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Rebel Capacity, Intelligence Gathering, and Combat Tactics

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Abstract: *Classic and modern theories of rebel warfare emphasize the role of resource endowments. We demonstrate that intelligence gathering, made possible by these endowments, plays a critical role in determining specifics of how rebels launch complex attacks against better equipped government forces. We test implications of a theoretical model using highly detailed data about Afghan rebel attacks, insurgent-led spy networks, and counterinsurgent operations. Leveraging quasi-random variation in opium suitability, we find that improved rebel capacity is associated with (1) increased insurgent operations; (2) improved battlefield tactics through technological innovation, increased complexity, and attack clustering; and (3) increased effectiveness against security forces, especially harder targets. These results show that access to capital, coupled with intelligence gathering, meaningfully impacts how and where rebels fight.*

Verification Materials: The data and materials required to verify the computational reproducibility of the results, procedures, and analyses in this article are available on the *American Journal of Political Science* Dataverse within the Harvard Dataverse Network, at: https://doi.org/10.7910/DVN/4EZPKF.

> Attack [the enemy] where he is unprepared, appear where you are not expected.
>
> Sun Tzu, "The Art of War," Fifth century BC

Intrastate conflicts have replaced interstate wars as the main source of human loss and population displacement. Generally, it is well understood that resource endowments shape how rebels recruit, retain, and deploy their fighters (Weinstein 2007). Fluctuations in rebel-held economic resources affect the scale of insurgent activity (Dube and Vargas 2013), their control of strategic territory (Kalyvas 2006), and how they treat civilians (Wood 2014). These factors, in turn, impact whether civilians cooperate with rebels or collude with government forces (Condra and Shapiro 2012a) and the ability of the government to engage in development and reconstruction (Sexton 2016).

In this article, we unpack the impact of resource availability on combat tactics at a much more granular level. In our model of irregular warfare, rebels gather information about vulnerability of the targets and choose the pattern of attacks based on this information. Positive economic shocks enable rebels to acquire relatively high-quality intelligence and their attacks become more complex, involve more sophisticated weapons, and are clustered on a set of most vulnerable targets. Our model is a novel version of Colonel Blotto game, a standard general model of two-parties conflict (Blackett 1958; Kovenock and Roberson 2012; Powell 2007). We add the possibility, for the attacking side, to gather additional

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information about targets' vulnerability: After the government has allocated its defense resources, each possible target is tested for vulnerability, and the rebels' choice of targets relies on results of these tests. In equilibrium, the optimal allocation of attacks across targets accounts for this additional information; this creates a link between the precision of information and allocation of attacks.

We test our model's implications using declassified military records provided by the U.S. government, which document hundreds of thousands of combat operations in Afghanistan during OEF. These data are unique in scope and scale; they encompass otherwise unobservable details about combat operations such as the location of insurgent surveillance operations, battlefield innovations by rebels, unit infiltration by insurgents, and use of deceptive weapon technologies. We combine these granular records with information on the location and intensity of microlevel opium production as well as satellite-derived measures of exogenous agronomic conditions that influence opium productivity. We leverage these high-resolution, high-frequency measures of agricultural inputs to construct a novel measure of exogenous opium suitability. We also gather a battery of additional information about agricultural price zones, infrastructure projects, irrigation technology, and use of coercive threats to manipulate local production to evaluate how shocks to rebel capacity impact rebel tactics.

We find consistent evidence that positive economic shocks to rebel organizations lead to an increase in violence and changes in *how* rebels produce violence. In particular, we find that increased rebel capacity is associated with more technological innovation by insurgents, additional attacks involving sophisticated infiltration of government forces, increased use of deceptive weapon technologies, and more complex, multitarget combat operations. We also find that rebels engage in more clustered attacks, both in time and space, as their access to capital grows. Importantly, because our combat records also include information about rebel-led surveillance, we can test the central conjecture of our theoretical model: Access to more precise information about government vulnerabilities allows rebels to convert capital into more sophisticated attacks. Insurgents were able to conduct surveillance operations in 70 of Afghanistan's 398 districts at the start of our sample, which we visualize in Figure 1. We find broad evidence of this mechanism: Violence and attack sophistication are particularly responsive to resource endowments in areas where insurgents conducted surveillance operations early in the campaign.

A meaningful gap exists, as Berman and Matanock (2015) point out, between our understanding of *when* and *how* rebels engage in armed combat. Our article helps to address this gap. Prior work provides compelling evidence that insurgents respond strategically to local economic shocks and aerial bombardment (Berman et al. 2017; Dell and Querubin 2018; Dube and Vargas 2013; Vanden Eynde 2018), form alliances during war (Konig et al. 2017), and calibrate their use of violence against civilian populations (Condra and Shapiro 2012b; Condra et al. 2018). Recent work also links exogenous economic shocks to terrorism financing and recruitment activity on the dark net (Limodio 2019). We contribute to this literature by providing credible evidence that economic shocks to rebel organizations influence changes in combat tactics, which, in turn, has effect on battlefield efficiency.

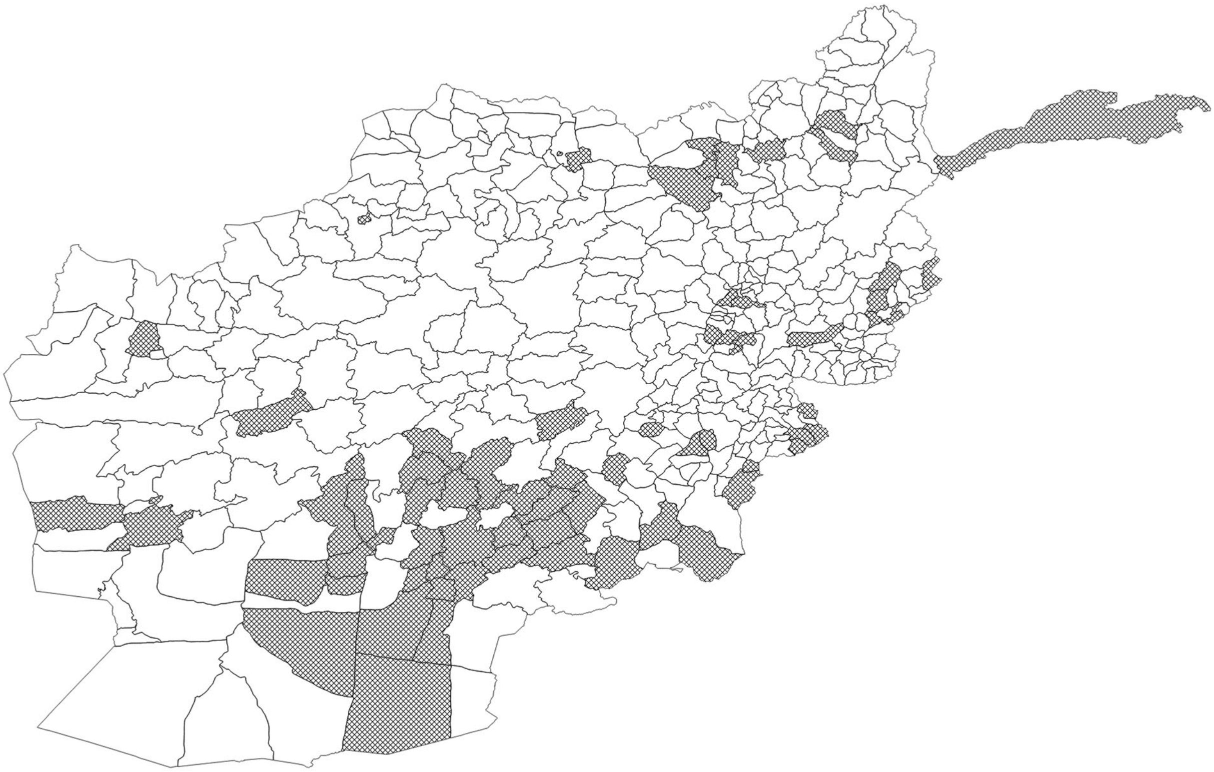
More generally, our article provides insights into the underlying mechanisms of insurgency. State capacity is central to economic theories of conflict (Besley and Persson 2011; Powell 2013). Yet, the resources available to the state's competitors also influence when conflicts emerge, how internal wars are fought, and whether they end in withdrawal.

