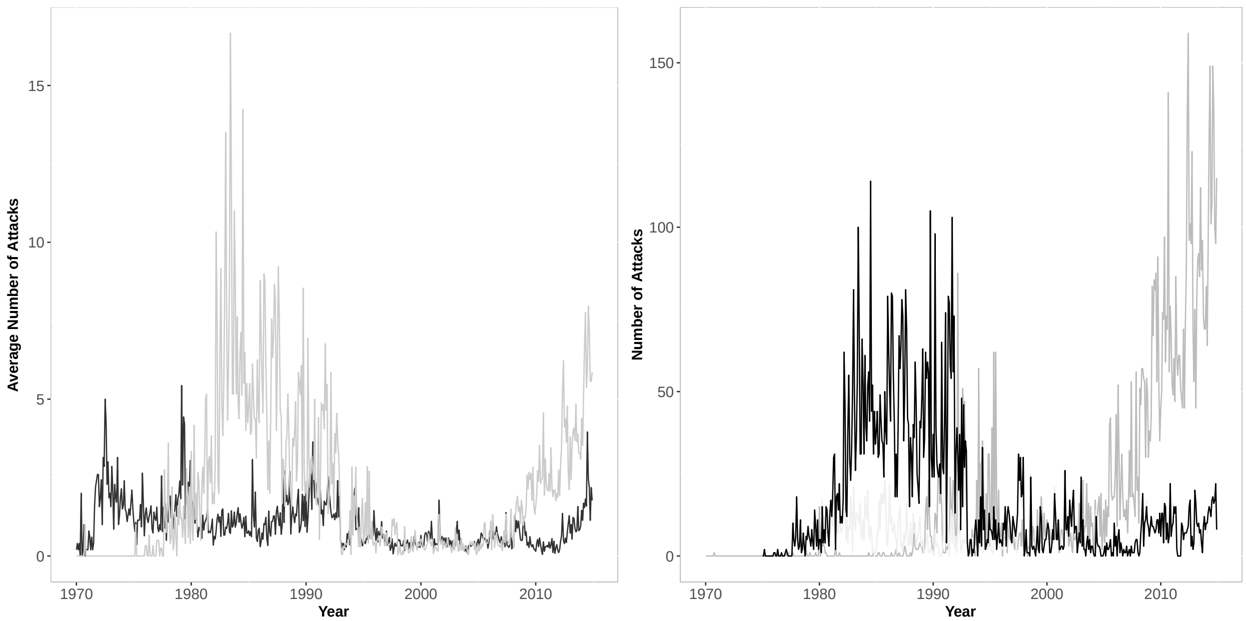
Results

Figure 1a provides a visualization of the over-time fluctuation in the average number of terrorist attacks between 1970–2014. The gray line represents the monthly average number of attacks for groups with inconsistent sources of funding (approximately 40% of the observations in the data), while the black line shows the monthly average number of attacks by groups with consistent sources of funding. As the figure shows, groups with inconsistent funding seem to engage in more attacks than groups with consistent funding. Even more importantly, the average number of attacks carried out by groups with inconsistent funding

[10] I use a measure of energy consumption over the more conventional measure of GDP per capita, because GDP data are not available for some of the key cases for the study, such as Afghanistan.

Figure 1: Average Number of Attacks for Groups with Consistent and Inconsistent Funding

(a) Consistent vs. Inconsistent Funding (b) By Drug Type



Note: In Subfigure a, black denotes groups with consistent sources of funding; gray represents groups with inconsistent funding. In Subfigure b, black denotes groups from cocaine-producing countries, dark gray denotes groups from opium-growing countries, and light gray represents cannabis-growing countries.

exhibits a much larger month-to-month variability than that of the groups with consistent funding.

Figure 1b separates the groups with inconsistent funding into three types, according to the type of narcotics cultivated in their country of origin. The monthly number of attacks by groups from cocaine-producing countries is displayed in black, the number of attacks perpetrated by groups from opium-growing countries is displayed in dark gray, and the number of attacks perpetrated by groups from cannabis-growing countries is displayed in light gray.[11] The number of attacks perpetrated by groups from cocaine- and opium-producing countries fluctuates wildly, albeit during different time periods: groups from cocaine-growing countries exhibit the largest month-to-month fluctuation in the number of attacks in the

[11]Notice that, due to post-1995 overlap in the production of cannabis and cocaine, the black and the light gray lines overlap during this time period.

Table 3: The Effect of Funding Inflows on Terrorist Attacks: All Terrorist Groups

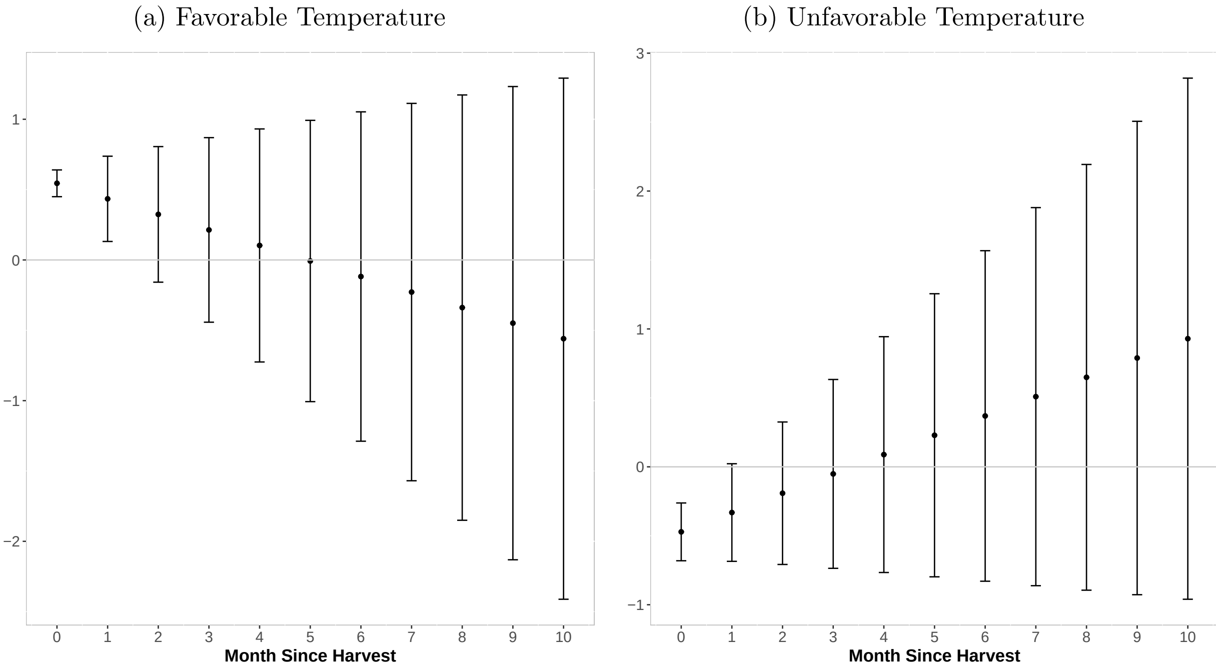
	Full Sample	*Weak Groups*†	*Strong Groups*‡
Narcotics	-0.612^{***}	-0.818^{***}	-0.677^{***}
	(0.092)	(0.108)	(0.205)
Narcotics*Fav. Temp	1.267^{***}	1.282^{***}	0.596^{**}
	(0.100)	(0.122)	(0.210)
Narcotics*Fav. Temp*Month	-0.251^{***}	-0.216^{***}	-0.158^{**}
	(0.031)	(0.042)	(0.054)
Narcotics*Month	0.140^{***}	0.035	0.141^{**}
	(0.027)	(0.037)	(0.044)
Rainfall	-0.002^{***}	-0.002^{***}	-0.001^{***}
	(0.001)	(0.001)	(0.001)
State Sponsorship	0.202^{***}		
	(0.045)		
Size	-0.095^{***}		
	(0.023)		
Territory	0.514^{***}	0.812^{***}	0.271^{**}
	(0.050)	(0.056)	(0.093)
Alliances	-0.033^{***}	-0.046^{***}	0.033^{*}
	(0.006)	(0.008)	(0.015)
Religious	-0.548^{***}	-0.704^{***}	-0.667^{***}
	(0.045)	(0.061)	(0.079)
Democracy (main target)	0.312^{***}	0.160^{**}	0.200^{**}
	(0.045)	(0.058)	(0.076)
State Capacity (main target)	-0.032^{***}	-0.051^{***}	-0.009
	(0.006)	(0.006)	(0.020)
Constant	1.452^{***}	1.738^{***}	1.369^{***}
	(0.058)	(0.052)	(0.074)
θ	1.230	1.233	1.401
	(0.032)	(0.042)	(0.061)
N	4047	2472	1575
Log-Likelihood	-10163.85	-6074.278	-3994.585

Notes: $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$, †,‡*Strong* groups are defined as groups that either large in size (*Size*=3) or are not sponsored by a state (*State Sponsorship*=1) or both.

late 1980s and early 1990s, while groups from opium-producing countries show the largest fluctuation in the number of attacks in the post-2005 time period. These visualizations support the premise of greater month-to-month variation in the number of attacks for groups with inconsistent funding.

