INSURGENT PREDATION AND WARTIME INFORMING *

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Abstract

Insurgent predation of non-combatants is common in civil war. Yet little is known about how civilians respond to armed extortion after their possessions have been expropriated. We argue that non-combatants respond to predation by punishing insurgents using a prominent but poorly understood mechanism: wartime informing. We present a model of armed extortion and wartime informing, assuming that civilians are rewarded for informing but face the risk of retribution from the rebels. Drawing on newly declassified military records and a novel instrumental variables approach, we find robust, direct evidence that civilians respond to insurgent predation by providing intelligence to security forces in Afghanistan. We find no evidence that the accumulation of lootable income by civilians moderates the propensity of non-combatants to inform against predatory rebels.

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1 Introduction

Economic predation is central to political theories of the modern state (de la Sierra, 2017). Banditry is curtailed by armed actors capable of establishing 'monopolies of violence'. Yet predation of civilian assets by rebel actors is a common feature of modern insurgencies. In these contexts, banditry and armed extortion may exist as an alternative means of rent capture, deployed alongside more legitimate forms of taxation by non-state actors. Relying on predation to generate capital, however, risks turning the civilian population against the rebellion. Despite the ubiquity of rent capture via predation, we still know little about how civilians respond to extortion by armed actors.

In this paper, we focus on one prominent, but poorly understood means of civilian revenge: wartime informing. Non-combatants are in a unique position to gather and share actionable information about rebel movements, attempts to recruit fighters, and positioning of rebels forces in preparation for battle engagements. Gathering such intelligence, as Kalyvas (2006, 173-5) argues, is essential to defeating insurgents. Investigating whether and how civilians use wartime informing to punish insurgents for wanton predation remains a prominent gap in the political economy of conflict (Berman and Matanock, 2015).

We theorize the conditions under which rebels engage in and civilians respond to armed extortion. Our model generates testable implications about rebel predation and wartime informing. It also highlights several cross-cutting effects of non-combatant income (Dube and Vargas, 2013; Vanden Eynde, 2016).

We study this model using newly declassified data on insurgent and counterinsurgent operations in Afghanistan. These military records span the duration of Operation Enduring Freedom, from 2003 to 2014, and document nearly half a million events. Importantly, this catalogue of wartime events includes instances of insurgent predation during which rebels demanded money at gunpoint from civilians as well as detailed intelligence reports, that allow us to identify when and where information was shared with security forces. These military records allow us to conduct direct tests of the relationship between insurgent behavior—specifically, predation—and wartime informing.

We address several weaknesses in current scholarship. First, we examine how *civilians* respond to insurgent predation. Wood (2014*a*) finds that rebels engage in looting and violence against civilians after experiencing battlefield losses. Wood (2014*b*) similarly argues violence against civilians is triggered by shifts in the relative capabilities of insurgent and government forces. Yet, as Kalyvas (2006) asserts, civilians are rarely neutral agents, and may respond to economic predation by punishing the actor that expropriated their assets. One means of revenge is sharing tactical intelligence with the opposing side. In the context we study, we observe predation by insurgents and information sharing with the government. This enables us to conduct a novel assessment of how civilians respond to rebel banditry.

Second, we rely on a wealth of granular data to provide a direct test of the link between predation and punishment. Reliable conflict data is notoriously difficult to collect. Recent work reveals that potentially large biases are present in media-derived data on conflict (Weidmann, 2016). Direct indicators of civilian collaboration with government forces are largely absent from media reports. Instead of relying on media-reported data, we utilize military records that document nearly the universe of armed engagements during the period of formal international operations in Afghanistan (Weidmann, 2016, 210-211). These records document types of insurgent behavior and civilian cooperation that are highly unlikely to be "reported" systematically in news stories. Our records include information on the time, location, and type of smuggling interdictions carried out by local and foreign security forces, which we use to isolate "as if" random acts of armed extortion.

The rest of the paper is organized as follows. The next section introduces our argument. The third section details the empirical strategy. The fourth section presents the fixed effects and IV results. We also discuss lootable income results. The final section concludes.

2 Theory

We analyze the interaction between two players — Rebels and Community. Rebels benefit from predation on the community, but suffer a cost when the community informs on them. Community, on the other hand, has several motives for (not) informing on the rebels.

