A Rebel-Group Theory of the Firm: Illicit Activities, Natural Resources, and Substitutability*

Preliminary: Please Do Not Circulate

Adam Soliman†

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Abstract

Non-renewable natural resources were seen as the source of many civil conflicts in the 1990s, as they often occurred in countries heavily dependent on oil and mineral exports. This spawned a large literature examining the "resource curse," which generally relied on country-level analysis. However, given the uneven spatial distribution of resource endowments and the ever-changing nature of warfare, the analysis needs to be more localized. Rebel groups are an ideal candidate for further study of this paradox, as they often directly profit from resource exploitation, yet we know very little about even their most basic decisions. Therefore, I present a rebel-group theory of the firm, which highlights the importance of relative costs in the substitutability of criminal activities. Using data on the illicit activities of 297 different rebel groups operating between 1990 and 2015, I examine the model's sufficient condition and find that rebel groups consistently substitute away from certain criminal activities when the world prices of the natural resources they exploit rise. I also find that a given resource-exploiting rebel group is less likely to forcibly recruit child soldiers over time. These results suggest that rebel groups seek to maximize organizational profit but consider the interactions between illicit activities, their associated social costs, and the returns to legitimacy.

Keywords: rebel groups, natural resources, crime, substitutability, resource curse, civil conflict, child soldiers

JEL Codes: D74, L70, O13, O17, Q34

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†Department of Economics, Duke University. Email: adam.soliman@duke.edu

1 Introduction

Countries rich in non-renewable natural resources often display poor economic performance. Conflict plays a major role in the mechanisms proposed to explain this well-documented paradox, yet much of the "resource curse" literature has relied on cross-country analysis. Given that natural resources are unevenly distributed spatially and the ever-changing nature of warfare, we need to focus more locally in order to better understand the dynamics between natural resources, civil conflict, and crime. An emerging literature studies variation in resource availability and conflict within countries, but there remains little evidence on how rebel groups, who often have access to or directly profit from such resources, substitute between various activities over time. More specifically, their insurgent activity, interactions with non-combatants, and economic incentives are not well understood. More evidence on why or how their decisions are made can eventually assist in addressing rebel group violence, providing more targeted legislation, or improving postwar conflict management.

I address this gap in the literature by first presenting a rebel-group theory of the firm, which highlights the importance of relative costs of different revenue streams. The model also provides a sufficient condition for the substitutability of these criminal activities. Using a unique panel dataset on the illicit activities of 297 different rebel groups, I examine this condition and find that rebel groups consistently substitute away from other criminal activities when the world price of the natural resource they exploit rises. In a related extension, I find that even though rebel groups that exploit natural resources are more likely to forcibly recruit child soldiers, within a given rebel group over time, natural resource exploitation is associated with a lower probability of using child soldiers. These results suggest that rebel groups seek to maximize organizational profit but consider the interactions between illicit activities, their associated social costs, and the returns to legitimacy.

The remainder of this paper is as follows: Section 2 discusses the relevant literature, Section 3 develops the theoretical framework, Section 4 introduces the data, Section 5 presents the econometric strategy and results, and Section 6 concludes.

2 Literature

The correlates of war are well-established. Blattman and Miguel (2010) summarize that civil conflict is more likely to occur in countries that are poor, subject to negative income shocks, have weak state institutions, and have regions that are remote, sparsely populated, and mountainous. With regards to the theoretical modeling in this literature, they state that a negative income shock is associated with an increased risk of conflict in models that focus on the diminished opportunity costs of soldiering, weaker state capacity, and the role of asymmetric information. On the other hand, it is associated with a decreased risk of conflict among models that stress capturing the state and its revenues as a prize.

Ross (2006) states that the empirical evidence on the relationship between natural resources and conflict has been mixed, likely due to the use of cross-country regressions that miss the inherent local dynamics. Ross (2015) highlights the fact that there have since been improvements in data quality and identification, and in terms of micro-level evidence of the resource-conflict relationship, a seminal paper is by Dube and Vargas (2013). The authors find that an increase in the international price of Colombia's main labor-intensive export, coffee, significantly reduces violence in coffee-producing regions, while an increase in the international price of its primary capital-intensive export, oil, increases violence in regions with oil reserves and pipelines.

Despite more causal evidence on the resource-conflict relationship and a growing literature examining violent non-state groups, we still know very little about some of the most basic decisions rebel groups make, such as how or why they allocate their recruits across various profit-driven, criminal, and ideological activities. Rebel groups often have access to or directly profit from natural resources, and given the ever-changing and localized nature of warfare, it is clear that their behavior needs to be studied further. This reality is gaining scholarly attention, for example, by researchers who utilize Olson's (1993) framework; he argues that authorities will provide order if it is part of their "encompassing interest." One such paper is by Maystadt et al. (2014), who find that natural resources provide benefits to those located near mines, as entrepreneurial rebel groups will want to protect their source of income and thus minimize conflict in the immediate vicinity of the mine. These same resources, however, are costly to the greater population, as conflict in surrounding areas increases and becomes more intense.

Parker and Vadheim (2017) study the impact of the 2010 Dodd-Frank Act, which cuts funding to warlords by discouraging manufacturers from sourcing metals from the Democratic Republic of the Congo (DRC). They find that this legislation increased looting of civilians and shifted battles towards unregulated gold-mining areas. Also in the DRC, Sanchez de la Sierra (2020) examines civil conflicts following coltan and gold price shocks. He finds that the former, which is a mineral that cannot be easily concealed, leads armed actors to provide protection at coltan mines, while the latter leads to stationary bandits in the villages where income from gold is spent; he suggests that armed actors may provide these functions of the state in order to better expropriate. Such papers provide us with invaluable insight into how rebel groups act within a given setting, and often focus on conflict as the main outcome, but there is little to no large-N examination of rebel group decision-making processes, let alone a study of their firm-like behavior; this paper attempts to address this.

3 Theoretical Framework

A rebel group seeks to maximize organizational profit by choosing a level of resource exploitation R and a *different* illicit activity A. The per-unit prices of a given resource and this illicit activity are denoted p_R and p_A, respectively. I normalize the price of the illicit activity to $p_A = 1$ and assume that the rebel group acts as a price taker. Assuming that there are no production synergies between R and A, and holding state capacity and rebel group competition fixed, it is without loss of generality to consider a profit function of the form $\Pi(R, A, p_R) = p_R R + A - C(R, A)$. Thus, the rebel-group's optimization problem is

$$\max_{R,A} \Pi(R, A, p_R) = p_R R + A - C(R, A). \tag{1}$$

Let $R^*(p_R)$ and $A^*(p_R)$ denote the components of a unique solution, which is guaranteed whenever $C(\cdot, \cdot)$ is continuous and strictly convex. I seek to identify conditions under which the optimal level of illicit activity, $A^*(p_R)$, is a decreasing function of p_R; a similar treatment can examine complementarity. To achieve this, I begin by recalling the following helpful result from Topkis (1978):

Theorem 1 *Consider the following optimization problem*

$$\text{max } f(x, y, t) \text{ subject to } (x, y) \in S_X \times S_Y.$$

Suppose that

$$(i)\ \frac{\partial^2 f}{\partial x \partial y} < 0 \qquad (ii)\ \frac{\partial^2 f}{\partial x \partial t} > 0 \qquad (iii)\ \frac{\partial^2 f}{\partial y \partial t} \leq 0,$$

then $x^*(t)$ is strictly increasing in t and $y^*(t)$ is strictly decreasing in t.

To apply this theorem in our context, we examine the following cross partials

$$(i)\ \frac{\partial^2 \Pi}{\partial R \partial A} = -\frac{\partial^2 C}{\partial R \partial A} < 0 \qquad (ii)\ \frac{\partial^2 \Pi}{\partial R \partial p_R} = 1 > 0 \qquad (iii)\ \frac{\partial^2 \Pi}{\partial A \partial p_R} = 0 \leq 0.$$

We see that conditions (ii) and (iii) are satisfied directly by differentiating equation (1), and thus $A^*(p_R)$ is decreasing in p_R whenever $\frac{\partial^2 C}{\partial R \partial A} > 0$. Inferring the sign of $\frac{\partial^2 C}{\partial R \partial A}$ empirically is the purpose of Section 5.1. Nevertheless, if this condition is satisfied, the likely mechanism is that as the world price of a given resource increases, a rebel group will want to increase its level of exploitation. Now that R has increased, the rebel group has a higher marginal cost of A because $\frac{\partial^2 C}{\partial R \partial A} > 0$, and thus the optimal A decreases as a result.

For intuition, the marginal cost of A may increase with R if resource wealth makes rebel groups more legitimate or increases their perceived time horizon; when they expect to control a given territory for longer, they substitute away from other costly illicit or predatory activities that hinder the economic activity of the civilians they control. An alternative explanation is that with more natural resource wealth, a rebel group is more susceptible to attack or revolts. Therefore, one way to protect this potentially more stable revenue source is by substituting away from other dangerous activities or ones that risk frustrating the citizenry they share a religion, ethnicity, culture, or ideology with.

Section A presents a different and more illustrative model of rebel group optimization that incorporates ideology. That said, the framework from (1) may relate easiest to an agricultural household model if one wants to consider ideology. In such a model, the decisions of a household are recursive if markets are complete: production decisions are made in the first stage and in the second, consumption decisions are made taking into account income from farm profits; consumption decisions depend on production choices, but not the other way around. In the model from this section, a rebel group's production choices are essentially how much R and A to choose. Then, in the second stage, ideological "consumption" choices are made based on the profits generated from the first stage's illicit activities. If markets are instead incomplete, we lose the separation property, and production decisions depend on the preferences and endowments of the household or rebel group. Nevertheless, rebel groups need economic resources in order to survive and achieve their ideological goals, and thus (1) can be considered the first stage in this decision-making process.

4 Data

The core data used in the analysis covers natural resource exploitation and other criminal activities for 297 unique rebel groups from 1990 to 2015. Each observation is a dyad-year, where a dyad is made up of two armed and opposing actors that have a stated incompatibility, with one or more being the government. There are 31 resources included in the dataset and is each coded by the funding strategy used to exploit it; the options are either extortion, theft, smuggling, or booty futures.[1] There are also non-natural resource-related crime variables, which include extortion, theft, human trafficking, smuggling, humanitarian aid, piracy, international kidnapping, and domestic kidnapping. To make this more concrete, one country-rebel group pair, or dyad, in the dataset is Colombia-Revolutionary Armed Forces of Colombia (FARC), where the FARC smuggled coca in 1992. In that same year, the FARC kidnapped both locals and foreigners, as well as participated in extortion and in large-scale theft.

Walsh et al. (2018) provide an excellent description of this dataset, and thus I only provide some descriptive statistics for context. Table 1 shows some of the most frequently exploited natural resources, as well as how many funding strategies were used to exploit them in a given dyad-year. For example, the M23 rebel group (DRC) only smuggled gold in both 2012 and 2013 and thus represent two observations in the *One Strategy* column for gold, while the Rally for Congolese Democracy (DRC) smuggled and extorted gold in 1999 and thus are the only gold observation in the *Two Strategy* column. Note that not every rebel group in the dataset exploits a resource, but amongst those that do, illicit drugs are some of the most commonly utilized resources. Furthermore, aside from timber and oil, we can see that "lootable" resources are exploited more frequently than "non-lootable" ones; lootability is an indication of how much coordinated effort it takes to steal a resource, and thus non-lootable resources would include most fossil fuels and deep-shaft minerals.

Table 2 shows the four funding strategies used for exploiting a given natural resource. We see that the vast majority of the natural resources are either extorted, say by taxing local farmers or oil companies, or smuggled, such as moving coca across an international border. The *# of Non-Zero Occurrences for a Given Dyad-Year* column captures the maximum number of times that a strategy is utilized to exploit resources in a given dyad-year. For example, the FARC and the Democratic Forces for the Liberation of Rwanda (FDLR) both were able to extort more than 10 resources in each of the years 2010, 2011, and 2012; the FARC has the most diverse resource portfolio in the dataset. Table 3 shows the pairwise correlations between the resource funding strategies, where we see that the use of extortion is (weakly) positively associated with theft and smuggling.

Table 4 shows the regional breakdown of natural resource funding strategies. Smuggling is relatively more common than extortion in the Middle East, while in Asia, the Americas, and Africa, extortion and smuggling are used in similar proportions. The *Total* column provides insight into where natural resources are being exploited, as well as how often rebel groups in

[1] Extortion is when a group uses violence or the threat of violence to earn money directly or indirectly from the *production* of natural resources. Theft refers to periodic theft of natural resources, not ongoing activities. Booty futures are when the rebel group earns income by promising another actor exploitation rights over the natural resource in the event that the rebel group gains formal control over the territory. Smuggling is when the rebel group earns income by directly engaging in or protecting those who smuggle resources illegally.

Table 1: Natural Resource by Amount of Funding Strategies Utilized in a Given Year

Resource	One Strategy	Two Strategies	Three Strategies	Total
Opium	201	79		280
Cannabis	190	26		216
Timber	133	61		194
Coca	66	71		137
Oil	116	4	9	129
Gold	126	1		127
Agriculture	95	22		117
Animals	99	1	1	101
Drugs	76	14		90
Tea	90			90
Diamonds (alluvial)	79	3		82
Coffee	71	1		78
Gems	53	25		78
Charcoal	50	4		54
Coal	48	1		49
Coltan	25	5		30
Wolframite	21			21
Cassiterite	17			17
Iron	14			14
Cocoa	13			13
Copper	7			7
Titanium	6			6
Rubber	5			5
Cobalt	1	1		2
Tin	2			2
Diamonds (primary)	1			1
Zinc	1			1

Notes: Each observation is a dyad-year and there are 1612 observations in the dataset. The *One Strategy* column captures the occurrence of a given resource being exploited by one funding strategy in one dyad in a given year. For example, in 2003 in the Afghanistan-Taliban dyad, opium was only smuggled. The *Two Strategy* column would be if it was instead 2004 and opium was both smuggled and extorted in the Afghanistan-Taliban dyad.