Our theoretical model and empirical tests also focus on a novel yet often overlooked dynamic of conflict: All sides collect information. Prior work on counterinsurgency has primarily studied how combat dynamics, including civilian harm, influence intelligence gathering by government forces (Condra and Shapiro 2012a). This is, in part, due to the difficulty of observing how and when nonstate actors engage in surveillance and manage the flow of information about combat activity and target vulnerabilities. Yet, Kalyvas (2006) and others have noted, using various ethnographic, historical, and archival methods, the importance of information to all sides during conflict, especially asymmetric wars. Our theoretical model emphasizes this mechanism, suggesting that intelligence gathering shapes where, how, and to what effect violence is produced by rebels.

Our study is among the first to estimate the impact of resource endowments on battlefield effectiveness, notably attacks involving vehicle and weapons system damage as well as soldier casualties. We find that these attacks increase significantly with positive shocks to opium suitability, especially against hard targets. We also find that the impact of these shocks to rebel capacity is moderated by the intelligence gathering mechanism: Increased combat effectiveness is sharpest in areas where insurgents have access to surveillance assets.

The rest of the article is organized as follows. Section "Theory" introduces our theoretical model. Section "Institutional Context: Afghanistan" provides a brief overview of the institutional context. Section "Empirical Design" details the empirical strat-

FIGURE 1 Rebel-Led Surveillance Operations Conducted in Afghanistan



Notes: Data on insurgent spy operations drawn from SIGACTS military records. Cross hatch pattern indicates insurgents conducted at least one detected surveillance operation during 2006, the first year of our sample. District boundaries are drawn from the ESOC Afghanistan map (398 districts).

egy. Section "Evidence" presents the main results and robustness checks. The final section concludes.

Theory

> The spot where we intend to fight must not be made known; for then the enemy will have to prepare against a possible attack at several different points; and his forces being thus distributed in many directions, the numbers we shall have to face at any given point will be proportionately few.
>
> Sun Tzu, *ibid.*

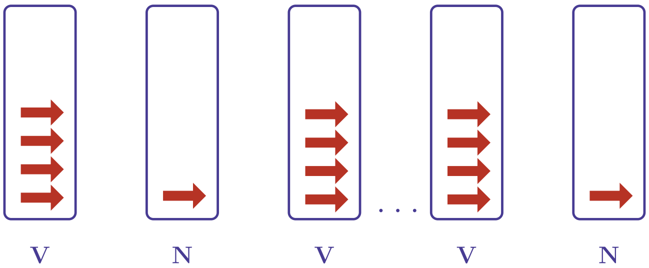
In our model, the government chooses which potential targets to defend and the rebel group chooses the number of attacks using information it gathered about the targets' vulnerability. This is a Colonel Blotto–type model with asymmetric information that yields empirical implications that we test using declassified military records from the recent Afghan conflict. We do not explicitly model the choice of weapons; it is relatively straightforward to demonstrate that an increase in endowments shifts the optimal choice toward the capital-intensive weapons, which is consistent with our empirical results. Instead, we focus on showing that improved intelligence results in more complex patterns of rebel attacks.

Setup

Consider a rebel group that attacks the government facilities using a certain technology (e.g., mortars). The group uses information of the quality $\theta \in [\frac{1}{2}, 1]$ to allocate the total of a attacks across different targets. The government optimally allocates resources to defeat attacks. This is visualized in Figure 2.

There are n potential targets for the government to protect. The government has resources to defend $r < n$ targets. Formally, the government strategy is a probability distribution $G(\cdot)$ over n-tuples $(g_1, \ldots, g_n)$ such that $\sum_{i \in n} g_i = r$ and $g_i \in \{0, 1\}$ for each $i \in n$. If an attack happens on the target that is defended, it does not succeed; if an attack is on an unprotected target, it

FIGURE 2 Optimal Rebels' Strategy in the Attacking Game



Notes: After rebels receive information about the targets' vulnerability, the optimal allocation of attacks across targets requires allocating more attacks on targets that are labeled "vulnerable" (V), and fewer attacks on other targets (N).

succeeds with probability $p \in (0, 1)$, which parameterizes the quality of the attack technology. Because any deterministic choice of protection will result in rebels concentrating on unprotected targets, any reasonable placement of protection should be randomized.

After the government allocates protection, rebels gather intelligence about different targets' vulnerability. Specifically, rebels receive noisy signals $(s_i)_{i\in n} \in \{0, 1\}^n$ that are determined according to

$$P(s_i = 0|g_i = 0) = P(s_i = 1|g_i = 1) = \theta.$$

We assume that the signals are informative: $\theta > \frac{1}{2}$, that is, a target that is unprotected is more likely, than not, to be marked "vulnerable" ($s_i = 0$). A higher θ results in more informative signals.

The rebels' strategy is a mapping $F(a_1, \ldots, a_n; \cdot)$ from the n-tuples of signals about periods' vulnerability $(s_1, \ldots, s_n)$ into a probability distribution on n-tuples $(a_1, \ldots, a_n)$ such that $\sum_{i\in n} a_i = a$ and a_i is a nonnegative integer for each $i \in n$. The possibility to base the attacking strategy on additional information about the vulnerability of targets is novel in the Colonel Blotto games and, more generally, formal conflict literature. If $\theta = \frac{1}{2}$, then the signals are totally uninformative and the game is a standard Colonel Blotto game with n targets (Kovenock and Roberson 2012). If $\theta > \frac{1}{2}$, then for each realization of signals $(s_1, \ldots, s_n)$, the attacker's optimization problem is similar to that in Powell (2007), in which targets have heterogeneous values rather than heterogeneous probabilities of being vulnerable.

The rebel group maximizes the probability of at least one successful attack. The government is interested in minimizing this probability.

The game starts with the government allocating its defensive resources across n targets. Then, rebels receive noisy signal $(s_i)_{i\in n} \in \{1, 0\}^n$ about the government's defense and choose the distribution of their attacks across the targets.

Definition 1. *Given the resources available to rebels, an equilibrium is rebels' choice of a c.d.f. $F^*(s_1, \ldots, s_n; \cdot)$, which is a function of signals about each target, into a probability distribution over a attacks on each of the n targets, and the government's choice of a c.d.f. G^* over r - combinations of n targets. Given G^*, F^* maximizes the probability of at least one successful attack; given F^*, G^* minimizes it.*

The Attacking Game

We start backwards. It is straightforward to establish that the government allocates resources into r targets chosen randomly and uniformly across all possible combinations. The rebels' optimal strategy depends on the signals that they observe. Information gathering results in x "vulnerable" ($s_i = 0$) and $n - x$ "defended" ($s_i = 1$) targets, where x is a random outcome. The rebel's assessment that a particular target i is vulnerable is based on two pieces of information: first, the signal about its vulnerability, s_i, and the total number of "vulnerable" signals, $x = \#\{j|s_j = 0\}$, which is a random variable, the sum of two random variables with binomial distributions with different probabilities of success: $n - r$ vulnerable targets produce signal 0 with probability θ, whereas r defended targets produce signal 0 with probability $1 - \theta$.

Intuitively, when resources are scarce, a signal about vulnerability of one target is informative about the vulnerability of other targets, even though signals are conditionally independent. The number of "vulnerable" signals x can be any integer between 0 and n with a nonzero probability. In the two extreme cases, $x = 0$ (intelligence signals that no target is vulnerable) and $x = n$ (all are "vulnerable"), there is no information to update upon. In all other cases, $1 \leq x \leq n - 1$, signals are informative:

$$P(g_i = 0|s_i = 0) > P(g_i = 0|s_i = 1).$$

Consider the rebels' choice of one attack across two targets with conditional (on x) probabilities of being vulnerable q_1 and q_2, respectively, with $q_1 > q_2$. If there are no attacks already planned on these targets, then an attack timed on the first one provides a higher marginal probability of success. Yet, the fact that the vulnerable target has a higher probability of success does not mean that all attacks should be concentrated on it. Indeed, suppose that there are already m attacks launched on the first target, $m \geq 1$, and no attacks launched on the second. One more attack on the first target results in $q_1(1 - p)^m$ of marginal probability of success. An attack on the second one contributes $q_2 p$. Thus, given sufficient capacity, it is optimal to launch some attacks on the second, less likely to be vulnerable, target.