First, the government may reward the community in exchange for informing. Second, civilians may have a revenge motive for informing on rebels in response to predation. The strength of the revenge motive in a civil war depends on a number of things, including the affinity between rebels and the civilians, such as from shared ethnic identity. In particular, in a survey experiment across 204 Afghanistan villages, Lyall, Shiraito and Imai (2015) find that the decrease in civilian support toward the Taliban in response to victimization by that group is much larger among tribes not affiliated with the Taliban.

Finally, sharing information with the government is not costless. An informant bears a risk of retribution from the rebels, as it is not always possible to provide information without revealing one's identity to the government forces (and, perhaps, to the rebels), and the anonymity of informing can depend on technological constraints.[1]

When choosing the level of predation, the rebels face a tradeoff, as there are potentially two ways how predation can lead to more informing. First, the extraction of resources produces grievances. Second, it makes the civilians more poor and, therefore, more willing to accept the government's reward for informing while facing the risk of retribution from the rebels.

The model generates several predictions with respect to the intensity of rebel predation and civilian informing. We find that both should increase if the value of predation increases.

[1]For example, Shapiro and Weidmann (2015) show that improvements in cell phone coverage have led to a reduction of rebel violence in post-Saddam Iraq, even though the rebels themselves may also have benefited from better communication technology.

That can happen, for example, after rebels have been successfully targeted in a government operation, and are severely resource-constrained. Both predation and informing should also be higher if there is less affinity between rebels and civilians, such as when the rebels and the civilian population belong to different ethnic groups. If the value of predation is large, or if there is little affinity between rebels and civilians, then positive shocks to the lootable income will also cause both predation and informing to increase.

The predictions generated by our analysis differ from previous attempts to model rebel (and government) predation and informing. In Berman et al. (2013), it was assumed that the rebels extracted revenue from firms, while information was provided by the community—a distinct entity. As a result, the magnitude of predation did not affect the decision whether to provide information.

Berman, Shapiro and Felter (2011) also considered the possibility of retribution for informing, but assumed that the civilians are punished if and only if informing has been successful and the government has retained control of the area. This way, the severity of punishment decreases informing, but this effect is independent of either risk preferences or income of the civilians. In our model, retribution happens with a certain probability, and the fall of income due to informing makes the civilians more willing to inform and bear the risks of punishment in exchange for a reward.

In Vanden Eynde (2016), the rebels decide how to spread their resources between punishing civilians for collaboration, and other activities. The positive effect of community income on the cost of informing is assumed explicitly, while in our case, it arises endogenously. The amount of rent extracted from the population is assumed to be fixed, while in our model it is a decision variable, affected, among other things, by changes in income of the civilians.

Consider a community endowed with a certain amount of income. A part of the income, y_L units, is observed by the rebels and is assumed to be lootable, subject to potential expropriation by the rebels. A further y_N units of income is unlootable, and cannot be expropriated.

The timing of the game is as follows.

$t = 1$ Rebels decide on the predation rate $\theta \in [0, 1]$. This is the fraction of the community's lootable income that is expropriated by the rebels.

$t = 2$ The community decides whether to inform on the rebels in exchange for a reward $r > 0$ from the government.

$t = 3$ Payoffs are realized. If the community has informed on the rebels, it is punished with probability $p \in (0, 1)$ and loses all of its income.

The value y_N is the community's private information. The rebels believe that it is distributed uniformly on $[0, \bar{y}]$, with $\bar{y} > \gamma(r + g)$, where $\gamma = \frac{(1-p)^2}{p(2-p)}$.

The expected payoff of the community is equal to

$$U_C(I = 0) = u_C(y_L(1 - \theta) + y_N)$$

if it did not provide information to the government, and

$$U_C(I = 1) = (1 - p)u_C(y_L(1 - \theta) + g\theta + y_N + r)$$

if it did. Here, $u_C(\cdot) = \sqrt{\cdot}$ is the utility function of the community. The value $g\theta$ reflects the revenge motive of the community for informing against the rebels. The value of the parameter $g > 0$ will be larger if there is less affinity between the community and the rebels. If, on the other hand, the rebels and the community have a shared identity — ethnic and, especially, tribal — then the value of g should be small.

