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A simulation approach to assess law enforcement intervention impact: How the efficiency/security trade-off affects drug trafficking networks' resilience to arrests

Deborah Manzi *, Francesco Calderoni

Faculty of Social and Political Sciences at Università Cattolica del Sacro Cuore of Milan and Researcher at Transcrime, Università Cattolica del Sacro Cuore and Transcrime, Largo A. Gemelli, 1, 20123 Milan, Italy

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ABSTRACT

Despite extensive research on criminal group disruption, little is known about how alternative efficiency/security configurations within drug trafficking organizations (DTOs) shape resilience under sustained law enforcement pressure. DTOs face a core trade-off: efficiency—achieved through coordination and information sharing—increases exposure, while security—based on compartmentalization and trust—constrains flexibility and scale. Although widely theorized, this trade-off has rarely been examined as alternative strategic profiles subjected to comparable enforcement conditions. We address three unresolved propositions about the efficiency/security trade-off in DTOs: whether different efficiency/security orientations within drug trafficking yield different resilience outcomes, whether security-oriented configurations should be expected to be more resilient, and how enforcement intensity and timing condition resilience. We build on MADTOR—an empirically grounded agent-based model calibrated on data from a major Italian investigation—to simulate DTO operations and multi-actor law enforcement interventions over five years. The model compares how secure, efficient, and intermediate DTOs respond to disruptions of varying intensity via survival, membership, and revenues. Results show that resilience varies across enforcement regimes: efficient DTOs perform better under lower-intensity disruption, whereas secure DTOs gain a survival advantage as arrest intensity increases and interventions are delayed through reduced exposure. These findings provide theory-driven insights that alternative strategic profiles within a shared activity domain produce distinct resilience trajectories and challenge portrayals of DTOs as uniformly profit-oriented enterprises. The study demonstrates how strategic configurations interact with enforcement intensity and timing to shape resilience outcomes, and offers a transparent simulation framework to evaluate the long-term impact of alternative interventions.

1. Introduction

Drug trafficking organizations (DTOs) operate in complex, high-risk environments where maintaining operational continuity requires constant adaptation to internal and external threats. Among the most pressing threats are law enforcement interventions, which can destabilize illicit markets through arrests and seizures. While such interventions aim to dismantle or weaken criminal enterprises, their actual impact is often limited or temporary. DTOs have repeatedly demonstrated the capacity to adapt and persist, raising fundamental questions about what structural and strategic features enable their resilience under pressure. Understanding how and why DTOs survive disruption is critical to improving intervention effectiveness and refining criminological theories of organized crime resilience.

A key factor shaping this resilience is the trade-off between organizational efficiency and security. Drawing from criminological literature, researchers have posited that DTOs must balance two competing priorities: maximizing efficiency through dynamic, interconnected structures, or minimizing exposure by adopting compartmentalized, low-visibility configurations (Morselli et al., 2007). Efficiency facilitates rapid coordination, high-volume transactions, and flexible labor deployment—traits that enhance performance but increase detectability (Bichler et al., 2017; Giménez-Salinas Framis & Fernández Regadera, 2017; Morselli, 2010). In contrast, secure configurations reduce risk

* Corresponding author.
E-mail address: deborah.manzi@unicatt.it (D. Manzi).

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through trust-based recruitment and information compartmentalization but constrain adaptability and scale (Bright et al., 2012; Eilstrup-Sangiovanni & Jones, 2008; Malm et al., 2017; Malm & Bichler, 2011; Spapens, 2010). Despite the centrality of this trade-off in theoretical and empirical studies, research has not yet clarified the resilience implications of alternative efficiency/security orientations within the same trafficking domain, whether either orientation can be expected to be uniformly more resilient, and how enforcement intensity and timing condition resilience over time. Against this backdrop, we ask: how do alternative efficiency/security organizational configurations respond over time to different enforcement regimes in terms of resilience outcomes?

This gap stems from empirical and methodological limitations. Most studies rely on static snapshots of disrupted networks, often drawn from single investigations, and cannot observe how different efficiency/security profiles respond to varying intensities and types of law enforcement intervention. Simulation studies have begun to address this issue but typically employ idealized or static network types, lack behavioral grounding, or simulate interventions unrealistically (e.g., sequential removals of key actors). Furthermore, few have linked efficiency/security profiles explicitly to resilience indicators such as survival, workforce retention, or revenue recovery over time. As a result, we still lack a robust understanding of how DTOs positioned along the efficiency/security spectrum adapt to law enforcement pressure—especially under realistic enforcement scenarios involving multi-actor arrests and repeated interventions.

This study addresses that gap by using a simulation-based approach to evaluate how efficiency/security profiles shape DTO resilience. Building on empirical insights from a major investigation into a large drug trafficking organization in Naples, Italy, we draw on an agent-based model (MADTOR) that replicates trafficking operations, workforce dynamics, and law enforcement interventions over a five-year period. The model examines how DTOs with secure, efficient, or intermediate profiles perform when subjected to varying intervention regimes, including variation in intensity and timing. By dynamically modelling recruitment, communication, financial flows, and arrest risk, we assess not only whether DTOs survive disruption, but how they recover operational functions and maintain organizational continuity over time. In the more empirically grounded scenario—featuring repeated interventions of varying intensity—secure DTOs tend to gain a survival advantage as intervention intensity increases and when exposure delays interventions, whereas efficiency-oriented configurations tend to perform better under lower-intensity disruption. These results provide simulation-based evidence that clarifies the efficiency/security trade-off by demonstrating how within-domain variation in efficiency/security orientation can produce different resilience trajectories under specified enforcement regimes—helping reconcile organizational accounts that emphasize adaptability with criminological accounts that emphasize concealment and risk minimization. This has important implications for our understanding of DTOs—not as uniformly profit-oriented enterprises across threat environments, but as constrained organizations navigating amid constant external threats.

The article proceeds as follows. The next section situates our work within the literature on criminal group resilience and the efficiency/security trade-off. We then introduce the MADTOR model and detail its data sources, design, and simulation parameters. The results section presents findings across two intervention scenarios—one standardized, one more realistic—highlighting how resilience varies by efficiency/security profile, disruption intensity, and timing. We conclude by discussing the theoretical and practical implications of our findings, emphasizing the need for nuanced enforcement strategies and a dynamic understanding of resilience in illicit markets.

2. Background

Criminal groups, like legitimate organizations, must adapt to internal and external changes to survive in complex, evolving environments (Decker & Chapman, 2008; Kleemans, 2014; Morselli, 2009; Morselli & Roy, 2008; Wood, 2017). In organizational research, resilience is a multidimensional concept referring to an organization's capacity to absorb shocks, adapt to disruptions, and maintain core functions under stress (Barasa et al., 2018; Hepfer & Lawrence, 2022; Lengnick-Hall & Beck, 2005). Resilient organizations typically combine resource availability with adaptive planning, decentralized decision-making, and redundancy to operate efficiently and flexibly in uncertain environments (Hepfer & Lawrence, 2022). In criminological research, resilience is commonly used to capture the ability of criminal organizations to withstand law enforcement pressure and to reorganize, recover, or rebound after disruption (Ayling, 2009; Bakker et al., 2012; Bouchard, 2007; Duxbury & Haynie, 2019). This juxtaposition surfaces a central paradox: whereas organizational research often treats efficiency and operational flexibility as core sources of resilience, criminological accounts frequently emphasize security and secrecy as the basis for organizational persistence under enforcement pressure. This difference motivates the efficiency/security trade-off: organizations gain coordination benefits from integration but incur exposure costs under enforcement pressure.

Classic accounts of illegal enterprise emphasize that criminal organizations operate under distinctive constraints—especially enforcement risk and weak contract enforceability—that limit scale, complicate coordination, and shape how groups organize for performance (Eck & Gersh, 2000; Erickson, 1981; Kenney, 2007a; Paoli, 2002; Reuter, 1983, 1985; Reuter & Haaga, 1989). Building on this tradition, Morselli et al. (2007) formalized these ideas as an efficiency/security trade-off: illicit organizations must balance the coordination and productivity gains of more integrated arrangements against the secrecy benefits of limiting information flows and reducing exposure to detection (Diviák et al., 2022; Morselli, 2010; Morselli et al., 2007).[1] Importantly, this logic does not imply uniform organizational solutions within a given illicit domain: even among drug trafficking organizations facing broadly similar activities, configurations may vary in how they prioritize efficiency versus security as operational pressures and resources differ and as activity constraints (often discussed via "time-to-task") shape the urgency of coordination relative to exposure risks.

Despite the trade-off's intuitive appeal, empirical evidence remains difficult to reconcile across studies. Early formulations were often proposition-driven, relying on descriptive comparisons rather than direct observation of disruption and recovery processes over time (Baker & Faulkner, 1993; Bakker et al., 2012; Morselli et al., 2007; Raab & Brinton Milward, 2003). In network research, claims also rest on metrics derived from heterogeneous data sources and tie definitions, and the trade-off is operationalized at different levels of analysis (network-level structure vs. individual strategy), complicating inference and comparison (Calderoni & Superchi, 2019; Morselli, 2010). Even within studies, common structural indicators (e.g., density, centralization, clustering) are often treated as proxies for "efficiency" or "security," yet the mapping between network measures and underlying organizational mechanisms is not unique and varies across settings (Bichler et al., 2017; Bright et al., 2019; Crossley et al., 2012).

Empirical work has begun to address this gap by observing illicit networks before and after enforcement interventions and documenting post-disruption adjustments such as member replacement, changes in communication, and scaled-down operations (Berlusconi, 2022; Diviák et al., 2022; Fabiani & Behlendorf, 2021; Manzi, 2025; Morselli & Petit,

[1] The efficiency/security trade-off has often been illustrated through contrasts between terrorist and criminal enterprise networks, with "time-to-task" used to motivate different organizational pressures. However, empirical evidence does not consistently support a categorical terrorist-versus-criminal divide, and similar secrecy–efficiency tensions are documented across covert political, terrorist, and criminal settings (Diviák et al., 2022; Ünal, 2019).

2007). Complementary dynamic network modelling has clarified mechanisms shaping tie formation and network evolution even in the absence of an explicit disruption episode (Bright et al., 2019; Calderoni et al., 2025). Yet, most studies focus on single disruption episodes and rarely examine how varying intervention intensity or timing interact with network structures. Complementary disruption modelling often abstracts enforcement as actor removal and recovery as stylized rewiring, limiting what it can say about behaviorally grounded adaptation under sustained pressure (Bright et al., 2017; Carley, 2006; Diviák, 2023; Keller et al., 2010).

Simulation approaches offer a way to address these limitations by enabling controlled comparisons under explicitly specified enforcement conditions and by implementing post-disruption restructuring mechanisms. However, existing ABM contributions only partially speak to the efficiency/security trade-off. Diviák (2023), for example, models recovery through relatively simple restructuring rules but does not examine how efficiency/security orientations condition resilience under sustained enforcement. Duxbury and Haynie (2019) compare resilience across predefined, stylized network types, but fixed configurations and generic disruption/adaptation rules can obscure heterogeneity in criminal groups and the mechanisms linking configuration to resilience. Recent simulation work (Manzi & Calderoni, 2024a, b) incorporates more sophisticated restructuring and intervention designs, but it did not focus on how the efficiency/security trade-off conditions resilience under sustained law enforcement pressure. In short, current simulations rarely vary both (i) organizational orientation and (ii) intervention intensity and timing in a way that allows resilience rankings to be compared across enforcement regimes within drug trafficking.

Taken together, existing research clarifies that illicit networks can be disrupted and often adapt, but it provides limited leverage on a foundational issue embedded in the efficiency/security trade-off: whether, within drug trafficking, organizations facing broadly similar activities vary systematically toward security or efficiency, and what such variation implies for resilience. Observed differences are often confounded with enforcement exposure and organizational capacity (e.g., workforce depth and replacement), and cross-study comparisons further vary in data sources and tie definitions. As a result, it remains unclear whether security-oriented structures are inherently more resilient within drug trafficking, or whether resilience depends on how coordination benefits and exposure costs interact under specific enforcement conditions—implying within-domain heterogeneity and the possibility that resilience rankings shift across enforcement regimes.

To guide our simulation experiments, we specify three propositions from the efficiency/security trade-off literature that require more systematic examination. First, within drug trafficking, alternative efficiency/security orientations have distinct implications for resilience. The trade-off presumes within-domain heterogeneity—DTOs facing broadly similar activities may nonetheless adopt more security- (e.g., compartmentalized) or efficiency-oriented (e.g., integrated/coordination-intensive) configurations— yet the resilience implications of this basic premise are rarely assessed; absent systematic comparisons across alternative profiles within a shared activity domain, claims about an efficiency/security "trade-off" risk collapsing into post hoc labeling of whatever structure is observed. Second, once activity type is held broadly constant, there is limited basis for assuming the universal superiority of one orientation: security may reduce exposure but constrain coordination and recovery, whereas efficiency may sustain performance and facilitate reorganization while increasing vulnerability to detection. Third, the resilience-maximizing configuration may be contingent on enforcement conditions: changes in intervention intensity (the arrest "dose," combining the share arrested and the frequency/number of arrest waves) and timing (when arrests occur) may shift the relative advantages of security- versus efficiency-oriented configurations, producing different resilience rankings across scenarios. The current study addresses these propositions through simulation experiments that vary organizational configurations and arrest conditions and assess resilience in terms of survival, workforce retention, and revenue generation.

3. The current study

The objective of this study is to improve our understanding of DTO resilience by integrating insights from organizational resilience research and criminological studies of illicit networks. Organizational research emphasizes adaptation and continuity following disruption (Barasa et al., 2018; Lengnick-Hall & Beck, 2005; Tierney, 2003), while criminological work has focused primarily on evasion and security features (Diviák et al., 2022; Morselli et al., 2007). We conceptualize DTO resilience as an emergent outcome of organizational configurations that prioritize efficiency and security differently, rather than as a static network structure. Our goal is not to assume that security- or efficiency-oriented forms are inherently superior, but to examine how differently oriented configurations translate into resilience outcomes under varying enforcement regimes. We examine how these configurations shape three resilience outcomes—survival, workforce retention, and revenue generation—under law enforcement pressure.

The central research question is: *How do different efficiency/security organizational configurations respond over time to varying law-enforcement interventions in terms of resilience outcomes?* To address this question, we develop an agent-based model that simulates DTO drug trafficking operations over five years, including drug acquisition, packaging and retail distribution; internal recruitment and role allocation; internal finances; and law enforcement interventions. The model is empirically informed by Operation Beluga, a large-scale police investigation into a Camorra drug trafficking organization in Naples, which provides unusually detailed information on internal organization and responses to arrests. While grounded in a single case, the modeled features are characteristic of large-scale DTOs (Calderoni, 2014; Calderoni & Piccardi, 2014; Curtis, 1996; Desroches, 2005, 2007; Duijn et al., 2014; Gundur, 2022; Kenney, 2007a, 2007b; Natarajan et al., 2015; Natarajan & Belanger, 1998), supporting broader applicability of the simulation dynamics.

Overall, with our analysis, we aim to introduce three key advancements to the field. First, we make the efficiency/security trade-off concrete. Instead of treating "efficiency" and "security" as labels inferred after the fact from network structure, we define them upfront as alternative ways of organizing drug trafficking operations. We draw on the efficiency/security trade-off literature and empirical research on how DTOs operate to translate these ideas into concrete rules for acquisition, recruitment and collaboration, internal organization, payments, and exposure to law enforcement. We then calibrate key features of these routines to what is observed in Operation Beluga. In our model, efficiency-oriented configurations achieve higher performance by accepting greater visibility and enforcement risk, whereas security-oriented configurations limit scale and coordination to reduce exposure. This clarifies what it means for a DTO to prioritize efficiency or security and allows us to examine how these choices shape resilience over time.

Second, we reconceptualize enforcement pressure as an intervention regime that organizations must absorb and adapt to. Rather than simulating the sequential removal of one or two actors—common in studies using network metrics (e.g., Agreste et al., 2016; Duxbury & Haynie, 2018; Morselli & Roy, 2008)—we model large-scale arrests involving multiple members, aligning more closely with real-world law enforcement interventions (Berlusconi, 2022; Calderoni, 2012). These interventions are implemented as coordinate, multi-member arrest events, capturing the scale and scale and event-based nature of disruption DTOs face.

Third, we advance a process-based conception of resilience by treating it as a temporal trajectory rather than a single end-state. We track organizational survival, workforce retention, and revenue generation as complementary resilience outcome indicators. Unlike static outcome measures (e.g., network size at time T), this approach captures both operational continuity and post-disruption recovery, revealing how configurations differ not only in survival probability but also in recovery speed and trajectory stability. By varying intervention intensity (the arrest "dose," combining the share arrested and the frequency/number of arrest waves) and timing, we identify conditions under which efficiency/security trade-offs translate into divergent resilience pathways.

4. Methodology

ABMs are computer-based simulations that recreate dynamic social environments by modelling interactions among heterogeneous, rule-based agents (Gilbert, 2007; Wilensky & Rand, 2015). Unlike traditional equation-based approaches, ABMs are particularly well-suited to capturing the complexity of real-world social systems, allowing researchers to explore how micro-level behaviors generate emergent macro-level outcomes (Bianchi & Squazzoni, 2020; Gerritsen, 2015). In criminology, where ethical and practical constraints often preclude real-world experimentation, ABMs offer a valuable alternative for examining crime dynamics and testing policy interventions (Berk, 2008; Calderoni et al., 2021; Groff et al., 2019). Recent studies have employed ABMs to investigate urban crime patterns, prevention strategies, organized crime, trafficking operations, and criminal groups' resilience (e.g., Diviák, 2023; Duxbury & Haynie, 2019, 2020; Elsenbroich, 2017; Groff, 2007; Magliocca et al., 2022). These applications demonstrate ABMs' potential to simulate disruptive actions, such as law enforcement interventions, and assess their impact across varied organizational structures and roles. In this study, we build on this tradition by using an ABM to explore the resilience of drug trafficking organizations under different enforcement scenarios. The following sections describe the model's data sources, design, and analytical strategy.

4.1. Data sources

Our primary source was the pretrial court order from Operation Beluga, a 984-page judicial document (Tribunale di Napoli, 2013). Operation Beluga was a five-year investigation into the Camorra's Di Lauro clan, active in northern Naples from 2007 to 2013. The group's main income came from cocaine trafficking, documented in 172 seized ledgers recording transactions by retailer and drug type (Tribunale di Napoli, 2013). Notably, the 2010 arrest of eight senior members severely disrupted the clan, providing a rare opportunity to examine its resilience. Fig. 1 provides a descriptive snapshot of the actors and roles documented during the first year of the investigation, offering an illustrative overview of the organizational setting from which the model is initialized. For a more detailed description of the organization, its activities, and financial structure, see Appendix A: Section 1.

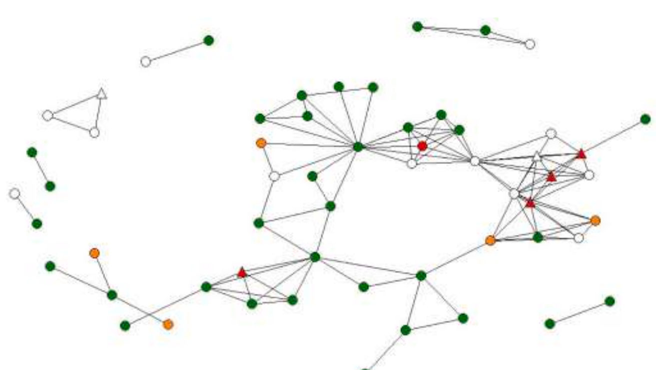


Fig. 1. Beluga group after the first year of investigation.
Note: The graph displays individuals involved in Beluga's group during the first year of the investigation. Colored nodes represent actors active in drug-trafficking activities—red for traffickers, orange for packagers, and green for retailers. Upward-pointing triangles indicate members who were arrested at the end of 2010.
This representation is not intended as a reconstructed empirical network for network analysis; rather, it serves to contextualize the types of actors, roles, and interactions informing the agent-based model, in which network structures emerge endogenously from simulated trafficking activities.

MADTOR's development and calibration also drew on additional sources. First, wholesale cocaine price data from UNODC (2008, 2009, 2010) informed economic modelling. Second, empirical literature on drug trafficking guided the design of disruption scenarios, drug acquisition behaviors, and patterns of collaborator selection. For additional information on the data sources we refer to the online documentation and previous studies using the MADTOR model.

MADTOR is based on detailed data from the Beluga court order, providing strong empirical basis, though its focus on a single DTO observed over a decade ago suggests that generalizability to other organizational and temporal contexts should be approached with caution. Nonetheless, many structural and behavioral patterns exhibited by the Beluga group align closely with those documented in DTOs across diverse settings and periods. Its internal organization reflects the communal-business and corporate models described by Curtis (1996) and repeatedly observed in subsequent research (e.g., Desroches, 2005, 2007; Gundur, 2022; Kenney, 2007a; Natarajan et al., 2015; Natarajan & Belanger, 1998), with trust reinforced through shared cultural and neighborhood ties, clearly differentiated roles, and small, semi-autonomous teams. The group's engagement in wholesale and regional distribution mirrors patterns highlighted by Natarajan et al. (2015), Natarajan and Belanger (1998), with DTOs typically participating in only a subset of market stages rather than controlling the full production-to-retail pipeline.

