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THE RESILIENCE OF CRIMINAL NETWORKS: AN AGENT-BASED SIMULATION ASSESSING DRUG TRAFFICKING ORGANIZATIONS REACTIONS TO LAW ENFORCEMENT ATTEMPTS AT DISRUPTION

Ph.D. thesis

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Al mio papà,

Il tuo coraggio, la tua forza e la tua tenacia sono fonte di immensa ispirazione.

Questo traguardo è anche tuo.

Abstract

Criminal organizations operate in complex changing environments. Being flexible and dynamic allows criminal networks not only to exploit new illicit opportunities but also to react to law enforcement attempts at disruption, enhancing the persistence of these networks over time. Most studies investigating network disruption have examined organizational structures before and after the arrests of some actors but have disregarded groups' adaptation strategies.

The present study investigated the resilience of drug trafficking organizations (DTOs) to law enforcement attempts at disruption, focusing on three main aspects: the ability to endure disruption, react quickly and efficiently to threats, and keep primary functions unaltered. The analysis relied on an agent-based model (ABM) that simulates drug trafficking and dealing activities by organized criminal groups and their reactions to law enforcement attempts at disruption. The simulation relied on information retrieved from a detailed court order against a large-scale Italian DTO and from the literature.

The results showed that the higher the proportion of members arrested, the greater the challenges for DTOs, with higher rates of disrupted organizations and long-term consequences for surviving DTOs. Second, targeting members performing specific tasks had different impacts on DTO resilience: targeting traffickers resulted in the highest rates of DTO disruption, while targeting actors in charge of more redundant tasks (e.g., retailers) had smaller but significant impacts. Third, the model examined the resistance and resilience of DTOs adopting different strategies in the security/efficiency trade-off. Efficient DTOs were more resilient, outperforming secure DTOs in terms of reactions to a single, equal attempt at disruption. Conversely, secure DTOs were more resistant, displaying higher survival rates than efficient DTOs when considering the differentiated frequency and effectiveness of law enforcement interventions on DTOs having different focuses in the security/efficiency trade-off. For surviving DTOs, drug trafficking and dealing performances were only slightly impacted by attempts at disruption, but the relational strategies implemented in response to the threatening events differed between secure and efficient DTOs: while secure DTOs decreased the direct connectivity among their members to minimize their visibility, efficient DTO members increased their direct connections to recoup prior losses. Overall, this research demonstrated that law enforcement interventions are often critical events for DTOs, with high rates of both first intention (i.e., DTOs directly disrupted by the intervention) and second intention (i.e., DTOs terminating their activities due to the unsustainability of the intervention's short-term consequences) culminating in dismantlement. However, surviving DTOs always displayed a high level of resilience, with effective strategies in place to react to threatening events and to continue drug trafficking and dealing.

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Introduction

Criminal organizations are entities pursuing illegal aims that are in constant struggle with law enforcement as it attempts to put an end to their activities (Bouchard 2007; Ayling 2009; Spapens 2011). Criminal network resilience refers to criminal organizations' ability to endure disruption, react quickly and efficiently to threats, and maintain primary functions unaltered (Bouchard 2007; Ayling 2009; Duxbury and Haynie 2019). Focusing on this concept allows explorations of how criminal networks operate in a hostile environment, especially in terms of *modus operandi*, adaptation strategies, strengths, and vulnerability when confronted with law enforcement interventions intended to jeopardize their criminal business and disrupt their organization.

Many aspects of criminal networks have been extensively researched over time; however, criminal network resilience is not one of them. It has only recently gained the attention of criminological scholars due to its impactful operational implications. Indeed, understanding the resistance and resilience of criminal organizations would allow researchers to foresee their responses and tactics in response to law enforcement interventions and possibly enable more accurate strategic planning of future law enforcement interventions.

The limited literature on the topic suffers from two main limitations. On the one hand, it often examines the structures of criminal organizations before and after simulating the arrests of some members, but it disregards the adaptation strategies of these groups. On the other hand, it tends to focus on the removal of actors with specific features and roles in the organization that are very difficult for law enforcement to identify in the preliminary phase of an investigation. The former approach leads to an incomplete image that lacks one of the most relevant strengths of criminal networks: their ability to evolve in response to changing circumstances. Due to its poor representativeness of reality, the latter prevents the possibility of relying on the knowledge developed to enhance future law enforcement interventions.

To compensate for the limitations identified in the literature, this study aims to investigate how drug trafficking organizations (DTOs) resist and react to massive law enforcement attempts at disruption. Specifically, the study sets two operational objectives and one theoretical objective. The operational objectives are to investigate the influence on DTO resilience of arresting different proportions of DTO members and of targeting DTO members performing different tasks in the organization. The theoretical objective is to explore the impact of law enforcement attempts at disruption on DTOs' resilience while considering organizations with different focuses in the efficiency vs. security trade-off.

To accomplish these objectives, an agent-based model (ABM) was developed. Relying on information from a court order against a large-scale Italian DTO and on the literature, the model simulated DTOs performing their drug trafficking and dealing with their daily routine. During the simulation, the DTOs had to confront different typologies of law enforcement interventions designed to disrupt them and their criminal activities. The results demonstrated that the simulated law enforcement interventions often caused substantial damage to the DTOs and led to high rates of disruption. At the same time, DTOs that survived disruption displayed significant levels of resilience and a limited impact on their criminal involvement.

To achieve its objectives, the work is structured as follows. Chapter 1 provides an overview of organized crime theoretical perspectives; it describes the main features of criminal organizations, with a particular focus on DTOs; and presents the concept of resilience, emphasizing the specificities of resilient criminal networks. Chapter 2 presents the motivations for the study, highlighting the knowledge gaps in the literature and revealing the research questions, objectives and hypotheses guiding the current study. Chapter 3 details the ABM that was built and the methods of analysis used in the research. Chapter 4 presents the main results. Chapter 5 discusses the results and presents the limitations of the study and related future challenges in this research domain. The last chapter concludes.

1. Background

This chapter reviews theoretical perspectives on criminal networks and organized crime (section 1.1), structural and operational strategies adopted by criminal networks (section 1.2), and DTO specificities (section 1.3). Next, in sections 1.4 and 1.5, it introduces the concept of resilience and its implications for criminal networks.

1.1. Theoretical perspectives on criminal networks and organized crime

Currently, organized crime is an accepted and central topic both in the political agendas of most countries, and in the scientific criminological discourse (Fijnaut and Paoli 2004; Paoli 2014a; Paoli and Vander Beken 2014). The term refers to groups of at least three persons committing one or various offenses during a period of time with the purpose of obtaining certain material gains (UNODC 2000, Article 2 (a)). Despite the relevance, the loose delineation of this concept has weakened efforts to develop theories and theoretical perspectives centered on organized crime, with the consequence that many imprecisely defined topics have been included under its broad umbrella (Kleemans 2014; Campana and Varese 2018).

1.1.1. Theoretical perspectives on co-offending behaviors

The lack of theoretical perspectives framing the concept of organized crime has partially been compensated by authors devoting their attention to co-offending behaviors, since both co-offending and organized crime deal with sets of individuals committing a criminal event together (Warr 2002; Felson 2009). The literature has identified four main theoretical perspectives that aim to explaining co-offending behaviors.

The first perspective has its foundation in Sutherland's differential association theory (1937), and it emphasizes the role of group influences on criminal behavior initiation. The commission of offenses together with criminal companions is the result of pressures and influences associated with group membership. Group members co-offend because they aspire to the social rewards associated with the act, and they are afraid of the disapproval of their companions in case of withdrawal (Warr 1996; 2002; Weerman 2003; Shaw and McKay 1931; Sarnecki 1990; 2001; M. L. Erickson and Jensen 1977; Haynie 2001).

According to the second, less popular, perspective (i.e., the social selection perspective), co-offending is the result of actors' individual features. Individuals sharing some characteristics (e.g., lack of self-control) select each other to spend time together, becoming friends, but possibly also companions in crime (Reiss and Farrington 1991; Weerman 2003). This perspective deviates from the general theory of crime in that, while emphasizing the role of low self-control in individual offending, it expresses skepticism about attributing the emergence of co-offending to individual features, and specifically to low self-control (Gottfredson and Hirschi 1990).

The third perspective is linked to rational choice theory (Clarke and Cornish 1986). Co-offending is seen as the result of a decision-making process. Individuals offend together with companions when, after weighting the expected costs and rewards, they realize that committing crime with associates would lead to higher profits, to the facilitated commission of crimes, or to the reduced likelihood of failure (Weerman 2003; Walsh 1986; Kroese and Staring 1993; Tremblay 1993; McCarthy, Hagan, and Cohen 1998).

Finally, a fourth perspective considers co-offending to be a social exchange among criminal actors (i.e., the social exchange theory of co-offending). Individuals will offend together when each of them would acquire enough social rewards from the commission of the crime. Here, social rewards comprehend both material compensation and immaterial rewards, such as the fulfilment of human desires and needs (e.g., appreciation from others or acquisition of skills or information) (Weerman 2003).

These perspectives contribute to explaining the factors that bring individuals together to commit offenses, offering some motivations for criminal groups' persistence over time despite the constraints of illegality. Nevertheless, these theoretical perspectives often refer exclusively to delinquency, that is, deviant and criminal behaviors among youths. Delinquency differs in many features from organized crime: it involves only youths, peaking in adolescence and then showing progressive rates of spontaneous desistance as they age toward first adulthood; it often involves small groups (i.e., two or three individuals) merging in shifting partnerships; and it is generally related to noncomplex criminal activities (Warr 2002; Weerman 2003). In contrast, in organized crime, the late onset and protraction of criminal behaviors in adulthood is common, groups of co-offenders are often larger and have a certain degree of stability, and the crimes committed are generally characterized by high levels of seriousness and complexity (Kleemans and van Koppen 2020).

1.1.2. Defining organized crime

Over time, many partially different organized crime definitions have proliferated. These definitions have shifted between those defining organized crime as organizations that are illegal or that have members who engage systematically in crime (focusing on the “who”), and those defining organized crime as complex and serious criminal activities (focusing on the “what”) (Maltz 1976; Hagan 1983; 2006; Varese 2010; Paoli and Vander Beken 2014). Nevertheless, an accepted common definition of organized crime still does not exist (Hagan 2006; Finckenauer 2005; Paoli 2002; Kleemans and van Koppen 2020; UNODC 2002). Various definitions have been developed in different social and geopolitical contexts, and each of these may well explain a number of criminal organizational features but may also miss other relevant ones (Varese 2010).

To capture the different nuances of organized criminal groups, especially in the international context, the tendency is to rely on broad definitions that could include organizations that differ in size, structure, and scope. In this regard, the most relied-upon definition, and the one that this study will follow, is the one developed in 2000 in Palermo, during the United Nations Convention against Transnational Organized Crime. This definition states that organized criminal groups are a “*structured group of three or more persons existing for a period of time and acting in concert with the aim of committing one or more serious crimes or offences in order to obtain, directly or indirectly, a financial or other material benefit*” (UNODC 2000, Article 2 (a)). Criminal groups falling within this definition may range from a small group of juveniles planning and perpetrating a single robbery together, to a Mexican cartel trafficking drugs for years (Paoli 2002; Fijnaut and Paoli 2004; Reuter and Paoli 2020). The differences among these criminal groups have important consequences in terms of security threats to society, and possible law enforcement strategies to dismantle the groups (Finckenauer 2005; UNODC 2002; Le 2012).

1.1.3. Theoretical perspectives on the organization of organized crime

As organized crime has come to be accepted as a relevant topic with significant policy implications, some scholars have pursued the goal of developing some perspectives specifically focused on organized crime (Fijnaut and Paoli 2004; Kleemans 2014). As for organized crime definitions, over time, these theories have shifted between those focusing on the “who”, and those focusing on the “what” (Paoli and Vander Beken 2014; Hagan 2006).

The topic first gained public attention in the United States in the 1920s-1930s, when, due to the constraints of prohibition, illegal markets began to flourish. Organized crime referred to activities such as racketeering, illicit gambling, and trafficking of drugs and liquors. Figures in the legal sphere, such as politicians and corrupt officials, played a fundamental role in supporting these criminal activities, or at least facilitating them by turning a blind eye (Fijnaut and Paoli 2004; Paoli and Vander Beken 2014).

From the late 1940s, a shift in the concept occurred as the *alien conspiracy* approach emerged. According to this approach, the imagery of organized crime overlapped with foreign criminal groups, and in particular the Italian mafia (i.e., the Sicilian *La Cosa Nostra*), threatening the morality of the United States. Organized crime was supposed to be a large hierarchical organization that dominated the illegal markets and their profits. This imagery lacked scientific support, and it was mainly an instrument to promote federal involvement in the detection of gambling and drug offenses. However, in 1963 the testimony of Joe Valachi, a low-ranking member of the Italian-American *La Cosa Nostra,* provided support for and consolidated this view (Fijnaut and Paoli 2004; Kleemans 2014; Paoli and Vander Beken 2014).

From the 1960s, grounded in Valachi's testimony, the *bureaucracy model* gained public attention. According to this perspective, organized criminal groups were formal pyramidal organizations, with strict rules and internal division of tasks resembling the Weberian ideal type of a legal-rational bureaucracy. This model was scientifically systematized by Cressey (1969) in his famous book "*Theft of the nation*", where he depicted the Italian-American *La Cosa Nostra* as a large and hierarchical bureaucratic organization (Cressey 1969; Fijnaut and Paoli 2004; Kleemans 2014; Paoli and Vander Beken 2014). From the 1970s the bureaucracy model received strong criticism since it represented an exception rather than the ordinary semblance of organized crime groups, and it was finally rejected in the scientific debate (Kleemans 2014).

The emerging alternative theoretical perspective was the *illegal enterprise model*. This model, once again, emphasized the commission of criminal activities; it characterized organized crime as a set of enterprises involved in the provision of illegal goods and services. According to this view, organized criminal groups were profit-oriented entities responding to an existing demand for illicit products. However, although they were driven by the same goals as legal entrepreneurs, illegality placed enormous constraints on the performance of their activities. In this regard, Reuter (1983) in his book "*Disorganized crime*" concluded that a major difference between legal and illegal enterprises was their size; whereas legal enterprises could benefit from growing (i.e., exploiting the advantages of economies of scale), growth was unfeasible for illegal ones because it enormously augmented their visibility and consequently their risk of being detected by law enforcement (Fijnaut and Paoli 2004; Kleemans 2013; 2014; Bouchard and Morselli 2014).

Protection theory offered a further explanation of organized crime; it focused on the control of specific territories and/or economic activities as the main feature of organized crime. This perspective specifically addressed certain manifestations of organized crime, such as the mafia groups in Sicily in the 19th century described by Gambetta (1993) in his book "*The Sicilian Mafia*". In these contexts, due to the weakness of the state as service provider, organized crime supplanted legal authorities in their tasks. Organized crime acted as a provider of private protection, defending population property rights and economic transactions through the use of violence and taxation (Gambetta 1993; Kleemans 2014).

A more recent approach to the study of organized crime is based on Granovetter's (1985) *social embeddedness theory*. According to Granovetter, economic transactions always bring some risk related to noncompliance with established arrangements. Economic transactions integrated into a network of existing social relations strongly contribute to reducing this risk (Granovetter 1985). In criminal settings, where the secrecy of the conducted activities eliminates the possibility of enforcing contracts, relying on trusted relations plays a fundamental role, augmenting confidence in positive outcomes. Social relations facilitate cooperation among criminal actors, on the one hand because they allow them to engage in partnerships with some information about each other and on the other hand because potential future partnerships reduce the likelihood of cheating and betrayal (Kleemans and Van de Bunt 1999; Kleemans 2007; 2013; 2014; Van de Bunt, Siegel, and Zaitch 2014; Kleemans and van Koppen 2020). Moreover, relying on trusted social relations could favor the emergence of new opportunities since trusted relations may help provide new resources, information, or partners. In a hostile environment, being embedded in the social context also allows prompt reactions to eventual law enforcement interventions, providing flexibility and the possibility of replacing actors quickly (Kleemans 2014).

Among the abovementioned theoretical perspectives, social embeddedness theory provides an accurate picture of existing organized crime groups and their strategies to protract their criminal activities over time despite the constraints of illegality. The theory's emphasis on social relations enables the accommodation and interpretation of any organizational structure, from flexible networks to more hierarchical groups (Spapens 2010; Gravel and Tita 2017). Indeed, criminal networks are defined as entities constituted by sets of actors who have in common an interest in committing illegal activities (von Lampe and Johansen 2004). Thus, the establishment of criminal networks, and the recruitment of participating actors favor the formation of ties facilitating the perpetration of criminal acts and minimizing the apprehension risk (Weerman 2003; Spapens 2010). Among available criminal partners, criminal actors are likely to rely on their social relations to recruit new partners. This increases the security of their profit-making activities and their confidence in succeeding in them (Granovetter 1985; Weerman 2003; Kleemans 2014).

1.2. Criminal groups' structural and operational strategies

1.2.1. Hierarchical and decentralized structures

The impossibility of agreeing on a single definition of organized crime and the various theoretical conceptualizations are driven by the existence of some degrees of variability in the way in which organized criminal groups are structured and operate (Paoli, Greenfield, and Reuter 2009; Reuter 2014; Bouchard and Morselli 2014; Block 1979; Eck and Gersh 2000; UNODC 2002). However, they are also strictly related to different views in the public discourse and political priorities that have alternated over time (Paoli 2002; Reuter 1983; Albini 1993; Albini and McIllwain 2012; von Lampe 2006; 2009; Calderoni 2019).

Despite the efforts of many scholars to identify typologies of criminal organization structures, assigning organizations to specific theory-driven structures is extremely challenging and hazardous. Criminal groups are complex and fast-changing entities; thus, encapsulating their organizations in theoretical structures results only in a limited and partial understanding. Nonetheless, bearing in mind the intrinsic fallibility of these categorizations, reasoning about possible group structures and configurations contributes to a better comprehension of organized criminal groups' dynamics and *modi operandi*.

In this regard, the literature often indicates that criminal group structures fall on a continuum from formal hierarchies to more decentralized configurations (Hagan 1983; Reuter 2014; von Lampe 2003; 2006; 2009; 2015a; 2015b; Best and Luckenbill 1980; Abadinsky 2010; Bouchard 2020). Hierarchical groups display a pyramidal structure: bosses coordinate and supervise criminal activities, and lower group members are ranked in relation to the roles and tasks of which they are in charge (Finckenauer 2005; von Lampe 2015a; 2011; Best and Luckenbill 1980; B. H. Erickson 1981; Williams 2001; Abadinsky 2010; Albanese 1989; 2007). Following the continuum, hybrid criminal organizations adopt some elements typical of hierarchies mixed with elements of flexibility. These groups are formed by central entrepreneurs conducting their illegal businesses, and many collaborators and associates with whom they occasionally co-operate (Hagan 1983; B. H. Erickson 1981; UNODC 2002). Decentralized criminal groups are on the other end of the continuum. Their members form loose relations, with no evidence of a larger and more comprehensive organization binding them together. Members are tied by interpersonal relations, and they form short-lived partnerships to perpetrate criminal activities (Finckenauer 2005; von Lampe 2015a; B. H. Erickson 1981; Best and Luckenbill 1980; Reuter 1983; Abadinsky 2010; Albanese 2007; Bouchard 2020).

Positioning a group closer to one end or the other of the continuum generates important consequences for how organized criminal groups can decide, implement and manage their illegal activities (Everton and Cunningham 2013; Catino 2014). Hierarchical structures are often employed by legal organizations. According to Weber (1978), hierarchies should allow the development of rational procedures that, in turn, lead to the highest level of efficiency. Rules and codes of conduct reduce uncertainty, allowing individuals' behaviors to be forecast and unexpected outcomes to be minimized (Weber 1978; Catino 2015). However, a hierarchical structure also has certain drawbacks, especially for illegal entities. This structure makes organizations very visible and rigid; adaptations to changes, which occur rarely, are time-consuming and costly (Williams 2001; Catino 2014). In contrast, the main advantage of a decentralized structure is that it is extremely flexible and adaptable to changing circumstances. These organizations rely on trust among individuals to achieve desirable outcomes. This flexibility allows decentralized structures to better exploit criminal market opportunities, switch to the most profitable illicit activities, and build optimal criminal partnerships from time to time (Abadinsky 2010; Albanese 2007; UNODC 2002; Calderoni 2018). However, developing entrepreneurial relations based on trust may be risky, on the one hand because of possible instability, on the other hand because relations of trust may not be the most appropriate in terms of the skills needed to conduct criminal business (Desroches 2007; Lawler and Bright 2020; Kleemans and van Koppen 2020).

When the debate on organized crime first arose, the emphasis was predominantly on hierarchical criminal organizations and their threats to licit society (e.g., Cressey 1969; Fijnaut and Paoli 2004). Over time, the focus shifted toward interpretations of organized crime through the lens of social network concepts, allowing a more dynamic and nuanced understanding of criminal groups and their structural organization (McIllwain 1999; Calderoni 2019). Moreover, this nuanced interpretation circumvented rigid assumptions about organized crime persistence and internal cohesion, bypassing Gottfredson and Hirschi's cogent critique of the organizational stability of criminal groups (Gottfredson and Hirschi 1990). This shift in the point of observation led to the belief, especially of public authorities, that most organized criminal organizations themselves had mutated from being hierarchically structured to more decentralized configurations (von Lampe 2006; 2009; Calderoni 2019). Despite changes in conceptualization, research tools, and political priorities, empirical evidence supports the idea that, through the whole history of organized crime, few hierarchical, more formally organized criminal organizations, and a majority of smaller and more flexible criminal networks have always existed (Finckenauer 2005; Kleemans 2007; Reuter and Paoli 2020; Paoli, Greenfield, and Reuter 2009; Reuter 2014; Bouchard and Morselli 2014; Block 1979; Eck and Gersh 2000; Natarajan, Zanella, and Yu 2015; UNODC 2002). This variability is driven by numerous factors, such as the social environment in which criminal organizations operate, the criminal activities they perform, their economic status, and the level of enforcement (Paoli, Greenfield, and Reuter 2009; von Lampe 2009; Bouchard and Ouellet 2011; Campana 2011; Campana and Varese 2018; Varese 2020).

Operating in illegal environments, in making their structural choices, criminal organizations must consider all the abovementioned factors in addition to the maximization of illegal profits. In the abstract, hierarchies may be more lucrative due to their expected enhanced capacity to enforce rules and achieve results, but criminal groups may grow and implement this pyramidal structure only in territories where state power is weak, and law enforcement is ineffective (Paoli, Greenfield, and Reuter 2009). Decentralized structures have lower expected profits than a hypothetical hierarchical group; nonetheless, considering the necessity of operating in secret to avoid law enforcement attention, they may often result in being more efficient overall (Reuter 1983). The security vs. efficiency trade-off is a criminological concept accounting for the structural and operational decisions of criminal networks (Morselli, Giguère, and Petit 2007).

1.2.2. The security vs. efficiency trade-off

Criminal groups, aiming to protract their illicit activities (and profits) over time, need to assure a certain level of security in their procedures so that they will not be disrupted by law enforcement after too few criminal operations. However, not all criminal groups face this issue in the same manner; thus, different criminal groups place different emphases on security according to their *time-to-task*. The term time-to-task refers to the time span between the actions of a specific criminal group. For example, criminal enterprises whose main goal is to earn money have a rather short time-to-task and need to act quite often to conduct their activities and to reach their aims. In contrast, terrorist networks, driven mainly by ideological reasons, have a longer time-to-task and can wait for the most appropriate moment to execute their attacks, prioritizing security (Morselli, Giguère, and Petit 2007; Morselli 2009a; Tenti and Morselli 2014; Gravel and Tita 2017; Lawler and Bright 2020).

To be efficient, the structure of the organization must facilitate communication flows within the group. This requires a structure with a network core in which members are closely connected with each other. In this way, communication is facilitated due to the direct reachability of the actors involved in the illicit activities (Gravel and Tita 2017; Morselli 2010a; Morselli, Giguère, and Petit 2007). On the one hand, this feature is fundamental in guaranteeing the operational efficiency needed to succeed in criminal activities, and it is an element of resilience because it ensures business continuity. Indeed, even if some members were arrested by the police, there would always be someone ready to replace them and to accomplish their tasks (Giménez-Salinas Framis and Fernández Regadera 2017). On the other hand, this structure is an element of vulnerability that reduces network security: by having many direct contacts, actors are highly visible and they can be easily identified by investigators, for example due to their frequent participation in intercepted communications (Morselli, Giguère, and Petit 2007). Moreover, when many members have several direct connections to other actors in the network, they have much information about both other members and illegal activities. Consequently, law enforcement could easily obtain access to a large number of the members and their activities by arresting just a few actors (Bichler, Malm, and Cooper 2017; Giménez-Salinas Framis and Fernández Regadera 2017).

To be secure, criminal groups instead need to reduce the risks they face when committing illegal activities. Relying on a sparse structure is a good strategy for making the organization less exposed to law enforcement attempts at disruption. In sparse organizations, individuals have only a few contacts with others, making it impossible to identify a core-group. Intermediaries are often employed to reach other members because they provide fast alternative routes or shortcuts to communicate with otherwise unconnected subgroups of the organization (Morselli, Giguère, and Petit 2007; Malm et al. 2017). Intermediaries are crucial players for criminal groups striving for a reasonable level of security without compromising business efficiency. They are able to improve communication flows that reduce long informational processes (Morselli, Giguère, and Petit 2007; Spapens 2010; Malm et al. 2017). In addition, a sparse structure minimizes the circulation of information about participants and their illicit activities; members are aware only of criminal tasks in which they are implicated, and even if detected, they cannot endanger the whole group by revealing sensitive details. This structure makes the organization less visible and targetable by law enforcement (Gravel and Tita 2017; Malm and Bichler 2011). However, sparse groups sometimes lack the operational efficiency to achieve their illegal goals: information may flow too slowly, compromising the success of criminal activities, and to avoid disruption, many tasks may be replicated, increasing expenses and making the criminal business less cost-effective (Bright, Hughes, and Chalmers 2012; Eilstrup-Sangiovanni and Jones 2008). Prioritizing security means renouncing the ambition of expanding criminal ventures and consequently accepting fewer profits. Nonetheless, for organized criminal groups, lower levels of efficiency are often tolerable when the counterfactual scenario is law enforcement disrupting the whole organization (Eck and Gersh 2000; Benson and Decker 2010; Calderoni 2018).

1.3. Drug trafficking organizations

Criminal organization members build and plan their activities coherently with their goals; this strategy often leads individuals involved in organizations with a specific focus to prefer certain procedures and tactics over others. DTOs are profit-driven entities, falling into the category of criminal networks with a rather short time-to-task. Individuals involved in drug trafficking want to gain money as a reward for the risk assumed and the time spent perpetrating illicit activities, disregarding any ideological aim (Layne et al. 2002). Therefore, DTO activities are planned to guarantee fluidity and efficiency, in part by sacrificing security (Gravel and Tita 2017; Morselli 2010a; Morselli, Giguère, and Petit 2007).

As profit-oriented organizations, DTOs tend to be dense, with a centralized structure and many direct contacts among members compared to other criminal groups, such as terrorist groups (Morselli 2010a; Morselli, Giguère, and Petit 2007; Bichler, Malm, and Cooper 2017; Calderoni 2019). The way in which DTOs are organized makes their members visible and exposes them to law enforcement strategies.

Despite these general features, the literature has identified differences among DTOs in relation to their internal structure, stages of their production-distribution chain, and division of tasks (Natarajan and Belanger 1998). Many scholars have devoted their attention to the internal structure of criminal organizations involved in the drug trade. Specifically, some have developed a variety of typologies to distinguish highly and loosely structured groups (see Johnson, Hamid, and Sanabria 1992; Adler 1993; Ruggiero and South 1995; Curtis 1996; Natarajan and Belanger 1998; Eck and Gersh 2000; Benson and Decker 2010; Natarajan, Zanella, and Yu 2015).

Loosely structured groups have little or no hierarchical structure, and the division of tasks merely reflects the actors' personal skills. These groups are often smaller (i.e., comprising a few dozen individuals at most), with many networks involved in the overall drug distribution process (i.e., manufacturing, trafficking, wholesale and regional distribution) (Johnson, Hamid, and Sanabria 1992; Ruggiero and South 1995; Curtis 1996; Natarajan and Belanger 1998; Eck and Gersh 2000; Benson and Decker 2010; Natarajan, Zanella, and Yu 2015). Conversely, other organizations follow a more hierarchical structure that resembles that of legal profit-making enterprises. In these cases, the division of tasks among participants is stricter and based on established rewards. Due to the highly organized nature of these groups, they generally comprise more members, and just a few groups manage the entire drug distribution process (Johnson, Hamid, and Sanabria 1992; Ruggiero and South 1995; Curtis 1996; Natarajan and Belanger 1998; Eck and Gersh 2000; Benson and Decker 2010; Natarajan, Zanella, and Yu 2015).

Based on these typologies, many scholars have positioned the DTOs that they have investigated in one of the identified categories. Despite the ascertained variability among DTO structures, this variability is not equally distributed, as loosely structured groups are predominant (see Reuter and Haaga 1989; Fuentes 1998; Eck and Gersh 2000; Natarajan 2000; Zaitch 2002b; Pearson and Hobbs 2001; Natarajan 2006; Kenney 2007; Decker and Chapman 2008; von Lampe 2009; Benson and Decker 2010; Bichler, Malm, and Cooper 2017).

As regarding the study of organized crime in general, the development of social network theories and their diffusion in criminology has encouraged more sophisticated investigation of DTOs and their internal structures (McIllwain 1999; Morselli 2009a; Calderoni 2019). Indeed, social network concepts have highlighted the partiality and superficiality of the developed theoretical typologies. Criminal organizations, including DTOs, are evolving and multifaceted entities the complexity of which cannot be reduced to rigid theory-driven categories. Despite their empirical foundation, these categorizations relied mostly on qualitative data retrieved from interviews with former DTO participants or investigators; thus, they inevitably provided a picture biased by personal experience and impressions. More recently, the application of social network concepts to the criminological domain has brought renewed vigor to the study of DTO structures. Many scholars have started investigating the structure of criminal groups involved in the trafficking and dealing of drugs exploring relational and organizational patterns among members (e.g., Bichler, Malm, and Cooper 2017; Bright and Delaney 2013; Calderoni 2014b; Calderoni and Piccardi 2014; Duijn, Kashirin, and Sloot 2014; Hofmann and Gallupe 2015; Berlusconi 2021; Mainas 2012; Malm and Bichler 2011; Malm, Kinney, and Pollard 2008; Morselli, Giguère, and Petit 2007; Morselli and Petit 2007; Morselli 2009b; 2009a; 2010a; Tenti and Morselli 2014; Xu and Chen 2008).

Several studies have highlighted the existence of structural strategies that aim to protect core members. Often, the most strategic actors in a network reduce their visibility, favoring indirect control of the organization and minimizing their direct involvement by operating from the periphery of the network. This results in significantly less exposure to eventual law enforcement interventions (see Morselli, Giguère, and Petit 2007; Malm, Kinney, and Pollard 2008; Morselli 2009b; 2010a; Duijn, Kashirin, and Sloot 2014; Calderoni 2014b).

In a quite different approach, Xu and Chen (2008) and Hofmann and Gallupe (2015) identified the need for group core members to be directly involved in the coordination of criminal activities, with short distances separating the network actors from the leaders. This structural configuration leaves the organization leaders particularly exposed and visible, with the consequence of being highly vulnerable to eventual police interventions.

Another structural feature that has been recurrently observed in several studies is the tendency for DTOs to become more decentralized over time, especially when compelled to deal with threats posed by law enforcement interventions. In addition, during periods of crisis and mutation, the most prominent figures of the organizations vary, signaling high adaptability in response to changing circumstances (see Morselli and Petit 2007; Bright and Delaney 2013; Berlusconi 2021).

Furthermore, there is strong evidence of the tendency for criminal networks involved in the trafficking and dealing of drugs to cluster in subgroups, highlighting the compartmentalization of most criminal organizations as a protective strategy to avoid cascade effects and damage to the group on the whole in the case of law enforcement interventions (see Malm, Kinney, and Pollard 2008; Malm and Bichler 2011; Mainas 2012; Calderoni and Piccardi 2014; Tenti and Morselli 2014; Hofmann and Gallupe 2015).

These recurrent structural features are the result of DTO members having to make decisions regarding how to balance two contrasting goals: efficiently perpetrating their criminal activities to gain the greatest profits possible and granting group members acceptable levels of security. Concerning security, there are two sources of danger to DTOs: the first is market dynamics (e.g., economic competition among actors in the market and rivalries with other competitor criminal groups), and the second is law enforcement attempt to disrupt the criminal group (Eck and Gersh 2000; Natarajan, Zanella, and Yu 2015). The second source of insecurity is particularly relevant since it can push DTOs to undertake countermeasures and structural modifications to avoid, face, and react to law enforcement disruption strategies (Johnson, Hamid, and Sanabria 1992; Natarajan and Belanger 1998; Dorn, Oette, and White 1998; Eck and Gersh 2000; Desroches 2007; Bagley 2013). Resilience is the ability to resist harsh conditions and, when possible, to benefit from them. Being resilient is an enormous strategic advantage for DTOs that are subjected to law enforcement interventions (Bouchard 2007).

1.4. The concept of resilience

The term resilience comes from the Latin word *resilire* which means "to jump back", or "to rebound", and it refers to the ability to recover after a shock or disaster. Over time, this concept has spread across different fields (Figure 1) (Carpenter et al. 2001; Klein, Nicholls, and Thomalla 2003; Tierney 2003; Templeman and Bergin 2008; Lucini 2014; Prezelj and Doerfel 2017).

Figure 1. Resilience fields of applications.

Source: Author's adaptation of Reghezza-Zitt et al. 2012

The concept of resilience was first used in the hard science domain (i.e., mathematics and physics) in reference to the capacity of certain materials to be restored after displacement (Norris et al. 2008). A system is resilient if it quickly absorbs a perturbation, resuming its prior condition (Bodin and Wiman 2004). In ecology, a system is resilient if its internal relations are durable (Holling 1973). Resilience is not the absence of vulnerability; rather it is a dynamic process of adaptation and recovery in adverse circumstances. It is determined by how much perturbation the system can manage while maintaining the state of equilibrium and the extent to which the system can self-organize in reaction to the disturbance (Waller 2001; Carpenter et al. 2001; Klein, Nicholls, and Thomalla 2003).

The concept of resilience has also been adopted in the social sciences domain. In the field of economics, an entity is resilient when, facing a shocking situation, it maintains its productivity. Static resilience refers to the balanced allocation of resources, whereas dynamic resilience refers to celerity in recovering from a shock (Rose 2007). From a sociological perspective, four elements build resilience: a response to a negative event, self-organization, a process of learning, and adaptation. After an adverse event, communities that quickly activate internal resources, regardless of the support of external actors, are more resilient than those that passively await external help. Resilient communities undertake activities to restore, or advance, the situation that existed before the negative event, highlighting opportunities for learning and enabling better future responses. Finally, resilient communities are capable of adaptation; returning to the predisaster situation is rarely possible, and promptly adapting to new circumstances leads to fewer negative consequences (Sapirstein 2006; Maguire and Hagan 2007).

From an organizational point of view, resilience is the ability of an organization to develop adaptive capacity to face environmental changes and withstand disruption (Ayling 2009; Lengnick-Hall and Beck 2005). According to Zhang and Liu (2012), when dealing with adversity, four scenarios are possible in relation to the level of adversity (i.e., high or low), and the outcome for the organization (i.e., favorable or unfavorable). Only organizations experiencing favorable outcomes from high-level adversity are resilient (Zhang and Liu 2012).

The resilience framework has also been adapted to family and individual contexts. Regarding the former, in circumstances of adversity (e.g., illnesses, deaths, or economic difficulties), resilient families exchange reciprocal help, support each other, comprehend personal emotions and needs, create meaning for the adverse event, and work together to reduce losses, accepting what cannot be changed (Rolland and Walsh 2006). Regarding the latter, resilience can be considered an individual resource. In this domain, it is the ability of an adult to face potentially disruptive events (e.g., the death of a close relative or violent or life-threatening circumstances) while maintaining his or her psychological and physical functioning (Bonanno 2004). Some protective factors have been identified as possible sources of resilience: high cognitive abilities, a positive vision of oneself, a sense of safety, a positive temperament, internal self-control, a prosocial personality, etc. (Bonanno 2004; Castelli 2011).

As the condensed review of the definitions demonstrates, the topic of resilience has spread across different fields over the years. This has led to the proliferation of many overlapping yet different interpretations, making it difficult to synthesize the information in a universally valid definition (Mayunga 2007). Nonetheless, some recurrent aspects can be distinguished: robustness, redundancy, resourcefulness, and rapidity (Tierney 2003). Robustness refers to the capacity of a system to resist perturbation without suffering damage. Redundancy is the ability of a system to display features that prepare it to respond to and recover from a shock. Resourcefulness is the ability of a system to be aware of sources of vulnerability, identify imminent threats, prioritize feasible responses to disruptive events and mobilize resources to deal with those events. Finally, rapidity is the ability of a system to meet the abovementioned requirements without delay (Tierney 2003).

Despite these common elements, other aspects are far more controversial. Among scholars, there is debate concerning whether resilience is a process that systems go through or a property inherent to systems. As a process, resilience is defined as the steps that systems undergo from the occurrence of a negative event to overcoming it. As a property, resilience is defined as a specific feature of systems revealed by the impact of a perturbation but preexisting it (Reghezza-Zitt et al. 2012). In the former case, resilience is a dynamic characteristic of entities: on the one hand, it refers to continuous adaptation to adversity, and on the other hand, the same system facing similar adverse events over time may respond differently (Reghezza-Zitt et al. 2012; Prezelj and Doerfel 2017; Zhang and Liu 2012; Waller 2001). In the latter case, resilience is a static feature of entities: it can be an innate quality, or it can be acquired through preventive and formative approaches aimed at improving systems capabilities when coping with a disaster (Reghezza-Zitt et al. 2012).