The rebels' optimal strategy is determined by $\rho_{n,r}(x|\theta)$, the ratio of the probability that the target is vulnerable to the probability that the target is defended, both probabilities conditional on the total number of "vulnerable" signals x. As demonstrated in the Supporting Information (see p. A-6 of the Supporting Information), this ratio can be derived using the following recursive formula:

$$\rho_{n,r}(x|\theta) = \frac{n-x+1+(x-1)\rho_{n-1,r}(x-1|\theta)}{\frac{n-x}{\rho_{n-1,r}(x|\theta)}+x}$$
$$\text{for } 1 \leq r,\ x \leq n-1,$$

with the recursion on both total number of targets, n, and the total number of "vulnerable" signals received, x. Using the vector of critical ratios $\rho_{n,r}(x|\theta)$, $1 \leq x \leq n$, one can demonstrate that the optimal strategy requires, for each x, allocating the first attacks against the targets with "vulnerable" markers until the threshold $d_{n,r}(x|\theta) = \min_{i\geq 1}\{i|\rho_{n,r}(x|\theta)(1-p)^i < 1\}$ for each "vulnerable" target is reached, the next n attacks against targets with "defended" signals, then against the "vulnerable" targets again, etc. Proposition 1 states the result formally.

Proposition 1. *There exists a unique equilibrium in the attacking game. The government protects r targets chosen randomly and uniformly across all possible combinations and rebels follow the signals that they receive. For any number x of targets that are "vulnerable" (have $s_i = 0$), there is an optimal number of attacks $\overline{a}(x)$ such that* $\min\{a, x\overline{a}(x)\}$ *attacks are distributed uniformly over x "vulnerable" targets. The remaining* $a - \min\{a, x\overline{a}(x)\}$ *attacks are distributed uniformly across n − x "defended" targets.*

The Role of Intelligence

The rebels' equilibrium strategy described in Proposition 1 depends on the quality of information parameterized by θ. Specifically, higher precision of information leads to a higher clustering of attacks: More attacks are launched on targets that intelligence gathering identified as vulnerable. In other words, the rebels' attacking strategy becomes more complex with more intelligence gathering. Mathematically, the information entropy, $\sum_{i=1}^{n} \frac{a_i}{a} \ln \frac{a_i}{a}$, a standard measure of complexity, is at its maximum when attacks are purely random, that is, distributed uniformly across targets, and goes down, when attacks become more sophisticated. In our case, an increase in complexity follows an improvement in intelligence gathering, which is consistent with the empirical results of section "Evidence." Proposition 2 provides a formal result.

Proposition 2. *For any amount of rebels' resources, the higher the precision of information that rebels receive,* θ*, the higher is the clustering (concentration) of attacks, that is, the lower is the expected number of unique targets attacked and the larger is the expected number of attacks, both total and successful, per target attacked.*

The critical element of Proposition 2 is that for any number x of "vulnerable" targets, the probability $q(x)$ that a target marked "vulnerable" is indeed vulnerable is (weakly) increasing in the precision of information θ, and thus the critical threshold $\overline{a}(x)$ is (weakly) increasing in θ for any x. As a consequence, more precise information leads to a higher clustering of attacks: More attacks are launched on a smaller number of targets.

In equilibrium, the optimal choice of rebels depends, in addition to precision of information θ, on the number of potential targets for attacks n, the resources in the disposal of the government r, and the efficiency of weapons p. Proposition 2 establishes that a higher precision of information, for example, as a result of an increase in revenues, leads to attacks becoming more sophisticated and, naturally, more effective. In line with the theoretical model, in Figure A-1 and Table A-2 (see pp. A-15 and A-16 of the Supporting Information, respectively), we present descriptive evidence indicating a robust association between exogenous variation in opium suitability and our benchmark measure of surveillance activity. More generally, the increase in complexity (mathematically, a decrease of entropy) as a result of an increase in resources is one of the central empirical implications tested in sections "Empirical Design" and "Evidence."

The comparative statics results with respect to the government's resources and rebels' weapons efficiency are intuitive. An increase in government resources, a higher r, decreases the probability of rebels' success as the *ex ante* probability that each target is protected increases. With a lower probability that each target is vulnerable, the marginal return to an increase in complexity (or to a move to a more sophisticated weapon) is lower. This has the same effect as the fall in rebels' revenues, which results in less information gathering and, therefore, less sophisticated attacks.

The theoretical model can be extended in a number of ways. At the expense of much cumbersome algebra, it is possible to incorporate the trade-off between an increase in the number of attacks and an increase in the precision of intelligence gathering as a result of an increase in rebels' resources. For our purposes, it is sufficient that an increase in rebels' resources cannot lead to a decrease in the quality of information. It is also possible, perhaps more realistically, to model a dynamic, rather than a one-shot interaction between the government and rebels. Given that our own estimates demonstrate the very limited ability of rebels to smooth the availability of their resources over fighting seasons (see Table A-3 on p. A-17 of the Supporting Information), we leave the dynamic extension for future papers.

Institutional Context: Afghanistan

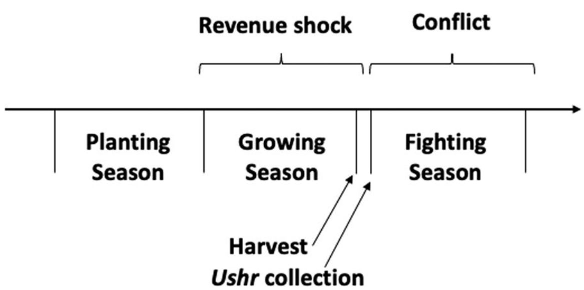
The literature on Afghanistan conflict is vast. Here, we briefly highlight several important dimensions: timeline, organization, opium cultivation and trafficking, and conflict dynamics. Prior to the U.S.-led invasion in 2001, the Taliban had held partial control of government operations since September 1996, when they seized Kabul from President Burhanuddin Rabbani. Following the Taliban's removal from power, Hamid Karzai was appointed as president and reelected in elections in 2004 and 2009. Forces representing the North Atlantic Treaty Organization (NATO) and coalition partners, including large detachments from the United States, supported Afghan reconstruction and provided security support to the Afghan army and, eventually, national and local police. While these forces gradually expanded their presence across the country, the Taliban regrouped in Pakistan. In 2006, the Taliban's insurgency began in force, engaging in attacks across the country. With violence on the rise and Afghanistan's emerging democratic institutions at risk, a surge of coalition forces was authorized in 2009, with the international troop presence reaching a peak in 2011. In March 2011, Karzai announced the first of five tranches of the security transfer from international to local forces. By the end of 2014, Operation Enduring Freedom (OEF) had concluded with the final International Security Assistance Force (ISAF) transition ceremony and shift to Operation Resolution Support. In this article, we study the period from 2006, when the Taliban's insurgency emerged, to 2014, with the end of OEF and the ISAF mission.

The Taliban also encouraged the production of opium during the study period, in a sharp contrast with the last years in power before the 2001 U.S.-led invasion. By 1999, after three years in power, the Taliban were largely isolated from the international community (Farrell and Thorne 2005). Islamic fundamentalism, including concerns about the treatment of women and ethnic minorities, coupled with concerns about the production and export of nearly 70% of the global supply of illegal opium were key to this political isolation. In exchange for extensive diplomatic engagement with the UNODC and promises of developmental aid from the United Nations more broadly, the Taliban announced a large-scale counternarcotics and eradication problem. Mullah Omar, leader of the Taliban at the time, issued a *fatwa* (religious decree) banning the production of opium. Continued cultivation risked public humiliation or execution. Production declined rapidly and farmgate prices increased significantly. This large-scale economic shock may have weakened Taliban control in opium-producing areas and beyond.