Table 2: Natural Resource Funding Strategies

	Number of Dyad-Years	# Non-Zero Occurrences for Given Dyad-Year
Extortion	562	1 to 12
Smuggling	546	1 to 4
Theft	53	1 to 2
Booty Futures	6	1 to 4
Any Strategy	830	

Note: The total number of dyad-years in the sample is 1612.

Table 3: Pairwise Correlations: Natural Resource Funding Strategies

	Extortion	Theft	Booty Futures	Smuggling
Extortion	1.00			
Theft	0.21	1.00		
Booty Futures	0.01	0.22	1.00	
Smuggling	0.14	-0.06	0.02	1.00

those regions are exploiting resources. There are more resources being exploited by rebel groups in Africa and Asia. It should be stressed that this data not only captures extraction or resource endowments of a given region, but more broadly exploitation, which could be along a trafficking route or supply chain and potentially far from the original extraction site.

Table 4: Natural Resource Funding Strategies by Region

	Dyad-Years				
	Extortion	Theft	Booty Futures	Smuggling	Total
Middle East	37	10	0	82	129
Asia	187	2	1	164	354
Americas	136	0	0	100	236
Africa	175	37	5	160	377
Europe	27	4	0	40	71
Total	562	53	6	546	1167

Note: The total number of dyad-years in the sample is 1612.

Tables 5 and 6 both examine non-natural resource criminal activity. Extortion is the most commonly utilized criminal activity, followed by kidnapping, smuggling, and theft. In Table 6, we see that rebel groups that participate in one criminal activity have a higher likelihood of participating in other ones.

Table 5: Criminal Funding Strategies (Non-Natural Resource)

	Number of Dyad-Years
Extortion	682
Kidnapping of Locals	225
Smuggling	220
Theft	207
Kidnapping of Foreigners	146
Human Trafficking	62
Humanitarian Aid	50
Piracy	23
Any Strategy	858

Note: The total number of dyad-years in the sample is 1612.

Table 6: Pairwise Correlations: Criminal Funding Strategies (Non-Natural Resource)

	Extortion	Smuggling	Kidnapping of Foreigners	Kidnapping of Locals	Theft	Humanitarian Aid	Human Trafficking
Extortion	1.00						
Smuggling	0.19	1.00					
Kidnapping of Foreigners	0.22	0.05	1.00				
Kidnapping of Locals	0.31	0.00	0.25	1.00			
Theft	0.29	0.20	0.38	0.34	1.00		
Humanitarian Aid	-0.05	0.13	0.03	-0.03	0.08	1.00	
Human Trafficking	0.19	0.28	0.04	-0.06	-0.01	0.08	1.00

Figure 1 shows conflict duration and their location for approximately 75% of the rebel groups. While the shape of the left figure is relatively uniform, note that for some conflicts, potentially several rebel groups may have participated in the same conflict at some point in time. Additional descriptive statistics are in Section C, which includes the most frequently observed rebel groups in Table C.1 and the distribution of unique rebel groups in Figure C.1.

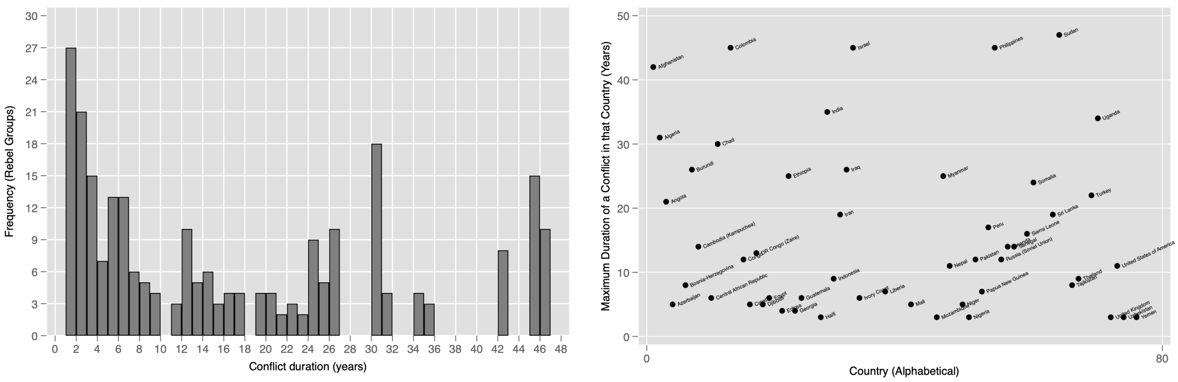

Figure 1: Conflict Duration and Location

Notes: The figure on the left shows how many rebel groups had a conflict lasting a given amount of years; this may represent several rebel groups in one country, such as Afghanistan, and not necessarily unique conflicts with 42 years. The figure on the right only shows countries where the maximum conflict lasted more than 2 years.

For pricing data, I use the International Monetary Fund's Commodity Data Portal, which includes monthly data on 68 commodities from four commodity asset classes (energy, agriculture, fertilizers, and metals) since 1980, which I aggregate to yearly averages. I also use the White House's National Drug Control Strategy and the United Nations Office on Drugs and Crime Data Portal for international drug prices; yearly trends for all prices can be found in Tables C.2 through C.4. Lastly, for data on child soldiers, I use Haer (2019).

5 Econometric Strategy and Results

I conduct two complimentary analyses. The primary is to better understand the substitution patterns of a rebel group by examining how they react to changes in world prices of the resources they exploit. An extension examines the impact of these price changes on conflict, and these can be found in Section 5.1. The second, found in Section 5.2, is to examine how natural resources relate to the incentives to restrain behavior that would lose civilian support, specifically in terms of the impacts of natural resource exploitation on child soldiering.

5.1 Substitution

In order to better understand the criminal substitution patterns of a rebel group, the primary econometric specification, run separately for each resource, is

$$C_{idt} = \gamma_0 + \gamma_1 R_{dt} + \gamma_2 (p_{Rt} \times R_{dt}) + \alpha_t + \delta_d + \epsilon_{dt}, \tag{2}$$

where $C_{idt} \in \{0, 1\}$ is a dummy variable for a non-resource criminal funding strategy i utilized in dyad d by a rebel group in year t, $R_{dt} \in \{0, 1\}$ is a dummy variable for exploitation of a resource in dyad d in year t, p_{Rt} is the log of the yearly world price of resource R, and α_t and δ_d are year and dyad fixed effects, respectively. The parameter of interest is γ_2, which if negative captures the average substitution effect of a resource's world price on a criminal activity among rebel groups that exploit that resource.[2]

Tables 7 through 15 show the results of estimating equation (2) separately for nine different resources.[3] For each natural resource, all five dependent variables are non-natural-resource crime dummy variables.[4] Upon examining the interaction terms in each table, there is a clear pattern of negative coefficients, suggesting that when the price of the natural resource rises, rebel groups substitute away from these criminal activities. This is true for approximately 75% of all models estimated using the full sample, which suggests that the sign of the sufficient condition from Section 3, $\frac{\partial^2 C}{\partial R \partial A}$, is likely positive.

In terms of interpretation of these results, consider the coefficient on the interaction term of model (1) in Table 7, which finds that a 10% increase in the price of oil is associated with a 1.91% decrease in the likelihood of extortion among rebel groups that exploit oil. The strongest results are for oil, gold, and other "legitimate" goods, which suggests that there may be higher returns to legitimacy, as they can be mixed with their legally-extracted counterparts.

Table 7: Impact of Oil Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft
oil	0.626***	0.207**	0.785***	0.601***	0.360***
	(0.158)	(0.0907)	(0.118)	(0.0929)	(0.101)
oil=1 × log of crudeweighted_price	-0.191***	-0.0211	-0.190***	-0.104***	-0.123***
	(0.0419)	(0.0241)	(0.0314)	(0.0247)	(0.0268)
yearsoperating	0.0108*	0.0245***	-0.0116**	-0.00918**	-0.00732*
	(0.00649)	(0.00373)	(0.00487)	(0.00382)	(0.00415)
# of natural resources	0.0946***	0.00511	0.0224***	0.0108	0.0304***
	(0.0114)	(0.00655)	(0.00854)	(0.00670)	(0.00728)
groupsincountry	0.0182**	0.0142***	0.00322	0.00644	-0.00660
	(0.00740)	(0.00425)	(0.00555)	(0.00435)	(0.00473)
Constant	0.190***	-0.103***	0.133***	0.158***	0.175***
	(0.0542)	(0.0312)	(0.0406)	(0.0319)	(0.0347)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tables B.1 through B.3 explore whether there is sufficient variation in all of these models. They show that there are several yearly extensive margin switches within a rebel group, both in terms of natural resource exploitation and other criminal activities. Put differently, a given rebel group goes from exploiting a given resource to not exploiting it the following year, or vice versa, relatively frequently, and this happens for other criminal activity participation as well.

I re-estimate equation (2) using both lagged prices and resources (Tables B.4 to B.12), only year fixed effects (Tables B.13 to B.21), clustered standard errors (Tables B.22 through B.30), and restricted samples (Tables B.31 to B.39).[5] For the restricted samples, I only consider dyads where a given resource was exploited at least once. The limiting method may not be ideal, but looking only at regions where the resource can be extracted is also troublesome, as one would miss out on resources that are smuggled, trafficked, or extorted along a supply chain. These

[2] Yearly world price is not included as a separate regressor because of the year fixed effect α_t.

[3] These are linear-log specifications with binary dependent and independent variables.

[4] These include *extortion* (the rebel group "taxes" economic activity that occurs in a particular area), *smuggle* (does not include human smuggling/trafficking), *theft* (only large-scale theft), and *kidnap* (the rebel group kidnaps people in exchange for payments, where L captures kidnapping of locals and F of foreigners).

[5] I also considered non-linear models, specifically Probit and Logit ones, but given the binary outcome variable, I ran into a perfect prediction problem.

Table 8: Impact of Gold Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft
gold	1.378***	0.359**	1.591***	0.319*	0.925***
	(0.305)	(0.176)	(0.228)	(0.182)	(0.194)
gold=1 × log of gold_priceperoz	-0.187***	-0.0544**	-0.247***	-0.0447*	-0.147***
	(0.0451)	(0.0260)	(0.0337)	(0.0270)	(0.0288)
yearsoperating	0.0107*	0.0251***	-0.0106**	-0.00865**	-0.00710*
	(0.00649)	(0.00374)	(0.00485)	(0.00389)	(0.00414)
# of natural resources	0.0916***	0.0124*	0.0394***	0.0157**	0.0371***
	(0.0121)	(0.00697)	(0.00903)	(0.00724)	(0.00772)
groupsincountry	0.0188**	0.0151***	0.00580	0.00697	-0.00529
	(0.00742)	(0.00427)	(0.00554)	(0.00444)	(0.00473)
Constant	0.173***	-0.109***	0.104**	0.163***	0.156***
	(0.0547)	(0.0315)	(0.0409)	(0.0328)	(0.0349)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Impact of Coca Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coca	0.839	1.131***	-0.452	0.0463	1.153***
	(0.633)	(0.329)	(0.342)	(0.440)	(0.361)
coca=1 × lcocaineprice_usavgpergm	-0.145	-0.191***	0.0813	0.0206	-0.203***
	(0.123)	(0.0638)	(0.0662)	(0.0853)	(0.0700)
yearsoperating	0.00250	0.0187***	-0.00642	-0.0204***	-0.00495
	(0.00873)	(0.00454)	(0.00472)	(0.00607)	(0.00498)
# of natural resources	0.0840***	-0.00469	0.0188***	0.0270***	0.0342***
	(0.0123)	(0.00640)	(0.00664)	(0.00856)	(0.00702)
groupsincountry	0.0185**	0.0156***	0.00751*	0.00597	-0.00539
	(0.00790)	(0.00411)	(0.00426)	(0.00549)	(0.00451)
Constant	0.244***	-0.0535	0.140***	0.168***	0.135***
	(0.0703)	(0.0366)	(0.0380)	(0.0489)	(0.0401)
Observations	1353	1353	1353	1353	1353

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Impact of Cannabis Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
cannabis	0.816***	0.430***	-0.0937	0.474**	0.221
	(0.275)	(0.144)	(0.149)	(0.191)	(0.157)
cannabis=1 × lmarijuana_usavgpergm	-0.272***	-0.134***	0.0243	-0.101*	-0.0345
	(0.0866)	(0.0453)	(0.0469)	(0.0599)	(0.0495)
yearsoperating	0.000241	0.0189***	-0.00698	-0.0190***	-0.00222
	(0.00875)	(0.00458)	(0.00475)	(0.00606)	(0.00500)
# of natural resources	0.0878***	-0.00432	0.0203***	0.0100	0.0230***
	(0.0136)	(0.00713)	(0.00739)	(0.00943)	(0.00779)
groupsincountry	0.0168**	0.0144***	0.00781*	0.00300	-0.00679
	(0.00792)	(0.00414)	(0.00429)	(0.00548)	(0.00453)
Constant	0.274***	-0.0401	0.141***	0.180***	0.127***
	(0.0697)	(0.0365)	(0.0378)	(0.0482)	(0.0398)
Observations	1353	1353	1353	1353	1353

