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The resilience of drug trafficking organizations: Simulating the impact of police arresting key roles

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ABSTRACT

Purpose: This research analyses the resistance and resilience of drug trafficking organizations against law enforcement interventions targeting specific operational roles.
Methods: Using the MADTOR agent-based model, which draws on extensive data from a significant police operation and relevant literature, we simulate the complex dynamics of a major cocaine trafficking and dealing group. The study examined the impact of different arrest scenarios targeting traffickers, packagers, or retailers, on the organization's survival, member count, and revenue.
Results: The findings reveal that interventions targeting traffickers lead to the most significant disruptions, while focusing on retailers also yields substantial impacts. Arresting packagers causes limited disruption.
Conclusions: The findings underscore the importance of role-specific law enforcement approaches in dismantling drug trafficking organizations, considering each role's distinct characteristics and operational importance.

1. Introduction

Drug trafficking spans a continuum involving production, manufacturing, trafficking, wholesale/regional distribution, and retail sales. This variety of activities reflects in the organizational structures of drug trafficking organizations, which range from small, loosely organized groups to larger, more structured entities, often specializing in one or two different stages of the drug trafficking continuum. All drug trafficking organizations, however, are primarily motivated by the pursuit of financial gain (Reuter & Kleiman, 1986).

While the profit motivation makes drug trafficking organizations like normal enterprises, their operational reality is substantially different. In most countries with functioning government and criminal justice systems (Campana & Varese, 2022; Paoli, 2016), these organizations operate without the support of the state for dispute resolution and rule of law enforcement. Concurrently, they exist in opposition to the state, constantly facing the threat of disruption by law enforcement agencies (Paoli, 2002; Reuter, 1983). This condition discourages the creation of large-scale, monopolistic, stable organizations while favoring small, competitive, and dynamic groups (Eck & Gersh, 2000). Despite these constraints, larger and more complex drug trafficking organizations do emerge in some areas and periods. These entities not only command a substantial market share but also pose a greater challenge to law enforcement due to their capacity for violence and resilience. Understanding the dynamics of these larger organizations is crucial for developing effective strategies to counter their influence and operations.

Research on drug trafficking organizations has previously focused on the structural analysis of these organizations, particularly how the removal of certain members influences their resistance and resilience. Resistance is the ability to withstand disruptions without altering their operations. Resilience, on the other hand, denotes the capacity to adapt and recover from disruptions, ensuring their survival and continued functionality. Essentially, resistance is about enduring attacks without change, while resilience involves adapting and evolving in response to challenges (Bakker, Raab, & Brinton Milward, 2012; Prezelj & Doerfel, 2017; Reghezza-Zitt, Rufeat, Djament-Tran, Le Blanc, & Lhomme, 2012). Studies have employed various methodologies, including network analysis and agent-based modeling (ABM), to examine the effects of law enforcement interventions on drug trafficking organizations (Dray, Mazerolle, Perez, & Ritter, 2008; Duxbury & Haynie, 2019, 2020; Magliocca et al., 2022; Romano, Lomax, & Richmond, 2009). However, these studies often rely on theoretical constructs or network metrics, which may not always translate effectively into actionable strategies for real-world law enforcement.

We introduce a new approach by examining the effects of targeting individuals enacting specific roles within drug trafficking organization.

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Using MADTOR (Model for Assessing Drug Trafficking Organizations Resilience), an agent-based model, we simulate various law enforcement arrest scenarios against a cocaine trafficking organization. MADTOR is informed by detailed qualitative and quantitative data from Operation Beluga, a significant investigation into an Italian large scale drug trafficking and distribution group, as well as comprehensive empirical literature on drug trafficking. While several studies have employed agent-based simulations to examine the resilience of drug trafficking groups, our approach's novelty relies in its explicit modeling of the drug trafficking and dealing processes, in the simulations of the arrest of multiple actors simultaneously, and in the modeling of the reaction strategies of drug trafficking organizations, including the recruitment of new members and the establishment of new ties. Furthermore, our simulations facilitate the testing of different types and intensities of law enforcement strategies.

This study examines the effects of law enforcement interventions targeting specific operational roles within drug trafficking organizations—traffickers, packagers, and retailers—on their survival, member count, and revenue. The aim is to understand the significance of distinct roles in the organization's resilience and resistance and to assess the effectiveness of role-specific law enforcement strategies in disrupting drug trafficking operations. Our analysis indicates that actions against traffickers are most disruptive, significantly affecting the organization's operations. Also targeting retailers results in relevant disruption, whereas targeting packagers appears to be the least effective method. While our results suggest that role targeting may improve the disruption of criminal groups, we argue that individuals in different roles have varying resources, skills, and visibility, influencing the feasibility and constraints of law enforcement actions. Therefore, effective strategies require a balanced approach to role targeting, aligning with the available resources and operational limits of law enforcement.

2. Background

2.1. Structures and roles in drug trafficking organizations

Drug trafficking encompasses several passages along the production-distribution continuum, including production, manufacturing, trafficking, wholesale/regional distribution, and retail (street-level) sale (Johnson, Hamid, & Sanabria, 1992; Natarajan & Belanger, 1998; Natarajan, Zanella, & Christopher, 2015; Reuter, 2014). Multiple drug trafficking organizations are involved in each of these phases and rarely any organization engages in the entire continuum; in fact, drug trafficking organizations tend to focus on one or some phases of the production-distribution process (Natarajan et al., 2015; Natarajan & Belanger, 1998).

The specialization on specific passages of the drug trafficking continuum affects the internal structure of drug trafficking organizations. Empirical evidence suggests that upper-level drug market sees informal, dynamic partnership leveraging on brokering skills (Desroches, 2007; Dorn, Levi, & King, 2005). While small and loosely structured entities appear to predominate also among regional and retail distribution phases, there are also indications of larger, more structured and organized groups (Natarajan et al., 2015; Natarajan & Belanger, 1998).

Most drug trafficking organizations are relatively small, often consisting of just a few dozen individuals; they are loosely structured, with minimal or no hierarchical organization, and a distribution of tasks primarily reflecting the individual capabilities of their members (Benson & Decker, 2010; Bichler, Malm, & Cooper, 2017; Decker & Chapman, 2008; Eck & Gersh, 2000; Kenney, 2007; Natarajan, 2000; Natarajan, 2006; Reuter & Haaga, 1989; von Lampe, 2009; Zaitch, 2002). Occasionally, however, larger, more structured, hierarchical organizations grow. Their internal structure is more closely resembling that of a legitimate enterprise: different management and supervision layers, predefined functional roles associated to different activities, rewards and incentives (Benson & Decker, 2010; Curtis, 1996; Eck & Gersh, 2000; Johnson et al., 1992; Natarajan et al., 2015; Natarajan & Belanger, 1998).

Research identified some common roles among drug trafficking organizations, despite their diversity in of size, geographic reach, and the types of drugs they handle (Bright, Hughes, & Chalmers, 2012; Calderoni, 2012; Natarajan, 2000, 2006). Traffickers, also known as sellers or wholesale dealers, procure significant quantities of drugs for their group. Traffickers often have prominent roles within the groups due to their skills and connections (Bright et al., 2012; Bright & Delaney, 2013; Calderoni, 2012; Natarajan, 2006). Drug trafficking organizations frequently include individuals responsible for safeguarding stash houses and assisting in the packaging of drugs in smaller retail quantities. These individuals may be referred to as field workers, laborers, managers, supporters (Bright et al., 2012; Bright & Delaney, 2013; Calderoni, 2012; Natarajan, 2000). Lastly, drug trafficking organizations engaged in the sale to drug users often employ retail dealers or retailers solely for street-level drug sales (Bright & Delaney, 2013; Calderoni, 2012; Natarajan, 2006). Due to their visibility and exposure to risks, more prominent members (e.g., traffickers) avoid these roles and assign them low-status individuals, seen as expendable and replaceable by the organization (Calderoni, 2012).