Operational dynamics documented in the Beluga court order are also consistent with broader comparative findings. Common features across DTOs include an overriding focus on profit—even at the expense of low-level operatives—systematic compartmentalization based on the "need-to-know" principle, delegation of high-risk tasks to lower-ranking members, and diversification of procurement and distribution channels. Regular and structured remuneration systems, observed in several empirical case studies, help maintain discipline and reduce incentives for cooperation with law enforcement (Calderoni, 2014; Calderoni & Piccardi, 2014; Desroches, 2005, 2007; Duijn et al., 2014; Gundur, 2022; Kenney, 2007a, 2007b).

As a final remark, although the Beluga DTO operated within the broader Camorra sphere—a context that might suggest mafia-specific influences—several characteristics of the Camorra actually increase its relevance as a model for non-mafia DTOs. Unlike other Italian mafias, the Camorra consists of fluid, urban-based clans forming rapidly shifting alliances and rivalries over local illicit markets (Reuter & Paoli, 2020; Catino, 1997, 2019; Scaglione, 2016; Direzione Nazionale Antimafia, 2018) and lacks a centralized governing authority (Brancaccio, 2014; Catino, 1997, 2019; Europol., 2013; Reuter & Paoli, 2020; Scaglione, 2016). This makes its groups organizationally closer to decentralized, market-oriented DTOs documented internationally (Catino, 2014, 2019; Dugato et al., 2017; Paoli, 2014, 2015; Reuter & Paoli, 2020; Scaglione, 2016). Despite its local specificity, the Beluga group thus embodies structural and operational characteristics widely observed in DTOs, providing a robust empirical foundation for the ABM.

4.2. MADTOR: Model for Assessing Drug Trafficking Organizations Resilience

4.2.1. Overview of the model

MADTOR is an agent-based model developed in NetLogo 6.2.0 (Wilensky, 1999, 2021) that simulates the daily operations of one drug trafficking organization over a five-year period. During this period, the offenders face the threat of law enforcement interventions intended to jeopardize their trafficking and dealing activities. Each simulation tick (the time measurement unit in NetLogo) corresponds to one day, with key activities—such as drug acquisition (monthly), wage payments (weekly), and drug retail (daily)—occurring at fixed intervals.

MADTOR rests on three core assumptions that characterize the model across all its applications. First, the model focuses exclusively on cocaine trafficking. This choice reflects the availability of detailed empirical data in the Beluga court order and related literature, which provides a consistent empirical foundation for parameterization and validation.[2] Second, the model represents only the trafficking and retail phases of the drug trade, excluding production and international smuggling. This segmentation reflects the empirical role of the Beluga group as a regional distributor and is consistent with research showing that drug markets are typically organized through functional specialization, with upstream and downstream activities handled by distinct actors and only limited overlap (Benson & Decker, 2010; Curtis, 1996; Decker & Chapman, 2008; Natarajan et al., 2015; Natarajan & Belanger, 1998; Reuter, 2014; Reuter & Haaga, 1989; Zaitch, 2002b). Third, MADTOR follows the "Keep It Simple, Stupid" (KISS) principle of agent-based modelling (Axelrod, 1997; Groff et al., 2019). Trafficking operations are therefore represented through four simplified stages: acquisition, processing and packaging, retail sales, and internal finances. These stages align with established frameworks in crime scripting and drug market research (Bright & Delaney, 2013; Chiu et al., 2011; Le, 2013), and are clearly observable in the Beluga case. Fig. 2 summarizes MADTOR's analytical architecture, linking these core organizational processes to the efficiency/security strategic profiles, law enforcement interventions, and resilience indicators examined in the simulation experiments.

During the setup phase, the model imports relevant data. This includes information related to the structure and features of the drug trafficking organization (members details and relational patterns) and data related to the drug trafficking and dealing activities (quantities of drug stored and sold, drug wholesale and retail costs, drug prices for end users, and members' rewards). The model updates these data every thirty simulated days to reflect the evolving structure of the Beluga group and the surrounding environment over time.[3]

The DTO starts with 44 members assigned to specific tasks: drug acquisition (5), packaging (5), and retail (34). The composition of the criminal workforce may change over time due to recruitments and defections. Recruitment is triggered by workload demands and the need to maintain operational capacity, while defection may result from voluntary withdrawal, law enforcement interventions, or member deaths. Each member is characterized by several attributes, inspired by the literature (Duxbury & Haynie, 2019; Weisburd et al., 2017): criminal expertise, organizational visibility, internal proximity, and collaboration record (Table 1 and Online model documentation). These attributes shape how individuals interact and participate in drug exchanges within the organization. The model updates all attributes dynamically on a daily basis, capturing changes in expertise, role centrality, and cooperation patterns as the DTO adapts to internal developments and external pressures. The model simulates four core activities (Fig. 3):

- *Drug acquisition*: The first modeled activity is drug acquisition, which occurs on a monthly basis. During each cycle, the organization's traffickers evaluate whether to procure new drug supplies. This evaluation is based on a set of factors common to all DTOs: the current stock level in the organization's warehouses (larger reserves reduce acquisition urgency), the prevailing wholesale price (higher prices discourage purchases), and a market favorability index capturing conditions such as drug availability and enforcement risk. Procurement decisions are made probabilistically through a composite index integrating these factors, further modulated by traffickers' criminal expertise—more experienced traffickers are better able to secure acquisitions despite adverse conditions. Across simulations, drugs are typically acquired at an average wholesale price of €40.45 per gram (SD = 4.24). After each attempt—successful or failed—the model updates traffickers' expertise levels, increasing them after positive outcomes and decreasing them after failures.
- *Drug processing and packaging*: The second modeled activity is drug packaging, which occurs on a daily basis. In this phase, packagers receive bulk quantities of drugs from traffickers, convert them into unit-dose packages, and then transfer the finished doses to retailers for street-level distribution. MADTOR simulates this process through two sequential exchanges—first from traffickers to packagers, and then from packagers to retailers—capturing the operational flow of drug processing within the DTO. Each packager operates under a maximum daily workload constraint, reflecting the physical and logistical limits of processing capacity. The model determines which members participate in these exchanges based on their criminal expertise, organizational visibility, internal proximity, and collaboration record, ensuring that interactions follow plausible social and operational logics observed in real DTOs.
- *Drug sales*: The third activity is drug sales. Retailers are responsible for selling unit-dose packages directly to consumers and collecting revenues, following the operational patterns documented in Operation Beluga. On average, the organization sustains daily sales of approximately 1900 cocaine doses, each weighing 0.25 g and sold at an average price of around €32 per dose. Each retailer is subject to a maximum daily profit cap of €500, reflecting operational limits. The exact number of doses sold per day is randomized within the minimum and maximum sales volumes observed for the Beluga group, introducing realistic market variability. Retailers retain a fixed 18% share of revenues as personal compensation, while the remaining funds are transferred to the group's leaders.
- *Internal finances*: The fourth activity tracks the organization's financial balance by aggregating revenues and expenditures on a weekly basis. Revenues derive exclusively from drug sales, while expenses encompass three main categories: (1) wages for traffickers and packagers, whose earnings are independent of sales performance; (2) payments to the families of arrested or deceased members (based on real proportions from the Beluga case), representing internal solidarity mechanisms and (3) variable operational costs, including bribes, legal fees, and warehouse rent. Additionally, the leaders periodically withdraw funds from the organization's cash reserves as personal profits. This process follows a stochastic rule that introduces controlled variability, adjusting the withdrawn share by ±10%, while constraining total withdrawals within 50–110% of the organization's net profit (excluding fixed costs). The remaining balance is retained as operational reserves, ensuring liquidity for future activities and mitigating short-term financial shocks.

For further details on the modelling and computation of the four core activities refer to the online model documentation. Appendix A, Section

[2] The literature offers extensive insights into the dynamics of cocaine trafficking and the criminal organizations engaged in this activity. Existing research has primarily focused on several key dimensions: the routes and logistics of cocaine trafficking (Benítez et al., 2019; Caunic et al., 2011; Eventon & Bewley-Taylor, 2016; Kenney, 2007b; Magliocca et al., 2019); the financial management and profitability of cocaine markets (Hall & Antonopoulos, 2017; O'Hagan & McNicholl, 2015; Terenghi, 2022); and the structural and organizational characteristics of the actors involved (Calderoni, 2012, 2014; Calderoni et al., 2014; Chandra & Joba, 2015; Giménez-Salinas Framis, 2013; Hofmann & Gallupe, 2015; Johnson et al., 1992; Morselli & Petit, 2007; Natarajan, 2000; Paoli et al., 2013; Reuter & Haaga, 1989; Roks et al., 2021; Stevanović, 2020; Zaitch, 2002a, 2002b).

[3] The Beluga court order provides data to calibrate MADTOR for the first two simulated years, updating actors, drug sales, and operational costs. For the following years, parameters are projected using logarithmic functions fitted to these empirical trends. This approach ensures continuity of the DTO dynamics while reflecting the empirically observed evolution. See the online model documentation for further details on the functions, procedures, and parameterization logic.

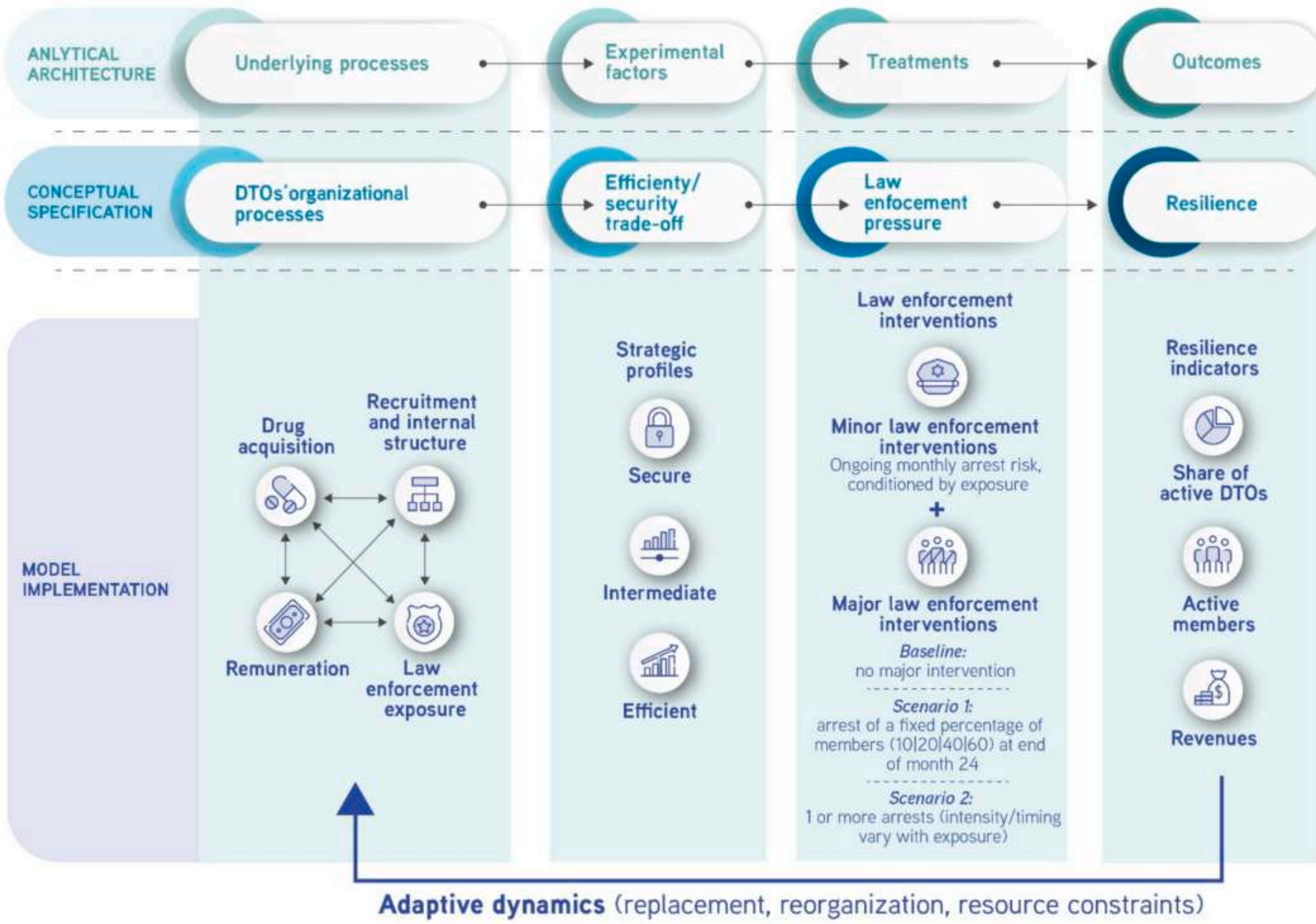


Fig. 2. Analytical architecture and conceptual-to-operational mapping of MADTOR.

Table 1
Agent attributes in MADTOR model.

Attribute	Definition
Task	Fixed function: trafficker, packager, or retailer.
Drug	Drug amount held per member at each tick.
Criminal expertise	Criminal ability (range 0–1), increases with successful exchanges.
Collaboration record	Number of past exchanges between two members.
Organizational visibility	Activity level: degree difference from most central actor; updated after each exchange (Duxbury & Haynie, 2019; Freeman, 1979).
Internal Proximity	Closeness centrality; updated after each exchange (Freeman, 1979).
Availability	Binary: whether packagers/retailers can receive drugs; based on daily workload; updated each tick.

2, additionally provides a toy example illustrating a single iteration of the model.

4.2.2. Operationalizing the efficiency/security trade-off in MADTOR

Building on MADTOR's prior applications, this study uses the model to examine how alternative theory-informed organizational configurations shape resilience under law enforcement interventions. This shifts the focus from variation in enforcement intensity or target characteristics to variation in internal organizational logics associated with the efficiency/security trade-off framework (Morselli et al., 2007).

The efficiency/security framework posits that drug trafficking organizations differ in how they balance profitability with the risk of detection. Whereas efficiency-oriented groups prioritize scale, revenue maximization, and rapid transactions, security-oriented groups privilege discretion, trust, and protection from law enforcement (Morselli & Petit, 2007; Paoli et al., 2009). Because the criminological literature offers conceptual descriptions rather than operational criteria to distinguish these organizational types, implementing this framework in a simulation requires explicit modelling choices.

In MADTOR, the efficiency/security continuum is formalized as a strategic parameter that shapes behavior across multiple organizational dimensions. Rather than treating efficiency and security as emergent network properties or outcomes, the model embeds them in agent-level decision rules governing drug acquisition, recruitment and collaboration, remuneration, and exposure to law enforcement. Organizational profiles are defined at the outset of each simulation and therefore precede any enforcement intervention.

The trade-off is operationalized as a continuous parameter. For analytical clarity, the study focuses on three representative

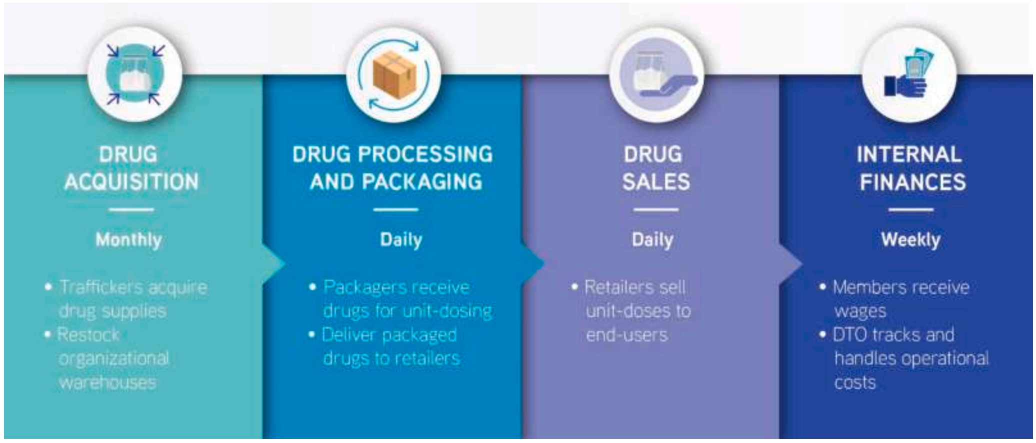


Fig. 3. Drug trafficking and dealing activities in the MADTOR model.

profiles—secure, intermediate, and efficient DTOs—although the model can simulate any position along the continuum.[4]

The strategic profiles affect the model through the following mechanisms:

- Drug quantities and acquisition behavior: Secure DTOs handle moderate drug volumes, distributing smaller packages across members to reduce exposure in case of seizure, though this limits adaptability to market shifts. Efficient DTOs favor larger transactions that increase profits under high demand but heighten vulnerability to enforcement (Bright et al., 2012; Eilstrup-Sangiovanni & Jones, 2008; Gravel & Tita, 2017; Morselli, 2010). In MADTOR, this is visible in the average drug stock held by the organization, which increases across the efficiency/security profiles. When focusing on the post-initial phase of the simulation (i.e., excluding the first 12 months), secure DTOs maintain on average approximately 7.0 kg of drugs, intermediate DTOs 7.7 kg, and efficient DTOs 8.8 kg. Dispersion around the mean is moderate across all groups (weighted SD $\approx$ 0.8–0.9 kg), while minimum–maximum ranges remain clearly stratified (Secure: 2.8–7.8 kg; Intermediate: 3.5–8.4 kg; Efficient: 4.8–9.7 kg).[5] Drawing on Ouellet and Bouchard (2017), we interpret higher revenues per transaction (typical of larger-volume deals) as a marker of efficiency-driven behavior, whereas lower per-transaction revenues correspond to smaller, more cautious transactions characteristic of secure DTOs.
- Importantly, while acquisition attempts occur on identical schedules across profiles, their realization depends on profile-specific risk assessments. The market favorability index is interpreted differently across strategic profiles: secure DTOs require more favorable conditions before proceeding, whereas efficiency-oriented DTOs display greater risk tolerance. Consequently, acquisitions occur less frequently for secure DTOs and more frequently for efficient DTOs, despite identical acquisition timing.
- Recruitment and collaborator selection: Recruitment in MADTOR follows a common set of empirically informed rules applied to all DTOs. At each time step, at most one actor per role can be recruited, and entry is allowed only if organizational resources are sufficient to sustain wages. Recruitment difficulty varies by task, with managerial roles (traffickers) being harder to fill than operational ones (retailers), reflecting differences in required skills, trust, and exposure (Calderoni, 2012; Desroches, 2007; Johnson & Natarajan, 1995; Spapens, 2010). Secure DTOs implement selective recruitment, privileging trust and reliability to mitigate insider threats. This enhances cohesion but constrains workforce flexibility and scale. In contrast, efficiency-oriented DTOs prioritize skill and task performance over loyalty, recruit more flexibly in response to workload demands, and select collaborators on a task-by-task basis (Duxbury & Haynie, 2019; Giménez-Salinas Framis & Fernández Regadera, 2017). During drug exchanges, agents evaluate potential partners by weighting trust-related attributes (past collaboration and organizational visibility) versus performance-related attributes (criminal expertise and internal proximity), with the relative importance of these criteria determined by the DTO's efficiency/security profile. These rule-based differences shape interaction patterns and may give rise to distinct network configurations, but such structures are emergent rather than imposed, as the model focuses on operational workflows rather than on predefined network topology.
- Member remuneration: In MADTOR, member remuneration follows task-specific, empirically informed rules that apply to all DTOs, while wage levels are modulated by the organization's efficiency/security profile. Traffickers and packagers receive daily wages drawn from the profits generated after accounting for supply costs. These amounts are divided equally among actors within each role. To ensure realistic compensation levels, minimum and maximum wage thresholds are imposed based on empirical evidence from the period considered. These thresholds vary by organizational profile: efficiency-oriented DTOs allow higher potential wages, reflecting greater exposure and risk, whereas secure DTOs operate within tighter remuneration bounds, consistent with lower turnover and a stronger emphasis on protection and secrecy. Retailers are

[4] MADTOR operationalizes the efficiency/security trade-off as a continuous spectrum, allowing the modelling of DTOs with any value between 0 (maximum security) and 1.0 (maximum efficiency). Simulations were explored at six points along this continuum (0, 0.2, 0.4, 0.6, 0.8, 1.0). For the main analyses, we opted to focus on three intermediate profiles—secure (0.4), intermediate (0.6), and efficient (0.8)—to facilitate comparison of resilience dynamics across enforcement scenarios. Extreme parameterizations (0.0 and 0.2) consistently yielded near-degenerate outcomes and thus provide limited analytical leverage for comparing resilience dynamics across enforcement scenarios. Specifically, the lowest values (0.0 and 0.2) led to near-certain disruption (>95%) across conditions, whereas 1.0 produced very low disruption ($\approx$20%) even under intensive enforcement. We therefore report results for the intermediate profiles, while noting that the full continuum remains part of the model and can be examined in future work.

[5] Non-parametric tests confirm that the differences between the three distributions are statistically significant (Kruskal–Wallis test, $p < 0.001$), with post-hoc pairwise comparisons indicating significant differences between all group pairs. The exclusion of the first year is intended to limit the influence of initial transient dynamics and to better capture the organizations' long-term structural behavior. Importantly, the results are robust to this choice: when the full simulation period is considered, differences between secure, intermediate, and efficient DTOs remain statistically significant, despite the presence of partial distributional overlap.