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Impact of Opium Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
opium	-0.0638	0.569***	-0.390*	-0.539*	0.187
	(0.418)	(0.217)	(0.225)	(0.291)	(0.240)
opium=1 × lheroineprice_usavgpergm	-0.00379	-0.0992***	0.0690**	0.0800*	-0.0303
	(0.0626)	(0.0325)	(0.0337)	(0.0435)	(0.0358)
yearsoperating	0.00245	0.0175***	-0.00511	-0.0192***	-0.00422
	(0.00878)	(0.00456)	(0.00473)	(0.00610)	(0.00503)
# of natural resources	0.0944***	0.00503	0.0126*	0.0311***	0.0372***
	(0.0134)	(0.00698)	(0.00723)	(0.00934)	(0.00770)
groupsincountry	0.0182**	0.0143***	0.00840**	0.00638	-0.00556
	(0.00792)	(0.00411)	(0.00426)	(0.00550)	(0.00454)
Constant	0.256***	-0.0258	0.122***	0.170***	0.138***
	(0.0703)	(0.0365)	(0.0378)	(0.0488)	(0.0403)
Observations	1353	1353	1353	1353	1353

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Impact of Timber Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
timber	0.0899	0.181	-0.345	-0.191	-0.0249
	(0.660)	(0.379)	(0.393)	(0.500)	(0.418)
timber=1 × log of softlogs_priceperm3	0.0104	-0.0424	0.0553	0.0484	0.0411
	(0.128)	(0.0732)	(0.0760)	(0.0968)	(0.0808)
yearsoperating	0.00977	0.0249***	-0.00850**	-0.0119**	-0.00837**
	(0.00653)	(0.00374)	(0.00388)	(0.00495)	(0.00413)
# of natural resources	0.0628***	0.0142*	0.0233***	0.00913	-0.00649
	(0.0137)	(0.00784)	(0.00813)	(0.0104)	(0.00865)
groupsincountry	0.0185**	0.0142***	0.00611	0.00324	-0.00578
	(0.00744)	(0.00427)	(0.00443)	(0.00564)	(0.00471)
Constant	0.215***	-0.101***	0.165***	0.154***	0.197***
	(0.0545)	(0.0313)	(0.0325)	(0.0413)	(0.0345)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Impact of Tea Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
tea	1.895**	0.371	-0.275	0.478	-0.589
	(0.871)	(0.499)	(0.510)	(0.660)	(0.558)
tea=1 × log of tea_pricecentsperkg	-0.369**	-0.0474	0.151	-0.0901	0.102
	(0.162)	(0.0927)	(0.0947)	(0.123)	(0.104)
yearsoperating	0.0113*	0.0237***	-0.0145***	-0.0117**	-0.00747*
	(0.00668)	(0.00383)	(0.00391)	(0.00506)	(0.00428)
# of natural resources	0.0854***	0.00633	0.00631	0.0180**	0.0244***
	(0.0112)	(0.00640)	(0.00653)	(0.00846)	(0.00715)
groupsincountry	0.0172**	0.0141***	0.00562	0.00273	-0.00696
	(0.00745)	(0.00427)	(0.00436)	(0.00564)	(0.00477)
Constant	0.203***	-0.0938***	0.194***	0.151***	0.182***
	(0.0548)	(0.0314)	(0.0320)	(0.0415)	(0.0351)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Impact of Coal Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coal	2.288***	-0.0316	-1.058***	0.235	-0.122
	(0.414)	(0.241)	(0.243)	(0.310)	(0.263)
coal=1 × log of coalZAR_priceperton	-0.591***	-0.0148	0.109**	-0.205***	-0.0984*
	(0.0909)	(0.0529)	(0.0534)	(0.0682)	(0.0578)
yearsoperating	0.0105	0.0250***	-0.00809**	-0.0110**	-0.00722*
	(0.00642)	(0.00374)	(0.00377)	(0.00481)	(0.00408)
# of natural resources	0.0970***	0.0113*	0.0316***	0.0399***	0.0410***
	(0.0114)	(0.00662)	(0.00667)	(0.00852)	(0.00722)
groupsincountry	0.0177**	0.0145***	0.00720*	0.00350	-0.00659
	(0.00732)	(0.00426)	(0.00430)	(0.00549)	(0.00466)
Constant	0.190***	-0.101***	0.160***	0.134***	0.171***
	(0.0536)	(0.0312)	(0.0315)	(0.0402)	(0.0341)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Impact of Coffee Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coffee	0.212	0.138	0.564**	0.841***	0.240
	(0.417)	(0.238)	(0.243)	(0.312)	(0.265)
coffee=1 × log of coffeearabica_priceperlb	-0.0279	-0.0214	-0.0554	-0.124**	-0.0145
	(0.0839)	(0.0480)	(0.0490)	(0.0629)	(0.0534)
yearsoperating	0.0104	0.0250***	-0.00816**	-0.0112**	-0.00752*
	(0.00654)	(0.00374)	(0.00382)	(0.00490)	(0.00416)
# of natural resources	0.0841***	0.00787	0.00625	0.0149*	0.0185**
	(0.0115)	(0.00659)	(0.00672)	(0.00864)	(0.00733)
groupsincountry	0.0173**	0.0144***	0.00600	0.00240	-0.00750
	(0.00746)	(0.00427)	(0.00435)	(0.00559)	(0.00474)
Constant	0.202***	-0.101***	0.163***	0.141***	0.181***
	(0.0547)	(0.0313)	(0.0319)	(0.0410)	(0.0348)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

re-estimation results are generally consistent with the main specification results.

5.1.1 Conflict

Similar to the previous estimating equation, (2), I examine the impact of price changes on conflict separately for each resource with

$$BD_{dt} = \beta_0 + \beta_1 R_{dt} + \beta_2 (p_{Rt} \times R_{dt}) + \alpha_t + \delta_d + \nu_{dt}, \tag{3}$$

where BD_{dt} is the number of battle deaths in a dyad d in year t and the remaining variables are identical to those found in (2). The parameter of interest is β_2, which captures the average effect of world prices on the amount of battle deaths among those rebel groups that exploit a given resource. Results for estimating equation (3) are in Tables B.41 and B.42. While most of the coefficients on the interaction terms are insignificant, conflict generally increases when the value of resources whose production is capital-intensive increases (state-as-prize effect), while it decreases for those that are labor-intensive (opportunity cost effect).

5.2 Testing the Incentives to Maintain Civilian Support

In order to examine whether the initial conditions of a given rebel group (i.e., whether they exploit natural resources) influence the incentives to restrain behavior that would lose civilian support, I use the following estimating equation

$$childsoldiers_{dt} = \zeta_0 + \zeta_1 N_{dt} + \mathbf{X}'_{dt} \mathbf{\Phi} + \mu_{dt}, \tag{4}$$

where $childsoldiers_{dt}$ defines the forcible recruitment of child soldiers in dyad d in year t using either an ordinal measure or a dummy variable, $N_{dt} \in \{0, 1\}$ is a dummy variable for exploitation of any resource in dyad d in year t, and $\mathbf{X}_{dt}$ is a vector of control variables.

The results of estimating equation (4) are in Tables 16 and 17. Columns 1 through 3 of Table 16 show that when a rebel group exploits natural resources, they are more likely to forcibly recruit children, which is consistent with Weinstein's (2007) model predictions and the results found in Haer el al. (2019). However, when dyad fixed effects are added (models 4 through 6 of Table 16), the signs switch. This finding fits well within the theoretical framework presented in Section 3, where the recruitment of child soldiers may be costly both financially and in terms of angering the non-combatants. Thus, when resources are exploited more, rebel groups want to substitute away from such activities. Another interpretation is that as local economic conditions within a dyad improve through resource exploitation, rebel groups are less likely to forcibly recruit children; this may be due to the fact that certain types of natural resource exploitation require a more sophisticated or skilled membership.

To further investigate this finding, I split natural resources into "lootable" and "non-lootable" in Table 17. Here, Columns 4 through 6 show us that the results in Table 16 are mainly driven by lootable resources. One possible explanation is that lootable resources have more sophisticated supply chains than non-lootable resources and thus require decision-making ability that children are not fit for. However, this could again be due to the relatively higher social costs of lootable resources, which include illicit drugs.

Table 16: Predictors of forced recruitment of children by rebel groups

	(1) forceindex	(2) anychild	(3) forcechild	(4) forceindex	(5) anychild	(6) forcechild
natural resource exploitation dummy	0.402***	0.112***	0.289***	-0.0404**	-0.0271***	-0.0133
	(0.0444)	(0.0258)	(0.0278)	(0.0189)	(0.00723)	(0.0160)
foreign support	-0.0432	-0.0774***	0.0342	0.0449	-0.0479***	0.0928***
	(0.0452)	(0.0263)	(0.0283)	(0.0361)	(0.0139)	(0.0307)
duration	0.0178***	0.00337**	0.0144***	0.0142***	0.0109***	0.00329*
	(0.00255)	(0.00148)	(0.00160)	(0.00204)	(0.000781)	(0.00173)
central control	0.00879	-0.0114	0.0202	-0.0324	0.0288***	-0.0612**
	(0.0240)	(0.0140)	(0.0150)	(0.0287)	(0.0110)	(0.0244)
democracy score	0.000411	-0.00715***	0.00756***	0.00460**	0.000243	0.00435**
	(0.00423)	(0.00246)	(0.00265)	(0.00205)	(0.000785)	(0.00174)
log of battle related deaths	0.0938***	0.0331***	0.0607***	0.00541	0.00246	0.00295
	(0.0146)	(0.00849)	(0.00913)	(0.00396)	(0.00152)	(0.00336)
log of GDP per capita	-0.124***	-0.0778***	-0.0459**	0.00596	-0.0207**	0.0267
	(0.0327)	(0.0190)	(0.0204)	(0.0247)	(0.00948)	(0.0210)
log of youth population	0.406***	-0.146*	0.553***	0.0504	0.0119	0.0385
	(0.137)	(0.0794)	(0.0854)	(0.137)	(0.0524)	(0.116)
political wing	0.0878*	0.0798***	0.00802	-0.0624	-0.00195	-0.0605
	(0.0448)	(0.0261)	(0.0280)	(0.0516)	(0.0198)	(0.0438)
forced recruitment by govt	0.363***	0.243***	0.120***	-0.155***	-0.0882***	-0.0664*
	(0.0465)	(0.0271)	(0.0291)	(0.0423)	(0.0162)	(0.0359)
Constant	-0.846	1.043**	-1.889***	0.455	0.244	0.210
	(0.709)	(0.413)	(0.444)	(0.597)	(0.229)	(0.507)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dyad FE	No	No	No	Yes	Yes	Yes
Observations	1002	1002	1002	928	928	928

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: *forceindex* is an ordinal measure equal to 0 if there was no forced recruitment of children, 1 if there was less than 20% of the child soldiers were forcibly recruited, and 2 if greater than 20% were. *anychild* is a dummy equal to one if *forceindex* equals 1 or 2 and *forcechild* equals one if *forceindex* equals 2.

Table 17: The impact of "lootability" on forcible recruitment of children

	(1) forceindex	(2) anychild	(3) forcechild	(4) forceindex	(5) anychild	(6) forcechild
lootable	-0.0311	-0.000688	-0.0304	-0.0474***	-0.0306***	-0.0168***
	(0.0535)	(0.0335)	(0.0323)	(0.0129)	(0.00891)	(0.00520)
foreign support	-0.0343	-0.132***	0.0980***	0.0492	-0.0597***	0.109***
	(0.0544)	(0.0341)	(0.0328)	(0.0307)	(0.0212)	(0.0124)
duration	0.0158***	0.00368**	0.0122***	0.0194***	0.0117***	0.00767***
	(0.00292)	(0.00183)	(0.00176)	(0.00158)	(0.00109)	(0.000637)
central control	-0.0878***	-0.119***	0.0311	0.00321	0.0385*	-0.0353***
	(0.0330)	(0.0207)	(0.0199)	(0.0328)	(0.0227)	(0.0132)
democracy score	-0.00622	-0.0182***	0.0120***	0.000824	0.000451	0.000373
	(0.00550)	(0.00345)	(0.00332)	(0.00193)	(0.00134)	(0.000779)
log of battle related deaths	0.0847***	0.0352***	0.0495***	0.00674*	0.00483*	0.00191
	(0.0203)	(0.0127)	(0.0123)	(0.00398)	(0.00275)	(0.00161)
log of GDP per capita	-0.191***	-0.0919***	-0.0987***	-0.0315	-0.0222	-0.00931
	(0.0415)	(0.0260)	(0.0250)	(0.0205)	(0.0142)	(0.00827)
log of youth population	0.127	-0.378***	0.505***	0.335***	0.0383	0.296***
	(0.172)	(0.107)	(0.103)	(0.122)	(0.0846)	(0.0494)
political wing	0.199***	0.187***	0.0124	0.0794	-0.0102	0.0896***
	(0.0582)	(0.0365)	(0.0351)	(0.0605)	(0.0418)	(0.0244)
forced recruitment by govt	0.596***	0.435***	0.161***	-0.0974*	-0.0959***	-0.00158
	(0.0611)	(0.0383)	(0.0368)	(0.0531)	(0.0367)	(0.0214)
Constant	1.178	2.221***	-1.042*	-0.216	0.166	-0.382*
	(0.885)	(0.554)	(0.533)	(0.538)	(0.372)	(0.217)
Observations	605	605	605	590	590	590

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This sample is limited to dyads where natural resources were exploited at least once. The lootable resources include diamonds (alluvial), gems, opium, cannabis, coca, drugs (other), and gold.