Another debated issue is the distinction between resistance and resilience. Resistance refers to the pressure needed for a perturbation to generate damage to the system; it is the magnitude of disturbance that a system absorbs without being affected by displacement (Carpenter et al. 2001). In contrast, resilience refers to the adaptability of a system when facing a hazardous situation; regardless of the severity of the adverse event, what is important is the system's reactivity to it and the level of operational activity the system can manage afterward (Reghezza-Zitt et al. 2012; Carpenter et al. 2001). Hence, resistance and resilience both contribute to the outcomes of systems passing through adversity. However, they cover different aspects: resistance refers to the ability of a system to avoid or withstand a certain degree of environmental disturbance, and resilience refers to active adaptation and the process of coping with and minimizing the consequences of the disturbance (Reghezza-Zitt et al. 2012).

The concepts of resistance and resilience can contribute to the analysis of criminal groups confronting adversity. They allow the examination of how organized criminal groups, including

DTOs, avoid, face, react to and overcome law enforcement attempts at disruption. Nevertheless, criminal groups differ in many features from legal organizations, and these differences also have implications for how resilience can be defined (Ayling 2009).

1.5. The resilience of criminal networks

1.5.1. Criminal network evolution over time

Criminal organizations and networks, as well as legitimate ones, operate in complex environments. To persist over time, they must face, react and adapt to changing conditions (Morselli and Roy 2008; Decker and Chapman 2008; Morselli 2009a; Kleemans 2014; Wood 2017; Castiello, Mosca, and Villani 2017). Organizations arise in response to certain needs, specifically those of the founding members; however, over time, the ideological basis of the organization is likely to change for a variety of reasons, both internal and external. A functional organization identifies these sources of change and recognizes when modifications are indispensable for its survival. For this reason, organizations must undergo an endless process of continuous learning, accommodating evolving circumstances according to failures and successes. Organizations that become too rigid and static will diverge from their expected goals and lose their efficacy and efficiency. This will possibly result in the voluntary or involuntary dismantlement of the organization (Butera 2005).

Criminal networks are also exposed to specific vulnerabilities due to the illegal nature of their activities (Beckert and Wehinger 2013; Catino 2015; Castiello, Mosca, and Villani 2017). This leads them to often evolve over time in response to internal and external factors (Bouchard 2007; Ayling 2009; Morselli 2009a; Spapens 2011; Everton and Cunningham 2013). Internal factors may include the recruitment of new members or the abandonment of old ones because of conflicts or personal choices, the reorganization of the group, or alliances with other organizations (Ayling 2009). External factors include the decision to operate in new sectors of the illicit market or external shocks due to law enforcement interventions (Ayling 2009; Bouchard 2007).

Regarding external shocks, law enforcement often implements two main types of interventions: the removal of members through arrests and the removal of assets (e.g., drugs, money, properties) through seizures (Bouchard 2007). Arrests and seizures can jeopardize the functioning of the drug market to a remarkable extent. The removal of dealers and drugs increases the difficulties faced by consumers in buying drugs; therefore, consumption is expected to decrease. Moreover, law enforcement interventions may have a deterrent effect, discouraging dealers and potential dealers from staying in the market or entering it, because of a high level of insecurity (Bouchard 2007).

Arrests and seizures can also have indirect impacts. The expectation of being targeted by law enforcement pushes criminal network members to change the organizational structure of the group, to modify previously used procedures, to decide to drop the involvement in one criminal activity in favor of others, etc. For this reason, among available criminal strategies and existing *modi operandi*, DTO members will from time to time ponder the expected rewards and the eventual risk of detection (Becker 1968; Clarke and Cornish 1985; Weerman 2003). Being better able to consider intervention factors in the commission of criminal activities will facilitate reactive adaptation to changing contextual conditions. These organizations and their members will have a higher probability of maintaining their criminal involvement for a longer time without being disrupted by law enforcement interventions.

1.5.2. Defining criminal network resilience

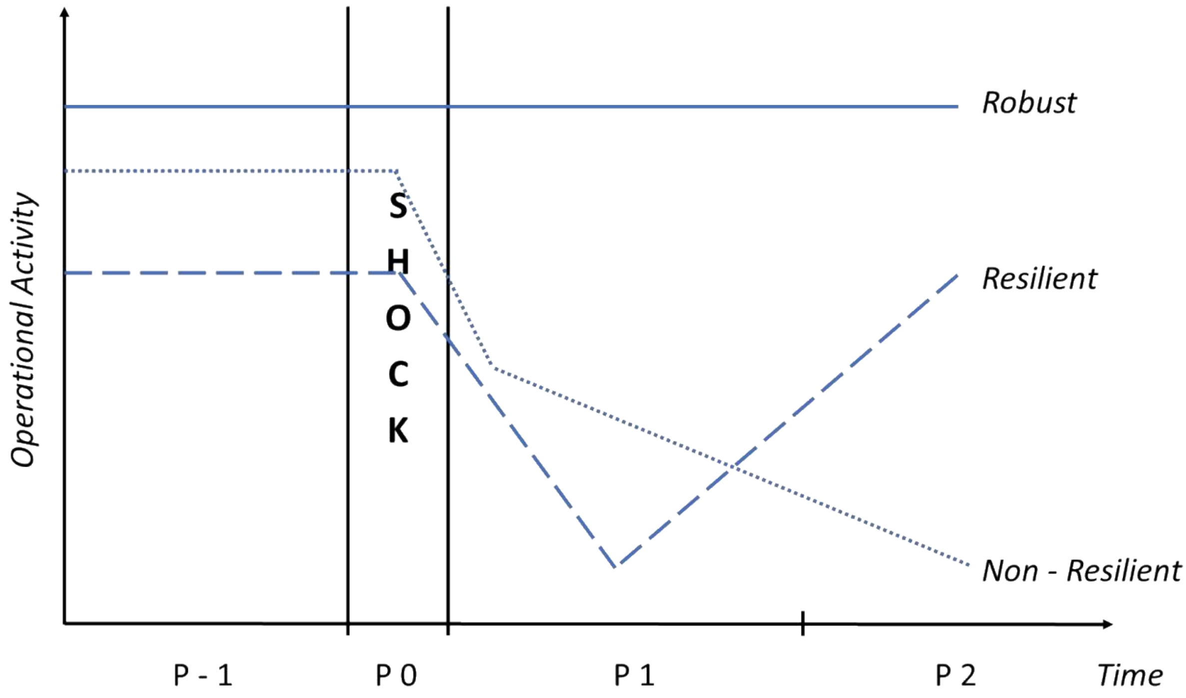
Understanding how criminal groups cope with adversity and their possible sources of resilience has both theoretical and operational implications. From a theoretical point of view, it acts as a stimulus encouraging academic discussion on organized crime and its distinctive traits. Ascertaining the evolving nature of criminal organizational structures indeed would lead to questioning the usefulness of characterizing criminal networks as having a supposedly fixed structure. From an operational point of view, it would provide an advantage to law enforcement attempts to disrupt these organizations. It would help in planning more efficient attacks by focusing on the vulnerabilities of criminal groups and avoiding wasting time and resources on operations that lead to few or no results (Bouchard 2007).

The literature on criminal network resilience is still underdeveloped since only a few scholars have been interested in this topic, and even fewer have thoroughly addressed the problem of defining the concept. Nonetheless, a few authors have occasionally pointed out some features to be examined when assessing criminal organization resilience.

According to Bouchard (2007), two characteristics must be present for a criminal group to have a resilient framework: it must be continuously at risk of external shocks and, despite this, it must be able to persist over time. A criminal group persisting over time when constantly under attacks is resilient if it maintains a structure similar to the one it had before the attacks or if it modifies it. Ayling (2009) stresses the importance of the capacity to endure disruption, to assimilate external tensions and pressures, and to maintain the criminal group primary functions unaltered. Bakker et al. (2012) distinguish two types of resilience. The first type implies that a criminal network has a robustness capacity, that is, the ability to maintain its functions and operativity even under attack. The second type includes criminal networks with a rebounding capacity, that is, the ability to withstand external shocks over time by transforming and adapting. Last, Duxbury & Haynie (2019) define a criminal organization as resilient if it is able to react in a fast and efficient way to attempts at disruption without interrupting its criminal activities. The assessment of the resilience of criminal groups must consider both robustness to disruption and time needed for recovery.

In addition to defining criminal network resilience, Bakker et al. (2012) operationalize it by focusing on operational activity. Operational activity refers to practical and observable activities demonstrating that the criminal network is executing its main tasks. These can include, according to the type of organization, homicides, bombings, drug exchanges or any other typical criminal activity. The assessment of resilience examines changes in operational activity due to uncertainties brought by external shocks (Bakker, Raab, and Milward 2012). Graph 1 displays a simplified scheme of the operationalization of the concept of resilience.

Graph 1. Operationalization of criminal network resilience



Source: Author's adaptation of Bakker, Raab, and Milward (2012)

At time P−1, each criminal organization has a certain level of operational activity; at P0, a shock occurs. In the following periods (namely, P1 and P2), it is possible to examine the eventual resilience of criminal networks. If no differences in the level of operational activity can be observed in P1 and P2, the organization is robust; the shock does not influence the normal routines of the organization, and activities and tasks continue to be carried out with no modification. If the operational activity of the organization continues to decrease through P1 and P2, the organization can be defined as nonresilient; it does not have the ability to react to and recover from the shock. The organization is strongly affected by the shock, and it cannot reorganize itself to continue its activities. The third possibility involves a criminal organization that is first shocked by the unexpected event, as is observable in an initial decrease in operational activity in P1; however, over time, the organization is able to reorganize and find alternative ways to recover from the shock, as is demonstrated by an increase in operational activity in P2 (Bakker, Raab, and Milward 2012; Berlusconi 2013a).

1.5.3. Sources of resilience of criminal networks

Different features of the environment in which criminal networks operate and both structural and strategic characteristics of networks themselves influence their resilience (Ayling 2009; Bakker, Raab, and Milward 2012). Moreover, criminal networks can actively implement some protective methods to safeguard their criminal activities and reduce their vulnerabilities to law enforcement attempts at disruption (Spapens 2011).

1.5.3.1. Environmental features increasing resilience

Illegality impedes criminal networks from operating in the same manner as legal entities, mostly because of the risk of detection and the uncertain environment (Reuter 1983; 1985; Kleemans and Van de Bunt 1999; Kleemans 2013; Aziani, Berlusconi, and Giommoni 2019). In these environments, criminal networks cannot invoke legal institutions to enforce agreements and resolve disputes (Paoli 2002; Jacques and Wright 2011), and cannot advertise their activities and products to secure customers (Gambetta 2009; Che and Benson 2014). As postulated by social embeddedness theory (Granovetter 1985), social relations in the environment bring strategic advantages to criminal networks since they augment levels of trust, reducing uncertainty and the abovementioned criticality (Kleemans and Van de Bunt 1999; Kleemans 2013; Aziani, Berlusconi, and Giommoni 2019). Specifically, three main environmental features increase resilience: thick crime habitats; community support and legitimacy; and high interpenetration among criminal networks, businesses in the legal economy and state authorities (Ayling 2009; Bakker, Raab, and Milward 2012).

First, a context in which many criminals coexist and where many opportunities for committing crimes are present is certainly an advantage for criminal organizations that can share information among themselves, find suitable co-offenders and learn *modi operandi* from experienced criminals; in turn, this situation augments the resilience of criminal groups (Ayling 2009; Spapens 2010; Castiello, Mosca, and Villani 2017; Kleemans and van Koppen 2020; Roks, Kruisbergen, and Kleemans 2022).

The second environmental feature is community support and legitimacy. Network members are often embedded in their community, and thus, the goals and means of the organization can be seen as legitimate and justified by the community. Consequently, the criminal group can gain deep support from the community that strengthens its radicalization in the territory (Gambetta 1993; Hallsworth and Young 2008; Ayling 2009; 2013; Bakker, Raab, and Milward 2012; Van de Bunt, Siegel, and Zaitch 2014; Beckert and Dewey 2017; Skinnari, Jonsson, and Vesterhav 2019; Roks, Kruisbergen, and Kleemans 2022).

The third environmental element is interpenetration with the licit world. Close relations with legal businesses make it difficult to clearly distinguish between what is legal and what is not. Moreover, many criminal organizations have collusive connections with authorities, which makes the organizations even more rooted in their environment (Reuter and Haaga 1989; Williams 2001; Finckenauer 2005; Kleemans 2007; Kenney 2007; Morselli and Giguere 2006; Xia 2008; Ayling 2009; 2013; Morselli 2009a; Spapens 2010; Dewey 2011; Beckert and Wehinger 2013; Van de Bunt, Siegel, and Zaitch 2014; Beckert and Dewey 2017; Lawler and Bright 2020; Kleemans and van Koppen 2020; Roks, Bisschop, and Staring 2021; Roks, Kruisbergen, and Kleemans 2022).

1.5.3.2. Network features increasing resilience

Specific structural features of criminal organizations increase network resilience. Considering group structures, the most efficient and adaptable structures are the simplest; groups that are minimally hierarchical can regulate themselves more easily, reducing eventual constraints, and they adapt more rapidly to changing conditions (Ayling 2009; Williams 2001; Desroches 2007; Xia 2008; Morselli and Roy 2008; Benson and Decker 2010; Le 2012). At the same time, more hierarchical groups may have advantages in the process of quick adaptation due to the existence of clear and definite directions from the apical body of the organization (Abadinsky 2010).

Redundancy also improves networks response to shocks, since redundant structures experience fewer difficulties in replacing actors removed by police interventions. Together with redundancy, compartmentalization is a feature that makes criminal networks more secure and resilient: highly clustered parts of the network are connected by weak ties and important information is not allowed to circulate through the whole network. Only selected members know specific critical information, and they cannot reveal it to others. This, in the case of shocks, reduces the risk of cascade effects and prevents damage to the totality of the criminal network since the undamaged clusters of the network can autonomously continue their criminal activities (Ayling 2009; Williams 2001; Burt 2005; Kenney 2007; Garoupa 2007; Decker and Chapman 2008; Spapens 2010; 2011; Duijn, Kashirin, and Sloot 2014; Calderoni and Piccardi 2014; Ozgul and Erdem 2015; Hofmann and Gallupe 2015; Castiello, Mosca, and Villani 2017; Jaspers 2020; Lawler and Bright 2020).

Another feature that increases network resilience is kinship and ethnicity. Ties based on family relationships and cultural commonalities are, indeed, stronger and they augment the level of trust, bringing strategic advantages within the organization (Gambetta 1993; 2000; Paoli 2002; Layne et al. 2002; Desroches 2007; Kenney 2007; Ayling 2009; Malm, Bichler, and Van De Walle 2010; Kleemans 2013; Duijn, Kashirin, and Sloot 2014; Hofmann and Gallupe 2015; Sergi 2019; Kleemans and van Koppen 2020; Roks, Kruisbergen, and Kleemans 2022).

Organizational learning is another strategic feature for criminal networks. In criminal settings, formal learning tends to be minimized, but organizational memory and learning by social interaction are key elements for criminal organizations. Being aware of what has gone wrong in the past is often fundamental to reorganize in a better way and adapting to new and unknown situations (Ayling 2009; Spapens 2011; Kenney 2007; Lawler and Bright 2020).

Finally, another strategic element is the ability of criminal networks to replace individuals and linkages among them while maintaining a certain level of operational activity. Moreover, the role of resources cannot be underestimated. Both material (e.g., money, property or weapons) and immaterial resources (e.g., the ability to recruit new people or specific skills) are fundamental to making networks more resilient to shocks and attacks (Bakker, Raab, and Milward 2012; Lawler and Bright 2020).

1.5.3.3. Protective methods increasing resilience

Criminal network members are aware of the illegality of their actions and the necessity of security. For this reason, they actively implement protective measures to avoid police investigations and to respond to them by minimizing the consequences (Spapens 2011; Jaspers 2020). Criminals are conscious of the possibility of wiretaps on telephone lines and thus will try to avoid speaking openly over the phone about criminal activities to the greatest extent possible, preferring to use phone communications only to arrange personal meetings. Moreover, criminals try to use communication devices that the police cannot easily tap to increase security (Spapens 2010; 2011; Kleemans 2007; Kenney 2007; Berlusconi 2013a; Catino 2015; Duijn, Kashirin, and Sloot 2014; Jaspers 2020). Other strategies are used to discourage covert investigations and make them more difficult. Meetings are often arranged in places that are difficult to reach and isolated, making it almost impossible for police officers to reach them without being noticed (Spapens 2010; 2011). Furthermore, criminal network members frequently employ intermediaries to avoid direct involvement in negotiations and exchanges (Desroches 2007; Kenney 2007; Spapens 2011; Leuprecht, Aulthouse, and Walther 2016).

However, criminal networks usually put these techniques in place only after they become aware of ongoing investigations. This happens due to a lack of technical and accurate knowledge about criminal investigations, because the effective implementation of countermeasures by default is costly and difficult, and because augmenting the security of the network would reduce the efficiency of their criminal business (Spapens 2011).

2. Motivation

This chapter describes knowledge gaps in the literature on criminal network resilience (section 2.1), and it presents the research questions, objectives and hypotheses guiding the current study (section 2.2).

2.1. Knowledge gaps in assessing criminal network resilience and vulnerabilities

Over time, the process through which criminal organizations react to law enforcement investigations has attracted scholars' attention. Understanding the strategies and vulnerabilities of criminal networks would allow law enforcement to plan and implement more effective investigation techniques, without wasting resources in inefficient operations (Bouchard 2007; Duijn, Kashirin, and Sloot 2014). The development of social network analysis (SNA) has taken interest in this domain even further since recognizing how criminal networks are structured and where the most important members are positioned within the organization can improve the comprehension of who are the best members to target (Morselli 2009b).

Many studies addressing this topic have relied on data from judicial documents to examine criminal networks' structure before and after simulating the removal of certain actors and ties. Different strategies are used to choose which actors to remove, and according to that choice, the effects on the network structure vary. Many methods are used to identify targets: random removal, removal of actors with the highest number of contacts (based on degree centrality), removal of actors who play strong brokerage roles in the network (based on betweenness centrality), removal of actors with significant social or human capital, or removal of actors possessing key resources (see Agreste et al. 2016; Castiello, Mosca, and Villani 2017; Cavallaro et al. 2020; Duxbury and Haynie 2018; Morselli and Roy 2008; Villani, Mosca, and Castiello 2019; Wood 2017). Overall, the analyzed criminal networks were highly vulnerable to the sequential removal of key actors (e.g., brokers of the network, actors closely connected with others, members with significant human capital); in contrast, attacks targeting operational members caused much less difficulty for the organizations (Agreste et al. 2016; Castiello, Mosca, and Villani 2017; Duxbury and Haynie 2018; Morselli and Roy 2008; Villani, Mosca, and Castiello 2019; Cavallaro et al. 2020; Wood 2017).

The merit of these studies is that they have shown that targeted removal of actors is more effective than random removal. However, these works have not considered one of the most important features of networks: they evolve and adapt over time (Bright and Delaney 2013; Duijn, Kashirin, and Sloot 2014; Giménez-Salinas Framis and Fernández Regadera 2017; Morselli and Petit 2007). For this reason, examining only how network structure changes after the removal of some actors, disregarding the strategy of adaptation, is not enough (Carley 2006; Morselli and Roy 2008; Duijn, Kashirin, and Sloot 2014).

Some innovative studies have taken a step further, assessing the problem of network disruption while also considering network reactions to law enforcement strategies (see Carley 2006; Keller, Desouza, and Lin 2010; Duijn, Kashirin, and Sloot 2014; Bright et al. 2017; Duxbury and Haynie 2019; 2020). These studies have confirmed that taking network adaptation strategies into account always results in a substantial reduction in the effectiveness of attempts at disruption. Therefore, they have emphasized the need for deep knowledge of the networks before standardized strategies are adopted. Moreover, they have recommended and encouraged the alternation of different strategies to make it difficult for networks to adapt and reorganize (Carley 2006; Keller, Desouza, and Lin 2010; Duijn, Kashirin, and Sloot 2015; Bright et al. 2017; Duxbury and Haynie 2019).

These innovative studies have suggested the importance of considering the flexibility and adaptability of criminal networks when facing law enforcement interventions. Nevertheless, they were based on simulations, and without effective validation techniques, they could not provide reliable knowledge of how real criminal networks would behave when compelled to deal with police operations. An alternative is that of employing the case study approach to observe whether real criminal networks approached by law enforcement actually adapt and evolve as proposed by the scientific literature.

The unique attempts to test network resilience to law enforcement interventions using data from real networks experiencing changes due to a variety of police interventions are those of Morselli and Petit (2007), Berlusconi (2013a), Manzi (2019), Fabiani and Behlendorf (2020), and Diviák and colleagues (2022). These studies have confirmed the importance of flexibility for criminal networks subjected to law enforcement interventions. The modifications of previously well-established practices allowed adaptation to new circumstances (e.g., substitution of prominent members, downsizing of criminal involvement in the short term, and variations in *modus operandi*). In addition, despite the implementation of sometimes opposite structural strategies (i.e., increasing or reducing members' cohesiveness), reliance on preexisting ties was often a feature that incrementally increased criminal network resilience (Morselli and Petit 2007; Berlusconi 2013a; Manzi 2019; Fabiani and Behlendorf 2020; Diviák et al. 2022).

Over the years, resilience has been increasingly investigated in the criminological field. Previous studies have focused from time to time on specific aspects of criminal network resilience greatly contributing to reducing knowledge gaps in this research domain. However, no studies have yet had the ambition of comprehensively covering all aspects of criminal network resilience: defining the concept, investigating various available strategies of disruption and their effectiveness, examining criminal network dynamic reactions, and validating the findings to augment their reliability and generalizability. For this reason, much room for further exploration still exists. As mentioned above, a first set of studies introduced the topic of resilience in the criminological debate and highlighted its importance to the strategic planning of law enforcement interventions (see Bouchard 2007; Ayling 2009; Bakker, Raab, and Milward 2012). A second set of studies investigated strategies for actor removal to determine the best targets for inflicting the most damage on criminal networks (see Agreste et al. 2016; Castiello, Mosca, and Villani 2017; Duxbury and Haynie 2018; Morselli and Roy 2008; Villani, Mosca, and Castiello 2019; Wood 2017). A third set of studies considered criminal networks to be dynamic entities and found that adaptation strategies to law enforcement interventions need to be contemplated (see Carley 2006; Keller, Desouza, and Lin 2010; Duijn, Kashirin, and Sloot 2014; Bright et al. 2017; Duxbury and Haynie 2019; 2020). Finally, a fourth set of studies specifically observed real network reactions and strategies to actual attempts at disruption (see Morselli and Petit 2007; Berlusconi 2013a; Manzi 2019; Diviák et al. 2022).

Although criminal network resilience has been defined, studies empirically testing criminal network resilience have not relied on these definitions, nor have they provided precise alternatives. Many removal strategies have been identified, but their effectiveness cannot be proven since criminal network adaptability is not often considered. Some advanced simulation strategies have been employed to account for network dynamism, but the assumptions that these simulation models were built on have not been validated, preventing the possibility of asserting that real criminal networks would behave as the simulated ones did. Few case studies have directly monitored criminal network reactions to real attempts at disruption; thus, there is no certainty that any other criminal group would behave in the same manner.

2.2. The current study

This study aims to investigate how DTOs and their members resist and react to large-scale law enforcement interventions, examining factors influencing their ability to avoid being targeted and to take advantage of existing sources of resilience when compelled to deal with attempts at disruption intended to jeopardize their illicit activities.

This study is unique since it contributes to the literature by exploring DTOs' resistance and reactions to attempts at disruption that, compared to those considered in prior research, are much more similar to real police interventions: on the one hand, the targets to be arrested are selected based on information available from the preliminary stages of police investigations (i.e., involvement in DTOs' criminal activities and cursory tasks accomplished in the organization); on the other hand, multiple actors are simultaneously arrested and removed from the same organization.

The choice of focusing on actors who, in most cases, are not special police targets (e.g., actors with the highest degree or betweenness centrality) is strictly linked to how law enforcement investigations work. In most jurisdictions, law enforcement starts an investigation by gathering evidence about all the suspects of a specific case; the investigative activities are then concluded when the police have gathered enough evidence to formulate charges and arrest the suspects (e.g., Calderoni 2012; 2014b; Berlusconi 2021). In contrast, most previous studies have analyzed the effects of removing specific actors from a network (i.e., those displaying peculiar features), but this is more a theoretical exercise than a realistic representation of how police interventions are conducted.

Consequently, removing only one or a few actors from an organization is far from what occurs in real police interventions, when the police remove from the network all actors for whom they have substantial evidence of their involvement in criminal activities, which often means most of the suspects (e.g., Calderoni 2012; 2014b; Berlusconi 2021). The sporadic arrest of a few members of criminal organizations, in certain peculiar circumstances, is also likely (e.g., arrests of some actors in flagrante delicto while committing criminal offences). Nonetheless, these arrests rarely involve criminal organizations' key members (i.e., those members with peculiar features whose removal has been simulated in previous studies). Conversely, it is far more likely that grassroots actors will be apprehended in flagrante delicto because they lack specific resources to protect themselves and their criminal involvement. Moreover, also considering low-ranking members' sporadic arrests, there is vast evidence that these attacks are not lethal for criminal groups, which are often able to rearrange their criminal activities and organigrams (Morselli 2010a; Calderoni 2014a; 2014b).[1] In contrast, much less is known about how criminal

[1] As an example, considering the Italian context, the semestral reports of the Direzione Investigativa Antimafia (DIA) systematically report detailed information on investigations and arrests against Italian mafias and criminal organizations. The reports mention both cases in which hundreds of members are simultaneously arrested at the end of extensive police operations and cases of arrests of single mafia members while fugitive or caught in flagrante delicto while committing offenses. However, the first type is often reported as potentially critical events for group criminal involvement (even though there is no possibility of verifying the real impact provoked by the

organizations respond to critical threatening events, such as the simultaneous removal of multiple members.

This study intends to contribute to the improvement of the understanding of DTOs' resistance and resilience under the conditions expressed above, assuming that it is possible to identify common patterns in the way in which DTOs face and react to law enforcement attempts at disruption. Relying on the most comprehensive definition of criminal network resilience, this study explores these common patterns examining three main abilities that DTOs must display to be resilient: the ability to endure disruption when compelled to deal with major threats; the ability to react quickly and efficiently to law enforcement interventions aiming to disrupt the criminal organization; and the ability to maintain primary functions and activities unaltered after an attempt at disruption (Bouchard 2007; Ayling 2009; Duxbury and Haynie 2019).

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

Developing knowledge on the usual behaviors and strategies adopted by DTOs when dealing with law enforcement attempts at disruption would allow advancements in two directions. From a theoretical point of view, it would enable the improvement and refinement of definitions of criminal network resistance and resilience. In turn, more precise definitions are the starting point for progressing in this underinvestigated field of research by identifying paths that are still in need of exploration. From an operational point of view, it reveals certain policy implications. Indeed, ascertaining the effectiveness and efficiency of law enforcement interventions under specific conditions would allow better planning of future police investigations. It would be possible to design police interventions on the basis of reliable information about the most appropriate balance between the resources to be employed and the effects that can be obtained from them.

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interventions), while the second often poses minor or no threats to the survival of the whole organization, clan, or family. The DIA reports are available at: https://direzioneinvestigativaantimafia.interno.gov.it/relazioni-semestrali/.

The developed ABM allows the following research questions to be answered:

> **RQ 1.** How does the proportion of arrested members to the whole organization affect the resilience of DTOs to law enforcement attempts at disruption?
>
> **RQ 2.** How does arresting members performing different tasks in the organization affect the resilience of DTOs to law enforcement attempts at disruption?
>
> **RQ 3.** How does a different focus in the efficiency vs. security trade-off impact the resilience of DTOs to law enforcement attempts at disruption?

These research questions can be transposed into the following objectives:

> **O 1.** Investigating whether and how arresting different proportions of DTO members affects the organization's resilience to law enforcement attempts at disruption.
>
> **O 2.** Examining whether and how arresting DTO members performing different tasks affects the organization's resilience to law enforcement attempts at disruption.
>
> **O 3.** Exploring whether and how a different focus in the efficiency vs. security trade-off affects DTOs' resilience to law enforcement attempts at disruption.

Considering the abovementioned research questions and related objectives and based on existing knowledge, the following hypotheses can be developed:

> **H 1.** The higher the proportion of arrested members, the greater the difficulties in rearranging and continuing criminal activities and thus the lower the resilience of DTOs.

Illegal organizations, among them DTOs, tolerate a certain amount of adversity. Indeed, operating in a hostile environment, they are consciously noncompliant with legal regulations, and they are aware of the risks and possible costs they may incur (Kleemans 2014; Basu 2014). More specifically, when the transaction cost model is applied to the illicit supply chain, illicit entities make decisions based on the understanding that a certain amount of costs and losses is inherent to their criminal activities (Basu 2014). However, as profit-oriented entities, their primary goal is to gain rewards from involvement in illicit activities; therefore, if the losses reach a critical threshold, the survival of the whole organization is at risk. Therefore, it is likely that DTOs will react calmly to first or sporadic attempts at disruption (i.e., the arrest of an exiguous proportion of members); these threatening events are likely to be accepted with resignation as an expected cost of involvement in illegal activities. Nonetheless, when losses reach the critical threshold, it is likely that DTOs will try to rearrange their activities to continue to meet the *raison d'être* of the organization itself (Butera 2005), which mostly concerns the ability to guarantee members the agreed-upon rewards for their involvement in illicit activities. In the case of massive attempts at disruption, it is possible that the organization will not have the necessary resources, in terms of economic means and/or workforce, to continue its criminal involvement. In this circumstance, the DTO is likely to be severely and irreparably affected by the attempt at disruption and will cease to exist.

> **H 2.** The removal of actors involved in trafficking activities affects DTOs' operational activity the most; the removal of actors involved in retailing activities is more manageable for DTOs, with higher levels of expected resilience.

The assessment of the impact of police investigations targeting categories of actors in charge of specific tasks within the organization can offer information on how best to exploit the time and resources available to law enforcement. Law enforcement often has to decide how to allocate its finite resources, which can imply having to plan investigations focused on a specific niche of the drug market. In this situation, having realistic expectations of which are the most vulnerable stages and actors of the trafficking chain is a strategic asset.

Targeting members of the organizations involved in trafficking activities is likely to be more challenging for the survival of the organization because it removes some of the connections between the drug production side of the market and the consumer side (Reuter 2014). In addition, the removal of these actors would greatly damage the DTO because these figures often have specific knowledge and competences that are difficult to replace (Johnson and Natarajan 1995; Calderoni 2012). Conversely, progressing toward the retail side of the drug market, DTOs may face fewer difficulties when compelled to deal with attempts at disruptions targeting their grassroots members. These actors do not need to have specific competences, and they are easily replaceable (Johnson and Natarajan 1995; Calderoni 2012).

Nonetheless, even though targeting the traffickers of the organization is likely to pose more challenges to DTOs' operational activity, identifying and arresting these actors could be far more difficult than focusing on members involved in the lower stages of the drug distribution chain. Traffickers are likely to have resources and to know tactics for how best to conceal themselves from law enforcement. In contrast, grassroots members are the most visible and consequently the most vulnerable to law enforcement interventions; they are less likely to have sensitive information about the criminal group, and they are considered expendable and replaceable by the management of the organization. For this reason, they need to be exposed to accomplish their tasks and are not provided with effective resources and strategies to protect themselves (Morselli 2010a; Calderoni 2014a; 2014b).

H 3. Different focuses in the efficiency vs. security trade-off affect the resilience of DTOs. Efficient organizations are more resilient to massive attempts at disruption. Nonetheless, their persistence over time is limited due to their high visibility. Secure organizations are less resilient, lacking the resources to face massive attempts at disruption. At the same time, the ability to better protect their members and criminal activities results in a prolonged persistence over time.

DTOs need to confront the trade-off between efficiency and security. This means that while pursuing their illegal profits, they also need to assure a certain level of security in their procedures. However, security and efficiency are inversely related: it is not possible to increase the efficiency of criminal activities without reducing the security of the group, and conversely, the security of the group cannot be increased without losing efficiency (Morselli, Giguère, and Petit 2007). Often, the optimal combination of efficiency and security is not strictly related to the willingness of the organization and its managerial figures, but the social context in which the organization is embedded plays an important role. Criminal groups have the opportunity to emphasize the efficiency side of the trade-off, also increasing their visibility, only in situations and territories where state power is underdeveloped, law enforcement is ineffective, or collusive connections with authorities are present and strong. Conversely, in contexts with high law enforcement pressure and low levels of corruption, criminal organizations must hide themselves and their activities as much as possible, with the inevitable consequence of favoring security over efficiency (Paoli, Greenfield, and Reuter 2009).

The security vs. efficiency trade-off also has important implications for resilience. DTOs prioritizing efficiency are characterized by direct reachability among actors, and this feature facilitates the possibility of protracting their criminal activities (Gravel and Tita 2017; Morselli 2010a; Morselli, Giguère, and Petit 2007). In addition, it ensures business continuity since, when and if the organization is subjected to some arrests by law enforcement, the replacement of the actors is usually smooth (Giménez-Salinas Framis and Fernández Regadera 2017). These factors are likely to make DTOs embed themselves in contexts that allow them to prioritize efficiency and resilience so that they can react quickly and efficiently to single attempts at disruption, even if they are massive.

In contrast, DTOs prioritizing security tend to rely on fewer trusted contacts to perform their criminal activities and are reluctant to recruit and replace actors in their organization unless the credentials of new recruits are extremely reliable. In addition, they are likely to lack the operational efficiency to achieve their illegal goals, thus compromising the success of their criminal activities (Bright, Hughes, and Chalmers 2012; Eilstrup-Sangiovanni and Jones 2008). This is likely to result in a lack of resources to face and react to law enforcement attempts at disruption, leading, in the best-case scenario, to the need for longer periods of time to rearrange criminal activities and, in the worst-case scenario, to the failure of the whole organization.

Notwithstanding the higher expected resilience to single attempts at disruption for DTOs prioritizing efficiency, the actual probability of efficient and secure DTOs being targeted by law enforcement attempts at disruption is not comparable between. Organizations prioritizing security are better able to protract their criminal activities unnoticed, and their members are better able to stay hidden from police investigations; thus, it is likely that they will be proficient in avoiding being targeted by law enforcement interventions for long periods of time (Morselli, Giguère, and Petit 2007). In contrast, DTOs prioritizing efficiency often disregard protective measures when conducting their criminal activities, resulting in extreme visibility (of both their activities and their members); thus, they are likely to undergo early and sequential targeting by law enforcement (Morselli, Giguère, and Petit 2007). Consequently, while efficient DTOs may be more resilient in reacting to single, even massive attempts at disruption, because they are targeted at an early stage of their involvement in criminal activities and experience intensive sequential targeting due to their great visibility, they may not have the capability of surviving subsequent attempts at disruption, resulting in a modest persistence over time. Conversely, secure organizations, even though a single massive attempt at disruption may be lethal to them, may be able to actively maintain their criminal activities without being noticed by law enforcement for a prolonged time, resulting in higher persistence over time (B. H. Erickson 1981; Reuter 1983; 1985; Morselli, Giguère, and Petit 2007).

3. Methodology

This chapter introduces agent-based modeling (section 3.1) and presents the data sources, the model, and the simulations (sections 3.2, 3.3, and 3.4). Last, it concludes by displaying the data analysis strategies (section 3.5).

3.1. Agent-based modeling

Agent-based modeling (ABM) is one of the best-known methodologies in the field of complex systems; it is a technique used to conduct computer-based experiments (Wilensky and Rand 2015). ABM replicates virtual societies where agents interact among them and with an environment according to designated rules (Gilbert 2007). It has the power of recreating complex systems relying only on three constituent elements: agents, rules of interactions among these agents, and the environment within which the agents are embedded (Gilbert 2007; Bianchi and Squazzoni 2015; Gerritsen 2015; Calderoni et al. 2021). Starting from individual dynamics at the microlevel among these basic factors, ABM allows the detection of emergent macrophenomena (Groff and Mazerolle 2008; Wilensky and Rand 2015; Bianchi and Squazzoni 2015; 2020; Elsawah et al. 2020; Schwarz et al. 2020; Wilensky 2021; An et al. 2021; Calderoni et al. 2021).

One peculiarity of ABM is that agents are autonomous entities assigned a set of individual characteristics that are allowed to be extremely heterogeneous, in contrast with equation-based models that have homogeneity as one of their main assumptions (Wilensky and Rand 2015; Bianchi and Squazzoni 2020). This heterogeneity influences the performance of the simulated system, and it enables the possibility of reproducing very complex interactions among agents (Wilensky and Rand 2015; Calderoni et al. 2021).

Agents behave according to the rules of interactions established by the model developer. These rules can be based on theoretical assumptions or on empirical evidence (Bianchi and Squazzoni 2015; Calderoni et al. 2021). In either cases, it is rarely possible to model every facet of reality; thus, ABM simulations are a simplified reality strictly dependent on the assumptions made by the designer of the model (Gerritsen 2015).

ABMs (agent-based models) are particularly useful for exploring social sciences dynamics due to the possibility of modeling heterogeneous agents and establishing a variety of interaction rules. Indeed, when considering human beings and collective entities, the assumption of homogeneity cannot be supported, and a mathematical description often produces an incomplete representation of reality (Wilensky and Rand 2015; Bianchi and Squazzoni 2015). In addition, ABM is a valuable alternative to real-world experiments due to its lower levels of ethical and security concerns (Berk 2008; Gerritsen 2015; Bianchi and Squazzoni 2020; Calderoni et al. 2021).

