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Title: Natural Resources and Beyond: How Armed Groups in Conflict Combine Illicit Markets and Criminal Activities

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Abstract

Armed groups involved in conflict are widely known to rely on illicit activities, particularly natural resource exploitation, yet how these activities are combined and evolve remain underexplored. Drawing on the Rebel Contraband Dataset, this study investigates patterns of illicit activity diversification among 121 armed groups involved in conflicts worldwide between 1990 and 2015. Three complementary methods are employed: latent class analysis to identify distinct diversification profiles, social network analysis to examine the co-occurrence of illicit activities, and trajectory analysis to assess changes in diversification over time. The results identify three distinct profiles of armed groups. The first comprises groups extensively involved in the exploitation of various natural resources, particularly through extortion. The second consists of groups with limited involvement in natural resource exploitation, relying primarily on other serious criminal activities. The third includes groups specializing in illicit drug markets, predominantly through smuggling. Network analysis reveals that extortion is recurrent across all three profiles, although the combinations of illicit activities differ substantially. Trajectory analysis further highlights variations in how armed groups expand, reduce, or maintain their involvement in different illicit activities over time. These findings contribute to bridging conflict research and criminology by providing a systematic understanding of how armed groups diversify their illicit activities during conflict.

1. Introduction

Armed groups involved in conflicts are regularly accused of participating in a wide range of illicit activities to sustain themselves and finance warfare (McMullin 2009). Illicit markets of natural resources appear to be of particular importance in this respect as armed groups have repeatedly been involved in the exploitation and trade of natural resources as a means of financing conflict (Rigterink 2010). Influential paper (and highly criticized) from Collier and Hoeffler (2004) argued that civil war was substantially more likely in countries that were both poor and richly endowed with exportable natural resources, which simultaneously provided the economic motive and the material opportunity for armed groups to engage in conflict. In line with this argument, UNEP estimates that approximately 40 percent of internal conflicts since the 1950s have been linked to natural resource exploitation (Matthew et al. 2009).

In this study, *armed groups* are defined as non-state organizations that use armed violence against the state to pursue specific objectives (Bellal 2020). The historical record offers several illustrations of their involvement in natural resource markets across the globe: in Colombia, the Revolutionary Armed Forces of Colombia (FARC) generated revenue from gold mining through the extortion of miners and involvement in mining operations (Massé and Le Billon 2018); the Islamic State in Iraq and Syria extracted hundreds of millions of dollars annually from illegal oil sales (Le Billon 2023); in Myanmar, the Kachin Independence Organization has derived significant revenue from the jade economy (Lin et al. 2019); The Taliban, long assumed to depend primarily on revenues from opium cultivation, have also generated substantial income from minerals, gemstones, and precious metals such as copper, iron, gold,

silver, and tantalum well into the late 2000s (Thachuk 2020). This pattern intensified following the end of the Cold War with the withdrawal of superpower patronage from many proxy conflicts, which pushed armed groups to seek alternative sources of financing (Humphreys 2012). The combination of globalization, improved communications, and expanding transnational criminal networks opened new channels connecting local conflict actors to illicit markets (Sullivan 2023).

These findings echo a parallel and relatively new strand of literature on the involvement of organized crime in the illicit markets of natural resources (van Uhm and Siegel 2019; Wyatt et al. 2020). Since the 1990s, the landscape of organized crime has undergone a profound transformation. Increasingly, criminal networks have expanded into the exploitation and trade of natural resources, turning environmental crime into a major and rapidly growing source of illicit revenue (Nellemann et al. 2016). This expansion reflects not only the rising demand for commodities such as timber, oil and minerals, but also the relative ease with which these resources can be extracted, transported, and integrated into legal markets. As transnational criminal organizations seek new and profitable opportunities, natural resources have become an attractive complement, or alternative, to their traditional involvement in drugs, arms, and human trafficking (Albanese 2020). Notably, the United Nations Security Council, through Resolution 2195 (2014), explicitly recognized that armed groups are increasingly engaging with organized crime and benefitting financially from illicit markets, including environmental ones.

This phenomenon has given rise to a growing scholarship on the convergence of environmental crime with other serious criminal activities (Massé et al. 2020; Thompson 2023; van Uhm 2019). Natural resources such as minerals, timber, and wildlife have proven especially attractive because they are often easier to smuggle than drugs, raise less customs scrutiny, and can be laundered through legitimate commodity markets (Nellemann et al. 2016; Van Solinge 2014). Criminal organizations have progressively adapted, diversifying into environmental crime markets as natural resources have grown scarcer, as their market value has risen, and as enforcement pressure on more "traditional" criminal activities has intensified (van Uhm and Nijman 2022; Zabyelina and van Uhm 2020). In several instances, organized crime groups have used these markets not merely as a source of revenue, but as a means of exercising broader territorial, economic and social control, regulating access to extraction sites, labor, and trade routes as well as provide justice and security in ways that mirror forms of local governance (Felbab-Brown 2018; McElwee 2016; van Uhm 2020). An interesting theoretical perspective for this phenomenon is the environmental crime continuum (van Uhm 2019), which conceptualizes the involvement of organized crime in environmental markets as a spectrum. At one end lies loose, opportunistic involvements in environmental crimes, where criminal actors engage in such crime sporadically, while being mostly involved in other criminal activities. At the other end lies full organizational embeddedness, where criminal groups come to dominate large parts of specific environmental markets by controlling supply chains and transport routes. Thus, this framework offers a tool to situate different actors along a continuum of involvement in illicit markets of natural resources.

This literature suggests that armed groups operating in conflict settings are drawn to natural resource markets for many of the same reasons that make them attractive to organized crime: the relative ease of

extraction, the comparatively low risk of detection, the opportunity of laundering resources through legitimate commodity chains, and the possibility such markets offer to consolidate control over territories and over the socio-economic lives of local populations (Nellemann et al. 2016; van Uhm and Nijman 2022). These conditions may be further amplified in conflict-affected areas, where institutional weakness, insecurity, disrupted state authority, and lack of economic opportunity can reduce constraints on the illicit exploitation and trade of natural resources (Cuvelier et al. 2014).