6 Conclusion

While countries plagued by the resource curse in the 1990s spawned a large literature examining the relationship between natural resources and conflict, it has become clearer that the analysis was often at too aggregate a level. Resources are unevenly distributed spatially within a country and conflict is generally quite localized. Rebel groups often participate in resource exploitation and conflict, as well as operate similar to a local government or firm, and thus they are an ideal candidate for studying the dynamics between natural resources and criminal activity.

The decision-making processes of these groups, however, have remained under-studied. Therefore, I present a rebel-group theory of the firm in order to provide some insight into how or why they pursue certain strategies. The model highlights the importance of relative illicit activity costs in substitution behavior, and I find empirically that rebel groups consistently substitute away from criminal activities when the world price of the natural resource they exploit rises. I also find that a given rebel group that exploits a natural resource is less likely to forcibly recruit child soldiers over time. These results suggest that rebel groups seek to maximize organizational profit but consider the interactions between illicit activities, their social costs, and the returns to legitimacy. However, they are only suggestive, and thus improvements in data and identification are needed. Nevertheless, this paper provides a framework for thinking about how rebel groups make decisions, which is helpful if we are to properly tackle rebel group violence, improve our policy-targeting, and address post-war conflict management.

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A Stylized Model: Rebel Groups and their Endowments

A rebel group's endowments influence the potential strategies that its leaders can implement. Those with access to economic or financial resources, often via natural resource exploitation, can use their endowments to provide incentives and recruit individuals, while resource-constrained ones must develop alternative strategies, often through appeals to religion, ethnicity, culture, or ideology. Weinstein (2007) thus defines two types of rebellion, activist ones and those that are opportunistic. Activist rebellions usually rely on citizenry for food, shelter, and protection; rebel participation is risky and short term gains are unlikely. Leaders of these rebellions maintain internal discipline by making use of norms and networks, which allow them to decentralize power and reach agreements with noncombatants. On the other hand, opportunistic rebellions often rely on resource endowments and outside funding. Their recruits face fewer risks and expect to be rewarded immediately. Therefore, their pool of recruits can be more transient or self-interested, and leaders generally permit indiscipline in order to maintain their membership (Weinstein, 2007).

Most rebel groups are not solely one type or the other, and thus a given group solves the following optimization problem,

$$\max_{G,\Pi} U = U(G(E, L_G), \Pi) \text{ subject to} \tag{5}$$

$$L = L_G + L_\Pi, \tag{6}$$

$$\Pi := \mathbf{pQ}(L_\Pi^*) - C(L_\Pi^*), \tag{7}$$

$$(\mathbf{Q}^*, L_\Pi^*) \equiv \arg\max_{\mathbf{Q}, L_\Pi} \mathbf{pQ}(L_\Pi) - C(L_\Pi) \text{ and } E \sim f_E(e),$$

where $G(\cdot)$ captures the degree to which a rebel group achieves its ideological goals, E is drawn from a distribution $f_E(e)$ and captures both economic and social endowments, such as access to oil due to geography and networks stemming from shared ethnicity, L is the total labor endowment, L_G is the labor spent on achieving ideological goals, L_Π is the labor spent on profit-driven activities, Π is the solution to the profit-maximization problem, $\mathbf{p}$ is a vector of output prices, $\mathbf{Q}$ is a production function that converts a vector of exploited natural resources and criminal activities that a rebel group participates in, along with L_Π, to output that can be sold, and $C(L_\Pi)$ is the associated cost function.

Similar to the labor-leisure tradeoff in a household model of production, constraint (6) captures the tradeoff between labor spent accumulating profit, such as extorting foreign oil producers or mining gold, and labor spent achieving the rebel group's ideological objective, such as overthrowing the government. Note that while utility is increasing in both G and Π, there is likely a tradeoff between G and Π; Figure A.1 shows this tradeoff graphically. The stems from the fact that an opportunistic rebellion, for example, may have to sacrifice fully achieving their initial ideological goal in order to fund or maintain their membership.[6]

With equations (5) through (7) in mind, it can be seen that the initial goal of a given rebel group may change over time, possibly due to an resource endowment price shock or a change in

[6] Mathematically, this is because $\frac{\partial G}{\partial L_G}, \frac{\partial \Pi}{\partial L_\Pi} > 0$, but $\frac{\partial L_G}{\partial L_\Pi} < 0$ and thus $\frac{\partial \Pi}{\partial L_G} < 0$. This can also be seen directly from the fact that $\Pi(L_\Pi) \equiv \Pi(L - L_G)$.

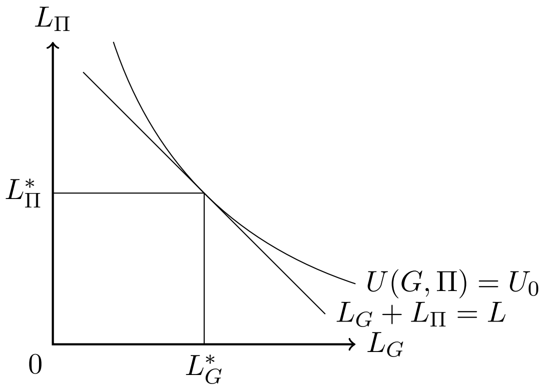

Figure A.1: Utility maximization for a given rebel group

membership composition. Peru's Sendero Luminoso (the Shining Path) is a suggestive example, as their initial objective was to overthrow the state by using guerrilla warfare and inducing a cultural revolution; certain factions then transitioned into large-scale drug trafficking. In order to motivate the study of changing objectives, I begin by discussing an asset-based approach to poverty traps by Carter and Barrett (2006). The authors consider a scenario where a household can allocate its productive assets or wealth to two different productive activities, L_1 and L_2. Both exhibit diminishing returns to wealth, but activity L_2 generates no return if the wealth dedicated to it is below a minimum asset level, A_S. Figure A.2 graphs these two production technologies; it also includes the steady state asset values a household would choose if it were restricted to only one activity.

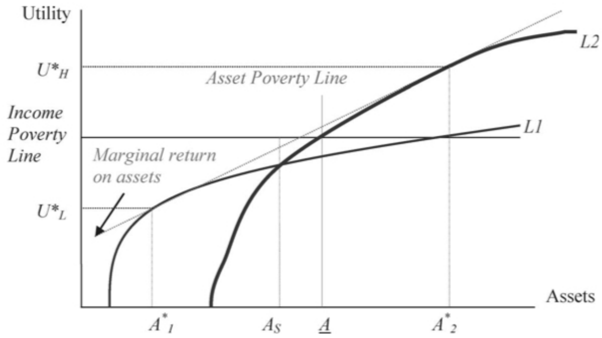

Figure A.2: Asset poverty with multiple livelihood options (Carter and Barrett [2006])

Figure A.3 is similar to Figure A.2 but from a rebel group decision-making perspective. In this scenario, productive activity L_1 is an ideologically-focused labor-sharing regime, while L_2 is one more focused on profit-driven production. Activity L_2 has a minimum scale of operation, possibly due to sunk costs of operation or switching to L_2 or due to composition and total number of recruits. Put differently, a high return production process or labor-sharing regime may require a minimum operation size such that only higher-profit rebel groups can afford to switch to and adopt it. An alternative explanation is that lower-wealth rebel groups allocate their assets and labor so as to minimize their risk exposure; they trade off expected gains for lower risk and thus the expected marginal returns to wealth are lower for them.

Assuming that there are no limitations to the adoption of either labor-sharing regime, Figure

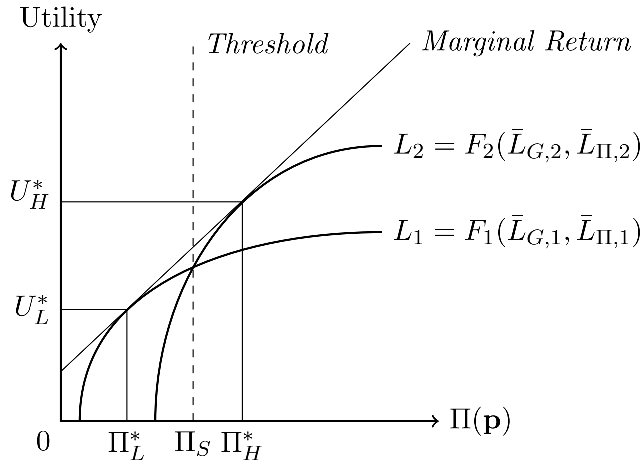

Figure A.3: The dynamics of different labor-sharing regimes

Notes: For a given rebel group, the value Π_L^* denotes the steady state value for a group restricted to activity or labor-sharing regime L_1, yielding income or material well-being level U_L^*; this is analogous for L_2, Π_H^*, and U_H^*. $F_1(\cdot), F_2(\cdot)$ are functions or fixed allocations of L_G and L_Π in the labor-sharing regimes of L_1 and L_2, respectively. Note that regime L_1 has a higher share of L_G than regime L_2, i.e., $\bar{L}_{G,1} > \bar{L}_{G,2} \iff \bar{L}_{\Pi,1} < \bar{L}_{\Pi,2}$.

A.3 shows that the optimal choice for rebel groups with profit stocks up to Π_S is regime L_1; for those with stocks in excess of Π_S, the optimal choice is L_2. Although each of these regimes exhibits diminishing returns, there are locally increasing returns in the neighborhood of Π_S, the threshold at which a rebel group optimally switches from L_1 to L_2.

B Tables

B.1 Tests for Sufficient Variation

Table B.1: R^2 of regressing the resource dummy (R_d^2), then the resource count variable (R_c^2), on year and dyad fixed effects

	Opium	Cannabis	Timber	Coca	Oil	Gold	Tea	Diamonds	Coffee	Charcoal	Coal
$R^2_{d,dyad}$	0.9037	0.8435	0.8167	0.9734	0.9360	0.8934	0.9635	0.9158	0.8499	0.9171	0.9068
$R^2_{c,dyad}$	0.9104	0.8864	0.8469	0.9897	0.9380	0.8896	0.9635	0.8962	0.8390	0.8863	0.8978

Table B.2: Persistence of Resource Exploitation

		Frequency	Percent
changeoil			
	0	136	83.95
	1	26	16.05
Total		162	100
changeopium			
	0	235	66.76
	1	117	33.24
Total		352	100
changecoca			
	0	129	90.21
	1	14	9.79
Total		143	100
changecannabis			
	0	166	61.25
	1	105	38.75
Total		271	100
changegold			
	0	93	54.39
	1	78	45.61
Total		171	100

		Frequency	Percent
changetimber			
	0	137	50.55
	1	134	49.45
Total		271	100
changetea			
	0	70	74.47
	1	24	25.53
Total		94	100
changecoal			
	0	43	62.32
	1	26	37.68
Total		69	100
changecoffee			
	0	25	27.47
	1	66	72.53
Total		91	100

Note: This table represents switches of going from exploitation of given natural resource within a dyad in one year to not exploiting it the following year, or vice versa, amongst dyads where the resource was exploited at least once. When the dummy variable change*resource* equals one, a switch in exploitation occurred from one year to the next and thus a zero means no changes occurred.

Table B.3: Persistence of Criminal Activities

changeextortion	Frequency	Percent
0	523	61.75
1	324	38.25
Total	847	100
changesmuggle		
0	189	64.29
1	105	35.71
Total	294	100
changekidnap_F		
0	90	34.88
1	168	65.12
Total	258	100
changekidnap_L		
0	219	64.22
1	122	35.78
Total	341	100

changetheft	Frequency	Percent
0	136	45.79
1	161	54.21
Total	297	100
changehumantraf		
0	33	34.02
1	64	65.98
Total	97	100
changeaid		
0	69	92
1	6	8
Total	75	100

Note: This table represents switches of going from participating in a criminal activity within a dyad in one year to not participating in it the following year, or vice versa, amongst dyads where we observe the criminal activity at least once. When the dummy variable change*crime* equals one, a switch in participation occurred from one year to the next and thus a zero means no changes occurred.