ABM has increasingly attracted interest in criminology. In this field, the possibility of conducting real-world experiments is more challenging than in the social sciences in general. First, there are ethical concerns about involving human beings in experiments due to the possibility of compromising their safety and quality of life. Second, there are privacy issues associated with collecting personal data on criminally-relevant aspects. (Calderoni et al. 2021; Groff, Johnson, and Thornton 2019). Finally, ABMs offer a valuable policy evaluation tool. Criminological theories can have strong implications, such as the development of strategies to contrast criminal activities, and crime prevention policies. These policies should require accurate testing before large-scale implementation. For the aforementioned security and ethical concerns, real-world testing is often impossible. (Groff and Mazerolle 2008; Calderoni et al. 2021).

Despite the relatively recent diffusion of ABM in criminology, a number of studies have explored several areas of interest such as the prediction of urban crime and the effectiveness of different preventive measures (e.g., Groff 2007; Wang, Liu, and Eck 2014; Weisburd et al. 2017; Zhu and Wang 2021); the recruitment to and withdrawal from organized crime (e.g., Calderoni et al. 2021; Acconcia et al. 2014); the countering of protection racketeering criminal groups (e.g., Elsenbroich 2017; Nardin et al. 2016; Nardin, Székely, and Andrighetto 2017; Székely, Nardin, and Andrighetto 2018); the exploration of the macro and micro dynamics of drug trafficking and dealing (e.g., Magliocca et al. 2019; 2022; Dray et al. 2008; Romano, Lomax, and Richmond 2009); and the assessment of criminal network resilience (e.g., Duxbury and Haynie 2019; 2020).

Nonetheless, no study has yet explored the resilience of DTOs when compelled to deal with law enforcement attempts at disruption. Magliocca and colleagues (2019; 2022) investigated the spatial displacement of narcotraffic organizations in Central America due to changing policy directions, disregarding specific strategies that organizations implement when directly subjected to law enforcement interventions. Dray and colleagues (2008) and Romano and colleagues (2009) focused their attention on the street-level market and how drug use is affected by the presence of police officials and treatment providers, overlooking the specificities of drug providers (e.g., individuals or organized groups). Duxbury and Haynie (2019; 2020) devoted their attention specifically to the resilience of criminal groups reacting to attempts at disruption; however, in one study, they examined only the structures of criminal networks involved in different criminal activities, disregarding the specificities of drug trafficking (Duxbury and Haynie 2019). In a second study, they explored the effects of attempts at disruption on a group of users exchanging drugs over the darknet (Duxbury and Haynie 2020). While offering useful insights, these studies provide only very general evidence of how organized crime groups in the drug market deal with law enforcement intentional attempts at disruption.

This study addresses these dynamics by developing an agent-based simulation. The author selected this methodology since it allows the gathering of empirical insights into a phenomenon that would be extremely challenging, if not impossible, to explore with field research due to the abovementioned security and ethical constraints. Moreover, starting from a few basic assumptions, ABM enhances the possibility of testing several "*what-if*" scenarios that are otherwise unexplorable.

The ABM was implemented using the software NetLogo (Wilensky 1999; 2021). Annex I reports additional information about the software and its functionalities.

3.2. Data sources

The rules governing the behaviors of the agents in an ABM can be established according to either theoretical assumptions or empirical evidence (Bianchi and Squazzoni 2015; Calderoni et al. 2021). The role of empirical evidence in developing an agent-based model is particularly relevant; it allows the alignment of the parameters of the model with mechanisms directly observed in a real-world environment. This enables the modeling of a scenario that is closer to the real world, and it increases the possibility of obtaining plausible results (Wilensky and Rand 2015).

Considering the focus of the present study, the reliance on strong empirical evidence is strategic. With the aim of expanding the knowledge of DTOs' resilience when confronted with law enforcement attempts at disruption, the similarity of the model to real-world dynamics is an essential precondition for identifying plausible theoretical and operational implications. With this purpose, the primary source of qualitative and quantitative information to calibrate the model was the Operation Beluga pretrial court order (hereafter "Beluga court order") (Tribunale di Napoli 2013). The main purpose of pretrial court orders is to limit the suspects' freedom by subjecting some of them to custody or pretrial detention. To do so, judges must thoroughly support their decision with evidence of the necessity of the precautionary measure (Calderoni

2012). For this reason, such court orders include many details about the suspects, their criminal activities, and their eventual organization, providing in-depth information that is also valuable for research purposes (Berlusconi 2013b; Bright et al. 2015; Calderoni 2012; 2014a; Morselli 2009b; Scaglione 2011; van der Hulst 2009).

3.2.1. Beluga case study: The Di Lauro clan and drug trafficking

The Beluga court order is 984 pages long and derives from an extensive police investigation of the *Camorra Di Lauro* clan that lasted more than 5 years, from December 2007 to April 2013. The investigators arrested 107 people. In contrast to the majority of cases, in Operation Beluga the arrests at the end of the investigation were not the only ones registered since some arrests were also registered during the investigations. Among these, on the December 21, 2010, 8 of the most prominent members of the *Di Lauro* clan were arrested, which had a strong impact on the criminal organization overall.

The *Di Lauro* clan is a *Camorra* group rooted in the northern part of Naples, in the area of the *Rione Terzo Mondo* (Tribunale di Napoli 2013). In the 2000s, the *Di Lauro* clan had strong control over the neighborhoods of *Secondigliano* and *Scampia*. The boss of the clan was Paolo Di Lauro, a highly competent drug trafficker who coordinated several other clan members. After Paolo Di Lauro became a fugitive, his sons took control of the group, but they were not as determined and respected as their father, and some rivals started to threaten the hegemony of the clan (Brancaccio 2014; Direzione Investigativa Antimafia 2012). The Beluga investigation covered the organization's activities in the context of the conflicts following the struggles of the Di Lauro brothers to manage the group (Direzione Investigativa Antimafia 2012; Tribunale di Napoli 2013).

The criminal group conducted several criminal activities, including general control and influence over the territory, drug trafficking and dealing, illicit firearms trafficking, and some illegal gambling activities. The illicit drug trade was the core activity of the group. The seizure of 172 accounting books demonstrated that the majority of the clan's revenues came from trafficking and retailing illicit drugs (Tribunale di Napoli 2013). Retailing drugs was clearly divided and organized in two open-air areas, both located in the *Rione Terzo Mondo*: in the area located in *Praga Magica* Street, hashish and marijuana were exclusively sold, whereas the area located in *Il Barbiere di Siviglia* Street was used exclusively to sell cocaine and crack. The dealing activities were meticulously organized, and at every moment, it was possible to know the quantity and type of drugs sold by each retailer. The management of these open-air markets required a complex internal organization that was revealed by information from the account books. Affiliates involved in drug trafficking and packaging activities received a fixed weekly payment, the so-called "*settimana*". Affiliates who were only involved, or also involved, in drug dealing at the street level were paid daily with a percentage of their sales (Tribunale di Napoli 2013). The revenues allowed the clan to purchase arms and munitions; to corrupt public officers; to financially support the relatives of incarcerated affiliates; to pay legal expenses for charged affiliates; to rent warehouses for cars, drugs, arms; and to pay for some personal purchases (Tribunale di Napoli 2013).

The richness of the data included in the Beluga court order and the peculiarities of the investigation make it an ideal source to inform and calibrate the ABM. It includes detailed information on both criminal actors and activities over a prolonged period, allowing the DTO structure and *modus operandi* to be inferred. It reports a rare case of some arrests of prominent members before the end of the investigation, providing information about real DTO reactions to a major attempt at disruption. It provides extremely detailed information on drug trafficking and dealing costs and revenues, offering the possibility of characterizing DTO behaviors from an economic point of view. All these elements are strategic for the calibration of the ABM.

3.2.2. Other sources

While the majority of quantitative and qualitative information derives from the Beluga court order, the characterization and calibration of the model also rely on other sources.

The first additional source is drug price information retrieved from UNODC. Specifically, the ABM uses as input the cocaine wholesale prices reported for Italy from 2008 to 2010. Moreover, the model relies on cocaine wholesale prices reported for other European countries for the same period as a basis for the simulation of wholesale price variability among different drug acquisitions over time (UNODC 2008; 2009; 2010).

The second additional source of information is the scientific criminological literature. In cases in which neither the Beluga court order nor other empirical sources could provide input data for the model, the author relied on information retrieved from the scientific literature. This comprises, for example, the factors included in the operationalization of the security vs. efficiency trade-off, the features characterizing attempts at disruption, the elements evaluated when making decisions about drug acquisitions, and the choices of criminal collaborators.[2]

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[2] Punctual references to the criminological literature are provided in section 3.3 presenting the model and in Annex II, where the model procedures are further detailed.

3.2.3. Generalizability of Beluga court order information

The calibration of the ABM relies on qualitative and especially quantitative data retrieved from the Beluga court order. This choice poses some challenges to the generalizability of the model, regarding the eventual overfitting of the model to the organization targeted by Operation Beluga (hereafter "Beluga group") and the consequent questionability of extending the results from the model to DTOs in general. However, several motivations behind the development of the ABM, and measures adopted while building the model indicate the possibility of generalizing the results of the research.

The first criticality may arise from the Beluga group being a *Camorra* group involved in drug trafficking activities. The *Camorra* has some traits of mafia-type organizations, which may influence the way in which the organization conducts its criminal activities. A specificity of mafias is that of having extensive control over specific territories and/or economic activities, supplanting legal authorities in the provision of certain essential services to the population (Gambetta 1993; Kleemans 2014). Nonetheless, the protection and racketeering market are certainly an important part of Italian mafias such as the *Cosa Nostra* or the *'Ndrangheta*, while they are much less relevant for the *Camorra*. Indeed, criminal organizations from the Campania region are different from other Italian mafia groups, mostly due to their internal fragmentation (Becucci 2004; Catino 2019; Direzione Investigativa Antimafia 2012; Direzione Nazionale Antimafia 2018). The *Camorra* comprises different urban clans, families and groups that form fast-changing coalitions and competitions to dominate a specific illegal market or delimited territory (Reuter and Paoli 2020; Catino 1997; 2019; Scaglione 2016; Direzione Nazionale Antimafia 2018). In contrast to other mafias, the *Camorra* lacks an apical body controlling, managing and governing the whole group (Reuter and Paoli 2020; Brancaccio 2014; Scaglione 2016; Catino 1997; 2019; Europol 2013). The absence of such a defined and hierarchical structure often leads to excessive use of violence, resulting in frequent feuds and struggles among clans (Catino 1997; Beatrice 2017). These features make *Camorra* groups much more similar in terms of structures and dynamics to nonmafia DTOs (Reuter and Paoli 2020; Catino 2014; 2019; Paoli 2014b; 2015; Scaglione 2016; Dugato, Calderoni, and Berlusconi 2017). Moreover, the evidence on the Beluga group shows important similarities with DTOs from other social and geographical contexts.

First, the internal structure and functioning of the Beluga group are similar to those of other drug trafficking groups. There is an extensive qualitative literature examining the structures and *modi operandi* of criminal organizations involved in drug trafficking activities. While this literature (e.g., Natarajan and Belanger 1998; Curtis 1996; Natarajan, Zanella, and Yu 2015; Desroches 2005; 2007) does not focus on mafia-type organizations, it points out dynamics and practices that are similar to those reported in the Beluga court order. For example, the organizational structure of the Beluga group falls within the categories of communal business and corporations defined by Curtis (1996) and repeatedly used by Natarajan and colleagues (1998; 2015). The presence of common cultural values and ethnic ties among members is an important trust-building element, and members are explicitly assigned to tasks, establishing hierarchies in the group.

Second, the Beluga group is predominantly involved in the wholesale and regional distribution of drugs, with no direct contacts in the producing countries. This is consistent with the results of Natarajan and colleagues (1998; 2015), who, relying on the classification of Johnson and colleagues (1992), found that it is more likely that organizations will engage in just a few stages of the process, such as wholesale and regional distribution, rather than being involved in all stages from production to retail activities.

Third, the *modus operandi* of the Beluga group is coherent with information from previous studies. In particular, the priority of the organization is making profits, even at the cost of sacrificing some low-level members who are considered expendable and replaceable (e.g., Desroches 2007). In addition, many strategies commonly reported as protective measures to minimize the risks to the business are recurrent practices in the events documented in the Beluga court order. Among them are the habit of working in small teams of associates (e.g., Desroches 2005; Kenney 2007; Calderoni and Piccardi 2014); the compartmentalization of information on the basis of the “need-to-know” principle (e.g., Desroches 2005; Kenney 2007; Calderoni and Piccardi 2014; Duijn, Kashirin, and Sloot 2014); the delegation of risky activities to medium- and low-ranking members (e.g., Desroches 2005; Kenney 2007; Calderoni 2014b); the reliance on different channels for the acquisition, processing and selling of drugs (e.g., Desroches 2005; Kenney 2007); and consistent payments to workers, associates and their families to minimize the risk of betrayal (e.g., Desroches 2005; Kenney 2007).

The second criticality is that the Beluga group is involved in other criminal activities beyond drug trafficking. This may affect the way in which drug trafficking and dealing are performed, eventually blurring the dynamics inherent to criminal organizations involved in drug trafficking only. However, this second criticality does not preclude the possibility of generalizing the results from the present study. Information in the Beluga court order is extremely detailed. This allowed the factors that influence group drug trafficking activities to be distinguished and isolated from those that are unrelated. For example, among the members of the Beluga group, only those accomplishing specific drug trafficking and dealing activities were included in the model. Even when considering the accounting of the group profits, the information provided by the court order is highly precise, allowing for the costs and revenues originating from the sales of different drugs to be distinguished.

For the reasons expressed above, the Beluga court order is a reliable source of information for calibrating an ABM of DTO activities and reactions to attempts at disruption. With the necessary caution, the information from the Beluga group can be generalized to other DTOs. The model supports many of the qualitative features of DTOs that are already widely recognized in the literature, and it provides a substantial contribution due to the richness of the quantitative information it contains. The possibility of relying on such precise input data is a significant added value, especially in a field such as criminology, where precise estimates of criminal profits are always difficult to obtain.

3.3. MADTOR: Model for Assessing Drug Trafficking Organizations Resilience

This section describes MADTOR, the ABM built to simulate drug trafficking and dealing activities by organized criminal groups and their reactions to law enforcement attempts at disruption. MADTOR was developed using version 6.2.0 of NetLogo (Wilensky 1999; 2021). Section 3.3.1 presents the main choices behind the development of the model, section 3.3.2 provides an overview of the model, and section 3.3.3 reports the temporal aspects of the model. Annex II and Annex III provide further methodological details about the development of MADTOR.[3]

3.3.1. Preliminary assumptions

The realistic simulation of DTO criminal activities and of the environment in which DTO members are embedded requires a few preliminary assumptions.

First, MADTOR focuses on cocaine trafficking. In the real world, DTOs differ in the type of drug they deal with, and a single DTO can be involved in the trafficking of multiple drugs simultaneously. However, trafficking and selling different drugs influence a variety of dynamics (e.g., countries of acquisition, processes of manufacturing, risks to conducting the

[3] The model and its code are available and downloadable here: https://www.comses.net/codebase-release/a5543b7a-8ed1-413b-88b8-5a44aed06c0d/

business, and costs and revenues), precluding the possibility of developing a single model aggregating the trafficking and dealing of multiple drugs. Considering that available data, both from the literature and from the Beluga court order, are significantly richer in relation to cocaine than to other drugs,[4] the focus on cocaine allows a simulation suitably close to reality in its input data and dynamics. Future research may build on the model to address the trafficking of other drugs.

Second, MADTOR disregards the production of cocaine. The Beluga group was not involved in this stage of the drug market. Furthermore, previous research has indicated that cocaine production is often performed by groups solely in charge of this step and possibly of manufacturing and trafficking from production countries to destination countries. These groups have limited influences in the subsequent wholesale and regional distribution phases, the main focus of the present study (Reuter and Haaga 1989; Curtis 1996; Zaitch 2002b; Natarajan and Belanger 1998; Natarajan, Zanella, and Yu 2015; Benson and Decker 2010; Decker and Chapman 2008; Reuter 2014).

Third, the “KISS” (i.e., “Keep it simple, stupid!”) ABM principle demands reducing the complexity of drug trafficking and dealing activities to the minimum. Indeed, a simple model is critical to disentangling and interpreting the effects of the hypothesized mechanisms (Axelrod 1997b; 1997a; Groff, Johnson, and Thornton 2019).

In MADTOR, drug trafficking and dealing activities comprise four steps:

1. Drug acquisition,
2. Drug processing and packaging,
3. Drug sales, and
4. Accounting of expenses.

These steps, while certainly overlooking some specificities of a complex process, mirror the macroscopic aspects of the phenomenon. They were chosen because they are clearly portrayed

[4] The literature provides a variety of information on the trafficking of cocaine and criminal organizations active in it. These studies focus on cocaine trafficking routes (e.g., Zaitch 2003; Kenney 2007; Caunic, Suciu, and Muntele 2011; Schultze-Kraft 2014; Eventon and Bewley-Taylor 2016; Benítez et al. 2019; Magliocca et al. 2019); on the financial management and profitability of cocaine markets (e.g., O’Hagan and McNicholl 2015; Hall and Antonopoulos 2017; Aziani 2018; Terenghi 2020); and on the structure and social organization of the actors involved in the activity (e.g., Reuter and Haaga 1989; Johnson, Hamid, and Sanabria 1992; Fuentes 1998; Natarajan 2000; Zaitch 2002b; 2002a; Gruter and Mheen 2006; Morselli and Petit 2007; Mejía and Posada 2008; Kostakos and Antonopoulos 2010; Giménez-Salinas Framis 2011; Paoli, Greenfield, and Zoutendijk 2013; Calderoni 2012; 2014b; Calderoni, Skillicorn, and Zheng 2014; Hofmann and Gallupe 2015; Chandra and Joba 2015; Caulkins et al. 2016; Calandra 2017; Stevanović 2020; Roks, Bisschop, and Staring 2021).

in the Beluga court order (Tribunale di Napoli 2013), they are recurrent steps in the existing crime script analysis of drug trafficking (Chiu, Leclerc, and Townsley 2011; Bright and Delaney 2013; Le 2013; Madarie and Kruisbergen 2020), and they are corroborated by the literature (Natarajan and Belanger 1998; Natarajan 2000; 2006; Bright, Hughes, and Chalmers 2012; Calderoni 2012; 2019).

The drug acquisition step consists of DTOs obtaining large quantities of drugs owing to specific members of the organization who are in charge of this task (Natarajan and Belanger 1998; Natarajan 2000; 2006; Bright, Hughes, and Chalmers 2012; Calderoni 2012; 2019).

Drug processing and packaging are sometimes disregarded in the literature. However, previous research has identified some support figures (e.g., workers/laborers, supporters, and field workers) who are often assigned to unspecified tasks. These members accomplish a variety of operational activities that are mostly functional in drug dealing activities (Natarajan 2000; Bright, Hughes, and Chalmers 2012; Calderoni 2012). The Beluga group includes members charged with receiving large quantities of drugs and preparing the unit-dose packages to be delivered to retailers.

The drug sales step consists of selling unit-dose quantities of a drug to the end users, and it is performed by members of the organization specifically in charge of retailing activities (Natarajan and Belanger 1998; Natarajan 2006; Calderoni 2012).

The last step is the payment of a series of expenses that managers of the DTOs need to deal with periodically. The existence of strategic financial management of criminal organizations has been recognized by the criminological literature; however, it has been relatively unexplored, especially from a quantitative point of view, due to the lack of precise and reliable information and data. The Beluga court order allows an array of expenses and strategies for the financial administration of the DTO to be identified and quantified; thus, the model also portrays these aspects.

Fourth, MADTOR includes DTOs adopting different strategies in dealing with the security vs. efficiency trade-off (Morselli, Giguère, and Petit 2007). This allows the resilience of groups with different focuses between security and efficiency to be assessed.[5] The strategy impacts

[5] In the model the security vs. efficiency trade-off is operationalized with an indicator ranging from 0 to 1. DTOs scoring 0 in this indicator are the most secure (and the least efficient). In contrast, DTOs scoring 1 in this indicator are the most efficient (and the least secure). DTOs reporting intermediate values are proportionally positioned in the continuum, with values closer to 0 identifying organizations prioritizing more security, and values closer to 1 identifying organizations prioritizing more efficiency.

four elements: the amounts of drugs acquired and available to the organization; the process of recruiting new actors, assigning tasks to members, and patterns of interaction in the organizations; the wages paid to members of the organization; and the likelihood of being periodically targeted by minor and major arrests performed by law enforcement.

First, in relation to amounts of drugs, organizations prioritizing security or efficiency may differ in the amounts of drugs they acquire and stock. Organizations more oriented toward security may acquire moderate quantities of drugs and allow single members to store smaller drug packages. This reduces drug losses in case of attempts at disruption and seizures, but it constrains the possibility of meeting unexpected increases in demand for a drug. In contrast, efficient organizations allow more numerous and larger drug acquisitions and disposals. This enables the possibility of higher profits in the case of unexpected drug demand, but it also generates greater losses in the case of law enforcement interventions (Eilstrup-Sangiovanni and Jones 2008; Morselli 2010b; Bright, Hughes, and Chalmers 2012; Gravel and Tita 2017).

Second, DTOs may follow different procedures when recruiting new members and assigning them to specific tasks. Secure organizations are very cautious in selecting and enrolling new actors; new members are recruited only if they are extremely trusted, with the aim of minimizing betrayals. The drawback is that the organization may face workforce scarcity, thus slowing the criminal business. Conversely, efficient organizations prioritize the continuity of the criminal business and they recruit new actors with fewer constraints, emphasizing their criminal ability and disregarding how much they can be trusted. Similarly, when assigning specific tasks to members, secure and efficient organizations differ in their procedures, resulting in diversified patterns of interaction. While secure organizations prioritize reliance on fewer trusted contacts among niches of the organization that recurrently perform criminal activities together, efficient organizations are open to shifting groups of collaborators from time to time with the aim of maximizing the profitability of their business (Giménez-Salinas Framis and Fernández Regadera 2017; Duxbury and Haynie 2019).

Third, DTOs may differ regarding the wages they pay to their members. Secure organizations give great importance to guaranteeing their members a relatively low risk when performing their criminal business. This results in lower profits for the organization, since some resources are used to increase the security of the group. Having lower profits, secure organizations can offer their members more exiguous wages. In contrast, efficient organizations emphasize the importance of making profits, even if this results in facing greater risks of apprehension. The reward offered to members for tolerating this high level of risk is remuneration with more generous wages (Morselli and Petit 2007; Paoli, Greenfield, and Reuter 2009).

Fourth, the likelihood of attempts at disruption by law enforcement varies depending on the security/efficiency focus. Prioritizing efficiency increases the visibility of an organization. Efficient DTOs are more likely to face periodic attempts at disruption. Conversely, secure DTOs may more effectively avoid attempts at disruption (Morselli and Petit 2007; Paoli, Greenfield, and Reuter 2009).

While this mechanism models most aspects identified in the literature as relevant in the security vs. efficiency trade-off, it does so in a simplified way. This, as in all the other simplifications implemented, was necessary for the model to remain feasible, but it at least partially affects the results of the model (e.g., tying some features to the security vs. efficiency trade-off when they are not or vice versa or failing to set accurate differentiating thresholds for secure and efficient DTOs).[6]

Finally, the last assumption behind the functioning of the model relates to law enforcement interventions targeting DTOs. First, DTOs must routinely face minor attempts at disruption; on a monthly basis, at least one member of the DTO may be arrested by law enforcement. Second, each DTO faces a major disruptive event at least once during the simulation. These major disruptive events have varying intensities, targets, timings, and frequencies. The specificities of both minor and major attempts at disruption relate to the security/efficiency focus of the DTOs, with DTOs prioritizing efficiency being targeted more often and more severely due to their high visibility and DTOs prioritizing security being targeted less often and less intensely due to their ability to hide their criminal activities from law enforcement (see sections 3.3.2 and 3.4).

3.3.2. Overview of the model

The aim of MADTOR is to examine DTOs' resistance and resilience to law enforcement attempts at disruption and investigate their reactions to external threats and strategies to survive

[6] The security vs. efficiency trade-off has received substantial scholarly attention (e.g., Morselli, Giguère, and Petit 2007; Morselli 2010; Paoli, Greenfield, and Reuter 2009; Eilstrup-Sangiovanni and Jones 2008; Bright, Hughes, and Chalmers 2012; Gravel and Tita 2017; Giménez-Salinas Framis and Fernández Regadera 2017; Calderoni 2014b; 2018; Berlusconi 2021). However, no study has operationalized the concept and tested how it affects the performance of criminal activities, and specifically the performance of drug trafficking and dealing. While the ABM developed by this study incorporates the most relevant insights from the literature, there is no evidence attesting that the thresholds set for secure and efficient organizations are accurate and coherent with real criminal organizations. Nonetheless, relying on a continuum of values for the security vs. efficiency trade-off indicator increases the confidence that the model captures dynamics similar to those of reality.

disruption. To accomplish this aim, MADTOR simulates DTOs members' drug trafficking and dealing day-to-day activities for a period of 5 years. During these 5 years of criminal involvement, DTO members must confront the threat of law enforcement interventions intended to jeopardize their trafficking and dealing activities.

During the setup phase, the data used for the calibration are imported into the model. This comprises information related to the structure and features of the DTO (i.e., members and their relational patterns) as reported by the Beluga court order and data related to DTO drug trafficking and dealing activities (i.e., quantities of drug stored and sold, drug wholesale and retail costs, drug prices for end users, and DTO members' rewards for trafficking). The model updates these input data once every 30 simulated days to resemble the structure of the Beluga group and the environment in which they operated over time.[7]

At the beginning of the simulation, the DTO comprises 44 members, each with a specific task within the organization. Specifically, 5 members are active in the trafficking activities of the DTO (i.e., the drug acquisition step), 5 members oversee the production of unit-dose packages of drugs (i.e., the drug processing and packaging step), and the remaining 34 members perform the dealing activities (i.e., the drug sales step). Over time, the DTO criminal workforce may vary with the recruitment or defection of members. The recruitment of new members is based on the need to have enough personnel to accommodate the DTO's current workload. The defection of members may be due to different reasons: the personal choice of some members to leave the organization, sporadic arrests performed by law enforcement, and the deaths of some members. Overall, during the simulated period, the DTO workforce substantially increases, registering the greatest expansion in its first year of criminal involvement (i.e., from 44 members to an average of almost 58 members) and then recording more stable growth rates over the following years (i.e., with an average of almost 64 members). The proportion of members accomplishing the different tasks in the organization does not register substantial modification over the simulated period.

DTO members, after their recruitment to the organization, are characterized by two features: a certain level of criminal ability (randomly assigned at the beginning of the simulation) and a level of connectivity with each of the other members of the organization (according to the Beluga court order information). The model updates these features every simulated day to

[7] The Beluga court order provides data and information to update the calibration of MADTOR for the first two simulated years. After this timeframe, the model parameters directly calibrated from the court order are estimated following the trends observed in the preceding period. More information is available in Annex II.

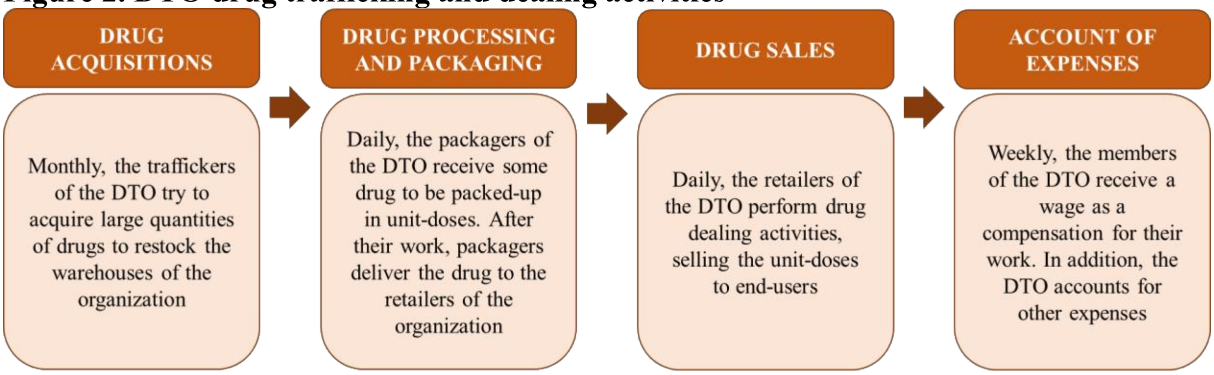
capture eventual increases/decreases in criminal skills and changing patterns of interaction among members.[8]

Regarding DTO drug trafficking and dealing activities, during the five simulated years, the traffickers of the DTOs acquire the drugs at the wholesale level for 42€/kg on average. Every simulated day, the DTO can sustain on average a volume of sales of almost 1,900 drug doses of 0.25 g each, which are sold to end users at an average price of approximately 32€ per dose.

During the simulation, DTO members perform a variety of actions to accomplish their drug trafficking and dealing activities and to earn their expected profits. While performing these activities, DTO members interact with each other. Each drug exchange among DTO members establishes a relational tie between the involved actors, and each additional relational tie among the same actors strengthens their connectivity. This forges the patterns of interaction in the organization.

Figure 2 displays and summarizes the day-to-day activities performed by the DTO and its members.

Figure 2. DTO drug trafficking and dealing activities



Source: Author's elaboration

The first activity that MADTOR simulates is drug acquisition. Indeed, the prerequisite for making profits from selling drugs is having drugs available. The traffickers of the organization are the individuals charged with the acquisition of large quantities of drugs. Once a month, they explore the possibility of acquiring drugs considering the following factors: the amount of drugs already available in the DTO warehouses (i.e., the greater the quantity of drugs available, the less urgent a new acquisition is); the favorability of the wholesale price (i.e., the higher the price, the lower the willingness to acquire new drugs); and the favorability of the market

[8] Members' individual attributes are not calibrated with empirical data. They have their theoretical foundation in the literature (e.g., Duxbury and Haynie 2019; Weisburd et al. 2017; Birks, Townsley, and Stewart 2012). More information is available in Annex II.

conditions, including the availability of drugs in the market and the expected risk of apprehension. (i.e., the more adverse the conditions are, the less likely a drug acquisition is).[9] After every attempt at acquisition, both successful and failed, the model updates the traffickers' criminal abilities. Positive acquisition outcomes result in an increase in criminal abilities; conversely, negative acquisition outcomes lead to a decrease in traffickers' criminal abilities.

The second activity that MADTOR simulates is the making of unit-dose packages of drug. The packagers of the DTO are the members specifically charged with this activity. Every simulated day on which they receive large quantities of drugs from the traffickers, they package the drug doses and deliver them to the retailers of the organization.[10] A critical factor for the performance of this step is the *criteria* that members utilize to decide on their criminal collaborators (i.e., the packagers to whom the traffickers deliver the acquired drugs and the retailers to whom the packagers deliver the unit doses). These *criteria* change according to the DTO security/efficiency focus; while members of secure organizations favor working relations with trusted and unexposed actors, members of efficient organizations privilege working relations with skilled and networked actors. This results in differentiated relational patterns in DTOs having a diversified positioning in the security vs. efficiency trade-off.[11]

The third activity that MADTOR simulates is the retailing of drugs. Every simulated day, the retailers of the organization sell unit-dose packages of drugs to consumers and cash in the DTO

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[9] MADTOR simulates the performance of drug acquisitions by DTOs traffickers once over 30 simulated days, and this takes place on a probability basis. The traffickers attempt to acquire drugs only when the warehouses of the organization have available capacity; in these circumstances, a composite index evaluating the amount of drugs the DTO already has in stock, the market conditions, and the drug wholesale price at the moment of the possible acquisition is computed. The level of criminal abilities of the trafficker attempting the acquisition is also incorporated into the acquisition outcome (i.e., the greater the criminal skills of the trafficker, the more likely the drug acquisition). The DTOs' position in the security/efficiency trade-off affects the parametrization of the composite index, making drug acquisitions more probable for efficient DTOs due to fewer constraints in terms of individual and organizational protective measures.

[10] MADTOR abstractly simulates the processing and packaging of drug. This step includes only two drug exchanges: the first from traffickers to packagers and the second from packagers to retailers. In between these two drug exchanges, DTOs packagers are supposed to package the drug doses. To increase the realism of this step, the model sets a maximum threshold for the quantity of drug each packager can receive and deliver in a single simulated day. This accounts for the workload that packagers can sustain every day.

[11] MADTOR models members' patterns of interaction, evaluating both members' individual features and their position in the organization. Specifically, four elements are considered: the familiarity between pairs of actors (i.e., how many drug exchanges two specific actors have already performed together), the trustworthiness of actors (i.e., how visible an actor is with respect to others DTO members in terms of the number of direct connections with others), DTO members' criminal abilities (i.e., the already mentioned randomly assigned score signaling actors' criminal skills), and the closeness of the actor to others (i.e., the SNA metric of closeness centrality). In DTOs that prioritize security, members privilege establishing relations with actors with whom they are familiar and whom they consider trustworthy. In DTOs that prioritize efficiency, members favor relations with actors who are highly skilled and centrally positioned in the organization. More information is available in Annex II.

revenues for the involvement in drug trafficking and dealing.[12] In doing so, the retailers retain an established percentage of the revenues (i.e., 18%) as compensation for their involvement and deliver the remaining portion to the managerial figures of the organization. As established by the DTO managerial figures, each retailer is not allowed to exceed the personal daily profit threshold of 500€; thus, once they have reached that threshold, they stop selling for that day.

After the performance of drug acquisitions and sales, once the revenues from drug dealing activities have been cashed in, the managers of the DTO deal with the costs and expenses for their involvement in drug trafficking and dealing. MADTOR abstractly accounts for expenses. There are no specific DTO members in charge of this step; it accounts for the reduction of the available money due to a variety of expenses that are sustained by the DTO overall. Specifically, there are three categories of weekly expenses that the DTO must pay: the wages of traffickers and packagers (who in contrast to the retailers earn a fixed weekly salary unrelated to drug dealing activities); payments to the families of some arrested or deceased members; and payments for other variable expenses (e.g., bribes to corrupt public officials, payments to lawyers in charge of defending DTO members in trials, and rent for warehouses where the drugs are stored) (see Annex II, "The account-for-expenses procedure" section for details). Despite covering the costs in various ways related to drug trafficking and dealing activities, money is also withdrawn from the DTO cashbox weekly as the personal profits of the bosses of the organization for their involvement in drug trafficking and dealing.

In the simulated environment, the members of the DTO perform these activities (i.e., drug acquisitions, drug packaging, drug sales, and payment of expenses) on a continuous basis for a period lasting five years. During this period, the DTO also faces minor and major law enforcement attempts to put an end to its criminal activities.

In relation to minor law enforcement attempts at disruption, MADTOR simulates the possibility that every month, the DTO may face the arrest of an unspecified member of the organization. The probability of being targeted by these sporadic periodic arrests is linked to the DTO security/efficiency focus, with secure DTOs having the lowest probability and efficient DTOs having the highest probability of experiencing periodic attempts at disruption.

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[12] Every simulated day the model computes the number of drug doses to be sold that day by DTO retailers. To do so, the model relies on information about the number of doses sold by the Beluga group according to the court order. The exact number of doses results from a randomization between the minimum and maximum number of doses sold per day by the Beluga group. More information is available in Annex II.

In relation to major law enforcement attempts at disruption, MADTOR simulates three scenarios of major interventions with an increasing level of complexity.

In the first scenario, DTO members must confront one attempt at disruption after two years of performing their drug trafficking and dealing activities.[13] A set share of members is arrested and removed from the organization, and the amount of drugs at their disposal is seized by law enforcement. This scenario is the baseline for testing the DTO's resilience when being targeted by the same attempt at disruption, disregarding eventual DTOs specificities.

In the second scenario, the same attempt at disruption after two years of criminal activities is influenced by the DTO's security/efficiency focus. The share of arrested members and the amount of seized drugs vary according to the DTO security/efficiency focus. Secure organizations often succeed in minimizing arrests and seizures because they are better able to stay hidden and to implement protective measures. Conversely, the effectiveness of the attempt at disruption is maximized when the intervention targets efficient organizations, since these DTO members are much more visible and unprovided with protective measures, resulting in a higher number of members arrested.

The third scenario, which is the most complex, also considers that the number and timing of law enforcement interventions may vary according to the DTO security/efficiency focus. This scenario departs from the second one (where the magnitude of the attempt at disruption after two years varies according to the DTO's security/efficiency focus) by introducing the possibility of multiple attempts at disruption at different moments during the five simulated years. Efficient DTOs, due to their higher visibility, are likely to be targeted by law enforcement interventions more often and earlier (i.e., receiving 2 law enforcement interventions on average, from the second year of criminal involvement onward). In contrast, secure organizations, due to their ability to conceal their criminal activities, are likely to attract less attention from law enforcement, avoiding attempts at disruption for longer periods of time (i.e., receiving 1 law enforcement intervention on average, likely during the fourth or fifth year of criminal involvement).[14]

[13] The choice of simulating the attempt at disruption after two years of involvement in drug trafficking and dealing is twofold. On the one hand, it resembles the timing of the real attempt at disruption that targeted the Beluga group. This facilitates the calibration and validation of the model. On the other hand, it increases the robustness of the results. It allows the DTOs *modus operandi* in the two years before the attempt at disruption to be observed, allowing eventual significant modifications in the remaining years after the law enforcement intervention to be determined.