Read together, this body of evidence suggests that illicit activities, particularly those tied to natural resources, are not incidental to conflicts, but often play a central role in how armed groups sustain their operations, assert authority over territory, and manage their relationship with local populations (Cuvelier et al. 2014; Kalyvas 2015). Yet academic literature as well as policy debates largely treated armed groups' involvement in illicit markets as instrumental, i.e., as a means of financing conflicts, rather than as a phenomenon worthy of examination in its own right. Far more systematic attention has been given to the conditions generating conflict onset, the organizational imperatives of rebel groups, the dynamics of violence, and the logic of territorial governance than to the structure and composition of armed groups' illicit activities (Kalyvas 2015; Weinstein 2006). As a result, we know relatively little about how armed groups diversify across different illicit markets and criminal activities during conflicts.

This article seeks to bridge that gap by investigating how armed groups diversify their illicit activities across a wide range of conflicts worldwide, with particular attention to illicit natural resource markets. More specifically, it seeks to identify common patterns in how armed groups engage in and combine different illicit activities, and how their involvement in these activities evolves over time. The study is guided by three research questions: (1) What distinct patterns of illicit activity diversification can be identified among armed groups in conflict? (2) Which illicit activities do armed groups tend to combine? (3) How does armed groups’ illicit activity diversification evolve over time?

Empirically, the analysis draws on the Rebel Contraband Dataset (Walsh et al. 2018), which provides systematic data on the illicit activities of armed groups across several conflicts around the world. Although still rarely used in research, this dataset offers a unique opportunity to examine illicit activities beyond traditional crime data sources. Its use responds to broader calls within criminology to engage with international and cross-disciplinary data in order to expand empirical inquiry and theoretical development (Nivette 2021). To address the three research questions, the study combines latent class analysis to identify distinct profiles of illicit activity diversification, network analysis to examine the co-occurrence of illicit activities, and a qualitative trajectory analysis to assess how diversification evolves over time. The following section describes the data and analytical methods employed in the study.

2. Methods

2.1 Data

This study relies on the Rebel Contraband Dataset (RCD) developed by (Walsh et al. 2018), which documents the illicit activities of armed groups involved in conflicts against states worldwide between 1990 and 2015. In the RCD, a conflict is defined as a contested incompatibility over government or territory, involving the use of armed force and resulting in a minimum of 25 battle-related deaths in a given year. The sample used in this study consists of 121 armed groups involved in 126 conflicts[1].

The RCD includes two main types of variables. First, natural resource variables capture whether and how armed groups exploit natural resources. These variables include thirty-one natural resources (e.g. gold, opium, coca, timber, wildlife, etc.) and four strategies through which armed groups derive profit from their exploitation: extortion, theft, smuggling, and booty futures. To distinguish these strategies that only concern natural resources from the crime-type variables described below, which include some of the same terms, they are referred to as *commodity extortion*, *commodity theft*, *commodity smuggling* and *commodity booty futures*.

Second, the dataset includes eight crime-type variables capturing involvement in criminal activities unrelated to natural resources (Table 4 in appendix). For instance, extortion refers to demands for payment from businesses or individuals outside the natural resource sector and smuggling refers to the illicit movement of goods other than natural resources. All variables are dichotomous and indicate whether armed groups are involved in a given activity in a given year. Main data preparation steps for the latent class, external validity, network and trajectory analyses are summarized in Table 5 (appendix).

2.2 Analytical strategy

Three complementary analyses were conducted to answer the three research questiosn: (1) a latent class analysis to identify patterns of diversification, followed by an external validation analysis; (2) a network analysis to assess which illicit activities tend to be combined; (3) a qualitative trajectory analysis to examine the temporal evolution of diversification. The section first presents the data and describes the methods.

Latent class analysis

First, a latent class analysis was conducted to identify patterns of diversification. Latent class analysis is a statistical method used to uncover unobserved heterogeneity in a population by identifying subgroups of cases that share similar characteristics (Weller et al. 2020). It aims to classify individuals into mutually exclusive latent classes based on their responses to observed indicators (Collins and Lanza 2010). Latent class analysis is conceptually similar to cluster analysis but provides a model-based approach, assigning probabilities of class membership to each case rather than deterministic classifications. This allows for a more robust identification of underlying patterns of diversification.

Given the initial number of variables, natural resource variables were merged into categories (see Table 5 in appendix) and a selection based on prevalence was applied: rarely observed variables were excluded

to avoid sparse data issues, resulting in a final set of 13 indicators for the latent class analysis. A total of seven models were estimated and fit indices were used to assess the best model (table 1).

Table 1 Fit indices for latent class models

Nb of classes	Log Likelihood	L^2	df	AIC	BIC	Entropy	VLMR
	-779,60	603,73***	106	1585,20	1621,33	NA	
2	-729,71	503,96***	92	1513,43	1588,46	0,93	99,77***
3	**-694,60**	**433,73*** **	**78**	**1471,20**	**1585,14**	**0,94**	**70,22*** **
4	-672,44	389,43***	64	1454,89	1607,74	0,90	44,30***
5	-658,05	360,64***	50	1454,10	1645,86	0,92	28,78***
6	-647,43	339,40***	36	1460,86	1691,53	0,90	21,24***
7	-636,41	317,36***	22	1466,82	1736,40	0,93	22,04***

Model selection was based primarily on the Bayesian Information Criterion (BIC), where lower values indicate better model fit (Schwarz 1978). Additional fit statistics were also examined, including the log-likelihood, likelihood ratio (L^2), degrees of freedom, Akaike Information Criterion (AIC), entropy and Vuong-Lo-Mendell-Rubin (VLMR) test.

External validity

To assess whether the latent classes reflect meaningful differences between armed groups rather than statistical artefacts of the model, we conducted an external validity verification (Weller et al. 2020). To do so, the RCD was matched with another dataset developed by Malone (2022): the Armed Group Dataset (AGD). The AGD records information on more than 1,400 armed groups active between 1970 and 2012. It contains several categories of variables such as organizational history, longevity, political aims, ideological orientations, transnational operations, etc. These variables are conceptually distinct from the illicit activity indicators used to construct the latent classes and were selected based on their theoretical relevance for assessing whether armed groups assigned to different classes also differ along meaningful organizational, political, and operational dimensions.

Bivariate tests were conducted to assess whether values for these variables differed across the latent classes. Statistically significant results were followed by pairwise tests to identify which classes differed from one another.

Networks of illicit activity co-occurrence

To examine how specific illicit activities are combined, co-occurrence networks were constructed for each of the three latent classes. In these networks, nodes represent individual illicit activities[2], and edges connect two activities whenever they co-occur, i.e. an armed group is involved in both activities. The weight of each edge reflects the number of armed groups combining the two activities.