B.2 Substitution Results: OLS with Dyad and Year Fixed Effects with Lagged Prices and Resources

Table B.4: Impact of Oil Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft
lagoil	0.516***	0.170*	0.544***	0.387***	0.347***
	(0.169)	(0.0948)	(0.124)	(0.0984)	(0.101)
lagoil=1 × lagoilprice	-0.208***	-0.0493**	-0.193***	-0.103***	-0.127***
	(0.0421)	(0.0235)	(0.0309)	(0.0244)	(0.0251)
yearsoperating	0.00463	0.0231***	-0.00960*	-0.00946**	-0.0108**
	(0.00744)	(0.00416)	(0.00545)	(0.00432)	(0.00444)
# of natural resources	0.109***	0.00693	0.0166*	0.00997	0.0395***
	(0.0124)	(0.00694)	(0.00910)	(0.00721)	(0.00741)
groupsincountry	0.0220***	0.0120**	0.00714	0.00148	-0.00955*
	(0.00843)	(0.00472)	(0.00618)	(0.00490)	(0.00503)
Constant	0.223***	-0.0957**	0.156***	0.213***	0.208***
	(0.0715)	(0.0400)	(0.0525)	(0.0415)	(0.0427)
Observations	1219	1219	1219	1219	1219

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: Impact of Gold Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft
laggold	2.188***	0.240	1.721***	0.487**	1.445***
	(0.325)	(0.186)	(0.241)	(0.193)	(0.196)
laggold=1 × laggoldprice	-0.301***	-0.0426	-0.258***	-0.0646**	-0.214***
	(0.0476)	(0.0273)	(0.0353)	(0.0283)	(0.0287)
yearsoperating	0.00911	0.0223***	-0.00608	-0.00824*	-0.00728
	(0.00741)	(0.00424)	(0.00549)	(0.00440)	(0.00446)
# of natural resources	0.121***	0.00914	0.0300***	0.0101	0.0542***
	(0.0132)	(0.00758)	(0.00980)	(0.00786)	(0.00797)
groupsincountry	0.0221***	0.0124***	0.00830	0.00150	-0.00759
	(0.00822)	(0.00471)	(0.00609)	(0.00488)	(0.00495)
Constant	0.125*	-0.0932**	0.0868	0.197***	0.138***
	(0.0711)	(0.0408)	(0.0527)	(0.0423)	(0.0429)
Observations	1225	1225	1225	1225	1225

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: Impact of Coca Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
lagcoca	0.552	0.870**	-0.632	0.00433	1.192***
	(0.759)	(0.376)	(0.386)	(0.516)	(0.390)
lagcoca=1 × lagcocaineprice	-0.127	-0.171**	0.118	-0.00835	-0.248***
	(0.147)	(0.0730)	(0.0750)	(0.100)	(0.0756)
yearsoperating	-0.00125	0.0155***	-0.00463	-0.0151**	-0.00511
	(0.0102)	(0.00503)	(0.00517)	(0.00691)	(0.00522)
# of natural resources	0.100***	-0.00611	0.0151**	0.0219**	0.0523***
	(0.0135)	(0.00671)	(0.00690)	(0.00921)	(0.00696)
groupsincountry	0.0225**	0.0136***	0.00222	0.0104*	-0.00846*
	(0.00887)	(0.00440)	(0.00452)	(0.00603)	(0.00456)
Constant	0.265***	-0.0182	0.161***	0.169***	0.142***
	(0.0929)	(0.0461)	(0.0474)	(0.0632)	(0.0477)
Observations	1105	1105	1105	1105	1105

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: Impact of Cannabis Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
lagcannabis	0.744**	0.510***	-0.164	0.357*	0.212
	(0.297)	(0.146)	(0.146)	(0.201)	(0.153)
lagcannabis=1 × lagmarijuanaprice	-0.234**	-0.156***	0.0347	-0.0834	-0.0401
	(0.0935)	(0.0462)	(0.0460)	(0.0632)	(0.0483)
yearsoperating	-0.00389	0.0182***	-0.00645	-0.0238***	-0.00358
	(0.0118)	(0.00584)	(0.00581)	(0.00800)	(0.00611)
# of natural resources	0.0954***	-0.00876	0.0198***	0.00982	0.0434***
	(0.0146)	(0.00721)	(0.00718)	(0.00987)	(0.00754)
groupsincountry	0.0217**	0.0124***	0.00115	0.00854	-0.00902**
	(0.00881)	(0.00435)	(0.00433)	(0.00596)	(0.00455)
Constant	0.286***	-0.0379	0.177***	0.242***	0.119**
	(0.105)	(0.0517)	(0.0515)	(0.0708)	(0.0541)
Observations	1111	1111	1111	1111	1111

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.8: Impact of Opium Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
lagopium	-0.310	0.905***	-0.0774	-0.366	0.208
	(0.489)	(0.241)	(0.250)	(0.331)	(0.254)
lagopium=1 × lagheroinprice	0.0335	-0.144***	0.0165	0.0607	-0.0311
	(0.0741)	(0.0366)	(0.0379)	(0.0501)	(0.0385)
yearsoperating	-0.000934	0.0132***	-0.00453	-0.0129*	-0.00462
	(0.0101)	(0.00498)	(0.00516)	(0.00684)	(0.00524)
# of natural resources	0.102***	-0.00424	0.0119*	0.0179*	0.0530***
	(0.0140)	(0.00690)	(0.00715)	(0.00947)	(0.00726)
groupsincountry	0.0246***	0.0125***	0.00213	0.0115*	-0.00847*
	(0.00881)	(0.00435)	(0.00450)	(0.00596)	(0.00457)
Constant	0.263***	0.00634	0.157***	0.142**	0.127***
	(0.0916)	(0.0452)	(0.0468)	(0.0620)	(0.0475)
Observations	1107	1107	1107	1107	1107

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.9: Impact of Timber Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
lagtimber	0.354	0.213	-0.379	-0.119	0.478
	(0.778)	(0.436)	(0.456)	(0.576)	(0.458)
lagtimber=1 × lagtimberprice	-0.0477	-0.0489	0.0711	0.0441	-0.0591
	(0.150)	(0.0842)	(0.0880)	(0.111)	(0.0885)
yearsoperating	0.0102	0.0243***	-0.00837*	-0.00636	-0.00730*
	(0.00742)	(0.00415)	(0.00435)	(0.00549)	(0.00437)
# of natural resources	0.0786***	0.00972	0.00867	-0.00403	0.00673
	(0.0142)	(0.00795)	(0.00831)	(0.0105)	(0.00836)
groupsincountry	0.0211**	0.0117**	0.000645	0.00690	-0.00798
	(0.00837)	(0.00469)	(0.00490)	(0.00620)	(0.00493)
Constant	0.188***	-0.105***	0.209***	0.131**	0.187***
	(0.0703)	(0.0394)	(0.0412)	(0.0521)	(0.0414)
Observations	1221	1221	1221	1221	1221

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.10: Impact of Tea Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
lagtea	1.689*	0.472	-0.266	0.459	-0.658
	(0.919)	(0.514)	(0.528)	(0.685)	(0.552)
lagtea=1 × lagteaprice	-0.339**	-0.0972	0.145	-0.0910	0.126
	(0.169)	(0.0942)	(0.0969)	(0.126)	(0.101)
yearsoperating	0.00858	0.0249***	-0.00770*	-0.00632	-0.00730
	(0.00766)	(0.00428)	(0.00440)	(0.00570)	(0.00460)
# of natural resources	0.0968***	0.00432	0.00616	0.00776	0.0331***
	(0.0122)	(0.00683)	(0.00703)	(0.00911)	(0.00734)
groupsincountry	0.0205**	0.0120**	-0.000111	0.00776	-0.00790
	(0.00844)	(0.00472)	(0.00485)	(0.00628)	(0.00507)
Constant	0.201***	-0.105**	0.175***	0.129**	0.173***
	(0.0731)	(0.0408)	(0.0420)	(0.0544)	(0.0438)
Observations	1223	1223	1223	1223	1223

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: Impact of Coal Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
lagcoal	2.403***	-0.00716	-1.184***	0.207	-0.242
	(0.428)	(0.239)	(0.240)	(0.312)	(0.252)
lagcoal=1 × lagcoalprice	-0.619***	-0.0167	0.125**	-0.209***	-0.0972*
	(0.0940)	(0.0526)	(0.0528)	(0.0687)	(0.0554)
yearsoperating	0.00902	0.0243***	-0.00759*	-0.00588	-0.00814*
	(0.00727)	(0.00407)	(0.00408)	(0.00531)	(0.00429)
# of natural resources	0.109***	0.00753	0.0250***	0.0299***	0.0545***
	(0.0126)	(0.00708)	(0.00710)	(0.00923)	(0.00745)
groupsincountry	0.0211**	0.0101**	0.00151	0.00756	-0.00900*
	(0.00841)	(0.00471)	(0.00472)	(0.00614)	(0.00496)
Constant	0.172**	-0.0969**	0.200***	0.113**	0.176***
	(0.0690)	(0.0386)	(0.0387)	(0.0504)	(0.0407)
Observations	1219	1219	1219	1219	1219

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.12: Impact of Coffee Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
lagcoffee	0.721	0.104	0.728***	0.812**	0.765***
	(0.450)	(0.249)	(0.259)	(0.334)	(0.268)
lagcoffee=1 × lagcoffeeprice	-0.119	-0.0235	-0.112**	-0.124*	-0.114**
	(0.0896)	(0.0497)	(0.0517)	(0.0667)	(0.0534)
yearsoperating	0.00878	0.0239***	-0.00800*	-0.00635	-0.00844*
	(0.00741)	(0.00411)	(0.00427)	(0.00551)	(0.00442)
# of natural resources	0.103***	0.00572	0.00618	0.00928	0.0336***
	(0.0130)	(0.00722)	(0.00750)	(0.00968)	(0.00775)
groupsincountry	0.0212**	0.0116**	0.000291	0.00700	-0.0101**
	(0.00848)	(0.00470)	(0.00489)	(0.00631)	(0.00505)
Constant	0.174**	-0.0984**	0.198***	0.117**	0.176***
	(0.0706)	(0.0392)	(0.0407)	(0.0525)	(0.0421)
Observations	1221	1221	1221	1221	1221

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.3 Substitution Results: OLS with Year Fixed Effects

Table B.13: Impact of Oil Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft
oil	-0.151	0.665***	0.561***	0.309**	0.303**
	(0.215)	(0.165)	(0.129)	(0.138)	(0.145)
oil=1 × log of crudeweighted_price	0.0640	-0.182***	-0.0768**	0.0669*	0.0137
	(0.0606)	(0.0464)	(0.0363)	(0.0389)	(0.0409)
yearsoperating	0.000384	0.00211	0.00122	-0.00969***	-0.00944***
	(0.00216)	(0.00165)	(0.00129)	(0.00139)	(0.00146)
# of natural resources	0.101***	0.0232***	0.0187***	0.0431***	0.0491***
	(0.00680)	(0.00521)	(0.00407)	(0.00437)	(0.00459)
groupsincountry	0.0446***	0.0114***	-0.0131***	0.0253***	-0.00874***
	(0.00469)	(0.00359)	(0.00281)	(0.00301)	(0.00316)
Constant	0.153***	0.0556***	0.0776***	0.0316**	0.134***
	(0.0233)	(0.0179)	(0.0140)	(0.0150)	(0.0157)
Observations	1612	1612	1612	1612	1612

Standard errors in parentheses
Year fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.14: Impact of Gold Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft
gold	0.876**	0.567*	2.084***	1.021***	1.337***
	(0.419)	(0.323)	(0.255)	(0.299)	(0.294)
gold=1 × log of gold_priceperoz	-0.164**	-0.0855*	-0.300***	-0.151***	-0.209***
	(0.0657)	(0.0507)	(0.0399)	(0.0468)	(0.0461)
yearsoperating	0.00132	0.00202	0.00260**	-0.00838***	-0.00819***
	(0.00217)	(0.00167)	(0.00132)	(0.00154)	(0.00152)
# of natural resources	0.120***	0.0223***	0.0197***	0.0695***	0.0685***
	(0.00782)	(0.00603)	(0.00475)	(0.00557)	(0.00548)
groupsincountry	0.0444***	0.0118***	-0.0128***	0.0256***	-0.00856***
	(0.00467)	(0.00360)	(0.00284)	(0.00333)	(0.00328)
Constant	0.143***	0.0565***	0.0756***	0.0287*	0.129***
	(0.0233)	(0.0180)	(0.0142)	(0.0166)	(0.0164)
Observations	1612	1612	1612	1612	1612

Standard errors in parentheses
Year fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.15: Impact of Coca Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coca	1.596	2.586***	-1.294	1.308**	2.487***
	(1.140)	(0.858)	(0.799)	(0.666)	(0.803)
coca=1 × lcocaineprice_usavgpergm	-0.246	-0.439***	0.284*	-0.191	-0.437***
	(0.219)	(0.165)	(0.154)	(0.128)	(0.154)
yearsoperating	-0.00228	-0.00254	-0.00929***	-0.00185	-0.0122***
	(0.00256)	(0.00193)	(0.00179)	(0.00149)	(0.00180)
# of natural resources	0.0844***	0.00572	0.0651***	0.0192***	0.0590***
	(0.00709)	(0.00534)	(0.00497)	(0.00414)	(0.00500)
groupsincountry	0.0509***	0.0195***	0.0292***	-0.00545*	-0.00317
	(0.00477)	(0.00359)	(0.00334)	(0.00278)	(0.00336)
Constant	0.139***	0.0538***	0.0102	0.0648***	0.133***
	(0.0246)	(0.0185)	(0.0172)	(0.0144)	(0.0173)
Observations	1450	1450	1450	1450	1450

Standard errors in parentheses
Year fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.16: Impact of Cannabis Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
cannabis	0.668	0.0555	0.126	0.558*	-0.00541
	(0.480)	(0.370)	(0.338)	(0.291)	(0.341)
cannabis=1 × lmarijuana_usavgpergm	-0.131	-0.00729	-0.0620	-0.156*	-0.0302
	(0.151)	(0.117)	(0.107)	(0.0920)	(0.108)
yearsoperating	-0.000908	0.00122	-0.00696***	0.00125	-0.00823***
	(0.00253)	(0.00195)	(0.00179)	(0.00154)	(0.00180)
# of natural resources	0.0762***	0.0207***	0.0835***	0.0314***	0.0830***
	(0.00790)	(0.00610)	(0.00557)	(0.00480)	(0.00563)
groupsincountry	0.0429***	0.0135***	0.0266***	-0.0118***	-0.00648*
	(0.00471)	(0.00364)	(0.00333)	(0.00286)	(0.00336)
Constant	0.157***	0.0519***	0.00569	0.0679***	0.121***
	(0.0249)	(0.0192)	(0.0175)	(0.0151)	(0.0177)
Observations	1450	1450	1450	1450	1450