[14] Detailed information about the simulation of DTOs' drug trafficking and dealing and the modeling choices behind them is available in Annex II.

Law enforcement attempts at disruption undermine DTOs' ability to continue drug trafficking and dealing. Indeed, attempts at disruption may irreparably damage DTOs' available resources in terms of both financial capacity and workforce availability. In MADTOR, active DTOs are organizations that are involved daily in drug trafficking and dealing; disrupted DTOs are organizations that can no longer perform drug trafficking and dealing. Two alternative causes lead to DTO disruption: economic inefficiency or law enforcement interventions.

Regarding the former, DTOs may be unable to gain enough profits to be sustainable over time. This may mean that DTO traffickers are able to acquire too small an amount of drugs, DTO retailers sell too few drug doses to end users, DTOs sustain too many expenses, etc. This cause of disruption may intervene both before and after the occurrence of any attempt at disruption; in the second case, it is likely that the cause, or at least a strongly contributing factor, of the shortage in resources is the scarcity in drug (due to seizures) or workforce (due to arrests) provoked by law enforcement interventions.

Regarding the latter, DTOs may be unable to protract their criminal involvement as a direct consequence of law enforcement interventions. This happens when the organization can no longer count on any member performing a specific task due to attempts at disruption, and it is incapable of recruiting new members to replace the arrested ones in a short period.[15]

3.3.3. Temporal aspects of the model

The "tick" is the time measurement unit in NetLogo. Each simulation tick represents the advancement of one time unit in the model. In the present ABM, each simulation tick is 1 day of real life. This is an arbitrary choice, and it should be adapted to the purposes of each model. Considering the *time-to-task* of DTOs and the necessity of observing the evolution of reactions

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[15] In most of the simulated cases (i.e., almost 99% of disrupted DTOs in the first law enforcement intervention scenario), the DTO's disruption is explicitly caused by economic inefficiency. The reason is that the attempts at disruption never target 100% of DTOs members (or 100% of members accomplishing a specific task); thus, it is highly unlikely that DTOs will terminate their criminal involvement due to the complete absence of actors in some categories. At the same time, it is far more likely that the attempts at disruption will reduce the organization, or some of its subgroups accomplishing specific tasks, to their minimum, with the consequence that in the short/medium term the DTO will no longer be economically sustainable. In these circumstances, while the cause of the disruption is explicitly economic inefficiency, the DTO's disruption is strongly related to the attempt at disruption, which implicitly induces DTOs failure.
The mentioned causes of DTOs disruption have different effects on the time frames of failure. While disruptions directly provoked by law enforcement interventions display their impact immediately after the occurrence of those interventions, disruptions that occur as an indirect consequence of the disruptive events may reveal their impact later. Indeed, immediately after attempts at disruption, DTOs continue their criminal involvement, relying on resources that are still available; however, in the short/medium term, available resources are no longer enough to grant economic sustainability, leading to DTO failure.

to law enforcement interventions, a longer time frame would not have allowed the granularity of the occurrences to be appreciated.

In MADTOR, the DTO members perform each activity only after a determined number of ticks have passed. For example, the DTO traffickers attempt to acquire drugs every 30 ticks (i.e., once a month), the traffickers and packagers receive their wages every 7 ticks (i.e., once a week), and the retailers sell unit-dose packages of drugs to end users every tick (i.e., daily).

3.4. Experimental design

One of the main advantages of ABM is the possibility of accounting for the heterogeneity of the agents (Wilensky and Rand 2015; Bianchi and Squazzoni 2020; Calderoni et al. 2021). The heterogeneity of actors and elements of stochasticity in the model imply that every run of the model, even under the same initial conditions, may yield different results. This leads to the need to run several iterations of the model to properly characterize it because a single run, considering the stochastic components, could produce anomalous patterns of behaviors. In contrast, running the model several times allows the usual model patterns of behavior to be identified (Wilensky and Rand 2015; Wilensky 2021).

To this end, the author ran multiple repetitions of MADTOR using BehaviorSpace, an integrated tool of NetLogo. BehaviorSpace allowed several iterations of the model, systematically varying its settings and collecting the results from each iteration (Wilensky and Rand 2015; Wilensky 2021).

This study considers different submodels, resulting from the intersection of four experimental conditions:

1. The target of the disruptive event; the condition can take four values: all members, traffickers, packagers, and retailers.
2. The share of arrested members within the target category in the disruptive event; the share can take the following values: 0%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90%.
3. The DTO's focus in the efficiency vs. security trade-off; the efficiency vs. security focus assumes the following six values: 0, 0.2, 0.4, 0.6, 0.8, and 1, where 0 corresponds to maximally secure DTOs and 1 corresponds to maximally efficient DTOs.
4. The type of major law enforcement intervention according to the three scenarios presented in section 3.3.2.

4.1. One attempt at disruption for each DTO after two years, equal to any values of the efficiency vs. security focus;

4.2. One attempt at disruption for each DTO after two years, diversified according to the DTO's focus in the efficiency vs. security trade-off; and

4.3. Potential multiple attempts at disruption at various times, with varying probability and intensity according to the DTO's focus in the efficiency vs. security trade-off.[16]

This results in 264 combinations for each law enforcement intervention scenario considered, that is, a total of 792 combinations (i.e., 4*11*6*3).[17] Each of these combinations was repeated 100 times, which, according to the literature (e.g., Weisburd et al. 2017; Duxbury and Haynie 2019; 2020; Calderoni et al. 2021), is a sufficient number of iterations to achieve robust results while ensuring a reasonable computing time for running the whole experiment. Each simulation was run for 1,825 ticks, corresponding to 5 years of simulated time.[18] This time frame guarantees that a DTO, if resilient, has time to recover from law enforcement attempts at disruption.

Running the simulations for the first law enforcement intervention scenario took 510 computational hours and took place from 14 February 2022 to 6 March 2022. Running the simulations related to the second law enforcement intervention scenario took 530 computational hours and was performed from 14 to 24 April 2022. Running the simulations for the third law enforcement intervention scenario took place from 31 August to 19 September 2022 and took 1,130 computational hours. The author relied on three personal computers with similar computational power to run all the experiments.[19]

[16] Two subsets of 264 simulations each pertaining to the third scenario were implemented. Considering the lack of information about law enforcement intervention strategies, they utilized diversified parameters to calibrate the frequency of attempts at disruption for DTOs with different focuses in the security/efficiency trade-off.

[17] Despite the total of 792 combinations, the final analyses of the research project considered a selection of only 36 combinations for each law enforcement intervention scenario (i.e., 108 combinations). The complete data are available for future analyses. Section 4.1 "Selection of experimental combinations for the final analyses" provides more details about the process of selection.

[18] In the final version of the experiments, each simulation lasted 1,825 ticks, corresponding to 5 years of simulated time. However, in a previous version of the experiments, each simulation ran for 3,650 ticks, corresponding to 10 years of simulated time. The choice of reducing by half the duration of the simulations was driven by two factors. First, the trends of most variables were almost constant from year 5 to 10; thus, those additional years of simulations provide little additional knowledge. Second, the reduction also considerably reduced the computational time needed for the simulations.

[19] The first version of the experiments in which each simulation had the possibility of lasting up to 10 years of simulated time took 750 computational hours. The simulations were performed from 29 September 2021 to 19 October 2021 using two personal computers with similar computational power.

3.5. Data analysis

This section presents the analytical strategies of the research project. It first illustrates the techniques used to examine the data retrieved from the simulations and then provide information about the validation of the model. The author performed the analyses using version 4.1.3 of R studio.[20]

3.5.1. Data analysis techniques

To evaluate the impact of the simulated law enforcement interventions and to assess DTO resistance and resilience, the trends of some variables over time were compared for the different scenarios tested. When comparing DTOs experiencing diversified attempts at disruption (i.e., different proportions of members arrested or disruptive events with different targets), the expectation was that the trends of the variables would be indistinguishable before the attempts at disruption; instead, eventual differences after the attempts at disruption would be imputed to the impact of the law enforcement intervention. In contrast, when the goal was to investigate DTOs with different positions in the security vs. efficiency trade-off, diversified trends could be significant from the beginning of the simulations.

Starting from the definition of criminal network resilience delineated in section 2.2, in the following analyses, the author evaluates six resilience indicators, divided among the three dimensions of the definition (Table 1).[21]

Table 1. Resilience indicators

Dimension of criminal network resilience	Resilience indicator	Interpretation
Ability of enduring disruption	*Share of active DTOs*	The share of active DTOs provides information about the capacity of organizations to survive over time, enduring law enforcement interventions aiming to jeopardize DTO criminal activities. The higher the share of active DTOs, the higher the ability to endure disruption.

[20] The following R packages have been employed: tidyverse (Wickham et al. 2019), stringr (Wickham 2019), ggpubr (Kassambara 2020), ggplot2 (Wickham 2016), gtable (Wickham and Pedersen 2019), grid (R Core Team, R Foundation for Statistical Computing 2022).

[21] The author selected the resilience indicators based on the available information in the Beluga court order and on indicators already tested in previous studies. However, the possibility that these indicators do not capture or misinterpret some aspects of resilience cannot be excluded. This may impact the results obtained from the study. While running the simulations, a larger number of indicators was computed and saved. This included: the number of DTO members and their partition by task, the number of components in the network and the size of the largest component; the minimum, maximum, and average degree centrality of DTO members; DTO degree centralization; the minimum, maximum, and average betweenness centrality of DTO members; DTO betweenness centralization; and DTO average geodesic distance. "The compute-statistics procedure" section in Annex II provides additional details. Only a selection of these indicators was considered for the final analyses.

Dimension of criminal network resilience	Resilience indicator	Interpretation
Ability of reacting fast and efficiently to law enforcements interventions	*Number of DTOs members*	The number of DTO members indicates the level of well-being of the organization. The greater the members, the more prosperous the organization is. After an attempt at disruption, this indicator provides information about DTO capability to react quickly to the experienced threat. The quick recruitment of new members signals the ability to recover from the shock.
	DTOs normalized average degree centrality	Degree centrality is the number of direct connections between two actors. The average degree centrality represents, on average, how many direct contacts with others each member has. The normalized version of degree centrality allows indicators for networks that differ in size to be compared, accounting for the percentage of others to whom each actor is connected. On the one hand, direct connections increase reachability among actors; on the other hand, they increase actors' visibility. Thus, DTOs with different focuses in the security/efficiency trade-off may have diversified degree centrality. After an attempt at disruption, modifications in actors' average degree centrality signal changes in a DTO's *modus operandi*, providing information about its reactions to law enforcement interventions.
	DTOs normalized average betweenness centrality	Betweenness centrality is the number of times a specific node lies in the shortest path between two other nodes in the network. It provides information about DTO members covering brokerage positions in the organization. High values of betweenness centrality imply that some members control flows of communication in the network. DTOs with a different focus in the security vs. efficiency trade-off may display diversified patterns. Variations in this metric after an attempt at disruption signal modifications in a DTO's *modus operandi*, indicating strategies adopted and reactions to law enforcement interventions.
Ability of maintaining primary functions and activities unaltered after the attempt of disruption	*Amount of drug in stock*	The amount of drugs available in DTO warehouses is an indicator of a DTO's level of well-being and its ability to protract proficient drug trafficking and dealing. High fluctuations in the quantities of drugs in stock signal the ability of DTOs traffickers to acquire drugs and the subsequent abilities of packagers and retailers to process and sell them. Modifications in this indicator after an attempt at disruption provide information about the eventual inability of DTOs to continue drug trafficking and dealing activities.
	DTOs revenues	The revenues that DTOs earn from their criminal activities is another immediate indicator of their capacity to perform drug trafficking and dealing and to profit from their criminal involvement. Major reductions in DTO revenues after an attempt at disruption signal the inability of the organizations to maintain its involvement in drug trafficking and dealing due to law enforcement interventions.

Source: Author's elaboration

Considering the virtual nature of the environment in which the DTOs operated, the interest is not in the effects on each simulated organization (i.e., each iteration of the model). Instead, the aim is to examine the magnitude and significance of the average effect of law enforcement interventions in simulations with the same initial conditions (i.e., the combinations resulting from the intersection of the experimental conditions).

To do so, the author aggregated the resilience indicator values for each step of the simulations (i.e., for each tick) in every iteration of the model with the same initial conditions. This means that the value of every resilience indicator for each combination tested results, at the beginning of the simulations, in an average of 100 values (since every combination was repeated 100 times). For subsequent simulation steps, the average value of the resilience indicators may be computed with fewer than 100 values; specifically, it includes the number of values corresponding to the active DTOs in that tick (i.e., there are no values for disrupted DTOs).

To test the significance of the differences observed among the combinations, the author relies on randomization-based two-sample Student's t tests and on the computation of confidence intervals. Randomization-based t tests are a nonparametric technique that relies on data permutation to infer significant differences among groups. It is well suited to testing differences among simulated data since it makes no assumptions about the data distribution and does not require a random sample of data from a general population. Randomization-based t tests also allow the computation of empirical p values (i.e., based on observed rather than theoretical data).

Randomization-based t tests are computed both for the entire time series between the two selected combinations (i.e., between the average values over time) and for specific points in time between the 100 iterations of the two selected combinations. The first allows a single empirical p value that provides information about the significance of the difference between the trends over time of two combinations; the second enables the evaluation of significant differences in specific sections of the time series, providing empirical p values for each point in time.[22] The second category of randomization-based t tests allows eventual differences provoked by law enforcement interventions to be identified. Indeed, the two combinations should be indistinguishable (apart from the effects of the stochastic elements included in the

[22] For the resilience indicator providing information about the share of active DTOs, only randomization-based t tests between the entire time series were computed. This indicator reports the number of surviving organizations in the 100 iterations of the model run with the same initial conditions; thus, as itis not an average of multiple values, it is not possible to compute the second typology of randomization-based t test mentioned.

model) before the attempts at disruption; conversely, after an attempt at disruption, it should be possible to observe the impact, if any, of the simulated interventions.[23]

Confidence intervals are then computed not only to provide information on the significance of the differences among combinations but also to examine the magnitude of the effects caused by law enforcement interventions.

3.5.2. Validation of MADTOR

MADTOR was developed with the intention of reconstructing plausible drug trafficking and dealing dynamics, both in relation to the performance of criminal activities and in relation to DTO members' behaviors. To calibrate the model, the author relied heavily on available quantitative data (mainly from the Beluga court order) and qualitative information both from the court order and from criminological theories and the literature. Indeed, adherence to real-life dynamics is the prerequisite for obtaining informative model outcomes. With this aim, the author validated the model on the basis of empirical data retrieved from the Beluga court order. In the simulations, the values fluctuated between the minimum and maximum of the real data figures to avoid an excessively deterministic approach. Table 2 reports the trends of some variables monitored over the five simulated years for the 4,800 simulations included in the final analyses when considering the first law enforcement intervention scenario.[24] These statistics provide a preliminary overview of the simulated DTOs and their criminal activities over time.[25]

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[23] The randomization-based t tests relied on 100 repetitions. Before determining the number of repetitions, in a preliminary phase of the analyses, different thresholds were tested (specifically, 100, 500, 1,000, and 10,000 repetitions). The author selected the 100 repetitions threshold since it produced results that were substantially comparable with those produced by higher numbers of repetitions, considerably reducing the computational time needed to perform the analyses.

[24] The simulations included in the final analyses are those resulting from the intersection of the following experimental conditions. They include 4 proportions of members arrested (i.e., 0%, 10%, 40%, and 80%), 4 targets (i.e., all members, traffickers, packagers, and retailers), and 3 focuses in the security/efficiency trade-off (i.e., secure, intermediate, and efficient DTOs). Section 4.1 "Selection of experimental combinations for the final analyses" provides details about the process of selection.
The number of simulations over time is reported in column "No." of Table 2; it displays a decreasing trend over the simulated period because some simulations, those reporting the performance of disrupted DTOs, were interrupted before the end of the simulated period.

[25] The summary statistics in Table 2 merge and synthesize information from iterations of the model with diversified initial conditions (i.e., simulating DTOs with different focuses in the security vs. efficiency trade-off, attempts at disruption targeting members accomplishing different tasks, and different proportions of members). Disaggregated summary statistics for each combination may yield substantially different results.

Table 2. Summary statistics per year[26]

Year	No.	Min	Mean	Max	SD	Confidence interval
Number of members						
0	4800	44	44	44	0	-
1	4654	49	57.74	60	1.86	57.68-57.79
2	3975	12	54.93	66	13.61	54.50-55.35
3	2026	24	64.46	70	7.06	64.15-64.77
4	1893	41	67.79	72	4.48	67.59-67.99
5	1820	51	70.40	75	3.51	70.24-70.56
Number of traffickers						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	5	5	5	0	-
1	4654	4	11.39	13	1.64	11.34-11.44
2	3975	0	12.85	16	4.26	12.72-12.98
3	2026	5	16.34	18	1.62	16.27-16.41
4	1893	9	17.34	19	1.41	17.27-17.40
5	1820	14	17.98	20	1.69	17.90-18.05
Number of packagers						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	5	5	5	0	-
1	4654	4	10.63	11	0.72	10.61-10.66
2	3975	0	10.91	13	3.52	10.80-11.02
3	2026	4	12.86	14	1.49	12.80-12.93
4	1893	10	14.15	15	0.91	14.11-14.19
5	1820	12	14.88	16	0.99	14.83-14.93
Number of retailers						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	34	34	34	0	-
1	4654	31	35.71	36	0.65	35.69-35.73
2	3975	4	31.17	37	9.74	30.86-31.47
3	2026	9	35.25	38	5.41	35.02-35.49
4	1893	14	36.31	38	3.63	36.14-36.47
5	1820	21	37.55	39	2.48	37.43-37.66
Number of unit-doses sold						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	0	0	0	0	-
1	4654	1284	1739.40	2197	231.99	1732.74-1746.07
2	3975	1376	1845.91	2328	243.14	1838.34-1853.47
3	2026	1426	1930.16	2413	254.18	1919.08-1941.23
4	1893	1463	1961.13	2462	256.53	1949.56-1972.69
5	1820	1500	1996.29	2516	260.64	1984.30-2008.27
Number of drug acquisitions						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	0	0	0	0	-
1	4654	31	86.38	119	16.78	85.90-86.86
2	3975	119	239.23	288	30.58	238.28-240.18
3	2026	251	417.93	486	37.45	416.30-419.56
4	1893	320	610.62	697	49.75	608.38-612.86
5	1820	507	811.15	918	63.77	808.22-814.02

[26] The summary statistics in Table 2 refer to the following ticks of simulations: 0, 366, 731, 1,096, 1,461, and 1,825.

Amount of drug in stock (kg)						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4.80	8.70	8.70	8.70	0	-
1	4.65	3.86	11.11	24.80	2.09	11.04-11.17
2	3.98	0.35	8.09	20.77	2.54	8.01-8.17
3	2.03	3.47	8.38	17.24	1.37	8.32-8.44
4	1.89	1.91	6.55	16.49	1.28	6.49-6.61
5	1.82	1.01	4.57	7.90	1.08	4.52-4.62
Revenues (k€)						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	620.77	620.77	620.77	0	-
1	4654	17.82	602.28	1570.22	256.12	594.92-609.64
2	3975	64.95	720.26	2268.90	286.37	711.35-729.16
3	2026	156.71	932.37	2209.05	372.95	916.12-948.62
4	1893	286.34	1283.89	2629.74	469.61	1262.72-1262.72
5	1820	448.32	1671.77	3468.13	607.34	1643.85-1699.69
Number of components in the DTOs						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	0	0	0	0	-
1	4654	1	1.89	20	2.29	1.82-1.96
2	3975	1	1.90	19	1.88	1.85-1.96
3	2026	1	1.98	15	1.55	1.91-2.05
4	1893	1	1.92	12	1.33	1.86-1.98
5	1820	1	1.90	11	1.21	1.85-1.96
Number of members in the main component of the DTOs						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	0	0	0	0	-
1	4654	35	56.85	60	3.10	56.76-56.93
2	3975	44	64.14	66	2.20	64.07-64.21
3	2026	24	63.48	70	7.01	63.18-63.79
4	1893	41	66.87	72	4.47	66.67-67.08
5	1820	51	69.50	75	3.58	69.33-69.66
Average nDegree centrality						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	0	0	0	0	-
1	4654	0.10	0.17	0.24	0.02	0.17-0.17
2	3975	0.12	0.19	0.26	0.02	0.19-0.19
3	2026	0.10	0.21	0.33	0.03	0.20-0.21
4	1893	0.12	0.22	0.30	0.02	0.22-0.22
5	1820	0.14	0.22	0.30	0.02	0.22-0.22
Average nBetweenness centrality						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	0	0	0	0	-
1	4654	0.01	0.02	0.02	0.00	0.02-0.02
2	3975	0.01	0.02	0.02	0.00	0.02-0.02
3	2026	0.01	0.02	0.04	0.00	0.01-0.02
4	1893	0.01	0.01	0.03	0.00	0.01-0.01
5	1820	0.01	0.01	0.02	0.00	0.01-0.01
Average geodesic distance						
Year	**No.**	**Min**	**Mean**	**Max**	**SD**	**Confidence interval**
0	4800	0	0	0	0	-
1	4654	1.84	2.12	3.78	0.23	2.11-2.12
2	3975	1.82	2.07	3.54	0.18	2.07-2.08
3	2026	1.78	2.04	3.13	0.16	2.03-2.05
4	1893	1.79	2.01	2.80	0.13	2.00-2.02
5	1820	1.78	2.00	2.80	0.12	1.99-2.00

Source: Author's elaboration

With respect to DTO features, the simulated members and their task distributions resemble those of the Beluga group. At the beginning of the simulations, there are 44 members of the organization, of which 5 are traffickers, 5 are packagers, and 34 are retailers (Table 3). During the simulations, the composition of the DTO varies due to recruitments or defections of members, law enforcement arrests, deaths, etc. These elements of variation are not predetermined in the model; however, the values registered in the second and third simulated years are comparable to those portrayed by the Beluga court order.[27] In the second year the Beluga group could rely on the cooperation of 59 actors involved in drug trafficking and dealing, which became 60 in the third year (Table 3). The simulated DTOs, on average, can rely on 57.74 and 54.93 members in the second and third years, respectively. Instead, the more prosperous among the simulated DTOs reach exactly the Beluga group thresholds. Similar trends are registered when considering the distribution over time of traffickers, packagers, and retailers (Table 2 and Table 3). The lower average values of the simulated DTOs reflect the effects of minor periodic attempts at disruption not systematically reported in the Beluga court order.

Table 3. Beluga group members summary statistics (before arrests) per year

Year	2008	2009	2010
Number of members	44	59	66
Number of traffickers	5	13	16
Number of packagers	5	13	13
Number of retailers	34	33	37

Source: Author's elaboration from Beluga court order (Tribunale di Napoli 2013)

Similarly, the volume of DTO drug trafficking and dealing activities is comparable to that of the Beluga group. The minimum number of unit doses sold by the organization in the second year is 1,376 for the simulated DTOs, whereas it was 1,370 doses daily in May 2010 for the Beluga group. The maximum for the simulated DTOs is 2,328 doses, and it was 2,340 daily for the Beluga group during a particularly profitable weekend in June 2010.[28] On average, the simulated DTOs sell 1,846 unit doses daily, which is between the minimum and maximum reported for the Beluga group (Table 2).

Table 2 also provides summary statistics that cannot be directly validated (e.g., the number of drug acquisitions and revenues, amount of drugs in stock, DTO SNA metrics). However,

[27] The simulated years after an attempt at disruption cannot be validated with information from the Beluga court order since MADTOR simulates a wide array of law enforcement interventions that deviate from the facts reported by the court order, affecting the outcomes of the model, and thus precluding the possibility of validation.

[28] The Beluga court order only reports, for example, the number of doses sold by the organization for specific days or periods. The author relies on elaborations from this information to calibrate the model.

considering that both the structure of the DTOs and their workload are validated by the Beluga court order and that the calibration of the most relevant aspects of the model rely on empirical data (e.g., wholesale and retail cocaine prices, members' wages, expenditures, and profits), or on the criminological literature (e.g., the establishment of criminal working relations and factors influenced by the security vs. efficiency trade-off), it is plausible that the outcomes obtained for the other variables also realistically portray DTOs' drug trafficking and dealing.

4. Results

This chapter presents the results of the simulations. Section 4.1 reports the motivation for the decision to select only a set of the conducted experimental combinations for the final analyses. Section 4.2 examines the impact on DTO resilience of arresting different proportions of members; section 4.3 analyses the effects on DTO resilience of targeting members accomplishing different tasks; and section 4.4 investigates how DTOs with different focuses in the security vs. efficiency trade-off try to avoid, face and react to law enforcement interventions.

4.1. Selection of experimental combinations for the final analyses

After the preliminary analysis of all 792 combinations of the ABM experiments run in NetLogo, the author selected 108 (i.e., 36 combinations for each law enforcement intervention scenario) for the final analyses. The choice to prioritize the examination of some combinations allows the focus of the analyses to be narrowed by synthesizing a massive amount of information into convenient and understandable outcomes. This facilitates the identification of trends and dynamics that are of interest for the advancement of the scientific criminological literature and informative for planning strategic future law enforcement interventions.

The share of disrupted DTOs in the first law enforcement intervention scenario (i.e., the share of interrupted simulations before the 5 planned years) is examined to select combinations for the final analyses. This investigation provides a first indication of DTOs' resilience, as it represents DTOs' ability to survive over time despite law enforcement interventions. The combinations selected for the final analyses are those displaying diversified trends in the share of disrupted DTOs, since these trends may be caused by variability in the features of attempts at disruption (i.e., the target of the attempt at disruption and proportion of members arrested), and DTO specificities (i.e., positioning in the security vs. efficiency trade-off).

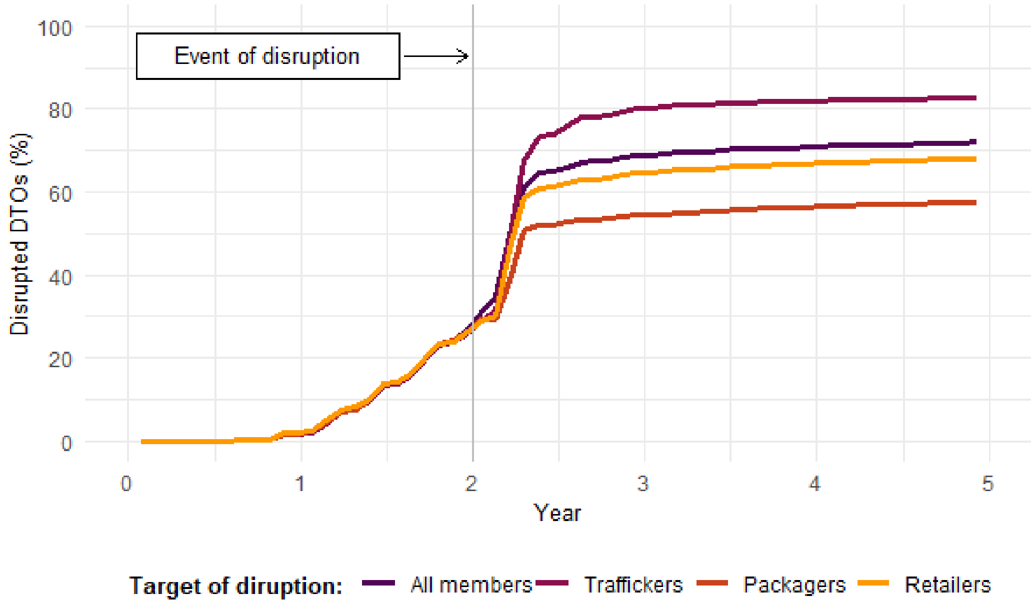
The target of the attempt at disruption assumes four values according to the categories of actors being targeted by the law enforcement intervention. It can target all the members of the organization, or only those accomplishing a particular task (i.e., only traffickers, only packagers, or only retailers). Table 4 reports the number and share of disrupted DTOs at the beginning of each simulated year when considering the 6,600 simulations run for each target of an attempt at disruption, and Graph 2 displays the trends over time.

Table 4. Disrupted DTOs per target of disruption per year[29]

Target of disruption	Year 0		Year 1		Year 2		Year 3		Year 4		Year 5	
	n	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*
All members	0	0%	159	2%	1945	29%	4549	69%	4689	71%	4755	72%
Traffickers	0	0%	135	2%	1908	29%	5296	80%	5408	82%	5454	83%
Packagers	0	0%	146	2%	1919	29%	3587	54%	3725	56%	3797	58%
Retailers	0	0%	173	3%	1899	29%	4268	65%	4420	67%	4489	68%

Source: Author's elaboration

Graph 2. Percentage of disrupted DTOs per target of disruption



Source: Author's elaboration

Targeting different categories of actors results in diversified percentages of disrupted organizations. Interventions targeting traffickers are the most disruptive (i.e., 83% of organizations are disrupted after five years of criminal activities), whereas interventions targeting packagers are the least disruptive (i.e., 58% of DTOs are disrupted after five years of criminal activities).

Since the target is a categorical variable and it is not possible to establish inherent similarities or an order among the values assumed by the variable, and considering the diversified trends observed, the following analyses take into consideration all four categories.

The proportion of members arrested during a disruptive event originally assumes eleven values corresponding to percentages of actors arrested (i.e., 0%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90%). It is directly proportionate to the percentage of disrupted organizations;

[29] Table 4 reports the summary statistics for the first day of each year corresponding to the following ticks of simulations: 0, 366, 731, 1,096, 1,461, and 1,825.

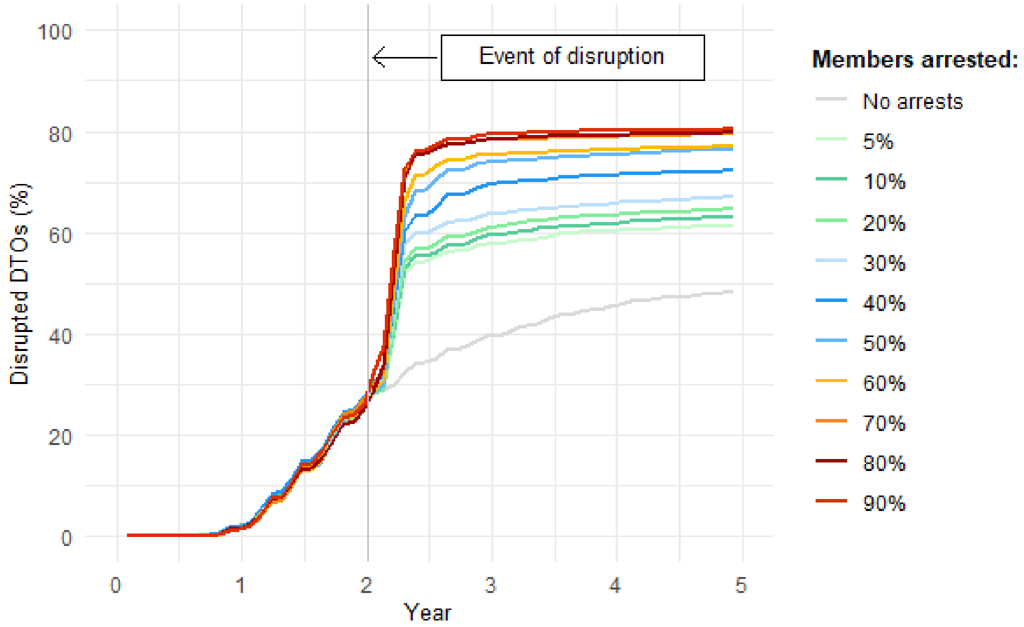
the higher the percentage of members arrested, the higher the percentage of disrupted organizations (Table 5 and Graph 3). The following analyses focus on only three categories of arrests selected as proxies for a low, medium, and high level of law enforcement intervention: 10% is the reference category for investigating the effects of arresting a low number of members, 40% is the reference category for investigating the effects of arresting a medium number of members, and 80% is the reference category for investigating the effects of arresting a high number of members. These categories result in 63%, 72%, and 80% of DTOs being disrupted after five years of criminal activities, respectively (Table 5).

Table 5. Disrupted DTOs per proportion of members arrested per year[30]

Share of members arrested	Year 0		Year 1		Year 2		Year 3		Year 4		Year 5	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
No arrests	0	0%	57	2%	694	29%	951	40%	1102	46%	1162	48%
5%	0	0%	57	2%	707	29%	1392	58%	1453	61%	1477	62%
10%	0	0%	63	3%	719	30%	1430	60%	1488	62%	1514	63%
20%	0	0%	55	2%	675	28%	1467	61%	1525	64%	1553	65%
30%	0	0%	54	2%	724	30%	1528	64%	1583	66%	1615	67%
40%	0	0%	66	3%	727	30%	1674	70%	1715	71%	1735	72%
50%	0	0%	50	2%	679	28%	1776	74%	1813	76%	1836	77%
60%	0	0%	56	2%	672	28%	1811	75%	1836	77%	1849	77%
70%	0	0%	48	2%	713	30%	1881	78%	1898	79%	1909	80%
80%	0	0%	57	2%	667	28%	1884	79%	1903	79%	1914	80%
90%	0	0%	50	2%	694	29%	1906	79%	1926	80%	1931	80%

Source: Author's elaboration

Graph 3. Percentage of disrupted DTOs per share of actors arrested



Source: Author's elaboration

[30] The summary statistics shown in Table 5 refer to the first day of each year, corresponding to ticks: 0, 366, 731, 1,096, 1,461, and 1,825.

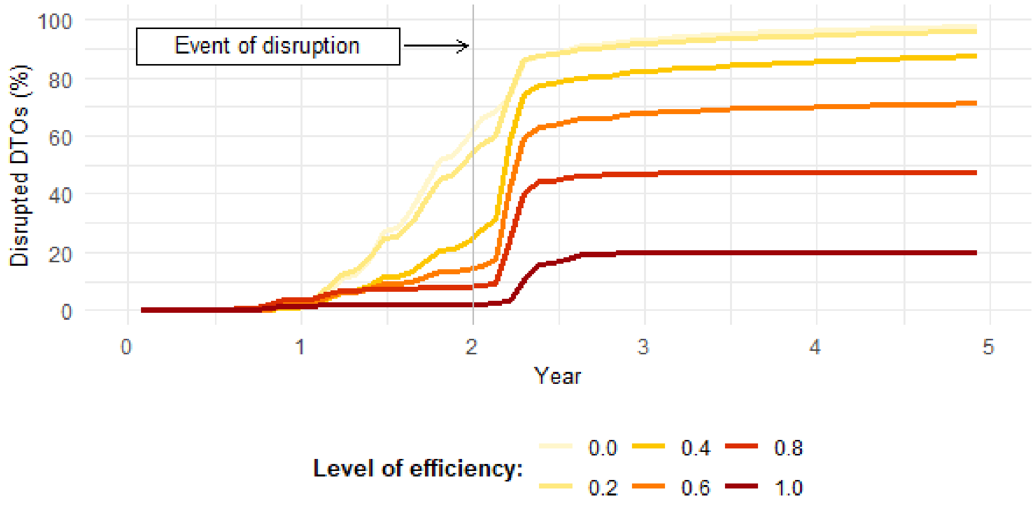
Finally, the DTOs' focus in the security vs. efficiency trade-off assumes six values (i.e., 0, 0.2, 0.4, 0.6, 0.8, and 1). DTOs scoring 0 maximally prioritize security, whereas organizations scoring 1 maximally prioritize efficiency. Table 6 and Graph 4 display the share of disrupted DTOs in the 4,400 simulations run for each of the DTO security/efficiency focuses.

Table 6. Disrupted DTOs per security/efficiency focuses per year[31]

DTOs security/efficiency focuses	Year 0		Year 1		Year 2		Year 3		Year 4		Year 5	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
0.0	0	0%	64	1%	2865	65%	4099	93%	4240	96%	4295	98%
0.2	0	0%	124	3%	2507	57%	4040	92%	4167	95%	4220	96%
0.4	0	0%	76	2%	1195	27%	3620	82%	3767	86%	3853	88%
0.6	0	0%	108	2%	668	15%	2982	68%	3084	70%	3140	71%
0.8	0	0%	174	4%	359	8%	2074	47%	2095	48%	2098	48%
1.0	0	0%	67	2%	77	2%	885	20%	889	20%	889	20%

Source: Author's elaboration

Graph 4. Percentage of disrupted organizations per DTO security/efficiency focus



Source: Author's elaboration

More efficient DTOs report the lowest percentages of disruptions. Conversely, secure organizations register higher percentages of disruption. The final analyses focus only on three categories: secure (0.4), intermediate (0.6), and efficient DTOs (0.8). These categories result in 88%, 71%, and 48% of disrupted organizations after five years of criminal involvement (Table 6), respectively. The extreme categories of the DTO security/efficiency focus (i.e., the 0.0, 0.2, and 1.0 categories) are discarded due to their scarce representativeness of reality. The 0.0 and 0.2 categories (i.e., maximum prioritization of security) result in more than 95% of DTOs being

[31] The summary statistics shown in Table 6 refer to ticks 0, 366, 731, 1,096, 1,461, and 1,825 (i.e., the first day of each simulated year).

disrupted at the end of the five simulated years (Table 6); thus, they portray an unaffordable way of protracting criminal activities that is implausible for real DTOs. At the same time, the 1.0 category (i.e., maximum prioritization of efficiency) leads to only 20% of DTOs being disrupted at the end of the simulations (Table 6). However, considering the criminological literature, it is unrealistic for illegal organizations to completely disregard the security of their criminal activities; thus, this category is also excluded due to its implausibility.