Network features and metrics, such as degree centrality, density, mean edge weight are also computed and compared across networks to assess how the structure of illicit activity combinations varies between classes.

The resulting networks highlight, for each class, which activities are most central and how they cluster together. By comparing these structures across classes, the analysis identifies whether distinct diversification profiles are associated with different combinations of illicit activities.

Trajectory analysis

To examine the trajectories of diversification, we analyzed how the number of distinct illicit activities in which each armed group was involved evolved over time. Two indicators were constructed to capture differences in these trajectories, distinguishing between the overall level of diversification and its temporal trend for each armed group.

1. The first indicator is the mean number of illicit activities in which each armed group is involved across all observed years, providing a measure of its overall level of diversification.
2. The second indicator is the slope of a simple linear model estimating the change in the number of illicit activities over time, capturing whether diversification tends to increase, decrease, or remain stable.

Based on these two indicators, armed groups were categorized according to their level and trend of diversification. First, armed groups were classified into three temporal trends (decreasing, stable, and increasing) using the 0.2 and 0.8 quantiles of group-level slopes (− 0.125 and 0.096, respectively). Groups with stable trends were then further divided into two categories, persistently low and persistently high diversification, using the median of group-level means as the threshold. This resulted in four categories of diversification trajectories: persistent-low, persistent-high, diversifying (increasing trend) and specializing (decreasing trend). Thresholds were selected based on the empirical distribution of the data, ensuring a balanced and data-driven classification of armed groups' diversification patterns.

Finally, to examine the relationship between latent classes and temporal trajectories, we calculated the proportion of armed groups belonging to each latent class within each of the four trajectory categories. These proportions were then compared with the overall distribution of latent classes in the sample, providing a baseline to assess whether certain diversification profiles were over- or underrepresented in specific trajectories.

3. Results

3.1 Patterns of diversification

Regarding the latent class analysis, Table 1 shows the fit statistics associated to the seven models estimated. Model selection was based primarily on the BIC, which reached its lowest value at the three-class solution (see Table 1 above). Entropy was also highest for this solution (0.94), indicating well-separated classes. Taken together, these results supported the three-class solution.

Table 2 presents the profiles of the three resulting classes, expressed as the mean probability of involvement in each illicit activity conditional on class membership.

Table 2
Profiles of three latent classes - mean probability of illicit activities based on class membership

Categories	**Variables**	**Class 1 (n = 60)**	**Class 2 (n = 32)**	**Class 3 (n = 29)**
Natural resources	Agricultural commodities	0,40	0,00	0,08
	Illicit drugs	0,42	0,00	0,82
	Forestry	0,46	0,00	0,04
	Fossil fuels	0,20	0,06	0,07
	Precious minerals	0,47	0,03	0,04
	Wildlife	0,15	0,03	0,07
Natural resource funding strategies	Commodity extortion	0,99	0,01	0,15
	Commodity smuggling	0,42	0,01	0,99
Criminal activities (unrelated to natural resources)	Extortion	0,69	0,78	0,52
	Human smuggling	0,02	0,03	0,07
	Smuggling (other)	0,17	0,13	0,42
	Theft	0,24	0,22	0,42
	Theft of humanitarian aid	0,08	0,06	0,04

Armed groups in class 1 (n = 60), the largest of the three classes, show relatively high and fairly evenly distributed probabilities of involvement across nearly all natural resource categories, with close to half of armed group in this class involved in precious minerals (0.47), forestry (0.46), illicit drugs (0.42), and agricultural commodities (0.40), alongside a near-certain reliance on commodity extortion as strategy to

profit from natural resources (0.99). Crime-type involvement in this class is moderate, dominated by extortion (0.69). This class therefore reflects wide engagement across different types of natural resources, primarily through extortion rather than smuggling. This class also shows a relatively high involvement in extortion unrelated to natural resoucres. Among armed groups in this class, the Allied Democratic Forces (ADF), which has operated in the Uganda–DRC borderlands since the 1990s, illustrates this pattern. Its economic activities have mostly relied on extortion businesses and workers involved in the production, extraction and trade of coffee, timber, marijuana, and minerals such as gold, diamonds, and coltan as well as cross-border trade and theft (Scorgie-Porter 2015), reflecting the broad resource-based diversification observed in this class.

Class 2 (n = 32) stands in sharp contrast, showing near-zero probabilities of involvement in every natural resource category. Its profile is instead defined almost entirely by criminal activities unrelated to natural resources, with the highest probability of extortion among the three classes (0.78) and a moderate probability of theft (0.22). In this class, the Euskadi ta Askatasuna (ETA) illustrates this predominantly specialized profile. ETA relied substantially on extortion of businesses as a source of revenue: between 1993 and 2002, extortion was estimated to be the second-largest source of income (behind public subsidies received by affiliated political and social organizations through various public funding mechanisms) (Buesa and Baumert 2013). Armed groups in this class show almost no involvement from natural resource exploitation, concentrating their illicit activities in non-resource-related crimes.

Class 3 (n = 29) is distinguished by a high probability of illicit drugs exploitation (0.82), well above the other natural resource categories, combined with an almost systematic reliance on smuggling as strategy (0.99). This class also shows elevated probabilities of theft (0.42) and smuggling other goods (0.42) relative to the other two classes, alongside a moderate probability of extortion (0.52). Among armed group in this class, the Kurdistan Workers' Party (PKK) illustrates this combination of drug-related activity and smuggling. Particularly during the 1990s, drug trafficking constituted one of the group's most important sources of illicit revenue, with the PKK reportedly participating in different stages of the drug trade, including transportation and distribution along routes connecting Southwest and Central Asia to European markets (Roth and Sever 2007). Its involvement extended to other illicit activities, including human and arms smuggling as well as extortion. This class points to armed groups displaying a more specialized pattern of diversification, centered on illicit drugs exploitation and smuggling-based crime.

Interestingly, we can observe an alignment between how armed groups profit from natural resources and their involvement in other criminal activities. Class 1, which exploits a wide range of resources primarily through commodity extortion, is also comparatively highly engaged in extortion unrelated to natural resources. Class 3, which relies almost exclusively on smuggling to profit from illicit drugs, similarly stands out for its more frequent engagement in smuggling other goods and, to some extent, human smuggling. This suggests that, to some extent, armed groups may reuse the same operational know-how across their natural resource and other criminal activities.

External validation

The external validation analysis revealed several differences in armed group characteristics across the three latent classes. Full results are presented in Table 6 (appendix).