Table 2
Share of members arrested during law enforcement intervention in Scenario 2.

Share of arrests in Scenario 1	Secure DTOs	Intermediate DTOs	Efficient DTOs
10%	8-9%	9.5-10.5%	11-12%
20%	16-18%	19-21%	22-24%
40%	32-36%	38-42%	44-48%
60%	48-54%	57-63%	66-72%

remunerated differently, as a fixed share of revenues from retail sales. Overall, these remuneration rules capture differences between security-oriented organizations—characterized by conservative earnings distribution and constrained individual compensation—and efficiency-oriented DTOs, which rely more heavily on financial incentives to attract and retain participants under conditions of higher turnover and operational risk (Bouchard & Ouellet, 2011; Gambetta, 1993; Levitt & Venkatesh, 2000; Morselli & Petit, 2007; Ouellet & Bouchard, 2017; Paoli, 2003; Paoli et al., 2009; Reuter & Kleiman, 1986).

- Law enforcement exposure: Due to their scale and operational aggressiveness, efficiency-oriented groups attract more frequent and more intense enforcement attention. Secure groups, by contrast, operate more discreetly and are therefore comparatively less likely to be detected (Morselli & Petit, 2007; Paoli et al., 2009). This asymmetry in enforcement exposure is a constitutive feature of the two organizational profiles and a necessary condition for operationalizing the efficiency/security trade-off: absent a countervailing enforcement cost, efficiency-oriented DTOs would mechanically dominate security-oriented ones. The modelling of these differences in law enforcement exposure is discussed in greater detail in Section 4.2.3.

Additional details on the specific operationalization of each parameter are provided in the online model documentation.

4.2.3. Law enforcement interventions and disruption of drug trafficking organizations

MADTOR models law enforcement interventions as a combination of minor and major actions that reflect the varying levels of scrutiny criminal organizations typically face. Because empirical research provides only partial guidance on how enforcement pressure unfolds in practice, the implementation adopted here balances empirical plausibility with model feasibility.

Minor interventions occur probabilistically and represent routine arrests and background enforcement risk. They involve the monthly arrest of one unspecified member. The probability of being targeted varies by efficiency/security profile: secure DTOs face a 10% monthly probability, intermediate DTOs 50%, and efficient DTOs 90%.

Major law enforcement interventions entail the arrest of a proportion of an organization's members and the seizure of the drugs in their possession. The arrest share can be set at 0%, 10%, 20%, 40%, or 60%. Such interventions may substantially weaken a drug trafficking organization by depleting both its workforce and financial resources, potentially leading to disruption—that is, the point at which the group can no longer sustain its operations.

In our model, arrests during major interventions are determined through random selection rather than by targeting specific actors or network positions. This choice reflects how law enforcement interventions typically unfold in practice. Large-scale crackdowns are based on accumulated intelligence rather than formal network metrics, and their timing and scope are shaped by procedural, legal, and logistical constraints rather than by full knowledge of a network's internal structure. Random selection therefore provides an approximation of the uncertainty and partial information that law enforcement agencies face when dismantling complex criminal groups. Furthermore, because interventions in MADTOR always involve arresting a substantial proportion of the organization's members simultaneously, using random selection does not risk consistently capturing only atypical or extreme actors. Arresting many members at once naturally produces variation across simulations while maintaining representative organizational disruption. Moreover, this approach allows us to isolate organizational-level differences across secure, intermediate, and efficient DTOs—the central focus of this study—without confounding effects introduced by actor-specific targeting. Previous network simulations often assume arrests of the most central or structurally critical members, but such strategies are rarely feasible in real-world enforcement contexts (e.g., Castiello et al., 2017; Cavallaro et al., 2020; Duxbury & Haynie, 2018; Villani et al., 2019; Wood, 2017). Compared with these simplified or idealized approaches, MADTOR's design provides a of law enforcement interventions that balances realism with analytical clarity, while the effects of actor-specific arrests are explored in our previous work (Manzi & Calderoni, 2024a).

Two distinct law enforcement intervention scenarios define the specific features of major actions.

4.2.3.1. Scenario 1: one identical intervention. All DTOs experience one identical major intervention after two years, involving the arrest of a fixed percentage of members and the seizure of their drugs. This two-year delay serves two purposes: it allows observation of the DTO's development and internal dynamics before the law enforcement intervention, and it mirrors the timing of the real-world intervention against the Beluga group. Aligning the model with actual events improves its accuracy and relevance, helping capture operational patterns more effectively.

4.2.3.2. Scenario 2: multiple, differential interventions. Scenario 2 introduces greater realism by accounting for heterogeneity in the major law enforcement interventions based on each DTO's efficiency/security profile. It introduces three key variations to the major law enforcement interventions compared to Scenario 1:

1) *Intensity:* the DTO's efficiency/security profile affects the proportion of arrested members. Secure DTOs, by virtue of their protective measures and lower visibility, are less affected, experiencing actual arrest rates that are 10–20% lower than the nominal target. Intermediate DTOs experience modest variation (±5%), while efficient DTOs, which are more exposed, experience higher actual arrest rates (10–20% above the nominal target) (see Table 2 for the modified arrest proportions).

2) *Frequency:* DTOs can now face multiple major law enforcement interventions, with up to five occurring during the simulation. There is no empirically grounded threshold for the average number of major interventions targeting DTOs with different profiles along the efficiency/security trade-off. We selected the final values after considering several plausible combinations, consistent with the theoretical expectation that efficiency-oriented DTOs are more exposed to enforcement. After an initial 15-month period without any law enforcement pressure, major interventions may take place every six months, resulting in up to seven possible intervention slots. The

Table 3
Expected vs. observed major law enforcement interventions by efficiency/security profile in Scenario 2.

(a) Average number of interventions per organization

	Secure	Intermediate	Efficient
Expected	1.002	1.518	2.513
Observed	0.707	0.971	1.152

(b) Distribution of expected and observed interventions (%)

No. of interventions	Secure		Intermediate		Efficient	
	Expected	Observed	Expected	Observed	Expected	Observed
0	–	29.30	–	12.45	–	7.78
1	99.80	70.70	62.83	78.45	22.70	72.90
2	0.18	0.00	25.23	8.65	29.70	16.15
3	0.03	0.00	9.55	0.45	27.13	2.78
4	0.00	0.00	2.10	0.00	14.53	0.38
5	0.00	0.00	0.30	0.00	5.95	0.03
Total	100.00	100.00	100.00	100.00	100.00	100.00

average number of expected interventions varies according to the efficiency/security profile: secure DTOs face about one, intermediate DTOs 1.5, and efficient DTOs around 2.5. However, the number of observed interventions is often lower, as some DTOs are disrupted before reaching their expected intervention count (Table 3).[6]

3) *Timing:* The timing of major law enforcement interventions is influenced by organizational visibility. Efficient DTOs, being more exposed, are more likely to be targeted and thus also tend to be targeted earlier during the simulation. In contrast, secure DTOs, due to their caution and lower visibility, are more likely to face fewer and later law enforcement interventions over time. Intermediate DTOs fall between these two extremes, experiencing mid-level intervention patterns over time.[7] The proportion of efficient DTOs subjected to interventions remains relatively stable over time, with an average of 35.8% of active organizations being targeted in each intervention slot. In contrast, secure DTOs experience the lowest targeting, with an average of 14.3% of organizations targeted in each intervention slot. Intermediate DTOs, positioned between the two categories, are targeted at an average rate of 21.5% per intervention slot. These probabilities result into earlier law enforcement interventions for efficient DTOs compared to intermediate and secure DTOs (see Appendix B, Fig. 16).

Scenario 2 generated the distribution shown in Fig. 4. Each DTO was assigned between one and five *expected* major interventions, based on its efficiency/security profile. Most secure DTOs were assigned one intervention, with very few facing a second. Among intermediate DTOs, over 60% expected one intervention, about 25% expected two, and the rest were assigned three to five. Efficient DTOs showed the greatest variation: roughly a quarter faced one, two, or three interventions each, while the remaining quarter were assigned four or five. DTOs often face fewer *observed* interventions than expected due to disruption before the simulation ends, caused by economic inefficiency or the cumulative impact of prior interventions. DTOs with no observed intervention were disrupted before the major law enforcement intervention. This is most common among secure DTOs, which tend to terminate earlier, and least frequent among efficient DTOs. Also, across all types, higher arrest percentages lead to increased disruption rates. For additional details on implementation, computation, and model parameters, refer to the online model documentation.

4.2.4. Resilience outcomes and disruption of drug trafficking organizations

We operationalized the concept of criminal group resilience presented in the background section into three dimensions drawn from the literature (Ayling, 2009; Bouchard, 2007; Duxbury & Haynie, 2019; Manzi & Calderoni, 2024a, b). First, we chose the *share of active drug trafficking organizations* for the ability to endure disruption dealing with major threats. 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 (Table 4).

In the model, disruption occurs when a DTO can no longer operate effectively and may arise from two mechanisms: economic inefficiency or direct law enforcement impact. Economic inefficiency occurs when the organization cannot generate sufficient profits, typically when liquidity falls to zero or below, due to low drug acquisitions, poor sales, high expenses, or a combination of these factors. Disruption due to law enforcement arises when arrests create critical shortages of personnel or drugs, halting operations. If all members assigned to a specific task are arrested, the organization has 30 ticks (approximately one month) to recruit replacements, failure to do so results in collapse.

Across simulations, disruption was primarily driven by economic inefficiency (~97% of cases). Arrests rarely eliminated all members outright, allowing some operations to continue, but often reduced the organization—or key roles—to a level where activities became unsustainable. Although economic inefficiency is the proximate cause of collapse, it is frequently triggered indirectly by law enforcement interventions.

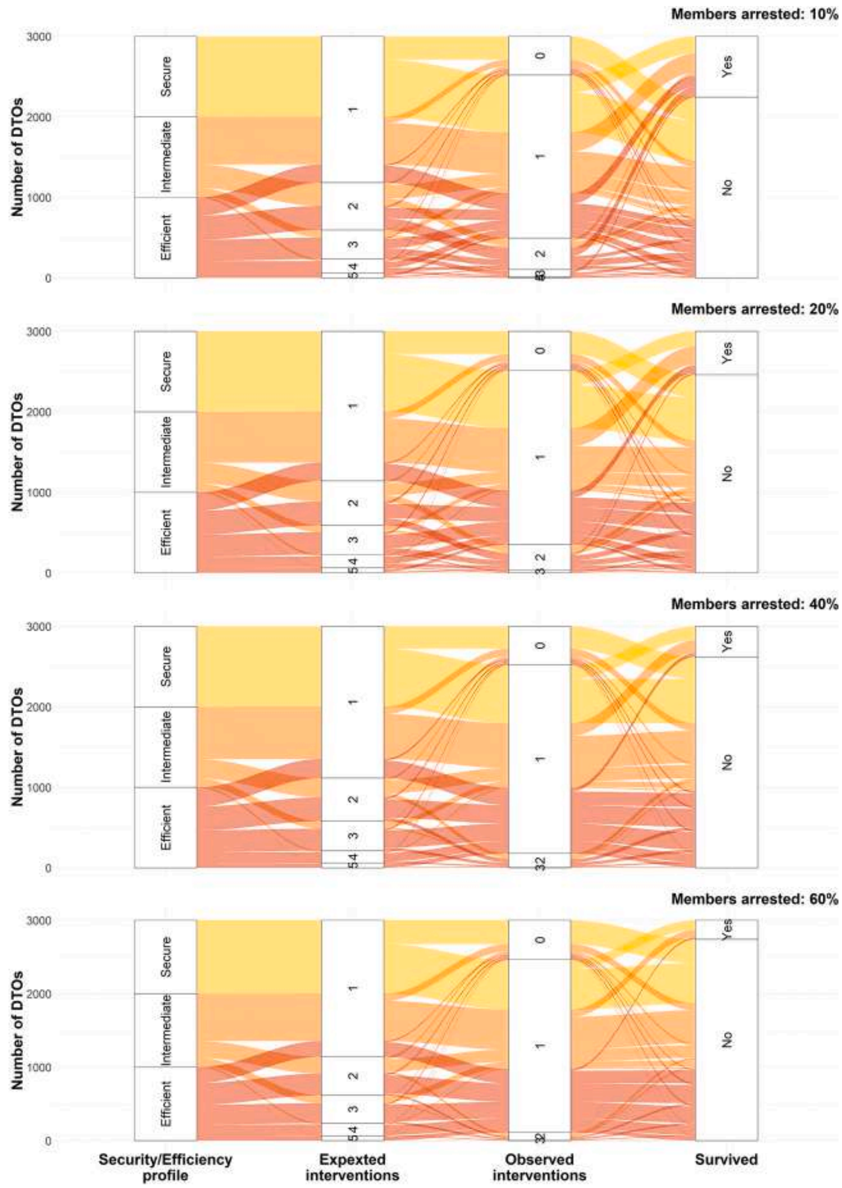
For a summary of MADTOR assumptions, agent attributes, and processes, see Appendix A, Section 3.

4.3. Simulation strategy, data analysis, and calibration

To assess how varying efficiency/security profiles influence the

[6] During setup, each trafficking organization is assigned a set number and schedule of law enforcement interventions, calibrated to its efficiency/security profile. However, the actual number of interventions may vary, as some groups cease operations prematurely due to economic failure or prior law enforcement interventions. When an intervention occurs, it always takes place in its preassigned timeslot.

[7] In the model, this differentiation is achieved through distinct probability thresholds assigned to organizations with varying efficiency/security profiles, which determine whether a law enforcement intervention is expected in a given timeslot. These thresholds remain constant across all intervention slots but vary according to the organization's efficiency/security profile. Efficient DTOs are assigned the lowest thresholds, resulting in a higher likelihood of being targeted. Conversely, secure DTOs have the highest thresholds, making them less likely to face interventions. Intermediate DTOs occupy a middle position. For additional details, refer to the online model documentation.



Notes: The figure shows the distribution of DTO survival outcomes in Scenario 2 by efficiency/security profile,expected and observed law enforcement interventions, and final survival status, across different shares of members arrested.

The four vertically stacked panels correspond to increasing arrest rates (10%, 20%, 40%, and 60%).

Within each panel, flows connect DTOs' efficiency/security profiles (left axis) to the number of expected interventions assigned at the beginning of the simulation (ranging from 1 to 5), the number of interventions actually observed during the simulation, and the final survival outcome. The width of each flow is proportional to the number of DTOs.

Secure DTOs are mostly assigned a single intervention, whereas intermediate and efficient DTOs show increasing heterogeneity, with efficient DTOs exhibiting the widest variation. Observed interventions are often fewer than expected due to early disruption from economic inefficiencies or cumulative intervention effects. DTOs with no observed interventions are disrupted before major law enforcement action, particularly among secure DTOs. Across all profiles, higher arrest rates correspond to lower survival.

Fig. 4. Scenario 2: DTOs' survival by efficiency/security profile, expected, and observed interventions across different shares of members arrested.

resilience of DTOs, we ran thirty MADTOR submodels. These submodels reflect the intersection of three parameters: 1) law enforcement intervention scenarios (i.e., Scenario 1 and Scenario 2); 2) the different efficiency/security profiles (i.e., secure, intermediate, and efficient DTOs); and 3) the proportion of members arrested (i.e., 0%, 10%, 20%, 40%, and 60%). Each submodel was simulated 1000 times to ensure statistically robust findings while maintaining computational feasibility. Each simulation covered 1825 ticks, equivalent to five years of simulated time, sufficient to evaluate both short- and long-term resilience following major law enforcement interventions.

We compared the trends of the three resilience indicators introduced in Section 4.2.4—share of active organizations, number of members, and revenues—across scenarios, using the 0% arrest scenario as a baseline. While we expected that the trends across efficiency/security profiles would be indistinguishable before the major law enforcement actions, we focused on the differences that emerged afterward to assess the impact of law enforcement interventions.

The resilience indicators were aggregated at each time step across simulations of the same submodel. To improve the readability and visualization of the results, for the number of members and revenues we computed the monthly mean of daily values and then averaged across all simulations of the same arrest scenario. At the beginning of the simulation every indicator is the average of 1000 simulations, while afterwards it draws on fewer simulations due to progressive disruption of some organizations.

MADTOR was calibrated to reproduce plausible dynamics of drug

Table 4
Criminal group resilience indicators.

Dimension of resilience	Resilience indicator	Interpretation
Endure disruption	*Share of active drug trafficking organizations*	Measures a DTO's ability to withstand law enforcement interventions; higher values reflect greater endurance over time.
React quickly and efficiently	*Number of members*	Indicates organizational stability and strength; higher numbers suggest robustness. Post-intervention growth reflects the DTO's capacity to recruit and recover.
Maintain primary functions and activities unaltered	*Revenues*	Proxy for the DTO's ability to sustain operations; sharp revenue declines signal failure to maintain trafficking activities after interventions.

trafficking and retail operations, with a focus on organizational performance and member behavior. Calibration relied primarily on quantitative data from the Operation Beluga court order, complemented by qualitative information drawn from the same source and from relevant criminological literature.

To avoid an overly deterministic setup, simulated parameters were allowed to fluctuate within the empirical ranges observed in the data. Table 5 compares the distribution of members across organizational roles as recorded in the Beluga investigation with the median simulation outputs for the first three years—prior to the onset of major law enforcement interventions. The correspondence between empirical and simulated values was strong, with simulated figures slightly below the real ones, likely reflecting minor enforcement interventions not explicitly reported in the court order.

The simulated scale of trafficking activity also closely matched that of the Beluga group. During the second year, organizations in MADTOR sold between 1376 and 2328 doses per day—comparable to Beluga's reported range of 1370–2340 daily doses. Average simulated sales (≈1850 doses per day) fell squarely within the empirical boundaries.

Some variables, such as the number of drug acquisitions, total revenues, and drug stock levels, were inferred from the Beluga documentation and cannot be independently validated. Nevertheless, because calibration was anchored in empirical data for the organization's structure, workload, pricing, wages, and profits—and informed by criminological research on relational and operational practices—it is reasonable to conclude that MADTOR captures the essential features of the trafficking system. Further technical details on the calibration process are provided in the online model documentation.

To assess the robustness of the model and its underlying assumptions, we conducted a series of sensitivity analyses, modifying selected parameters not directly grounded in empirical data. These included variations in market conditions (e.g., wholesale price fluctuations), arrest intensities, and the timing of law enforcement interventions. A detailed account of these sensitivity tests is provided in Appendix C.

Table 5
Drug trafficking size and role composition. Beluga vs. MADTOR simulations.*

	Year		
	0	1	2
Beluga members	44	59	66
MADTOR, median members	44	57	64
Beluga traffickers	5	13	16
MADTOR, median traffickers	5	12	15
Beluga packagers	5	13	13
MADTOR, median packagers	5	10	13
Beluga retailers	34	33	37
MADTOR, median retailers	34	36	37

* For Beluga, we report values for the years 2008, 2009, and 2010. For the simulations, we report median values at months 1, 12, and 24 across all simulations who reached at least month 27.

5. Results

5.1. Baseline

We first present the results in the baseline scenario, where no major interventions occur (Fig. 5). Like legal enterprises, some drug trafficking organizations disband due to internal inefficiencies, even in the absence of major law enforcement actions. In 2022, the business closure rate was 8.7% in the European Union (Eurostat., 2024) and 6.5% in Italy (ISTAT, 2024). MADTOR reflects this reality: some DTOs collapse before or after minor interventions, driven by economic instability. The yearly DTO closure rate across all simulations is 7.2%, positioning in-between the European Union and Italian closure rate in 2022 (see Appendix B, Fig. 15).

Efficient DTOs outperform secure ones, with approximately 85% remaining active by the end of the simulation, compared to fewer than 50% of secure DTOs. The pursuit of profit appears to underpin the long-term survival of efficient organizations, enabling them to sustain operational continuity, reinvest in their activities, and recover more rapidly from adverse conditions. These findings are consistent with the broader literature on organizational resilience, which highlights the importance of resource availability—particularly financial capital—in enhancing a system's adaptability and capacity to maintain core functions under stress or uncertainty (Barasa et al., 2018; Hepfer & Lawrence, 2022; Lengnick-Hall & Beck, 2005; Norris et al., 2008). In this context, access to monetary resources allows DTOs to absorb short-term losses, reconfigure internal operations, and recruit new members, thereby strengthening their ability to respond to external shocks. In contrast, secure DTOs—primarily focused on caution and risk avoidance—tend to sacrifice adaptability and operational effectiveness, leading to higher failure rates over time.

Despite these differences, membership growth is broadly similar. However, similar member counts can reflect different turnover dynamics: in MADTOR, membership reflects the balance of recruitment and enforcement-driven exits over time. Each profile starts with about 40 members and grows to just over 70. Efficient DTOs, facing more frequent minor interventions, offset higher arrests through greater recruitment. Secure DTOs, exposed to fewer minor interventions, grow more slowly due to strict entry criteria but maintain stability. Revenues and expenses rise over time across all DTOs. Efficient organizations consistently earn and spend €5000 to €10,000 more than secure ones, reflecting greater market activity and profit (Fig. 5).

5.2. Scenario 1: one identical intervention

Scenario 1 subjects all DTOs to an identical law enforcement intervention, comprising the arrest of a percentage of their members and the seizure of their drug supplies. Organizations prioritizing efficiency demonstrate higher survival rates compared to intermediate and, particularly, secure DTOs (Fig. 6).