The community provides information to the government if and only if $U_C(I = 0) \leq U_C(I = 1)$, or

$$y_N \leq \gamma(r + g\theta) - y_L(1 - \theta) \equiv M < \bar{y}. \tag{1}$$

Knowing the distribution of y_N, from (1) we can calculate the probability that the community informs of the rebels. This value will be given by

$$P = \begin{cases} 0, & M \leq 0 \\ \frac{M}{\bar{y}}, & M \in (0, \bar{y}). \end{cases} \tag{2}$$

If $M = 0$, informing is deterred for all levels of unlootable income. If $M > 0$, the probability that the community informs on the rebels is increasing in the predation rate θ. This happens for two reasons. First, the revenge motive is present. Second, receiving a reward for informing is more attractive to a community that had been robbed of a large share of its income, as it becomes less sensitive to the risk of punishment from the rebels. Similarly, informing is decreasing in lootable income y_L and the probability of punishment p, and is increasing in the reward r and the revenge motive parameter g.

Let the expected payoff of the rebels be

$$U_R = v u_R(\theta y_L) - P,$$

where $u_R(\cdot) = 2\sqrt{\cdot}$, and $v > 0$ is the relative value of predation income to the rebels (it should be higher if the rebels are cash-constrained, such as after a successful government operation against the rebels).

Maximizing U_R with respect to θ, we calculate the predation rate θ^* in the subgame-perfect Nash equilibrium:

Proposition 1 Denote

$$\underline{\theta} = \frac{y_L - \gamma r}{y_L + \gamma g}$$

to be the solution in θ to $M = 0$, and let

$$\theta_1 = \frac{v^2 \bar{y}^2 y_L}{(y_L + g\gamma)^2}.$$

If $\theta_1 \geq 1$, then $\theta^* = 1$. Otherwise, $\theta^* = \max\{\underline{\theta}, \theta_1\}$.

The equilibrium probability of informing P^* is obtained by substituting θ^* into (2). We next investigate the comparative statics of the model. The following is true:

Proposition 2 Let $\theta^* < 1$. Then θ^* and P^* are increasing in v and decreasing in g.

Both the equilibrium predation rate θ^* and the corresponding probability of informing P^* are increasing with the value of predation relative to the damage done by informing, until eventually, for a large enough v, the rebels expropriate all lootable income from the community. If there is less affinity between the rebels and the community (and the revenge motive following predation is stronger), then both predation θ^* and the equilibrium probability of informing P^* should be lower.

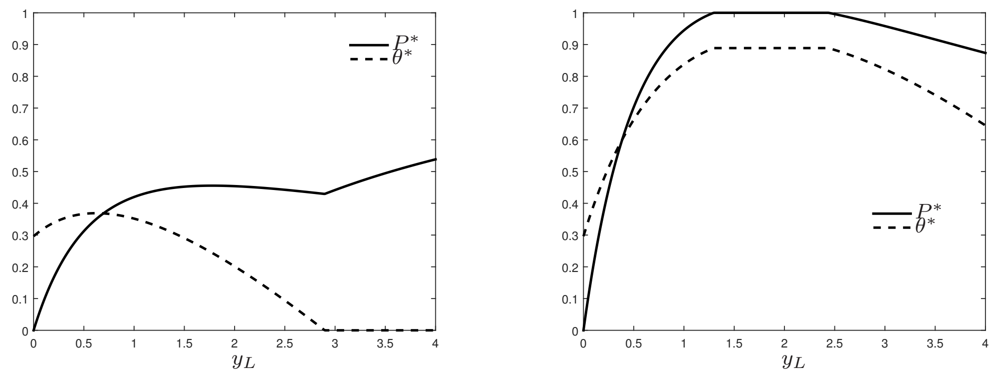
With respect to the effects of lootable income on predation and informing, the following is true:

Proposition 3 Then there exists $y' > 0$ such that θ^* is increasing in y_L on $[0, y']$. If $\phi\sqrt{g\gamma} < v$, then P^* is increasing on $[0, y']$ as well.

On Figure 1 we provide an example how equilibrium levels of θ^* and P^* vary depending on the lootable income y_L.

An increase in the lootable income y_L has two opposing effects on predation. If the income increases, then the probability of informing P becomes more sensitive to changes in the predation rate, so a decrease in θ will result in a larger decrease in the probability of informing. At the same time, more income means that rebels' the marginal utility from predation is larger. The second effect dominates if income is small, and informing is motivated by revenge to a larger degree than by low income. If informing is not too damaging to the rebels, then the increase in predation will be sufficiently large to also cause an increase in informing. Finally, if y_L is sufficiently large, the rebels may find it optimal to choose $\underline{\theta}$ —

Figure 1: Predation and informing depending on community income, $g = 1$,$p = 0.2$, $r = 0.5$, $\bar{y} = 3$.