Once the Taliban were removed from power in 2001, they recognized that taxes collected from opium farmers and protection payments from traffickers could support their war efforts and quasi-state public goods provision (Felbab-Brown 2006). By 2006, the beginning of our study, the UNODC estimates that more than half of the Afghan GDP was tied to the drug trade. Afghan opium production reached a record high in 2014, the final year of our study, with estimated production exceeding 210,000 hectares for the first time.

We visualize the opium planting and growing and fighting seasons in Figure 3. In the primary opium-producing regions, seeds are planted in late fall and early winter. The growing season typically ranges from February to April, with most opium latex harvested and packaged in April, May, and June. Peters (2009) provides a thorough review of the industrial organization of the Taliban. Taliban commanders and veteran fighters

FIGURE 3 Seasonality of Revenue Extraction and Conflict in Afghanistan



Notes: Various seasons visualized drawing on UNODC descriptions of production cycles and seasonality of conflict present in combat records. Planting occurs in late fall and early winter; growing season primarily ranges from February to April; harvest and tax collection is conducted in April, May, and June; fighting season runs until late September.

return from Pakistan in June to collect taxes from opium farmers (*ushr*, typically a flat 10% fee mandated by the Quran). Taxes can be paid in currency, opium blocks, or other goods, such as motorcycles, offroad vehicles, and weaponry. The Taliban also benefits from protection fees levied on opium traffickers as they pass through rebel-held territories. Opium farmers, refiners, and traffickers rely on the Taliban to sustain a political and security environment and ensure that cultivation, refinement, and exports continue with minimal government interference (Giustozzi 2019; Na 2018).[1]

Taxes are collected by fighters and receipts are distributed to farmers to prevent double taxation. Fighters pass their collections to district-level commanders (equivalent in scale to U.S. counties). Taxes are subsequently passed upward to provincial and regional commanders, who keep ledgers of their annual revenue and are subject to audit by the Taliban's Central Finance Committee, based out of southwestern Pakistan. Most proceeds remain with the district commander, for conducting operations in the subsequent fighting season, which typically lasts until September. These funds can be used to purchase weapons and ammunition, as well as covering the salaries of fighters and rebel informants. The Central Finance Committee (CFC) retains the authority to demote or relocate field commanders to less desirable fronts if audit irregularities are found. The remaining revenue is split between supporting operations conducted in resource-poor districts where local taxes alone are insufficient for supporting rebel attacks and developing Taliban infrastructure in Pakistan (including small-scale hospitals for wounded fighters).

We focus primarily on the period from 2006 to 2014. The industrial organization of the insurgency, most notably the taxation and command structures oriented around administrative districts, which are central to our argument that revenue influences combat tactics, emerged in 2006. Our military records track insurgent operations until the end of 2014, when the NATO OEF was transitioned to Mission Resolute Support.

Empirical Design

In this section, we review our microdata, and introduce our identification strategy.

Conflict Microdata

We exploit declassified records of the U.S. Department of Defense in 2006 to 2014, which catalog combat engagements and counterinsurgent operations during OEF in Afghanistan. The data platform was populated using highly detailed combat reports logged by NATO-affiliated troops as well as host nation forces (Afghan military and police forces). Data of this type differ substantially in coverage and precision from media-based collection efforts. For example, the combat records we study include information about the timing of any given attack, usually accurate to within minutes. In addition, our records include georeferences that are derived from satellite-linked devices that were deployed in the field rather than georeferencing of landmarks mentioned in journalistic coverage. As Weidmann (2016) notes, this compilation of conflict events is the most complete catalog of combat engagements during the war in Afghanistan.

These data include information about a number of types of violence, including direct fire engagements, indirect fire events, and improvised explosive device (IED) explosions. Direct fire attacks are primarily line-of-sight, close combat events. Indirect fire consists of mortars and other weapons that can be deployed without close contact with military forces. IEDs consist of explosives that have been emplaced and are detonated through a variety of trigger mechanisms (pressure plate, cable-to-battery, radio signal, laser beam, etc.). For each event, we can track the target or targets involved as well as the outcome of the event (whether an attack caused damage or casualties). We also observe information about when coalition forces engaged in search and seize operations, gathering potentially actionable information about insurgent operations, as well as insurgent detentions. The records include additional information about insurgent activity that could influence civilian involvement in opium production. In particular, insurgents may use violent and nonviolent tactics to intimidate civilians, such as killings of government collaborators and the posting of "night letters" and other nonlethal shows of force. Our military records include information about these tactics as well, enabling us to address potential concerns about rebel involvement in local opium production.

In addition, we have information on several novel, previously unreleased dimensions of combat. First, soldiers on deployment were told to document instances of tactical innovation by insurgents. These tactics and procedures reports identify instances of rebels engaging in new attack formations, focusing on new targets, developing and/or deploying new weapons technology,

[1]We discuss additional Taliban income sources in the Supporting Information (see p. A-10 of the Supporting Information).

or otherwise adopting an unexpected improvement in their combat operations. Although the original text files attached to each event would have provided extensive details about what specific innovation was observed for each report, this information was removed from authors' access during declassification. On its own, however, this measure serves as an indicator of technological innovation in the battlefield. Second, our combat records include information about false or hoax explosive devices deployed by insurgents. These events indicate where and when rebels are engaging in active deception as a tactic. There are several purposes for this type of deception. One is to learn about coalition movement, counter-IED technologies, or counterinsurgent activities. Another potential purpose is to pull government soldiers and assets toward one area while insurgents engage in a countermaneuver, taking advantage of depleted forces in another area. Although we cannot deduce the motive for use of these deceptive tactics, we infer that the use of fake devices reveals a degree of technological sophistication. Third, our data contain a detailed record of insurgent-led insider attacks. These events occur when insurgents have infiltrated one or more Afghan security units, "turning" members of the security forces against fellow members of the Afghan army and, in other cases, coalition forces. These attacks require cultivation of an insider or the recruitment of individuals to serve as double-agents, joining the armed forces with the intent of harming other members of the security force. These events are also uniquely disruptive to collaborative patrol operations as insider attacks typically led to segregation of forces and diminished joint operations. Fourth, the depth of our records enables us to identify complex events involving multiple targets. These events can involve, for example, an attack on infrastructure (e.g., a base), a force in transit to the infrastructure (e.g., a patrol returning to base), and government countermeasures (e.g., surface-to-air engagement). These complex events potentially suggest a high degree of coordination and fighting capacity. Finally, our records include information about rebel-led surveillance operations detected by counterinsurgents. This measure captures instances of suspected insurgents monitoring troop movements in and out of base locations, changes of guard or other base-specific activities, and patrol movement. These efforts to monitor troop and base activity are likely attempts to identify target vulnerabilities for later exploitation in combat.

Opium Cultivation, Suitability, and Prices

Opium production estimates are derived from ground-validated remote sensing techniques, which use high-resolution satellite imagery to track changes in vegetation during the spring harvest. UNODC-Afghanistan randomly spatially samples potential agricultural zones within provinces and acquires preharvest and postharvest imagery (see Figure A-2 on p. A-15 of the Supporting Information, panel (a)). These images are then examined for changes in vegetative signatures consistent with the volatile wetness of opium plants after lancing. From this sampling technique, officers estimate the spatial risk and calculate granular estimates of opium production (see Figure A-2 on p. A-15 of the Supporting Information, panel (b)). These gridded estimates are then compiled as the annual amount of opium production (in hectares) for each district. We correct for changes in the administrative boundaries of districts over time using the Empirical Studies of Conflict (ESOC) administrative shapefile. To translate production into yields, we compile additional details about annual yield (kilograms per hectare) from UNODC-Afghanistan annual reports.