The superior performance of efficient DTOs is most pronounced in interventions targeting a relatively low proportion of members (i.e., 10% and 20%). In these scenarios, efficient DTOs consistently exhibit survival rates more than twice as high as those of secure DTOs (i.e., 49.1% vs. 16.5% in the 10% arrest scenario and 36.0% vs. 15.2% in the 20% arrest scenario). However, as the intensity of the law enforcement intervention increases (i.e., 40% of members arrested), the differences in survival rates among DTOs with different efficiency/security profiles become less pronounced. While efficient DTOs continue to outperform secure ones, overall survival rates decline sharply, particularly for efficient DTOs, with only 19.2% remaining active compared to 14.9% of secure DTOs (Fig. 6).

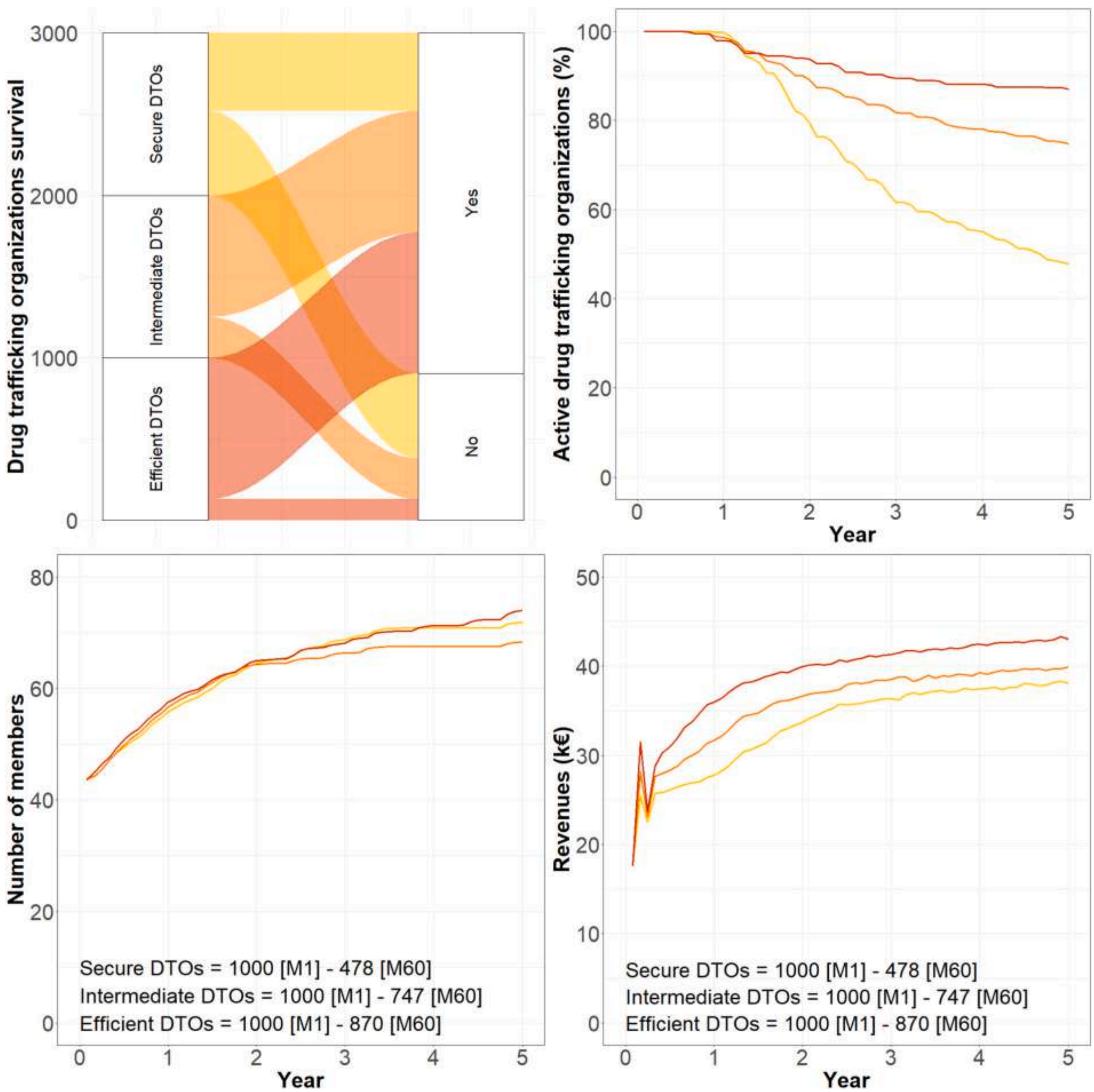


Fig. 5. Baseline scenario: DTOs' survival rate, average membership size, and revenues.

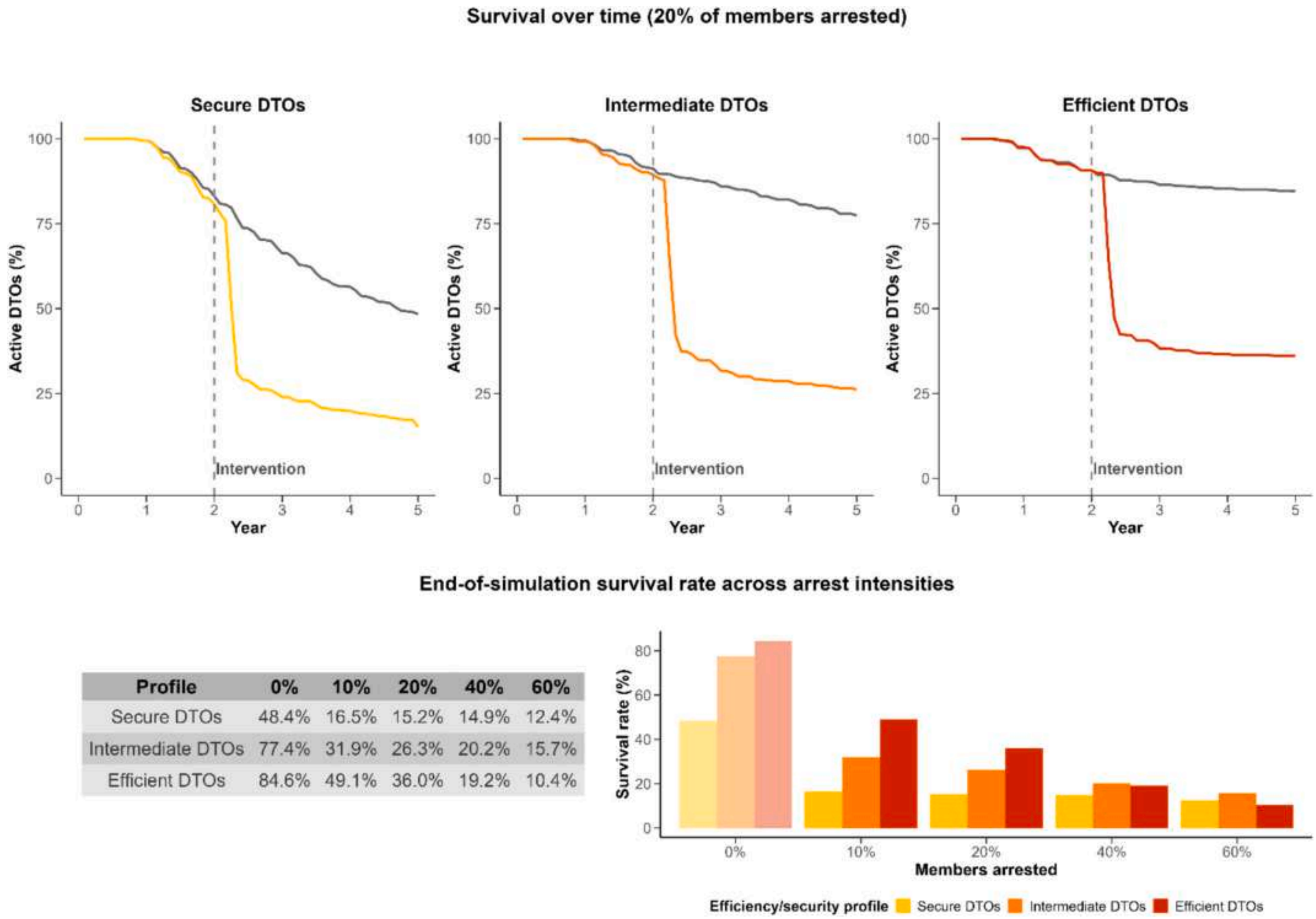
In the most extreme intervention scenario (i.e., 60% of members arrested), secure DTOs slightly surpass efficient DTOs in terms of survival rates (12.4% vs. 10.4%) (Fig. 6). However, these low survival rates suggest that beyond a certain threshold of arrested members, the challenges posed by law enforcement interventions become nearly insurmountable for any organization.

Law enforcement interventions also have significant structural and economic impacts on DTOs, leading to an immediate post-intervention decline in both the number of members and revenue generation (for simplicity we report here figures for the 20% scenario, additional scenarios are reported in Appendix D). The decline in membership is proportional to the percentage of members arrested for both secure and efficient organizations. A few months after the intervention, DTOs attempt to recover by recruiting new members; however, they never fully return to baseline levels, with efficient organizations experiencing a slightly more pronounced shortfall. Regarding financial performance, law enforcement interventions trigger a sharp decline in revenues in the period immediately following their implementation. Nevertheless, both secure and efficient organizations manage to restore their baseline revenue levels within a few months. Except in the most severe scenarios (i.e., 60% arrests), efficient DTOs are better able to mitigate short-term revenue losses, experiencing less severe declines compared to secure DTOs (Fig. 7).

5.3. Scenario 2: multiple, differential interventions

We developed a second law enforcement intervention scenario that accounts for the ability of secure drug trafficking organizations to minimize law enforcement attention. This ability influences three key factors: (1) the intensity; (2) the likelihood; and (3) the timing of major law enforcement interventions. As illustrated in Fig. 8, secure DTOs typically encounter 1 major law enforcement intervention, whereas these events are more frequent for intermediate and efficient DTOs, with a small subset of efficient DTOs facing as many as four or five interventions.

The differential law enforcement targeting introduced in Scenario 2 significantly influences the survival rates of both secure and efficient organizations. Secure DTOs outperform efficient DTOs in all arrest



Profile	0%	10%	20%	40%	60%
Secure DTOs	48.4%	16.5%	15.2%	14.9%	12.4%
Intermediate DTOs	77.4%	31.9%	26.3%	20.2%	15.7%
Efficient DTOs	84.6%	49.1%	36.0%	19.2%	10.4%

Fig. 6. Scenario 1: DTOs' survival rate over time and across different arrest intensities.

intensities except for the 10% arrest intensity, where the superior operational efficiency of efficient DTOs offsets the impact of repeated, low-intensity interventions. Comparing these results to Scenario 1, secure DTOs demonstrate improved survival rates, with percentage increases ranging from 29% in the 10% arrest intensity to less than 5% in the 60% arrest intensity. Conversely, efficient DTOs experience sharp declines in survival, with reductions ranging from 47% in the most favorable scenario (i.e., 10% of members arrested) to 75% in the most severe scenarios (i.e., 40% and 60% of members arrested) (Fig. 9, see Appendix D: Results for survival rates over time for arrest intensities other than 20%).

In the second scenario, law enforcement interventions continue to affect both workforce size and organizational revenues. Overall patterns are consistent with previous observations: higher arrest rates lead to greater reductions in membership, and membership rebounds among surviving DTOs after disruptions, but this occurs alongside sharp declines in the share of active DTOs at higher arrest intensities (Fig. 24 in Appendix D). Efficient DTOs tend to suffer larger initial losses but exhibit greater capacity for rebound, though rebounds become more volatile and less complete as intervention intensity increases. Secure DTOs experience slightly smaller workforce reductions, consistent with their lower exposure. Across profiles, membership trajectories appear less sensitive to intervention timing than survival, although later disruptions mechanically leave less time for recovery within the simulation horizon.

In terms of revenues (Fig. 25 in Appendix D), DTOs that fail due to economic inefficiency before enforcement perform even worse than those in the baseline scenario, with lower and more erratic earnings. Among surviving organizations, revenue trends are broadly similar regardless of the number of interventions experienced. Overall, revenues among survivors typically rebound after arrests and remain in broadly comparable ranges to the no-arrest baseline Intervention timing has a limited effect, though later disruptions lead to slightly longer recoveries, likely influenced by the shorter observation window.

Taken together, these results indicate that while enforcement intensity shapes workforce contraction and short-term economic volatility, survival outcomes are primarily driven by two interrelated dimensions: the number and timing of law enforcement interventions. We therefore turn to a more focused analysis of these aspects, concentrating on the 20% arrest intensity for simplicity (figures for the other arrest intensities are reported in Appendix D).

5.3.1. Number of interventions

Fig. 10 presents the survival rates of organizations across different efficiency/security profiles, categorized by the number of law enforcement interventions encountered. Secure DTOs never undergo multiple interventions—only 3 out of 1000 were expected to face two, and none sustain the full sequence of planned interventions, as all were dismantled early. In contrast, intermediate and especially efficient DTOs are more frequently subjected to repeated interventions. Across all profiles, survival rates decline as the number of interventions increases. Among organizations targeted only once, efficient and intermediate DTOs show the highest survival rates, with just over 40% remaining active at the end of the simulation, compared to fewer than 30% for secure DTOs. When facing multiple interventions, survival declines more sharply for intermediate DTOs—dropping to 20%—while efficient DTOs maintain

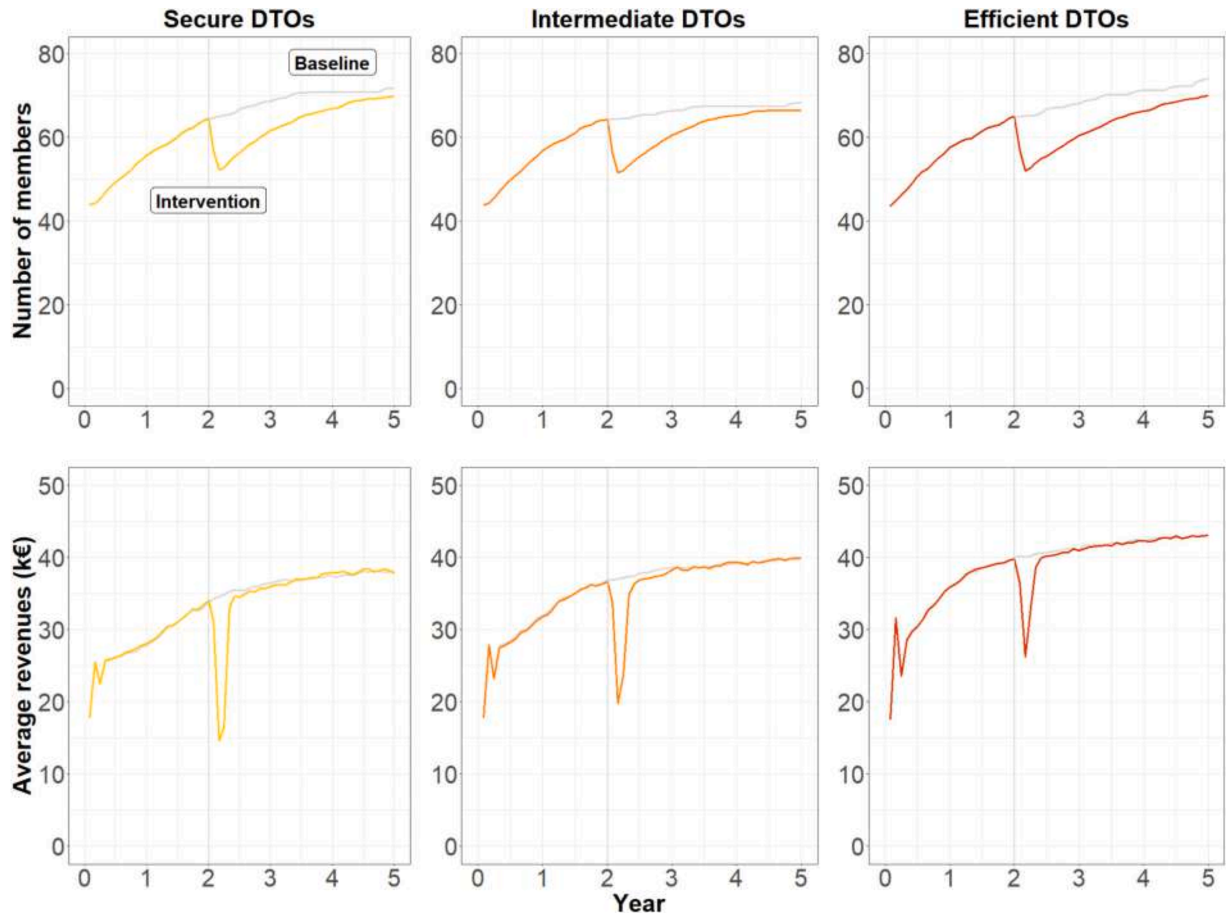
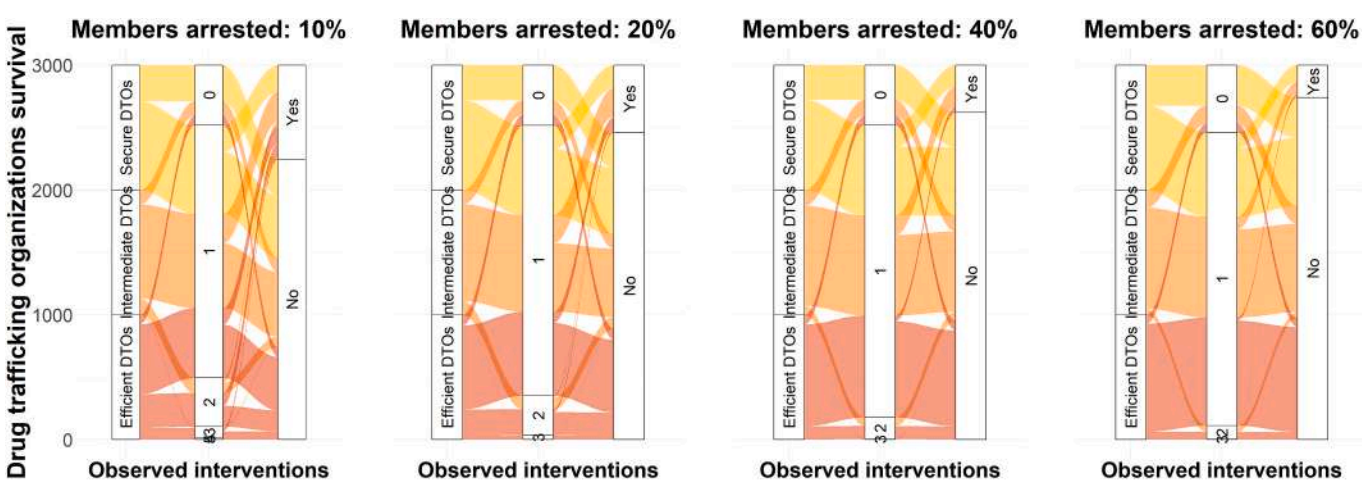


Fig. 7. Scenario 1: DTOs' average membership size and average revenues (20% of members arrested).

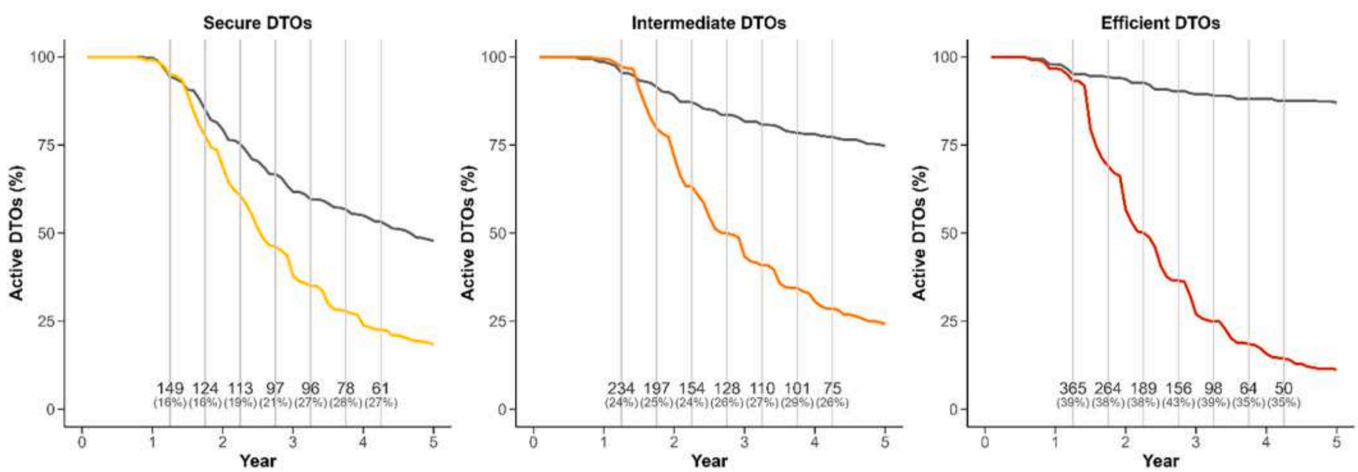


Notes: The figure displays DTO survival outcomes at the end of the simulation by efficiency–security profile and observed law enforcement interventions, across different shares of members arrested. The four panels correspond to arrest rates of 10%, 20%, 40%, and 60%.