Bivariate tests provide the following results: group longevity did not differ significantly across classes, suggesting that diversification patterns are not simply driven by how long armed groups have been active. Political and ideological characteristics, however, distinguished the classes in several respects. Class 1 groups were more likely to pursue regime change (55%, compared to 23% and 41% in classes 2 and 3, respectively), while class 2 groups were more likely to make territorial claims (48%) and had a higher proportion of ethnonationalist groups (77%, against 50% and 48% in classes 1 and 3). Class 3, in turn, stood out for a comparatively larger share of Islamist groups (45%, against 24% and 23%). In addition, significant differences were found in operational characteristics: class 3 groups were considerably more likely to conduct transnational attacks (59%, against 28% and 10%), operate from an external base (62%, against 45% and 32%), and benefit from explicit state endorsement (14%, against 0% and 0%).

Overall, these results suggest that the three classes correspond to different types of armed groups. Although not all variables differ significantly across classes, several political, ideological, and operational characteristics do. This external validation indicates that the classes capture more than just statistical patterns in illicit activities, but also correspond to distinct profiles of armed groups.

3.2 Illicit activity co-occurrence

To further explore how specific illicit activities combine within each class, three co-occurrence networks were constructed in which nodes represent illicit activities and edges represent the co-occurrence of two activities within the same armed group. Edge width and darkness reflect the number of armed groups combining the two connected activities, while node size represents the degree centrality. Figures 1, 2, and 3 display these networks for class 1, class 2, and class 3, respectively, and Table 3 reports the corresponding network metrics.

Table 3
Network metrics across classes

Metrics	Class 1	Class 2	Class 3
Number of armed groups	60	32	29
Nodes	38	11	17
Edges	368	12	73
Mean degree	19,37	2,18	8,59
Mean weighted degree	96,53	9,82	42,12
Density	0,52	0,22	0,54
Mean edge weight	6,28	4,50	4,97

The Class 1 network displays the broadest range of illicit activities and the largest number of connections between them. It contains 38 nodes connected by 368 edges, indicating that armed groups in this class are involved in a wide variety of activities that frequently occur in combination. This is also reflected in the high mean degree (19.37), meaning that, on average, each activity is connected to approximately 19 other activities. Within this highly interconnected structure, extortion (unrelated to natural resources) occupies a particularly central position, with strong connections to both natural resources and other criminal activities. Armed groups in this class most frequently combine extortion with kidnapping, agricultural commodities, timber, gold, or theft. A broad range of other natural resources, including cannabis, oil, animals, opium and unknown gems are also moderately connected with extortion. Beyond extortion, timber exploitation also appears to be an important point of co-occurrence, with armed groups exploiting timber frequently involved in agricultural commodities and opium exploitation as well as theft. Overall, the network reinforces the LCA results by showing that Class 1 is characterized not only by involvement in numerous natural resources but also by their frequent combination with other illicit activities, particularly extortion.

The Class 2 network presents a markedly different structure, with a much narrower range of illicit activities and substantially fewer connections between them. The network contains only 11 nodes and 12 edges, with a mean degree of 2.18, by far the lowest values among the three classes. This indicates that illicit activities among Class 2 groups are less varied and less frequently combined. The network is organized around a small core of activity composed primarily of extortion, kidnapping, theft, and smuggling. Extortion is again central, with the extortion-kidnapping combination constituting the strongest co-occurrence in the network. Natural resources are largely peripheral or absent, and the few resource-related activities represented in the network have weak connections. The co-occurrence structure therefore shows that Class 2 groups concentrate on a comparatively restricted set of criminal activities, concentrating mostly around extortion.

Class 3 occupies an intermediate position in terms of the range of activities but exhibits a comparatively interconnected network. Its 17 nodes are connected by 73 edges, producing a mean degree of 8.59. Thus, although Class 3 groups engage in fewer types of illicit activities than Class 1 groups, the activities that are present tend to form a relatively cohesive set of combinations. This is also reflected in the network density of 0.54, slightly higher than that of Class 1 (0.52). At the center of the network, extortion, theft, and smuggling form a strongly interconnected core that is closely linked to drug-related activities, including opium, coca, cannabis, and unknown drugs. The network therefore further specifies the profile of Class 3: rather than broad diversification across many types of natural resources, these groups display a more concentrated pattern in which drug-related activities are embedded within a wider set of smuggling, extortion, and theft activities.

Taken together, these networks show that the three classes diversify around markedly different cores of activity. Despite these differences in the range and type of illicit activities involved, extortion, and to a lesser extent theft, emerge as central nodes across all three networks. This suggests that these two

crime types may function less as class-specific features and more as a baseline layer of predatory activity that armed groups engage in.

3.3 Diversification trajectory

The trajectory analysis is presented qualitatively, based on visual inspection of trends of illicit activity diversification over time. Figure 4 displays the mean number of different illicit activities in which armed groups are involved on a standardized time scale, where year 0 corresponds to each group's first year of observation in the RCD, year 1 to the following year, and so forth. Because fewer armed groups are observed at later years on this standardized time scale, the mean values for the later years (e.g. years 15 to 25) rest on an increasingly small subset of the sample and should therefore be interpreted with caution, as they are less representative of the sample.

Note

Nine armed groups in the RCD were recorded for only one year and were excluded from this analysis (n = 112). Diversifying/specializing/persistent trajectories are based on the linear slope of each group's trend over time (above/below/between the 0.2/0.8 quantiles). Low/high trajectories are distinguished by diversification level below/above the sample median. The time scale has been standardized to years since first observation. Since armed groups are not observed in the RCD for the same number of years, the bar chart below reports the number of armed groups included in the calculation of the mean for each year. C1asses from LCA are abbreviated (C1 = class 1, etc.). Source: Author's own elaboration based on data from Walsh et al. (2018).

To interpret how the classes relate to these trajectory types, it is useful to first establish a baseline for comparison: in the overall sample, class 1 accounts for 50% of all armed groups (n = 60), class 2 for 26% (n = 32), and class 3 for 24% (n = 29). Comparing the class composition of each trajectory to this baseline distribution can reveal meaningful deviations and could suggest that the three diversification profiles identified through the latent class analysis are not evenly exposed to the same trajectories over time.

Class 1, the class most defined by involvement in the exploitation of several natural resources, is markedly overrepresented in the diversifying trajectory (68.2%, well above its 50% baseline share), while being close to its baseline share in the other trajectories. This pattern suggests that class 1 groups are the main drivers of the diversifying trajectory, progressively broadening the range of illicit activities they engage in over time, consistent with a profile built around the accumulation of multiple natural resource categories.