4.2. The impact on DTO resilience of the proportion of members arrested

MADTOR is used to test the resilience of a DTO to the arrests of different proportions of members from the organization. The author ran sets of simulations reproducing scenarios in which there are no arrests (i.e., baseline scenario) and 10%, 40%, and 80% of members arrested (i.e., alternative scenarios). The analyses and comparisons of the trends over time of the resilience indicators presented in Table 1 of section 3.5.1 help in understanding the resilience of DTOs targeted by the arrests of different proportions of members.

In the following analyses, the focus is on DTOs with an intermediate focus in the security vs. efficiency trade-off targeted by law enforcement interventions regardless of the tasks accomplished by different DTO members. Since the impact of the attempt at disruption is also affected by a DTO's focus in the security vs. efficiency trade-off and the target of law enforcement interventions, sections 4.3 and 4.4 and Annex IV provide additional information on the specificities of each scenario.

In the following graphs, gray lines represent the trends of the resilience indicators for the baseline scenario in which there are no arrests, green lines represent those of the 10% arrests scenario, light-blue lines represent those of the 40% arrests scenario, and red lines represent those of the 80% arrests scenario. In the graphs reporting DTOs' abilities of to react quickly and efficiently and to maintain their primary functions unaltered, the colored areas represent the share of active DTOs over time in each scenario. The red and green dots on the x-axis show the significance of the differences at each point in time for the comparison of the baseline and alternative scenarios (red= nonsignificant, green=significant).

In the following tables summarizing the statistics of the resilience indicators per year, the information refers to the first day of each year, corresponding to ticks of simulations: 0, 366, 731, 1,096, 1,461, and 1,825.

4.2.1. Ability to endure disruption

The ability to survive over time despite being targeted by law enforcement attempts at disruption is the necessary but not sufficient condition for resilience. Indeed, the ability to survive disruption is the precondition for DTO resilience. Only after this precondition is satisfied can attention be paid to the quality and strategies of reactions to threatening events.

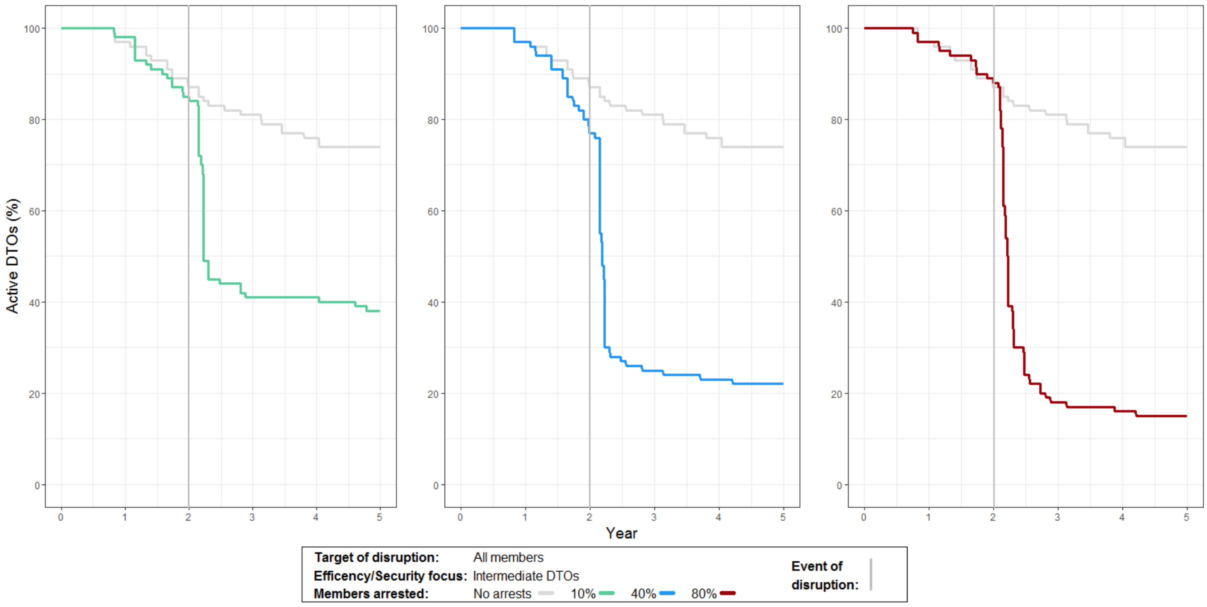
Graph 5 displays the percentage of active DTOs in scenarios in which 10%, 40% and 80% of members are targeted by law enforcement interventions, and Table 7 reports the proportion of active DTOs per year and the results of the randomization-based t tests between the different scenarios.

In line with expectations, the higher the proportion of members arrested, the greater the percentage of disrupted organizations. In the baseline scenario (i.e., no arrests simulated), 74% of DTOs remain active in the drug market until the end of the five simulated years, with the most challenging period being the second year of activity (Graph 5).[32] The apprehension of some DTO members, even when considering low percentages of arrests, always provokes a strongly significant impact on the share of DTOs surviving attempts at disruption (Table 7).

Considering the 10% arrests scenario, less than 40% of DTOs maintain their criminal involvement until the end of the five years, and almost half of active DTOs are disrupted in the year immediately after the attempt at disruption. Furthermore, in the 40% and 80% arrests scenarios, the attempt at disruption is even more impactful, with almost 25% and 15% of active DTOs maintaining their criminal activities from the third to the fifth simulated years, respectively (Graph 5 and Table 7).

[32] Even in the baseline scenario (i.e., 0% of arrests), some DTOs cannot maintain their criminal involvement for the whole simulated period. The failure of these organizations is linked to their ability to perform drug trafficking and dealing proficiently from an economic point of view. With no attempts at disruption, DTOs' ability to persist over time is tied to their focus in the security vs. efficiency trade-off; secure DTOs are the weakest from an economic point of view, with the lowest percentage of active organizations (i.e., 39%) at the end of the five years, and efficient DTOs are the strongest (i.e., 94% of active organizations at the end of the five years). In this section, the analyses consider DTOs with an intermediate focus in the security/efficiency trade-off; section 4.4 offers further consideration of how the security vs. efficiency trade-off affects DTO resilience.

Graph 5. Share of active DTOs (Target of disruption: all members; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 7. Share of active DTOs per year (Target of disruption: all members; Security vs. efficiency focus: intermediate)

Share of arrests	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
0%	100%	97%	87%	81%	76%	74%
10%	100%	98%	84%	41%	41%	38%
40%	100%	97%	77%	25%	23%	22%
80%	100%	97%	89%	18%	16%	15%
Randomization-based t tests						
Compared scenarios	**Group 1 Mean (SD)**		**Group 2 Mean (SD)**		**Significance**	
0%-10%	85.51	(9.59)	64.63	(26.55)	***	
0%-40%	85.51	(9.59)	54.19	(34.46)	***	
0%-80%	85.51	(9.59)	52.18	(38.29)	***	
10%-40%	64.63	(26.55)	54.19	(34.46)	***	
10%-80%	64.63	(26.55)	52.18	(38.29)	***	
40%-80%	54.19	(34.46)	52.18	(38.29)	*	

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

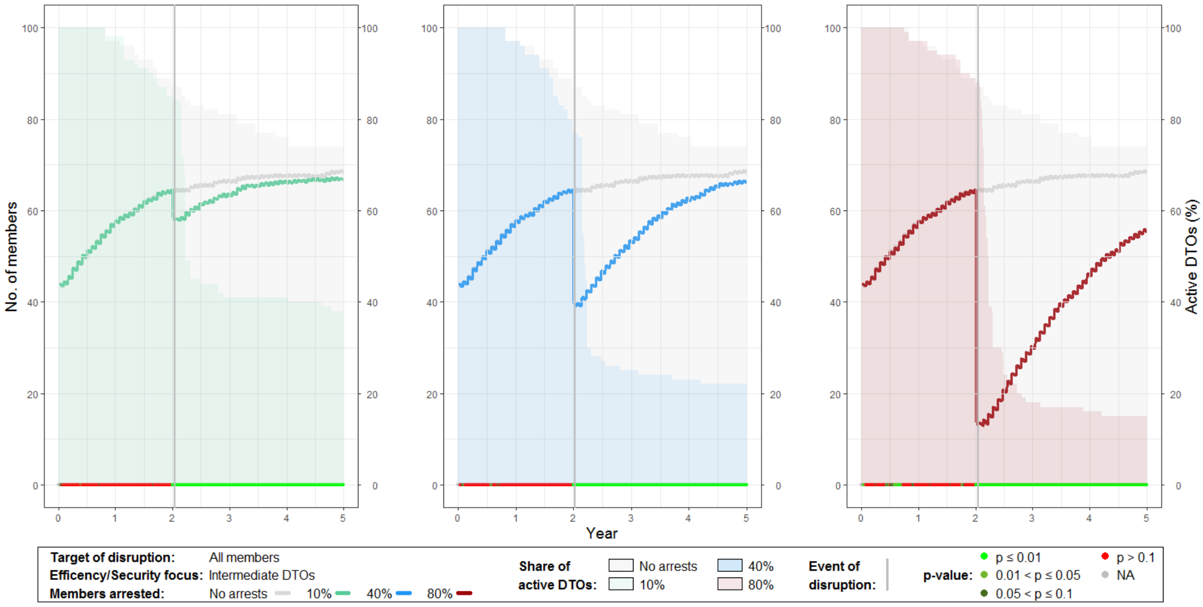
Source: Author's elaboration

4.2.2. Ability to react quickly and efficiently to law enforcement interventions

In addition to the ability to survive disruption, a second fundamental ability that resilient DTOs must display is the capacity to react quickly and efficiently to law enforcement interventions. The number of members currently involved in DTO activities, the average normalized degree centrality of members, and the average normalized betweenness centrality are the indicators examined for this purpose.

At the beginning of the simulations, DTOs comprise 44 members, and they reach 66 members at most after two years of criminal involvement. This trend is equal in all the scenarios tested (Graph 6 and Table 8). The analysis of the impact of an attempt at disruption at the end of the second year shows, understandably, that the greater the proportion of members arrested by law enforcement, the lower the number of DTO members. In all three alternative scenarios, an attempt at disruption produces a reduction in the number of members that remains significant until the end of the five simulated years. However, in the 10% and 40% arrests scenarios, during the fifth year, DTO members in the organizations targeted by the arrests reach values that are lower than but not very distant from those of nontargeted DTOs, even though in the 40% arrests scenario, the recovery time is much longer (i.e., approximately doubled compared to the 10% arrests scenario). Conversely, in the 80% arrests scenario, at the end of the five simulated years, DTOs can count on a workforce with almost 18 fewer members than that in the baseline scenario (Graph 6 and Table 8).

Graph 6. Number of DTOs members (Target of disruption: all members; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 8. Number of DTOs members per year (Target of disruption: all members; Security vs. efficiency focus: intermediate)

Share of arrests	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
0%	0	100	44	44	44.00	0.00	-
	1	97	51	60	57.82	1.70	57.48-58.17
	2	87	61	65	64.57	0.71	64.42-64.73
	3	81	63	67	66.11	0.81	65.93-66.29
	4	76	65	68	67.39	0.71	67.23-67.56
	5	74	66	69	68.22	0.73	68.05-68.38
10%	0	100	44	44	44.00	0.00	-
	1	98	52	60	57.82	1.86	57.44-58.19
	2	84	54	59	58.55	0.92	58.35-58.75
	3	41	59	65	63.24	1.26	62.85-63.64
	4	41	63	67	66.02	1.04	65.70-66.35
	5	38	64	68	66.68	0.93	66.38—66.99
40%	0	100	44	44	44.00	0.00	-
	1	97	54	60	57.81	1.60	57.49-58.14
	2	77	38	40	39.70	0.49	39.59-38.81
	3	25	47	57	52.88	2.52	51.84-53.92
	4	23	57	66	62.04	2.44	60.99-63.10
	5	22	64	67	66.23	1.02	65.77-66.68
80%	0	100	44	44	44.00	0.00	-
	1	97	53	60	57.78	1.75	57.43-58.14
	2	89	13	15	13.78	0.47	13.68-13.87
	3	18	24	38	29.89	3.29	28.25-31.52
	4	16	41	54	45.69	2.68	44.26-47.11
	5	15	51	65	55.47	3.16	53.72-57.22

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
0%-10%	62.42 (6.87)	60.90 (6.24)	***
0%-40%	62.42 (6.87)	56.19 (7.75)	***
0%-80%	62.42 (6.87)	44.45 (14.48)	***
10%-40%	60.90 (6.24)	56.19 (7.75)	***
10%-80%	60.90 (6.24)	44.45 (14.48)	***
40%-80%	56.19 (7.75)	44.45 (14.48)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

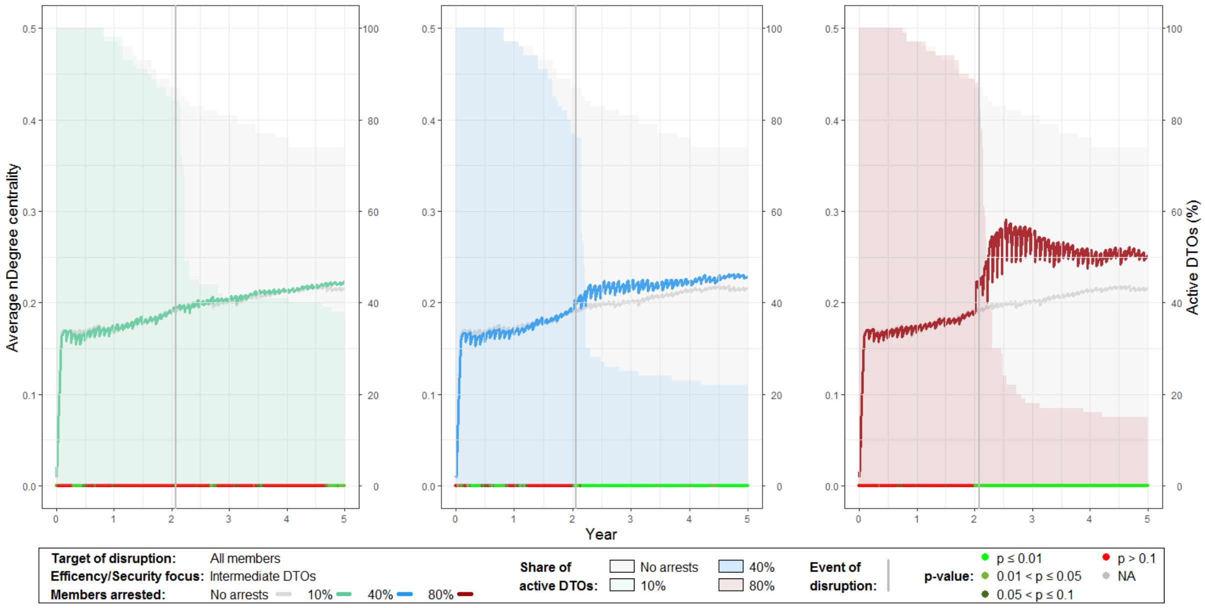
The average normalized degree centrality of DTO members is the second resilience indicator analyzed to investigate DTOs' ability to react quickly and efficiently to law enforcement attempts at disruption. Graph 7 reports the trends of this metric for the baseline and alternative scenarios. Table 9 provides additional information on the descriptive statistics, confidence intervals, and randomization-based t tests of the same scenarios.

Because DTOs operate in an illegal context, the average normalized degree centrality among their members is always kept quite low with the intention of reducing direct connections among criminal actors and consequently their potential visibility to law enforcement. In the simulated period, regardless of the specificities of each scenario, members are connected on average to almost 20% of their companions, with a minimum of connections to 12% of them and a maximum of 32%. The lowest values are registered in the first two years of criminal involvement when, in the scenarios both with and without arrests, on average DTO members are connected to 16-19% of their criminal partners (Table 9).

The arrests of a modest number of DTO members, such as in the 10% arrests scenario, do not impact the usual working and communication strategies in the organizations, with differences in average normalized degree centrality that are mostly not significant when comparing this scenario with the baseline one. In contrast, the arrests of higher proportions of members, as in the cases of the 40% and 80% arrests scenarios, provoke significant increases in the average normalized degree centrality of DTO members. However, in the scenario in which 40% of members are arrested, this increase is modest in magnitude, with some exceptional points in time where the difference between this scenario and the baseline is only slightly significant or nonsignificant. Conversely, the differences between each point in time when comparing the 80% arrests scenario and the baseline are always strongly significant (Graph 7 and Table 9).

In the scenarios in which the arrests target a consistent proportion of members, the initial increase is inherent in the way in which the metric is computed. Indeed, considering the proportion of direct connections to the total possible connections among members, a drastic reduction in the number of members also reduces the total possible connections, resulting in a higher average normalized degree centrality. Nonetheless, the increase registered, especially in the 80% arrests scenario, remains consistent and stable until the end of the simulated period, when number of DTO members reach values closer to the prearrest scenario, thus signaling modifications in working and relational patterns among DTO members. An augmented average normalized degree centrality may indicate the necessity for DTOs heavily targeted by law enforcement to modify their *modi operandi*, sacrificing the security and protection of members in favor of more direct reachability with the aim of compensating for losses and continuing their involvement in and profits from drug trafficking and dealing.

Graph 7. DTOs members average normalized degree centrality (Target of disruption: all members; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 9. DTOs members average normalized degree centrality per year (Target of disruption: all members; Security vs. efficiency focus: intermediate)

Share of arrests	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
0%	0	100	0.000	0.000	0.000	0.000	-
	1	97	0.125	0.196	0.168	0.013	0.165-0.170
	2	87	0.155	0.232	0.190	0.016	0.187-0.194
	3	81	0.158	0.242	0.201	0.016	0.198-0.205
	4	76	0.175	0.254	0.214	0.015	0.210-0.217
	5	74	0.183	0.254	0.216	0.016	0.212-0.220
10%	0	100	0.000	0.000	0.000	0.000	-
	1	98	0.141	0.202	0.170	0.013	0.167-0.173
	2	84	0.154	0.235	0.190	0.018	0.187-0.194
	3	41	0.173	0.239	0.204	0.017	0.199-0.210
	4	41	0.181	0.247	0.214	0.016	0.209-0.219
	5	38	0.190	0.265	0.223	0.018	0.217-0.229
40%	0	100	0.000	0.000	0.000	0.000	-
	1	97	0.120	0.222	0.166	0.015	0.163-0.169
	2	77	0.155	0.237	0.193	0.016	0.189-0.196
	3	25	0.165	0.246	0.219	0.018	0.212-0.226
	4	23	0.202	0.249	0.224	0.014	0.218-0.230
	5	22	0.204	0.255	0.229	0.013	0.223-0.235
80%	0	100	0.000	0.000	0.000	0.000	-
	1	97	0.122	0.209	0.170	0.015	0.167-0.173
	2	89	0.127	0.228	0.189	0.018	0.185-0.192
	3	18	0.212	0.320	0.275	0.029	0.261-0.290
	4	16	0.230	0.276	0.255	0.014	0.248-0.263
	5	15	0.209	0.274	0.251	0.016	0.243-0.260

Randomization-based t tests			
Compared scenarios	**Group 1 Mean (SD)**	**Group 2 Mean (SD)**	**Significance**
0%-10%	0.192 (0.023)	0.193 (0.025)	*
0%-40%	0.192 (0.023)	0.199 (0.03)	***
0%-80%	0.192 (0.023)	0.222 (0.046)	***
10%-40%	0.193 (0.025)	0.199 (0.03)	***
10%-80%	0.193 (0.025)	0.222 (0.046)	***
40%-80%	0.199 (0.030)	0.222 (0.046)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

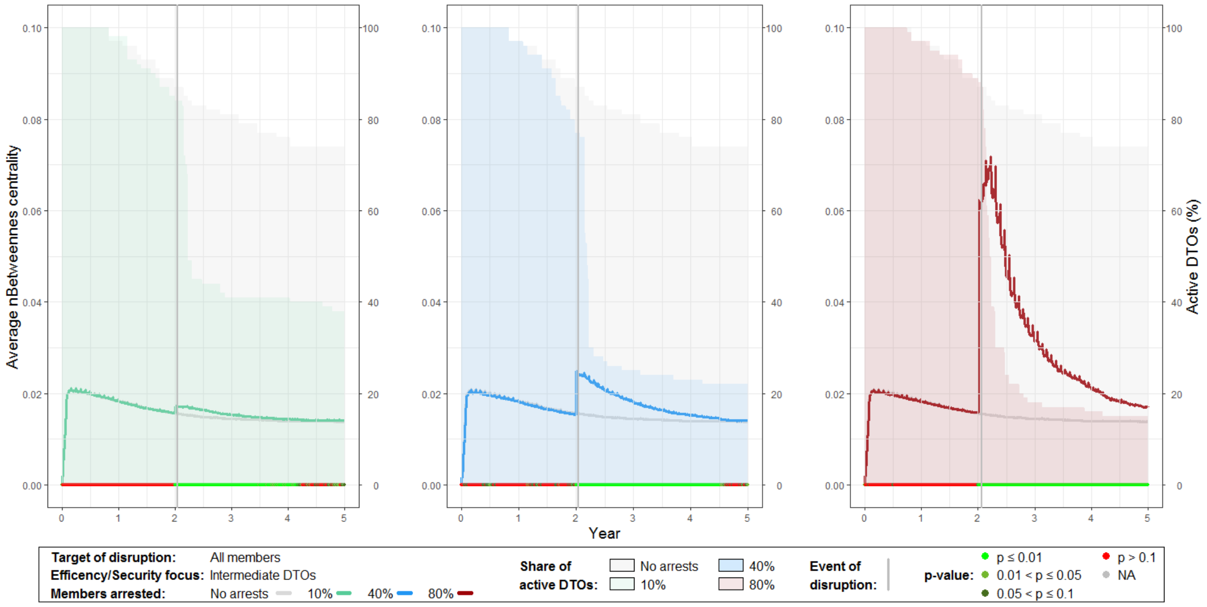
Source: Author's elaboration

The last indicator providing information about DTOs' efficient and fast reactions to law enforcement attempts at disruption is average normalized betweenness centrality (Graph 8 and Table 10). As for average normalized degree centrality, the values of average normalized betweenness centrality are generally quite low, meaning that among DTO members, there are no individuals occupying predominant positions in managing and controlling the flows of communication (i.e., playing the broker role). DTO members register the lowest values of average normalized betweenness centrality (i.e., 0.010) during the first year of criminal involvement, whereas the highest values (i.e., 0.041) are registered by DTOs targeted by 80% arrests during their third year of criminal involvement, immediately after the attempt at disruption (Table 10).

At the beginning of the simulations, DTO members display values of average normalized betweenness centrality of approximately 0.018 and then register a decrease toward the end of the second simulated year, with values of approximately 0.016. This trend may signal that over time, more DTO members communicate with each other, increasing the direct connectivity in the organization and consequently mitigating the strategic role of brokers (Table 10).

The attempt at disruption provokes an increase in this metric because of the normalization process after the reduction in DTO members caused by the arrests. In the 10% and 40% arrests scenarios, the increase is modest and is significant only in the first years after the law enforcement intervention, after which the values return to levels that are indistinguishable from those of the baseline scenario. In contrast, the increase is more pronounced in the 80% arrests scenario, with 0.032 average normalized betweenness centrality immediately after the attempt at disruption (Table 10). Additionally, in this scenario, the tendency is to decrease steeply in the years after the law enforcement arrests, even though, at the end of the simulated period, DTO members' average betweenness centrality is still higher than in the baseline scenario, demonstrating a long-term impact of the arrests on relational patterns in the organization (Graph 8). Indeed, it may be that, after the arrests, DTO members try to increase their reliance on indirect connections to balance the contrasting needs of members' security and continuing their criminal involvement in drug trafficking and dealing.

Graph 8. DTOs members average normalized betweenness centrality (Target of disruption: all members; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 10. DTOs members average normalized betweenness centrality per year (Target of disruption: all members; Security vs. efficiency focus: intermediate)

Share of arrests	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
0%	0	100	0.000	0.000	0.000	0.000	-
	1	97	0.012	0.022	0.018	0.001	0.018-0.019
	2	87	0.013	0.018	0.016	0.001	0.015-0.016
	3	81	0.012	0.018	0.015	0.001	0.014-0.015
	4	76	0.012	0.016	0.014	0.001	0.014-0.014
	5	74	0.012	0.016	0.014	0.001	0.014-0.014
10%	0	100	0.000	0.000	0.000	0.000	-
	1	98	0.014	0.022	0.018	0.002	0.018-0.019
	2	84	0.013	0.020	0.016	0.001	0.015-0.016
	3	41	0.014	0.019	0.015	0.001	0.015-0.016
	4	41	0.012	0.017	0.014	0.001	0.014-0.015
	5	38	0.011	0.016	0.014	0.001	0.014-0.014
40%	0	100	0.000	0.000	0.000	0.000	-
	1	97	0.011	0.021	0.018	0.002	0.018-0.019
	2	77	0.011	0.018	0.015	0.001	0.015-0.016
	3	25	0.016	0.021	0.018	0.001	0.018-0.019
	4	23	0.014	0.018	0.015	0.001	0.015-0.016
	5	22	0.013	0.016	0.014	0.001	0.014-0.014
80%	0	100	0.000	0.000	0.000	0.000	-
	1	97	0.010	0.022	0.018	0.002	0.018-0.019
	2	89	0.013	0.019	0.016	0.001	0.016-0.016
	3	18	0.024	0.041	0.032	0.004	0.030-0.034
	4	16	0.018	0.024	0.021	0.002	0.020-0.022
	5	15	0.013	0.020	0.017	0.001	0.016-0.018

Randomization-based t tests					
Compared scenarios	**Group 1 Mean (SD)**		**Group 2 Mean (SD)**		**Significance**
0%-10%	0.016	(0.002)	0.016	(0.002)	***
0%-40%	0.016	(0.002)	0.017	(0.003)	***
0%-80%	0.016	(0.002)	0.026	(0.014)	***
10%-40%	0.016	(0.002)	0.017	(0.003)	***
10%-80%	0.016	(0.002)	0.026	(0.014)	***
40%-80%	0.017	(0.003)	0.026	(0.014)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

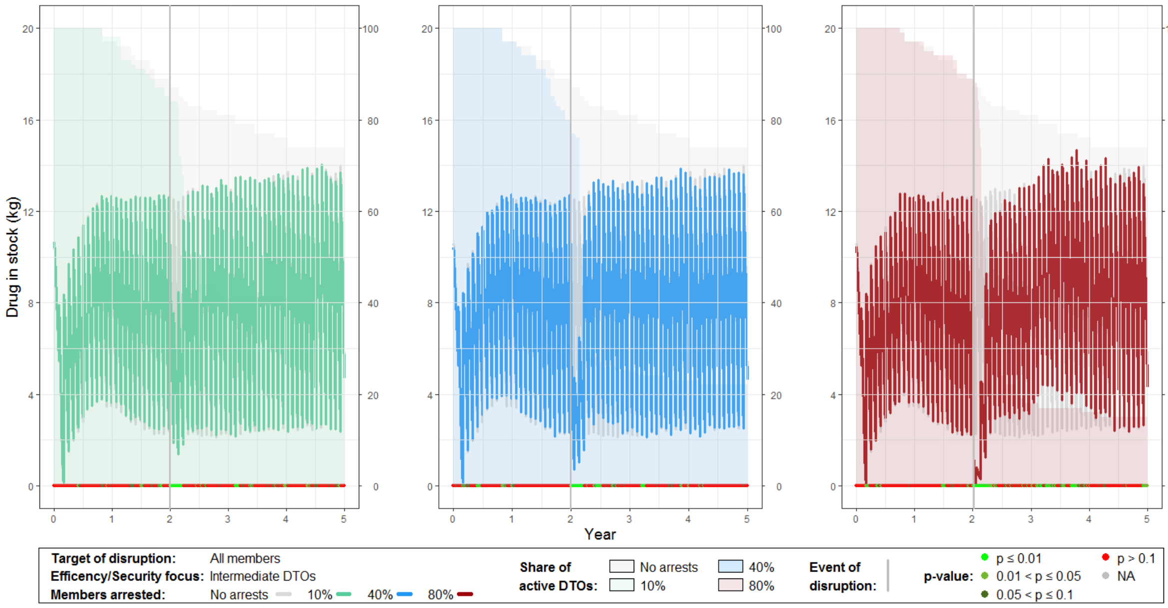
Source: Author's elaboration

4.2.3. Ability to maintain primary functions and activities unaltered after disruption

The third condition that resilient criminal organizations must display is the ability to maintain their primary functions unaltered. For DTOs this means being able to continue drug trafficking and dealing activities with no substantial differences in their business volume. The amount of drugs stored in DTO warehouses and DTO revenues over time are the resilience indicators examined to this end.

Regardless of the specificities of each scenario, on average, DTOs store 7-8 kilos of cocaine in their warehouses, with high short-term oscillations over time due to continuous drug acquisitions and sales (Graph 9). From the beginning of the simulations until the disruptive event, DTOs augment their workload with increasing amounts of drugs in stock (from almost 9 kilos during the first year of criminal involvement to 16-18 kilos in the second year) (Table 11). One effect of law enforcement intervention is the immediate and substantial reduction of the cocaine stored by the DTOs, especially in the scenarios with the highest proportions of members arrested. Indeed, when DTO members are arrested, the quantities of drugs at their disposal are seized by law enforcement, resulting in the minimum reserves of drugs during the whole period (Graph 9). However, despite the threat represented by the arrests, also in the harshest scenarios, remaining DTO members, apart from the days immediately after the attempt at disruption, are always able to sustain their prearrest workload, and the differences between the baseline and alternative scenarios are always minor and nonsignificant (Graph 9 and Table 11). The DTOs' capacity to maintain their involvement in drug trafficking and dealing suggests good levels of resilience for DTOs that manage to reorganize and continue their primary activities despite facing a challenging event. Nonetheless, it is worth noting that while surviving DTOs seem to cope well with the consequences of arrests, the vast majority of DTOs cannot survive, especially major, attempts at disruption, with only 38-15% of active DTOs remaining active at the end of the five simulated years (Graph 9 and Table 11).

Graph 9. Amount of drug in stock (Target of disruption: all members; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 11. Amount of drug in stock (in kg) per year (Target of disruption: all members; Security vs. efficiency focus: intermediate)

Share of arrests	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
0%	0	100	8.70	8.70	8.70	0.00	-
	1	97	6.11	16.71	10.96	2.05	10.55-11.38
	2	87	6.58	10.95	9.41	1.04	9.19-9.63
	3	81	4.04	9.98	8.01	1.29	7.73-8.30
	4	76	2.90	7.79	6.30	1.16	6.04-6.57
	5	74	2.37	5.73	4.38	0.77	4.20-4.56
10%	0	100	8.70	8.70	8.70	0.00	-
	1	98	6.29	18.09	11.26	2.19	10.82-11.70
	2	84	5.04	11.74	8.55	1.15	8.30-8.80
	3	41	4.02	9.24	8.00	1.10	7.65-8.34
	4	41	3.32	7.74	5.97	1.08	5.63-6.31
	5	38	2.56	5.66	4.27	0.79	4.01-5.53
40%	0	100	8.70	8.70	8.70	0.00	-
	1	97	6.70	18.14	11.35	1.98	10.95-11.75
	2	77	2.76	7.45	5.55	0.94	5.34-5.77
	3	25	4.92	10.70	8.16	1.34	7.61-8.71
	4	23	4.53	7.82	6.03	0.91	5.64-6.42
	5	22	2.46	5.72	4.22	0.94	3.80-4.64
80%	0	100	8.70	8.70	8.70	0.00	-
	1	97	6.66	17.29	11.19	2.02	10.79-11.60
	2	89	0.39	4.11	1.91	0.68	1.77-2.05
	3	18	3.47	11.41	7.99	1.95	7.02-8.96
	4	16	3.39	10.78	6.80	1.60	5.95-7.65
	5	15	2.24	5.24	3.91	1.13	3.28-4.53

Randomization-based t tests					
Compared scenarios	**Group 1 Mean (SD)**		**Group 2 Mean (SD)**		**Significance**
0%-10%	7.79	(3.16)	7.77	(3.17)	n.s.
0%-40%	7.79	(3.16)	7.68	(3.23)	n.s.
0%-80%	7.79	(3.16)	7.71	(3.34)	n.s.
10%-40%	7.77	(3.17)	7.68	(3.23)	n.s.
10%-80%	7.77	(3.17)	7.71	(3.34)	n.s.
40%-80%	7.68	(3.23)	7.71	(3.34)	n.s.

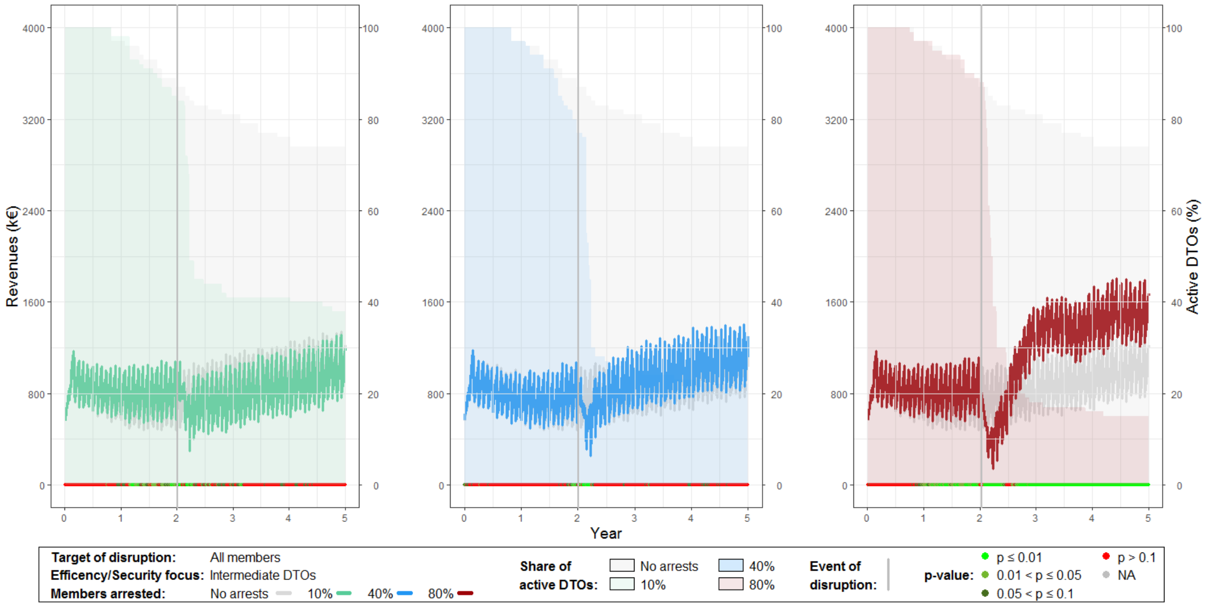
**Significance at 95% level, **99%, ***99.9%, [n.s]Nonsignificant*

Source: Author's elaboration

DTO revenues are the last indicator investigated to assess the resilience of DTOs when facing the arrests of varying proportions of their members (Graph 10 and Table 12). Regarding the amount of drugs in stock, DTOs' revenues also present an oscillatory trend over time related to constant drug acquisitions and sales. In the two years before the attempt at disruption, the DTOs have quite stable revenues, ranging from a minimum of 32.05 k€ to a maximum of 1,290.14 k€, with average values ranging from 592.60 to 656.78 k€ (Table 11). In the alternative scenarios, the law enforcement intervention causes a decrease in DTO revenues that is commensurate with the proportion of members arrested. Indeed, the higher the proportion of arrests, the larger the quantity of drugs seized by law enforcement and the greater the losses provoked by the missed drug sales (Graph 10).

The long-term consequences of the disruptive event differ according to the proportion of members arrested. In the 10% arrests scenario, DTOs respond well to the law enforcement intervention, with no significant differences in revenues compared to the baseline scenario. Similarly, the arrests of 40% of members provoke limited differences in revenues compared to the 0% arrests scenario; in the latter case, average revenues are modestly higher, but these differences are not significant. Conversely, the impact of arrests on DTO revenues in the long term is strongly significant in the 80% arrests scenario. After a major reduction in the revenues in the year after law enforcement intervention, DTO members achieve a steady increase in their revenues, registering values that are far higher than those recorded by DTOs not experiencing an attempt at disruption, with an average of 1,711.69 k€ in contrast to 1,267.74 k€ (Graph 10 and Table 11). This result suggests that massive arrests may also be beneficial for DTOs in terms of economic profits. The threatening event obliges DTO members who remain active in the organization to reorganize their working strategies, probably increasing their individual workload, but it also severely reduces the costs of the organizations (mainly because of the reduction in wages to be paid to DTO members no longer present in the group). Nonetheless, considering that in the 80% arrests scenario, only 15% of DTOs survive disruption, this situation is extremely rare. In addition, while this scenario can be beneficial for the organization as a whole, it is important to note that many former members of the group are caught and imprisoned, with relevant personal negative consequences; thus, this situation, even though advantageous from the economic point of view, may not be preferred by DTO members.