To measure opium suitability, we gather climatic data, daily, district-level temperature (Kelvin), and precipitation (mm) measures from the National Centers for Environmental Prediction (NCEP) and the Department of Energy, which prepared the baseline climate reanalysis by using state-of-the-art assimilation techniques (see Saha et al. 2010, for full details). We construct parameters capturing the number of days within each growing season these data fall within a particular set of binned ranges, which enables us to account for nonlinear relationships between weather conditions and agricultural productivity (Dell, Jones, and Olken 2014). We supplement these data with information from Food and Agriculture Organization's Harmonized World Soil Database, extracted using the district-level cross section. We include nutrient availability, nutrient retention, rooting conditions, oxygen availability, excess soil salts, toxicity, and packedness and workability (which impacts the ability to manage fields). For each district, we calculate the percentage of land mass where these soil features present no or slight limitations to productivity (Class 1 under the FAO guidelines). Because various combinations of weather and soil conditions may produce high- and low-productivity zones in a complex system, we interact these measures with our degree-day and precipitation-day measures. We merge these data with our panel data on opium production and produce a standardized fitted value of opium productivity given these exogenous parameters. We use the least squares estimation equation below.

$$ln\ (production_{d,t} + 1)$$
$$= \alpha + \sum_{i=1}^{7} (\vartheta_i Precip - Day_{d,t}) + \sum_{i=1}^{7} (\zeta_i Precip - Day_{d,t}^2)$$

$$+\sum_{i=1}^{10}(\eta_i Temp-Day_{d,t})+\sum_{i=1}^{10}(\rho_i Temp-Day_{d,t}^2)$$
$$+\sum_{i=1}^{7}(\mu_i SoilQual_d)+\tau_{ij}\sum_{i=1}^{7}(Precip_{d,t})\times\sum_{j=1}^{7}(SoilQual_d)$$
$$+\phi_{ij}\sum_{i=1}^{10}(Temp-Day_{d,t})\times\sum_{j=1}^{7}(SoilQual_d)+\gamma X_y+\varepsilon_d, \quad (1)$$

where $log(production_{d,t}+1)$ is the production (log) for a given district, *d*, and growing season, *y* (year). X_y captures growing season fixed effects. $Precip-Day_{d,t}$ and $Temp-Day_{d,t}$ capture the effect of our precipitation-day and degree-day (temperature-day) parameters. We also include the square of these counts. $SoilQual_d$ captures the soil quality features noted above. We then fully interact these base terms. From this regression, we produce $ln(\widehat{production}_{d,t}+1)$, which is our unstandardized fitted value. Denote this value as $\Lambda_{d,t}$. We standardize this value using the following expression:

$$Suitability_{d,t}=\frac{\Lambda_{d,t}-\bar{\Lambda}_{d,t}}{var(\Lambda_t)^{-1}}. \quad (2)$$

$Suitability_{d,t}$ is demeaned and standardized with respect to the standard deviation of the fitted values. This approach is most similar to Mejía and Restrepo (2014), who use land features and soil characteristics to predict coca production in Colombia. The primary difference between our two methods is the use of high-frequency climatic inputs as well as the use of interactions to capture heterogeneous climatic effects via soil quality conditions.

Opium price data are compiled at national and regional levels. We rely on UNODC-Afghanistan documentation to assign districts to price zones. Although Afghanistan's aggregate opium exports represent more than 75% of global exports, only a small subset of district-years (0.1%) reaches the price-maker threshold set in Bazzi and Blattman (2014) (10% of global exports). In addition, no district is a potential price-maker in our sample for more than half of the sample years. This suggests that nearly all districts are price-takers for nearly (or) all of the study period. Because of this, use of the aggregate price to calculate revenue is unlikely to be substantively biased. However, given the data available, we can implement an alternative supply-driven approach to price variation. Following UNODC reports, we find that aggregate, country-level production in the prior year is a primary driver of year-over-year variation in prices. We denote this quantity as $AggProd_{t-1}$. Naturally, increased aggregate production from the prior year drives down national prices in the subsequent year. Leveraging aggregate production yields plausibly exogenous variation in the price component of revenue (once we invert the value).

Empirical Strategy

We study the relationship between rebel capacity and violence, leveraging plausibly exogenous variation in opium suitability. Our baseline sample is a balanced panel of district-years from 2006 to 2014. We estimate the following OLS regression:

$$viol_{d,t}=\alpha_d+\gamma_t+\delta_{pz}t+\beta_1 endowment_{d,t}$$
$$+\Lambda X_{d,t}+\epsilon_d, \quad (3)$$

where $viol_{d,t}$ is the level of violence (per capita) for a given district, *d*, and year, *t*. These violence levels are calculated in the postharvest fighting season, following the sequence illustrated in Figure 3. We study a range of violence measures, each following the same benchmark specification. α_d and γ_t capture district and year fixed effects, accounting for district-specific omitted variables that remain fixed over time and time-varying common shocks, including troop surges. $\delta_{pz}t$ denotes prize zone–specific time trends. These trends, following the specification in Dube and Vargas (2013), account for potential omitted variables across opium-producing regions that vary with time. We also include an array of additional district-specific control variables, denoted by $\Lambda X_{d,t}$. These include, for example, enhanced market access due to expansion of the road network, allocation of small-scale development projects, and the use of coercive tactics by rebels during the planting and growing seasons. Regressions are weighted by population.

The primary quantity of interest in Equation (3) is β_1, which captures the effect of $endowment_{d,t}$ on the violence outcomes. There are several approaches that can be taken to measure $endowment_{d,t}$. The first is to simply study $Opium_{d,t}\times Price_t$. Using this measure would tell us the association between intensity of violence in the fighting season and potential revenue from the opium trade. Although any given district is unlikely to be a price-maker (i.e., $Price_t$ is unlikely to be substantively biased), variation in $Opium_{d,t}$ is only exogenous under the condition that potential sources of bias are captured by the fixed effects and controls. This is unlikely to be the case. Instead, we prefer to capture $endowment_{d,t}$ using $Suitability_{d,t}\times AggProd_{t-1}$. This term captures exogenous variation in suitability driven by climatic and soil conditions as denoted in Equation (1) and standardized as in Equation (2). Suitability is then weighted by time-series variation in aggregate production in the prior year, $AggProd_{t-1}$. Once inverted, this captures plausibly exogenous variation in prices due to broader market dynamics: Higher aggregate production in the prior year is negatively associated with prices in the current year.

In Figure 4, we illustrate the bivariate fit between various measures of revenue and our preferred suitability measure. Notice that the two measures are strongly positively correlated. In Table A-4 (see p. A-18 of the Supporting Information), we demonstrate that this relationship is robust to the panel model specification introduced in Equation (3). Although these results suggest that $Suitability_{d,t} \times AggProd_{t-1}$ is a strong instrument for $Opium_{d,t} \times Price_t$, we prefer a reduced-form approach. Focusing on the reduced form enables us to more reliably estimate the marginal effects of $endowment_{d,t}$ in the presence of rebel-led surveillance networks as well as sidestep potential (though largely implausible) concerns that agronomic conditions during the growing season directly influence combat tactics during the fighting season (i.e., a violation of the exclusion restriction).