(a) $v = 0.6$ (b) $v = 0.9$

the maximum level of predation that results in zero informing (this happens for $y_L > 2.9$ on Figure 1 for $v = 0.6$). Given the reward for informing and the probability of punishment, that level will be larger for wealthier communities.

3 Empirical Design

This section discusses the setting of our investigation, reviews the declassified military records used to track armed extortion by insurgents and wartime informing by non-combatants, and introduces our identification strategies.

3.1 Setting

Afghanistan represents a "hard" case for testing how civilians respond to armed extortion. Wright et al. (2017) review several reasons why. First, the insurgency is primarily concentrated in rural settings. Responding to information shared with the government would require allocating scarce resources across sparsely populated areas. This means, as Berman and Matanock (2015) note, that intelligence gathering is likely to attract less investment than in urban insurgencies where the tactical value of information sharing is greater. Second, terrain conditions and frictions between the national military units coordinated under the ISAF banner might have also reduced the capacity of security forces to gather intelligence from civilians willing to share it in response to armed extortion. Finally, existing survey research suggests that non-combatants in Afghanistan are particularly unlikely to share information on insurgent operations, even when rebels physically harm civilians (Lyall, Blair and Imai, 2013). Experimental designs produce similar findings (Lyall, Shiraito and Imai, 2015). These dynamics imply that positive findings in this conflict are likely to generalize to other contexts where rebels operate in urban environments (e.g., Iraq), counterinsurgent operations are coordinated by domestic security forces (e.g., the Philippines), or where civilians are more open to provide information (e.g., Thailand).[2]

3.2 Data

Our declassified military records on insurgent activity, armed extortion, and intelligence reports were compiled by International Security Assistance Force (ISAF) and host nation forces starting in 2003. These records of significant activities (SIGACTS) cover nearly the entire duration of Operation Enduring Freedom, which ceased on December 31, 2014. These data represent the most complete catalogue of formal and informal security operations collected during the Afghanistan conflict currently in the public domain. The data are further detailed in [AUTHOR et al 2017].

We observe details on more than 97,000 intelligence reports. These reports are collected through a variety of mechanisms, including direct civilian-to-military interactions, cultivated sources, and hotline calls. Our data do not distinguish the source of information and do not reveal the means of information sharing (e.g., in-person, call).

We measure insurgent predation by identifying when and where insurgents were operating illegal roadside checkpoints. At these checkpoints, rebels block traffic in order to demand payment for road use. Importantly, the Taliban engages in formal taxation of opium pro-

[2] See, for example, Shaver and Shapiro (2016); Berman et al. (2013).

duction and business operations (Peters, 2009). Checkpoints are operated outside this 'legitimate' context, and can be considered extralegal taxation. Because payment is demanded at gunpoint, we consider these checkpoints a form of armed extortion. We restrict our analysis to insurgent extortion. Although it is possible that government (local police and militias) units engage in armed extortion, our data do not include these records.

Our military records also include information on smuggling interdiction operations. These operations include interdiction of convoys trafficking weapons and narcotics, as well as raids of gun and drug caches. Participation in smuggling is a source of lucrative rents for insurgents, even if they are not directly moving the illicit items. Under the latter condition, they provide protection services for smugglers running guns and drugs out of the country into Iran and Pakistan.

We provide additional details in Supporting Information.

3.3 Identification Strategies

We conduct our analysis at the district level because this is the level at which ISAF and Afghan Government forces were organized during the campaign. Taliban units were also organized around districts. We sum collected intelligence reports, armed extortion events, and insurgent operations—including direct line-of-sight attacks, indirect mortar and rocket engagements, and improvised explosive device (IED) detonations—by district-week and standardize per 1,000 district inhabitants.

We identify the effect of insurgent extortion on information sharing with security forces using two different identification strategies.

We begin with the assumption that, conditional on appropriate controls for trends in the conflict, armed extortion is "as if" randomly assigned. This approach is the benchmark specification in previous work on wartime informing (Condra and Shapiro, 2012). After conditioning out district and week-of-year fixed effects, as well as short-run trends in overall violence, we identify the residual variation in armed extortion that is arguably random.

Our base model is captured by equation 3:

$$Y_{dt} = \alpha + \beta_1 Armed\_Extortion_{dt} + \mu_d + \eta_t + \gamma X_{dt} + \epsilon_{dt} \tag{3}$$

where Y_{dt} is the number of intelligence reports shared with counterinsurgents in district d in week t; $Armed\_Extortion_{dt}$ is the sum of armed extortion events in a given district; μ_d is a district fixed effect; η_t denotes a week-of-year fixed effect; X_{dt} is a vector of district-week enemy force operation controls, included in all specifications; and ϵ_{dt} is the error term. The regression is weighted by population. In all models we cluster standard errors at the district level.