Standard errors in parentheses
Year fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.17: Impact of Opium Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
opium	-1.477**	-0.480	1.277***	0.116	-0.167
	(0.603)	(0.458)	(0.419)	(0.363)	(0.426)
opium=1 × lheroineprice_usavgpergm	0.229**	0.0875	-0.205***	-0.0232	0.0235
	(0.0922)	(0.0700)	(0.0641)	(0.0556)	(0.0652)
yearsoperating	0.00216	0.00106	-0.00758***	0.00231	-0.00900***
	(0.00254)	(0.00193)	(0.00177)	(0.00153)	(0.00180)
# of natural resources	0.104***	0.0181***	0.0795***	0.0410***	0.0733***
	(0.00699)	(0.00531)	(0.00486)	(0.00421)	(0.00494)
groupsincountry	0.0441***	0.0138***	0.0265***	-0.0115***	-0.00750**
	(0.00477)	(0.00362)	(0.00331)	(0.00287)	(0.00337)
Constant	0.133***	0.0437**	0.0155	0.0638***	0.130***
	(0.0250)	(0.0189)	(0.0173)	(0.0150)	(0.0176)
Observations	1450	1450	1450	1450	1450

Standard errors in parentheses
Year fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.18: Impact of Timber Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
timber	-0.405	1.277	-0.615	-0.800	-2.200***
	(1.151)	(0.883)	(0.816)	(0.709)	(0.811)
timber=1 × log of softlogs_priceperm3	0.0403	-0.279	0.0858	0.121	0.411***
	(0.223)	(0.171)	(0.158)	(0.137)	(0.157)
yearsoperating	0.00156	0.00243	-0.00823***	0.00209	-0.00873***
	(0.00215)	(0.00165)	(0.00152)	(0.00132)	(0.00151)
# of natural resources	0.120***	0.0370***	0.0886***	0.0495***	0.0763***
	(0.00694)	(0.00532)	(0.00492)	(0.00427)	(0.00489)
groupsincountry	0.0471***	0.0142***	0.0279***	-0.0104***	-0.00766**
	(0.00469)	(0.00359)	(0.00332)	(0.00289)	(0.00330)
Constant	0.143***	0.0498***	0.0229	0.0706***	0.131***
	(0.0232)	(0.0178)	(0.0165)	(0.0143)	(0.0164)
Observations	1612	1612	1612	1612	1612

Standard errors in parentheses
Year fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.19: Impact of Tea Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
tea	1.200	0.243	1.246	0.710	-0.542
	(1.521)	(1.172)	(1.076)	(0.946)	(1.069)
tea=1 × log of tea_pricecentsperkg	-0.192	-0.0417	-0.193	-0.148	0.0827
	(0.282)	(0.218)	(0.200)	(0.176)	(0.199)
yearsoperating	0.000953	0.00169	-0.00865***	0.00114	-0.00930***
	(0.00215)	(0.00166)	(0.00152)	(0.00134)	(0.00151)
# of natural resources	0.102***	0.0241***	0.0711***	0.0372***	0.0715***
	(0.00636)	(0.00490)	(0.00450)	(0.00395)	(0.00447)
groupsincountry	0.0372***	0.0110***	0.0166***	-0.00894***	-0.00415
	(0.00526)	(0.00405)	(0.00372)	(0.00327)	(0.00370)
Constant	0.168***	0.0599***	0.0502***	0.0711***	0.126***
	(0.0238)	(0.0183)	(0.0168)	(0.0148)	(0.0167)
Observations	1612	1612	1612	1612	1612

Standard errors in parentheses
Year fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.20: Impact of Coal Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coal	1.867***	0.167	1.829***	3.046***	1.891***
	(0.556)	(0.424)	(0.384)	(0.334)	(0.382)
coal=1 × log of coalZAR_priceperton	-0.456***	-0.117	-0.337***	-0.688***	-0.372***
	(0.138)	(0.105)	(0.0951)	(0.0829)	(0.0945)
yearsoperating	0.000495	0.00160	-0.00912***	0.00108	-0.00919***
	(0.00215)	(0.00164)	(0.00149)	(0.00129)	(0.00148)
# of natural resources	0.105***	0.0354***	0.0597***	0.0285***	0.0573***
	(0.00675)	(0.00515)	(0.00466)	(0.00406)	(0.00463)
groupsincountry	0.0453***	0.0124***	0.0258***	-0.0118***	-0.00824**
	(0.00469)	(0.00358)	(0.00324)	(0.00282)	(0.00322)
Constant	0.149***	0.0529***	0.0356**	0.0778***	0.137***
	(0.0233)	(0.0178)	(0.0161)	(0.0140)	(0.0160)
Observations	1612	1612	1612	1612	1612

Standard errors in parentheses
Year fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.21: Impact of Coffee Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coffee	1.121*	-1.494***	0.214	0.668*	1.201***
	(0.639)	(0.491)	(0.456)	(0.397)	(0.449)
coffee=1 × log of coffeearabica_priceperlb	-0.265**	0.296***	-0.0445	-0.117	-0.240**
	(0.135)	(0.103)	(0.0961)	(0.0835)	(0.0945)
yearsoperating	0.000822	0.00123	-0.00900***	0.00148	-0.00878***
	(0.00216)	(0.00166)	(0.00154)	(0.00134)	(0.00152)
# of natural resources	0.111***	0.0285***	0.0748***	0.0306***	0.0669***
	(0.00680)	(0.00522)	(0.00486)	(0.00422)	(0.00478)
groupsincountry	0.0432***	0.0110***	0.0257***	-0.0115***	-0.00778**
	(0.00472)	(0.00362)	(0.00337)	(0.00293)	(0.00331)
Constant	0.154***	0.0634***	0.0308*	0.0748***	0.131***
	(0.0234)	(0.0179)	(0.0167)	(0.0145)	(0.0164)
Observations	1612	1612	1612	1612	1612

Standard errors in parentheses
Year fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.4 Substitution Results: OLS with Dyad and Year Fixed Effects with Clustered Standard Errors (Dyad)

Table B.22: Impact of Oil Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft
oil	0.626	0.207*	0.785***	0.601***	0.360**
	(0.412)	(0.125)	(0.272)	(0.219)	(0.175)
oil=1 × log of crudeweighted_price	-0.191	-0.0211	-0.190***	-0.104**	-0.123**
	(0.131)	(0.0279)	(0.0622)	(0.0519)	(0.0499)
yearsoperating	0.0108	0.0245**	-0.0116	-0.00918*	-0.00732
	(0.0129)	(0.0114)	(0.00886)	(0.00512)	(0.00517)
# of natural resources	0.0946**	0.00511	0.0224	0.0108	0.0304
	(0.0453)	(0.0150)	(0.0227)	(0.0117)	(0.0339)
groupsincountry	0.0182	0.0142	0.00322	0.00644	-0.00660
	(0.0138)	(0.00972)	(0.00548)	(0.00689)	(0.00454)
Constant	0.190	-0.103	0.133**	0.158***	0.175***
	(0.116)	(0.0929)	(0.0644)	(0.0462)	(0.0342)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.23: Impact of Gold Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft
gold	1.378	0.359*	1.591***	0.319	0.925
	(1.291)	(0.187)	(0.581)	(0.557)	(0.597)
gold=1 × log of gold_priceperoz	-0.187	-0.0544*	-0.247***	-0.0447	-0.147*
	(0.193)	(0.0324)	(0.0866)	(0.0783)	(0.0833)
yearsoperating	0.0107	0.0251**	-0.0106	-0.00865	-0.00710
	(0.0130)	(0.0120)	(0.00888)	(0.00555)	(0.00529)
# of natural resources	0.0916*	0.0124	0.0394	0.0157	0.0371
	(0.0527)	(0.0187)	(0.0256)	(0.0143)	(0.0355)
groupsincountry	0.0188	0.0151	0.00580	0.00697	-0.00529
	(0.0138)	(0.00975)	(0.00551)	(0.00690)	(0.00430)
Constant	0.173	-0.109	0.104	0.163***	0.156***
	(0.127)	(0.0975)	(0.0675)	(0.0483)	(0.0385)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.24: Impact of Coca Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coca	0.839	1.131	-0.452	0.0463	1.153**
	(1.569)	(1.081)	(0.286)	(0.267)	(0.575)
coca=1 × lcocaineprice_usavgpergm	-0.145	-0.191	0.0813	0.0206	-0.203*
	(0.307)	(0.214)	(0.0524)	(0.0489)	(0.117)
yearsoperating	0.00250	0.0187	-0.00642	-0.0204	-0.00495
	(0.0208)	(0.0134)	(0.00865)	(0.0132)	(0.00316)
# of natural resources	0.0840	-0.00469	0.0188	0.0270	0.0342
	(0.0536)	(0.0130)	(0.0117)	(0.0221)	(0.0380)
groupsincountry	0.0185	0.0156	0.00751	0.00597	-0.00539
	(0.0147)	(0.00944)	(0.00744)	(0.00532)	(0.00475)
Constant	0.244	-0.0535	0.140**	0.168*	0.135***
	(0.171)	(0.103)	(0.0673)	(0.0965)	(0.0364)
Observations	1353	1353	1353	1353	1353

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.25: Impact of Cannabis Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
cannabis	0.816	0.430	-0.0937	0.474	0.221*
	(0.718)	(0.559)	(0.152)	(0.430)	(0.125)
cannabis=1 × lmarijuana_usavgpergm	-0.272	-0.134	0.0243	-0.101	-0.0345
	(0.218)	(0.179)	(0.0451)	(0.143)	(0.0445)
yearsoperating	0.000241	0.0189	-0.00698	-0.0190	-0.00222
	(0.0202)	(0.0139)	(0.00901)	(0.0136)	(0.00301)
# of natural resources	0.0878	-0.00432	0.0203	0.0100	0.0230
	(0.0603)	(0.0158)	(0.0139)	(0.0260)	(0.0289)
groupsincountry	0.0168	0.0144	0.00781	0.00300	-0.00679
	(0.0140)	(0.00876)	(0.00758)	(0.00502)	(0.00494)
Constant	0.274	-0.0401	0.141**	0.180*	0.127***
	(0.170)	(0.104)	(0.0710)	(0.0981)	(0.0451)
Observations	1353	1353	1353	1353	1353

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.26: Impact of Opium Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
opium	-0.0638	0.569	-0.390	-0.539	0.187
	(1.681)	(1.007)	(0.388)	(0.376)	(0.206)
opium=1 × lheroineprice_usavgpergm	-0.00379	-0.0992	0.0690	0.0800	-0.0303
	(0.255)	(0.150)	(0.0536)	(0.0534)	(0.0364)
yearsoperating	0.00245	0.0175	-0.00511	-0.0192	-0.00422
	(0.0207)	(0.0129)	(0.00884)	(0.0135)	(0.00339)
# of natural resources	0.0944	0.00503	0.0126	0.0311	0.0372
	(0.0590)	(0.0117)	(0.0108)	(0.0224)	(0.0451)
groupsincountry	0.0182	0.0143	0.00840	0.00638	-0.00556
	(0.0155)	(0.00893)	(0.00759)	(0.00553)	(0.00501)
Constant	0.256	-0.0258	0.122*	0.170*	0.138***
	(0.165)	(0.0941)	(0.0738)	(0.0976)	(0.0293)
Observations	1353	1353	1353	1353	1353

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.27: Impact of Timber Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
timber	0.0899	0.181	-0.345	-0.191	-0.0249
	(0.522)	(0.248)	(0.450)	(0.340)	(0.217)
timber=1 × log of softlogs_priceperm3	0.0104	-0.0424	0.0553	0.0484	0.0411
	(0.0690)	(0.0471)	(0.0839)	(0.0562)	(0.0400)
yearsoperating	0.00977	0.0249**	-0.00850	-0.0119	-0.00837
	(0.0129)	(0.0121)	(0.00552)	(0.00945)	(0.00520)
# of natural resources	0.0628*	0.0142	0.0233	0.00913	-0.00649
	(0.0353)	(0.0171)	(0.0284)	(0.0299)	(0.0231)
groupsincountry	0.0185	0.0142	0.00611	0.00324	-0.00578
	(0.0135)	(0.00970)	(0.00681)	(0.00520)	(0.00439)
Constant	0.215**	-0.101	0.165***	0.154**	0.197***
	(0.109)	(0.0993)	(0.0590)	(0.0769)	(0.0371)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.28: Impact of Tea Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
tea	1.895	0.371	-0.275	0.478*	-0.589
	(1.188)	(0.275)	(0.842)	(0.276)	(0.409)
tea=1 × log of tea_pricecentsperkg	-0.369*	-0.0474	0.151	-0.0901*	0.102
	(0.222)	(0.0423)	(0.150)	(0.0526)	(0.0651)
yearsoperating	0.0113	0.0237**	-0.0145*	-0.0117	-0.00747
	(0.0139)	(0.0115)	(0.00795)	(0.00950)	(0.00491)
# of natural resources	0.0854*	0.00633	0.00631	0.0180	0.0244
	(0.0433)	(0.0143)	(0.0158)	(0.0260)	(0.0347)
groupsincountry	0.0172	0.0141	0.00562	0.00273	-0.00696
	(0.0138)	(0.00977)	(0.00663)	(0.00564)	(0.00478)
Constant	0.203*	-0.0938	0.194***	0.151**	0.182***
	(0.122)	(0.0931)	(0.0650)	(0.0739)	(0.0407)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.29: Impact of Coal Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coal	2.288***	-0.0316	-1.058**	0.235	-0.122
	(0.787)	(0.158)	(0.515)	(0.584)	(0.709)
coal=1 × log of coalZAR_priceperton	-0.591***	-0.0148	0.109	-0.205	-0.0984
	(0.180)	(0.0373)	(0.117)	(0.129)	(0.152)
yearsoperating	0.0105	0.0250**	-0.00809	-0.0110	-0.00722
	(0.0129)	(0.0121)	(0.00534)	(0.00883)	(0.00538)
# of natural resources	0.0970**	0.0113	0.0316**	0.0399*	0.0410
	(0.0456)	(0.0164)	(0.0125)	(0.0225)	(0.0335)
groupsincountry	0.0177	0.0145	0.00720	0.00350	-0.00659
	(0.0138)	(0.00973)	(0.00703)	(0.00541)	(0.00444)
Constant	0.190	-0.101	0.160***	0.134**	0.171***
	(0.116)	(0.0976)	(0.0438)	(0.0629)	(0.0319)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.30: Impact of Coffee Price on Alternative Criminal Activities