The first model of Table 3 displays the results of a negative binomial regression with

Figure 2: The Effect of Narco-Trafficking on the Number of Attacks, by Month

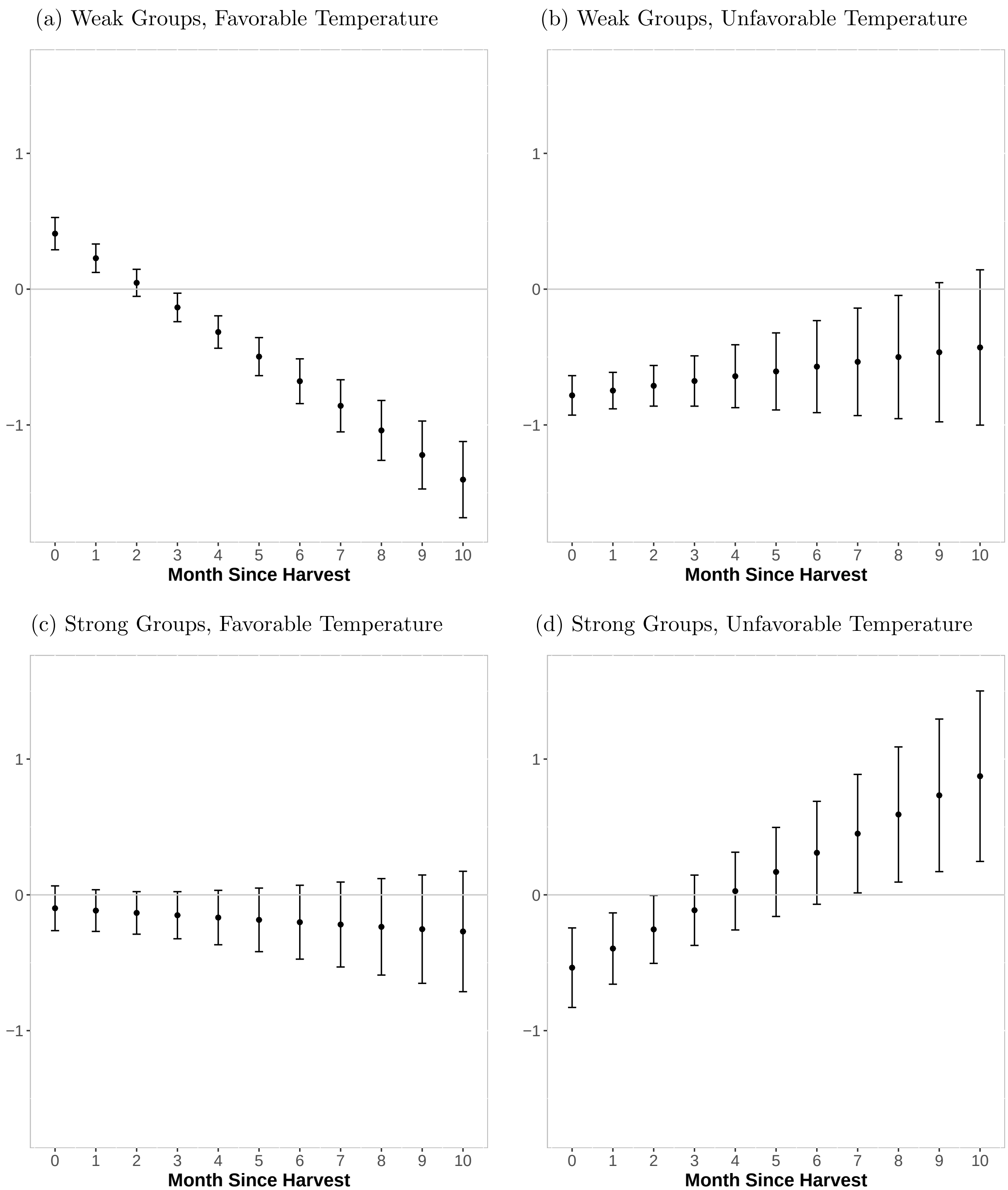


Note: Error bars represent 90% confidence intervals. All quantities are calculated using coefficients and variance-covariance matrix from Model 1 in Table 3.

the monthly count of terrorist attacks as the dependent variable. The primary independent variables of interest are *Narcotics*, which is a binary indicator of whether a group operates in a country known for producing cocaine, opium, or cannabis, and the interactions between *Narcotics*, *Favorable Temperature*, and *Month Since Harvest*.[12] To help interpret the effect of *Narcotics*, I plot the marginal effect of this variable, along with a 90% confidence interval in Figure 2. The Figure shows that, when *Favorable Temperature* is equal 1, *Narcotics* has a positive and statistically significant effect on the number of attacks during the month of harvest, as well as in the subsequent month. In contrast, when *Favorable Temperature* is equal 0, *Narcotics* has negative and statistically significant effect during the month of harvest. These results provide support for the research hypothesis, and indicates that narco-

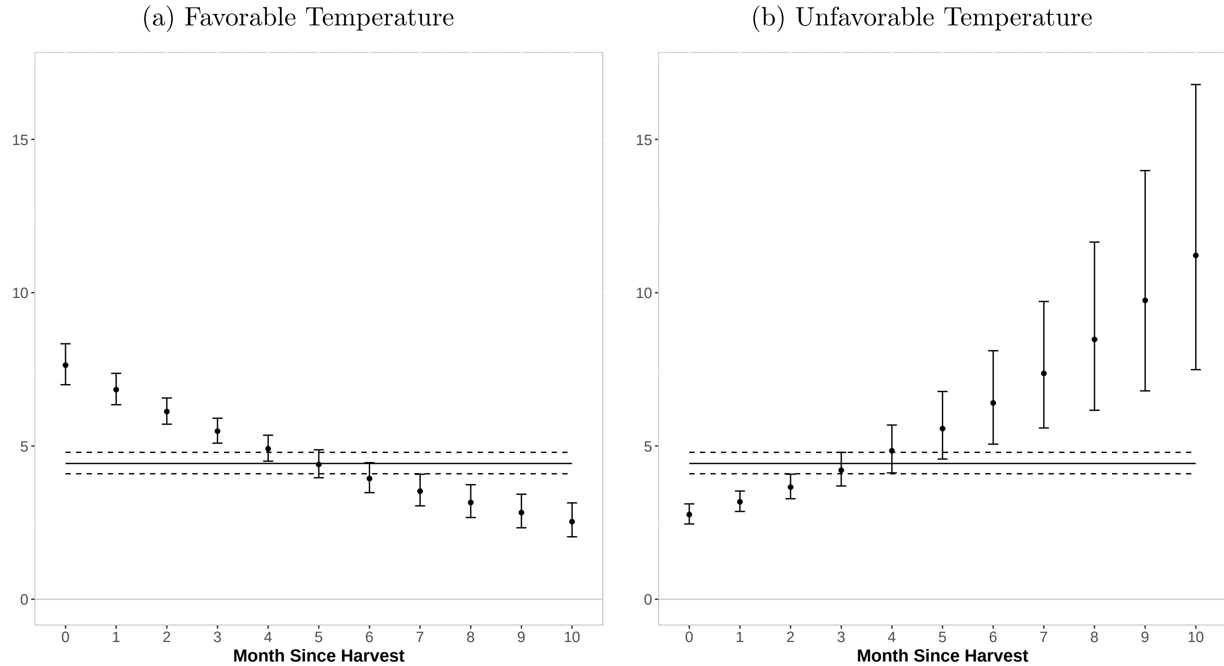
[12]Note that the model does not include all of the constitutive terms of the interaction, as the effects of *Favorable Temperature* and *Month Since Harvest* are only possible for countries that produce narcotics in the first place. For countries that do not produce narcotics, these variables are not meaningful, and therefore they do not belong in the model. For an in-depth treatment of model specification for models with interactions, see Kam and Franzese (2007, 99-102).