Graph 10. DTOs revenues (Target of disruption: all members; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 12. DTOs revenues (in k€) per year (Target of disruption: all members; Security vs. efficiency focus: intermediate)

Share of arrests	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
0%	0	100	620.77	620.77	620.77	0.00	-
	1	97	35.79	1258.95	595.53	242.82	546.59-644.47
	2	87	227.11	1348.03	642.61	247.79	589.79-695.42
	3	81	196.09	1693.26	840.66	314.93	771.02-910.30
	4	76	357.51	1848.84	1040.01	330.58	964.47-1115.55
	5	74	582.57	2324.99	1267.74	385.06	1178.53-1356.95
10%	0	100	620.77	620.77	620.77	0.00	-
	1	98	95.08	1290.14	647.97	279.10	592.01-703.93
	2	84	166.47	1669.26	725.53	291.47	662.27-788.78
	3	41	341.77	2022.27	752.19	334.95	646.47-857.92
	4	41	446.28	2404.61	983.64	378.41	864.20-1103.08
	5	38	550.45	2595.50	1242.16	407.94	1108.07-1376.24
40%	0	100	620.77	620.77	620.77	0.00	-
	1	97	32.05	1248.87	592.60	265.95	539.00-646.20
	2	77	217.22	1565.22	711.11	283.25	646.82-775.40
	3	25	342.14	1834.12	897.65	379.90	740.83-1054.47
	4	23	502.15	1917.99	1162.41	391.21	993.23-1331.58
	5	22	880.05	2129.02	1340.35	369.99	1176.30-1504.39

Share of arrests	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
80%	0	100	620.77	620.77	620.77	0.00	-
	1	97	77.46	1168.32	656.78	266.55	603.06-710.50
	2	89	137.33	1294.59	737.08	306.89	672.44-801.73
	3	18	243.49	2056.73	1345.80	595.42	1049.70-1641.89
	4	16	445.76	2249.74	1543.11	474.54	1290.24-1795.98
	5	15	674.49	2494.10	1711.69	470.89	1450.92-1972.46

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
0%-10%	847.58 (168.00)	824.80 (157.05)	***
0%-40%	847.58 (168.00)	880.66 (193.58)	***
0%-80%	847.58 (168.00)	1068.52 (353.90)	***
10%-40%	824.80 (157.05)	880.66 (193.58)	***
10%-80%	824.80 (157.05)	1068.52 (353.90)	***
40%-80%	880.66 (193.58)	1068.52 (353.90)	***

**Significance at 95% level, **99%, ***99.9%, $^{n.s}$Nonsignificant*

Source: Author's elaboration

4.2.4. Research question 1: Summary of the results

The first research question of the study investigates the impact of arresting different proportions of members from the organization on DTOs' resistance and resilience. Concerning DTOs' resistance in terms of their ability to survive disruption, the arrest of even a few members affects DTO survival rates. Unsurprisingly, the higher the proportion of members arrested, the greater the percentage of disrupted organizations, with 38%, 22%, and 15% of DTOs active at the end of the simulated period for the 10%, 40%, and 80% arrests scenarios, respectively.

Law enforcement intervention always causes structural reactions in DTOs surviving disruption as they confront an unexpected reduction in their workforce. The first reaction concerns the recruitment of additional personnel to replace the arrested members. While in the scenarios with fewer arrests, these recruits restore the prearrest situation in terms of the number of DTO members, in the scenario with more arrests, the workforce is unable to return to the previous levels. In these cases, DTOs undergo modifications in relational and working patterns, with increases in both direct (i.e., degree centrality) and indirect (i.e., betweenness centrality) reachability among members so that they can continue their involvement in drug trafficking and dealing without sacrificing too much security.

In terms of the performance of drug trafficking and dealing, DTOs surviving disruption are highly resilient. Their capacity to continue drug acquisitions and sales, even when substantial rates of arrests occur, is affected by law enforcement intervention only in the period immediately after the disruptive event, with no negative impact on the workload and the related profits a few months after the arrests.

4.3. The impact on DTO resilience of targeting members performing different tasks

An additional purpose of MADTOR is that of testing DTOs' resilience when facing attempts at disruption targeting members of the organization who perform different tasks. This section analyses the resilience indicators presented in Table 1 of section 3.5.1 when considering the sets of simulations reproducing attempts at disruption targeting all members of the DTO, only the traffickers, only the packagers, or only the retailers.

To this end, the following analyses concentrate on DTOs with an intermediate focus in the security vs. efficiency trade-off facing an attempt at disruption that results in the arrests of 40% of the selected target (i.e., all members, only the traffickers, only the packagers, or only the retailers). Arresting different shares of DTO members or targeting DTOs with a dissimilar focus in the security vs. efficiency trade-off may impact the outcomes of the attempt at disruption. The effects of arresting different proportions of members are examined in section 4.2, and the influence of DTO strategies adopted in relation to the security vs. efficiency trade-off will be investigated in section 4.4. Annex IV provides additional information.

The graphs included in this section report in gray the trends of resilience indicators for the baseline scenario in which there are no arrests. This scenario refers to DTOs with an intermediate focus in the security/efficiency trade-off that are not targeted by any arrests. To maintain comparable levels of statistical robustness, 100 separate iterations were run for each target; thus, there are minor differences among the four baseline scenarios that are imputable to the elements of stochasticity in the model. Dark purple lines report the trends of resilience indicators for DTOs in which members are targeted by law enforcement intervention regardless of the tasks they perform, plum purple lines report the trends for DTOs in which law enforcement intervention targets the traffickers, dark orange lines report the trends for DTOs in which the packagers are targeted, and light orange lines report the DTOs in which the retailers are targeted. Apart from the graph showing the share of active DTOs, the colored areas indicate the proportions of DTOs still active in each scenario. The red and green dots on the x-axis report the significance of the differences at each point in time for the baseline and alternative scenarios (red= nonsignificant, green=significant).

The following tables report the summary statistics of resilience indicators per year, referring to the first day of each year (i.e., ticks of simulations 0, 366, 731, 1,096, 1,461, and 1,825). When referring to the baseline scenario, the tables report the average, minimum and maximum values registered among the four baseline scenarios (i.e., one for each target).

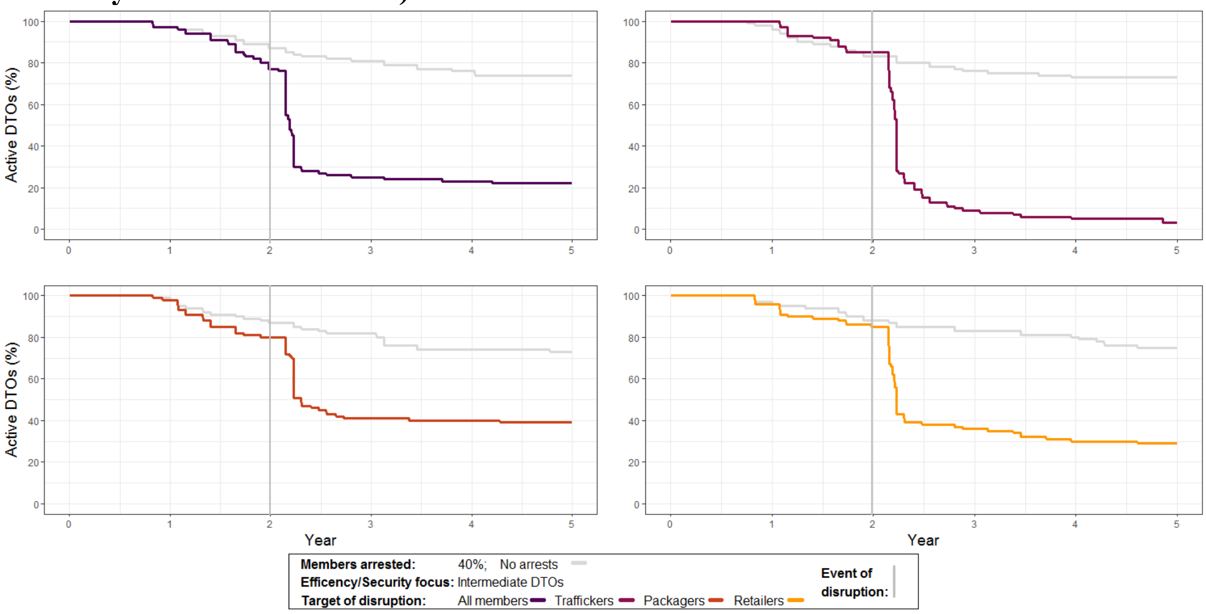
4.3.1. Ability to endure disruption

The ability to endure disruption, that is, DTOs' capacity to survive law enforcement interventions, is the first indicator analyzed to investigate DTOs' resilience.

Attempts at disruption with different targets result in varying shares of DTOs active at the end of the five simulated years (Graph 11), with differences among the tested scenarios that are all strongly significant (Table 13). Law enforcement interventions targeting DTO traffickers are the most disruptive, passing from 85% of DTOs active at the end of the second year of criminal involvement to 9% of DTOs active in the year after the attempt at disruption. Interventions without a specific target (i.e., that disregard the tasks performed by DTO members) are the second most disruptive, with almost 20-25% of DTOs remaining active in the years following the attempt at disruption (Graph 11 and Table 13).

Conversely, attempts at disruption targeting DTO packagers and retailers are the least disruptive. Targeting retailers results in 29% of DTOs surviving at the end of the five simulated years, whereas targeting the packagers leads to almost 40% of DTOs still being active in the drug market after the five simulated years (Graph 11 and Table 13).

Graph 11. Share of active DTOs (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 13. Share of active DTOs per year (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)

Target of disruption	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Average baseline	100%	97%	86%	81%	76%	74%
All members	100%	97%	77%	25%	23%	22%
Traffickers	100%	100%	85%	9%	5%	3%
Packagers	100%	98%	80%	41%	40%	39%
Retailers	100%	96%	85%	36%	30%	29%

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
All members-Traffickers	54.19 (34.46)	46.37 (42.93)	***
All members-Packagers	54.19 (34.46)	63.48 (25.86)	***
All members-Retailers	54.19 (34.46)	59.65 (30.05)	***
Traffickers-Packagers	46.37 (42.93)	63.48 (25.86)	***
Traffickers-Retailers	46.37 (42.93)	59.65 (30.05)	***
Packagers-Retailers	63.48 (25.86)	59.65 (30.05)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

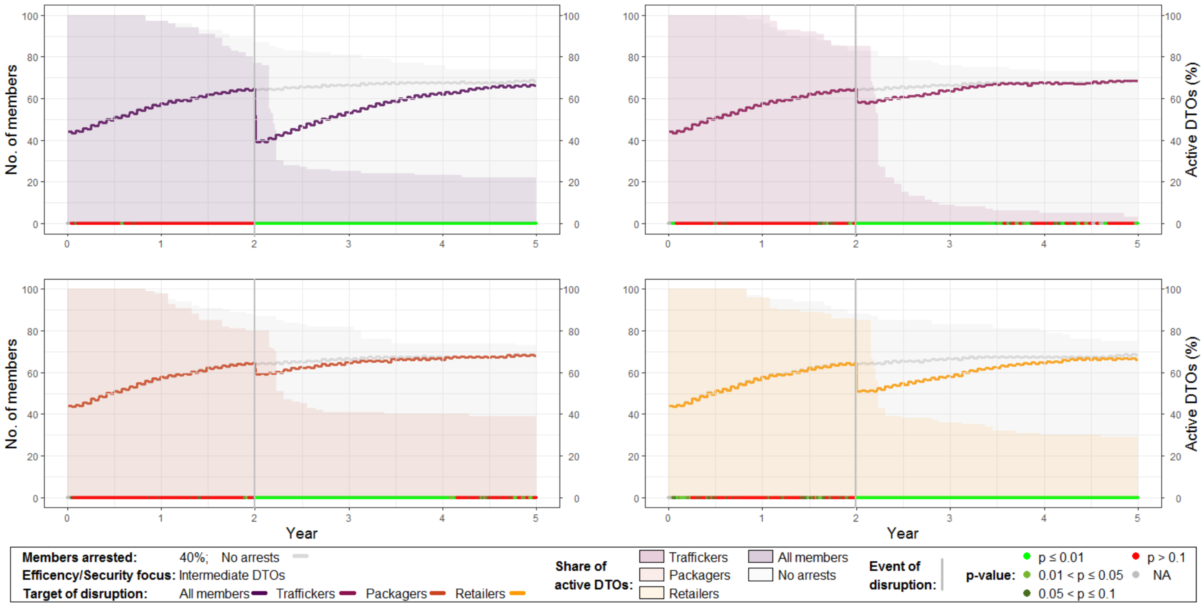
Source: Author's elaboration

4.3.2. Ability to react quickly and efficiently to law enforcement interventions

Among DTOs surviving disruption, their ability to react quickly and efficiently to the threats posed by law enforcement is the first element providing information about their resilience. To this end, this section examines three resilience indicators: the number of members currently involved in DTO activities, the average normalized degree centrality of members, and the average normalized betweenness centrality of members.

Regarding the number of members in the DTO, the arrest of some members (i.e., 40% of the selected category) provokes an immediate reduction in DTO members after the attempt at disruption. The reduction is larger when all members or retailers are targeted and smaller when traffickers and packagers are targeted since fewer members perform these tasks in the organization. In each scenario, over time, the number of DTO members increases in the months after the attempt at disruption because of the recruitment of replacements for the arrested members (Graph 12). In the scenarios in which traffickers and packagers are targeted, at the end of the simulated period, DTOs rely on a workforce that is indistinguishable from that in the scenarios with no attempt at disruption; however, when all members or retailers are targeted, the number of members at the end of the simulation is significantly lower than that in the baseline scenario (Table 14).

Graph 12. Number of DTOs members (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 14. Number of DTOs members per year (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)

Target of disruption	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Average baseline	0	100	44	44	44	0	-
	1	97	51	60	57.89	1.78	57.53-58.25
	2	86	61	65	64.63	0.67	64.49-64.78
	3	81	63	67	66.19	0.74	66.02-66.35
	4	76	65	68	67.27	0.72	67.10-67.43
	5	74	66	69	68.21	0.70	68.04-68.37
All members	0	100	44	44	44	0	-
	1	97	54	60	57.81	1.60	57.49-58.14
	2	77	38	40	39.70	0.49	39.59-39.81
	3	25	47	57	52.88	2.52	51.84-53.92
	4	23	57	66	62.04	2.44	60.99-63.10
	5	22	64	67	66.23	1.02	65.77-66.68
Traffickers	0	100	44	44	44	0	-
	1	100	52	60	57.82	1.71	57.48-58.16
	2	85	57	59	58.71	0.59	58.58-58.83
	3	9	62	65	63.44	1.01	62.67-64.22
	4	5	67	68	67.40	0.55	66.72-68.08
	5	3	68	69	68.67	0.58	67.23-70.10
Packagers	0	100	44	44	44	0	-
	1	98	53	60	57.92	1.77	57.56-58.27
	2	80	56	60	59.65	0.75	59.48-59.82
	3	41	63	66	64.68	0.91	64.40-64.97
	4	40	64	67	66.25	0.71	66.02-66.48
	5	39	66	69	68.15	0.78	67.90-68.41

Target of disruption	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Retailers	0	100	44	44	44	0	-
	1	96	52	60	57.82	1.75	57.47-58.18
	2	85	47	52	51.32	1.04	51.09-51.54
	3	36	52	64	58.00	2.29	57.22-58.78
	4	30	60	66	64.63	1.38	64.12-65.15
	5	29	65	67	66.24	0.51	66.05-66.44

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
All members-Traffickers	56.19 (7.75)	61.26 (6.57)	***
All members-Packagers	56.19 (7.75)	61.43 (6.51)	***
All members-Retailers	56.19 (7.75)	58.85 (6.33)	***
Traffickers-Packagers	61.26 (6.57)	61.43 (6.51)	n.s.
Traffickers-Retailers	61.26 (6.57)	58.85 (6.33)	***
Packagers-Retailers	61.43 (6.51)	58.85 (6.33)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

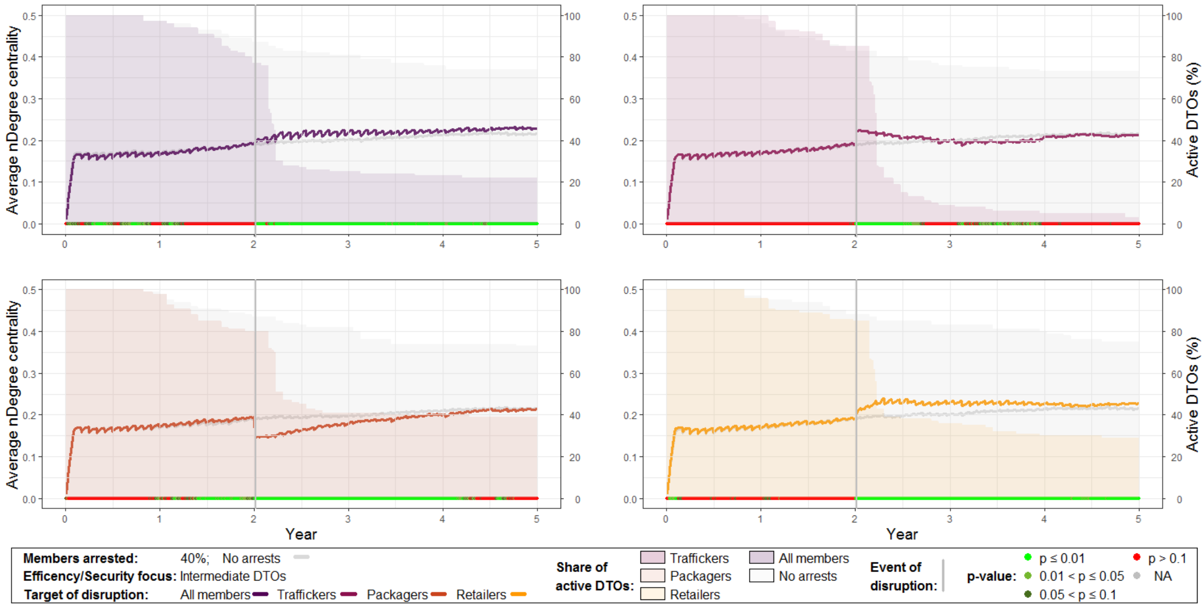
Regarding normalized average degree centrality, over the five simulated years, DTO members are directly connected with almost 20% of their companions on average (Table 15). This relational pattern is slightly affected by attempts at disruption (Graph 13), with minor differences after law enforcement intervention. In three of the four scenarios (i.e., all except for the one targeting DTO packagers), the attempt at disruption induces a limited but significant increase in the values registered by this metric, signaling the need for surviving DTOs to increase their direct connectivity to continue drug trafficking and dealing.[33] These differences remain significant over time, even though they decrease in magnitude in the scenarios in which all members and retailers are targeted. Conversely, for the scenario targeting DTO traffickers, these differences are significant only in the first year after the disruptive event and then register values that are indistinguishable from those of the baseline scenario (Graph 13 and Table 15).

Law enforcement interventions targeting DTO packagers produce different changes in relational patterns. Normalized average degree centrality decreases immediately after the arrests, with DTO members being connected to almost 5% less of their companions and returning to prearrest values only in the last part of the simulated period (Graph 13). This trend suggests that the arrest of packagers is handled quite easily by DTOs and their members. Indeed, members still active in the organizations do not need to engage in new working relations to replace those that were in effect with the arrested packagers. Because of law enforcement

[33] The increase in normalized average degree centrality immediately after the attempt at disruption must be imputed partially to the normalization process that accounts for the total number of DTO members that is reduced by the attempt at disruption.

intervention, DTO members begin to more extensively exploit their existing connections with remaining DTO packagers, avoiding exposure to new, possibly untrusted relations with other members.

Graph 13. DTOs members average normalized degree centrality (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 15. DTOs members average normalized degree centrality per year (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)

Target of disruption	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Average baseline	0	100	0	0	0	0	-
	1	97	0.12	0.21	0.17	0.01	0.17-0.17
	2	86	0.14	0.23	0.19	0.02	0.19-0.19
	3	81	0.16	0.24	0.20	0.02	0.20-0.20
	4	76	0.16	0.25	0.21	0.02	0.21-0.22
	5	74	0.17	0.26	0.22	0.02	0.21-0.22
All members	0	100	0	0	0	0	-
	1	97	0.12	0.22	0.17	0.01	0.16-0.17
	2	77	0.16	0.24	0.19	0.02	0.19-0.20
	3	25	0.16	0.25	0.22	0.02	0.21-0.23
	4	23	0.20	0.25	0.22	0.01	0.22-0.23
	5	22	0.20	0.26	0.23	0.01	0.22-0.23
Traffickers	0	100	0	0	0	0	-
	1	100	0.12	0.20	0.17	0.01	0.17-0.17
	2	85	0.16	0.24	0.19	0.01	0.19-0.19
	3	9	0.18	0.22	0.20	0.01	0.19-0.21
	4	5	0.20	0.22	0.21	0.01	0.19-0.22
	5	3	0.20	0.22	0.21	0.01	0.19-0.24

Target of disruption	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Packagers	0	100	0	0	0	0	-
	1	98	0.14	0.21	0.17	0.01	0.17-0.18
	2	80	0.16	0.23	0.19	0.01	0.19-0.20
	3	41	0.15	0.21	0.18	0.01	0.17-0.18
	4	40	0.17	0.24	0.20	0.02	0.20-0.21
	5	39	0.18	0.26	0.21	0.02	0.21-0.22
Retailers	0	100	0	0	0	0	-
	1	96	0.14	0.19	0.17	0.01	0.17-0.17
	2	85	0.15	0.24	0.19	0.02	0.19-0.19
	3	36	0.20	0.27	0.23	0.02	0.22-0.24
	4	30	0.20	0.25	0.23	0.01	0.22-0.23
	5	29	0.19	0.26	0.23	0.01	0.22-0.23

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
All members-Traffickers	0.199 (0.03)	0.191 (0.024)	***
All members-Packagers	0.199 (0.03)	0.182 (0.023)	***
All members-Retailers	0.199 (0.03)	0.204 (0.031)	***
Traffickers-Packagers	0.191 (0.024)	0.182 (0.023)	***
Traffickers-Retailers	0.191 (0.024)	0.204 (0.031)	***
Packagers-Retailers	0.182 (0.023)	0.204 (0.031)	***

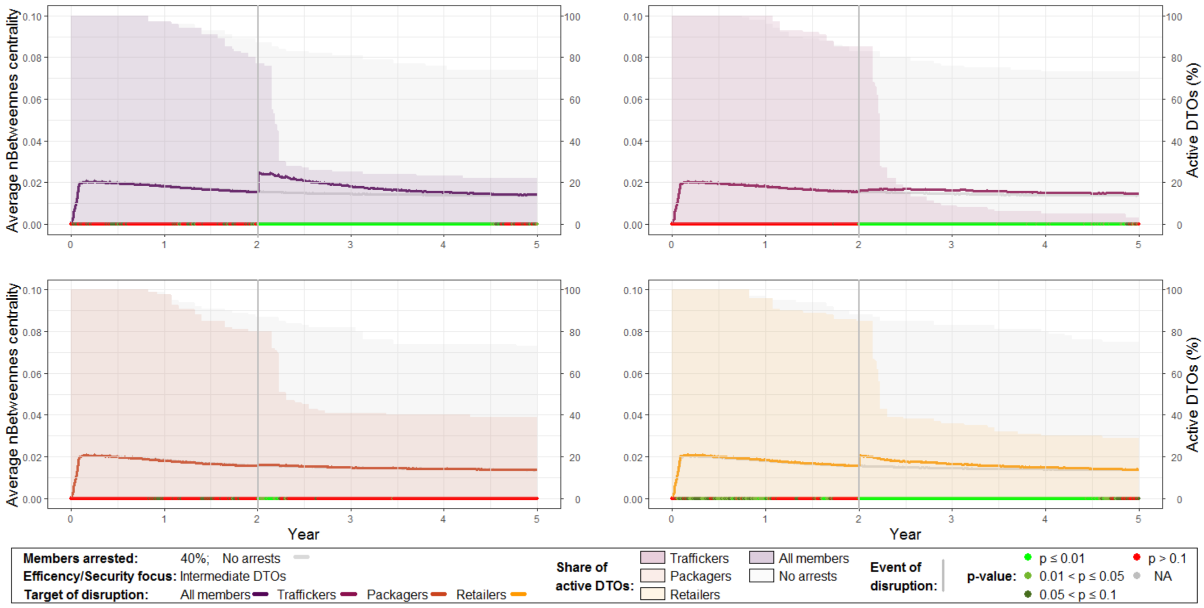
**Significance at 95% level, **99%, ***99.9%, ^n.s^Nonsignificant*

Source: Author's elaboration

Concerning average normalized betweenness centrality, the arrests of a limited number of DTOs members, such as in the scenarios targeting traffickers or packagers, have marginal effects on average betweenness centrality (Graph 14 and Table 16). Conversely, arresting more actors, as occurs when an attempt at disruption targets all the members or DTO retailers, results in an immediate, but moderate, increase in average betweenness centrality. Additionally, in these scenarios, the magnitude of the increase is reduced over time, with values indistinguishable from the baseline scenarios at the end of the five simulated years (Graph 14 and Table 16).[34]

[34] Despite being very limited in magnitude, some differences are significant (as in the case of the scenario targeting DTO traffickers in Graph 13). This is because, especially when the share of active DTOs is very small, the variability in the values registered in the different iterations of the model can be very low. This provokes differences that, although very small, appear to be significant. However, considering the information provided by average betweenness centrality, minor differences, even though significant, have a limited impact on DTOs relational patterns.

Graph 14. DTOs members average normalized betweenness centrality (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 16. DTOs members average normalized betweenness centrality per year (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)

Target of disruption	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Average baseline	0	100	0	0	0	0	-
	1	97	0.011	0.022	0.018	0.002	0.018-0.019
	2	86	0.010	0.019	0.016	0.001	0.015-0.016
	3	81	0.011	0.019	0.015	0.001	0.014-0.015
	4	76	0.011	0.017	0.014	0.001	0.014-0.014
	5	74	0.011	0.017	0.014	0.001	0.013-0.014
All members	0	100	0	0	0	0	-
	1	97	0.011	0.021	0.018	0.002	0.018-0.019
	2	77	0.011	0.018	0.015	0.001	0.015-0.016
	3	25	0.016	0.021	0.018	0.001	0.018-0.019
	4	23	0.014	0.018	0.015	0.001	0.015-0.016
	5	22	0.013	0.016	0.014	0.001	0.014-0.014
Traffickers	0	100	0	0	0	0	-
	1	100	0.010	0.022	0.018	0.002	0.018-0.018
	2	85	0.011	0.021	0.016	0.001	0.015-0.016
	3	9	0.014	0.018	0.016	0.001	0.016-0.017
	4	5	0.014	0.016	0.015	0.001	0.014-0.016
	5	3	0.014	0.016	0.015	0.001	0.012-0.017
Packagers	0	100	0	0	0	0	-
	1	98	0.010	0.022	0.018	0.002	0.018-0.018
	2	80	0.011	0.018	0.016	0.001	0.015-0.016
	3	41	0.012	0.017	0.015	0.001	0.015-0.015
	4	40	0.012	0.016	0.014	0.001	0.014-0.015
	5	39	0.012	0.015	0.014	0.001	0.013-0.014

Target of disruption	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Retailers	0	100	0	0	0	0	-
	1	96	0.011	0.021	0.018	0.001	0.018-0.019
	2	85	0.010	0.018	0.016	0.001	0.015-0.016
	3	36	0.015	0.021	0.017	0.001	0.016-0.017
	4	30	0.013	0.017	0.015	0.001	0.015-0.015
	5	29	0.012	0.017	0.014	0.001	0.014-0.014

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
All members-Traffickers	0.017 (0.03)	0.016 (0.02)	***
All members-Packagers	0.017 (0.03)	0.016 (0.02)	***
All members-Retailers	0.017 (0.03)	0.017 (0.02)	***
Traffickers-Packagers	0.016 (0.02)	0.016 (0.02)	***
Traffickers-Retailers	0.016 (0.02)	0.017 (0.02)	***
Packagers-Retailers	0.016 (0.02)	0.017 (0.02)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

4.3.3. Ability to maintain primary functions and activities unaltered after disruption

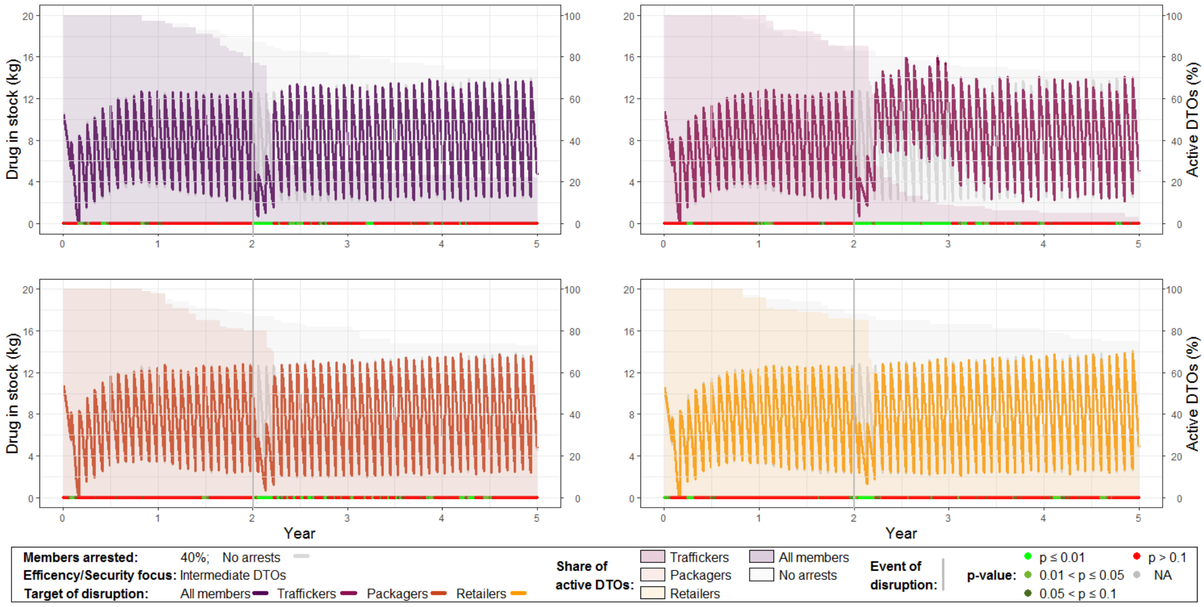
Maintaining primary functions unaltered is the last condition that resilient DTOs must display. The amount of drugs DTOs have in stock and DTO revenues are the indicators analyzed for this purpose.

Attempts at disruption targeting different categories of DTO members have a limited impact on the amount of drugs that DTOs preserve in their warehouses (Graph 15). In all four scenarios tested and the baseline scenario, the amount of drugs in stock oscillates widely because of continuous drug acquisitions and sales, with minimum values, on average, of approximately 5 kilos and maximum values of approximately 10 kilos (Table 17).

Law enforcement interventions, in all scenarios, provoke a significant reduction in the amount of drugs in stock only in months immediately after the arrests due to the seizure of drugs at the disposal of the arrested members (Graph 15).

On average, targeting DTO traffickers results in larger quantities of drugs in stock, with significant differences in both the baseline scenario and the alternative scenarios. While this result reflects the situation of the minority of DTOs surviving disruption (i.e., less than 10% of DTOs are active after three years of criminal involvement when DTO traffickers are targeted), it may signal that attempts at disruption targeting DTO traffickers are perceived as the most challenging by DTO members themselves. As a countermeasure, in the period following the disruptive event, DTOs' managerial figures may invite active traffickers to acquire and store more drugs to be prepared to sustain drug sales in the short and medium term in the case of additional threatening events (Table 17).

Graph 15. Amount of drug in stock (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 17. Amount of drug in stock (in kg) per year (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)

Target of disruption	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Average baseline	0	100	8.70	8.70	8.70	0	-
	1	97	5.64	17.54	10.92	1.98	10.52-11.32
	2	86	4.59	20.77	9.55	1.36	9.26-9.84
	3	81	4.04	9.98	7.94	1.17	7.68-8.20
	4	76	2.90	7.80	6.19	1.10	5.93-6.44
	5	74	1.01	5.73	4.25	0.93	4.03-4.47
All members	0	100	8.70	8.70	8.70	0	-
	1	97	6.11	16.71	10.96	2.05	10.55-11.38
	2	77	6.58	10.95	9.41	1.04	9.19-9.63
	3	25	4.04	9.98	8.01	1.29	7.73-8.30
	4	23	2.90	7.79	6.30	1.16	6.04-6.57
	5	22	2.37	5.73	4.38	0.77	4.20-4.56
Traffickers	0	100	8.70	8.70	8.70	0	-
	1	100	6.33	16.89	10.78	1.97	10.38-11.18
	2	85	5.27	15.67	9.55	1.46	9.23-9.87
	3	9	4.58	9.47	7.74	1.13	7.48-8.00
	4	5	3.18	7.74	6.15	1.05	5.91-6.40
	5	3	1.01	5.69	4.27	0.92	4.05-4.48
Packagers	0	100	8.70	8.70	8.70	0	-
	1	98	5.64	17.54	10.99	2.07	10.58-11.41
	2	80	6.03	20.77	9.67	1.71	9.31-10.03
	3	41	4.77	9.66	7.86	1.19	7.60-8.12
	4	40	3.29	7.80	6.20	1.11	5.94-6.46
	5	39	1.05	5.65	4.08	1.10	3.83-4.34

Target of disruption	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Retailers	0	100	8.70	8.70	8.70	0	-
	1	96	6.30	16.60	10.96	1.82	10.59-11.32
	2	85	4.59	12.56	9.58	1.22	9.32-9.84
	3	36	5.17	9.61	8.16	1.05	7.93-8.39
	4	30	3.36	7.56	6.09	1.09	5.85-6.33
	5	29	2.11	5.65	4.27	0.94	4.05-4.48

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
All members-Traffickers	7.68 (3.23)	8.19 (3.30)	***
All members-Packagers	7.68 (3.23)	7.62 (3.24)	n.s.
All members-Retailers	7.68 (3.23)	7.67 (3.18)	n.s.
Traffickers-Packagers	8.19 (3.30)	7.62 (3.24)	***
Traffickers-Retailers	8.19 (3.30)	7.67 (3.18)	***
Packagers-Retailers	7.62 (3.24)	7.67 (3.18)	n.s.

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

Similarly, the trends of DTO revenues oscillate over time following drug acquisitions and sales (Graph 16 and Table 18). In the period before the attempt at disruption, DTOs' revenues fluctuate around 600 k€. After the attempt at disruption, this resilience indicator produces the most differentiated trends according to tasks performed by the targeted members.

Arresting members without considering the task they perform for the organization produces a significant reduction in the first months after law enforcement intervention, but a semester after the event, DTOs' revenues are already indistinguishable from those of DTOs not targeted by any attempt at disruption.

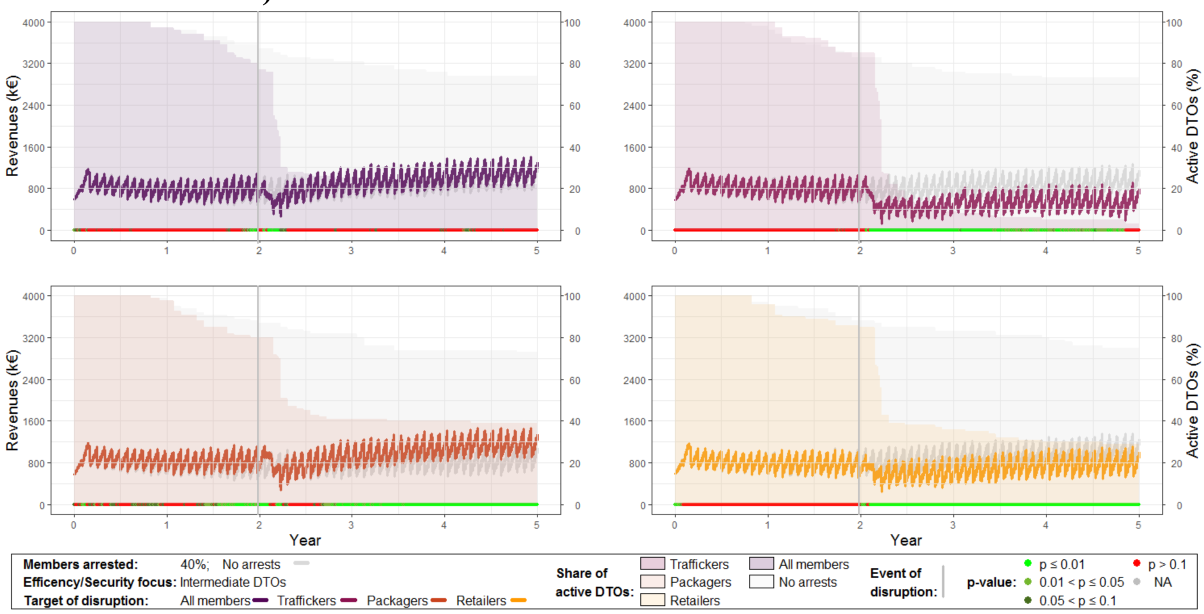
Targeting DTO traffickers and retailers results in significantly lower revenues in both the short and long terms in both to the baseline scenario and the alternative scenarios. Indeed, targeting DTO members regardless of their tasks in the organization generates average DTO revenues of 800.66 k€, whereas targeting DTO traffickers and retailers generates revenues of 641.48 k€ and 736.29 k€, respectively.

Last, attempts at disruption targeting DTO packagers are confirmed to be the least challenging. In the period after the disruptive event, DTOs' revenues increase in comparison to the baseline scenario, with the highest average revenues registered in all scenarios tested (i.e., 927.13 k€).

DTOs' revenues appear to be significantly affected by the target of an attempt at disruption. Targeting DTO members who are most involved in activities with direct economic implications, such as traffickers acquiring drugs at the wholesale level and retailers active in street dealing, produces significant losses in terms of revenues. The removal of these actors from the organization leads to substantial problems in drug trafficking and dealing in the short term, with a shortage of drugs in stock and the consequent impossibility of profiting from drug sales. In the long term, DTO members can reorganize drug trafficking and dealing activities; however, they cannot completely bridge the gap, so their revenues will remain substantially and significantly lower than in the baseline scenario.