2.2. Drug trafficking roles and network disruption

Researchers have often analyzed how the removal of specific members may affect their resistance and resilience of drug trafficking groups. Studies examined the structure of criminal networks before and after simulating the removal of certain actors and ties (Castiello, Mosca, & Villani, 2017; Cavallaro et al., 2020; Duxbury & Haynie, 2018; Villani, Mosca, & Castiello, 2019; Wood, 2017). Researchers have often analyzed how the removal of specific members may affect their resistance and resilience of drug trafficking groups. Studies examined the structure of criminal networks before and after simulating the removal of certain actors and ties (Castiello et al., 2017; Cavallaro et al., 2020; Duxbury & Haynie, 2018; Villani et al., 2019; Wood, 2017). Some more advanced approaches have also considered network reactions and adaptation strategies to law enforcement actions (Carley, 2006; Keller, Desouza, & Lin, 2010; Duijn, Kashirin, & Sloot, 2014; see Bright, Greenhill, Britz, Ritter, & Morselli, 2017; Duxbury & Haynie, 2019, 2020). These studies identified targets for arrest through multiple methods, including the highest number of direct contacts (degree centrality), brokerage roles (betweenness centrality), social or human capital, or key resources, and compared the effect of arresting the target versus random target selection. Some more advanced approaches have also considered network reactions and adaptation strategies to law enforcement actions (Carley, 2006; Keller et al., 2010; Duijn et al., 2014; see Bright et al., 2017; Duxbury & Haynie, 2019, 2020). These studies identified targets for arrest through multiple methods, including the highest number of direct contacts (degree centrality), brokerage roles (betweenness centrality), social or human capital, or key resources, and compared the effect of arresting the target versus random target selection.

Overall, this research demonstrated that criminal networks were highly vulnerable to the sequential removal of key targets whereas attacks targeting operational, non-key, members caused much less difficulty for the organizations (Agreste, Catanese, De Meo, Ferrara, & Fiumara, 2016; Castiello et al., 2017; Cavallaro et al., 2020; Duxbury & Haynie, 2018; Morselli & Roy, 2008; Villani et al., 2019; Wood, 2017). In addition, taking into account network adaptation strategies always resulted in a substantial reduction in the effectiveness of law enforcement interventions (Bright et al., 2017; Carley, 2006; Duijn et al., 2014; Duxbury & Haynie, 2019; Keller et al., 2010).

While prior research offered important insight into the resilience of drug trafficking organization to law enforcement action, target selection relied on network analysis metrics or extensive assessment of the internal functioning of the drug trafficking groups. These methods are rarely accessible to law enforcement agencies during their operations. In contrast, there is considerably less information available regarding the effectiveness of targeting individuals performing specific roles within drug trafficking organizations. This information may be more easily accessible to law enforcement agencies even during the initial phases of investigations. Law enforcement agencies frequently face the challenge of allocating finite resources, often requiring them to plan investigations focused on a specific niche of the drug market. A clearer understanding of the most vulnerable stages and actors within the trafficking chain would provide a strategic asset, potentially leading to more effective interventions.

Limited research exists on the impact of arresting individuals with different roles in drug trafficking organizations. However, insights from previous studies on the internal structure of these groups offer considerations. Targeting traffickers may threaten the organization's survival by severing connections between the drug production and consumer sides of the market (Babor et al., 2018; Malm & Bichler, 2011; Reuter, 2014). Removing these figures, who possess unique knowledge and skills, can significantly damage the drug trafficking organization (Calderoni, 2012; Johnson & Natarajan, 1995). Conversely, disrupting lower-level members involved in the retail side of the drug market may pose fewer challenges for organizations (Malm & Bichler, 2011). These individuals, easily replaceable and lacking specialized skills, are more susceptible to intervention (Calderoni, 2012; Johnson & Natarajan, 1995). Arresting traffickers is often more challenging than targeting lower-level members due to their resources and expertise in evading law enforcement. In contrast, grassroots members, more visible and vulnerable, are deemed replaceable and lack sensitive information about the criminal group. They are exposed, lacking protective strategies (Calderoni, 2014; Morselli, 2010).

2.3. The current study

This study investigates the resilience of drug trafficking organizations to large-scale law enforcement interventions that target actors fulfilling specific roles. It examines the factors that influence their ability to avoid being targeted and their capacity to leverage existing sources of resilience when faced with disruption attempts aimed at undermining their illicit activities.

This study's contributions lie in the implementation of more realistic law enforcement disruption attempts compared to those employed prior research. First, we select targets based on information available from the early investigation stages (i.e., involvement criminal activities and roles accomplished in the organization). In most jurisdictions, law enforcement starts an investigation by gathering evidence about all the suspects of a specific case. Investigative activities conclude when the police have gathered enough evidence to formulate charges and arrest the suspects (e.g., Berlusconi, 2022; Calderoni, 2012, 2014). In contrast, most previous studies have analyzed the effects of removing specific actors from a network (i.e., those displaying peculiar features), but this is more a theoretical exercise than a realistic representation of how police interventions are conducted.

Second, we simultaneously arrest multiple members of the organization rather than few members sequentially. The practice of removing only one or a few actors from an organization is far from what occurs in real police interventions. Law enforcement typically removes from the network all actors for whom they have substantial evidence of their involvement in criminal activities, which often means most of the suspects (Calderoni, 2012, 2014; e.g., Berlusconi, 2022). While sporadic arrests of a few members of criminal organizations may occur in certain peculiar circumstances (e.g., arrests of some actors in flagrante delicto while committing criminal offences), these arrests rarely involve key members of the organization (i.e., those members with peculiar features whose removal has been simulated in previous studies). Conversely, it is far more likely that grassroots actors will be apprehended in flagrante delicto because they lack specific resources to protect themselves and their criminal involvement. Moreover, considering the sporadic arrests of low-ranking members, there is vast evidence that these attacks are not lethal for criminal groups, as they often rearrange their criminal activities and organigrams (Calderoni, 2014; Morselli, 2010). In contrast, much less is known about how criminal organizations respond to critical threatening events, such as the simultaneous removal of multiple members assigned to specific roles.

Third, we consider the organization's reactions to the disruption attempt. Most studies on criminal network disruption often neglected the dynamic nature of networks, only examining criminal networks' structure before and after the simulated removal of certain actors and ties based on network metrics (see Agreste et al., 2016; Castiello et al., 2017; Cavallaro et al., 2020; Duxbury & Haynie, 2018; Morselli & Roy, 2008; Wood, 2017). Studies explicitly addressing reaction (Carley, 2006; Keller et al., 2010; Duijn et al., 2014; e.g., Bright et al., 2017; Duxbury & Haynie, 2019, 2020; Diviák, 2023), demonstrated that the inclusion of network adaptation significantly diminishes the efficacy of disruption attempts. At the same time, these studies still suffer from the pitfalls of previous research highlighted above; they focus on the arrest of a few specific actors identified relying on information and metrics that remain inaccessible to law enforcement during the investigative phase.

This study aims to address the following research questions: What is the impact of arresting members performing different roles on the resistance and resilience of drug trafficking organizations to law enforcement disruption attempts? Specifically, how does it affect the survival of the group, the number of active members, and the organization's revenues?

The authors explore drug trafficking organizations' resilience, in terms of resistance and reactions to law enforcement disruption attempts by developing and analyzing data extracted from an agent-based model simulating law enforcement intervention scenarios attempting to jeopardize the organizations' drug trafficking and dealing. Information from a detailed court order against a large-scale Italian DTO and from the literature enabled the calibration and validation of the model, ensuring the simulation of drug trafficking organizations displaying features comparable to those of real ones in terms of both organizational structure and involvement in the drug market.

3. Methodology

Employing computer-based experiments, ABM creates simulated societies where independent agents interact (Wilensky & Rand, 2015). These agents, each with their unique traits, follow rules set by the model developer, creating a dynamic environment that mirrors real-life complexity; thus, facilitating the investigation of emergent macro-phenomena arising from micro-level interactions (Gerritsen, 2015; Gilbert, 2007). Unlike conventional equation-based models, the distinctive feature of ABM lies in its accommodation of highly heterogeneous agents, thereby enabling the reproduction of intricate and diverse interactions reflective of real-world complexities (Bianchi & Squazzoni, 2020; Wilensky & Rand, 2015). Agents act based on rules set by researchers, whether grounded in theories or empirical real-world observations. In either cases, acknowledging the impossibility of fully capturing every facet of reality, ABM simulations are a simplified version of society that, relying on the assumptions of the model designer, create virtual worlds to understand the complex interactions of individuals in society (Gerritsen, 2015).