Class 2, by contrast, is underrepresented in both the persistent-high (11.1%, compared to its 26% baseline) and diversifying (13.6%) trajectories, while being overrepresented in the persistent-low trajectory (35.6%). Given that class 2 is characterized by near-zero natural resource involvement and a stronger orientation toward extortion, this suggests that groups in this class are disproportionately likely to maintain a persistently low level of diversification, rather than expanding their activities over time.

Class 3, characterized by illicit drugs exploitation through smuggling, departs from its 24% baseline mainly in the persistent-high trajectory, where it is overrepresented (38.9%), while being slightly underrepresented in both the diversifying (18.2%) and persistent-low (20%) trajectories. This suggests that class 3 groups tend to establish and sustain a high level of diversification during conflicts, rather than gradually building up illicit activities.

Overall, this trajectory analysis suggests that the diversification profiles identified through the latent class analysis are not static snapshots but correspond to distinct dynamics over time: natural resource-oriented groups tend to diversify progressively, drug- and smuggling-oriented groups tend to sustain high diversification, and groups specialized on extorsion tend to remain persistently low in diversification.

4. Discussion

This study examined the diversification of armed groups' illicit activities during conflict, with particular attention to their involvement in natural resource exploitation. The findings reveal substantial variation in both the extent and the structure of armed groups' involvement in illicit markets. An important finding is that natural resources constitute central illicit markets that armed groups draw on to survive or sustain their operations during conflicts. Half of armed groups in the sample are characterized by substantial involvement in natural resource exploitation. Such findings resonate with the conflict literature interested in the role of natural resource markets in fueling conflicts (Klare 2002; Ross 2004). This research has long argued that resource abundance provides both the economic incentive and the material opportunity for armed groups to sustain conflict (Collier 2000; Sachs and Warner 1995). This literature, however, has been extensively criticized for overstating the causal role of natural resources in the onset of conflict (Cramer 2002; Nathan 2003).

From a criminological perspective, the wide involvement of armed groups in natural resource markets, primarily through extortion (and smuggling in the case of drugs) can be read less as evidence that resources cause conflict, and more as a strategy through which armed groups establish and maintain authority over local populations and territory. Illicit markets built around resources such as gold, timber, coca, or poppy can create opportunities for armed groups to extract revenue from populations and businesses involved at different points along the supply chain, from extraction sites to transport routes and border crossings, generating revenue while simultaneously asserting a form of territorial and economic authority (Arjona 2017; Vlassenroot and Raeymaekers 2004). This taxation is often only one part of a broader form of governance: in many contexts, armed groups have also intervened directly in social lives, regulating economic activity, settling disputes, or administering forms of justice within the areas they control (Mampilly 2011; Revkin 2017).

From this standpoint, this study supports a shift in perspective, away from treating natural resources primarily as a cause of conflict, and toward understanding them as illicit markets that allow armed groups to embed themselves in the social and economic lives of civilians, securing not only profit, but

also control over local populations and territories. The wide involvement of armed groups in natural resource exploitation observed in this study is in line with this reading.

Beyond natural resource exploitation, this study finds that armed groups are also widely involved in a broad range of other illicit activities, suggesting that resource-based markets, while central, constitute only one component of a more diversified set of activities. This reading is reinforced by the network analysis, in which extortion and, to a lesser extent, theft emerged as central and recurrent activities across all three classes identified in this study. These two crime types appear to constitute a baseline layer of predatory activity that armed groups draw on almost independently of their broader diversification profile. This aligns with the literature on extortion, which characterizes it as requiring comparatively little capital investment and no specialized logistical infrastructure, relying instead on the credible threat of coercion directed at a local population or businesses (Konrad and Skaperdas 1998). Theft shares this same logic of low organizational complexity, generating revenue through direct, opportunistic appropriation rather than through the coordination of extraction, processing, or transport that natural resource exploitation typically requires (Weinstein 2006). Extortion and theft may thus represent activities with comparatively low entry requirements which armed groups can draw on regardless of whether they also engage in more organizationally demanding forms of diversification, such as natural resource exploitation or cross-border smuggling.

The trajectory analysis adds a temporal dimension to these findings. Over time, the class most broadly engaged in natural resource exploitation is also the one that expand the range of illicit activities it engages in, whereas the other two classes tend to maintain a comparatively stable level of diversification. This progressive broadening among resource-exploiting groups resonates with the logic of the environmental crime continuum (van Uhm 2019; van Uhm and Nijman 2022), originally developed to describe how organized crime groups deepen their engagement with environmental crime over time. This suggests that this same underlying logic of progressive diversification may extend, at least partially, to armed groups operating in conflict settings.

At the same time, applying a framework developed for organized crime to armed groups involved in conflict calls for some caution, and the findings of this study point to two important limits to this parallel. First, a significant share of armed groups in the sample, corresponding to class 2, shows virtually no involvement in natural resource exploitation and no meaningful diversification of its illicit activities over time. This suggests that the continuum's implicit assumption that criminal actors will tend, over time, to move toward environmental crime, does not hold as a near-universal trajectory. Second, class 3, largely defined by involvement in drug markets, sustained through smuggling, combines this activity with a persistently high level of diversification into other, non-resource-related forms of crime. This pattern is more difficult to reconcile with a framework centered specifically on environmental crime, since it suggests that for at least some armed groups, natural resource exploitation is only one strand within a broader, sustained pattern of criminal versatility, rather than the culmination of a progressive process of specialization. Overall, the environmental crime continuum offers a useful lens for interpreting part of the diversification patterns observed among armed groups, particularly the diversifying trajectory of armed

groups involved in natural resource exploitation, but the findings of this study point to several distinct empirical paths rather than a single, converging trajectory toward environmental crime.