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coffee	0.212	0.138	0.564*	0.841**	0.240
	(0.711)	(0.158)	(0.300)	(0.368)	(0.535)
coffee=1 × log of coffeearabica_priceperlb	-0.0279	-0.0214	-0.0554	-0.124*	-0.0145
	(0.151)	(0.0345)	(0.0477)	(0.0672)	(0.0797)
yearsoperating	0.0104	0.0250**	-0.00816	-0.0112	-0.00752
	(0.0134)	(0.0122)	(0.00546)	(0.00926)	(0.00514)
# of natural resources	0.0841*	0.00787	0.00625	0.0149	0.0185
	(0.0456)	(0.0162)	(0.0175)	(0.0282)	(0.0372)
groupsincountry	0.0173	0.0144	0.00600	0.00240	-0.00750
	(0.0138)	(0.00972)	(0.00700)	(0.00569)	(0.00487)
Constant	0.202*	-0.101	0.163***	0.141**	0.181***
	(0.120)	(0.0985)	(0.0495)	(0.0675)	(0.0331)
Observations	1500	1500	1500	1500	1500

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.5 Substitution Results: OLS with Dyad and Year Fixed Effects and a Restricted Sample

Table B.31: Impact of Opium Price on Alternative Criminal Activities (Restricted Sample)

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
opium	1.177*	1.283***	-0.390	0.0712	0.737*
	(0.703)	(0.461)	(0.296)	(0.478)	(0.414)
opium=1 × lheroineprice_usavgpergm	-0.166	-0.207***	0.0710	-0.00162	-0.103*
	(0.106)	(0.0696)	(0.0447)	(0.0721)	(0.0625)
Constant	0.482***	0.230***	0.165***	0.131***	0.222***
	(0.0427)	(0.0280)	(0.0180)	(0.0290)	(0.0252)
Observations	320	320	320	320	320

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: the sample is restricted to dyads where opium was exploited at least once.

Table B.32: Impact of Coca Price on Alternative Criminal Activities (Restricted Sample)

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coca	-1.708	-1.948	5.53e-14	-1.948	-1.988
	(5.840)	(3.813)	(1.736)	(1.616)	(2.880)
coca=1 × lcocaineprice_usavgpergm	0.410	0.410	-1.07e-14	0.410	0.410
	(1.133)	(0.740)	(0.337)	(0.313)	(0.559)
Constant	0.459**	0.246*	0.380***	0.269***	0.323***
	(0.197)	(0.129)	(0.0586)	(0.0545)	(0.0972)
Observations	129	129	129	129	129

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: the sample is restricted to dyads where coca was exploited at least once.

Table B.33: Impact of Cannabis Price on Alternative Criminal Activities (Restricted Sample)

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
cannabis	1.671*	0.208	-1.627***	-0.708	0.101
	(0.980)	(0.506)	(0.469)	(0.771)	(0.545)
cannabis=1 × lmarijuana_usavgpergm	-0.479	-0.0682	0.532***	0.295	0.0157
	(0.314)	(0.162)	(0.150)	(0.247)	(0.175)
Constant	0.713***	0.196***	0.197***	0.0448	0.0681**
	(0.0582)	(0.0300)	(0.0278)	(0.0458)	(0.0324)
Observations	247	247	247	247	247

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: the sample is restricted to dyads where cannabis was exploited at least once.

Table B.34: Impact of Gold Price on Alternative Criminal Activities (Restricted Sample)

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft
gold	1.210	0.108	0.331	-0.215	0.191
	(0.764)	(0.176)	(0.327)	(0.456)	(0.432)
gold=1 × log of gold_priceperoz	-0.130	-0.00786	-0.0174	0.0520	-0.00212
	(0.122)	(0.0281)	(0.0521)	(0.0726)	(0.0688)
Constant	0.337***	0.169***	0.0953***	0.243***	0.157***
	(0.0836)	(0.0193)	(0.0358)	(0.0499)	(0.0473)
Observations	170	170	170	170	170

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: the sample is restricted to dyads where gold was exploited at least once.

Table B.35: Impact of Timber Price on Alternative Criminal Activities (Restricted Sample)

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
timber	-0.916	0.532	-1.366*	-1.367*	-1.278
	(1.578)	(0.670)	(0.703)	(0.710)	(0.933)
timber=1 × log of softlogs_priceperm3	0.235	-0.0976	0.261*	0.277**	0.293
	(0.306)	(0.130)	(0.136)	(0.138)	(0.181)
Constant	0.270***	0.111***	0.172***	0.00235	0.000429
	(0.0486)	(0.0206)	(0.0216)	(0.0219)	(0.0287)
Observations	267	267	267	267	267

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: the sample is restricted to dyads where timber was exploited at least once.

Table B.36: Impact of Tea Price on Alternative Criminal Activities (Restricted Sample)

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
tea	2.260	0	22.38***	0	-0.326
	(8.370)	(.)	(3.273)	(.)	(3.671)
tea=1 × log of tea_pricecentsperkg	-0.456	0	-4.070***	0	0.0594
	(1.563)	(.)	(0.611)	(.)	(0.686)
Constant	0.998***	0.216	-0.0740	0	0.0869
	(0.183)	(.)	(0.0718)	(.)	(0.0805)
Observations	88	88	88	88	88

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: the sample is restricted to dyads where tea was exploited at least once.

Table B.37: Impact of Coal Price on Alternative Criminal Activities (Restricted Sample)

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coal	2.754***	0	-0.821	0.374	0.277
	(0.538)	(.)	(0.600)	(0.606)	(0.578)
coal=1 × log of coalZAR_priceperton	-0.583***	0	0.0999	-0.133	-0.0932
	(0.140)	(.)	(0.157)	(0.158)	(0.151)
Constant	0.623***	0	1.190***	0.771***	0.875***
	(0.0912)	(.)	(0.102)	(0.103)	(0.0981)
Observations	67	67	67	67	67

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: the sample is restricted to dyads where coal was exploited at least once.

Table B.38: Impact of Coffee Price on Alternative Criminal Activities (Restricted Sample)

	(1) extortion	(2) smuggle	(3) kidnap_L	(4) kidnap_F	(5) theft
coffee	0.651	-0.640	-1.403***	-0.874**	-1.082
	(0.950)	(0.419)	(0.497)	(0.410)	(0.654)
coffee=1 × log of coffeearabica_priceperlb	-0.104	0.142	0.363***	0.242***	0.269*
	(0.197)	(0.0870)	(0.103)	(0.0851)	(0.136)
Constant	0.421***	0.202***	0.0134	0.0347	0.179***
	(0.0724)	(0.0319)	(0.0379)	(0.0312)	(0.0499)
Observations	88	88	88	88	88

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: the sample is restricted to dyads where coffee was exploited at least once.

Table B.39: Impact of Oil Price on Alternative Criminal Activities (Restricted Sample)

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft
oil	-0.583*	-0.426	0.834**	1.498***	0.185
	(0.321)	(0.282)	(0.399)	(0.342)	(0.278)
oil=1 × log of crudeweighted_price	0.212**	0.168**	-0.182*	-0.351***	-0.0541
	(0.0872)	(0.0765)	(0.108)	(0.0929)	(0.0753)
Constant	0.500***	0.0549	0.208***	0.431***	0.497***
	(0.0588)	(0.0517)	(0.0731)	(0.0627)	(0.0508)
Observations	154	154	154	154	154

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The sample is restricted to dyads where oil was exploited at least once.

B.6 Additional Results and Tests

Table B.40: Impact of Covariates on Alternative Criminal Activities (OLS with FEs)

	(1) extortion	(2) smuggle	(3) kidnap_F	(4) kidnap_L	(5) theft	(6) battledeaths	(7) logbd
yearsoperating	0.0102	0.0249***	-0.0118**	-0.00880**	-0.00787*	-12.21	0.0527*
	(0.00654)	(0.00374)	(0.00494)	(0.00388)	(0.00418)	(41.06)	(0.0307)
# of natural resources	0.0856***	0.00826	0.0183**	0.0137**	0.0233***	314.9***	0.127**
	(0.0110)	(0.00629)	(0.00831)	(0.00653)	(0.00702)	(74.16)	(0.0555)
groupsincountry	0.0174**	0.0144***	0.00282	0.00658	-0.00716	-58.14	0.0451
	(0.00745)	(0.00426)	(0.00563)	(0.00443)	(0.00476)	(48.93)	(0.0366)
Constant	0.205***	-0.0991***	0.151***	0.171***	0.184***	641.0*	4.478***
	(0.0545)	(0.0312)	(0.0412)	(0.0324)	(0.0348)	(334.5)	(0.250)
Observations	1500	1500	1500	1500	1500	1128	1128

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.41: The Impact of Price on Conflict

	(1) battledeaths	(2) battledeaths	(3) battledeaths	(4) battledeaths	(5) battledeaths	(6) battledeaths	(7) battledeaths	(8) battledeaths	(9) battledeaths
oil=1 × log of crudeweighted_price	2783.9***								
	(401.3)								
opium=1 × lheroineprice_usavgpergm		-1003.3***							
		(356.9)							
cannabis=1 × lmarijuana_usavgpergm			-360.7						
			(603.7)						
coca=1 × lcocaineprice_usavgpergm				-948.4					
				(877.9)					
gold=1 × log of gold_priceperoz					-617.3				
					(464.2)				
timber=1 × log of softlogs_priceperm3						-1.662			
						(1706.4)			
tea=1 × log of tea_pricecentsperkg							-636.9		
							(2331.9)		
coal=1 × log of coalZAR_priceperton								17.76	
								(889.5)	
coffee=1 × log of coffeearabica_priceperlb									-595.5
									(907.9)
Constant	908.7**	-2999.4***	-429.4	-4471.4***	-1429.0	1803.8	-1934.3	70.25	-943.8
	(425.0)	(902.9)	(720.8)	(1418.3)	(896.3)	(2766.7)	(2049.9)	(636.4)	(965.9)
Observations	1243	1098	1098	1098	1243	1243	1243	1243	1243

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.42: The Impact of Price on Conflict

	(1) battledeaths	(2) battledeaths	(3) battledeaths	(4) battledeaths	(5) battledeaths	(6) battledeaths	(7) battledeaths	(8) battledeaths	(9) battledeaths
oil	745.3								
	(1014.0)								
oil=1 × log of crudeweighted_price	58.79								
	(259.7)								
opium		-1452.3							
		(2394.8)							
opium=1 × lheroineprice_usavgpergm		277.4							
		(360.4)							
cannabis			2143.9						
			(1536.1)						
cannabis=1 × lmarijuana_usavgpergm			-555.8						
			(484.4)						
coca				2494.4					
				(3550.6)					
coca=1 × lcocaineprice_usavgpergm				-526.1					
				(691.5)					
gold					2495.3				
					(1996.1)				
gold=1 × log of gold_priceperoz					-359.4				
					(287.3)				
timber						-334.8			
						(4850.1)			
timber=1 × log of softlogs_priceperm3						234.8			
						(942.8)			
tea							2982.9		
							(7096.1)		
tea=1 × log of tea_pricecentsperkg							-458.9		
							(1306.2)		
coal								-1170.6	
								(2628.4)	
coal=1 × log of coalZAR_priceperton								118.9	
								(581.4)	
coffee									2208.6
									(2462.5)
coffee=1 × log of coffeearabica_priceperlb									-373.8
									(494.0)
Constant	685.6***	580.2***	579.4***	668.8***	761.3***	673.7***	753.3***	805.1***	754.2***
	(64.70)	(60.42)	(58.15)	(79.74)	(56.05)	(53.32)	(72.79)	(46.97)	(48.50)
Observations	1128	1000	1000	1000	1128	1128	1128	1128	1128

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.43: The Role of Natural Resource Exploitation Diversity on Crime