In social sciences, ABMs are valuable for exploring social dynamics, especially when considering heterogeneous agents, offering an alternative to real-world experiments with lower ethical and security concerns. In criminology, where real-world experiments face major ethical and privacy challenges, ABM may also serve as a policy evaluation tool (Berk, 2008; Bianchi & Squazzoni, 2020; Calderoni, Campedelli, Szekely, Paolucci, & Andrighetto, 2021; Gerritsen, 2015; Groff, Johnson, & Thornton, 2019). Criminologists exploited ABMs to gain insights into urban crime prediction, preventive measures' effectiveness, organized crime dynamics, drug trafficking, and criminal network resilience (Acconcia, Immordino, Piccolo, & Rey, 2014; Calderoni et al., 2021; Diviák, 2023; Dray et al., 2008; Duxbury & Haynie, 2019, 2020; Elsenbroich, 2017; Groff, 2007; Magliocca et al., 2022; Romano et al., 2009; Székely, Nardin, & Andrighetto, 2018; Wang, Liu, & Eck, 2014; Weisburd, Braga, Groff, & Wooditch, 2017; Zhu & Wang, 2021). These studies demonstrated the benefits of employing the ABM perspective to investigate complex criminological dynamics that are challenging to study through traditional methods.

ABMs are thus ideal for examining the resilience and resistance of drug trafficking organizations to the arrest of members in various roles. They allow simulation of the arrest of different numbers of members across diverse roles, assessing the effectiveness of various scenarios in disrupting drug trafficking networks. By exploring a range of hypothetical scenarios grounded in key assumptions, ABMs enhance our understanding of drug trafficking organizations' responses to deliberate law enforcement disruptions and support the refinement of law enforcement strategies. The following subsections outline the sources and functioning of our ABM and the analytical strategy we have adopted for this study. For further detail, we direct readers to the comprehensive online model documentation.[1]

3.1. Data sources

The primary source of qualitative and quantitative information to empirically inform MADTOR (Model for Assessing Drug Trafficking Organizations Resilience) was the pre-trial order of Operation Beluga, a 984-page judicial document containing many details about the suspects, their criminal activities and their organization. This document resulted from a five-year investigation into the Camorra's Di Lauro clan operating in Naples between the end of 2007 and the spring of 2013 (Tribunale di Napoli, 2013).

The criminal group targeted by Operation Beluga (hereinafter the Beluga group) was involved in multiple illegal activities, notably drug and firearms trafficking. However, the discovery of 172 accounting books revealed that drug sales were its primary income source. The group meticulously managed drug retailing in two distinct areas, specializing in different drugs. Payment structures varied, with fixed weekly payments for those involved in drug trafficking and packaging, and daily payments based on sales percentages for street-level dealers. These profits funded various criminal endeavors, including acquiring weapons, corrupting officials, and supporting the families of incarcerated affiliates (Tribunale di Napoli, 2013). The extensive information from the Beluga court order informed MADTOR, serving as a vital source for comprehensive data on criminal activities and economic aspects of drug trafficking. Additionally, the arrest of eight key Di Lauro clan members in 2010 during the investigation provided a unique opportunity to study the group's resilience and resistance.

The development and calibration of MADTOR also relied on other sources. The first source was UNODC's cocaine wholesale price data (UNODC, 2010). A second source was the empirical literature on drug trafficking, which guided the modeling of disruption attempt features, elements considered in drug acquisition decisions, and the selection of criminal collaborators.

Although MADTOR's use of data from the Beluga court order may raise concerns about biases stemming from the specific dynamics of the Beluga group, there are reasons to believe that these biases should not significantly affect the model's applicability to other drug trafficking organizations. One challenge is that the Beluga group exhibits characteristics of mafia-type organizations. Unlike other mafias, the Camorra comprises various urban clans and groups that form fluid coalitions, lacking a central coordinating body (Brancaccio, 2014; Reuter & Paoli, 2020; Scaglione, 2016). This similarity to non-mafia drug trafficking organizations in terms of structure and dynamics mitigates the potential bias. Its organizational structure aligns with communal business and corporate models, emphasizing cultural values, role division, and hierarchical structures. The group focuses on regional and retail distribution, consistent with specialization observed in drug trafficking organizations. Their modus operandi prioritizes profit maximization, even at the expense of lower-level members, employing protective strategies commonly found in similar cases: working in small teams, compartmentalizing information based on the "need-to-know" principle, assigning risky roles to lower-ranking members, utilizing multiple channels for drug acquisition, processing, and sales, and ensuring consistent payments to minimize the risk of betrayal (Curtis, 1996; Desroches, 2005, 2007; Duijn et al., 2014; Kenney, 2007; Natarajan et al., 2015; Natarajan & Belanger, 1998). While the group was involved in various criminal activities beyond drug trafficking, the detailed data available in the Beluga court order allows for the precise isolation of factors influencing drug trafficking activities and the distinction of costs and revenues related to different drugs. Overall, although we recognize the significant influence of the Beluga court order on the model's development, we contend that the characteristics of the Beluga group are representative of many other large, structured drug trafficking organizations. Additionally, the MADTOR code is freely accessible, allowing for easy adaptation of the model to various contexts and organizational types.

3.2. MADTOR: Model for Assessing Drug Trafficking Organizations Resilience

3.2.1. Preliminary assumptions

The simulation of the criminal activities of a drug trafficking organization required four key assumptions, each tailored to simplify the model and focus on specific aspects.

First, MADTOR primarily focused on cocaine. Although real-world drug trafficking organizations often deal with multiple drugs, each drug type introduces unique dynamics such as acquisition sources, manufacturing processes, risks, costs, and revenues. To maintain a close resemblance to real-world data, MADTOR concentrated on cocaine because available information regarding trafficking routes, financial aspects, and structure of organizations, both from the literature and the Beluga court order, is richer for cocaine than for other drugs (e.g., Calderoni, 2012, 2014; Johnson et al., 1992; Morselli & Petit, 2007; Natarajan, 2000; Reuter & Haaga, 1989; Roks, Bisschop, & Staring, 2021; Terenghi, 2022; Zaitch, 2002).

Second, MADTOR omitted cocaine production and large-scale smuggling from its scope, as these activities were outside the purview of the Beluga group. Research also indicates that cocaine production is typically managed by separate groups with limited influence on subsequent phases like wholesale and regional distribution, which are the central focus of MADTOR (Benson & Decker, 2010; Curtis, 1996; Decker & Chapman, 2008; Natarajan et al., 2015; Natarajan & Belanger, 1998; Reuter, 2014; Reuter & Haaga, 1989).

Third, following the "KISS" (i.e., "Keep it simple, stupid!") ABM principle, MADTOR simplified the complexity of the organization's structure and drug trafficking and dealing activities to the essentials (Axelrod, 1997; Groff et al., 2019). Regarding the former, while in real organizations members may accomplish multiple roles simultaneously, or they may modify their role over time, the authors reduced this complexity by carefully interpreting available information in the Beluga court order to assign a primary role in the organization for the period under consideration. Regarding the latter, MADTOR identified four core steps in drug trafficking and dealing: drug acquisition, processing and packaging, drug sales, and accounting of expenses. These steps aligned

[1] We have made available the code, an extensive narrative documentation outlining the model's characteristics, and an ODD+D protocol at the following link: https://www.comses.net/codebase-release/a5543b7a-8ed1-413b-88b8-5a44aed06c0d/.

with established crime scripts (Bright & Delaney, 2013; Chiu, Leclerc, & Townsley, 2011; Le, 2013) and the existing literature on the social organization of drug trafficking (Calderoni, 2012, 2019; Natarajan, 2000, 2006; Natarajan & Belanger, 1998). The detailed descriptions of these steps in the Beluga court informed the model.

Lastly, the model assumed that drug trafficking organizations regularly encounter minor disruptions, leading to the arrest of a maximum of one member per month by law enforcement (e.g., arrests of some actors in flagrante delicto while committing criminal offences). Additionally, each organization experiences a major disruptive event at the end of the second year (Tribunale di Napoli, 2013; Fabiani & Behlendorf, 2021; Morselli & Petit, 2007).