Figure 3: The Effect of Narco-Trafficking on the Number of Attacks, by Month and Group Strength



Note: Error bars represent 90% confidence intervals. All quantities are calculated using coefficients and variance-covariance matrix from Models 2 and 3 in Table 3.

Figure 4: Predicted Number of Attacks, by Funding Type and Month



Note: Error bars represent 90% confidence intervals. All quantities are calculated using estimates from Model 1 of Table 3 while holding the control variables at their mean and modal values. Solid black lines and dashed lines represent the predicted number of attacks for groups from non-drug-trafficking countries, along with a 90% confidence interval.

terrorists engage in a higher number of attacks than terrorist groups that obtain funding from more consistent sources, as long as the weather conditions are favorable for harvesting drugs. These effects are statistically significant during the month of harvest as well as the subsequent month. In contrast, when the weather is not favorable for harvesting drugs, narco-terrorist groups perpetrate fewer attacks than groups that derive funding from other sources.

The theoretical model predicts that the effect of variation in funding will be the strongest for weaker terrorist groups, i.e. those that cannot supplement their income with other more stable sources, such as state sponsorship. To test this nuanced prediction, I re-estimated the model on two subsamples of the data: (1) *weak* groups, operationalized as neither large in size nor sponsored by a state (Model 2), and (2) *large* groups, operationalized as either large in size or receiving state sponsorship, or both. Figure 3 presents plots of marginal effects of *Narcotics* by *Month Since Harvest* and *Favorable Weather* for each of these models. Consistent with the theoretical expectations, for weak groups, *Narcotics* has a positive and statistically significant effect during the month of harvest and the subsequent month, as long as the weather was favorable for harvesting the specific narcotics plant. The same effect is not statistically significant for strong groups, which implies that large groups or groups with state sponsorship are not as susceptible to fluctuation in drug-related funding. The effect *Narcotics* is reversed under the unfavorable weather conditions: in that case, reliance on drug-related funding has a negative effect on the number of attacks for both weak and strong groups. The latter negative effect is the strongest for weak groups and dissipates as we move further away from the month of harvest.

To explore the substantive significance of these results, I plot the predicted counts of attacks from Model 1 of Table 3, varying *Narcotics*, *Favorable Temperature*, and *Month*, while holding all the control variables at their mean or modal values. These plots are presented in Figure 4. The predicted number of attacks for non-narco-terrorists is represented by a horizontal black line (dashed lines represent a 90% confidence interval for this prediction), while the black dots along with the error bars represent the corresponding values for narco-terrorists. Subfigure 4a shows these quantities under *Favorable Temperature*, and Subfigure 4b presents the corresponding quantities assuming that *Favorable Temperature* equals 0. To facilitate a visual comparison, I use the same range for the y-axis in both subfigures. We see that the predicted number of attacks for groups that are not directly linked to narco-trafficking is just under 5 per month. In the meantime, under favorable temperature conditions, narco-terrorists execute approximately 7.5 attacks during the month of harvest, approximately 7 attacks in the following month, 6 more attacks in the month after, and 5.5 attacks in the third month after harvest—this totals to approximately 6 additional attacks within four months of harvest. Given favorable temperature during harvest, narco-terrorists also execute fewer attacks as they are further temporally removed from the month of harvest. The pattern reverses under unfavorable temperature (Subfigure 4b): narco-terrorists execute approximately 3 attacks during the month of harvest, 3.5 in the month after, and 4 two months after—a total of 4.5 fewer attacks than groups with other sources of funding, who average about 5 attacks per month. The pattern reverses, as narco-terrorists are further temporally removed from a bad harvest and presumably find other sources to supplement losses in funding: thus, the predicted number of attacks under these conditions increases to about 6 in the fifth month, and continues to increase in the subsequent months (although the widening 90% confidence interval makes the predictions less precise).

Before discussing results of additional analyses, let us briefly turn to the control variables. Some of the control variables act as expected, while others highlight some directions for future research. The coefficient on *Rainfall* is negative and statistically significant in all three models, suggesting that rain decreases the number of terrorist attacks. The coefficient on *State Sponsorship* is positive and statistically significant in the full sample, suggesting that groups with state sponsorships engage in more attacks. The latter result is consistent with Carter (2012), who argues that state sponsors may pressure groups to attack.

The effect of *Alliances* is somewhat conflicting: while it is negative and statistically significant in the overall sample and in the subsample for weak groups, it is positive in the subsample of strong groups. The literature suggests that ties to other groups increase a group's effectiveness through sharing technology and strategic information (Horowitz 2010). In view of this literature, we may speculate that weak groups use technology and strategic information to plan fewer more effective attacks to conserve resources, while strong groups may use their ties to perpetrare additional attacks through their allies. The effect of *Religious Goals* is negative and statistically significant, which suggests that, at least among groups with inconsistent funding, religiously motivated groups engage in fewer attacks. Finally, groups whose primary target is a democratic state engage in more attacks, as indicated by a positive and statistically significant coefficient on *Democracy*. This finding is consistent with Gelpi and Avdan (2018), who show that democratic states are more likely to become

Table 4: The Effect of Funding Inflows on Terrorist Attacks for Groups with Inconsistent Funding