Yet assuming that armed extortion is plausibly random is strong and largely unverifiable. For this reason, we turn to a second identification strategy. We instrument for armed extortion events using idiosyncratic variation in the location and timing of interdiction shocks. These shocks—where potentially large quantities of drugs and guns are confiscated—represent a significant constraint on rebel operations. Although capture of rebel capital stocks may induce a change in rebel tactics (Wright, 2016; Wood, 2014*a*), these seizure events also create incentives for insurgents to capture revenue through other means, including extortion. Importantly, the interdiction events we observe are unlikely to be meaningfully related to information sharing except through their influence on predation. The types of intelligence reports we study are primarily related to security threats to police and military actors, not information about suspected smuggling (which could lead to interdiction events). The interdiction shocks documented in our data are also 'high value' seizures, not low-level, small-scale opium and weapon confiscations in local markets. This is critical since bazaar raids may cause income shocks to the informant pool, which could potentially violate the exclusion restriction.

Our first stage regresses the number of armed extortion events per district-week on the number of interdiction events for each district, by week. We estimate equation 4:

$$Armed\_Extortion_{dt} = \alpha + \beta_1 Interdiction\_Shock_{dt} + \mu_d + \eta_t + \gamma X_{dt} + \epsilon_{dt} \tag{4}$$

The parameters in equation 4 follow equation 3. From equation 4, we derive $\widehat{Armed\_Extortion}_{dt}$. We then estimate equation 5:

$$Y_{dt} = \alpha + \beta_1 \widehat{Armed\_Extortion}_{dt} + \mu_d + \eta_t + \gamma X_{dt} + \epsilon_{dt} \tag{5}$$

where the point estimate on $\widehat{Armed\_Extortion}_{dt}$ is the quantity of interest, the armed extortion events in the current district-week. Information sharing, Y_{dt}, is measured as in equation 3 above, and the regression is weighted by population. Our covariates X_{dt} include district and year-week fixed effects. Standard errors are clustered at the district level.

3.4 Heterogeneous Models

We also examine heterogeneous effects of lootable income. We calculate annual revenue from opium production for each district (log production $\times$ log price). We then interact these measures with $Armed\_Extortion_{dt}$ in our base model (equation 3). For these models, we focus only on the 16 weeks immediately following the spring opium harvest, when most farmers sell their yearly crop (Peters, 2009).

4 Results

We review our main results in this section. We find that armed extortion by insurgents is associated with a significant increase in civilian cooperation with security forces.

Table 1 shows the estimated impact of armed extortion on wartime informing using equation 3. Across all specifications in Table 1, there is a statistically significant association between insurgent predation and the number of tips that counterinsurgents receive from civilians. The estimated coefficient on armed extortion is stable across specifications, and indicates that a one standard deviation increase in insurgent predation is associated with a

51.8% to 52.7% increase in informant reports over the weekly mean level. A one standard deviation increase in insurgent predation is equivalent to .11 more illegal checkpoints per week in an average sized district, or 6.11 weekly extortion events in a large district, like Kabul. We perform a standard diagnostic and confirm population weights improve precision (table SI-6). Our results are robust to sequentially excluding provinces as well (figure SI-3).

In tables SI-1 and SI-2, we adopt alternative measures of the outcome, by winsorizing and logging intelligence flows, respectively, to ensure that our results are robust to transformations common in the literature and are not driven by outliers. The benchmark specification in table SI-1 indicates a one standard deviation increase in civilian abuse is associated with a 37.1% increase in wartime informing. The same specification in table SI-2 estimates a 21.3% increase in collaboration following a comparable shock. Alternatively, we could estimate these models using first differences, which we do in table SI-3, and find consistent results.

To increase confidence in the causal interpretation of our results, we now turn to our IV estimates of equations 4 and 5. We begin by assessing the relevance of our instrument—interdiction shocks—to insurgent predation. These results are reported in table SI-4. Our results indicate that the severity of armed extortion is significantly, positively associated with the number of smuggling seizures carried out by counterinsurgents. We find consistent effects in our supplemental tests as well (tables SI-9 and SI-12). In our preferred specification, the Kleibergen-Paap F statistic is 15.96, well above the standard threshold of 10. The lowest observed Kleibergen-Paap F across all specifications is 11.84. These results empirically confirm that rebels respond to capital losses by capturing rents by extorting civilians.