We next turn to Equation (4), where we investigate the role of intelligence gathering:

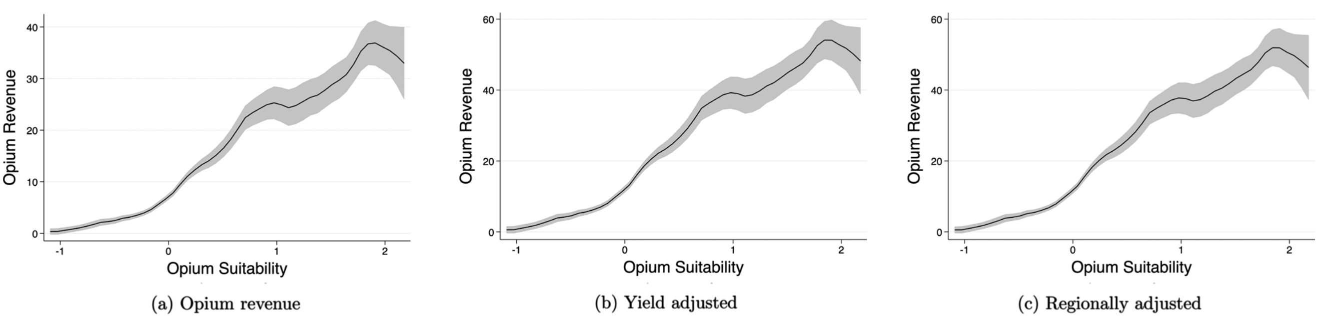
$$\begin{aligned} viol_{d,t} = \alpha_d + \gamma_t + \delta_{pz} t + \beta_1 endowment_{d,t} \\ + \beta_2 endowment_{d,t} \times surveillance_d + \Lambda X_{d,t} \\ + \epsilon_d, \qquad (4) \end{aligned}$$

where notation follows from Equation (3) and the additional term, $endowment_{d,t} \times surveillance_d$ is the marginal effect of endowment shocks in the presence of the surveillance network. To study this marginal effect, we rely on records gathered by security forces in 2006—the first year of our sample—about rebel-led intelligence gathering (i.e., the areas where they attempted to monitor troop movement and base activities). We leverage cross-sectional variation in this measure to address concerns that the surveillance network adjusts endogenously from year to year, significantly complicating estimation in the absence of a plausible district-specific and time-varying instrument for intelligence gathering. Notice that the base term for $surveillance_d$ is absorbed by α_d (district fixed effects) in Equation (4).

Evidence

In this section, we introduce a series of related results. First, we focus on the correlation between rebel capacity and conflict production generally. The primary purpose of these results is to evaluate theoretical claims central to prior related work, most notably (Dube and Vargas 2013), which link specific economic shocks to capital-intensive activities. In our setting, we apply this general logic to the most capital-intensive conflict type, direct fire engagements, which typically involve at least several fighters deployed in high-risk, line-of-sight attacks. Second, we consider the relationship between exogenous variation of endowments and rebel innovation and attack patterns. This section is most closely aligned with the theoretical model and investigates *how* rebels fight. Third, we evaluate the link between economic shocks and combat effectiveness. In particular, we evaluate whether disruptive and potentially fatal attacks increase with revenue and whether this effectiveness is observed for hardened targets (i.e., Coalition forces). In each section, we also review evidence of whether intelligence gathering is a mechanism that enhances the ability of insurgents to produce more intense, more innovative, and more effective attacks.

FIGURE 4 Robust Association between Endogenous Revenue Measures and Exogenous Suitability Parameter



(a) Opium revenue (b) Yield adjusted (c) Regionally adjusted

Notes: The figures depict local polynomial regressions evaluating the relationship between various measures of potential opium revenue and exogenous variation in opium suitability, derived using Equations (1) and (2). For ease of visualization, suitability is trimmed at −1.104 and 2.18. Panel (a) depicts log output in hectares by log of the simple average national price. Panel (b) adjusts (a) using an annual yield calibration weight, allowing us to convert hectares under production to approximate kilograms. Panel (c) allows for regional yield adjustment as well as price zone-by-year price changes.

Conflict in Levels

We begin by studying the impact of rebel capacity on combat engagements generally. These results are presented in Panel A of Table 1. In the first column, we find that combat activity overall increases significantly. The magnitude of this increase is substantial, with a one standard deviation increase in opium suitability increasing combat activity by 0.2 standard deviations.[2] In the remaining columns, we split apart this combat measure, considering the three primary combat types most frequently observed during the conflict. In the second and third columns, we find that direct fire and IED explosions significantly increase with potential revenue from the opium trade (0.2 and 0.25 standard deviation increases, respectively). In the final column, on the other hand, we find that production of indirect fire attacks is largely unresponsive to positive shocks to rebel capacity. Of these three combat types, direct fire involves the most significant inputs, requiring both labor (a potentially large number of fighters) and capital (armaments to engage in line-of-sight attacks). The input intensity of roadside bombs varies. One the one hand, emplacing and detonating large-scale bombs can be capital intensive—involving accumulation of bomb making materials, securing a transport vehicle, locating an ideal target site, and planting the device—as well as labor intensive, involving one or more skilled bomb makers and a fighter on location to trigger the device. On the other, bombs can be small scale, involve the use of easily available unexploded ordnance, and remote trigger mechanism (i.e., no fighter is present when the device is triggered). We lack the technical information on bomb and weapon fragments recovered from the field, which limits our ability to identify more input-intensive attacks. However, we anticipate that on average, the input intensity lays between direct fire and indirect fire, which involves the least risk to fighters. This is due to the remote nature of these attacks, which enable fighters using rocket propelled grenades, mortars, and related weapon types to flee the scene of an attack before counterinsurgents can respond directly. We anticipate, applying the general logic of Dube and Vargas (2013), that these various combat types respond differently to endowment shocks due to their distinct input intensities, with the most capital- and labor-intensive attacks increasing most sharply.

In Panel B of Table 1, we introduce results from Equation (4), where we are focused on the marginal effects of rebel capacity in the presence of rebel surveillance. Although the baseline effects are consistently positive (though imprecise with the exception of IED explosions), the marginal effect of exogenous variation in potential revenue had a large, precise, and positive effect on combat activity overall, as well as the production of high-risk, input-intensive attacks: direct fire and indirect fire. The magnitude of these increases ranges from 0.3 to 0.4 standard deviations (with a standard deviation increase in rebel capacity). As with Panel A, relatively low-risk, indirect fire engagements are largely unresponsive to positive endowment shocks, even in areas where insurgents have previously been engaged in intelligence gathering.

Robustness. In the notes for Table 1, we note the additional controls included in the main specification. The main specification accounts for time-varying effects of opium price zones and irrigation intensity as well as development assistance and changes in market access. In Table A-5, Panels A and B (see p. A-19 of the Supporting Information), we supplement these covariates with a battery of additional factors that could influence opium productivity and combat activity. All regressors are added to the benchmark specification. These additional covariates include time trends for terrain ruggedness, coethnic density, and a historical measure of the Taliban's consolidation of control at the end of 1996, when they initially seized control of Kabul and, with it, the central government. We also incorporate measures of coercive violence and intimidation by insurgents as well as counterinsurgent operations by security forces during the planting and growing seasons, including safe house raids and detentions of suspected fighters and collaborators. Taken together, these results suggest a robust correlation between plausibly exogenous variation in potential opium revenue and the production of violence, especially capital- and labor-intensive attacks.

Combat Innovation and Sophistication

In this section, we focus on how shocks to rebel capacity influence combat innovation, sophistication, and attack patterns. In Table 2, we focus on four measures of combat innovation, coordination, and complexity. In the first column, we examine the impact of rebel capacity on tactical innovation. As we detail above, coalition forces were instructed to document instances of unexpected tactics and procedures used by insurgents. These technological changes could involve new attack formations and novel weapon systems as well as combat

[2] Summary statistics are presented in each table (for outcomes) and in Table A-1 (see p. A-2 of the Supporting Information).

TABLE 1 Impact of Rebel Capacity and Surveillance on Combat Outcomes

	Combat	Direct Fire	IED Explosion	Indirect Fire
Panel A: Baseline Effects				
Opium Suitability	0.450*	0.357†	0.094**	−0.001
	(0.228)	(0.202)	(0.029)	(0.006)
Summary Statistics				
Outcome Mean	0.352	0.223	0.071	0.058
Outcome SD	1.227	0.963	0.224	0.228
Model Statistics				
Observations	3582	3582	3582	3582
Clusters	398	398	398	398
R^2	0.580	0.519	0.627	0.597
Panel B: Heterogeneous Effects				
Opium Suitability	0.079	0.036	0.038**	0.005
	(0.058)	(0.046)	(0.013)	(0.007)
Suit. × Rebel Surveillance	0.744†	0.643†	0.111*	−0.011
	(0.416)	(0.366)	(0.053)	(0.012)
Summary Statistics				
Outcome Mean	0.352	0.223	0.071	0.058
Outcome SD	1.227	0.963	0.224	0.228
Model Parameters				
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Price Zone Trends	Yes	Yes	Yes	Yes
Irrigation Intensity Trends	Yes	Yes	Yes	Yes
Dev aid: Ag/Irrigation	Yes	Yes	Yes	Yes
Market Access	Yes	Yes	Yes	Yes
Model Statistics				
Observations	3582	3582	3582	3582
Clusters	398	398	398	398
R^2	0.590	0.533	0.634	0.597

Notes: Outcome of interest varies by column and is indicated in the column heading. The quantity of interest is opium suitability. All regressions include district and year fixed effects as well as controls as specified under model parameters. Heteroskedasticity robust standard errors clustered by district are reported in parentheses.
$^{\dagger} p < .1$, $^{*} p < .05$, $^{**} p < .01$.