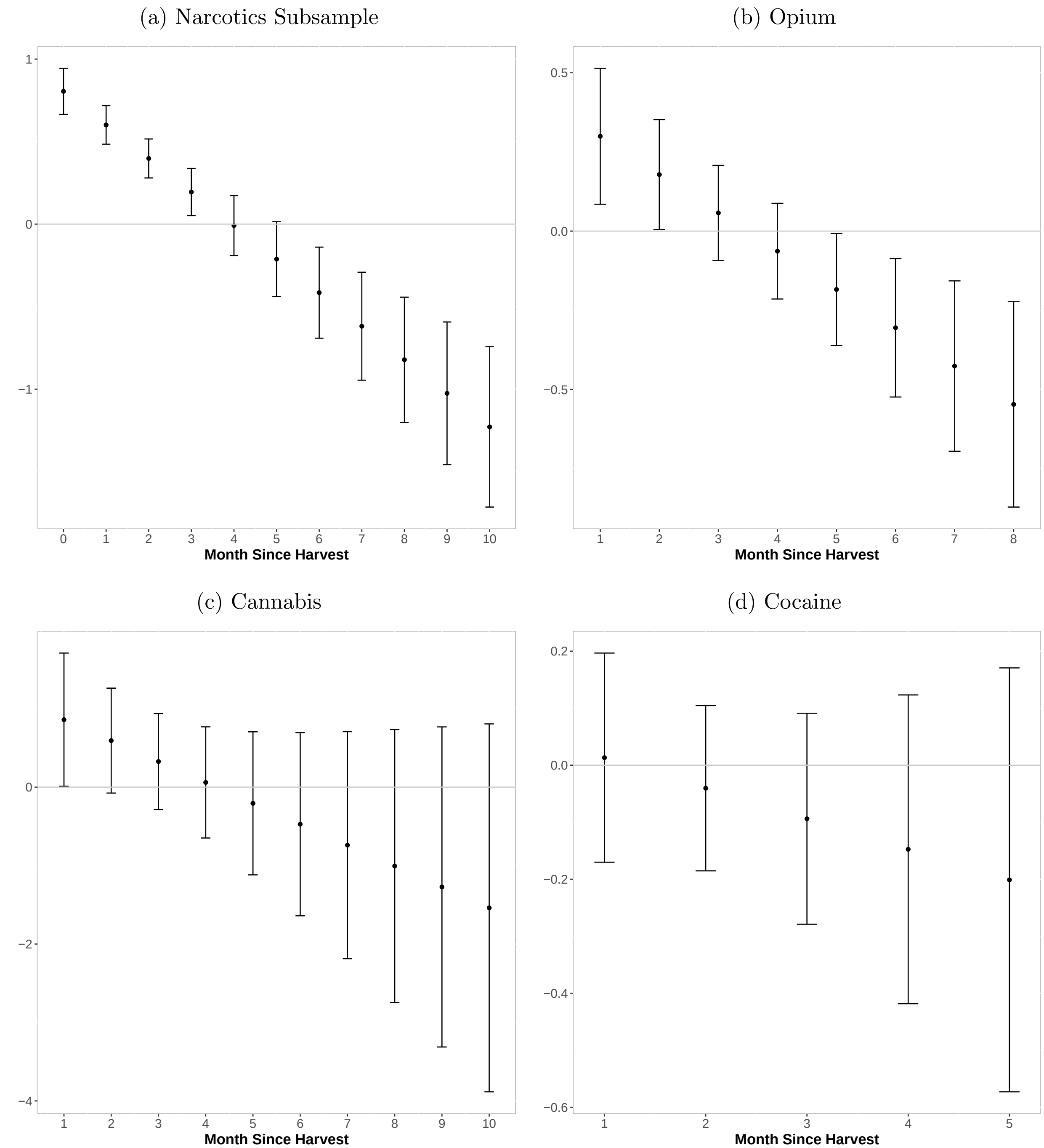
	Narcotics Subsample	*Opium*	*Cannabis*	*Cocaine*
Favorable Temperature	1.008***	0.420***	1.126*	0.146
	(0.108)	(0.161)	(0.665)	(0.196)
Month Since Harvest	0.102***	0.075***	0.252	0.107
	(0.029)	(0.028)	(0.193)	(0.066)
Fav. Temperature × Month	−0.203***	−0.121***	−0.266	−0.086
	(0.034)	(0.039)	(0.193)	(0.072)
Rainfall	−0.001***	−0.001	−0.001**	−0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
State Sponsorship	1.318***	0.109	−0.389	
	(0.106)	(0.129)	(0.472)	
Size	−0.303***	0.247***	−0.369***	−0.460***
	(0.040)	(0.078)	(0.102)	(0.111)
Territory	1.215***	−0.516***	−0.153	1.752***
	(0.078)	(0.121)	(0.325)	(0.158)
Alliances	−0.086***	0.081***	0.322***	−0.090*
	(0.013)	(0.016)	(0.074)	(0.046)
Religious	−0.686***	−0.548***	−1.314***	
	(0.105)	(0.128)	(0.367)	
Democracy (main target)	0.770***	0.212	0.045	1.282***
	(0.093)	(0.138)	(0.296)	(0.128)
State Capacity (main target)	−0.020	−0.018	−0.094	−0.297
	(0.034)	(0.046)	(0.063)	(0.333)
Constant	0.489***	0.045	0.210	0.933**
	(0.136)	(0.215)	(0.711)	(0.355)
θ	1.150	1.610	2.055	1.537
	(0.047)	(0.110)	(0.175)	(0.089)
N	1562	761	539	786
Log-Likelihood	-4182.118	-1573.984	-1325.454	-2349.728

Notes: *p<0.1; **p<0.05; ***p<0.01. Variables *Religious* and *State Sponsorship* dropped out of the *Cocaine* equation due to perfect collinearity.

targets of terrorist attacks.

Now that there is some initial evidence of a difference in the timing of attacks between groups with consistent and inconsistent funding, let's look at some additional analyses just on the subsample of narco-terrorists (Table 4). Model 1 is estimated on a subsample that includes just the groups that operate in countries known for growing one or more of the

Figure 5: The Effect of Temperature on the Number of Attacks, by Month



Note: Error bars represent 90% confidence intervals. All quantities are calculated using the estimates from Table 4 while holding the control variables at their mean and modal values.

drugs[13], while Models 2 through 3 are estimated on subsets of groups from opium-, cannabis-, and cocaine-trafficking countries. To help interpret the effect of *Favorable Temperature*, which enters the models as part of an interaction, Figure 5 presents the marginal effect of *Favorable Temperature* by *Month Since Harvest* for each of the four models. As shown in Subfigure 5a, *Favorable Temperature* has a positive and statistically significant effect on the number of attacks during the month of harvest and the three subsequent months (months 0–4), though this effect weakens with time. As the time since harvest continues to increase (months 6-10), the effect of *Favorable Temperature* becomes negative.[14] This indicates that terrorist groups with inconsistent funding engage in the highest number of attacks during and immediately after an influx in funding due to harvest; once this funding runs out, they have to wait until the next favorable harvest season to fund attacks. The same pattern in observed in each of the subsamples (Subfigures 5b-5d), although the effect of favorable temperature is not statistically significant in the cocaine subsample. Taken together, these results support the research hypothesis.

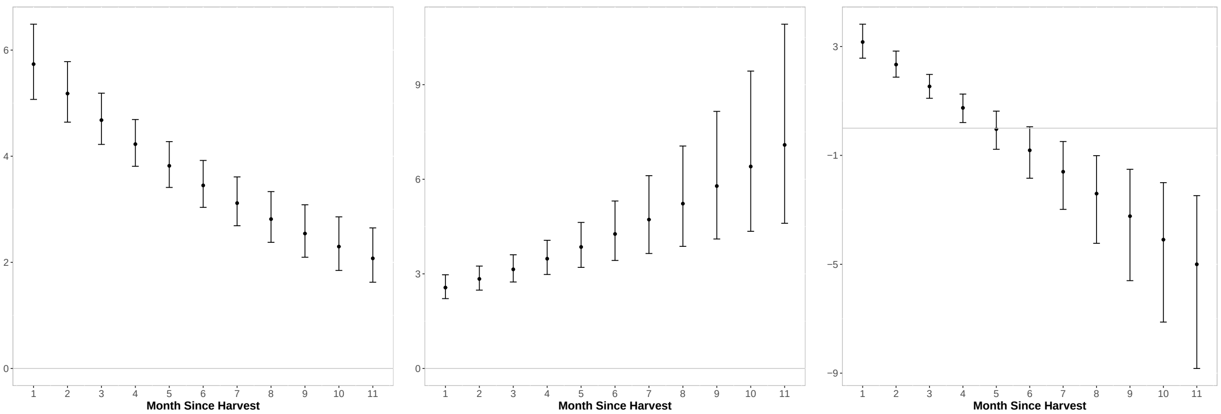
Figures 6 and 8 demonstrate the predicted number of attacks by temperature and month since harvest (Subfigures 6a, 6b, 7a, 7b, 8a, and 8b), as well as the differences in the expected number of attacks resulting from a change from favorable to unfavorable temperature during the month of harvest (Subfigures 6c, 7c, and 8c). These graphs show the variation in the predicted number of attacks as a function of variation in *Favorable Temperature* (Favorable to Unfavorable) for each month since harvest, while holding all control variables at their means and/or modes. Figure 6 displays these quantities for the full sample (groups from countries with any type of drug trafficking), while Figures 7 and 8 visualize the corresponding quantities just for the subsamples of groups from countries, known for trafficking opiates and

[13]Groups from countries with more than one drug enter into the analysis once per each drug they produce. Such groups make up a very small part of the sample, and the results are robust to this coding decision.

[14]Note that the lengths of growth cycles vary by the type of drug and country of origin. For example, groups from cocaine-producing areas are able to harvest 3 times a year, so harvests happen every 3-5 months, while groups from cannabis- or opiates-producing countries may have to wait up to 11 months for the next harvest.