Finally, the wide range of illicit activities armed groups engage in, as shown in this study, also points to a more general explanation rooted in the conditions associated with conflict-affected areas. Armed conflict creates structural conditions conducive to criminal diversification, largely independent of the specific natural resource endowments of a given context (De Boer and Bosetti 2015). The weakening or collapse of formal and informal mechanisms of social control in conflict-affected areas, including the erosion of policing, judicial institutions, and community structures, reduces the risks historically associated with engagement in illicit activity and leaves such markets largely unregulated (Thyne and Schroeder 2012). Conflict also actively generates new criminal opportunities: the surge in demand for weapons and ammunition, combined with low risk and high potential profit, makes a range of illicit markets, not only natural resources but also arms and drug trafficking, particularly attractive to armed actors operating in these settings (De Boer and Bosetti 2015). Finally, the socio-economic degradation that typically accompanies conflict, including displacement, the breakdown of formal economic activity, and rising grievances, can further entrench cycles of violence and illicit activity, as material deprivation and disrupted livelihoods can push both combatants and affected populations toward informal and criminal means of survival (Gurr 1970). Taken together, this suggests that armed groups' diversification into criminal activities should not be understood solely as a function of the natural resources available in a given conflict setting, but also as a broader by-product of the permissive, under-governed environments that conflict itself tends to produce.

Several limitations should be acknowledged in this study. First, regarding the data, we acknowledge that illicit activities are concealed by nature, making them inherently difficult to document comprehensively. Although the RCD incorporates source triangulation and verification, some activities may have gone unrecorded or been misattributed. More structurally, the RCD relies on UCDP's conflict criteria (notably a minimum of 25 battle-related deaths per year) to define inclusion, meaning armed groups are primarily observed during years meeting this threshold. This limitation is partly mitigated by the RCD's inclusion of gap years, that is, years falling between two periods of recorded conflict activity, for which illicit activity data were also coded. Nonetheless, gaps in the data may still occur for years preceding an armed group’s first appearance or following its last. Findings should therefore be understood as applying primarily to periods of active conflict rather than to groups' full lifespans.

Second, regarding methodological choices: this study is exploratory and does not establish causal relationships, associations should be read descriptively. Latent class analysis produces classes that are, to some extent, statistical constructs shaped by modeling choices rather than necessarily naturally occurring types. While external validation offers some reassurance, it does not guarantee these classes exist as such, and they should be treated as a useful simplification rather than a definitive typology. Finally, the trajectory analysis involved subjective choices, notably the thresholds distinguishing trajectory types. Although justified and made transparently, these leave room for alternative

categorizations and potentially alternative results. Therefore, the resulting trajectories should be read as one plausible interpretation among others.

5. Conclusion

This study examines how armed groups involved in conflicts diversify their illicit activities, with a focus on natural resources. Drawing on data from 121 armed groups across 126 conflicts, the analysis combined latent class analysis, social network analysis, and a qualitative examination of diversification trajectories over time. Rather than considering individual illicit markets separately, this approach examined how different illicit activities are combined, how these combinations vary across armed groups, and how diversification evolves during periods of conflict.

The findings show that armed groups display substantial heterogeneity in both the extent and structure of their illicit activities. Natural resource exploitation occupies an important position within these activities, but it does not constitute a uniform model of conflict financing. Some armed groups engage broadly across several illicit markets of natural resources, others remain largely outside these markets and rely on a narrower range of criminal activities, while others combine specialization in particular resource markets, especially illicit drugs, with wider smuggling and predatory activities. At the same time, criminal activities such as extortion and theft are widely used by most armed groups, suggesting that certain forms of predatory crime constitute a common foundation upon which more differentiated forms of illicit involvement can develop. The temporal analysis further shows that diversification follows distinct dynamics across armed groups: groups broadly involved in natural resource exploitation tend to expand their range of illicit activities over time, whereas groups centered on drug markets and smuggling tend to sustain high levels of diversification, and groups relying primarily on extortion tend to remain comparatively less diversified.

These findings contribute empirically to the study of armed groups and illicit economies by moving beyond the predominantly case-based or market-specific approaches that have characterized much of the existing literature. Looking simultaneously across multiple conflicts and multiple illicit activities reveals that armed groups' involvement in criminal economies is better understood as a set of interconnected activities rather than as participation in isolated markets. More broadly, the study contributes to bridging research on armed conflict with criminological scholarship on illicit markets and organized crime. The findings suggest that concepts developed to understand organized crime can provide useful insights into armed groups, while also requiring adaptation to the distinctive political, territorial, and organizational conditions of conflict. Ultimately, examining illicit activities as an integral dimension of armed groups' organization and operation provides a more complete understanding of the relationship between conflict and crime. Rather than viewing criminal activities solely as secondary mechanisms for financing warfare, this study highlights them as diverse, interconnected, and evolving components of the environments in which armed groups operate.

Declarations

Author Contribution

L.T.R: Conceptualization, methodology, data preparation, data analysis, visualization, writing, editing.S.C: Conceptualization, supervision.

Data Availability

This study uses the Rebel Contraband Dataset (RCD), developed by Walsh et al. (2018). The dataset is publicly available through the original data repository: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/COQ65B

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Footnotes

1. The Rebel Contraband Dataset originally covers 318 conflicts in which 299 armed groups are involved. The dataset was first reorganized so that the unit of analysis became armed group-year (rather than conflict-year), and armed groups with no recorded illicit activity were excluded, reducing the sample to 154 armed groups. Of these, 121 could be matched with the Armed Group Dataset (used for the external validity), constituting the final analytical sample.
2. Unlike the latent class analysis, which relied on a subset of natural resource categories and crime types, the networks use the full set of illicit activities recorded in the RCD: natural resources are disaggregated into their original, uncategorized variables (e.g., gold, timber, opium), and all crime-type variables are included. For each class-specific network, illicit activities with no armed groups involved in that class were excluded. Moreover, strategies used to derive revenue from natural resources (e.g., commodity extortion, commodity theft) were excluded from the networks.