3.2.2. Overview of the model

MADTOR, built on NetLogo version 6.2.0 (Wilensky, 1999), models the daily operations of a drug trafficking organization over a 5-year span (Fig. 1). Throughout this timeframe, the participants contend with the risk of law enforcement interventions designed to disrupt their illicit activities. Each simulation tick (the unit of time measurement in NetLogo) represents one day of real life, and the various activities occur after a different number of ticks.

In the setup phase, the model imports crucial data. This includes details about the drug trafficking organization's structure (member information and relationships) and data regarding its activities (drug quantities, costs, prices, and rewards). To adapt to changes in the Beluga group and its environment, the model refreshes this data every thirty simulated days.[2]

At the simulation's start, the drug trafficking group has 44 members with distinct roles: 5 traffickers dedicated to drug acquisition, 5 packagers responsible for drug processing and packaging, and 34 retailers engaged in drug sales. The group's composition may change due to recruitment and defection. Recruitment occurs based on the organization's workload needs, while defection results from personal choices, arrests by law enforcement, or member deaths.

The members of the organization possess two key attributes which have their foundation in the literature: a specific criminal ability level (assigned randomly at the simulation's outset) and a level of connectivity with other organization members (based on information from the Beluga court order) (Duxbury & Haynie, 2019; Weisburd et al., 2017). Each drug movement among members establishes a relational tie between the involved actors, and each additional relational tie among the same actors strengthens their connectivity, forging the patterns of interaction in the organization. The model updates these attributes daily to reflect any fluctuations in criminal skills and evolving patterns of member interaction.

The first activity is the drug acquisition. Monthly, traffickers in the organization evaluate drug acquisition feasibility based on stockpile levels, wholesale prices, and market conditions. These factors contribute to a composite index that guides acquisition probability. Success also depends on the criminal ability of the trafficker, with higher skills increasing the likelihood of success. On average, drugs are acquired at the wholesale level for 40.45€/g (SD: 4.24). Outcomes, successful or not, impact the traffickers' abilities, enhancing or decreasing them accordingly (see online model documentation for detailed computation).

The second activity is the making of unit-dose drug packages. Daily, packagers receive large drug quantities from traffickers, process them into doses, and pass these to retailers. MADTOR simulates the processing and packaging of drugs through two drug exchanges: one from traffickers to packagers and another from packagers to retailers. Between these exchanges, packagers handle the packaging the drug doses. The model considers factors like familiarity, trustworthiness, criminal abilities, and closeness to determine exchange participants. Familiarity tracks past exchanges, trustworthiness reflects visibility within the organization, and criminal abilities are assigned randomly at simulation start. Closeness centrality measures an actor's network proximity (see online model documentation for more details).

The third activity involves drug sales, where retailers distribute unit-dose packages to consumers. To minimize complexity, consumers are not explicitly modeled, and therefore, there is no actual negotiation involved in sales transactions. The organization maintains an average daily sales volume of approximately 1900 cocaine doses, with some variability in the exact number of doses, bounded by the Beluga group's minimum and maximum daily sales. This mechanism approximates the existing consumer demand in the market. Each dose, priced at approximately 32€, weighs 0.25 g. Retailers are compensated on a piecework basis, receiving an 18% share of the revenues for their work, with the remaining funds channeled to group leaders. They never exceeded a personal profit of 500€, which corresponds approximately to 2500–3000€ per day in drug sales (see online model documentation for more details).

The final activity pertains to financial accounting within MADTOR. Instead of attributing this role to individual members, the model assesses the organization's financial status by tracking revenues and expenses. Revenues solely originate from drug sales, while expenses encompass three categories: wages for traffickers and packagers, disbursements to the families of arrested or deceased members, and flexible expenditures including bribes, legal fees, and warehouse rental fees. Furthermore, the organization's leaders extract funds from the group's cash reserves for personal gain (see online model documentation for more details).

3.2.3. Law enforcement interventions and disruption of drug trafficking organizations

During the five-year simulation, the drug trafficking organization encounters both minor and major law enforcement actions. Minor actions involve the monthly arrest of a random member based on a probability distribution. These minor actions have been incorporated into the model because both the literature and existing case studies recognize that criminal networks, such as drug trafficking organizations, operate in a hostile environment. Members of these networks are inclined to tolerate such adversities as inherent risks (Fabiani & Behlendorf, 2021; Morselli & Roy, 2008; Paoli, 2002; Reuter, 1983). Thus, including this aspect in the model enhances its realism. Major actions take place after two years and entail larger-scale police operations, providing the opportunity to assess drug trafficking organizations' ability to endure disruption attempts and their responses to such events. The major actions can vary in intensity, ranging from no intervention (baseline scenario) to the arrest of different numbers of members accomplishing various roles in the organizations, for a total of 15 scenarios (Table 1). The temporal collocation of the major action after two years serves two key purposes. Firstly, it allows for the examination of the organization's operations in the two years leading up to the disruptive event, enabling a more comprehensive understanding of the internal functioning of the organization and how this functioning is eventually affected by the intervention. Secondly, the period aligns with the timing of a major disruption attempt against the Beluga group. This allowed calibration of the model to mirror actual events, enhancing its accuracy and relevance to real-world situations, and enabling it to capture critical dynamics and patterns more akin to operational settings, thereby validating its effectiveness.

The major actions have significant repercussions for drug trafficking organizations, severely damaging the organization's financial resources and workforce availability, potentially leading to their disruption. Disruption can result from either economic inefficiency or law enforcement interventions. Economic inefficiency disrupts the organization when it fails to generate adequate profits to sustain its operations,

[2] The Beluga court order provides data and information to update the calibration of MADTOR for the first two simulated years. After that, model parameters are estimated using logarithmic functions, chosen for their best fit to empirical data after evaluating various functional forms. Refer to the online model documentation for more information.

Fig. 1. Drug trafficking and dealing activities in the MADTOR model.

Table 1
Arrest scenarios.

Scenarios	Number of arrests	Target
1) Baseline	0	–
2) Arrests	5	Random selection
3) Arrests	5	Traffickers
4) Arrests	5	Packagers
5) Arrests	5	Retailers
6) Arrests	10	Random selection
7) Arrests	10	Traffickers
8) Arrests	10	Packagers
9) Arrests	10	Retailers
10) Arrests	15	Random selection
11) Arrests	15	Retailers
12) Arrests	20	Random selection
13) Arrests	20	Retailers
14) Arrests	25	Random selection
15) Arrests	25	Retailers

leading to zero or negative liquidity. Causes of inefficiency include insufficient drug acquisitions, low sales, excessive expenses, and other financial challenges, and all may occur independently or because of arrests. Disruption due to law enforcement interventions occurs when arrests create a shortage of drugs or workforce, jeopardizing the organization's criminal activities. Such interventions directly make the organization unable to continue its criminal activities, due to the loss of drugs and members and the inability to quickly recruit replacements. If all members assigned to a specific role are arrested, the organization may attempt recruitment for 30 ticks (one month). If recruitment is unsuccessful, the organization is disrupted.

In nearly 97% of disrupted organizations, economic inefficiency was the primary cause of disruption.[3] Arrests did not target all members, allowing organizations to persist in some capacity. However, the arrests often reduced the organization or specific role-performing members to a minimum, rendering criminal activities economically unsustainable in the short-medium term. While economic inefficiency was the most common reason for disruption, it was closely tied to arrests, which indirectly contributed to the organization's failure.

3.3. Simulation strategy and data analysis

Our primary analytical strategy consistent in assessing the impact of different arrest scenarios on drug trafficking organizations' resilience and resistance. We conducted 15 MADTOR submodels, representing a different major law enforcement intervention at the end of the second year (Table 1). To ensure reliable results, each submodel was simulated 1000 times over a span of 1825 ticks, equivalent to 5 years in simulated time. This duration allowed for a comprehensive examination of how drug trafficking organizations respond to major disruptions while maintaining computational efficiency.