Figure 6: Predicted Number of Attacks, by Temperature and Month Since Harvest (Table 4 Model 1: Narcotics Sample)

(a) Favorable (b) Unfavorable (c) Difference



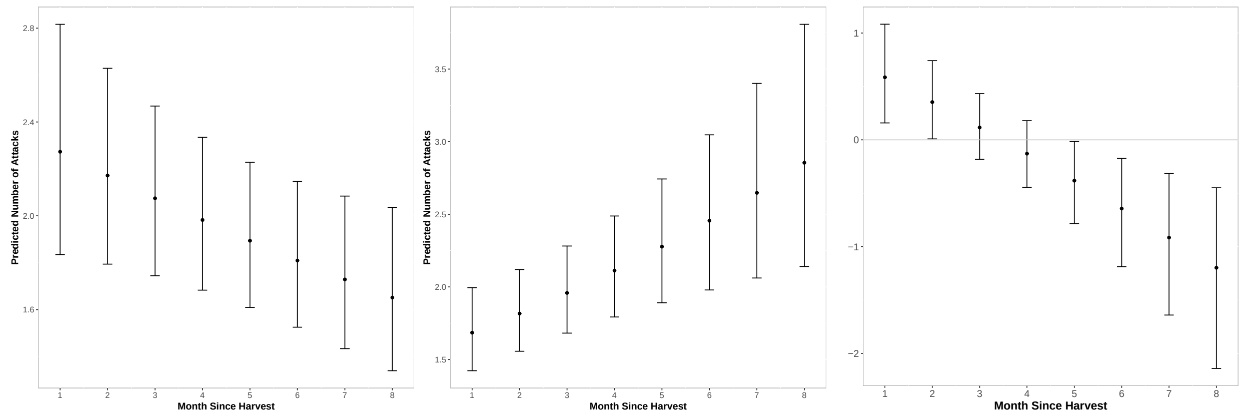
Note: Error bars represent 90% confidence intervals for the predicted values. All quantities are calculated while holding the control variables at their mean and modal values.

cannabis, accordingly.[15] Subfigure 6a shows that favorable temperature during the month of harvest results in approximately 5.8 terrorist attacks during the month of harvest, 5.2 attacks during the following month, 4.7 attacks two month after harvest, and so on. In contrast, Subfigure 6b shows that unfavorable temperature at harvest is associated with approximately 2.5 attacks during the month of harvest, which increases to 2.9 attacks in the subsequent month, to 3.3 attacks two months since harvest, and so on. As highlighted by Subfigure 6c, the difference between favorable and unfavorable temperature during the month of harvest results in a difference of approximately 3.2 attacks in that month, 2.5 attacks in the subsequent month, 1.5 attacks two months since harvest, and so on. Notably, the difference dissipates by the fourth month after the harvest and, in fact, turns negative as we continue moving away from the month of harvest. This suggests, that in the medium- to long-run, terrorist groups may be able to make up for the dips in resources that are due to poor harvesting conditions with other types of funding. Figures 7 and 8 show very similar, albeit weaker, patterns for terrorist groups that originate just from the countries that are

[15]The effect of *Favorable Temperature* for cocaine (Model 4) is not statistically significant, and hence, substantive effects for this model are not plotted.

Figure 7: Predicted Number of Attacks, by Temperature and Month Since Harvest (Model 2: Opium Subsample)

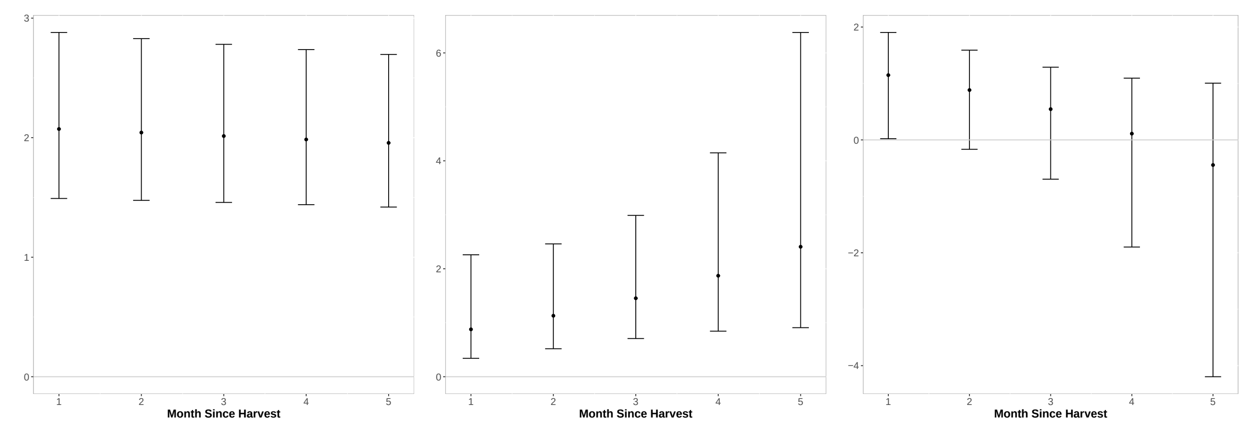
(a) Favorable (b) Unfavorable (c) First Difference



Note: Error bars represent 90% confidence intervals for the predicted values. All quantities are calculated while holding the control variables at their mean and modal values.

Figure 8: Predicted Number of Attacks, by Temperature and Month Since Harvest (Model 3: Cannabis Subsample)

(a) Favorable (b) Unfavorable (c) First Difference



Note: Error bars represent 90% confidence intervals for the predicted values. All quantities are calculated while holding the control variables at their mean and modal values.

known for trafficking opiates and cannabis.

Most of the control variables act the same as in the previous models. The result related to the effect of territory, however, is somewhat conflicting, as the coefficient on *Territory* is positive and statistically significant in the overall sample and in the subsample of groups from cocaine-trafficking countries, yet negative and statistically significant in the subsample of groups from opium-trafficking countries. This result may have to do with dynamics between the terrorist groups and the government or other actors that are not modeled in this paper (e.g., Bapat and Zeigler 2016). Poppies may also be more susceptible to eradication than the other two drug crops, especially since, outside of monsoon climate countries, opiates are frequently grown in open fields, while the other two drugs are typically hidden in forests or on mountain slopes. In this case, control over territory may result in larger fluctuation in funding, as on one hand, more opiates can be planted, but on the other hand, there is a greater risk of eradication. The effect of *Alliances* is again conflicting; while it is negative and statistically significant in the narcotics subsample and in the subsample of cocaine-traffickers, it is positive and statistically significant in the subsamples of opiate- and cannabis-trafficking groups. This again may be indicative of additional dynamics related to trafficking of specific drugs that are not modeled here: e.g., trafficking of some drugs may necessaitate more links to other groups.

Although not the central focus here, one may hypothesize that processing a plentiful drug harvest and converting it to liquid cash may require some time at least in some cases (although, as discussed above, groups may also be able to borrow against expected harvest to obtain immediate cash). To explore this, I estimated an additional model, in which I treat *Month Since Harvest* as a nominal rather than an ordinal variable. These results are presented in Table 6 and Figure 11 of the Appendix. These results show some support for the above intuition, as the marginal effect of *Month*, while positive and statistically significant during the first three months within harvest (assuming favorable temperature), reaches the greatest magnitude in the second month following harvest rather than in the month of harvest. Although interesting, this result must be taken with a grain of salt, as the *Month Since Harvest* measure is a rather rough approximation and likely suffers from some noise.

One may also expect that harvests may be affected by more than just temperature. As mentioned above, opium harvests, in particular, are susceptible to excessive rainfall. To explore this, I estimated an additional model, in which the number of attacks is regressed on *Favorable Weather* rather than *Favorable Temperature*. *Favorable Weather* equals 1 if, during the month of harvest, both the average monthly temperature fell within an acceptable range and the monthly amount of precipitation did not exceed its third quartile.[16] These results are presented in Table 5 and Figures 9 and 10 of Appendix. These results are very similar to those dicussed above.

Conclusion

Logic suggests that the terrorists' goal of maximizing fear and uncertainty is best achieved by timing their attacks in a seemingly unpredictable manner. Such timing minimizes the government and the public's preparedness and ability to prevent attacks. The caveat is that terrorist groups' ability to time their attacks in a strategic manner is constrained by the predictability and reliability of their sources of funding. Terrorist groups with stable and consistent sources of funding, such as state sponsorship, private donations, natural resources, or even criminal activities, have more flexibility in timing, planning, and executing attacks than groups with inconsistent and unreliable sources of funding, such as groups that rely on drug trafficking. As a result, groups with inconsistent funding may be unable to time their attacks in a seemingly random manner. Instead, the timing of attacks perpetrated by such groups may follow the cycle of drug harvests, with poor harvests corresponding to dips in the number of attacks and plentiful harvests associated with spikes in the number of attacks.