TABLE 2 Impact of Rebel Capacity and Surveillance on Combat Innovation, Coordination, and Complexity

	Tactical Innovation	Deceptive Tech	Unit Breach	Complex Target
Panel A: Baseline Effects				
Opium Suitability	0.004*	0.007**	0.001**	0.043**
	(0.002)	(0.002)	(0.000)	(0.016)
Summary Statistics				
Outcome Mean	0.003	0.004	0.001	0.014
Outcome SD	0.014	0.021	0.004	0.085
Model Statistics				
Observations	3582	3582	3582	3582
Clusters	398	398	398	398
R^2	0.262	0.355	0.200	0.385
Panel B: Heterogeneous Effects				
Opium Suitability	−0.001	0.003†	0.000†	0.015*
	(0.001)	(0.002)	(0.000)	(0.007)
Suit. × Rebel Surveillance	0.010*	0.007*	0.001†	0.056*
	(0.004)	(0.003)	(0.001)	(0.026)
Summary Statistics				
Outcome Mean	0.003	0.004	0.001	0.014
Outcome SD	0.014	0.021	0.004	0.085
Model Parameters				
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Price Zone Trends	Yes	Yes	Yes	Yes
Irrigation Intensity Trends	Yes	Yes	Yes	Yes
Dev aid: Ag/Irrigation	Yes	Yes	Yes	Yes
Market Access	Yes	Yes	Yes	Yes
Model Statistics				
Observations	3582	3582	3582	3582
Clusters	398	398	398	398
R^2	0.276	0.358	0.203	0.398

Notes: Outcome of interest varies by column and is indicated in the column heading. The quantity of interest is opium suitability. All regressions include district and year fixed effects as well as controls as specified under model parameters. Rounded coefficient in column 3, Panel B is 0.0004. Heteroskedasticity robust standard errors clustered by district are reported in parentheses.
† $p < .1$, * $p < .05$, ** $p < .01$.

engagement with unique targets. The results in this column suggest that innovation is increasing in rebel capacity. The increase is equivalent to 0.24 standard deviations with each standard deviation increase in suitability. In the second column, we investigate whether the use of deceptive technologies—false and hoax explosive devices—also increases in endowments. Indeed, these results suggest a large increase (0.24 SD). In the next column, we evaluate how unit breaches with attacks carried by security force insiders respond to potential revenue shocks. We find that these attacks, which typically require cultivation of an asset already present in the security forces or the deployment of fighters to infiltrate security force units, increase in exogenous endowment variation (0.15 SD). In the last column, we consider the association between revenue and attack complexity. We measure target complexity using information about the number of targets involved in a given attack. Complex targets typically include attacks on forces during movement as well as infrastructure. Notice that attacks involving complex targets significantly increase with exogenous access to potential revenue (0.3 SD).

In Panel B of Table 2, we return to the mechanism at the core of our theoretical model: intelligence gathering. Although these measures of innovation, coordination, and complexity generally increase in revenue, the marginal effects of revenue in the presence of rebel-led surveillance are large, positive, and consistently precise. The magnitude of these effects is also substantial, ranging from 0.2 to 0.4 standard deviations. This result suggests that the ability to convert fighting capacity into battlefield innovations largely hinges on the presence of networks that enable rebels to gather information about the vulnerabilities of rival forces.

In Table 3, we take these results a step further. In this set of results we consider another implication of the theoretical model, that attack patterns may become more clustered in time or space as rebels gather more information about their opponent's defensive or offensive weaknesses. To study clustering, we consider two novel measurement strategies.

We begin by focusing on temporal clustering—the concentration of attacks in certain windows of time during a given day. We quantify patterns of combat operations using randomization inference and the bootstrap Kolmogorov–Smirnov method developed by Abadie (2002). Using this approach, lower values of the dependent variable reveal attack patterns that are more easily differentiated from randomness; that is, they are more clustered. We provide a more detailed description of the method in the Supporting Information (see p. A-13). In the first two columns of Panel A, we consider whether combat clustering increases in revenue. For interpretation, recall that lower values indicate more robust clustering patterns. Therefore, we anticipate a negative coefficient on our measure of resource endowments. In the first and third columns do not include unit fixed effects because these measures of clustering yield an unbalanced panel. In the second and fourth columns, we add unit fixed effects to the model specification. Indeed, though we do find a negative association with respect to temporal clustering, it is imprecise in Panel A. In Panel B, however, we find evidence of a large, and precisely estimated increase in clustering with respect to endowments in areas where rebels may acquire information through base and troop surveillance (0.2 SD increase).

In Panel A, the final two columns, we turn to another measure of attack clustering. In these specifications, we are focused on spatial clustering. To investigate spatial clustering, we develop a 5 km × 5 km grid of Afghanistan, linking observed combat activity to this grid. We then calculate an *Index of Dispersion* for each district-fighting season by linking grid cells to their corresponding parent administrative unit (Perry and Mead 1979). This type of index is common in the study of spatial point processes (e.g., seedling dispersion). Higher values indicate that the spatial pattern was highly unlikely to have occurred by random chance and exhibits characteristics of uneven density (i.e., spatial clustering of attacks). Given the flipped interpretation of the outcome variable (relative temporal clustering), we expect a positive correlation with suitability if our model extends to spatial allocation of attacks as well as temporal clustering. Notice, in these columns, spatial clustering of attacks increases with potential revenue (0.27 SD). In Panel B, we consider whether these revenue effects are largest in areas where rebels have been able to conduct surveillance historically. Indeed, we find that the margin effect of revenue in these areas is large and positive, indicating that clustering increases the most with exogenous endowments when rebels are capable of coordinated intelligence gathering (0.48 SD).

Robustness. In Panels A and B of Tables A-6 and A-7 (see pp. A-20 and A-21 of the Supporting Information, respectively), we supplement the main specification with additional covariates, including trends for terrain ruggedness, coethnicity, and historical Taliban control as well as measures of insurgent coercion and counterinsurgent operations for thwarting insurgent coordination and surveillance. The results overall are highly consistent, with innovation, deception, complexity, and clustering sharply increasing in suitability overall and heterogeneously with rebel-led surveillance activity. Although infiltration is precisely correlated with our measure of potential revenue overall, the heterogeneous effect with respect to surveillance loses precision at the 10% threshold ($t = 1.54$).