We operationalized the resilience and resistance of criminal networks into three dimensions identified from the definition of criminal network resilience. First, we chose the *share of active drug trafficking organizations* for the ability to endure major disruptions. Active drug trafficking organizations are those that engage in drug trafficking and dealing on a daily basis. Each scenario begins with 1000 simulated groups, and over the simulated time, some groups are disrupted, either before or after the major law enforcement action. Therefore, the ratio between the active organizations at any given moment and the initial 1000 organizations provides the share of active organizations. Second, we considered the *number of members* as a measure of the ability to react quickly and efficiently to law enforcement interventions. Third we measured the ability to maintain primary functions and activities unaltered through the *revenues* of the drug trafficking organizations (Ayling, 2009; Bouchard, 2007; Duxbury & Haynie, 2019) (Table 2).[4]

[3] We note that enterprise mortality is a common phenomenon across all industries. For instance, in the European Union in 2021, the average rate of enterprise closure was 8.5% (Eurostat, 2023), with Italy experiencing a rate of 7% (ISTAT, 2023). Therefore, in MADTOR, we observe that some drug trafficking organizations are disrupted before the major law enforcement action or several months after it. This can be attributed partly to minor law enforcement interventions but also to other challenges related to the economic sustainability of the group.

[4] In the outputs obtained from the simulations, we included a wide range of potential resilience indicators, which encompassed several network measures such as the number of components in the network and the size of the largest component, the minimum, maximum, and average degree centrality of DTO members, DTO degree centralization, the minimum, maximum, and average betweenness centrality of DTO members, DTO betweenness centralization, and DTO average geodesic distance. However, for our final analyses, we selected only a subset of these indicators to ensure simplicity and ease of interpretation. Specifically, we chose to exclude network measures due to their high variability and limited responsiveness to law enforcement interventions, given the nature of our simulated organizations.

Table 2
Resilience indicators.

Dimension of criminal network resilience	Resilience indicator	Interpretation
Endure disruption	*Share of active drug trafficking organizations*	A resilience measure for drug trafficking organizations' ability to withstand law enforcement interventions, with a higher share indicating greater endurance over time.
React quickly and efficiently	*Number of members*	An indicator of drug trafficking organizations' stability and strength. A larger member count suggests a more robust organization, providing insights into its post-disruption recovery efficiency.
Maintain primary functions and activities unaltered	*Revenues*	A proxy for drug trafficking organizations' capacity to sustain illicit trade. Substantial revenue drops post-arrest indicate operational sustainability challenges.

Table 3
Results of the one-way randomization-based ANOVA tests.

Resilience indicator		Before the arrests (year 1–2)	After the arrests (year 3–5)
Active DTOs	F statistic	0.110	47.852
	Pr (>F)	0.999	0.000
Number of members	F statistic	0.000	25.326
	Pr (>F)	1.000	0.000
Revenues	F statistic	0.003	8.020
	Pr (>F)	1.000	0.000

10,000 repetitions for each randomization-based ANOVA test.

We compared the trends of the three indicators across the different arrest scenarios. We confirmed that the trends across the different arrest scenarios were indistinguishable before the arrests, as determined by a one-way randomization-based ANOVA test focusing on the period between the start of the simulation and end of year 2 (Table 3). Conversely, after the major law enforcement action at the end of year 2, one-way randomization-based ANOVA tests reported statistically significant differences in the average trends of the three resilience indicators across the arrest scenarios (Table 3). We investigated differences across specific arrest scenarios with Tukey's HSD Test for multiple comparisons, not reported for brevity.

Then, we aggregated resilience indicators at each step across simulations of each sub-model. To ensure clarity, we calculated monthly means of daily values for the number of members and revenues, averaging them across simulations of the same arrest scenario. Initially, each indicator is based on 1000 simulations, but as organizations get disrupted, the sample size decreases.

We implemented a secondary analytical approach to validate and enhance the findings from our primary strategy. The primary strategy focused on assessing the effects of arresting members engaged in the same role against random arrests or no arrest. While this approach isolated the effects of targeting one role at a time, it had limitations in representing real-world dynamics. In our secondary approach we leveraged the abundant data from simulations to delve deeper into the consequences of arresting members engaged in various roles, thus examining more realistic, real-world situations. Initially, we focused on simulations with random arrests to assess how groups responded to the arrest of varying numbers of individuals performing specific role. Subsequently, we investigated baseline simulations with minor arrests but no major law enforcement actions, aiming to determine how occasional arrests of individual members might impact the overall survival and profitability of the group based on their roles.

4. Results

We first report the results of the primary analytical strategy, starting from the number of active drug trafficking organizations in the different simulated scenarios (Table 4 and Fig. 2, first row). In the baseline scenarios, with no arrests, the number of active criminal organizations gradually decreased. From the initial 1000 active organizations, only 738 reached the end of the simulated 5-year period. The failure of organizations, in the absence of major law enforcement intervention, can be attributed to two factors. Firstly, minor law enforcement interventions partially affect the organization's ability to conduct drug trafficking and dealing proficiently. Secondly, like enterprises in any other industry, some organizations fail due to the unsustainability of their activities and resulting negative profits.

All the intervention scenarios substantially affected the survival rate of drug trafficking organizations. While the number of active groups was comparable to the baseline during the first two years ($F = 0.110$; p-value $= 0.999$), the arrests at the end of year 2 caused a decrease in the active organizations ranging from −35% to −100% (corresponding to no active organization) between the end of year 2 (before the arrest) and the end of the simulations. The arrest of traffickers resulted as the most disruptive intervention. Arresting 5 traffickers led to the failure of nearly 90% of drug trafficking organizations between end of year 2 and end of year 5. Arresting 10 traffickers left only one active organization already during the third year and no active organization in the following years. Conversely, arresting packagers generated much less disruption: about −43% and − 35% between year 2 and end of year five for arresting 5 and 10 packagers, respectively. Arresting retailers or random arrest were in the middle, with post-hoc Tukey's HSD test finding no statistically significant differences among the two strategies when targeting the same number of members.

Second, we examined the number of members in the active organizations, as a proxy of the groups' capacity to react quickly and efficiently to law enforcement disruption (Fig. 2, second row). In the no-arrest baseline scenario, the number of members grew from 44 at the start of the simulation to about 65 at the end of year 2. Subsequently, the growth decreased, and the size of the group reached nearly 70 members by the end of the simulated period. The intervention scenarios immediately affected the size of the group by arresting a predetermined number of members. In all scenarios, the groups that remained active managed to (almost) recover the number of members in the baseline, except for the retailers #20 and #25 scenarios. However, the time to recover varied substantially across scenarios, and proportionally to the number of members arrested in each scenario (see also Table A.1 in the Annex).

Third, we examined the monthly revenues of the drug trafficking groups as a proxy to maintain primary functions and activities unaltered (Fig. 2, third row). In the baseline scenario the revenues started around €20,000 and gradually grew to €40,000 by the end of year 5. All arrest scenarios generate a major blow to the group's revenues in the first months after the arrests. While the drop in the revenues appeared proportional to the number of arrested members, in the random, packagers, and retailers scenarios, the surviving organizations were able to recoup the baseline revenue levels within less than six months in year 3. The

Table 4
Number of active drug trafficking organizations at the end of each year by type of intervention.

Number of members arrested	Target of the arrests	Start	Year 1	Year 2	Year 3	Year 4	Year 5	Change% year 5 vs. year 2
0	–	1000	985	863	804	773	738	−14.48%
5	Random	1000	986	863	405	366	343	−60.25%
10	Random	1000	989	844	345	311	288	−65.88%
15	Random	1000	980	848	301	277	259	−69.46%
20	Random	1000	972	852	262	241	227	−73.36%
25	Random	1000	984	870	222	204	188	−78.39%
5	Retailers	1000	975	862	403	374	349	−59.51%
10	Retailers	1000	977	873	377	349	331	−62.08%
15	Retailers	1000	984	864	332	296	258	−70.14%
20	Retailers	1000	984	858	261	234	212	−75.29%
25	Retailers	1000	981	861	197	190	177	−79.44%
5	Traffickers	1000	988	845	143	106	85	−89.94%
10	Traffickers	1000	978	847	1	0	0	−100.00%
5	Packagers	1000	979	842	504	496	483	−42.64%
10	Packagers	1000	972	848	551	549	547	−35.50%