Figures

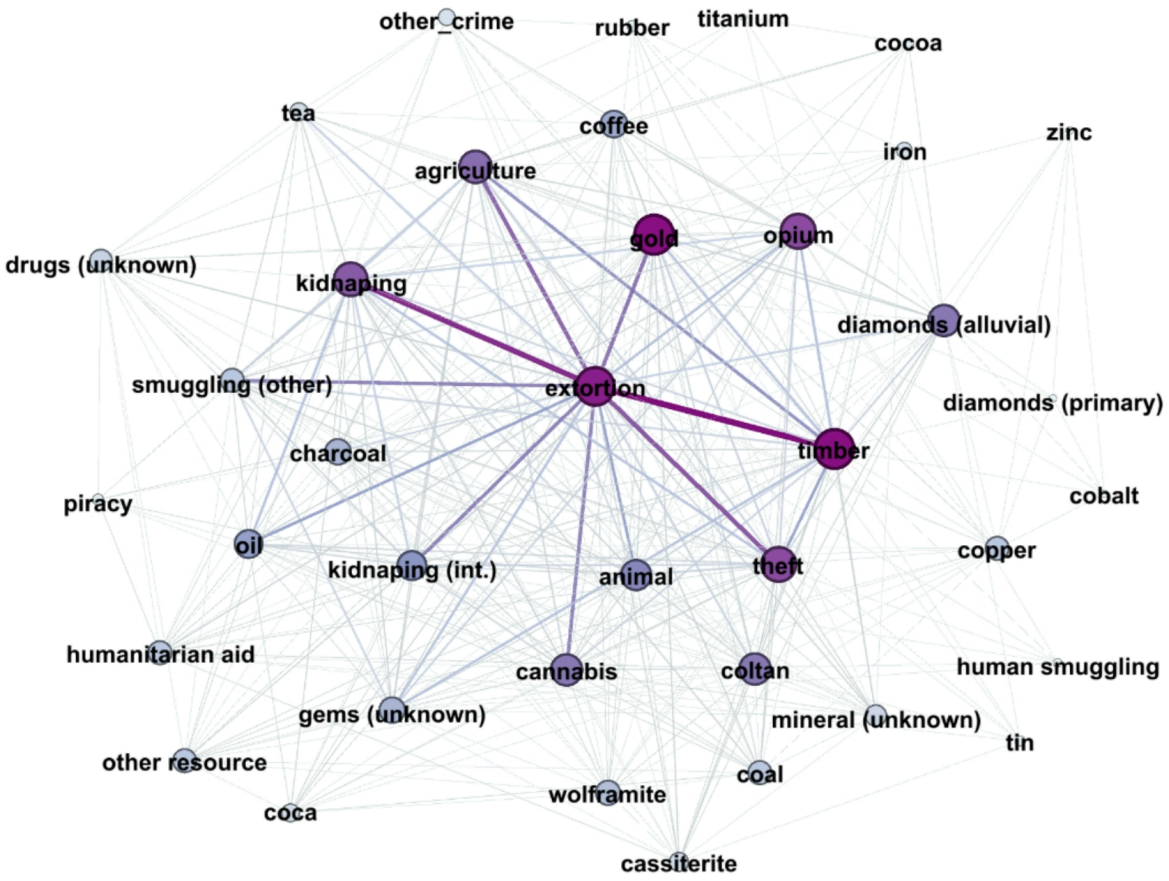


Figure 1

Network of illicit activity co-occurrence for class 1. Source: Author's own elaboration based on data from Walsh et al. (2018)

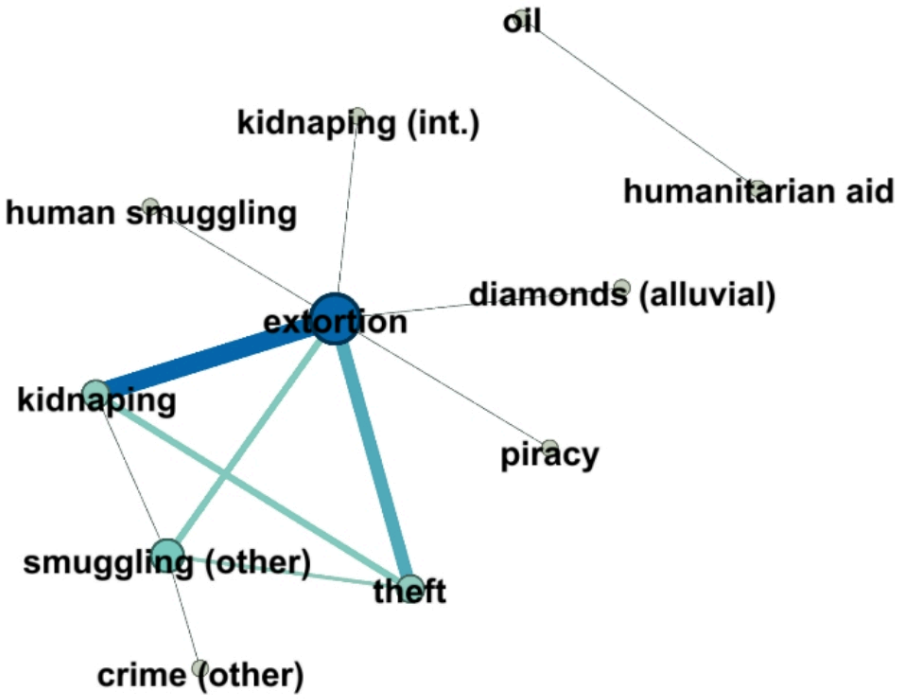


Figure 2

Network of illicit activity co-occurrence for class 2. Source: Author's own elaboration based on data from Walsh et al. (2018)