	(1) crime	(2) extortion	(3) smuggle	(4) theft	(5) theft	(6) kidnap_L	(7) kidnap_F	(8) aid
1.diverse_nat	0.153***	0.137***	0.00336	0.0103	0.0103	0.0896***	0.0977***	0.00520
	(0.0348)	(0.0331)	(0.0193)	(0.0203)	(0.0203)	(0.0181)	(0.0238)	(0.00873)
2.diverse_nat	0.181***	0.178***	0.0459*	0.0323	0.0323	0.0962***	0.0930***	0.0252**
	(0.0424)	(0.0402)	(0.0235)	(0.0247)	(0.0247)	(0.0220)	(0.0290)	(0.0106)
3.diverse_nat	0.269***	0.326***	0.0290	0.0693**	0.0693**	0.0709**	0.233***	0.0241*
	(0.0542)	(0.0514)	(0.0300)	(0.0315)	(0.0315)	(0.0282)	(0.0371)	(0.0136)
4.diverse_nat	0.232***	0.495***	0.0201	0.232***	0.232***	0.115***	0.323***	0.0499***
	(0.0714)	(0.0678)	(0.0396)	(0.0416)	(0.0416)	(0.0371)	(0.0488)	(0.0179)
5.diverse_nat	0.558***	0.483***	0.0525	0.303***	0.303***	0.105**	-0.0411	0.0760***
	(0.0820)	(0.0778)	(0.0454)	(0.0477)	(0.0477)	(0.0426)	(0.0561)	(0.0205)
6.diverse_nat	0.556***	0.535***	0.305***	-0.145*	-0.145*	0.0230	0.0467	0.0290
	(0.149)	(0.142)	(0.0828)	(0.0870)	(0.0870)	(0.0777)	(0.102)	(0.0375)
7.diverse_nat	0.511***	0.496***	0.281***	-0.0273	-0.0273	0.235***	0.0237	0.0212
	(0.169)	(0.161)	(0.0939)	(0.0987)	(0.0987)	(0.0881)	(0.116)	(0.0425)
9.diverse_nat	0.556**	0.595***	0.275**	-0.0191	-0.0191	0.170	0.0398	0.0250
	(0.220)	(0.209)	(0.122)	(0.128)	(0.128)	(0.114)	(0.150)	(0.0551)
10.diverse_nat	0.470**	0.545***	0.242**	-0.635***	-0.635***	-0.656***	-0.652***	0.0277
	(0.204)	(0.194)	(0.113)	(0.119)	(0.119)	(0.106)	(0.140)	(0.0511)
11.diverse_nat	0.477**	0.581***	0.265**	-0.311***	-0.311***	0.0374	-0.350**	0.0290
	(0.205)	(0.194)	(0.113)	(0.119)	(0.119)	(0.106)	(0.140)	(0.0513)
_cons	0.00474	0.0102	-0.00773	0.0259	0.0259	0.0164	-0.0353	-0.00770
	(0.106)	(0.100)	(0.0585)	(0.0615)	(0.0615)	(0.0550)	(0.0723)	(0.0265)
N	1612	1612	1612	1612	1612	1612	1612	1612

Standard errors in parentheses
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.44: The Role of Natural Resource Exploitation Diversity on Battle Deaths

	(1) battledeaths	(2) battledeaths
naturaldummy	185.0	
	(201.5)	
diverse_nat=1		-94.32
		(218.6)
diverse_nat=2		161.6
		(259.5)
diverse_nat=3		1385.4***
		(338.8)
diverse_nat=4		2706.2***
		(472.3)
diverse_nat=5		1585.8***
		(606.6)
diverse_nat=6		1883.6**
		(838.8)
diverse_nat=7		2629.3***
		(943.1)
diverse_nat=9		2159.4*
		(1213.6)
diverse_nat=10		1741.6
		(1147.8)
diverse_nat=11		2046.8*
		(1154.7)
Constant	875.6	888.7
	(592.7)	(579.4)
Observations	1243	1243

Standard errors in parentheses; the omitted category in (2) is 0
Year and dyad fixed effects included in all models
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Additional Information on the Data

Table C.1: Most Frequently Observed Rebel Groups

Side A	Side B	Side B ID	Years in Dataset
India	Kashmir Insurgents	1168	26
Uzbekistan	IMU	1202	26
Turkey	PKK	1166	26
Colombia	FARC	1604	26
Myanmar	KIO	1043	26
Uganda	LRA	1336	26
Philippines	CPP	1010	26
Ethiopia	OLF	1404	25
Philippines	MILF	1118	24
Afghanistan	Hizb-i Islami-yi Afghanistan	1141	24
Colombia	ELN	1605	24
Israel	Hezbollah	1209	23
Algeria	AQIM	1391	23
Philippines	ASG	1119	23
Myanmar	KNU	1021	22
Senegal	MFDC	1381	22
Ethiopia	ONLF	1346	22
Israel	Hamas	1051	22
Peru	Sendero Luminoso	1611	21
India	ULFA	1169	21
Uganda	ADF	1337	21
Sri Lanka	LTTE	1163	20
Israel	PIJ	1050	19
Myanmar	RCSS	1098	18
Israel	Fatah	1049	18
India	NDFB	1206	18
Myanmar	UWSA	1207	18
Georgia	Republic of South Ossetia	1186	17
India	UNLF	1158	16
Angola	FLEC-FAC	1393	16
Afghanistan	Taleban	1146	15
Sudan	SPLM/A	1312	15
India	PWG	1035	15
United States of America	al-Qaida	1630	15
Russia (Soviet Union)	Chechen Republic of Ichkeria	1195	14
Angola	UNITA	1421	13
Thailand	Patani insurgents	1208	13
Tajikistan	UTO	1188	12
Rwanda	FDLR	1380	12
Pakistan	BLA	1129	12
India	NLFT	1150	12
Angola	FLEC-R	1392	12
Burundi	Palipehutu-FNL	1278	12
Algeria	GIA	1390	11
India	CPI-Maoist	1037	11
Nepal	CPN-M	1100	11
Philippines	MNLF	1117	11
Sierra Leone	RUF	1384	11
India	MCC	1036	10

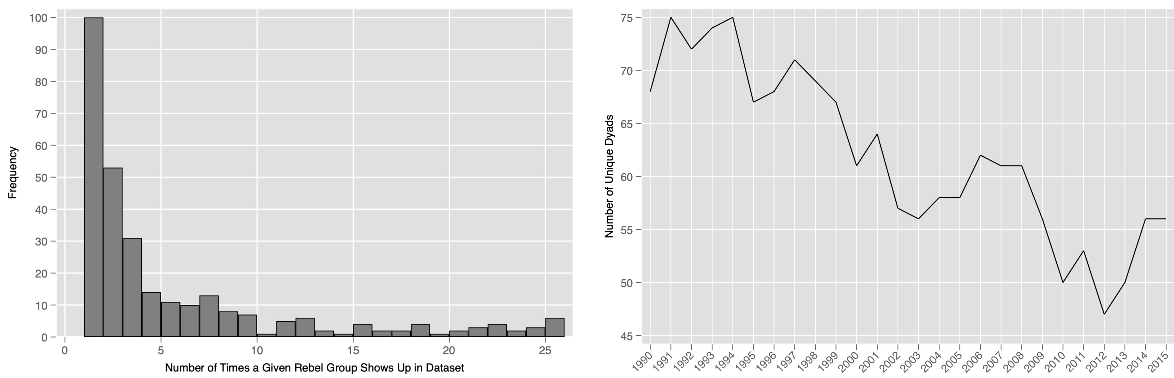

Figure C.1: Distribution of Unique Rebel Groups and Number of Active Dyads per Year

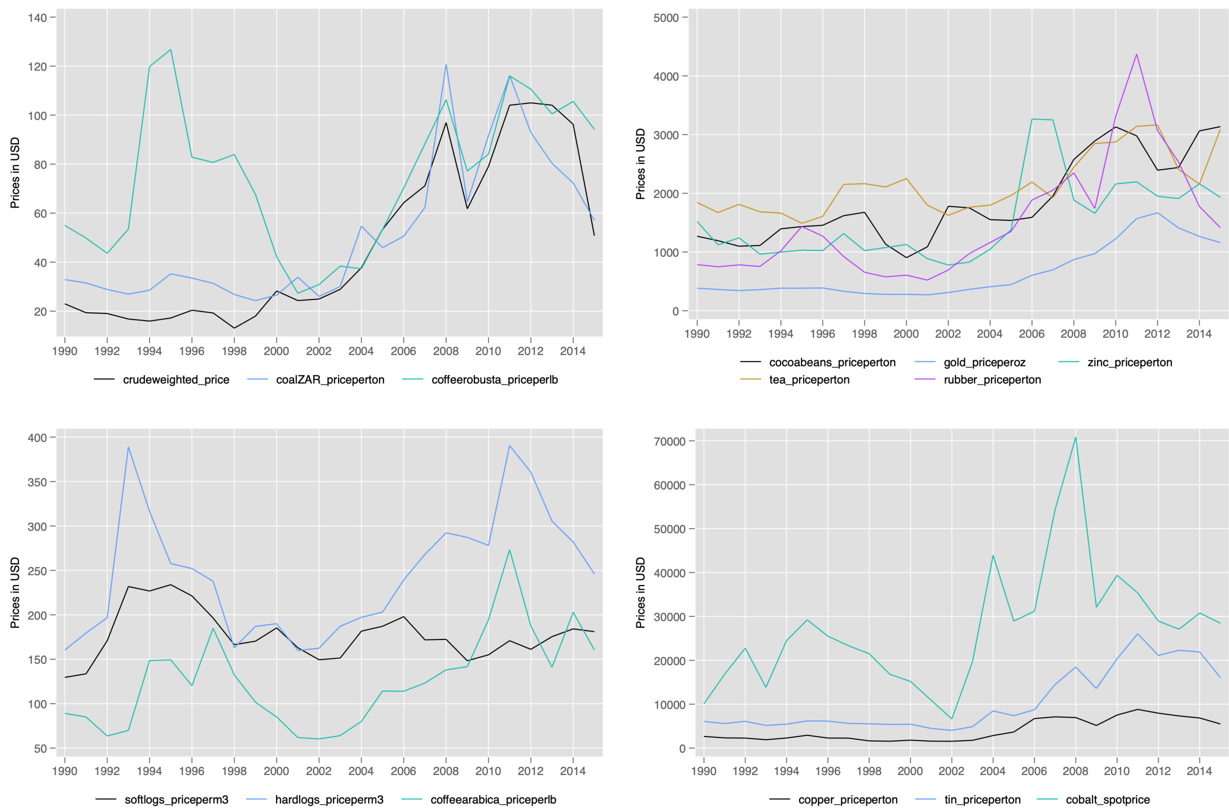

Figure C.2: Primary Commodity Prices (Legal/Non-Illicit) from IMF

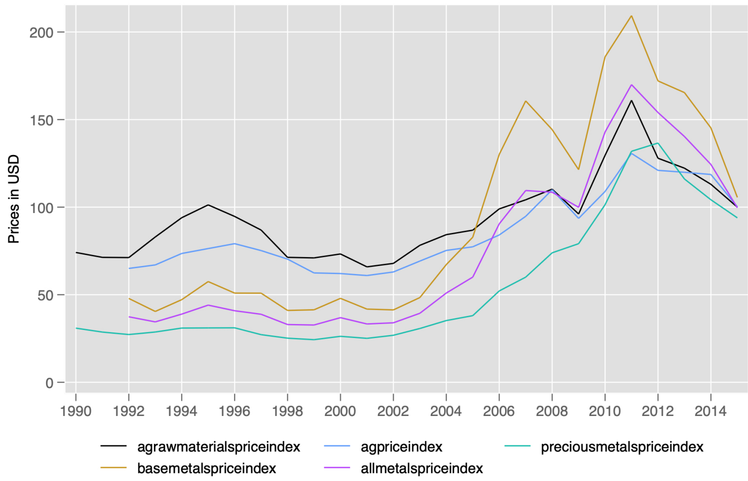

Figure C.3: Primary Commodity Indices from IMF

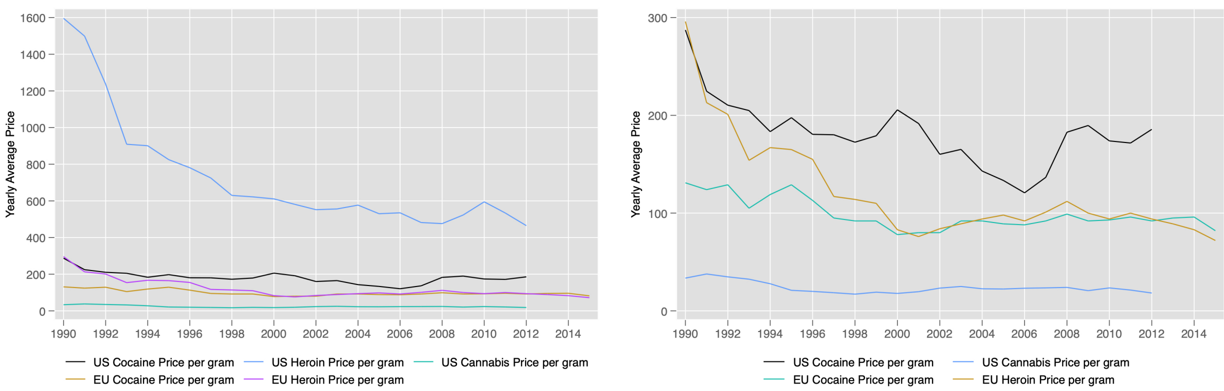

Figure C.4: Illicit Drug Prices in the US and Europe

Note: The right figure removes US heroin prices to see the dynamics better.