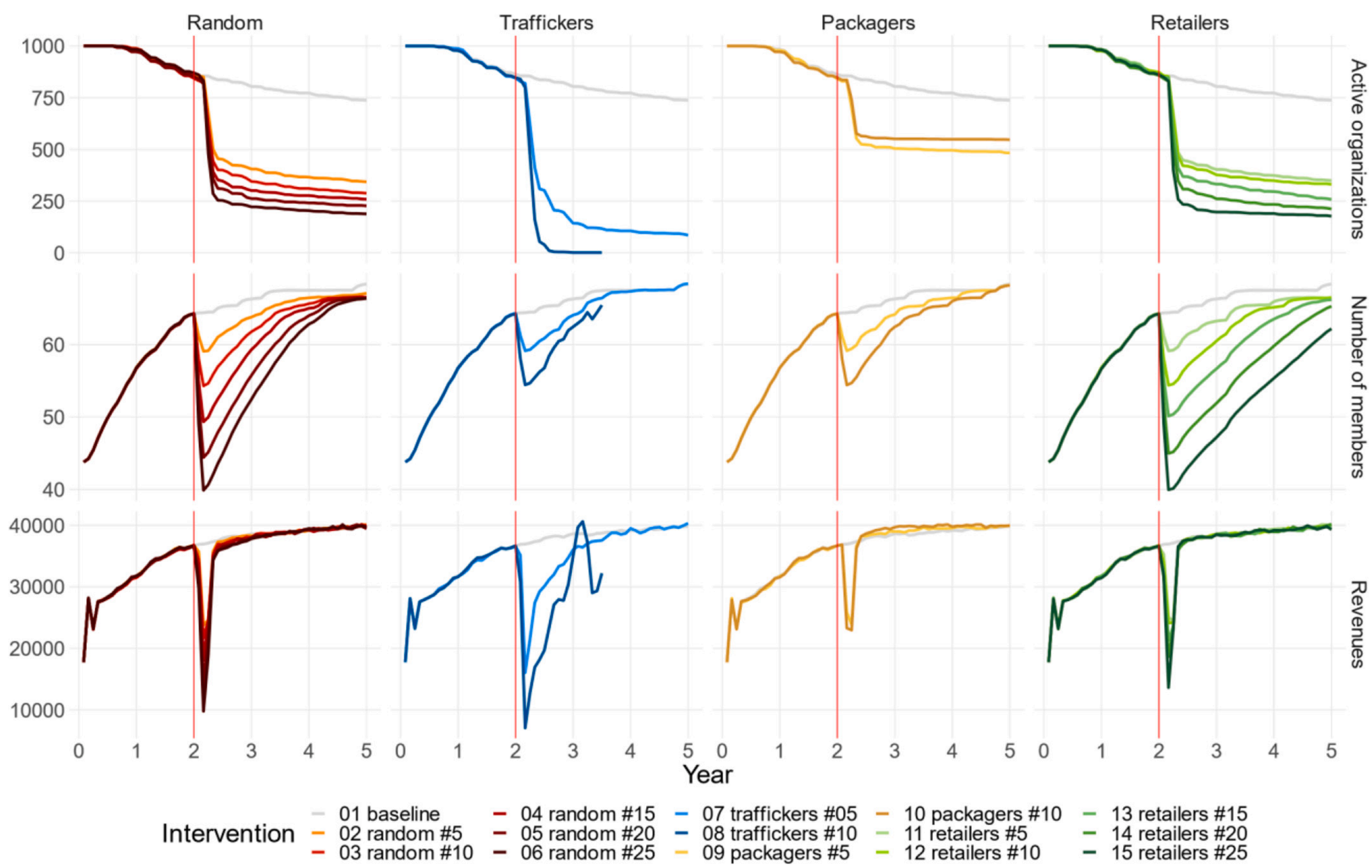

Fig. 2. Resilience indicators by target of the arrests and type of intervention.

traffickers scenarios showed a different pattern: the scale of the revenue drop was larger compared to other scenarios for a similar number of arrested members. Furthermore, the few surviving organizations struggled to recover their revenue levels. For the traffickers #05 scenario this occurred only well into the fourth year of the simulation. The traffickers #10 scenario reported a remarkable growth, but this pattern was biased by the extremely low survival rate from the second half of the third year, when only a handful of drug trafficking organizations remained active (see also Table A.2 in the Annex).

The secondary analytical strategy confirmed that the arrest of traffickers carries a greater impact on the drug trafficking groups. Among simulations arresting a random set of actors, an increase in the number of arrested traffickers resulted in decreasing survival rates and average revenues. The opposite occurred for packagers and retailers (Fig. 3). For instance, in simulations where 5 members were arrested at the end of year 2, only 30% of runs involving the arrest of 3 traffickers reached the simulation's conclusion, reporting revenues of approximately €35,000 at month 30. In contrast, more than 55% of runs arresting 3 packagers survived until the end, with average revenues around €39,000 at month 30. We observed similar patterns also in the baseline simulations, with no major arrests. We examined the number of minor arrests collected by baseline simulations at month 30: the higher the number of arrested traffickers the lower the survival rate and average revenues. Packagers and retailers did not report this trend (Fig. 4).

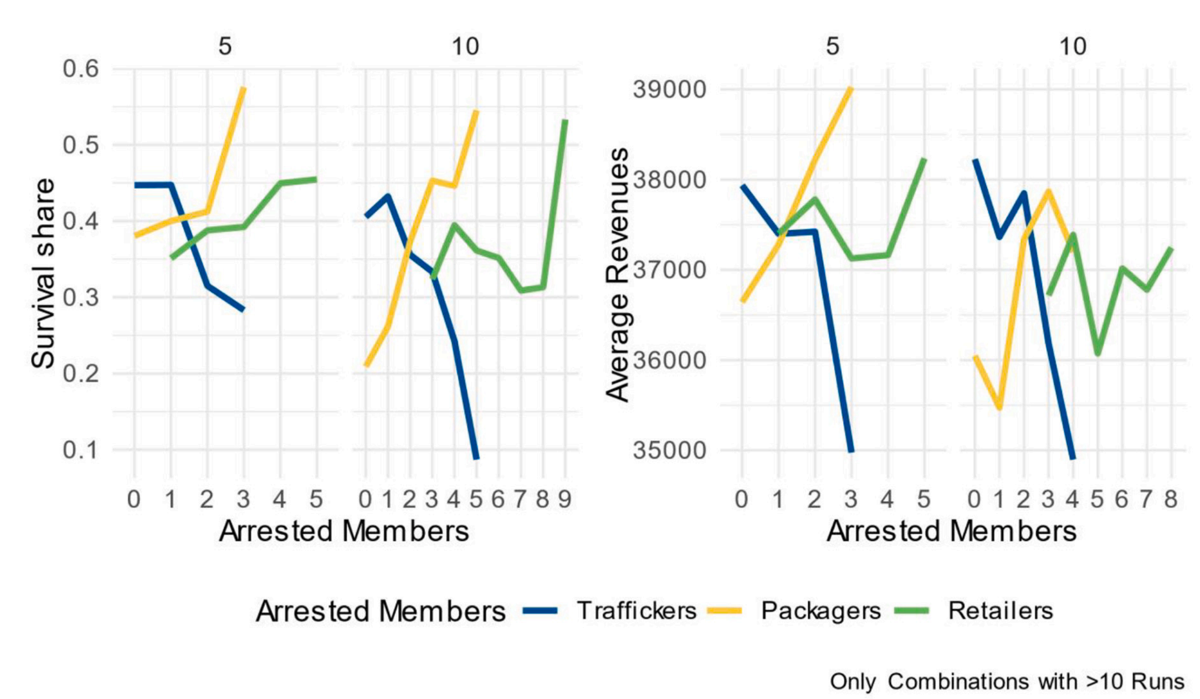

Fig. 3. Random arrests: survival at month 60 and average revenues at month 30 by role and number of arrests. Random #5 and random #10 scenarios.