Within each panel, flows connect DTO efficiency–security profiles (left axis) to the number of observed interventions during the simulation (central axis). The right-hand bar indicates final survival status (Yes/No). The width of each flow is proportional to the number of DTOs. DTOs with zero observed interventions were disrupted before major law enforcement action due to economic weakness and financial unsustainability; consistently with the Baseline Scenario, this subgroup is larger among secure DTOs. Across all profiles, higher arrest rates are associated with fewer surviving DTOs.

Fig. 8. Scenario 2: DTOs' survival rates under different shares of arrested members and observed interventions.

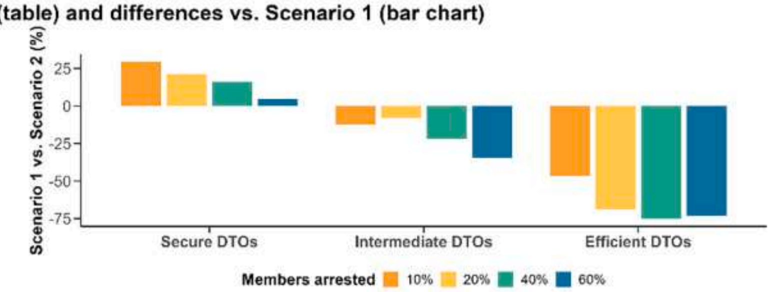
Scenario 2: Survival over time (20% of members arrested)



Note: The grey vertical lines indicate the intervention time slots when DTOs may experience disruptions. The numbers at the bottom of each line are the total interventions faced by each efficiency/security profile. Percentages in parentheses denote the proportion of active DTOs experiencing an intervention at that time.

Scenario 2: Survival rates (table) and differences vs. Scenario 1 (bar chart)

Profile	0%	10%	20%	40%	60%
Secure DTOs	47.8%	21.3%	18.4%	17.3%	13.0%
Intermediate DTOs	74.7%	28.0%	24.2%	15.8%	10.3%
Efficient DTOs	87.0%	26.2%	11.3%	4.8%	2.6%



Note: The table reports the survival rates at the end of the simulations per profile and share of arrested members. The bar chart shows the percentage differences in survival rates relative to Scenario 1 for each profile, by share of arrested members.

Fig. 9. Scenario 2: survival rate and percentage differences relative to Scenario 1.

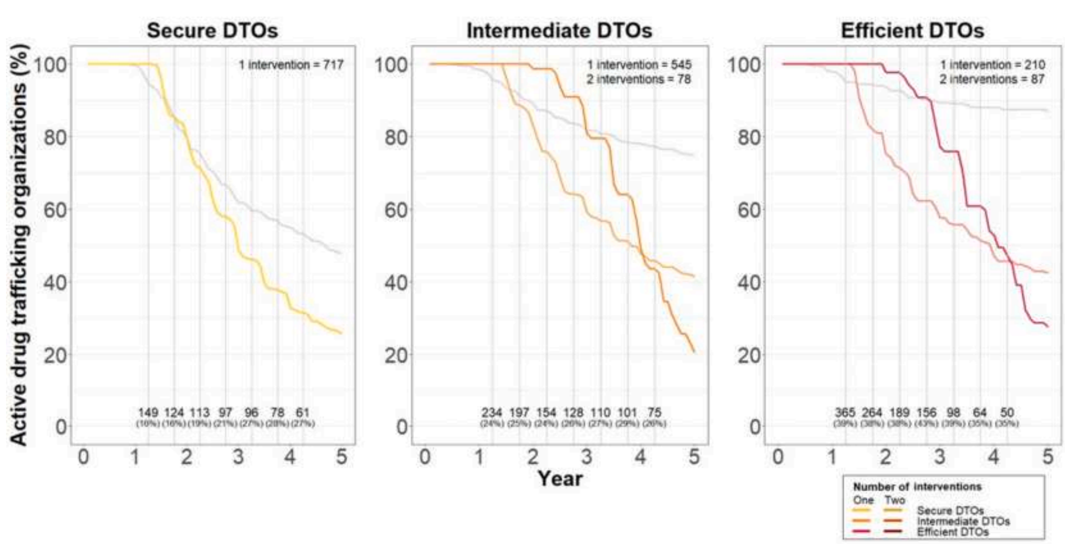


Fig. 10. Scenario 2: DTOs' survival rate by number of interventions (20% of members arrested).
Note: The grey vertical lines indicate the intervention time slots when DTOs may experience disruptions. Only DTOs that experienced all expected interventions (i.e., expected interventions = observed interventions) are included in this figure.

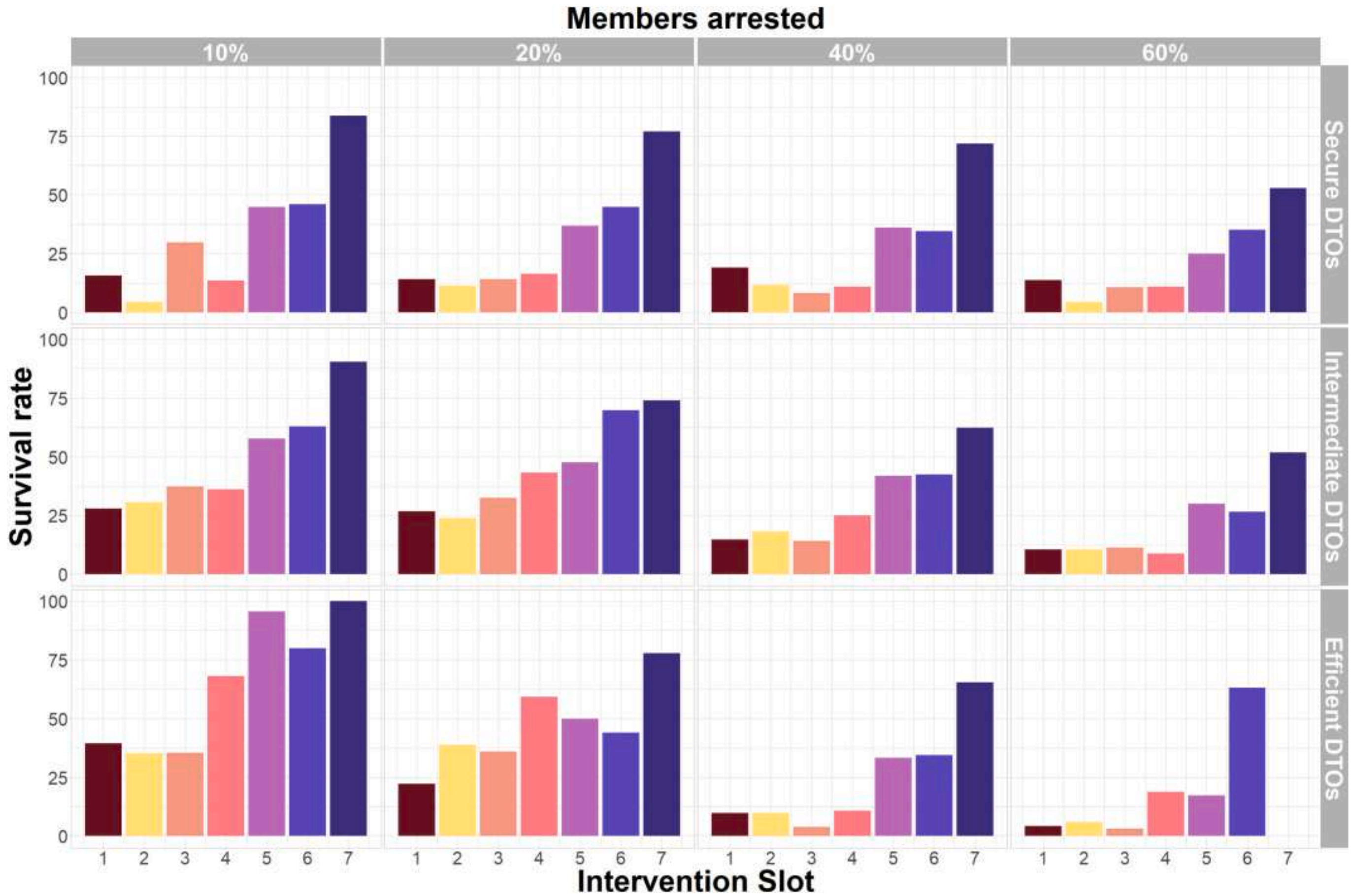


Fig. 11. Scenario 2: DTOs' survival rate by intervention slot.
Note: The bar charts report the survival rates of each DTO category at the end of the simulations, across various arrest intensities and accounting for the timing of the intervention. Only DTOs with one expected intervention are included.

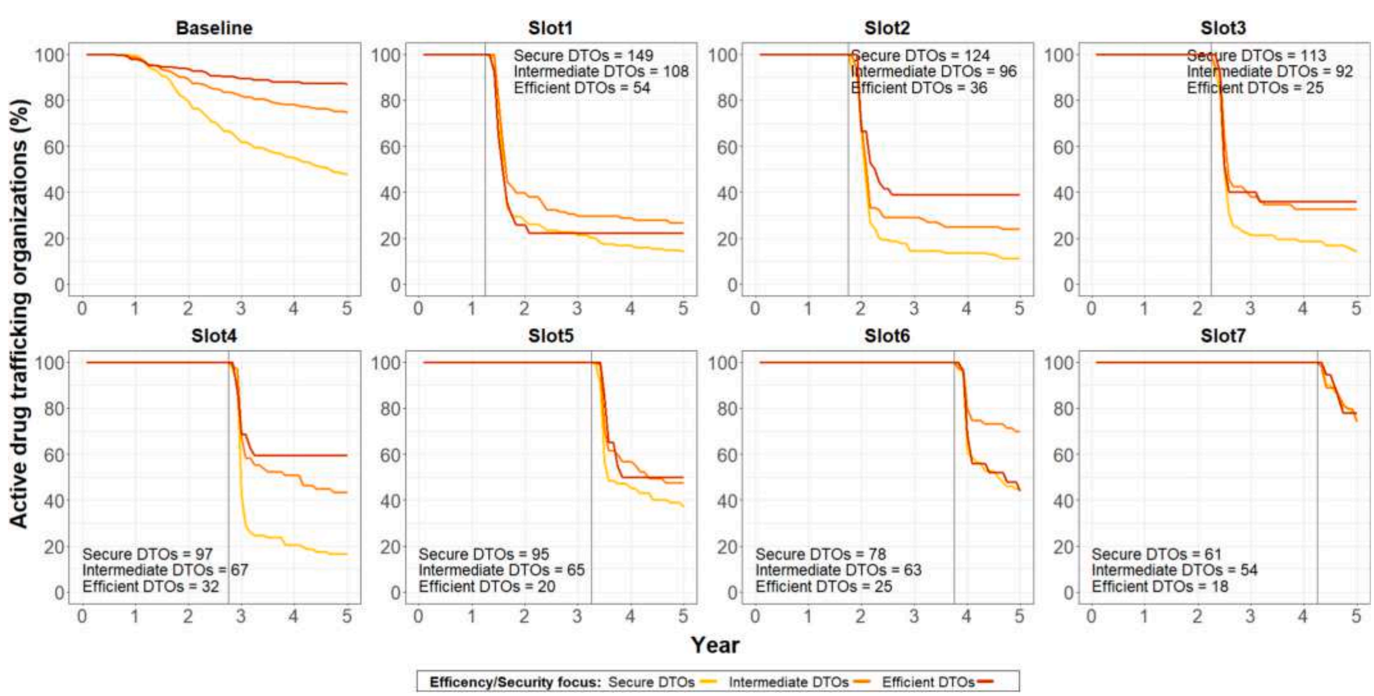


Fig. 12. Scenario 2: DTOs' survival rate by intervention slot (20% of members arrested).
Note: Each line chart reports the survival rates of DTOs experiencing the intervention in the same time slot across the three efficiency/security profiles. Only DTOs with one expected intervention are included.

comparatively higher resilience, with 30% still active at the end of the simulation.

5.3.2. Timing

The timing of law enforcement interventions strongly influences DTO survival (Fig. 11). Early interventions (Slots 1–3) consistently yield the lowest survival rates across all organizational profiles and arrest intensities, indicating that striking before DTOs consolidate is substantially more effective. In contrast, late-stage interventions (Slots 6–7) result in dramatically higher survival, even when a large share of members is arrested. Overall, this pattern holds for secure, intermediate, and efficient DTOs: delaying action allows structures to adapt, reorganize, and retain operational capacity.

By focusing exclusively on organizations subjected to a single intervention involving the arrest of 20% of their members allows us to isolate and more precisely assess the effect of intervention timing across different organizational profiles (Fig. 12). All other factors being equal, efficient DTOs demonstrate higher survival rates than secure DTOs. However, the timing of the intervention proves to be a critical factor: the later it occurs, the higher the likelihood of organizational survival. Furthermore, when interventions take place at later stages of the simulation, the survival rate gap between secure and efficient DTOs narrows considerably, with both types exhibiting comparable levels of resilience (Fig. 12). This is confirmed by the results comparing DTOs subjected to single versus multiple interventions: organizations experiencing repeated interventions exhibit lower survival rates, particularly when interventions occur in close succession. Detailed trends by intervention timing and intensity are provided in the Appendix D (Fig. 22 and Fig. 23).[8]

6. Discussion and conclusion

Our study indicates that strategic profiles along the efficiency/security trade-off shape DTO resilience under law enforcement pressure. In baseline conditions, efficient DTOs—those prioritizing profitability and operational flexibility—exhibit higher survival rates and stronger economic performance than secure DTOs, consistent with insights from organizational resilience research. Enforcement alters these patterns. Under identical interventions (Scenario 1), efficient DTOs outperform secure ones at lower arrest intensity, but the survival gap narrows as intensity increases; at the highest intensity (60% arrested), secure DTOs slightly surpass efficient ones (Fig. 13). Under differential targeting linked to exposure (Scenario 2), secure DTOs—benefiting from reduced exposure and delayed interventions—show higher survival rates, particularly at higher arrest intensity. Workforce and revenues among surviving DTOs generally rebound after disruptions, but efficient DTOs experience deeper post-arrest shocks and greater volatility; moreover, at higher arrest intensity the main resilience loss operates through a sharp decline in the share of active DTOs. Timing and frequency of interventions also matter: early and repeated interventions significantly reduce survival across profiles. Sensitivity analyses indicate that these comparative patterns are robust to plausible variations in market and enforcement parameters.

These results address the three propositions outlined in the Background. First, they indicate that, within a single activity domain, alternative efficiency/security configurations can produce meaningfully different resilience trajectories, so the trade-off is more than a post hoc label. Second, they offer little basis for treating “security” or “efficiency” as uniformly advantageous: which orientation performs better depends on enforcement conditions. Third, they suggest that resilience rankings can shift across intervention regimes—especially with changes in the arrest “dose” (share arrested and frequency) and the timing of arrests—highlighting that resilience emerges from the interaction between organizational configuration and external threat.

Taken together, these patterns align with the efficiency/security trade-off and help clarify its implications for resilience under enforcement pressure. The differential survival patterns observed—where secure DTOs benefit from reduced exposure and delayed interventions, while efficient DTOs are more vulnerable to early and frequent interventions—support the idea that concealment and risk minimization are key assets under sustained external threat. These dynamics are consistent with prior studies that show how illicit actors balance operational efficiency and risk through structural mechanisms such as brokerage, clustering, and trust-based ties (Bright et al., 2019; Diviák et al., 2022; Van Der Zwet et al., 2025). In particular, our findings expand on Duxbury and Haynie's (2019) demonstration that secure configurations enhance organizational robustness while sacrificing adaptability and speed. This helps interpret mixed findings in prior research as reflecting differences in enforcement regimes and exposure rather than a single, universally resilient organizational form.

While corroborating previous empirical and simulation-based work, our study advances how the efficiency/security trade-off can be evaluated. We treat efficiency and security as alternative strategic profiles implemented through explicit organizational rules, and we apply these profiles to a shared structural baseline rather than comparing entirely different network forms. This design isolates the contribution of the position along the trade-off to resilience outcomes while holding structural and contextual conditions constant. MADTOR also incorporates empirically grounded representations of drug supply activities, law enforcement processes, and organizational adaptation, linking the trade-off to observable operational mechanisms rather than post hoc interpretations of network structure. In doing so, the model provides a transparent platform for exploring how strategic profile shapes resilience under enforcement pressure and for connecting criminological research with organizational resilience theory.

This study contributes to theoretical understanding by indicating that resilience in DTOs is not solely a function of structural type, but of how strategic priorities interact with enforcement pressure over time. In low-pressure situations, efficiency-oriented DTOs benefit from features typically associated with organizational resilience—such as coordination capacity, resource availability, and adaptability (Barasa et al., 2018; Hepfer & Lawrence, 2022; Lengnick-Hall & Beck, 2005). However, under heightened enforcement pressure—such as the high-intensity anti-drug strategies common in many advanced economies (Campana & Varese, 2022; Paoli, 2016)—secure DTOs, despite slower growth and reduced profitability, often exhibit greater resilience due to their focus on concealment and risk minimization (Bright et al., 2012; Diviák et al., 2022; Morselli et al., 2007). This finding reinforces a key insight: under sustained threat, the most resilient organizations are not necessarily the most efficient, but those that effectively reduce their visibility and delay detection (Eck & Gersh, 2000; Erickson, 1981; Paoli, 2002; Reuter, 1983, 1985).

These findings also qualify enterprise-based interpretations that treat DTOs as rational, profit-oriented actors across threat environments. In high-risk settings, DTOs may accept lower efficiency in exchange for reduced exposure, adopting efficiency/security profiles that prioritize survival over growth or adaptability. This strategic shift aligns with resilience theory, which highlights the trade-offs organizations make under persistent threat (Benson & Decker, 2010; Calderoni, 2018; Eck & Gersh, 2000), and echoes criminological research emphasizing concealment, fragmentation, and risk diffusion as key to enduring in illicit markets (Ayling, 2009; Bouchard & Ouellet, 2011; Malm & Bichler, 2011). In this light, DTOs resemble less profit-oriented enterprise pursuing growth under all conditions than adaptive systems navigating volatile and hostile environments.

Our results carry important implications for both criminological theory and law enforcement practice. Theoretically, they indicate that DTO resilience is not determined by structural form alone, but by how

[8] Additional figures illustrating the impact of different intervention timings on DTO survival, membership size, and revenues are available upon request.

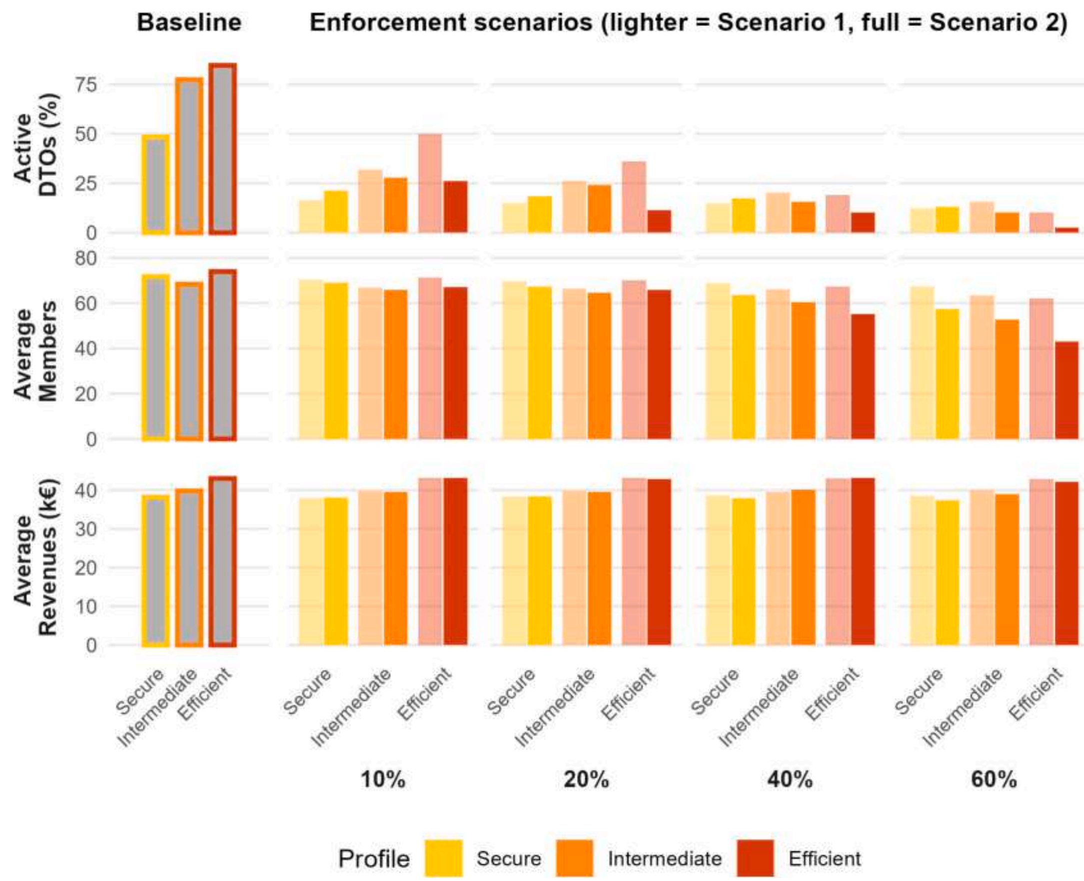


Fig. 13. Summary results for Scenario 1 and Scenario 2.

strategic priorities interact with the intensity, frequency, and timing of external threats. The durability of secure DTOs, alongside the tendency to adopt lower-efficiency configurations under pressure, challenges static or idealized models of criminal organization and supports more dynamic, context-sensitive frameworks that account for adaptive strategies and threat environments. More broadly, the findings suggest that the efficiency/security trade-off has its strongest theoretical leverage in explaining *within-domain heterogeneity*. Even among organizations engaged in broadly similar drug trafficking activities, configurations can differ systematically in their orientation toward security or efficiency, with consequential differences for resilience—rather than the trade-off serving mainly as a coarse contrast across fundamentally different organizational contexts (e.g., terrorist cells versus DTOs).