Conversely, targeting DTO packagers generates economic advantages for the DTO overall, with revenues in the last years of criminal involvement that are even higher than in the baseline scenario. Indeed, because packagers perform unspecialized tasks, they can be replaced with relative ease by still active DTO packagers increasing their workload in the short term. This allows a reduction of expenses in the short term (i.e., due to savings from arrested packagers' wages) while maintaining the pre arrest level of involvement in drug trafficking and dealing.

Graph 16. DTOs revenues (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)



Source: Author's elaboration

Table 18. DTOs revenues (in k€) per year (Proportion of members arrested: 40%; Security vs. efficiency focus: intermediate)

Target of disruption	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Average baseline	0	100	620.77	620.77	620.77	0	-
	1	97	29.49	1375.20	618.39	245.40	568.88-667.91
	2	86	131.96	1372.91	652.99	259.41	597.46-708.51
	3	81	192.07	1766.64	829.66	295.90	764.04-895.29
	4	76	357.51	1995.22	1010.52	313.35	938.84-1082.19
	5	74	505.94	2435.22	1218.97	369.63	1133.19-1304.75

Target of disruption	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
All members	0	100	620.77	620.77	620.77	0	-
	1	97	35.79	1258.95	595.53	242.82	546.59-644.47
	2	77	227.11	1348.03	642.61	247.79	589.79-695.42
	3	25	196.09	1693.26	840.66	314.93	771.02-910.30
	4	23	357.51	1848.84	1040.01	330.58	964.47-1115.55
	5	22	582.57	2324.99	1267.74	385.06	1178.53-1356.95
Traffickers	0	100	620.77	620.77	620.77	0	-
	1	100	64.58	1222.30	638.57	228.03	592.36-684.77
	2	85	153.35	1363.54	654.13	250.29	599.48-708.79
	3	9	272.17	1484.15	839.51	275.99	776.44-902.58
	4	5	417.93	1781.39	997.91	314.82	924.46-1071.37
	5	3	526.68	2435.22	1191.30	390.78	1100.12-1282.47
Packagers	0	100	620.77	620.77	620.77	0	-
	1	98	29.49	1238.03	612.59	268.68	558.72-666.45
	2	80	170.23	1372.91	634.53	261.74	578.75-690.31
	3	41	192.07	1406.80	753.73	276.23	693.03-814.42
	4	40	439.40	1545.53	926.50	264.24	865.28-987.72
	5	39	505.94	1806.30	1124.55	325.03	1048.72-1200.39
Retailers	0	100	620.77	620.77	620.77	0	-
	1	96	48.95	1375.20	626.88	242.07	577.84-675.93
	2	85	131.96	1226.97	680.68	277.81	621.81-739.54
	3	36	238.84	1766.64	884.75	316.47	815.65-953.85
	4	30	418.25	1995.22	1077.64	343.77	1001.13-1154.14
	5	29	552.61	2117.05	1292.29	377.66	1205.4-1379.18

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
All members-Traffickers	880.66 (193.58)	641.48 (198.42)	***
All members-Packagers	880.66 (193.58)	927.13 (198.74)	***
All members-Retailers	880.66 (193.58)	736.29 (158.08)	***
Traffickers-Packagers	641.48 (198.42)	927.13 (198.74)	***
Traffickers-Retailers	641.48 (198.42)	736.29 (158.08)	***
Packagers-Retailers	927.13 (198.74)	736.29 (158.08)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

4.3.4. Research question 2: Summary of the results

The second research question considers the impact of law enforcement interventions targeting DTO members performing different tasks in the organization. DTOs facing the arrests of traffickers are the least resistant, with only 3% of organizations still active at the end of the simulations. Interventions regardless of the tasks accomplished by DTO members are the second most disruptive, with 22% of DTOs remaining active after five simulated years. Conversely, attempts at disruption targeting retailers and packagers have lower impacts, with 29% and 39% of DTOs active during the fifth year, respectively.

For DTOs that survive disruption, the immediate reaction is to replace the arrested members. When targeting traffickers and packagers, simulations end with a workforce similar to the one in the baseline scenario; when disruption attempts target retailers or no specific task, DTOs cannot recover completely and rely on fewer members at the end of the simulated period. DTO members increase their level of direct connectivity as a response to law enforcement interventions, aiming to establish new relations with other members to continue performing their tasks. As an exception, in attempts at disruption targeting packagers, DTO members decrease their level of connectivity overall, losing their connections with the arrested members without exploiting new relations.

Aside from the reorganization of working relations, the activities of DTOs surviving disruption are only marginally affected by attempts at disruption. Concerning the amount of drugs in stock, DTOs register some drug shortages immediately after the law enforcement intervention, but there is no long-term impact. In relation to profits, DTOs are extremely resilient to attempts at disruption targeting packagers and regardless of the tasks performed by DTO members, registering increasing or comparable revenues compared to the baseline scenario, respectively. In contrast, attempts at disruption targeting traffickers and retailers are more challenging, causing a significant reduction in DTO revenues in both the short and long term.

4.4. The impact on DTO resilience of a diversified focus in the security vs. efficiency trade-off

The last objective of the research is investigating whether and how DTOs with different focuses in the security vs. efficiency trade-off display diversified resistance and resilience abilities. To this end, MADTOR reproduces reactions to law enforcement interventions by DTOs alternatively prioritizing the security side of the trade-off, prioritizing the efficiency side, or not having a preference for either security or efficiency.

The security vs. efficiency trade-off affects DTOs differently. MADTOR incorporates variations in the amount of drugs acquired and sold, recruitment strategies, members' retribution, and the likelihood and intensity of law enforcement interventions (see section 3.3.1). Regarding the latter, MADTOR tested different law enforcement intervention scenarios: the first scenario is the arrest of a set proportion of members and the seizure of the drugs at their disposal; in the second scenario, the share of arrested members and the amount of seized drugs vary according to the DTO security/efficiency focus; and in the third scenario, DTOs may confront multiple attempts at disruption distributed differently over time according to their security/efficiency focus (see section 3.3.2 and "The periodically-arrests and attempt-at-disruption procedure" section of Annex II).

The following analyses investigate the trends of the resilience indicators presented in Table 1 of section 3.5.1, concentrating mostly on attempts at disruption targeting 40% of DTO members regardless of their tasks in the organization.[35] The influence of targeting different proportions of members, or actors accomplishing different tasks was discussed in sections 4.2 and 4.3, respectively. This section reports some additional specifications, while Annex IV provides complete information on all the experimental combinations.

In the following graphs, gray lines display the trends of resilience indicators for the baseline scenarios in the absence of any attempt at disruption for each DTO's security vs. efficiency trade-off focus (i.e., secure DTOs, intermediate DTOs, and efficient DTOs). Yellow lines report the trends of resilience indicators for secure DTOs, orange lines for DTOs with an intermediate focus in the security/efficiency trade-off, and red lines for efficient DTOs. The colored areas in the graphs in sections 4.4.2 and 4.4.3 report the shares of active DTOs over time in each scenario. The dots in red and green on the x-axis report the significance of the differences between the baseline and alternative scenarios at each point in time (red= nonsignificant, green=significant). For graphs related to the third law enforcement intervention scenario, vertical lines signal the points in time when disruptive events may occur; the thickness of the lines and the figures above them provide information about the number of interventions actually performed in that temporal instant. Graphs in the upper part of the image report the overall trends of resilience indicators; graphs in the lower part of the image report in nuanced colors the resilience indicator trends broken into DTOs expecting different numbers of law enforcement interventions (i.e., one, two, or three or more).[36]

The tables in this section report summary statistics of resilience indicators for the first day of each simulated year (i.e., ticks of simulations 0, 366, 731, 1,096, 1,461, and 1,825).

[35] In the first law enforcement intervention scenario, exactly 40% of DTO members are arrested during the attempt at disruption. In the second and third law enforcement intervention scenarios, this baseline percentage (i.e., 40%) is randomly modified according to the security/efficiency trade-off, with secure DTOs having a higher probability of being targeted by the arrests of a lower proportion of members and efficient DTOs having a higher probability of being targeted by a larger proportion of arrests (see "The periodically-arrests and attempt-at-disruption procedure" sections in Annex II for additional details).

[36] The subdivision by the number of law enforcement interventions relies on the expected number of law enforcement interventions. At the beginning of the simulations, DTOs are assigned an expected number of events of disruption to endure according to established probability thresholds (see "The periodically-arrests and attempt-at-disruption procedure" section in Annex II for additional details). It may happen that DTOs end their criminal involvement (i.e., are disrupted) before having experienced all the expected attempts at disruption.

4.4.1. Ability to endure disruption

The strategies that DTOs adopt in relation to the security vs. efficiency trade-off influence their ability to persist over time and, eventually, their capacity to survive disruption. Managerial figures of secure DTOs prioritize the possibility of granting their members a protected environment in which to perform drug trafficking and dealing in the safest possible way, even at the cost of suboptimal profitability. This makes DTOs that prioritize security particularly vulnerable from an economic point of view, with more than 50% of these organizations terminating their criminal involvement before the end of the five simulated years even in scenarios without attempts at disruption because of their unsustainability (Graph 17, Graph 19, and Graph 23). Conversely, managerial figures of efficient DTOs prioritize drug trafficking and dealing with profits, even if this leads to a greater risk of apprehension for their members. This results in extraordinary economic performance, with more than 90% of organizations remaining active in the no arrests scenario (Graph 17, Graph 19, and Graph 23). Intermediate DTOs balance security and efficiency, aspiring to earn acceptable profits without compromising members' personal security too much. This strategy leads to almost 75% of DTOs remaining active in the baseline scenarios (Graph 17, Graph 19, and Graph 23).

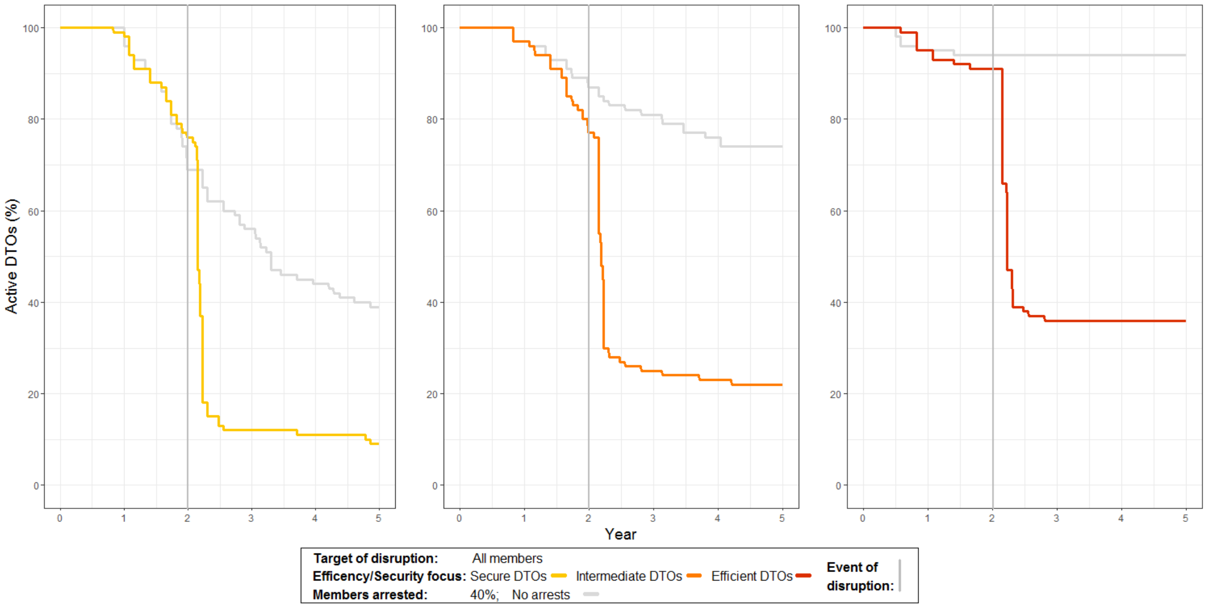
4.4.1.1. First law enforcement intervention scenario

The arrest of several members and seizure of the drugs at their disposal affects DTOs' persistence over time, with different levels of capacity to survive disruption for DTOs with different focuses in the security/efficiency trade-off (Graph 17 and Table 19).

In the first law enforcement intervention scenario, the attempt at disruption causes the dismantlement of more than half of DTOs in the subsequent year (Table 19). Secure DTOs are the most impacted by the disruptive event, with 76% of DTOs active the day after the arrests and only 12% of DTOs active one year after them. Conversely, efficient DTOs are the least impacted by law enforcement interventions (i.e., 91% and 36% of DTOs active one day and one year after the arrests, respectively). Regardless of DTOs' focus in the security vs. efficiency trade-off, the impact of the attempt at disruption is almost completely absorbed in the fourth and fifth simulated years, with a proportion of active DTOs that is nearly identical to the proportion in the third year (Table 19).

This result should be interpreted in light of the inherent fragility of DTOs with different focuses in the security/efficiency trade-off. While in all scenarios, the proportion of DTOs active at the end of the simulated period is significantly lower with respect to the corresponding baseline scenario, secure DTOs are those registering the smallest differences from the baseline scenario (i.e., -30%), and efficient DTOs are those with the greatest differences (i.e., -58%) (Graph 17 and Table 19).

Graph 17. Share of active DTOs (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)



Source: Author's elaboration

Table 19. Share of active DTOs per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)

DTOs security/efficiency focus	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Baseline – Sec. DTOs	100%	96%	69%	56%	44%	39%
Secure DTOs	100%	98%	76%	12%	11%	9%
Baseline – Int. DTOs	100%	97%	87%	81%	76%	74%
Intermediate DTOs	100%	97%	77%	25%	23%	22%
Baseline – Eff. DTOs	100%	95%	94%	94%	94%	94%
Efficient DTOs	100%	95%	91%	36%	36%	36%

Randomization-based t tests

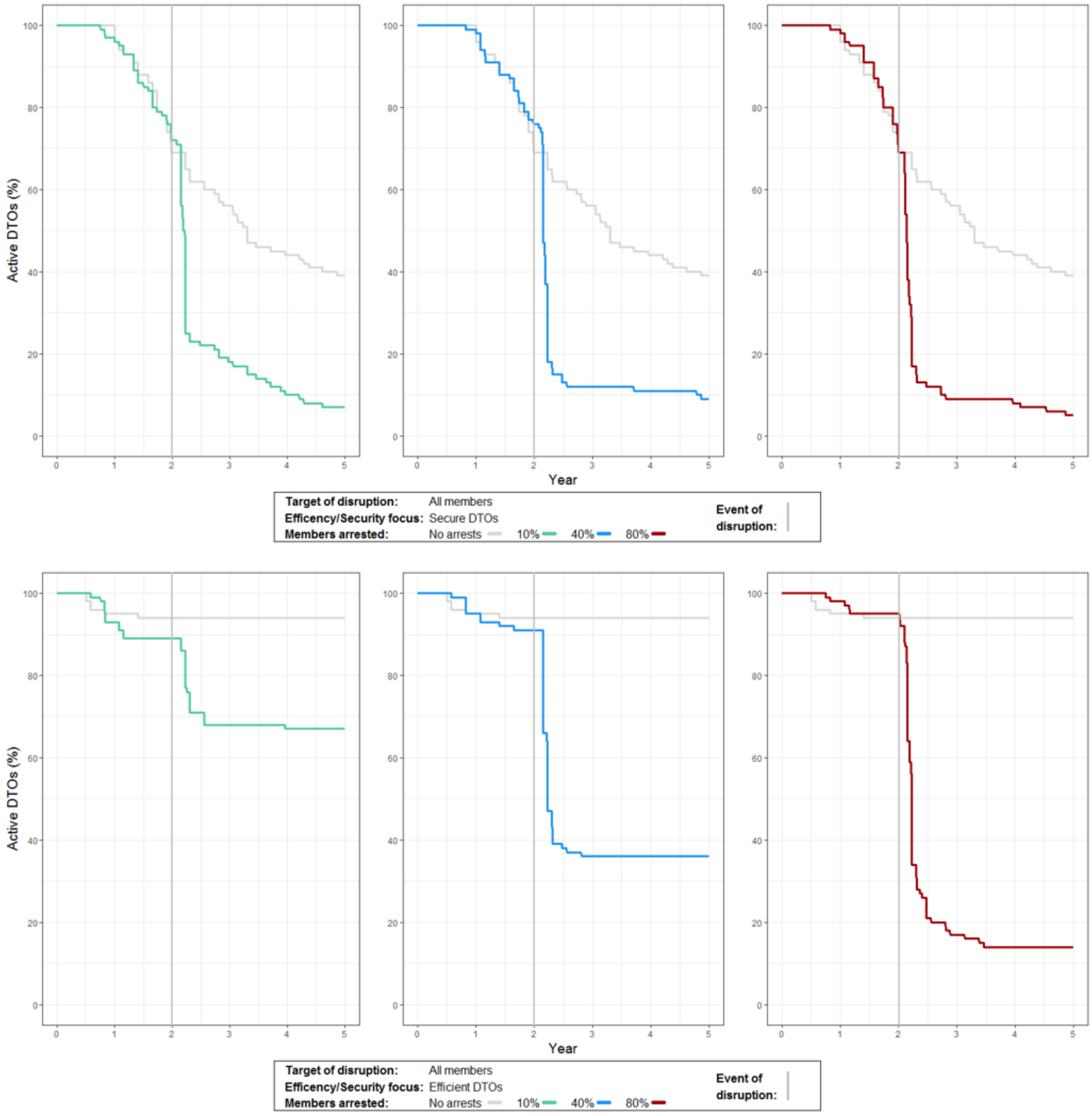
Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	67.59 (22.84)	46.82 (40.03)	***
Baseline – Int. DTOs	85.51 (9.59	54.19 (34.46)	***
Baseline – Eff. DTOs	94.88 (1.85)	62.29 (28.99)	***
Sec. DTOs – Int. DTOs	46.82 (40.03)	54.19 (34.46)	***
Sec. DTOs – Eff. DTOs	46.82 (40.03)	62.29 (28.99)	***
Int. DTOs – Eff. DTOs	54.19 (34.46)	62.29 (28.99)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

Law enforcement intensity impacts the survival rates of secure and efficient DTOs differently. The share of secure DTOs active at the end of the simulated period is always approximately 10-15% despite the proportion of members targeted, signaling that for secure DTOs, the softest scenario (i.e., 10% of members arrested) is already difficult to overcome, and further increasing the proportion of members arrested has only a limited effect (Graph 18 and Annex IV, Graph 45). In contrast, the survival of efficient DTOs is much more influenced by the number of arrests, with the arrest of 10% of members causing limited damage (i.e., almost 70% of active DTOs) and the arrests of 80% of members strongly threatening the survival of the organization (i.e., 17% of active DTOs) (Graph 18 and Annex IV, Graph 45).

Graph 18. Share of active DTOs (Target of disruption: all members; Security vs. efficiency focus: secure and efficient DTOs; Law enforcement intervention scenario: 1)



Source: Author's elaboration

4.4.1.2. Second law enforcement intervention scenario

The second law enforcement intervention scenario considers the different level of effectiveness of law enforcement interventions targeting organizations with different focuses in the trade-off due to the visibility of members in accomplishing their tasks. Thus, the higher the prioritization of efficiency, the higher DTO members' visibility, and consequently, the higher the proportion of members arrested. Conversely, the higher the prioritization of security, the lower members' visibility and the lower the proportion of arrests.

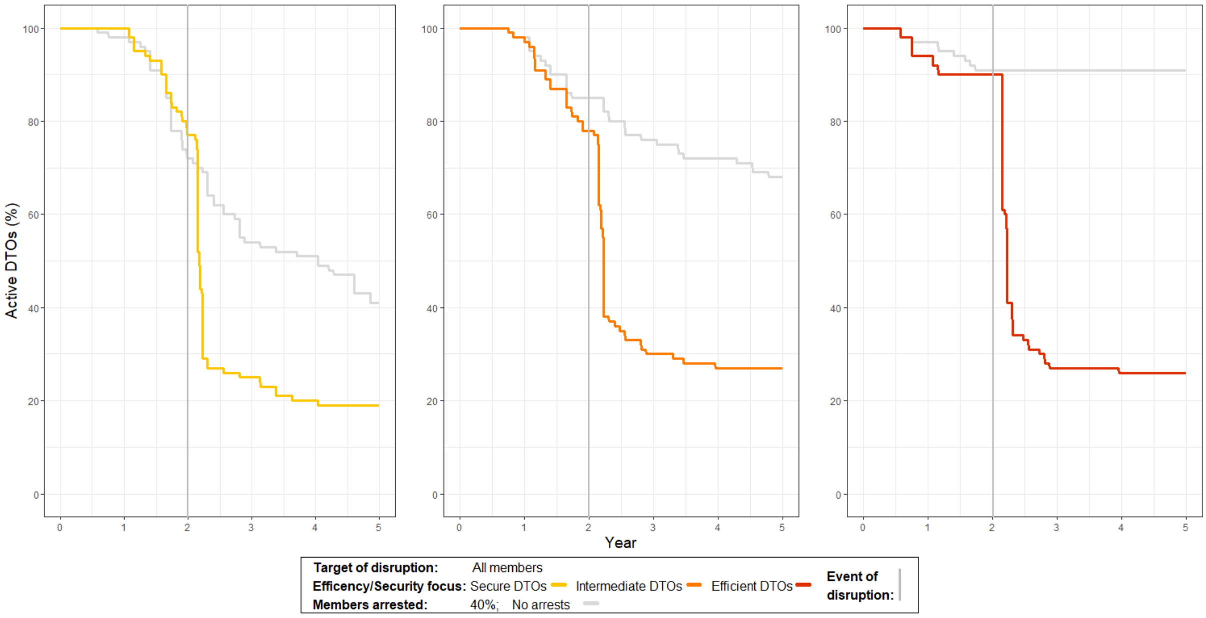
This results in a significant reduction in disrupted organizations, especially when considering secure but also intermediate DTOs. Indeed, the better concealment of criminal activities leads to fewer arrests and thus to an extended ability to continue drug trafficking and dealing. In the second law enforcement intervention scenario, at the end of the simulated period, there are 19% active secure DTOs (i.e., +10% compared to the first scenario) and 27% active intermediate DTOs (i.e., +5% compared to the first scenario) (Table 19 and Table 20).

The reduced intensity of the second law enforcement intervention scenario for secure DTOs is confirmed by the results of other experimental combinations. When considering attempts at disruption targeting 10% and 40% of traffickers or retailers, in addition to the higher survival rates, DTOs that are unable to survive until the end of the simulated period remain active for longer periods of time (Graph 20 and Graph 21). As a clear example, when 40% of traffickers are targeted, in the first law enforcement intervention scenario, no secure DTOs survive one year after the event, and in the second scenario, in the same time span, almost 10% of organizations are still active (Graph 20) (see also Annex IV, Graph 47, Graph 48,Graph 51, and Graph 52).

In contrast, efficient DTOs, being more heavily targeted (i.e., experiencing from 8% to 16% more arrests), register a decrease in the share of active organizations. In the first law enforcement intervention scenario, 36% of efficient DTOs are still active at the end of the simulated period, whereas in the second scenario, the share of active DTOs shows a 10% decrease, with only 26% of efficient DTOs being active (Graph 17 and Graph 19).

Considering attempts at disruption targeting 80% of members, the differences in the impact of the second law enforcement intervention scenario are even more pronounced (Graph 22). Indeed, while in the first scenario, efficient DTOs outperformed secure ones (i.e., 14% as opposed to 5% of active organizations at the end of the simulated period), this trend is reversed in the second scenario with 9% of active secure DTOs and only 7% of active efficient DTOs (Graph 22).

Graph 19. Share of active DTOs (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)



Source: Author's elaboration

Table 20. Share of active DTOs per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)

DTOs security/efficiency focus	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Baseline – Sec. DTOs	100%	98%	72%	54%	51%	41%
Secure DTOs	100%	100%	77%	25%	20%	19%
Baseline – Int. DTOs	100%	98%	85%	76%	72%	68%
Intermediate DTOs	100%	97%	78%	30%	27%	27%
Baseline – Eff. DTOs	100%	97%	91%	91%	91%	91%
Efficient DTOs	100%	94%	90%	27%	26%	26%

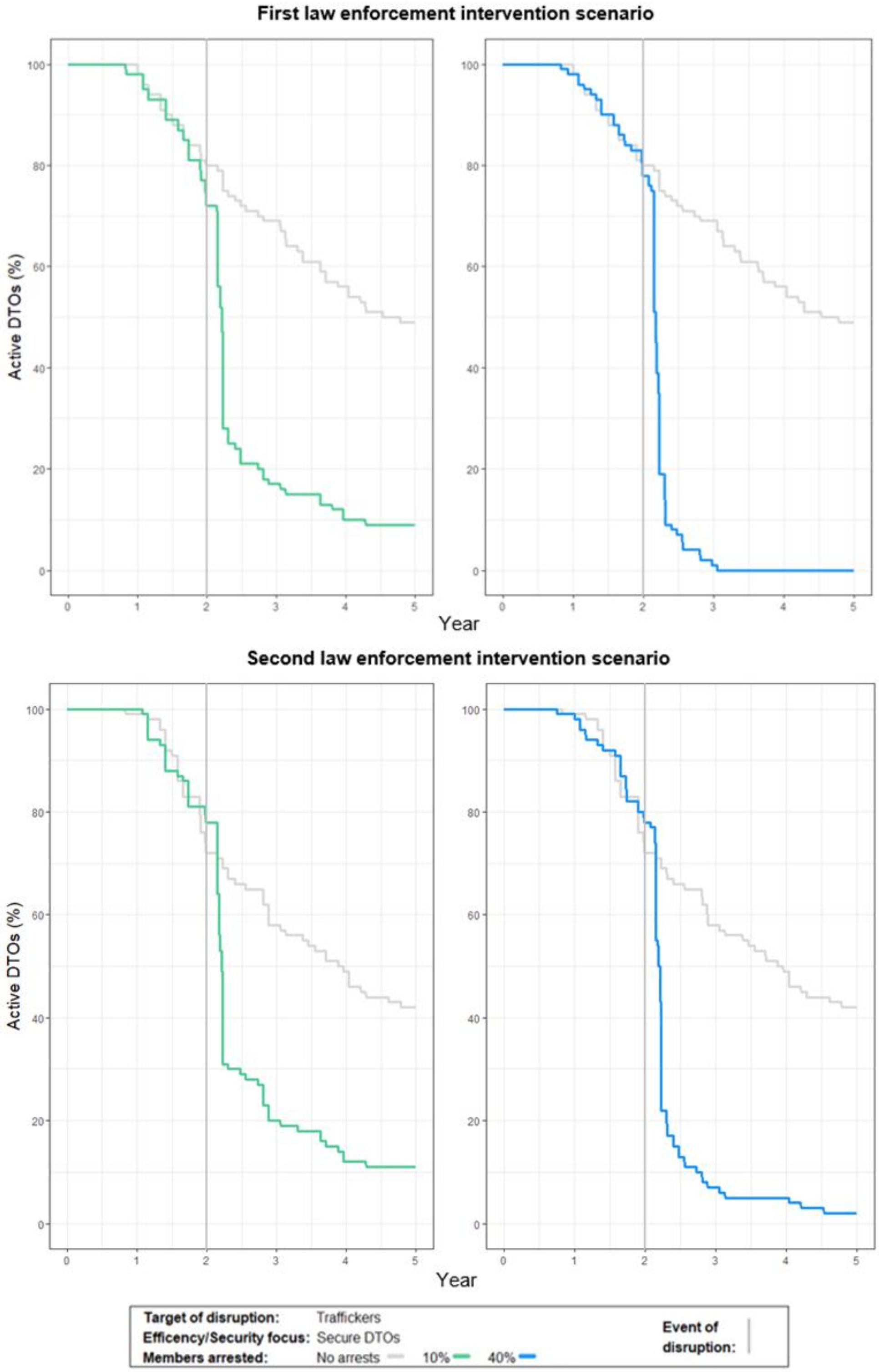
Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	69.74 (21.41)	53.33 (35.87)	***
Baseline – Int. DTOs	82.56 (11.23)	56.92 (31.42)	***
Baseline – Eff. DTOs	93.12 (3.27)	67.45 (26.54)	***
Sec. DTOs – Int. DTOs	53.33 (35.87)	56.92 (31.42)	***
Sec. DTOs – Eff. DTOs	53.33 (35.87)	67.45 (26.54)	***
Int. DTOs – Eff. DTOs	56.92 (31.42)	67.45 (26.54)	***

**Significance at 95% level, **99%, ***99.9%, [n.s]Nonsignificant*

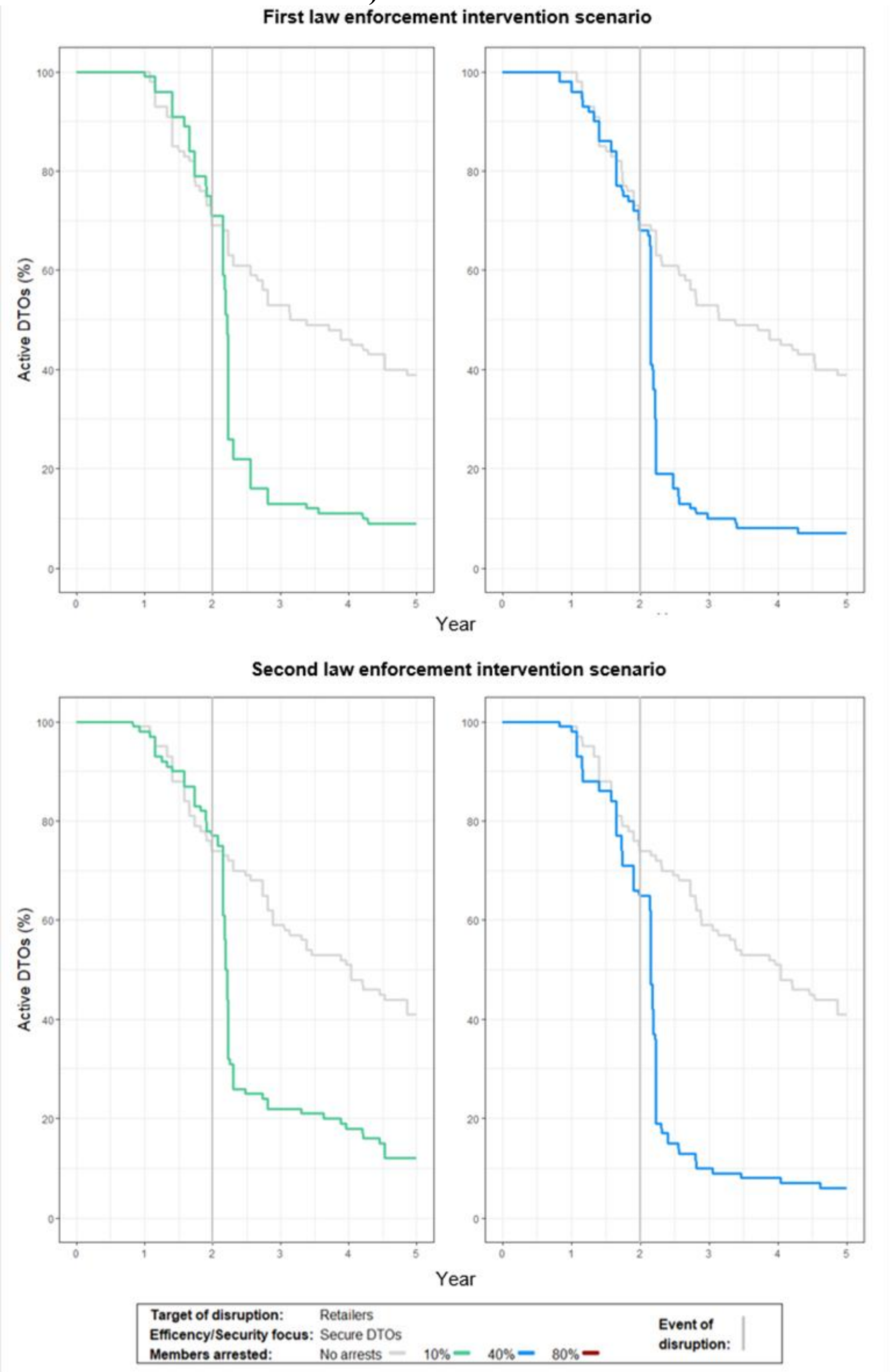
Source: Author's elaboration

Graph 20. Share of active DTOs (Security vs. efficiency focus: secure DTOs; Proportion of members arrested: 10% and 40%; Target of disruption: Traffickers; Law enforcement intervention scenario: 1 and 2)



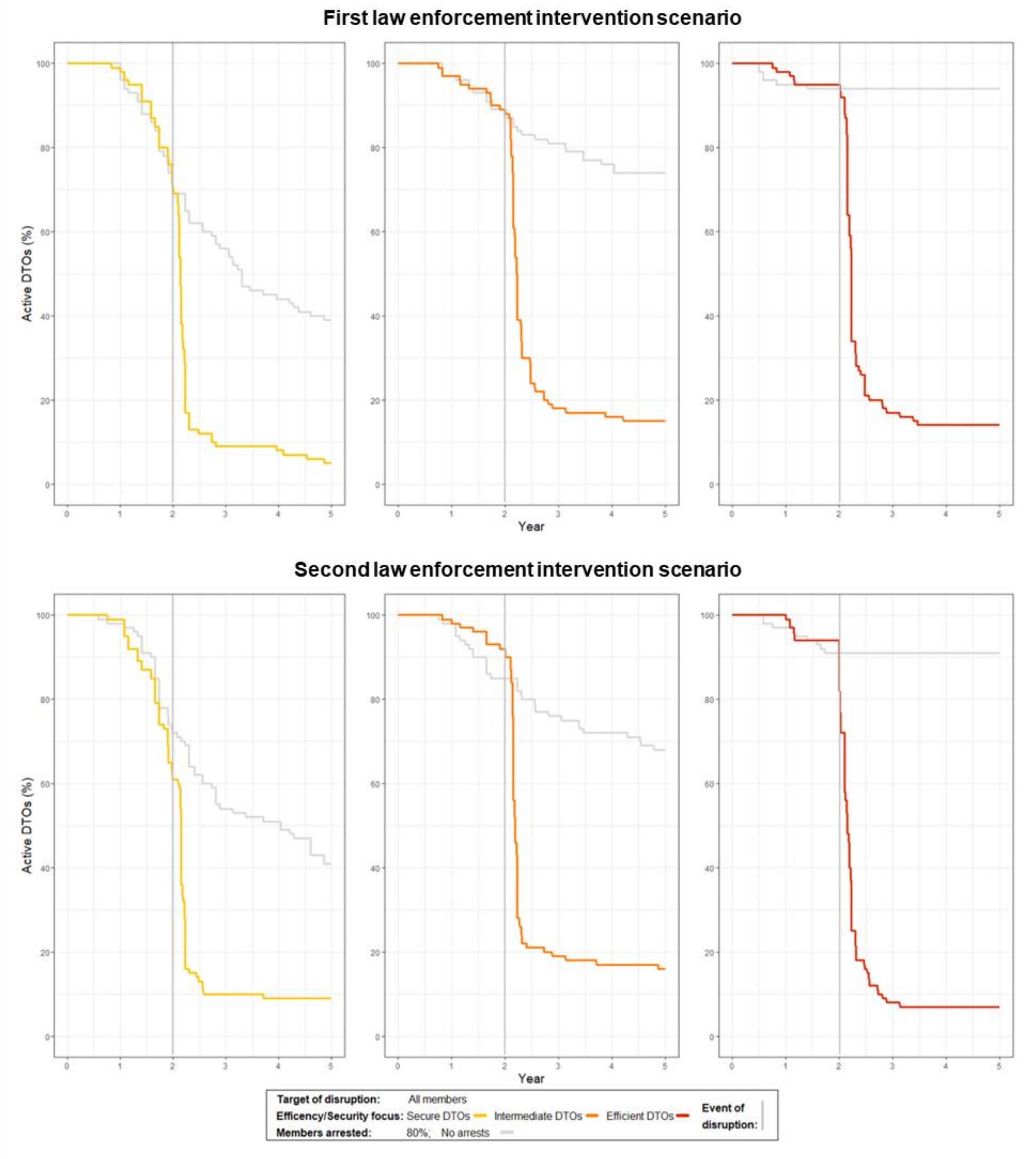
Source: Author's elaboration

Graph 21. Share of active DTOs (Security vs. efficiency focus: secure DTOs; Proportion of members arrested: 10% and 40%; Target of disruption: Retailers; Law enforcement intervention scenario: 1 and 2)



Source: Author's elaboration

Graph 22. Share of active DTOs (Proportion of members arrested: 80%; Target of disruption: all members; Law enforcement intervention scenario: 2)



Source: Author's elaboration

4.4.1.3. Third law enforcement intervention scenario

The third scenario further increases the level of realism by introducing the possibility of multiple attempts at disruption differently distributed over time according to DTOs' security/efficiency focuses. Secure DTOs, prioritizing the protection of their members, minimize attempts at disruption and avoid being targeted for longer periods of time. They expect to receive an average of 1.043 attempts at disruption, with 96.5% of secure DTOs expecting to be targeted by 1 intervention only, and the remaining 3.5% of secure DTOs expecting 2 or 3 interventions. In contrast, efficient DTOs, due to their high visibility, incur more law enforcement interventions from the early stage of their criminal involvement (i.e., expecting an average of 2.105 interventions per organization), with almost two-thirds of efficient DTOs expecting alternatively 1 or 2 interventions, more than 20% of them expecting 3 interventions, and approximately 10% expecting 4 or 5 interventions. Intermediate DTOs, positioned in between, confront an average of 1.463 expected law enforcement interventions, with almost 65% of DTOs expecting only 1 intervention, almost 30% expecting 2 interventions, and the remaining DTOs expecting 3 or more interventions (Table 21).[37]

Table 21. Percentage of expected attempts at disruption per DTO security/efficiency focus in the third scenario of law enforcement intervention

Average attempts at disruption	**Secure DTOs**	**Intermediate DTOs**	**Efficient DTOs**
	1.043	1.463	2.105
No. of attempts at disruption	**Secure DTOs (%)**	**Intermediate DTOs (%)**	**Efficient DTOs (%)**
1	96.50	63.25	33.75
2	2.75	28.50	34.50
3	0.75	7.00	21.25
4	0.00	1.25	8.50
5	0.00	0.00	2.00
Total	**100.0**	**100.0**	**100.0**

Source: Author's elaboration

Table 22 displays the frequency and timing of observed law enforcement interventions over time for DTOs with different focuses in the security/efficiency trade-off. Secure DTOs experience a total of 55 attempts at disruption, and most of these occur after some years of criminal involvement. Specifically, more than 85% of law enforcement interventions take place during the fourth and especially in the fifth simulated year. In contrast, efficient DTOs are targeted by 113 law enforcement interventions (i.e., more than double the number for secure DTOs), and these interventions are more concentrated during the first years of criminal involvement, with more than 60% occurring during the second year of criminal involvement.