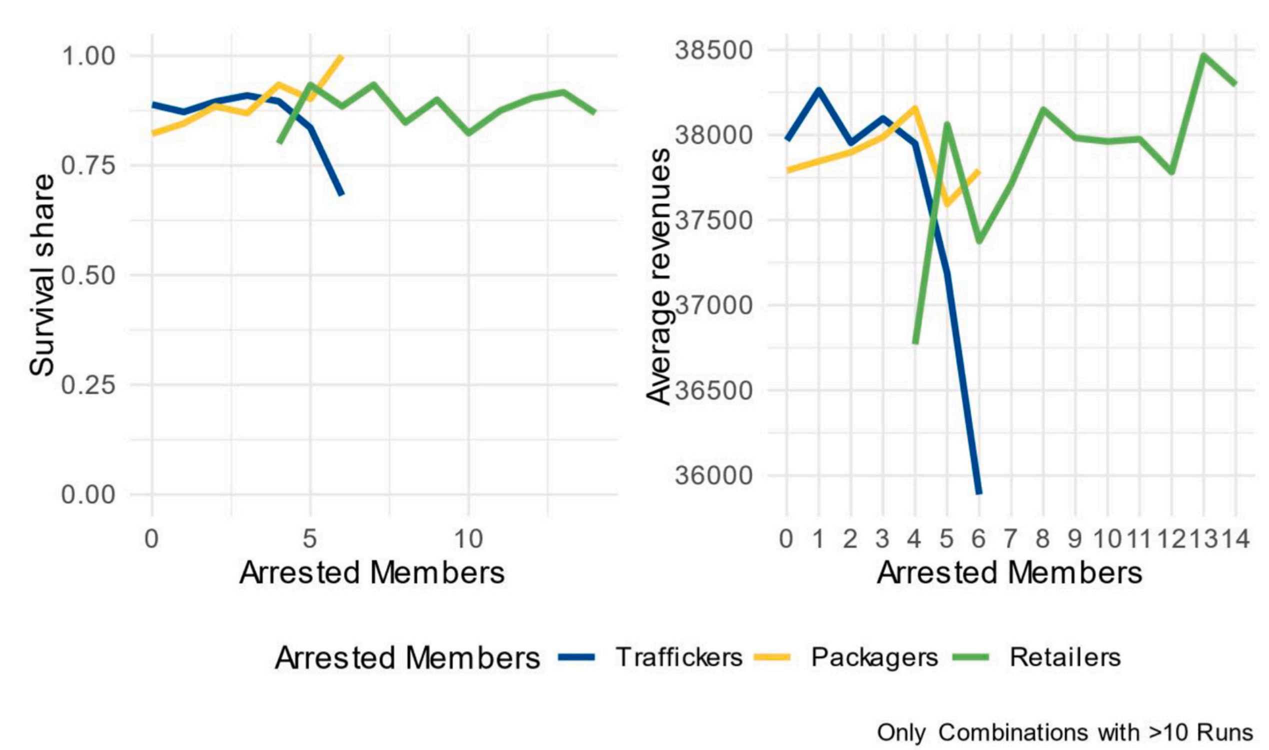

Fig. 4. Minor arrests: survival at month 60 and average revenues at month 30 by role and number of arrests. Baseline scenarios.

5. Discussion and conclusions

We showed that targeting different roles within drug trafficking organizations substantially influenced their resistance and resilience. First, actions against traffickers yielded the most disruption: apprehending five traffickers led to only 8.5% of the groups enduring till the simulation's conclusion; detaining 10 traffickers ensured the collapse of all organizations by the onset of the fourth year. These actions also markedly reduced the organization's revenue. Second, arresting 5 to 10 retailers resulted in roughly 40% of the organizations surviving by the simulation's end. This figure decreased to 20–30% with the arrest of 15, 20, or 25 retailers. Third, targeting packagers showed the least effect. The apprehension of 5 or 10 packagers saw nearly 50% of the organizations persisting until the period's end. Last, evidence from strategies involving random member targeting or minor arrests corroborated these findings. Organizations with a higher count of arrested traffickers reported lower survival rates and revenues, followed by those with apprehended retailers and packagers.

Our findings align with existing literature, affirming that apprehending the most strategic players within organizations, such as traffickers active in the smuggling niche of the drug market, constitutes the most effective disruption strategy (Bright et al., 2017; Calderoni, 2012; Castiello et al., 2017; Duijn et al., 2014; Duxbury & Haynie, 2018, 2019; Johnson & Natarajan, 1995; Malm & Bichler, 2011; Morselli & Roy, 2008; Villani et al., 2019; Wood, 2017). Disruption strategies that target traffickers capitalize on the irreplaceable nature of their roles and the complexity of replacing them due to their strategic skills. Such arrests lead to an immediate, significant drop in revenue and challenges in revenue recovery for the surviving organizations. Traffickers, solely responsible for drug procurement, have unique knowledge of contacts, channels, and methods (Calderoni, 2012; Johnson & Natarajan, 1995).

The results challenge previous research on the least effective disruption strategies against drug trafficking organizations, revealing non-negligible impacts of interventions directed towards the retail activity niche of the drug market. The simulations demonstrate that focusing on retailers substantially affects the resilience and resistance of these organizations. This finding stands in contrast to earlier studies that considered such interventions ineffective (Calderoni, 2012; Castiello et al., 2017; Duijn et al., 2014; Johnson & Natarajan, 1995; Malm & Bichler, 2011; Morselli & Roy, 2008). Retailers, typically less skilled, are easier to replace, allowing more organizations to stay active in the market (Calderoni, 2012; Johnson & Natarajan, 1995). However, arresting retailers affects organizations due to their role in generating revenue from drug sales. Their removal temporarily hinders profit-making. Yet, the financial impact of law enforcement on revenues is short-lived, with surviving organizations regaining pre-intervention revenue levels within six months. In contrast, disruption attempts directed at packagers present the fewest challenges to drug trafficking organization resilience. This observation may be attributed to the fact that packagers represent a range of support roles easily replaced that have received limited attention in prior studies.

Overall, law enforcement disruption strategies could benefit from considering the targets' roles within drug trafficking networks. Directing efforts at traffickers, for instance, would inflict the most significant damage on these organizations and their illicit activities. However, traffickers often have the resources and tactics to evade disruption, posing considerable challenges to law enforcement. Retailers, on the other hand, are more accessible targets. They are often perceived as expendable by the organization's leadership, have high visibility in street dealing, and have limited means to hide from law enforcement, making them easier to apprehend (Calderoni, 2014; Morselli, 2010). Given that interventions against retailers can disrupt 60% (arresting 5 retailers) to 80% (arresting 25 retailers) of organizations and considering the relatively lesser effort required for law enforcement to identify and arrest these members, targeting retailers, in conjunction with traffickers, is expected to have substantial disruptive potential.

Our study faces several limitations. Firstly, ABM simulations, by nature, are simplifications that cannot encompass all complexities of drug trafficking and dealing. For instance, while MADTOR focuses specifically on cocaine trafficking, it is important to be cautious when applying these findings to other drugs. Additionally, the model's reliance on data from Operation Beluga, although it allowed for a detailed simulation of that organization's internal workings, inherently limits the broader applicability of our results. This reliance narrows the study's scope, as the unique characteristics of the Beluga group might not reflect the diversity of drug trafficking organizations at large. Despite finding substantial support in the literature for features common to large-scale drug trafficking organizations, our findings, though valuable, require careful interpretation when applied to groups with differing structures and methods. Therefore, our conclusions might be more representative of structured, large-scale drug trafficking entities, rather than a comprehensive portrayal of the entire spectrum of drug trafficking organizations.

Future research has the potential to explore various directions. Firstly, MADTOR, with appropriate adaptations, can delve into additional facets of the resilience of drug trafficking organizations. This includes investigating the impact of different geographical scopes on reactions to law enforcement intervention, assessing the resistant and resilient abilities of groups trafficking drugs other than cocaine, as well as investigating the impact of different organizational arrangements of drug trafficking organizations along the security versus efficiency trade-off (Morselli, Giguère, & Petit, 2007). Secondly, future efforts can focus on expanding the dataset for model calibration and validating the results through the inclusion of additional case studies. This approach will enhance the robustness and applicability of the model, providing a more comprehensive understanding of the dynamics involved in the resilience of drug trafficking organizations.

Model documentation

The code, the ODD+D protocol and a detailed narrative documentation of the model are available and downloadable at the following link: https://www.comses.net/codebase-release/a5543b7a-8ed1-413b-88b8-5a44aed06c0d/

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Deborah Manzi: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Francesco Calderoni:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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Both authors contributed to the study conception and design. XX (omitted to ensure manuscript anonymity) wrote the simulation code in NetLogo, and prepared the data. Both authors analyzed the data, drafted the manuscript, and approved the final version.