We next turn to our second stage results, reported in table 2. These findings indicate that information sharing following acts of insurgent predation increases by 28-fold over the weekly mean, leading to roughly ten more tips per week in small districts and more than 500 additional pieces of intelligence in large districts. Population weights improve the precision of our estimates (table SI-7). Given the geographic density of extortion and interdiction events proximate to the Ring Road (figures SI-1 and SI-2), we test and confirm the results are insensitive to sequentially dropping provinces from the estimating sample (figure SI-4). We observe comparably scaled responses if we instead winsorize (table SI-8) or log transform (table SI-11) our outcome of interest. We also confirm the results are consistent when accounting for other forms of extortion that may be triggered by interdiction events, such as kidnapping for ransom (table SI-15). Given the empirical distribution of our endogenous regressor, however, we caution against an overinterpretation of these large substantive results.[3] The reduced form estimates imply a more modest 82% increase in tips following a standard deviation increase in interdiction shocks. This corresponds to roughly .3 and 16.2 more weekly tips in small and large districts, respectively.

We study heterogeneous lootable income effects in tables SI-18. Notice that the interaction terms are statistically insignificant. The results in table SI-18 imply that the propensity to punish rebels for predation is not moderated by the wealth of civilians. We find similar evidence using alternative outcome measures in tables SI-19 and SI-20. We also confirm the results are robust to alternative definitions of the post-harvest period (see Supporting Information SI-L). In this case, we use annual opium revenue as a measure of lootable assets, observable to the insurgency. Interestingly, however, opium revenue is positively correlated with intelligence sharing. This association holds, even after controlling for trends in violence (as well as Regional Command linear trends and Regional Command-by-Year fixed effects).

5 Conclusion

We have shown direct evidence that civilians respond to insurgent predation by cooperating with government forces. Previous research has focused on the conditions under which rebels engage in looting and other predatory behavior. We focus on how non-combatants punish rebels for relying on armed extortion by sharing intelligence with security units. We

[3] Armed extortion events, as our descriptive statistics reveal, are relatively rare events.

supplement our main specifications with a novel instrumental variables approach, leveraging interdiction shocks that "as if" randomly trigger armed extortion. We find evidence that capital constrained combatants do engaged in more predation. Our IV estimates reveal that civilians sharply punish rebels for employing extralegal taxation at gunpoint. Drawing on insights from our model, we test heterogeneous effects of lootable civilian income. We find no evidence that civilian wealth moderates the willingness of civilians to punish predation.

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Table 1: Impact of insurgent predation on wartime informing by civilians to security forces

	Column 1	Column 2	Column 3
ARMED EXTORTION	1.700***	1.673***	1.673***
	(0.346)	(0.342)	(0.342)
SUMMARY STATISTICS			
Outcome Mean	.006	.006	.006
Outcome Std. Dev.	.0238	.0238	.0238
Treatment Mean	.00008	.00008	.00008
Treatment Std. Dev.	.00186	.00186	.00186
PARAMETERS			
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
District Violence Trend	Yes	Yes	Yes
Reg. Command Trends	No	Yes	No
Reg. Command-Year FE	No	No	Yes
MODEL STATISTICS			
Number of Observations	248352	248352	248352
Number of Clusters	398	398	398
R^2	0.272	0.282	0.282

Notes: Outcome of interest is intelligence reports shared with local and foreign security forces standardized by population. All regressions are weighted by district population. Regional command designations are assigned to districts and used for calculating linear time trends (column 2) and command-by-year fixed effects (column 3). Standard errors clustered at the district level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Instrumental variables estimates of impact of insurgent predation on wartime informing by civilians to security forces

	Column 1	Column 2	Column 3
$\widehat{\text{ARMED EXTORTION}}$	91.29***	92.34***	92.34***
	(19.37)	(19.27)	(19.29)
SUMMARY STATISTICS			
Outcome Mean	.006	.006	.006
Outcome Std. Dev.	.0238	.0238	.0238
Treatment Mean	.00008	.00008	.00008
Treatment Std. Dev.	.00186	.00186	.00186
PARAMETERS			
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
District Violence Trend	Yes	Yes	Yes
Reg. Command Trends	No	Yes	No
Reg. Command-Year FE	No	No	Yes
MODEL STATISTICS			
Number of Observations	248352	248352	248352
Number of Clusters	398	398	398
Kleibergen-Paap F	15.96	16.45	16.42

Notes: Outcome of interest is intelligence reports shared with local and foreign security forces standardized by population. All regressions are weighted by district population. Regional command designations are assigned to districts and used for calculating linear time trends (column 2) and command-by-year fixed effects (column 3). Standard errors clustered at the district level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

SUPPORTING INFORMATION
— For Online Publication Only —

A Proofs

Proof of Proposition 2.