I tested this theory by proxying funding inflows with data on optimal temperatures and harvest time for groups that operate in narcotic-growing countries. I found strong support for the research hypothesis. The results show that attacks perpetrated by terrorist groups

[16] The threshold for precipitation was calculated by summarizing precipitation during the months of harvest rather than annual precipitation, as some of the countries in the sample experience monsoon seasons during non-harvest months.

with inconsistent funding closely follow the drug harvesting cycles. These findings have important implications for counter-terrorist strategies. The results point to such policies as drug eradication missions or dismantling drug cartels as an effective means for reducing the short-term threat of terrorist attacks from groups that rely on this type of funding.

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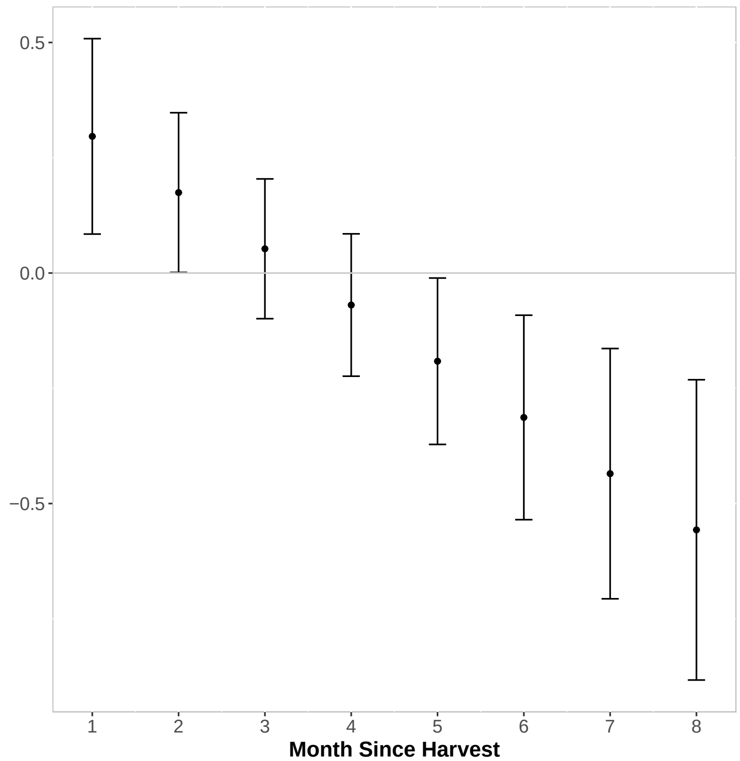
Online Appendix

Table 5: The Effect of Favorable Weather on Number of Attacks: Opiates Subsample

Favorable Weather	0.418***
	(0.158)
Month since Harvest	0.077***
	(0.027)
Fav. Weather × Month	-0.120***
	(0.039)
Rainfall	-0.001
	(0.001)
State Sponsorship	0.107
	(0.129)
Size	0.247***
	(0.078)
Territory	-0.516***
	(0.121)
Alliance	0.081***
	(0.016)
Religious	-0.548***
	(0.128)
Democracy	0.214
	(0.138)
State Capacity	-0.018
	(0.046)
Constant	0.044
	(0.215)
θ	1.610
	(0.110)
N	761
Log Likelihood	-1574.008

Notes: *p<0.1; **p<0.05; ***p<0.01 .

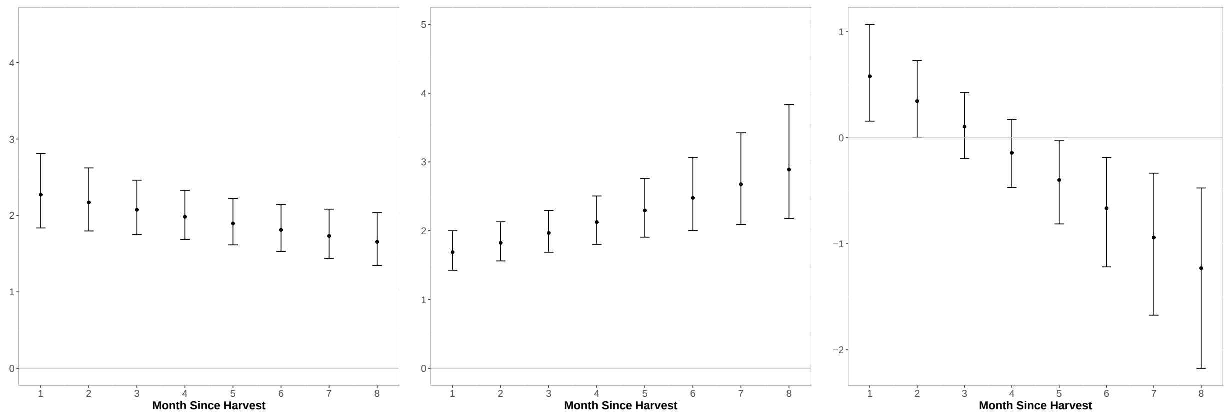
Figure 9: Marginal Effect of Weather Condition on the Number of Attacks, by Month: Opiates Subsample



Notes: Marginal effects were calculated using estimates from Table 5.

Figure 10: Predicted Number of Attacks, by Month and Weather

(a) Favorable (b) Unfavorable (c) Difference



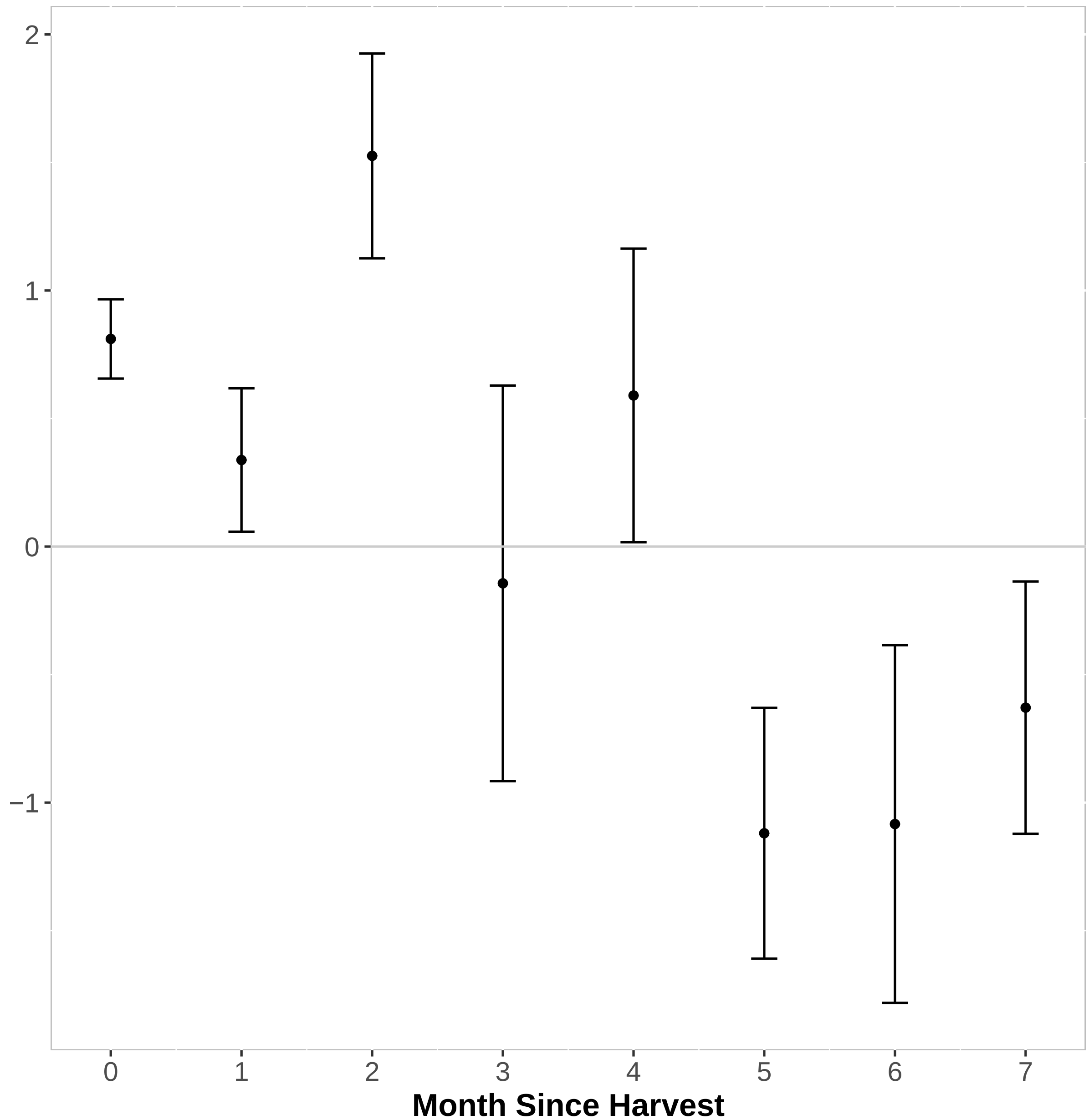
Note: Error bars represent 90% confidence intervals. All quantities are calculated based on estimates from Table 5, holding all control variables at their mean and modal values.