For enforcement practice, our results suggest that, in the modeled setting, DTOs can be structurally and economically fragile, with some collapsing without targeted intervention (Reuter, 1997). This challenges assumptions of DTO robustness and highlights the potential of well-timed, repeated interventions to yield disproportionate effects. Rather than relying solely on broad crackdowns, enforcement strategies that exploit specific vulnerabilities—such as repeated, closely timed interventions, or financial or operational disruption—may be especially consequential under certain conditions. At the same time, overly aggressive strategies can produce diminishing returns, reinforcing the value of intelligence-led, adaptive enforcement.

At a broader systems level, organizational fragility must be contextualized within the dynamics of illicit drug markets. While our analysis captures the challenges and constraints faced by a single organization, drug markets are large, competitive, and adaptive. The collapse of one DTO may not disrupt supply for long, as failed groups are often replaced by others drawn by the enduring profitability of the trade. This replacement dynamic underscores a key limitation: tactical successes at the organizational level do not necessarily translate into strategic disruption. As much of the literature suggests, lasting impact on illicit markets remains elusive, as enforcement gains are often temporary and offset by systemic regeneration (Babor et al., 2018; Caulkins & Reuter, 2010; Pollack & Reuter, 2014; Reuter, 2013; Reuter et al., 2016).

Our study presents several limitations. First, although our findings suggest that DTOs can be inherently fragile and prone to collapse under sustained law enforcement pressure in the modeled setting, this does not imply that the overall drug supply is equally disrupted. A central limitation lies in the model's focus on a single DTO in a closed-system environment. In practice, drug markets are dynamic and competitive: when one organization weakens or collapses, others may expand their market share, and new actors may emerge. By isolating one DTO, the model does not account for inter-organizational dynamics, substitution effects, or broader market adaptations that shape systemic resilience. Nonetheless, this approach enables a focused analysis of how internal structural configurations influence resilience under enforcement pressure—an essential step toward more effective disruption strategies.

Second, while MADTOR integrates key insights from the efficiency/security trade-off literature, it necessarily simplifies complex dynamics for model feasibility. Relatedly, arrests are implemented as probabilistic removal among exposed members rather than as an intelligence-led selection rule tied to individual roles or network position. This choice captures the breadth of large-scale operations but does not allow us to evaluate how alternative targeting strategies (e.g., role-based or centrality-based arrests) might interact with efficiency/security configurations. Some traits associated with secure or efficient profiles may be represented only through parameterized mechanisms rather than fully observed causal processes, and the thresholds used to distinguish DTO types—though implemented on a continuous scale—cannot fully capture the diversity of real-world organizations. That said, MADTOR represents a significant advancement in the field. It offers a more detailed and empirically grounded simulation than existing ABMs, including realistic representations of drug supply chains, multi-actor law enforcement interventions, and adaptive organizational responses. The model's structure and logic are fully documented in previous studies by the authors and supported by open-access materials.

Third, the model's scope and empirical grounding limit the generalizability of its results. While MADTOR advances prior models by simulating core dynamics such as recruitment, tie formation, and law enforcement disruption, it still abstracts from broader market complexities. The model focuses specifically on cocaine trafficking and is calibrated using data from Operation Beluga—an in-depth investigation of a single Italian DTO. Although the Beluga group reflects features common to many DTOs—such as compartmentalization and profit-driven strategies—its specific configuration likely shapes simulation outcomes. Generalizing results to other DTOs, organizational roles, or substances should therefore be done with caution.

Despite these limitations, MADTOR offers a flexible and transparent framework for testing theoretical propositions about DTO resilience and for assessing how conclusions vary under alternative enforcement and adaptation assumptions. By publicly sharing the codebase and documentation, we hope to facilitate future empirical refinement, comparative analysis, and methodological innovation. While ABMs are not a substitute for other approaches, they allow researchers to simulate dynamics that are often empirically inaccessible, making MADTOR a valuable tool for advancing the study of criminal group resilience.

In conclusion, this study contributes to a more nuanced theoretical understanding of resilience in illicit networks by empirically operationalizing the efficiency/security trade-off—a concept widely discussed but seldom examined systematically within a single activity domain. Through the development of a dynamic agent-based model, we move beyond static or idealized accounts of criminal organizations and offer a theory-driven, empirically grounded framework to systematically assess how within-domain variation in structural configuration shapes resilience under law enforcement pressure. This work brings criminological insights into closer conversation with organizational resilience theory, highlighting how adaptability, concealment, and strategic compromise interact in shaping long-term survival under different intervention regimes. While our model necessarily simplifies certain dynamics, it represents a significant step forward in theorizing and evaluating how different efficiency/security profiles mediate both vulnerability and adaptive capacity. Rather than proposing definitive conclusions, we see MADTOR as a generative platform—one that can be refined, expanded, and adapted to different empirical contexts and to alternative enforcement and market assumptions. By bridging disciplinary perspectives and translating theoretical assumptions into testable simulations, this study opens new avenues for both conceptual development and applied research on the resilience of criminal 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/7081410a-8070-4c81-928e-f0736e366807/(Manzi, 2026).[9]

CRediT authorship contribution statement

Deborah Manzi: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Francesco Calderoni:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization.

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.

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. DM wrote the simulation code in NetLogo, prepared, and analyzed the data. Both authors drafted the manuscript and approved the final manuscript.

Appendix A. Methodological details

A.1. Operation Beluga and the Di Lauro clan

This study is grounded in Operation Beluga, a large-scale judicial investigation into the Di Lauro clan, a Camorra organization operating in northern Naples, with a consolidated presence in the Rione Terzo Mondo area (Tribunale di Napoli, 2013). During the early 2000s, the clan exercised extensive territorial control over the neighborhoods of Secondigliano and Scampia, emerging as a dominant actor in the local drug market. At its peak, the organization coordinated a complex system of drug procurement, processing, and retail distribution, supported by a sizable workforce and a highly structured internal division of labor.

Initially, the clan was led by Paolo Di Lauro, widely regarded as a skilled and strategic trafficker capable of maintaining cohesion across the organization. Following his transition to fugitive status, leadership passed to his sons, whose more limited authority and strategic capacity weakened internal coordination and exposed the clan to increasing pressure from rival groups and law enforcement (Brancaccio, 2014; Direzione Investigativa Antimafia, 2012). Operation Beluga documents this period of organizational instability, during which the Di Lauro brothers struggled to maintain operational control and territorial dominance.

Judicial records provide detailed information on the size and composition of the organization during the investigation period. In 2008, the drug trafficking apparatus consisted of 5 traffickers, 5 packagers, and 34 retailers. In 2009, the number of traffickers and packagers increased substantially,

[9] The link provides access to a compressed folder containing the full model package. This includes: (i) the runnable model, which also allows direct consultation of the complete source code (in the code subfolder); (ii) all input files required to execute the model (in the data subfolder); and (iii) the ODD+D protocol together with additional narrative documentation detailing all procedures and parameter settings (in the docs subfolder).

reaching 13 in both roles, while the number of retailers slightly declined to 33. By 2010, traffickers further increased to 16, the number of packagers remained stable at 13, and retailers rose to 37. These figures reflect a period of organizational expansion in upstream and processing roles, coupled with relative stability at the retail level.

Although the Di Lauro clan was involved in multiple illicit activities—including territorial governance, firearms trafficking, and illegal gambling—drug trafficking constituted its primary economic engine. The seizure of 172 accounting ledgers during Operation Beluga offered unusually granular insight into the scale and organization of the clan's drug business. These records demonstrate that the overwhelming majority of revenues derived from narcotics trafficking and retail sales (Tribunale di Napoli, 2013).

Drug distribution was organized through two distinct open-air markets located within Rione Terzo Mondo, each specializing in specific substances. Hashish and marijuana were sold in Praga Magica Street, while cocaine and crack were distributed in Il Barbiere di Siviglia Street. Sales activity was closely monitored through systematic accounting practices, with precise records of quantities sold and revenues generated by individual dealers. Judicial documentation highlights substantial variability in daily sales volumes. For example, on 16 June 2010, the organization sold 1498 doses. Average sales reached approximately 2340 doses per day during the weekend of 11–13 June 2010, while averaging around 1370 doses per day in May 2010. These figures illustrate both the scale of the retail operation and the volatility of daily demand.

The court order also provides detailed evidence on the financial performance of the organization. In May 2010, total revenues amounted to €2685475, of which profits accounted for 32%, corresponding to €870795. Using documented cocaine revenues from 16 June 2010 (€39800), this translates into an estimated daily profit of approximately €12900, equivalent to a weekly profit of €90300. At the same time, operating costs were substantial. In May 2010, costs represented 68% of total revenues, amounting to €1814680. Based on daily cocaine revenues observed in June 2010, this corresponds to estimated daily operating costs of approximately €26900.

The organization relied on a differentiated internal division of labor, supported by a structured compensation system. Members involved in trafficking and packaging activities received fixed weekly payments (the settimana), while street-level retailers were remunerated daily as a percentage of their sales. Judicial records indicate that retailers earned 18% of the retail price per dose, with an empirically documented upper limit of €500 per day. This compensation structure combined fixed payments for more sensitive roles with performance-based incentives at the retail level.

Beyond wages and drug acquisition costs, financial records document a range of additional expenditures essential to sustaining the organization. These included logistical expenses, corruption of public officials, legal fees, and the rental of warehouses used to store drugs, vehicles, and weapons. A significant share of resources was also allocated to supporting the families of arrested or deceased members. According to the Beluga court order, families of arrested retailers received between €200 and €250 per week, while families of members imprisoned for homicide received between €3000 and €4000 weekly. Families of deceased members were allocated €500 per week. These payments constituted a non-negligible and recurrent cost, reflecting the organization's efforts to maintain loyalty and internal stability under conditions of sustained law enforcement pressure.

Overall, Operation Beluga provides an unusually detailed empirical portrait of a large-scale drug trafficking organization, documenting not only its organizational structure and division of labor, but also the scale of its drug markets, revenue streams, and cost structure. This richness of judicial data offers a rare opportunity to reconstruct the economic and organizational dynamics of the clan, forming the empirical basis for the parameterization of drug quantities, prices, wages, and operational costs used in the MADTOR model.

A.2. Toy example of a single MADTOR iteration

To illustrate how MADTOR operates under routine conditions, consider a single month (30 ticks) in the life of a DTO engaged in cocaine trafficking and retailing under the baseline scenario, in which no major law enforcement intervention occurs (Fig. 14). At this stage of the simulation, the organization has moved beyond the initial transient phase and operates in a relatively stable regime. The DTO consists of 15 traffickers, 12 packagers, and 37 retailers and holds sufficient cash reserves to sustain its daily operations. Over these 30 ticks, all standard operational processes unfold.

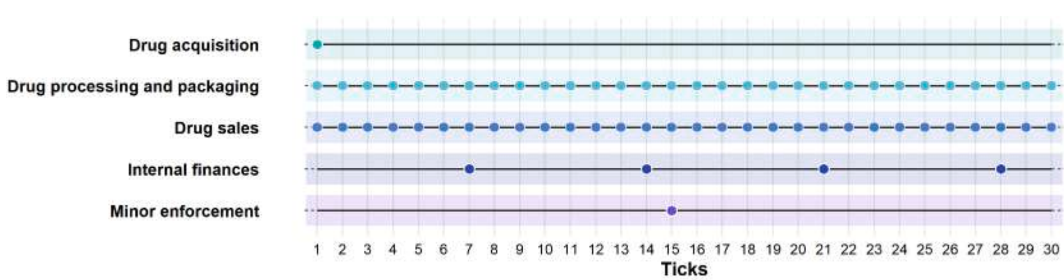


Fig. 14. MADTOR: Timeline of routine DTO operations (30 ticks).

1. *Drug acquisition (monthly, every 30 ticks):* On the acquisition day, each trafficker evaluates the DTO's current drug stock. Because the available stock is below the level required to sustain uninterrupted retail activity (approximately 3 kg, with half typically allocated to packagers and half to retailers), traffickers decide to attempt drug acquisition. The probability of successful acquisition depends on several factors, including current stock levels, market favorability, wholesale prices, and the trafficker's individual expertise.

   In this tick, 14 out of 15 traffickers successfully acquire drugs, generating a substantial inflow of approximately 10.5 kg into the organization. The current wholesale market price of drugs is about €35 per gram, which is considerably lower than the average wholesale price observed across the simulation. This favorable price, together with the low stock level, explains why most traffickers decide to proceed with acquisition during this tick. Overall, the DTO spends more than €383000 to replenish its drug stock. Most of the newly acquired drugs are initially held by traffickers before being redistributed downstream. By the end of the acquisition phase, the organization's overall stock position increases markedly.
2. *Drug processing and packaging (daily, every tick):* Once drugs are acquired, traffickers allocate portions of their stock to packagers for processing. On each day, traffickers identify which packagers are available based on their daily processing capacity and compute a weighted score for each, combining trust (derived from past collaboration and organizational visibility) and appeal (based on criminal expertise and internal network proximity). The relative weights assigned to trust and appeal depend on the DTO's efficiency/security profile. Each trafficker then selects a single

packager with the highest trust-appeal score.

In this example, the DTO is efficiency-oriented, and appeal therefore receives greater weight. The selected packager receives approximately 35 g of drugs, collaboration records are updated, and the packager's expertise increases accordingly. Drug stock levels are updated at each step.

Within the same tick, packagers distribute the processed drugs to retailers, following the same trust- and appeal-based selection process. Each packager delivers drugs to a single retailer with the highest trust-appeal score, and each delivery consists of approximately 6 g.

3. *Drug sales (daily, every tick):* Retail sales take place continuously throughout the day. Each retailer determines how many doses they can sell, subject to two constraints: their available stock and the €500 daily profit cap. Retailers with larger inventories sell first, distributing doses to end users one by one. Each sale reduces both the retailer's inventory and the warehouse supply, while generating revenue for the retailer. Once a retailer reaches the €500 cap, they stop selling for the remainder of the day.

   During this tick, retailers collectively sell almost 1400 doses. This represents a less profitable day relative to the organization's average of approximately 1900 doses sold per day. Nonetheless, retail activity still generates substantial revenues. Specifically, the organization earns about €28000 from drug sales during this tick, net of retailer remuneration. This corresponds to 18% of the value of each dose sold and translates into roughly €230 earned per retailer during this tick.
4. *Internal finances (weekly, every 7 ticks):* This tick coincides with a weekly accounting update. Wages for traffickers and packagers are calculated based on weekly profits and organizational rules, subject to minimum and maximum thresholds. During this tick, traffickers receive wages of approximately €520 each, while packagers receive around €280 each. Retailers retain their share of sales revenues and therefore do not receive weekly wage payments.

   In addition to wages, the DTO incurs substantial operational expenses related to procurement and logistics, amounting to nearly €10000 for the week. Moreover, the leadership of the DTO deducts a substantial weekly amount from the organization's cash reserves as personal remuneration. In this week, this amount corresponds to approximately €57000. Overall, total weekly expenses reach about €153000. As a result, despite ongoing retail revenues, the DTO's cash reserves decline sharply during this tick due to the scale of operational expenditures.
5. *Minor law enforcement interventions (monthly, every 30 ticks):* At the end of the tick, the DTO is subject to a routine law enforcement intervention. Given its strategic profile as an efficiency-oriented DTO, the probability of arrest is relatively high, and a minor arrest indeed occurs. One high-level member of the organization—a trafficker—is arrested and removed from the DTO. Any drugs held by the arrested individual are seized, resulting in a reduction of total stock of approximately 0.65 kg. No additional members are affected, and the core organizational structure remains intact. While the immediate operational impact is limited, this event contributes to cumulative enforcement pressure over time.

By repeating these steps at their respective intervals—drug acquisition every 30 ticks, processing and retail every tick, wages every 7 ticks, and minor interventions every 30 ticks—MADTOR accumulates dynamic interactions across acquisition, processing, sales, remuneration, and enforcement.

A.3. Summary of MADTOR assumptions, agents, and processes

MADTOR core assumptions	- Focus on cocaine trafficking - Focus on trafficking and retail phases (excludes production and international smuggling) - Trafficking represented through four simplified stages: acquisition, processing/packaging, retail, and internal finances - DTOs adopt different strategic profiles along the efficiency–security trade-off, which shape decision rules and interaction patterns - DTOs are subject to minor and major law enforcement interventions
DTO strategic profiles	- Strategic profiles (secure–intermediate–efficient) shapes multiple pre-intervention organizational dimensions: o Drug handling volumes o Recruitment and internal structure o Member remuneration o Exposure to law enforcement
Definition of active and disrupted DTOs	- *Active DTO*: organization able to conduct drug trafficking and dealing, with functioning acquisition, processing/packaging, retail activities, and sufficient financial liquidity to cover operating costs - *Disrupted DTO*: organization no longer able to sustain drug trafficking and dealing activities. Disruption occurs when: o *Economic inefficiency*: organizational liquidity falls to zero or below, preventing continued operations; or o *Law enforcement impact*: arrests lead to critical shortages of drugs or workforce.
Member attributes	- *Task*: trafficker, packager, or retailer - *Drug stock*: quantity of drugs held by each member at each tick - *Criminal expertise*: individual criminal ability (range 0–1), increases with successful exchanges - *Collaboration record*: number of past exchanges between pairs of members - *Organizational visibility*: elative activity level, measured as distance from the most central actor; updated after each exchange - *Internal Proximity*: closeness centrality within the organization; updated after each exchange - *Availability*: whether packagers/retailers can receive drugs, based on daily workload (binary); updated each tick
MADTOR stages and decision rules	
Drug acquisition	- Models the decision-making process underlying DTO drug acquisitions - Occurs monthly (every 30 ticks) - *Procedure:* o Check existing drug stock o If stock < two months of average activity → attempt acquisition o Acquisition success depends on: ■ Current drug stock ■ Market favorability (influenced by DTO efficiency/security profile) ■ Wholesale price favorability ■ Trafficker criminal expertise o If acquisition succeeds: ■ Drug stock is updated ■ Trafficker criminal expertise increases

(*continued on next page*)

(*continued*)

Drug processing and packaging	- Connects acquisition and retail phases through drug transfers - Occurs daily (1 tick) - *Procedure:* o Two weighted criteria (based on DTO efficiency/security profile) are evaluated to select exchange partners: ■ *Trust*: prior collaboration and organizational visibility (favored by secure DTOs) ■ *Appeal*: criminal expertise and internal proximity (favored by efficient DTOs) o Drugs are transferred from traffickers to packagers and from packagers to retailers o Drug stocks are updated after each exchange
Drug sales	- Models retail drug sales to end users - Occurs daily (1 tick) - *Procedure:* o Compute expected number of doses to be sold that day o Check retailer availability (daily profit < €500) o Retailers with larger drug stocks sell first; all available retailers can sell each day o Drug stocks are updated after each sale o Retailers reaching the €500 daily profit cap become unavailable for the remainder of the day
Internal finances	- Tracks wages, expenditures, and profits - Occurs weekly (every 7 ticks) - *Procedure:* o Identify four expense categories: ■ Wages for traffickers and packagers ■ Payments to families of arrested retailers ■ Payments to families of members arrested for homicide ■ Payments to families of deceased members o Compute weekly DTO profit o Deduct expenses and profits from the DTO cash balance
Law enforcement interventions	
Minor interventions	- Represent routine, low-intensity law enforcement activity - Occur monthly (every 30 ticks), starting from day 15 - *Procedure:* o Arrest probability depends on DTO strategic profile: ■ Secure DTOs: 10% ■ Intermediate DTOs: 50% ■ Efficient DTOs: 90% o Determine whether an arrest occurs based on these probabilities o If an arrest occurs: ■ The arrested member is removed ■ Drugs held by the member are seized and removed from the system
Major interventions	- Represent large-scale law enforcement crackdowns - Two intervention scenarios are implemented - *Procedure:* o Identify intervention target (all, traffickers, packagers, or retailers) o Determine the percentage of members to be arrested o *Scenario 1:* ■ Single major intervention ■ Arrests occur after two simulated years ■ Arrested members are removed and their drugs seized ■ Remaining drug stocks are updated o *Scenario 2:* ■ Up to five major interventions per DTO (minimum one) ■ Interventions may occur every six months starting from month 15 ■ At simulation start, each DTO is assigned the number and timing of major interventions ■ For each intervention, the arrest share depends on the DTO efficiency/security profile ■ Arrested members are removed and their drugs seized ■ Remaining drug stocks are updated

Appendix B. Supplementary descriptive analyses

This appendix reports additional results that complement the analysis presented in the main text, including details on intervention targeting and the empirical plausibility of the baseline scenario.