Let $\theta_1 < 1$. We have

$$\frac{\partial \theta_1}{\partial g} = \frac{-2\gamma v^2 \bar{y}^2 y_L}{(y_L + g\gamma)^3} < 0, \ \frac{\partial \theta_1}{\partial v} = \frac{2v\bar{y}^2 y_L}{(y_L + g\gamma)^2} > 0,$$

and, assuming $\underline{\theta} < \theta_1$,

$$\bar{y}\frac{\partial P^*}{\partial g} = \gamma\theta_1 + \frac{\partial \theta_1}{\partial g}(\gamma g + y_L) = -\frac{\gamma v^2 \bar{y}^2 y_L}{(y_L + g\gamma)^2} < 0$$

and

$$\bar{y}\frac{\partial P^*}{\partial v} = \frac{\partial \theta_1}{\partial v}(\gamma g + y_L) = \frac{2v y_L}{(y_L + g\gamma)\phi^2} > 0.$$

We also have

$$\frac{\partial \underline{\theta}}{\partial g} = -\frac{y_L - \gamma r}{(y_L + g\gamma)^2},$$

which is negative if $\underline{\theta} > 0$.

Proof of Proposition 3.

Differentiating $\frac{v^2\bar{y}^2 y_L}{(y_L+g\gamma)^2}$ with respect to y_L yields unique global maximum at $y_L = g\gamma$. If $2\sqrt{g\gamma} \geq \bar{y}v$, then the maximum of $\frac{v^2\bar{y}^2 y_L}{(y_L+g\gamma)^2}$ with respect to y_L is no larger than 1, so θ_1 is increasing in y_L on $[0, g\gamma]$. If $2\sqrt{g\gamma} < \bar{y}v$, then θ_1 is increasing on $[0, y_-]$, where y_- is the smaller solution to $v^2\bar{y}^2 y_L = (y_L + g\gamma)^2$.

Now we know that $\underline{\theta} \leq 0$ for all $y_L \leq \gamma r$, so θ^* is increasing on $[0, \min\{y_-, \gamma r\}]$.

Assuming $\theta_1 = \theta^* < 1$, we get

$$\frac{1}{\phi}\frac{\partial P^*}{\partial y_L} = \theta^* - 1 + \frac{\partial \theta^*}{\partial y_L}(\gamma g + y_L) = \frac{g\gamma v^2}{(y_L + g\gamma)^2\phi^2} - 1.$$

If $\phi\sqrt{g\gamma} < v$, then $\frac{\partial P^*}{\partial y_L} > 0$ at $y_L = 0$. Moreover, P^* will be increasing on $[0, y_-]$ if $2\sqrt{g\gamma}\phi < v$, and on $[0, y']$, with $y' \leq g\gamma$, if $2\sqrt{g\gamma}\phi \geq v$.

B Additional data details

Military records: Our data include records on nearly 200,000 close combat, remote combat, and IED explosion events. Close and remote combat events are more commonly described as direct and indirect fire attacks. The former category includes ambushes on convoys, pitched engagements, and other line-of-sight encounters, while the latter category is primarily characterized by mortar fire and other forms of distant engagement where the likelihood of return fire is low. Additionally, our data may include information on insurgent operations that were intercepted through signals intelligence collection. For security reasons, it is unlikely that these types of events (threat reports that did not involve civilian cooperation) were released in our data request. If, however, these records were included in our data, our results would be biased toward zero.

Opium production and price data: We also gather opium production and farmgate price data from annual reports of the United Nations Office on Drugs and Crime. These data include estimates of the annual amount of opium production (hectares) for each district since 2006 and the average price per kilogram (US dollars) in April and May, the period immediately following the annual harvest.