Table 6: The Effect of Weather on Number of Attacks, Treating Month as a Nominal Variable

Fav. Temp.	0.811^{***}	(0.094)
One Month Since Harvest* Fav. Temp.	-0.473^{**}	(0.190)
Two Months Since Harvest* Fav. Temp.	0.715^{***}	(0.258)
Three Months Since Harvest* Fav. Temp.	-0.955^{**}	(0.481)
Four Months Since Harvest* Fav. Temp.	-0.221	(0.364)
Five Months Since Harvest* Fav. Temp.	-1.931^{***}	(0.315)
Six Months Since Harvest* Fav. Temp.	-1.895^{***}	(0.437)
Seven or More Months Since Harvest* Fav. Temp.	-1.440^{***}	(0.313)
One Month Since Harvest	0.342^{**}	(0.171)
Two Months Since Harvest	-0.683^{***}	(0.244)
Three Months Since Harvest	0.791^{*}	(0.468)
Four Months Since Harvest	-0.058	(0.329)
Five Months Since Harvest	0.882^{***}	(0.253)
Six Months Since Harvest	0.493	(0.384)
Seven Months Since Harvest	0.872^{***}	(0.269)
Rainfall	-0.001^{***}	(0.001)
State Sponsorship	1.312^{***}	(0.105)
Size	-0.256^{***}	(0.040)
Territory	1.115^{***}	(0.078)
Alliances	-0.091^{***}	(0.013)
Religious	-0.672^{***}	(0.105)
Democracy (main target)	0.813^{***}	(0.092)
State Capacity (main target)	-0.048	(0.035)
Constant	0.562^{***}	(0.129)
	1.199	(0.049)
N	1574	
Log Likelihood	-4155.991	

Notes: *p<0.1; **p<0.05; ***p<0.01 .

Figure 11: Marginal Effect of Favorable Temperature, by Month



Note: Error bars represent 90% confidence intervals. All quantities are calculated using coefficients and variance-covariance estimates associated with the model in Table 6.

Table 7: Data on Terrorist Groups and Narco-Trafficking

	Group	**Country**	**Narcotic**
	Group	Country	Narcotic
1	1920 Revolution Brigades	Iraq	none
2	Abu Hafs al-Masri Brigades	United Kingdom	none
3	Abu Sayyaf Group (ASG)	Philippines	none
4	Achik National Volunteer Council (ANVC)	India	opium
5	Action Directe	France	none
6	Adan Abyan Islamic Army (AAIA)	Yemen	none
7	Ahrar Al-Jalil (Free People of the Galilee)	Israel	none
8	Al-Aqsa Martyrs Brigade	Israel	none
9	Al-Arifeen	Pakistan	opium
10	Al-Badr	Pakistan	opium
11	Al-Haramayn Brigades	Saudi Arabia	none
12	Al-Madina	India	opium
13	Al-Mansoorian	India	opium
14	Al-Nawaz	Pakistan	opium
15	Al-Qassam Brigades	Israel	none
16	Al-Umar Mujahideen	Pakistan	opium
17	Albanian National Army (ANA)	Macedonia	none
18	Alex Boncayao Brigade (ABB)	Philippines	none
19	All Tripura Tiger Force (ATTF)	India	opium
20	Amal	Lebanon	cannabis, opium
21	Anarchist Faction	Greece	none

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
22	Anarchist Liberation Brigade	Greece	none
23	Anarchist Struggle	Greece	none
24	Angry Brigade (Italy)	Italy	none
25	Animal Liberation Front (ALF)	United States of America	none
26	Ansar al-Islam	Iraq	none
27	Ansar al-Jihad	Iraq	none
28	Ansar al-Sunna	Iraq	none
29	Ansar Allah	Lebanon	cannabis, opium
30	Anti-Communist Command (KAK)	Indonesia	none
31	Anti-Racist Guerrilla Nuclei	Italy	none
32	Anti-State Action	Greece	none
33	Anti-Zionist Movement	Italy	none
34	Arbav Martyrs of Khuzestan	Iran	opium
35	Armata Corsa	France	none
36	Armata di Liberazione Naziunale (ALN)	France	none
37	Armed Forces Revolutionary Council (AFRC)	Sierra Leone	none
38	Armed Islamic Group (GIA)	Algeria	none
39	Army of God	United States of America	none
40	Asbat al-Ansar	Lebanon	cannabis, opium
41	Association Totalement Anti-Guerre (ATAG)	France	none

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
42	Autonomous Decorators	Germany	none
43	Babbar Khalsa International (BKI)	India	opium
44	Baloch Liberation Army (BLA)	Pakistan	opium
45	Basque Fatherland and Freedom (ETA)	Spain	none
46	Bersatu	Thailand	cannabis, opium
47	Black Panther Group (Palestinian)	Israel	none
48	Black Star	Greece	none
49	Black Widows	Russia	cannabis
50	Bodo Liberation Tigers (BLT)	India	opium
51	Brigades of Iman Hassan-al-Basri	Iraq	none
52	Cambodian Freedom Fighters (CFF)	United States of America	none
53	Catholic Reaction Force	United Kingdom	none
54	CCCCC	Italy	none
55	Children of November	Greece	none
56	Chukakuha (Middle Core Faction)	Japan	none
57	Clandestini Corsi	France	none
58	Coalition to Save the Preserves (CSP)	United States of America	none
59	Communist Party of India - Maoist (CPI-Maoist)	India	opium

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
60	Conscientious Arsonists (CA)	Greece	none
61	Continuity Irish Republican Army (CIRA)	United Kingdom	none
62	Corsican National Liberation Front (FLNC)	France	none
63	Democratic Front for the Liberation of Palestine (DFLP)	Israel	none
64	Democratic Karen Buddhist Army (DKBA)	Myanmar (Burma)	opium
65	Devrimici Halk Kurtulus Cephesi (DHKP/C)	Turkey	opium
66	Earth Liberation Front (ELF)	United States of America	none
67	East Turkistan Liberation Organization	China	opium
68	Ejercito Revolucionario Guevarista (Guevarist Revolutionary Army)	Colombia	cannabis, cocaine
69	First of October Antifascist Resistance Group (GRAPO)	Spain	none
70	Free Aceh Movement (GAM)	Indonesia	none
71	Free Democratic People's Government of Laos	Laos	opium

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
72	Free Papua Movement (OPM-Organisasi Papua Merdeka)	Indonesia	none
73	Front for the Liberation of the Enclave of Cabinda (FLEC)	Angola	none
74	Gazteriak	France	none
75	Global Intifada	Sweden	none
76	God's Army	Myanmar (Burma)	opium
77	Great Eastern Islamic Raiders Front (IBDA-C)	Turkey	opium
78	Group of Carlo Giuliani	Greece	none
79	Hamas (Islamic Resistance Movement)	Israel	none
80	Harakat ul-Mujahidin (HuM)	Pakistan	opium
81	Hizb-I-Islami	Afghanistan	opium
82	Hizbul Mujahideen (HM)	Pakistan	opium
83	Holders of the Black Banners	Iraq	none
84	Indigenous People's Federal Army (IPFA)	Philippines	none
85	Informal Anarchist Federation	Italy	none
86	International Solidarity	Italy	none
87	Iparretarrak (IK)	France	none
88	Irish National Liberation Army (INLA)	Ireland	none