Combat Losses and Casualties

In this section, we turn to a first-order question regarding civil conflict: Do resource endowments increase the effectiveness of rebel attacks? We investigate this question in Table 4, Panel A. In the first column, we focus on variation in combat events that caused vehicular damage or

TABLE 3 Impact of Rebel Capacity and Surveillance on Attack Clustering

	Temporal	**Temporal (TWFE)**	**Spatial**	**Spatial (TWFE)**
Panel A: Baseline Effects				
Opium Suitability	−0.659	−0.349	496.815*	346.963†
	(0.448)	(0.510)	(236.005)	(198.850)
Summary Statistics				
Outcome Mean	−7.048	−7.110	343.140	350.022
Outcome SD	4.355	4.368	1072.541	1083.435
Model Statistics				
Observations	1467	1435	1467	1435
Clusters	266	234	266	234
R^2	0.116	0.387	0.186	0.599
Panel B: Heterogeneous Effects				
Opium Suitability	0.093	0.471	80.005	37.973
	(0.246)	(0.361)	(68.404)	(67.666)
Suit. × Rebel Surveillance	−1.558*	−1.529†	867.764*	576.607†
	(0.728)	(0.834)	(369.321)	(315.301)
Summary Statistics				
Outcome Mean	−7.048	−7.110	343.140	350.022
Outcome SD	4.355	4.368	1072.541	1083.435
Model Parameters				
District Fixed Effects	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Price Zone Trends	Yes	Yes	Yes	Yes
Irrigation Intensity Trends	Yes	Yes	Yes	Yes
Dev aid: Ag/Irrigation	Yes	Yes	Yes	Yes
Market Access	Yes	Yes	Yes	Yes
Model Statistics				
Observations	1467	1435	1467	1435
Clusters	266	234	266	234
R^2	0.144	0.391	0.259	0.609

Notes: Outcome of interest varies by column and is indicated in the column heading. The quantity of interest is opium suitability. All regressions include year fixed effects as well as controls as specified under model parameters. Even columns include district fixed effects. Heteroskedasticity robust standard errors clustered by district are reported in parentheses. Symbols indicate † $p < .1$, * $p < .05$, ** $p < .01$.

TABLE 4 Impact of Rebel Capacity and Surveillance on Combat Losses and Casualties

	Disrupt: Government	Casualties: Government	Disrupt: Coal	Casualties: Coal
Panel A: Baseline Effects				
Opium Suitability	0.061*	0.029†	0.071**	0.039*
	(0.024)	(0.016)	(0.026)	(0.016)
Summary Statistics				
Outcome Mean	0.079	0.060	0.031	0.017
Outcome SD	0.255	0.202	0.142	0.083
Model Statistics				
Observations	3582	3582	3582	3582
Clusters	398	398	398	398
R^2	0.615	0.598	0.449	0.436
Panel B: Heterogeneous Effects				
Opium Suitability	0.012	−0.006	0.025*	0.009
	(0.010)	(0.008)	(0.010)	(0.006)
Suit. × Rebel Surveillance	0.099*	0.070**	0.092†	0.061*
	(0.042)	(0.027)	(0.048)	(0.029)
Summary Statistics				
Outcome Mean	0.079	0.060	0.031	0.017
Outcome SD	0.255	0.202	0.142	0.083
Model Parameters				
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Price Zone Trends	Yes	Yes	Yes	Yes
Irrigation Intensity Trends	Yes	Yes	Yes	Yes
Dev aid: Ag/Irrigation	Yes	Yes	Yes	Yes
Market Access	Yes	Yes	Yes	Yes
Model Statistics				
Observations	3582	3582	3582	3582
Clusters	398	398	398	398
R^2	0.619	0.601	0.461	0.452

Notes: Outcome of interest varies by column and is indicated in the column heading. The quantity of interest is opium suitability. All regressions include district and year fixed effects as well as controls as specified under model parameters. Heteroskedasticity robust standard errors clustered by district are reported in parentheses. Symbols indicate $^{\dagger}p < .1$, $^{*}p < .05$, $^{**}p < .01$.

security forces casualties. In the second column, we focus more narrowly on events involving casualties. In the final two columns, we focus on damage and casualties inflicted on harder targets, specifically Coalition forces. Notice that all four measures of combat losses and casualties are increasing in revenue. Also importantly, the coefficient magnitudes are larger when we focus on hard targets (final two columns), indicating that combat effectiveness is increasing against otherwise more battle-ready units. Comparing the first and third columns, the magnitude of these differences is substantial: a 0.14 standard deviation increase versus a 0.29 standard deviation increase for the equivalent shock to suitability. These differences are even larger in standardized terms regarding the second and fourth columns, where size of the effect for coalition targets is roughly three times larger than government targets generally (0.09 SD vs. 0.28 SD). Panel B, where we introduce marginal effects for intelligence gathering, suggests that the increased combat impact is greatest in areas where rebels have previously engaged in surveillance. In Table A-8 Panels A and B (see p. A-22 of the Supporting Information), we present results from a more saturated set of model specifications. The additional covariates follow the discussion above, with the supplemental models accounting for time trends with respect to terrain ruggedness, coethnicity, and historical control by the Taliban. These models also account for the possibility that coercion by insurgents and efforts to disrupt rebel operations by government forces are correlated with opium production and downstream combat tactics. Overall, these results suggest that damage and casualties to government forces overall, and hardened coalition targets specifically, increase with exogenous variation in opium suitability and surveillance by rebels.

Conclusion

Rebel tactics are an overlooked feature of internal warfare. Our article aims to address this gap, coupling insights about the economic effects of resource endowments during conflict with theories of information dynamics. The argument we advance is that resource endowments, especially when coupled with information about potential enemy vulnerabilities, enhance the ability of insurgents to initiate violence, engage in tactical and technological innovation, and improve the efficiency and effectiveness of their attacks. Our model of these dynamics extends prior work on Colonel Blotto–type games and has implications for variety of important conflict dynamics, including when and where combatants attack and the complexity of their attack patterns. Our focus on the role of intelligence gathering by nonstate actors develops observations in other qualitative and ethnographic work, including Kalyvas (2006), and deepens the set of theoretical models of insurgent behavior during conflict by highlighting how information flow—to rebels—may undermine government operations.

Studying these dynamics requires unusually rich microdata. Using data collected during OEF in Afghanistan, we study a range of combat outcomes, including previously unreleased measures of tactical innovation, deceptive weaponry, and target complexity. We couple these outcomes with plausibly exogenous, microlevel measures of opium suitability and leverage the industrial organization of the Taliban, including their highly institutionalized taxation system, to estimate the impact of potential revenue from the drug trade on combat tactics in the subsequent fighting season. Our data also yield a unique opportunity to assess the underlying mechanism suggested by our theoretical model: intelligence gathering.

Consistent with the argument, we find that as rebels accumulate fighting capacity, their attacks increase in intensity, become more sophisticated, and yield more government combat losses and casualties. Overall, we find that these battlefield consequences of resource endowments are greatest in areas where rebels have engaged in troop and base surveillance operations. Whereas prior quantitative and theoretical work has detailed the role of information in shaping counterinsurgency effectiveness (i.e., civilian tips to government forces), our model and results help clarify the value and consequences of rebel-led information gathering through surveillance.

In the aftermath of the Taliban's military offensive and capture of Kabul in 2021, it is important to reflect on the broader lessons that can be drawn from this study. As Barnett Rubin, a former State Department adviser on Afghanistan has noted, the narcotics sector is "the country's largest industry except for war." Afghanistan's economic development after the war industry subsides will likely hinge both on how the Taliban manage their relations with foreign aid donors and whether a government under Taliban rule promotes or prohibits opium production. Mullah Omar's struggle with this diplomatic and economic trade-off is likely to reflect a future policy dilemma: Substantive efforts to appease international counternarcotics demands will undermine rural economies and weaken the Taliban's hold on power. The very resource endowment that enabled their survival after removal from power and rise to power after the U.S. withdrawal may constrain their ability to rule.

Our findings are more broadly relevant to how civil conflicts are fought and how they end. We present evidence highlighting the role of these resource endowments in shaping how the group engaged in violence; developed innovative, sophisticated combat techniques;

and waged combat effectively against technologically superior coalition forces, echoing results in Fetzer et al. (2021) about the Taliban's strategic use of violence during the phased withdrawal of international troops. From a more global perspective, our article suggests that illicit economies can enable armed groups to survive and outlast even high-capacity international military forces. In this sense, the Afghan experience mirrors other civil conflicts, including Colombia, Iraq, and the Philippines, where rebels developed sophisticated institutions to gather or capture resources from civilians and private firms, monitor state forces, and engage in political violence.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix A: Summary Statistics
Appendix B: Theory
Appendix C: Additional Institutional Details
Appendix D: Research Design
Appendix E: Supplemental Figures and Results