Fig. 15 compares the yearly number of active DTOs in MADTOR with equivalent trajectories derived from ISTAT and Eurostat statistics. For the latter two, the lines are calculated by applying their respective annual business closure rates to an initial population of 1000 enterprises. This comparison illustrates how the baseline dynamics produced by MADTOR align with empirically observed closure patterns in legal markets.

Survival rates	Setup	Year 1	Year 2	Year 3	Year 4	Year 5
Secure DTOs	1000	997	794	617	550	478
Intermediate DTOs	1000	986	891	817	781	747
Efficient DTOs	1000	979	937	894	881	870
Istat	1000	935	874	817	764	715
Eurostat	1000	913	834	761	695	634

Closure rates	Average	Year 1	Year 2	Year 3	Year 4	Year 5
Secure DTOs	0.134	0.003	0.204	0.223	0.109	0.131
Intermediate DTOs	0.056	0.014	0.096	0.083	0.044	0.044
Efficient DTOs	0.027	0.021	0.043	0.046	0.015	0.012
All DTOs	0.072	0.013	0.114	0.117	0.056	0.062
Istat	0.065	NA	NA	NA	NA	NA
Eurostat	0.087	NA	NA	NA	NA	NA

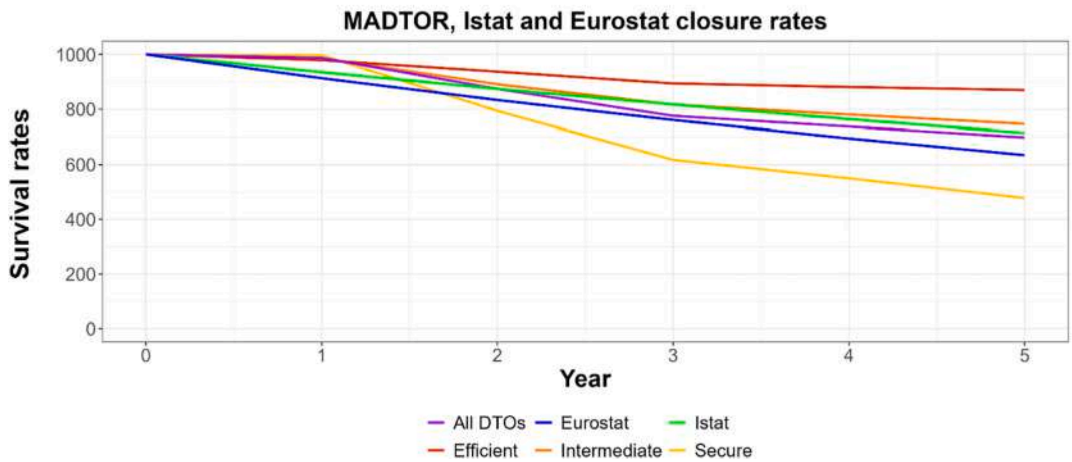


Fig. 15. Comparison of simulated DTOs' survival rates with business survival rates in Italy and the EU.
Note: The Italian and EU business survival rates are calculated based on the yearly closure rates reported in official statistics.

Fig. 16 displays the probability of DTOs being targeted during each intervention slot, calculated as a proportion between the expected major law enforcement intervention and the total organizations simulated per each efficiency/security profile.

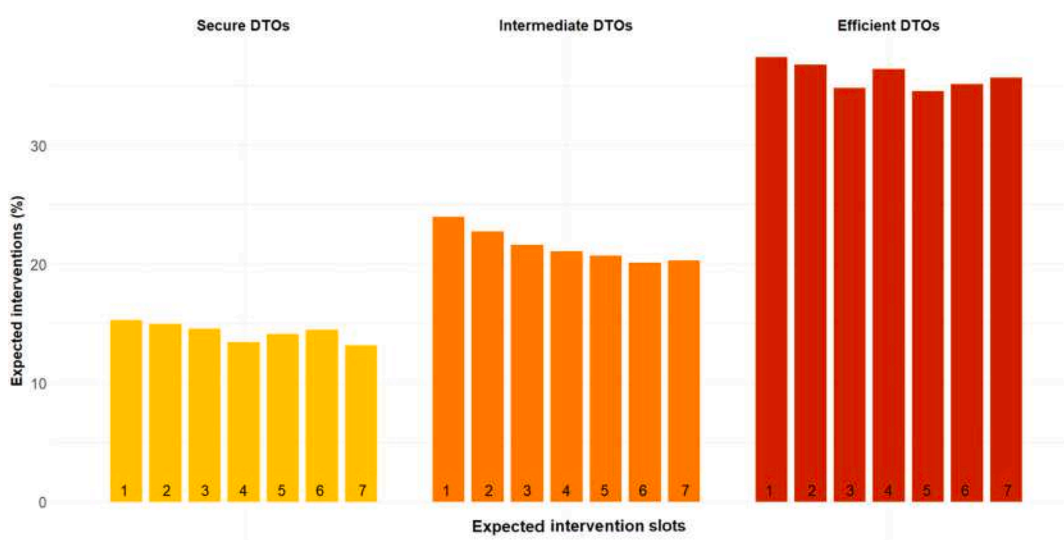


Fig. 16. Probability of expected major law enforcement intervention per efficiency/security profile in Scenario 2.
Note: The data in this figure aggregate all arrest intensities (i.e., 10%, 20%, 40%, and 60% of members arrested), as the timing of intervention is not influenced by its intensity. This aggregation also increases the robustness of the statistics by incorporating a larger number of simulations.

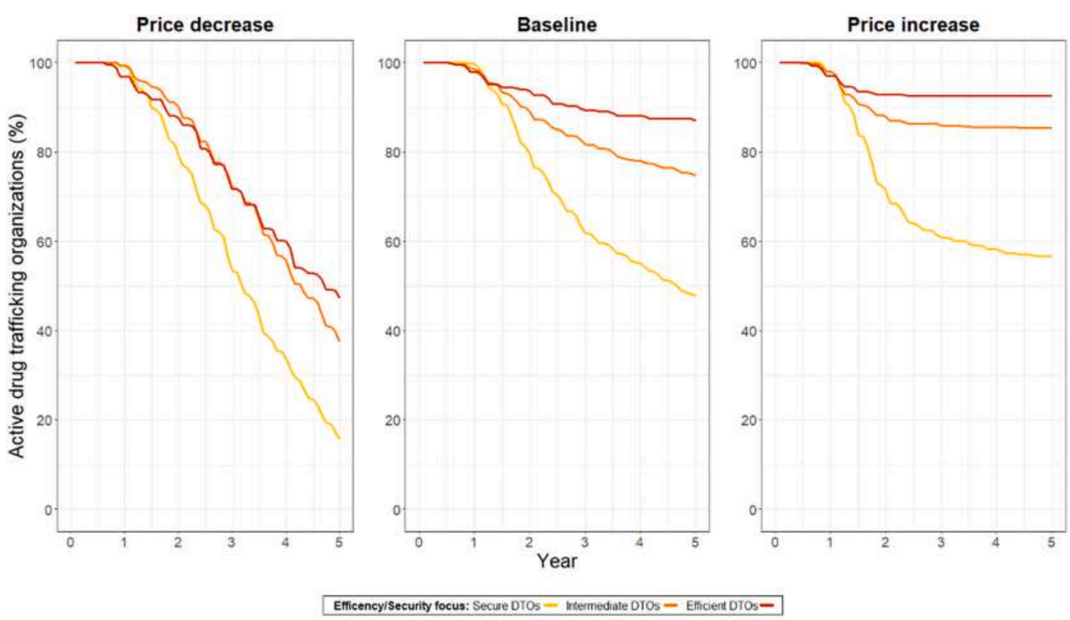
Appendix C. Sensitivity tests

In previous work using MADTOR (*BLINDED FOR REVIEW*), we conducted several sensitivity analyses to assess the robustness of the model and its findings, altering parameters not directly grounded in empirical data—specifically, the distribution of criminal expertise, the inclusion of minor law enforcement interventions, and fluctuations in wholesale cocaine prices. To keep computational time manageable, these tests were run across a broad range of arrest intensities (0%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90% of members arrested) but limited to intermediate DTOs. Across all tests, the Baseline Scenario consistently showed the highest survival rates, with survival declining as arrest intensity increased. Trends in organization size and revenue remained largely stable, supporting the reliability of the model's core dynamics.

Results confirmed that randomizing criminal expertise levels had minimal impact, indicating this variable's effects are mediated by broader structural factors. Removing minor law enforcement interventions modestly improved survival, especially under low-arrest intensities, suggesting a cumulative attrition effect. Changes in wholesale cocaine prices produced the most relevant, although expected, results: a 10% increase improved survival through higher margins, while a 10% decrease compressed profits and significantly reduced DTO viability. Overall, the model proved robust across plausible variations, consistently with the literature (Caulkins & Reuter, 2010; *BLINDED FOR REVIEW*).

In this study, given our focus on the efficiency/security trade-off, we introduced additional ad hoc sensitivity tests. The first builds on the sensitivity tests previously conducted that demonstrated to have the greatest impact on the model outcomes: wholesale price variations.

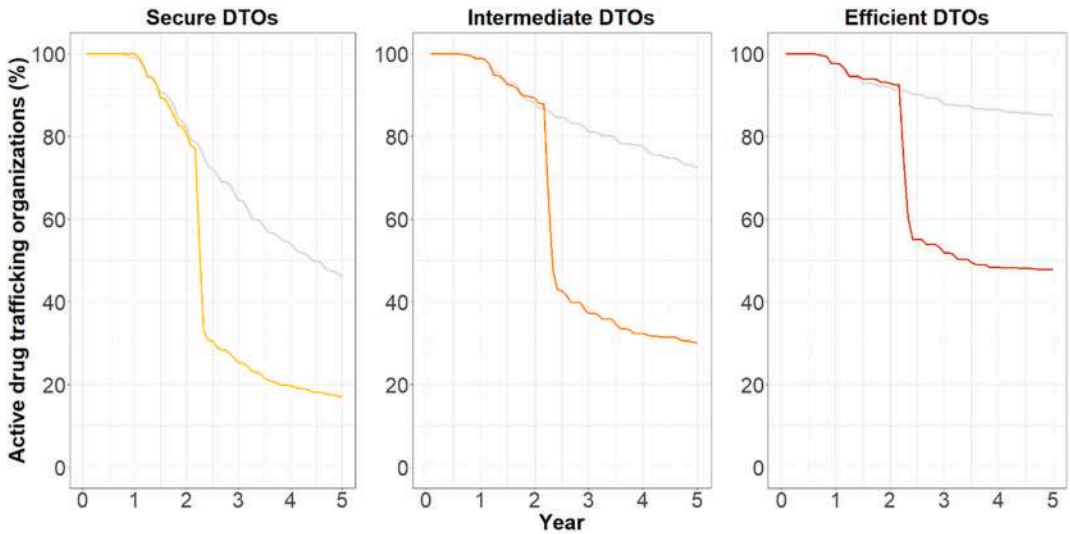
Building on previous findings that identified price fluctuations as especially impactful, we simulated ±10% changes in wholesale drug prices within the Baseline Scenario (0% arrests) to examine how these shifts affect DTOs with different trade-off profiles. Results showed that both secure and efficient DTOs respond similarly in direction: price decreases reduce survival, while increases enhance it. However, two important differences emerged. First, price drops have a much stronger negative effect than price increases have a positive one—e.g., survival drops by over 20 percentage points for secure DTOs and nearly 15 for efficient ones, while gains from price increases remain under 20% and 5%, respectively. Second, secure DTOs are more sensitive to price changes overall, indicating less market stability. Even minor shocks can substantially undermine their survival prospects. These findings align with both organizational and criminological literature on resilience, which emphasize that the impact of adverse events—whether market-related or linked to law enforcement—is often nonlinear and disproportionately affects more vulnerable actors. The greater economic fragility of secure DTOs, characterized by limited flexibility and narrower margins, makes them less capable of absorbing profit losses from price shocks. In contrast, efficient DTOs perform more robustly in stable, non-threatening environments due to their stronger margins (Fig. 17).



Price variation	Secure DTOs	Intermediate DTOs	Efficient DTOs
Decrease	-67.15%	-49.67%	-45.63%
Increase	18.41%	14.19%	6.32%

Fig. 17. Sensitivity Test 1: Impact of price variation on survival rates and percentage changes relative to baseline models.

In a second sensitivity test we introduced an Intermediate Scenario between Scenarios 1 and 2, applied to the 10% arrest condition across secure, intermediate, and efficient DTOs. This test incorporated only the variation in intervention intensity that distinguishes the two scenarios. Specifically, secure DTOs experienced arrest rates 10–20% below the nominal target, intermediates varied ±5%, and efficient DTOs faced arrest rates 10–20% above the nominal target. As expected, survival rates slightly improved for secure DTOs due to less intensive targeting, while efficient DTOs showed a modest decline in survival under increased enforcement pressure (Fig. 18).



10% members arrested	Scenario 1	Sensitivity test 2	% differences
Secure DTOs	13.7%	17.1%	+24.8%
Intermediate DTOs	31.9%	30.1%	-5.6%
Efficient DTOs	49.1%	47.9%	-2.4%

Fig. 18. Sensitivity Test 2: Survival rate and percentage changes relative to Scenario 1 (20% of members arrested).

As a third sensitivity test, we modified Scenario 2 to more closely align with the intervention timing of Scenario 1, focusing on the 10% arrest intensity and applying these changes uniformly across all efficiency/security profiles. Specifically, we fixed a single law enforcement intervention and scheduled it in either the second (month 21) or third (month 27) timeslot—both close to the disruption timing in Scenario 1 (end of year two). We compared these simulations with those from Sensitivity test 2, which maintained Scenario 2's differentiated arrest intensities. As expected, survival rates in Sensitivity test 2 fell between those of the two Sensitivity test 3 variations: earlier interventions (timeslot 2) modestly reduced survival across all DTO profiles, while later interventions (timeslot 3) slightly improved survival—but only for efficient DTOs. For intermediate and secure DTOs, survival rates remained largely stable, echoing the results of Sensitivity test 2. These findings confirm that intervention timing has a measurable effect, especially for efficient DTOs, but offers limited benefit for more fragile organizations when intervention intensity is low (Fig. 19).

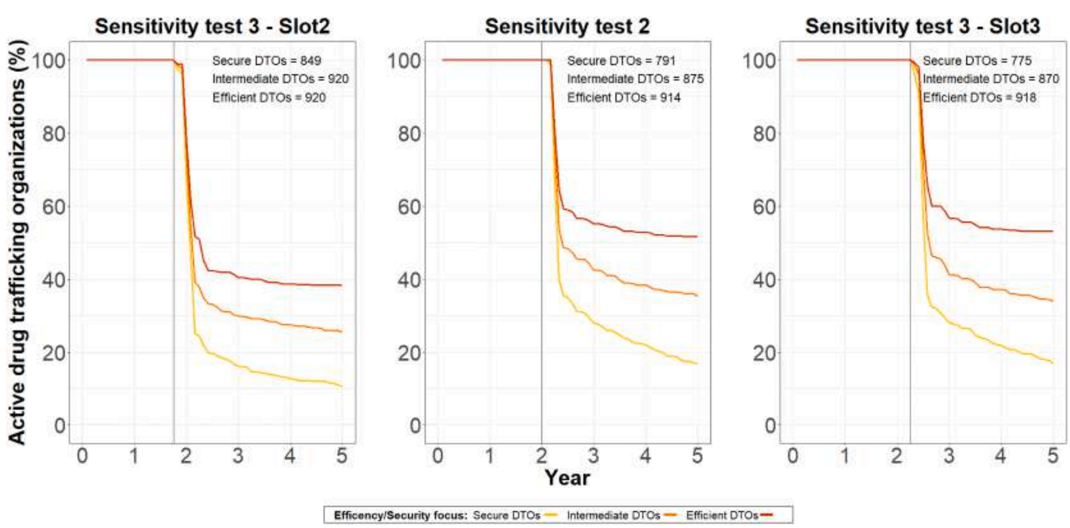


Fig. 19. Sensitivity Test 3: Survival rate comparison between Tests 2 and 3, timeslots 2–3 (10% of members arrested)

Appendix D. Results

Table 6
Summary results for Scenario 1 and Scenario 2.

Scenario	Arrest intensity	Secure	Intermediate	Efficient
Panel A. Active DTOs (%)				
Baseline	0%	48.4	77.4	84.6
Scenario 1	10%	16.5	31.9	49.9
	20%	15.2	26.3	36.0
	40%	14.9	20.2	19.2
	60%	12.4	15.7	10.4
Scenario 2	10%	21.3	28.0	26.2
	20%	18.4	24.2	11.3
	40%	17.3	15.8	10.3
	60%	13.0	10.3	2.6
Panel B. Average members				
Baseline	0%	71.8	68.4	74.0
Scenario 1	10%	70.3	67.0	71.3
	20%	69.7	66.5	70.0
	40%	68.9	66.2	67.5
	60%	67.3	63.3	62.1
Scenario 2	10%	69.2	65.8	67.2
	20%	67.5	64.6	65.8
	40%	63.7	60.4	55.3
	60%	57.5	52.8	43.1
Panel C. Average revenues (k€)				
Baseline	0%	38.2	39.8	43.0
Scenario 1	10%	37.9	39.8	43.2
	20%	38.4	39.9	43.1
	40%	38.6	39.6	43.0
	60%	38.5	40.0	42.9
Scenario 2	10%	38.1	39.6	43.1
	20%	38.4	39.6	42.8
	40%	38.0	40.1	43.1
	60%	37.3	38.9	42.2

D.1. Full results for Scenario 1: one identical intervention

Figs. 20 and 21 present the main outcomes of Scenario 1, showing the number of active members and organizational revenues across the five simulated years, for arrest scenarios targeting 10%, 40%, and 60% of members.

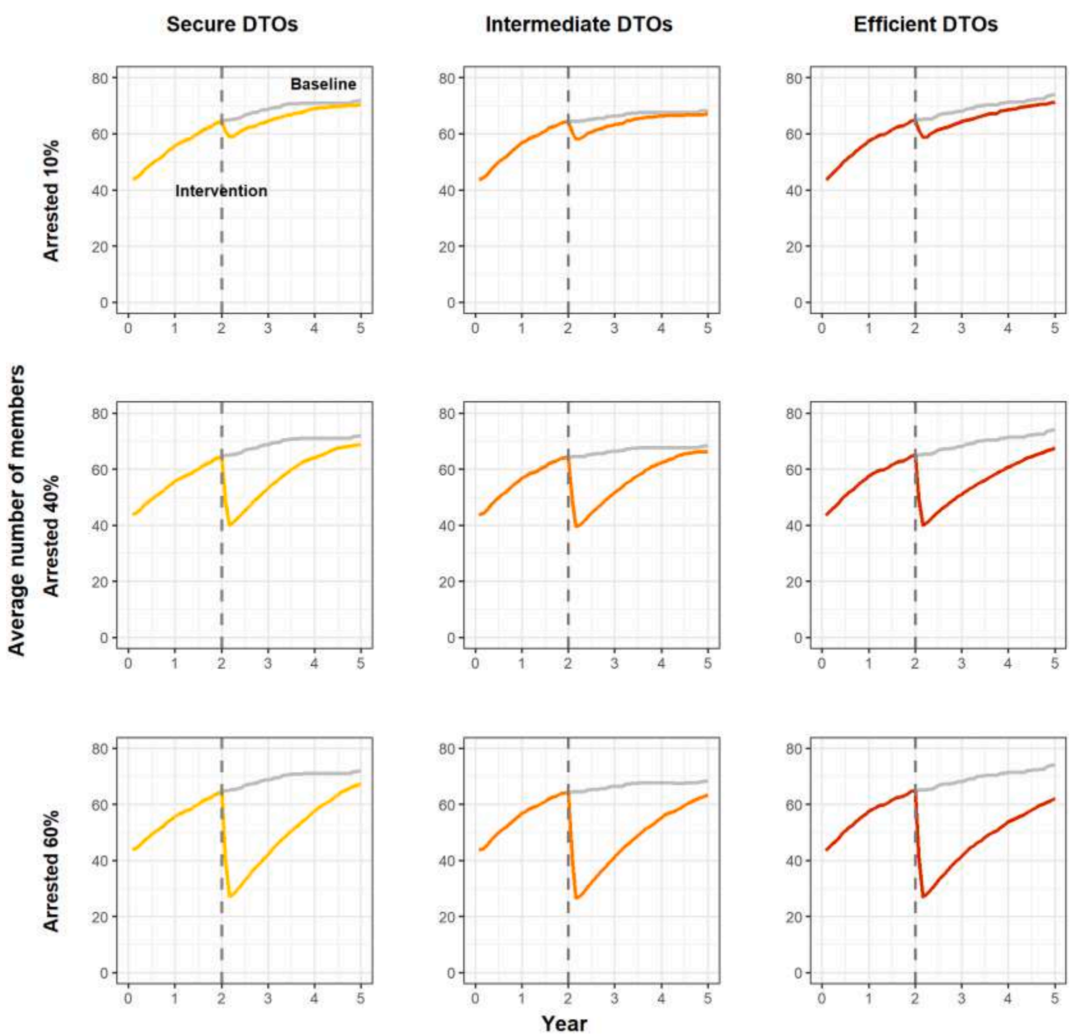


Fig. 20. Scenario1: number of members (10, 40, and 60% of members arrested).