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
89	Irish Republican Army (IRA)	United Kingdom	none
90	Islamic Army in Iraq (al-Jaish al-Islami fi al-Iraq)	Iraq	none
91	Islamic Defenders' Front (FPI)	Indonesia	none
92	Islamic Jihad Brigades	Iraq	none
93	Islamic Movement of Uzbekistan (IMU)	Uzbekistan	none
94	Islamic Shashantantra Andolon (ISA)	Bangladesh	none
95	Jaime Bateman Cayon Group (JBC)	Colombia	cannabis, cocaine
96	Jaish-e-Mohammad (JeM)	Pakistan	opium
97	Jaish al-Ta'ifa al-Mansura	Iraq	none
98	Jama'atul Mujahideen Bangladesh (JMB)	Bangladesh	none
99	Jamiat ul-Mujahedin (JuM)	Pakistan	opium
100	Jemaah Islamiya (JI)	Indonesia	none
101	Jenin Martyrs Brigades	Israel	none
102	Kach	Israel	none
103	Kanglei Yawol Kanna Lup (KYKL)	India	opium
104	Kangleipak Communist Party (KCP)	India	opium
105	Kosovo Liberation Army (KLA)	Macedonia	none
106	Kuki Liberation Army (KLA)	India	opium

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
107	Kurdistan Freedom Hawks (TAK)	Turkey	opium
108	Kurdistan Workers' Party (PKK)	Turkey	opium
109	Lashkar-e-Jhangvi	Pakistan	opium
110	Lashkar-e-Omar	Pakistan	opium
111	Lashkar-e-Taiba (LeT)	Pakistan	opium
112	Laskar Jihad	Indonesia	none
113	Liberation Tigers of Tamil Eelam (LTTE)	Sri Lanka	none
114	Lord's Resistance Army (LRA)	Uganda	none
115	Loyalist Volunteer Forces (LVF)	United Kingdom	none
116	M-19 (Movement of April 19)	Colombia	cannabis, cocaine
117	Macheteros	United States of America	none
118	Mahdi Army	Iraq	none
119	Maoist Communist Center (MCC)	India	opium
120	Mariano Moreno National Liberation Commando	Venezuela	none
121	Mayi Mayi	Congo, Democratic Republic of / Zaire	none
122	Moro Islamic Liberation Front (MILF)	Philippines	none
123	Moro National Liberation Front (MNLF)	Philippines	none

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
124	Movement for Democracy and Justice in Chad (MDJT)	Chad	none
125	Movement of the Revolutionary Left (MIR) (Bolivia)	Chile	none
126	Mujahedin-e Khalq (MEK)	Iraq	none
127	Muslim United Army (MUA)	Pakistan	opium
128	Muslims Against Global Oppression (MAGO)	South Africa	cannabis
129	Muttahida Qami Movement (MQM)	Pakistan	opium
130	National Army for the Liberation of Uganda (NALU)	Uganda	none
131	National Democratic Front of Bodoland (NDFB)	India	opium
132	National Liberation Front of Tripura (NLFT)	India	opium
133	National Socialist Council of Nagaland-Isak-Muivah (NSCN-IM)	India	opium
134	National Union for the Total Independence of Angola (UNITA)	Angola	none
135	New People's Army (NPA)	Philippines	none
136	New Revolutionary Alternative (NRA)	Russia	cannabis

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
137	New Revolutionary Popular Struggle (NELA)	Greece	none
138	November 17 Revolutionary Organization (N17RO)	Greece	none
139	Odua Peoples' Congress (OPC)	Nigeria	none
140	Orange Volunteers (OV)	United Kingdom	none
141	Oromo Liberation Front	Ethiopia	cannabis
142	Palestinian Islamic Jihad (PIJ)	Israel	none
143	Pattani United Liberation Organization (PULO)	Thailand	cannabis, opium
144	Peasant Self-Defense Group (ACCU)	Colombia	cannabis, cocaine
145	People's Liberation Forces (FPL)	El Salvador	none
146	People's Revolutionary Militias (MRP)	Ecuador	none
147	People's War Group (PWG)	India	opium
148	People Against Gangsterism and Drugs (PAGAD)	South Africa	cannabis
149	Popular Front for the Liberation of Palestine (PFLP)	Israel	none
150	Popular Resistance (Laiki Antistasi)	Greece	none
151	Popular Resistance Committees	Israel	none
152	Popular Revolutionary Action	Greece	none

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
153	Popular Revolutionary Army (Mexico)	Mexico	none
154	Proletarian Nuclei for Communism	Italy	none
155	Protectors of Islam Brigade	Iraq	none
156	Purbo Banglar Communist Party	Bangladesh	none
157	Real Irish Republican Army (RIRA)	United Kingdom	none
158	Red Brigades	Italy	none
159	Red Hand Defenders (RHD)	United Kingdom	none
160	Red Line	Greece	none
161	Resistenza Corsa	France	none
162	Revolutionary Armed Forces of Colombia (FARC)	Colombia	cannabis, cocaine
163	Revolutionary Army	Japan	none
164	Revolutionary Leninist Brigades	Italy	none
165	Revolutionary Liberation Action (Epanastatiki Apelevtherotiki Drasi) - Greece	Greece	none
166	Revolutionary Nuclei	Greece	none
167	Revolutionary Perspective	Spain	none
168	Revolutionary Proletarian Initiative Nuclei (NIPR)	Italy	none
169	Revolutionary Struggle	Greece	none
170	Revolutionary United Front (RUF)	Sierra Leone	none

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
171	Revolutionary Workers' Council (Kakurokyo)	Japan	none
172	Riyadus-Salikhin Reconnaissance and Sabotage Battalion of Chechen Martyrs	Russia	cannabis
173	Saif-ul-Muslimeen	Afghanistan	opium
174	Salafia Jihadia	Morocco	cannabis
175	Salafist Group for Preaching and Fighting (GSPC)	Algeria	none
176	Salah al-Din Squad	Israel	none
177	Sardinian Autonomy Movement	Italy	none
178	Save Kashmir Movement	India	opium
179	Shining Path (SL)	Peru	cocaine
180	South Londonderry Volunteers (SLV)	United Kingdom	none
181	Students Islamic Movement of India (SIMI)	India	opium
182	Sudan People's Liberation Army (SPLA)	Sudan	none
183	Sword of Islam	Russia	cannabis
184	Takfir wal-Hijra (Excommunication and Exodus)	Iraq	none
185	Taliban	Afghanistan	opium
186	Tanzim	Israel	none
187	Tawhid and Jihad	Iraq	none
188	The Inevitables	Bolivia	cocaine
189	Tigers	Swaziland	cannabis

Continued on next page

Table 7 – continued from previous page

	Group	Country	Narcotic
190	Tupac Amaru Revolutionary Movement (MRTA)	Peru	cocaine
191	Tupamaro Revolutionary Movement	Venezuela	none
192	Turkish Communist Party/Marxist (TKP-ML)	Turkey	opium
193	Turkish People's Liberation Front (TPLF)(THKP-C)	Turkey	opium
194	Ulster Freedom Fighters (UFF)	United Kingdom	none
195	Ulster Volunteer Force (UVF)	United Kingdom	none
196	Ummah Liberation Army	Sudan	none
197	United Kuki Liberation Front (UKLF) - India	India	opium
198	United Liberation Front of Assam (ULFA)	India	opium
199	United National Liberation Front (UNLF)	India	opium
200	United People's Democratic Solidarity (UPDS)	India	opium
201	United Revolutionary Front	Venezuela	none
202	United Self Defense Units of Colombia (AUC)	Colombia	cannabis, cocaine
203	Vigorous Burmese Student Warriors	Myanmar (Burma)	opium
204	Young Liberators of Pattani	Thailand	cannabis, opium
205	Zomi Revolutionary Army (ZRA)	India	opium