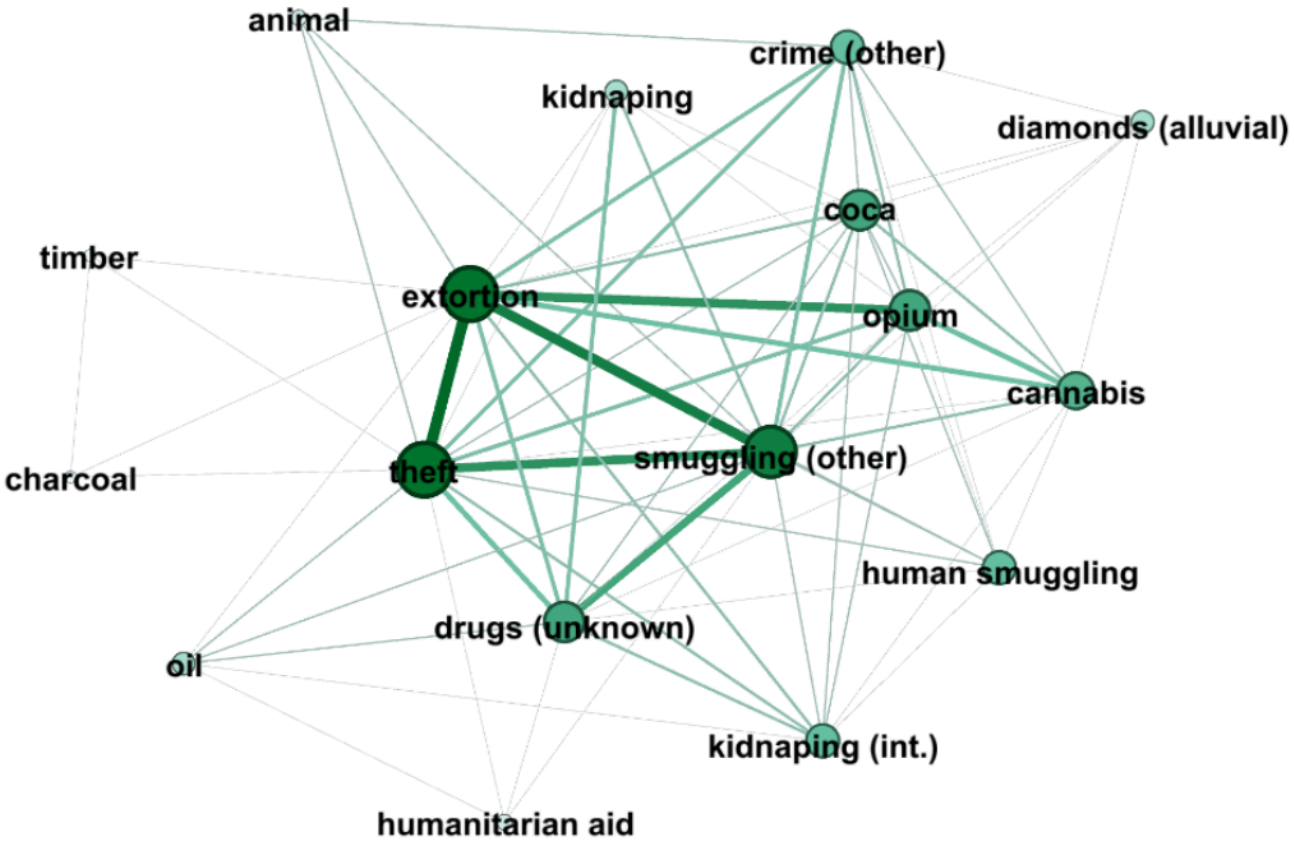


Figure 3

Network of illicit activity co-occurrence for class 3. Source: Author's own elaboration based on data from Walsh et al. (2018)

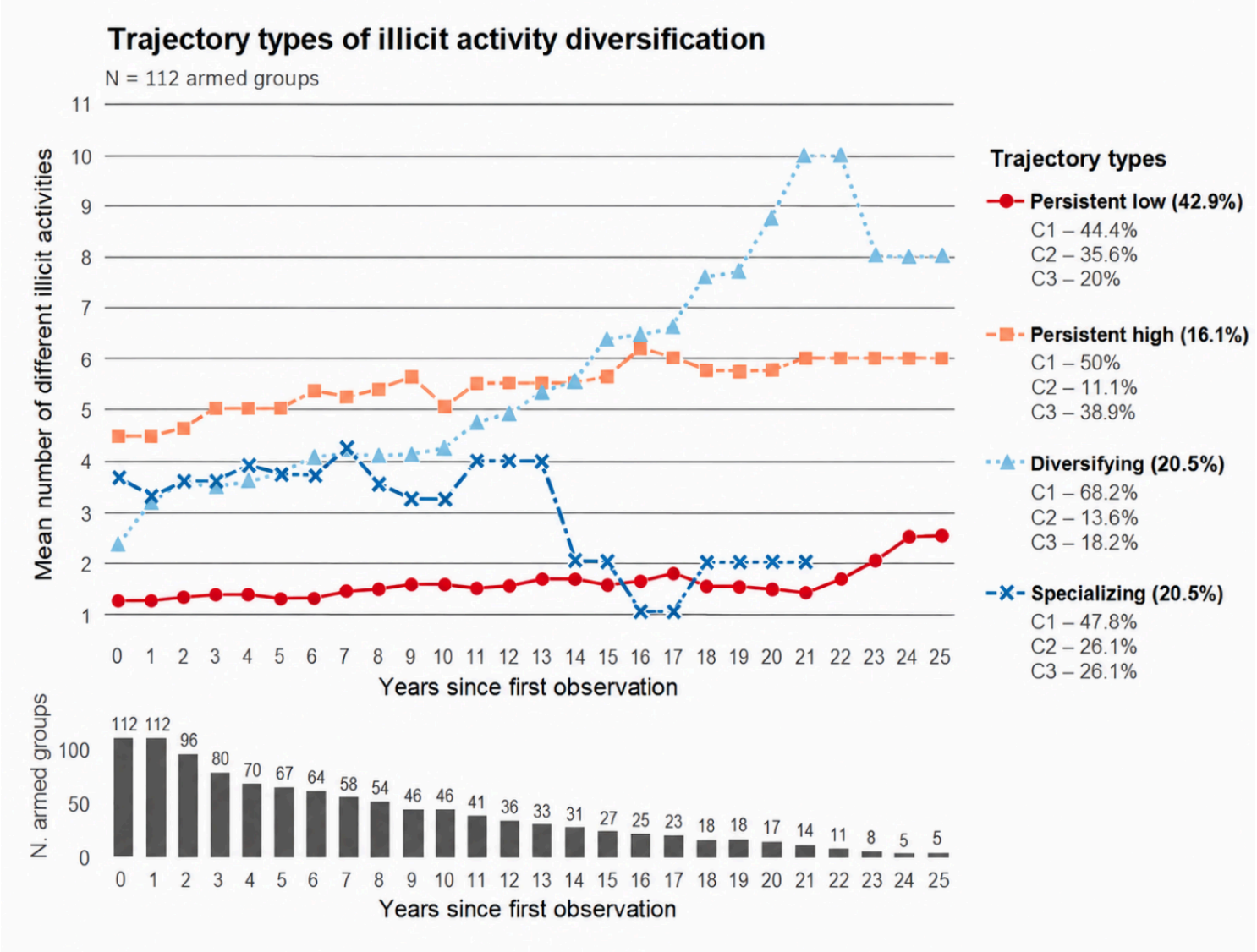


Figure 4

Trajectories of diversification

Note: *Nine armed groups in the RCD were recorded for only one year and were excluded from this analysis (n=112). Diversifying/specializing/persistent trajectories are based on the linear slope of each group's trend over time (above/below/between the 0.2/0.8 quantiles). Low/high trajectories are distinguished by diversification level below/above the sample median. The time scale has been standardized to years since first observation. Since armed groups are not observed in the RCD for the same number of years, the bar chart below reports the number of armed groups included in the calculation of the mean for each year. C1asses from LCA are abbreviated (C1=class 1, etc.). Source: Author's own elaboration based on data from Walsh et al. (2018).*

Supplementary Files

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- Appendix.docx