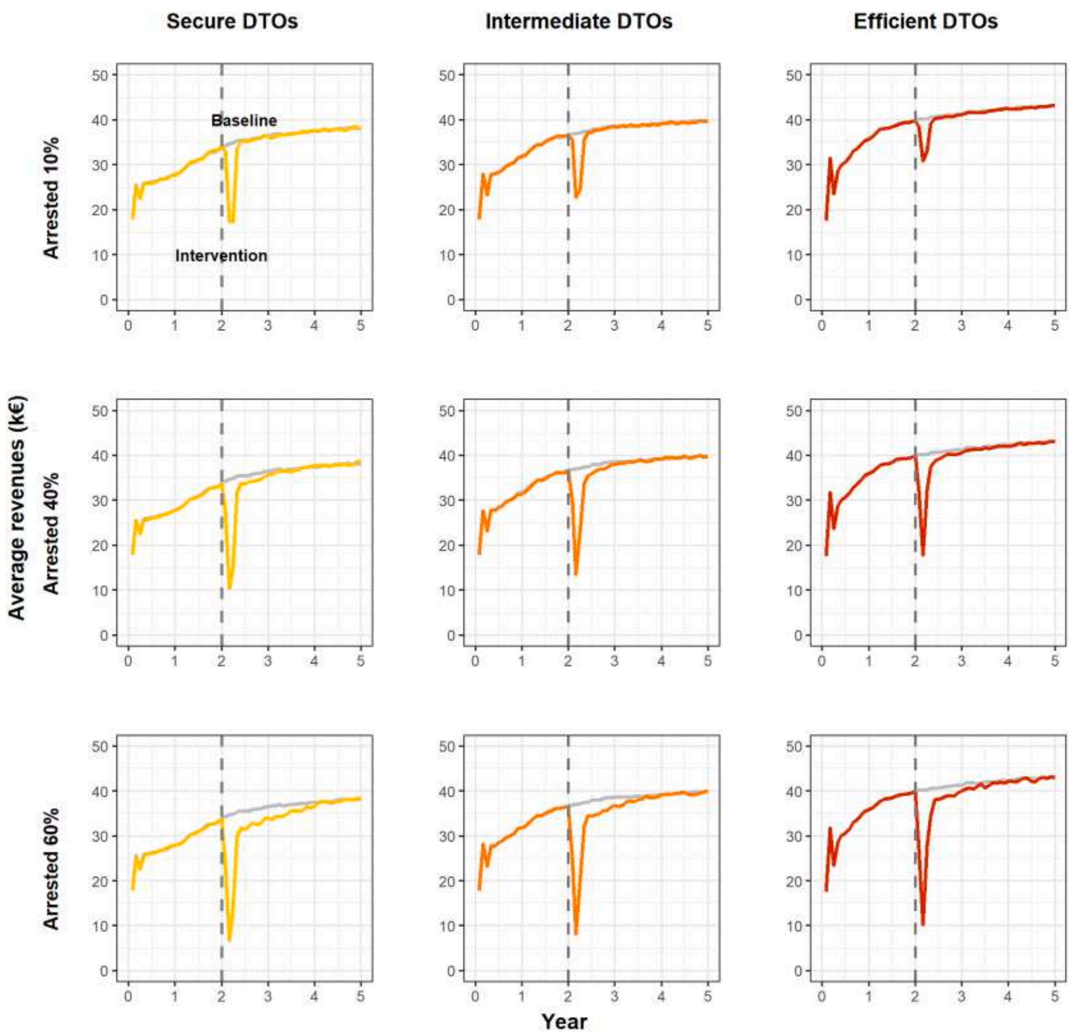
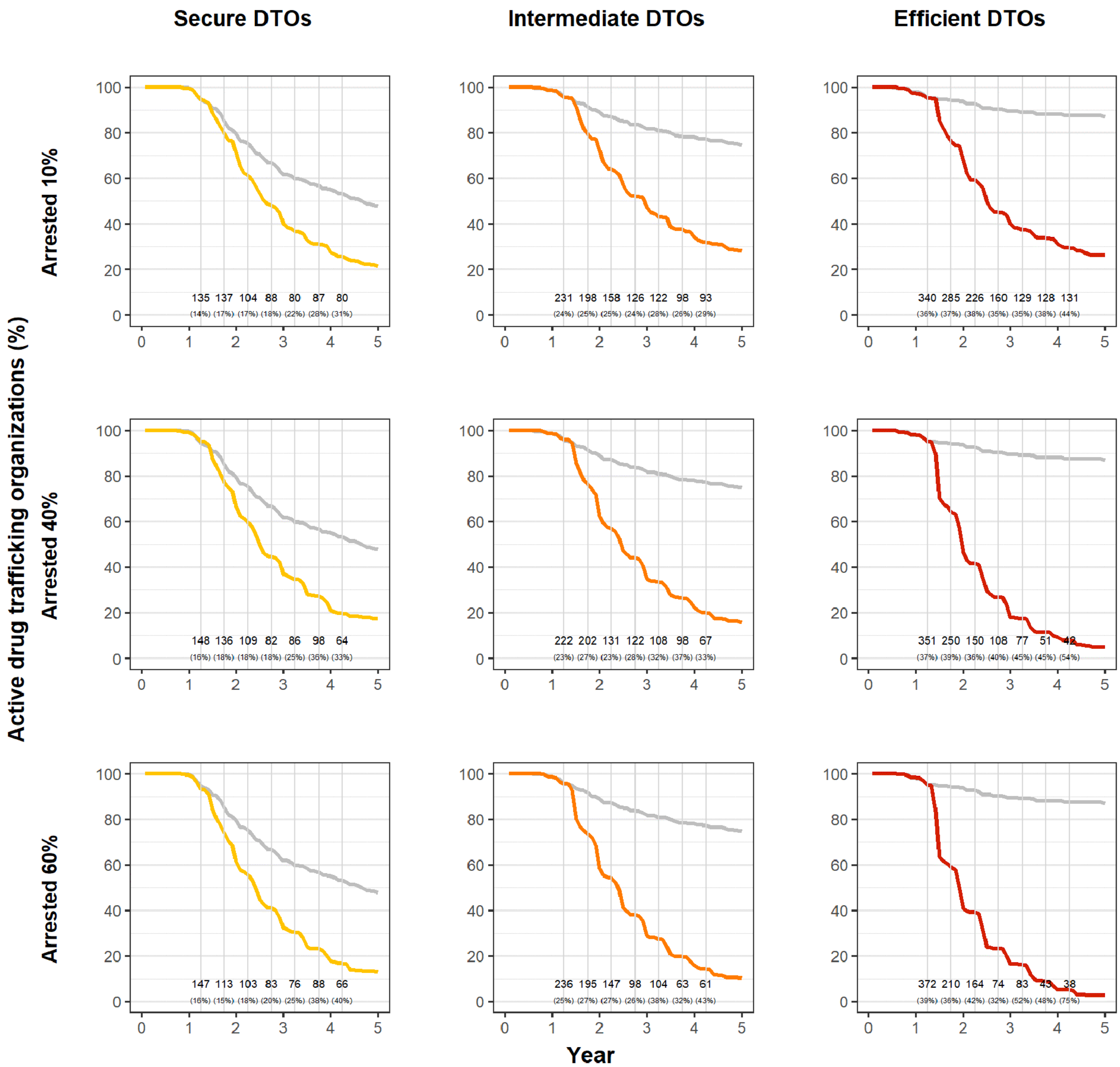


Fig. 21. Scenario 1: average revenues (10, 40, and 60% of members arrested)

D.2. Full results for Scenario 2: multiple, differential interventions

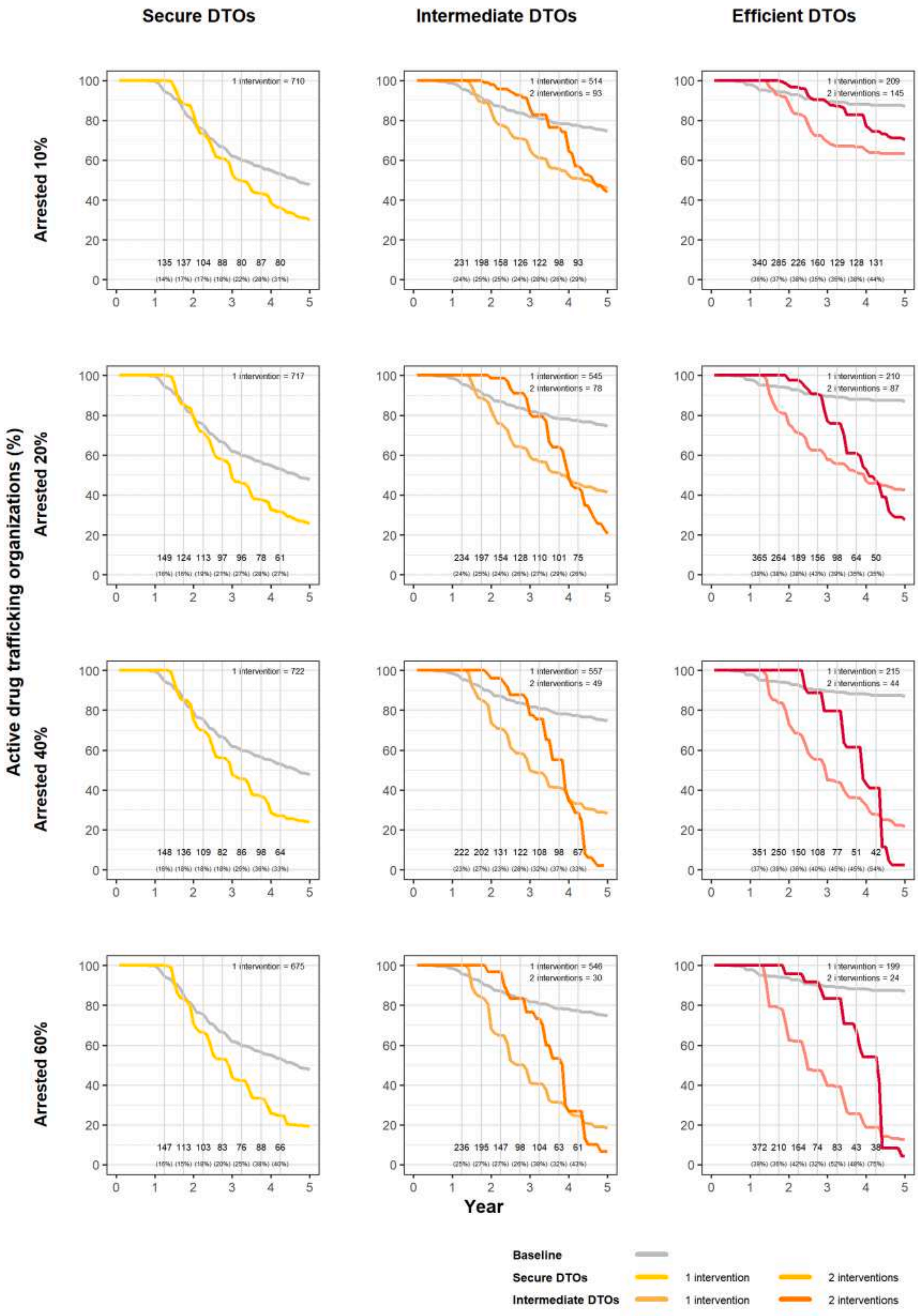
Figs. 22 and 23 illustrate the survival rates of secure, intermediate, and efficient DTOs under the second law enforcement intervention scenario. Fig. 22 displays the trends for all simulated organizations, while Fig. 23 focuses exclusively on organizations that were subjected to the full sequence of planned interventions as defined in the simulation setup. Consequently, organizations that ceased operations before any intervention, or after experiencing only a portion of the scheduled interventions, are excluded from Fig. 23.

Figs. 24 and 25 present trends in the number of members and average revenues of DTOs under Scenario 2, distinguishing results by the number of interventions experienced.



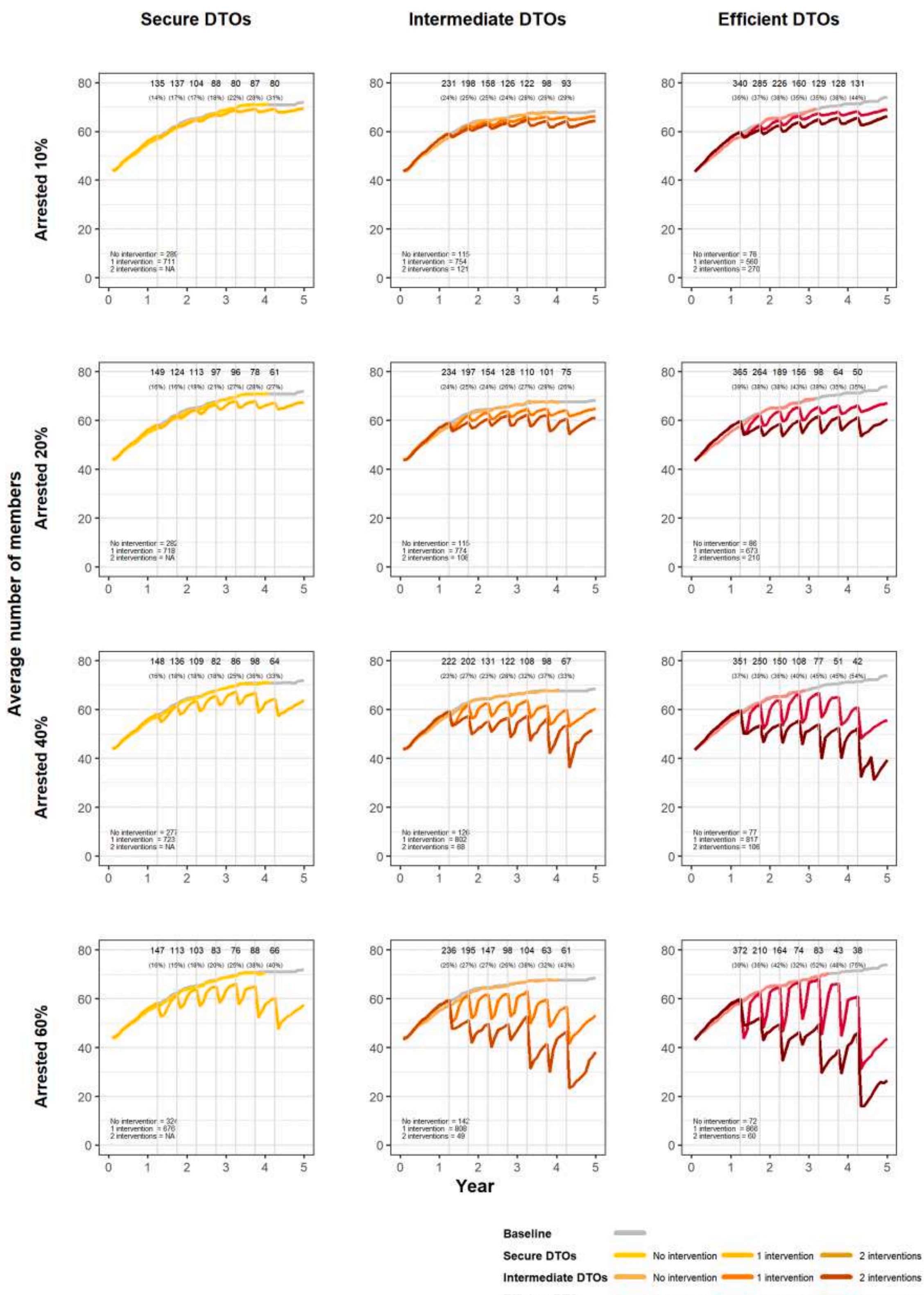
Note: The grey vertical lines indicate the intervention time slots when DTOs may experience disruptions. The numbers at the bottom of each line are the total interventions faced by each efficiency/security profile. Percentages in parentheses denote the proportion of active DTOs experiencing an intervention at that time.

Fig. 22. Scenario 2: DTOs' survival rate (10, 40, and 60% of members arrested).



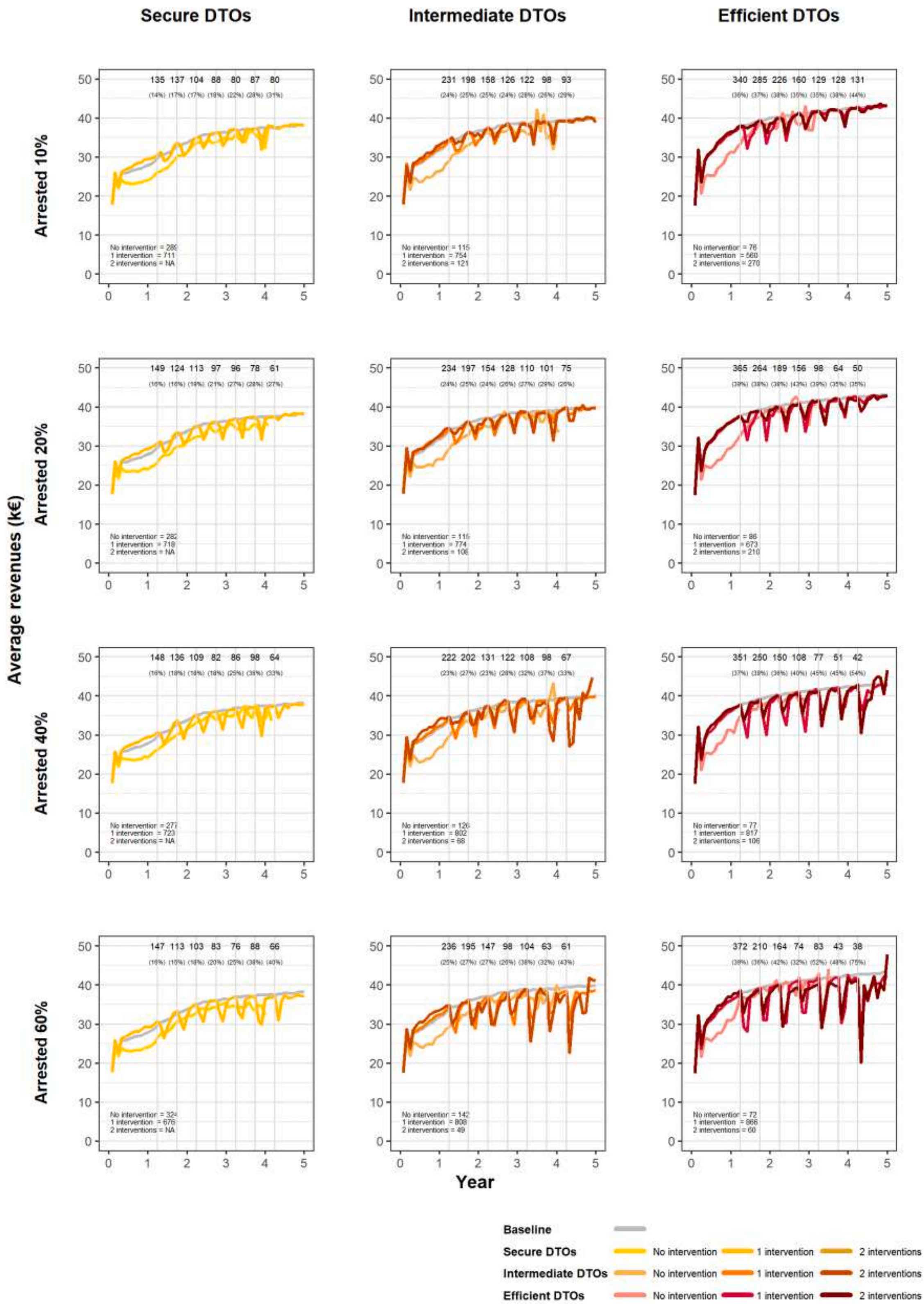
Note: The grey vertical lines indicate the intervention time slots when DTOs may experience disruptions. The numbers at the bottom of each line are the total interventions faced by each efficiency/security profile.Percentages in parentheses denote the proportion of active DTOs experiencing an intervention at that time. Only DTOs targeted by the full set of expected interventions are plotted. DTOs targeted by more than two interventions have been omitted due to low numerosity.

Fig. 23. Scenario 2: survival rate of DTOs targeted by all expected interventions (10, 40, and 60% of members arrested).



Note: The grey vertical lines indicate the intervention time slots during which DTOs may experience disruptions. The numbers at the top of each line represent the total number of interventions faced by each efficiency/security profile. Percentages in parentheses denote the proportion of active DTOs experiencing an intervention at that time. DTOs targeted by more than two interventions have been omitted due to their low numerosity.

Fig. 24. Scenario 2: number of members (10, 20, 40, and 60% of members arrested).



Note: The grey vertical lines indicate the intervention time slots during which DTOs may experience disruptions. The numbers at the top of each line represent the total number of interventions faced by each efficiency/security profile. Percentages in parentheses denote the proportion of active DTOs experiencing an intervention at that time. DTOs targeted by more than two interventions have been omitted due to their low numerosity.

Fig. 25. Scenario 2: average revenues (10, 20, 40, and 60% of members arrested).

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