C Explanation of baseline tables

In this section, we detail the model sequence in the main results. Column 1 presents results from our baseline, population-weighted fixed effects model, which regresses incidents of information sharing on the number of armed extortion events in a district-week. The model controls for the total number of direct fire attacks, indirect fire attacks, and IEDs detonated, and clusters standard errors at the district level. It includes district and year-week fixed effects. Column 2 adds regional-command-specific (RC) time trends to this baseline model. Specifically, the model in Column 2 includes the interaction of a RC dummy (e.g., Regional Command East, West, North, South) with a linear year trend. This is to account for any linear changes in the conflict specific to each regional command, such as the accumulation of insurgent capabilities in opium producing regions. In Column 3, we add a regional command-year fixed effect. In these models, all variation we study is demeaned by district, week-of-year, and regional command-year. This allows us to address macroscale changes in coalition and host nation force composition, such as coalition troop rotations and annual revisions to rules of engagement.

D Baseline results with alternative outcome measures

In the main analysis, we measure the outcome of interest—information sharing—per 1,000 district inhabitants. This transformation adjusts for the varying population scales (and conflict intensities) of each district. In the Supporting Information, we present the results from alternative model specifications for both the two-way fixed effects estimations and the IV estimations to show that the results are robust to different ways of accounting for the non-normal distribution of the dependent variable. In the first alternative specification, we winsorize the dependent variable at the 99th percentile. In the other alternative specifications, we perform a log transformation, adding one to all units. Results are unaffected.

Table SI-1: Impact of insurgent predation on wartime informing by civilians to security forces, winsorized at the 99th percentile

	Column 1	Column 2	Column 3
Armed Extortion	1.818***	1.784***	1.784***
	(0.320)	(0.309)	(0.309)
Summary Statistics			
Outcome Mean	.3633	.3633	.3633
Outcome Std. Dev.	1.508	1.508	1.508
Treatment Mean	.0041	.0041	.0041
Treatment Std. Dev.	.0757	.0757	.0757
Parameters			
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
District Violence Trend	Yes	Yes	Yes
Reg. Command Trends	No	Yes	No
Reg. Command-Year FE	No	No	Yes
Model Statistics			
Number of Observations	248352	248352	248352
Number of Clusters	398	398	398
R^2	0.351	0.370	0.369

Notes: Outcome of interest is intelligence reports shared with local and foreign security forces, winsorized at the 99th percentile. Regional command designations are assigned to districts and used for calculating linear time trends (column 2) and command-by-year fixed effects (column 3). Standard errors clustered at the district level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table SI-2: Impact of insurgent predation on wartime informing by civilians to security forces, log transformed (plus one)

	Column 1	Column 2	Column 3
Armed Extortion	0.420***	0.412***	0.412***
	(0.0483)	(0.0474)	(0.0475)
Summary Statistics			
Outcome Mean	.1491	.1491	.1491
Outcome Std. Dev.	.4333	.4333	.4333
Treatment Mean	.0041	.0041	.0041
Treatment Std. Dev.	.0757	.0757	.0757
Parameters			
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
District Violence Trend	Yes	Yes	Yes
Reg. Command Trends	No	Yes	No
Reg. Command-Year FE	No	No	Yes
Model Statistics			
Number of Observations	248352	248352	248352
Number of Clusters	398	398	398
R^2	0.397	0.411	0.410

Notes: Outcome of interest is intelligence reports shared with local and foreign security forces, log transformed (plus one). Regional command designations are assigned to districts and used for calculating linear time trends (column 2) and command-by-year fixed effects (column 3). Standard errors clustered at the district level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E First differences estimates

Table SI-3: Impact of changes in insurgent predation on changes wartime informing by civilians to security forces (first differences)

	Column 1	Column 2	Column 3
Armed Extortion	0.269***	0.183**	0.0619***
	(0.0980)	(0.0859)	(0.0167)
Outcome			
Outcome measure	Intel per 1000 residents	Winsorize, 99th Perc.	log(intel.+1)
Summary Statistics			
Outcome Mean	.006	.3633	.1491
Outcome Std. Dev.	.0238	1.508	.4333
Treatment Mean	.00008	.0041	.0041
Treatment Std. Dev.	.00186	.0757	.0757
Parameters			
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
District Violence Trend	Yes	Yes	Yes
Reg. Command Trends	No	No	No
Reg. Command-Year FE	No	No	No
Model Statistics			
Number of Observations	243576	243576	243576
Number of Clusters	398	398	398
R^2	0.0164	0.0148	0.0124

Notes: Outcome of interest is intelligence reports shared with local and foreign security forces standardized by population. All regressions are weighted by district population. Regional command designations are assigned to districts and used for calculating linear time trends (column 2) and command-by-year fixed effects (column 3). Standard errors clustered at the district level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.