Annex

Table A.1
Monthly average number of members by arrest scenario and year.

Arrest scenario	Year	Start	1	2	3	4	5
	Mean number of members	43.76	56.8	64.3	66.32	67.52	68.38
No arrests	*SD of number of members*	0.23	1.81	0.82	0.73	0.53	0.66
	Active organizations	1000	985	863	804	773	738
Number of arrests: 5	*Mean number of members*	43.78	56.85	64.26	63.81	66.48	67.1
Target: random	*SD of number of members*	0.23	1.91	0.78	0.95	0.71	0.71
	Active organizations	1000	988	845	143	106	85
Number of arrests: 5	*Mean number of members*	43.77	56.71	64.34	64.08	67.37	68.42
Target: traffickers	*SD of number of members*	0.23	1.86	0.78	0.86	0.59	0.68
	Active organizations	1000	979	842	504	496	483
Number of arrests: 5	*Mean number of members*	43.77	56.8	64.32	64.17	66.49	68.22
Target: packagers	*SD of number of members*	0.23	1.81	0.76	0.8	0.58	0.75
	Active organizations	1000	975	862	403	374	349
Number of arrests: 5	*Mean number of members*	43.77	56.8	64.31	63.26	65.97	66.52
Target: retailers	*SD of number of members*	0.23	1.88	0.76	0.83	0.79	0.5
	Active organizations	1000	989	844	345	311	288
Number of arrests: 10	*Mean number of members*	43.77	56.74	64.3	61.79	65.68	66.56
Target: random	*SD of number of members*	0.23	1.91	0.81	1.3	0.75	0.54
	Active organizations	1000	978	847	1	0	0
Number of arrests: 10	*Mean number of members*	43.77	56.8	64.27	62.47	0	0
Target: traffickers	*SD of number of members*	0.23	1.91	0.84	0	0	0
	Active organizations	1000	972	848	551	549	547
Number of arrests: 10	*Mean number of members*	43.76	56.78	64.26	62.46	66.01	68.22
Target: packagers	*SD of number of members*	0.23	1.85	0.8	1.34	0.83	0.76
	Active organizations	1000	977	873	377	349	331
Number of arrests: 10	*Mean number of members*	43.76	56.84	64.32	60.51	65.17	66.5
Target: retailers	*SD of number of members*	0.23	1.93	0.78	1.95	1.03	0.55
	Active organizations	1000	980	848	301	277	259
Number of arrests: 15	*Mean number of members*	43.77	56.72	64.29	59.31	65.03	66.54
Target: random	*SD of number of members*	0.23	1.96	0.79	1.73	0.99	0.53
	Active organizations	1000	984	864	332	296	258
Number of arrests: 15	*Mean number of members*	43.78	56.71	64.3	56.67	63.54	66.21
Target: retailers	*SD of number of members*	0.23	1.82	0.84	2.01	2.23	1.17
	Active organizations	1000	972	852	262	241	227
Number of arrests: 20	*Mean number of members*	43.77	56.7	64.24	55.75	64.03	66.41
Target: random	*SD of number of members*	0.23	1.83	0.85	2.15	1.55	0.81
	Active organizations	1000	984	858	261	234	212
Number of arrests: 20	*Mean number of members*	43.76	56.65	64.26	51.9	59.82	65.31
Target: retailers	*SD of number of members*	0.23	1.9	0.83	2.02	2.39	1.8
	Active organizations	1000	984	870	222	204	188
Number of arrests: 25	*Mean number of members*	43.77	56.82	64.31	52.44	62.84	66.4
Target: random	*SD of number of members*	0.23	1.79	0.81	2.2	2.12	0.88
	Active organizations	1000	981	861	197	190	177
Number of arrests: 25	*Mean number of members*	43.77	56.66	64.26	47.18	55.37	62.2
Target: retailers	*SD of number of members*	0.23	1.9	0.82	1.91	2.54	3.18

Table A.2
Monthly averages of daily DTOs revenues (in k€) by arrest scenario and year.

Arrest scenario	Year	Start	1	2	3	4	5
	Active organizations	1000	985	863	804	773	738
No arrests	*Mean of daily revenues*	17.76	31.77	36.65	38.62	39.16	39.82
	SD of daily revenues	0.39	4.44	2.77	2.93	3.06	3.14
	Active organizations	1000	986	863	405	366	343
Number of arrests: 5 Target: random	*Mean of daily revenues*	17.76	31.74	36.75	38.31	39.16	40.07
	SD of daily revenues	0.41	4.44	2.91	2.86	2.9	2.77
	Active organizations	1000	988	845	143	106	85
Number of arrests: 5 Target: traffickers	*Mean of daily revenues*	17.75	31.67	36.57	36.04	39.49	40.32
	SD of daily revenues	0.4	4.69	2.83	3.89	2.83	2.91
	Active organizations	1000	979	842	504	496	483
Number of arrests: 5 Target: packagers	*Mean of daily revenues*	17.72	31.69	36.72	38.98	39.55	39.95
	SD of daily revenues	0.42	4.44	2.89	2.81	3.02	3.05
	Active organizations	1000	975	862	403	374	349
Number of arrests: 5 Target: retailers	*Mean of daily revenues*	17.77	31.73	36.53	38.44	39.38	39.84
	SD of daily revenues	0.4	4.42	2.87	2.82	3.02	3.15
	Active organizations	1000	989	844	345	311	288
Number of arrests: 10 Target: random	*Mean of daily revenues*	17.74	31.47	36.69	37.98	39.4	40.06
	SD of daily revenues	0.39	4.51	2.95	2.97	2.96	2.79
Number of arrests: 10	*Active organizations*	1000	978	847	1	0	0
Target: traffickers	*Mean of daily revenues*	17.75	31.62	36.68	34.95	0	0

(continued on next page)

Table A.2 (*continued*)

Arrest scenario	Year	Start	1	2	3	4	5
	SD of daily revenues	0.42	4.55	2.84	0	0	0
Number of arrests: 10 Target: packagers	*Active organizations*	1000	972	848	551	549	547
	Mean of daily revenues	17.74	31.55	36.69	39.69	39.77	39.96
	SD of daily revenues	0.39	4.52	2.86	2.62	2.85	3.06
Number of arrests: 10 Target: retailers	*Active organizations*	1000	977	873	377	349	331
	Mean of daily revenues	17.75	31.63	36.75	38.55	39.22	40.02
	SD of daily revenues	0.4	4.42	2.85	2.81	3.06	2.88
Number of arrests: 15 Target: random	*Active organizations*	1000	980	848	301	277	259
	Mean of daily revenues	18.89	40.52	44.82	45.76	45.3	47.32
	SD of daily revenues	0.41	4.63	2.75	3.38	2.83	2.86
Number of arrests: 15 Target: retailers	*Active organizations*	1000	984	864	332	296	258
	Mean of daily revenues	19.29	41.86	43.48	46.69	47.38	46.9
	SD of daily revenues	0.41	4.45	3	2.85	2.81	2.82
Number of arrests: 20 Target: random	*Active organizations*	1000	972	852	262	241	227
	Mean of daily revenues	19	40.59	43.12	47.08	45.78	45.96
	SD of daily revenues	0.39	4.52	2.86	3.29	2.94	2.89
Number of arrests: 20 Target: retailers	*Active organizations*	1000	984	858	261	234	212
	Mean of daily revenues	19.14	39.97	43.4	44.04	46.2	46.54
	SD of daily revenues	0.43	4.57	2.97	2.48	2.97	3.08
Number of arrests: 25 Target: random	*Active organizations*	1000	984	870	222	204	188
	Mean of daily revenues	19.07	42.71	43.55	44.76	46.11	46.62
	SD of daily revenues	0.4	4.5	2.85	3.69	3.2	3.26
Number of arrests: 25 Target: retailers	*Active organizations*	1000	981	861	197	190	177
	Mean of daily revenues	18.94	41.01	43.12	44.02	45.3	45.54
	SD of daily revenues	0.39	4.44	2.91	2.59	2.84	2.89

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