[37] Table 21 reports the expected attempts at disruption that DTOs should incur. For some DTOs, the number of expected attempts at disruption may differ from the observed (i.e., experienced) number of attempts at disruption. Conversely, Table 22 reports the distribution over time of observed attempts at disruption of DTOs.

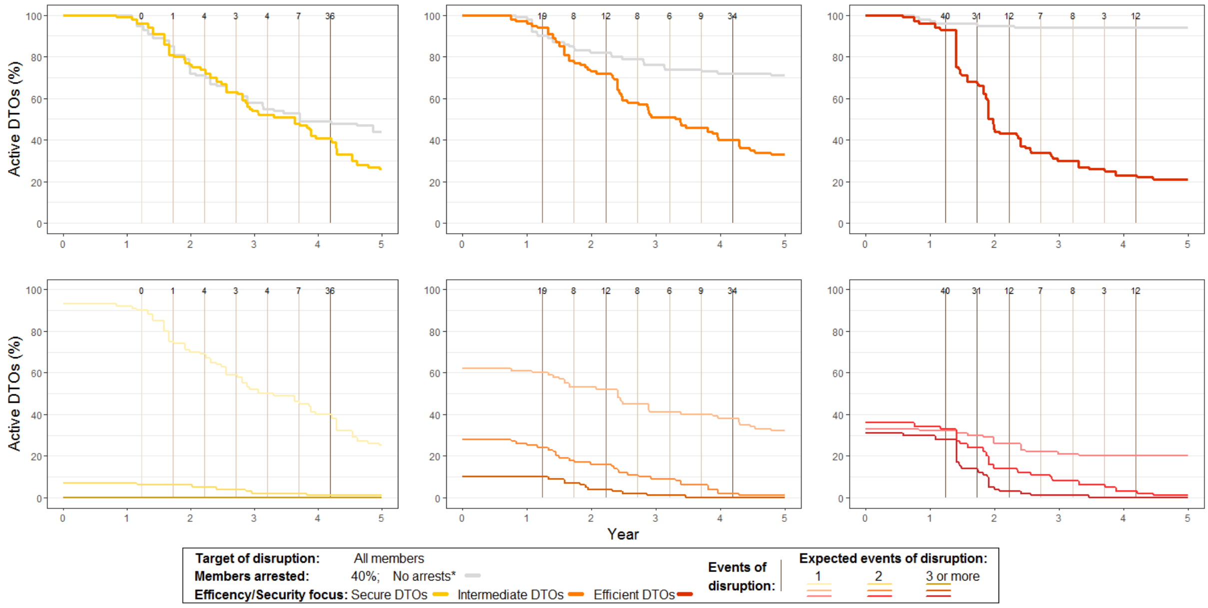
Table 22. Experienced attempts at disruption per security/efficiency focus in the third scenario of law enforcement intervention

Year	Month of the attempt at disruption	Secure DTOs		Intermediate DTOs		Efficient DTOs	
		n	*%*	*n*	*%*	*n*	*%*
2	15	0	0.0	19	19.8	40	35.4
	21	1	1.8	8	8.3	31	27.4
3	27	4	7.3	12	12.5	12	10.6
	33	3	5.5	8	8.3	7	6.2
4	39	4	7.3	6	6.3	8	7.1
	45	7	12.7	9	9.4	3	2.7
5	51	36	65.5	34	35.4	12	10.6
	Total	**55**	**100**	**96**	**100**	**113**	**100**

Source: Author's elaboration

This results in a further escalation of the trend observed in the second scenario. The rates of surviving secure DTOs further increase (i.e., 26% of secure DTOs active at the end of the simulated period, +7% compared to the second scenario), whereas the share of surviving efficient DTOs drops to 21% (i.e., -5% compared to the second scenario) (Graph 23). In most of the cases (i.e., more than 95%), both secure and efficient surviving DTOs experience only 1 attempt at disruption. The minority of active DTOs targeted by multiple interventions experience at most 2 attempts at disruption (Table 23).[38]

Graph 23. Share of active DTOs (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)



Source: Author's elaboration

[38] When considering active DTOs, at the end of the simulated period, expected and observed (i.e., experienced) attempts at disruption correspond. Indeed, organizations protracting their criminal involvement until the end of the five simulated years incur all the expected attempts at disruption foreseen in the setup of the model. In contrast, DTOs terminating their criminal involvement before the end of the simulated period may experience fewer attempts at disruption than the expected number.

When considering disrupted DTOs, the picture is more diversified. Disrupted secure DTOs in more than 60% of cases terminate their criminal involvement, having experienced no attempts at disruption. This confirms the economic fragility of secure DTOs that, aiming to minimize their visibility to avoid law enforcement interventions, overlook the profitability of their activities. In the remaining 35% of cases, secure DTOs terminate their criminal involvement after experiencing 1 intervention. In contrast, efficient DTOs end their criminal involvement before any attempt at disruption in only 10% of cases, confirming their excellent economic performance in the absence of threats. Nevertheless, attempts at disruption are always a significant obstacle for efficient DTOs. Among disrupted efficient DTOs, almost 65% interrupt their drug trafficking and dealing after being the subject of a single intervention, whereas the remaining 25% of efficient DTOs cannot survive 2 law enforcement interventions. No DTOs, either active or disrupted, survive enough to experience 3 law enforcement interventions (Table 23).

Table 23. Active and disrupted DTOs at the end of the simulated period per experienced attempts at disruption in the third scenario of law enforcement intervention

	Total		**0 attempts at disruption**		**1 attempt at disruption**		**2 attempts at disruption**		**3 or more attempts at disruption**	
Secure DTOs										
	n	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*
Active DTOs	26	26.0%	0	0.0%	25	96.2%	1	3.8%	0	0.0%
Disrupted DTOs	74	74.0%	47	63.5%	26	35.1%	1	1.4%	0	0.0%
Intermediate DTOs										
	n	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*
Active DTOs	33	33.0%	0	0.0%	32	97.0%	1	3.0%	0	0.0%
Disrupted DTOs	67	67.0%	13	19.4%	46	68.7%	8	11.9%	0	0.0%
Efficient DTOs										
	n	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*
Active DTOs	21	21.0%	0	0.0%	20	95.2%	1	4.8%	0	0.0%
Disrupted DTOs	79	79.0%	8	10.1%	51	64.6%	20	25.3%	0	0.0%

Source: Author's elaboration

The timing of attempts at disruption differs according to DTOs' security/efficiency focuses, reflecting the distribution of law enforcement interventions over time (Table 22). Secure DTOs display the most scattered rates of disruption, with comparable rates of disruption (i.e., from 13 to 23%) from the second year of criminal involvement until the end of the simulated period. This trend is due to the inherent economic fragility of secure DTOs in the first simulated years, whereas it is more heavily impacted by law enforcement attempts at disruption in the fifth simulated year. Instead, efficient DTOs display a sharp increase in their disruption rate condensed between the first and second years of criminal involvement (i.e., over 50%), which is determined by the early pressure caused by attempts at disruption (Table 24).

Table 24. Share of active DTOs per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)

DTOs security/efficiency focus	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Baseline – Sec. DTOs	100%	100%	72%	58%	49%	44%
Secure DTOs	100%	99%	76%	54%	41%	26%
Baseline – Int. DTOs	100%	98%	82%	76%	72%	71%
Intermediate DTOs	100%	96%	73%	51%	40%	33%
Baseline – Eff. DTOs	100%	97%	95%	94%	94%	94%
Efficient DTOs	100%	96%	44%	30%	23%	21%

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	70.89 (20.73)	67.36 (25.30)	***
Baseline – Int. DTOs	82.52 (10.47)	66.18 (24.10)	***
Baseline – Eff. DTOs	95.54 (2.18)	52.30 (31.11)	***
Sec. DTOs – Int. DTOs	67.36 (25.30)	66.18 (24.10)	**
Sec. DTOs – Eff. DTOs	67.36 (25.30)	52.30 (31.11)	***
Int. DTOs – Eff. DTOs	66.18 (24.10)	52.30 (31.11)	***

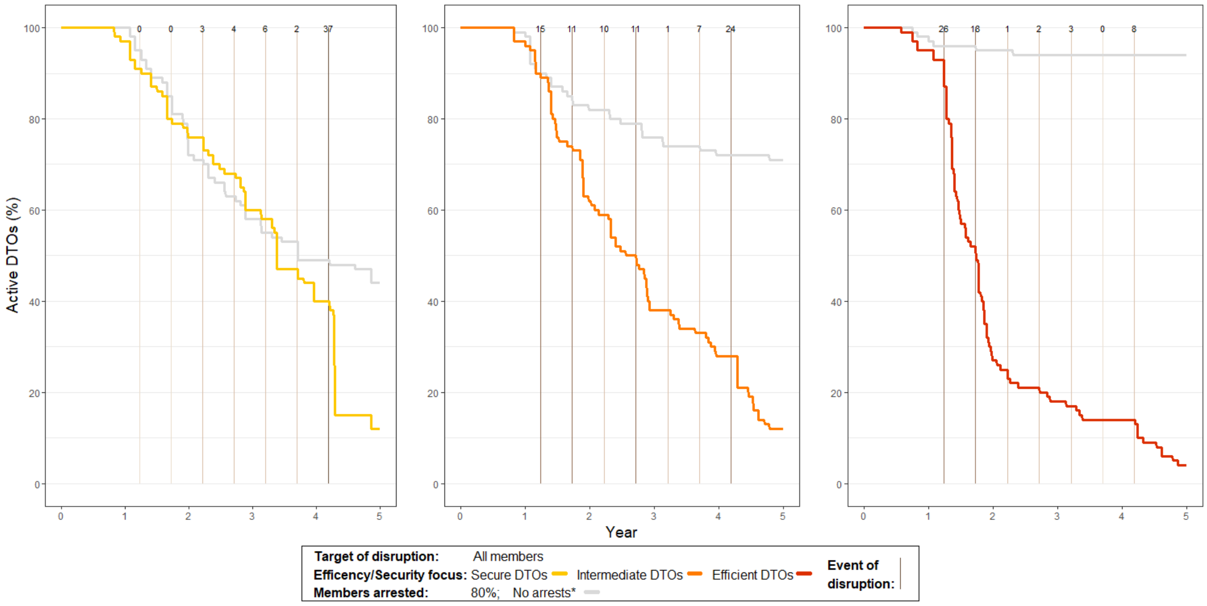
**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

The percentage of members targeted by attempts at disruption influences the proportion of DTOs that survive disruption. In terms of harsher law enforcement interventions, such as those targeting 80% of DTOs members, both secure and efficient DTOs display a decrease in their survival rates. Among secure DTOs, 12% survive at the end of the simulated period (i.e., -14% compared to the scenario targeting 40% of members). Efficient DTOs are more severely impacted by incremental increases in the percentage of members arrested, with only 4% surviving at the end of the five simulated years (-17% compared the scenario targeting 40% of members) (Graph 24).

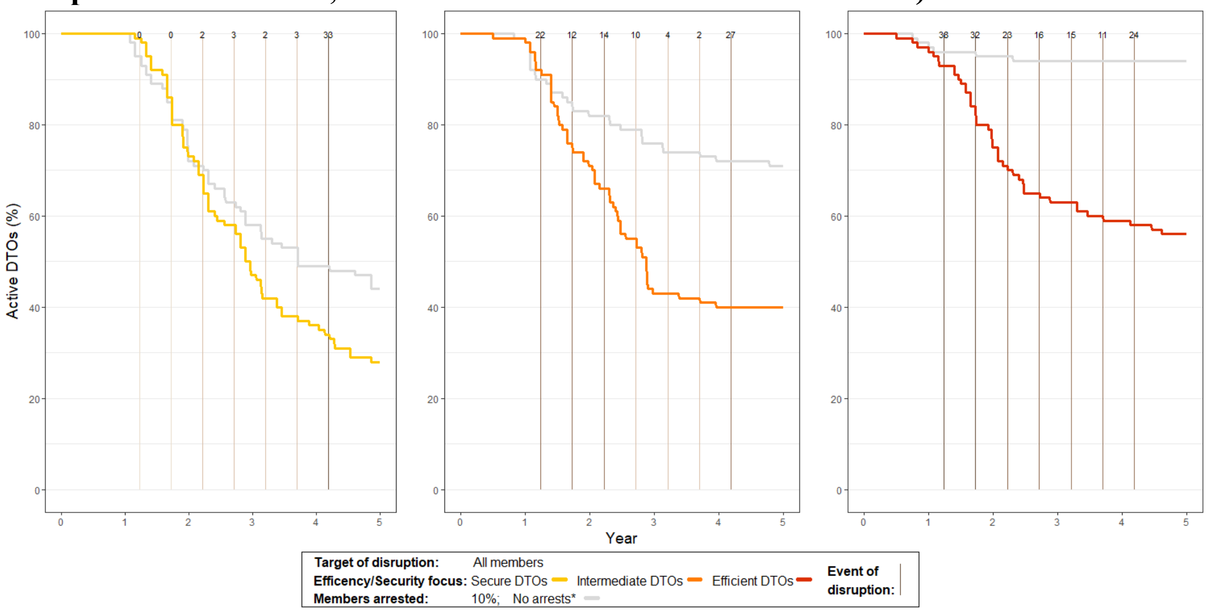
In contrast, when 10% of DTO members are targeted, the outcomes are similar to those of the first and second law enforcement intervention scenarios. Efficient DTOs display the highest rates of survival (i.e., 56% of active DTOs). Secure DTOs are most heavily impacted by the arrests, registering a survival rate of 28% at the end of the simulated period. This signals that the threat posed by arresting only 10% of members is too feeble to undermine efficient DTOs' survival. Most efficient DTOs, possibly because of their economic strength, can cope well with the consequences of repeated, but mild, law enforcement interventions. In contrast, the survival rate of secure DTOs does not benefit much from reducing the percentage of members arrested. This is additional evidence that the inherent fragility of secure DTOs might, regardless of the experienced attempts at disruption, encounter difficulties in maintaining their criminal involvement. Indeed, considering the differences from to the baseline scenario, efficient DTOs are still the ones for which the survival rate decreases the most (i.e., -38%), whereas for secure DTOs, it decreases the least (i.e., -10%) (Graph 25).

Graph 24. Share of active DTOs (Proportion of members arrested: 80%; Target of disruption: all members; Law enforcement intervention scenario: 3)



Source: Author's elaboration

Graph 25. Share of active DTOs (Proportion of members arrested: 10%; Target of disruption: all members; Law enforcement intervention scenario: 3)



Source: Author's elaboration

4.4.2. Ability to react quickly and efficiently to law enforcement interventions

The investigation of DTOs' ability to react quickly and efficiently to law enforcement attempts at disruption relies on three resilience indicators: the number of DTO members, average normalized degree centrality and average normalized betweenness centrality.

In the baseline scenarios, DTO members follow a growth trend until the end of the second simulated year, increasing from 44 to 64-65 members on average. From the third year, the trends of DTOs with different focuses in the security/efficiency trade-off start to vary. At the end of the simulated period, secure and efficient DTOs reach an average of almost 72 and 74 members, respectively, while intermediate DTOs reach an average of 68 members. Members of secure DTOs are more numerous because of their ability to avoid minor periodic attempts at disruption; in contrast, for efficient DTOs, this reflects their effective recruitment strategies that effectively compensate for the sporadic arrests. Intermediate DTOs cannot so easily avoid minor attempts at disruption, nor they are as good at recruiting new members; thus, their workforce is comparatively exiguous (Graph 26, Graph 30, and Graph 34).

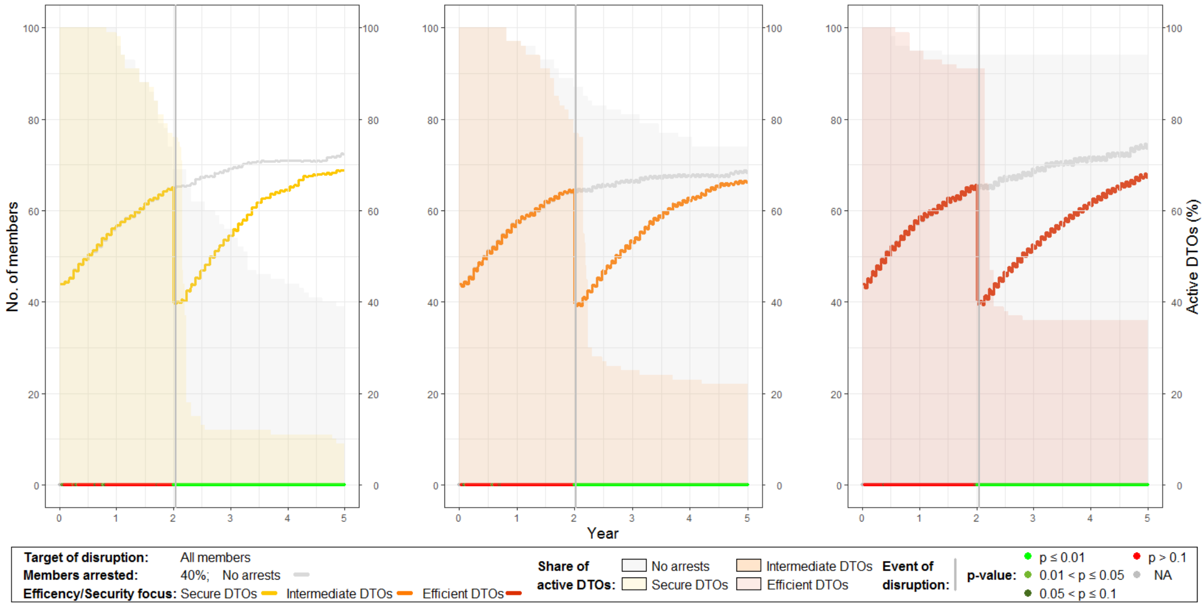
With respect to average normalized degree centrality, DTOs with different strategies regarding the security vs. efficiency trade-off display partially different relational strategies. Secure DTOs minimize direct connections among their members, and thus, their visibility (i.e., on average each member is connected to 17.9% of others). Conversely, efficient DTOs maximize their direct connectivity, improving the efficacy of their working relations (i.e., with each member being connected on average to 20.6% of others). Intermediate DTOs are positioned in between, with each member having connections to 19.2% of others (Table 26, Table 29, and Table 32).

In the absence of law enforcement interventions, there are no significant differences in the average betweenness centrality scores of members participating in DTOs with different focuses in the security vs. efficiency trade-off, with average values that are always very low (i.e., close to 0.016) (Table 27, Table 30, and Table 33).

4.4.2.1. First law enforcement intervention scenario

The attempt at disruption produces a steep reduction in the number of DTOs members. After the arrests, some replacement strategies are introduced; however, DTOs are never able to recover completely from the shock, and the number of members remains significantly lower than in the baseline scenario (Graph 26 and Table 14). Efficient DTOs display the greatest differences to the baseline scenario (i.e., more than six members less on average), while intermediate DTOs register the lowest differences (i.e., almost two members less on average) (Table 14).

Graph 26. Number of DTOs members (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)



Source: Author's elaboration

Table 25. Number of DTOs members per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	44	44	44	0	-
	1	96	52	60	56.78	1.89	56.4-57.16
	2	69	61	66	65.12	1.22	64.82-65.41
	3	56	65	70	69.13	0.95	68.87-69.38
	4	44	70	71	70.89	0.32	70.79-70.98
	5	39	71	73	72.36	0.63	72.16-72.56
Secure DTOs	0	100	44	44	44	0	-
	1	98	51	60	56.86	1.94	56.47-57.25
	2	76	37	41	39.88	0.89	39.68-40.09
	3	12	50	60	54.50	2.71	52.78-56.22
	4	11	61	66	64.45	1.44	63.49-65.42
	5	9	67	70	68.89	0.93	68.18-69.6
Baseline, Intermediate DTOs	0	100	44	44	44	0	-
	1	97	51	60	57.82	1.70	57.48-58.17
	2	87	61	65	64.57	0.71	64.42-64.73
	3	81	63	67	66.11	0.81	65.93-66.29
	4	76	65	68	67.39	0.71	67.23-67.56
	5	74	66	69	68.22	0.73	68.05-68.38
Intermediate DTOs	0	100	44	44	44	0	-
	1	97	54	60	57.81	1.60	57.49-58.14
	2	77	38	40	39.70	0.49	39.59-39.81
	3	25	47	57	52.88	2.52	51.84-53.92
	4	23	57	66	62.04	2.44	60.99-63.1
	5	22	64	67	66.23	1.02	65.77-66.68

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Efficient DTOs	0	100	44	44	44	0	-
	1	95	55	60	58.69	1.28	58.43-58.96
	2	94	62	66	65.57	0.66	65.44-65.71
	3	94	66	70	68.27	0.87	68.09-68.44
	4	94	69	72	70.81	0.53	70.7-70.92
	5	94	72	75	73.63	0.70	73.48-73.77
Efficient DTOs	0	100	44	44	44	0	-
	1	95	55	60	58.69	1.23	58.44-58.95
	2	91	39	41	40.45	0.64	40.32-40.58
	3	36	46	58	51.64	2.46	50.81-52.47
	4	36	53	65	60.97	2.89	59.99-61.95
	5	36	62	69	67.25	1.89	66.61-67.89

Randomization-based t tests

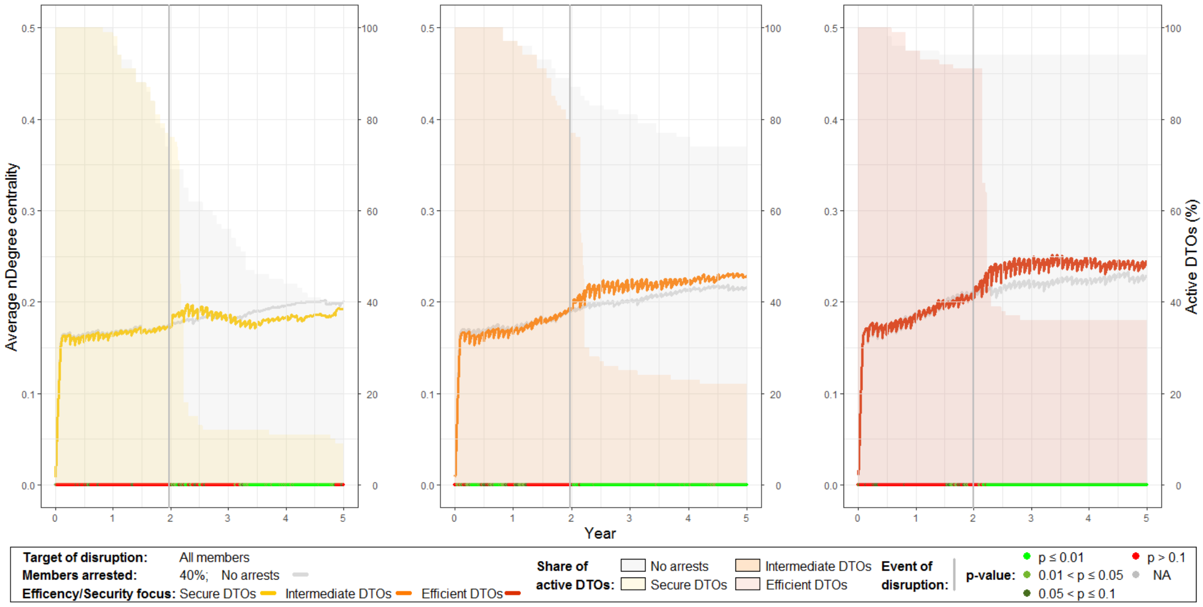
Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	63.86 (8.22)	57.16 (8.44)	***
Baseline – Int. DTOs	62.42 (6.87)	56.19 (7.75)	***
Baseline – Eff. DTOs	64.41 (8.03)	56.10 (7.76)	***
Sec. DTOs – Int. DTOs	57.16 (8.44)	56.19 (7.75)	***
Sec. DTOs – Eff. DTOs	57.16 (8.44)	56.10 (7.76)	***
Int. DTOs – Eff. DTOs	56.19 (7.75)	56.10 (7.76)	n.s.

**Significance at 95% level, **99%, ***99.9%, $^{n.s}$Nonsignificant*

Source: Author's elaboration

The attempt at disruption produces different effects on DTO members' direct connectivity according to the focus in the efficiency vs. security trade-off. Intermediate and efficient surviving DTOs increase their level of direct connectivity to regain their operational activity, as soon as possible minimizing the losses caused by the disruptive event (Graph 27 and Table 26). Conversely, secure surviving DTOs display the opposite pattern. After a first limited increase in average degree centrality (very likely due to the normalization process), they register a significant decrease in the average number of direct connections among members in the fourth and fifth years of criminal involvement, signaling a willingness to reduce their exposure and visibility to avoid future law enforcement interventions. However, in the case of exceptionally threatening situations, surviving secure DTOs renounce their preferred *modi operandi* in favor of more risky behaviors that allow their criminal activities to be protracted over time. In the case of attempts at disruption targeting 80% of members, surviving secure DTOs' reactions immediately after the attempt at disruption are comparable to those of intermediate and efficient DTOs. In the long term, once the direct impact of the law enforcement intervention is overcome, the tendency is to resume usual relational strategies (Graph 28 and Annex IV, Graph 69).

Graph 27. DTOs members average normalized degree centrality (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)



Source: Author's elaboration

Table 26. DTOs members average normalized degree centrality per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	0	0	0	0	-
	1	96	0.108	0.189	0.165	0.014	0.162-0.168
	2	69	0.139	0.203	0.175	0.013	0.172-0.178
	3	56	0.158	0.207	0.183	0.012	0.180-0.186
	4	44	0.175	0.220	0.196	0.010	0.193-0.199
	5	39	0.178	0.244	0.201	0.014	0.197-0.206
Secure DTOs	0	100	0	0	0	0	-
	1	98	0.118	0.196	0.163	0.015	0.161-0.166
	2	76	0.132	0.197	0.172	0.014	0.169-0.176
	3	12	0.163	0.213	0.183	0.017	0.172-0.194
	4	11	0.155	0.219	0.184	0.017	0.172-0.195
	5	9	0.169	0.226	0.193	0.019	0.178-0.207
Baseline, Intermediate DTOs	0	100	0	0	0	0	-
	1	97	0.125	0.196	0.168	0.013	0.165-0.170
	2	87	0.155	0.232	0.190	0.016	0.187-0.194
	3	81	0.158	0.242	0.201	0.016	0.198-0.205
	4	76	0.175	0.254	0.214	0.015	0.210-0.217
	5	74	0.183	0.254	0.216	0.016	0.212-0.220
Intermediate DTOs	0	100	0	0	0	0	-
	1	97	0.120	0.222	0.166	0.015	0.163-0.169
	2	77	0.155	0.237	0.193	0.016	0.189-0.196
	3	25	0.165	0.246	0.219	0.018	0.212-0.226
	4	23	0.202	0.249	0.224	0.014	0.218-0.230
	5	22	0.204	0.255	0.229	0.013	0.223-0.235

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Efficient DTOs	0	100	0	0	0	0	-
	1	95	0.140	0.229	0.180	0.016	0.177-0.184
	2	94	0.173	0.256	0.208	0.016	0.204-0.211
	3	94	0.173	0.255	0.220	0.017	0.217-0.223
	4	94	0.192	0.263	0.224	0.015	0.221-0.227
	5	94	0.195	0.268	0.230	0.014	0.227-0.233
Efficient DTOs	0	100	0	0	0	0	-
	1	95	0.147	0.224	0.181	0.015	0.178-0.184
	2	91	0.158	0.236	0.206	0.014	0.203-0.209
	3	36	0.183	0.286	0.244	0.024	0.236-0.252
	4	36	0.213	0.296	0.246	0.020	0.239-0.253
	5	36	0.214	0.272	0.246	0.015	0.241-0.251

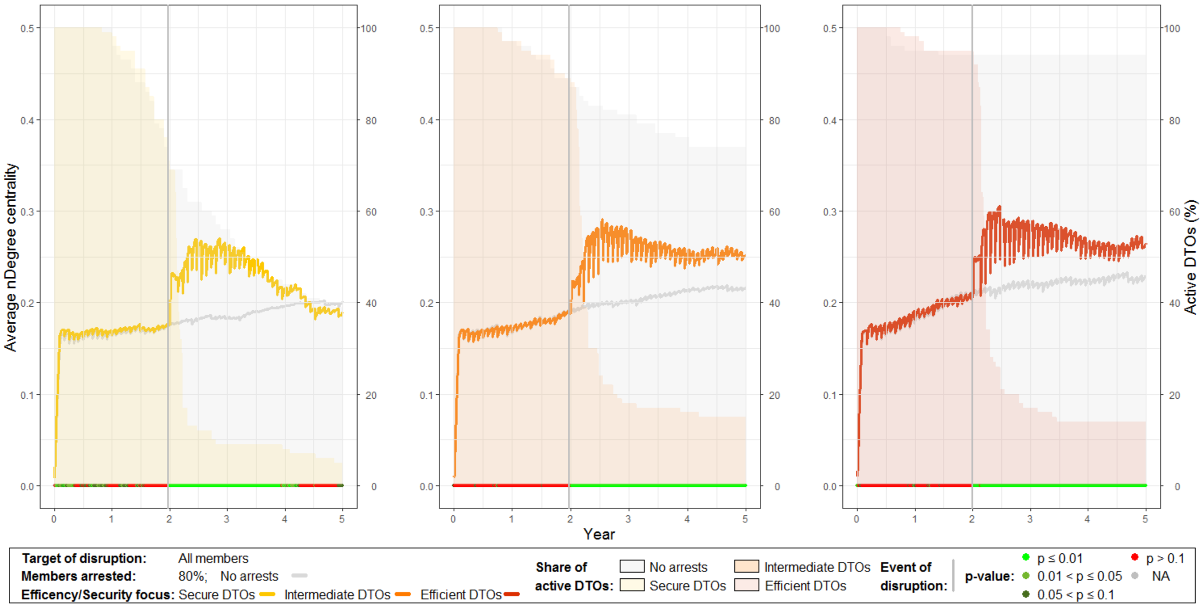
Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	0.179 (0.019)	0.175 (0.017)	***
Baseline – Int. DTOs	0.192 (0.023)	0.199 (0.030)	***
Baseline – Eff. DTOs	0.205 (0.026)	0.216 (0.033)	***
Sec. DTOs – Int. DTOs	0.175 (0.017)	0.199 (0.030)	***
Sec. DTOs – Eff. DTOs	0.175 (0.017)	0.216 (0.033)	***
Int. DTOs – Eff. DTOs	0.199 (0.030)	0.216 (0.033)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

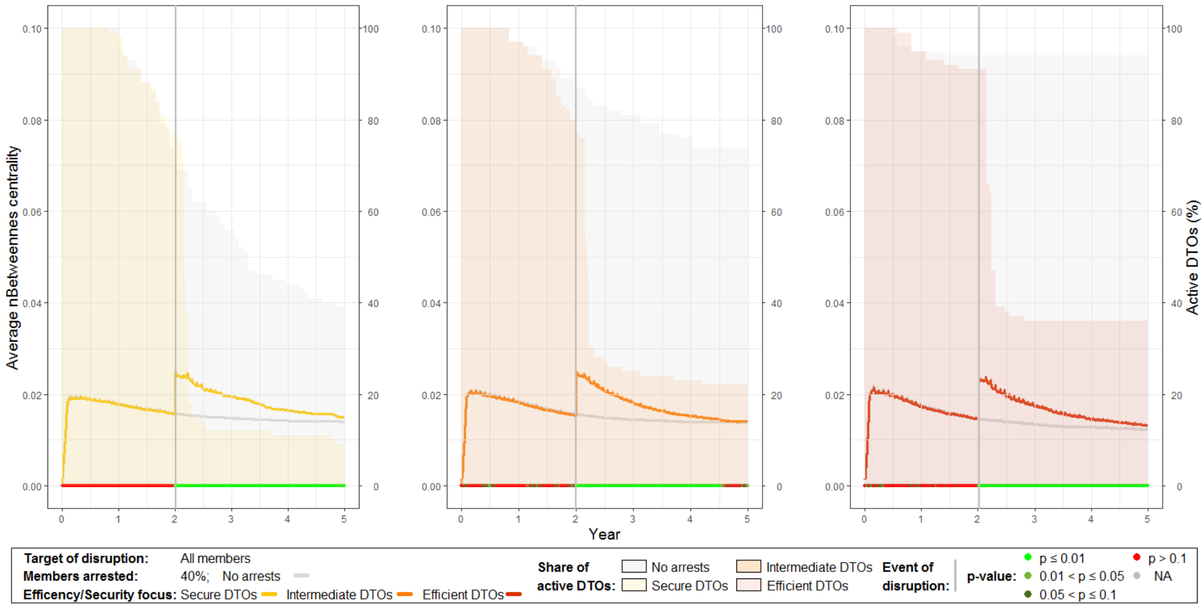
Graph 28. DTOs members average normalized degree centrality (Proportion of members arrested: 80%; Target of disruption: all members; Law enforcement intervention scenario: 1)



Source: Author's elaboration

In terms of brokerage power (i.e., average normalized betweenness centrality), there are no major differences in the impact caused by the attempt at disruption on DTOs with different focuses in the security vs. efficiency trade-off. Overall, the law enforcement intervention results in an immediate increase in the average intermediary power of members (partially related to the normalization process), followed by decreasing values that, at the end of the simulated period, are very close to those of the baseline scenarios (Graph 29 and Table 27).

Graph 29. DTOs members average normalized betweenness centrality (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)



Source: Author's elaboration

Table 27. DTOs members average normalized betweenness centrality per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	0	0	0	0	-
	1	96	0.008	0.022	0.018	0.002	0.017-0.018
	2	69	0.008	0.020	0.016	0.002	0.015-0.016
	3	56	0.010	0.018	0.015	0.002	0.014-0.015
	4	44	0.010	0.017	0.014	0.001	0.014-0.015
	5	39	0.010	0.016	0.014	0.001	0.013-0.014
Secure DTOs	0	100	0	0	0	0	-
	1	98	0.010	0.021	0.018	0.002	0.017-0.018
	2	76	0.009	0.019	0.016	0.002	0.015-0.016
	3	12	0.018	0.023	0.019	0.002	0.018-0.021
	4	11	0.015	0.018	0.016	0.001	0.016-0.017
	5	9	0.013	0.016	0.015	0.001	0.014-0.016
Baseline, Intermediate DTOs	0	100	0	0	0	0	-
	1	97	0.012	0.022	0.018	0.001	0.018-0.019
	2	87	0.013	0.018	0.016	0.001	0.015-0.016
	3	81	0.012	0.018	0.015	0.001	0.014-0.015
	4	76	0.012	0.016	0.014	0.001	0.014-0.014
	5	74	0.012	0.016	0.014	0.001	0.014-0.014

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Intermediate DTOs	0	100	0	0	0	0	-
	1	97	0.011	0.021	0.018	0.002	0.018-0.019
	2	77	0.011	0.018	0.015	0.001	0.015-0.016
	3	25	0.016	0.021	0.018	0.001	0.018-0.019
	4	23	0.014	0.018	0.015	0.001	0.015-0.016
	5	22	0.013	0.016	0.014	0.001	0.014-0.014
Baseline, Efficient DTOs	0	100	0	0	0	0	-
	1	95	0.013	0.021	0.018	0.001	0.017-0.018
	2	94	0.012	0.017	0.015	0.001	0.014-0.015
	3	94	0.012	0.017	0.014	0.001	0.013-0.014
	4	94	0.010	0.015	0.013	0.001	0.013-0.013
	5	94	0.010	0.014	0.012	0.001	0.012-0.012
Efficient DTOs	0	100	0	0	0	0	-
	1	95	0.013	0.020	0.017	0.001	0.017-0.018
	2	91	0.012	0.017	0.015	0.001	0.014-0.015
	3	36	0.016	0.020	0.018	0.001	0.017-0.018
	4	36	0.013	0.017	0.015	0.001	0.014-0.015
	5	36	0.012	0.015	0.013	0.001	0.013-0.013

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	0.016 (0.002)	0.018 (0.003)	***
Baseline – Int. DTOs	0.016 (0.002)	0.017 (0.003)	***
Baseline – Eff. DTOs	0.015 (0.003)	0.017 (0.003)	***
Sec. DTOs – Int. DTOs	0.018 (0.003)	0.017 (0.003)	***
Sec. DTOs – Eff. DTOs	0.018 (0.003)	0.017 (0.003)	***
Int. DTOs – Eff. DTOs	0.017 (0.003)	0.017 (0.003)	***

**Significance at 95% level, **99%, ***99.9%, $^{n.s}$Nonsignificant*

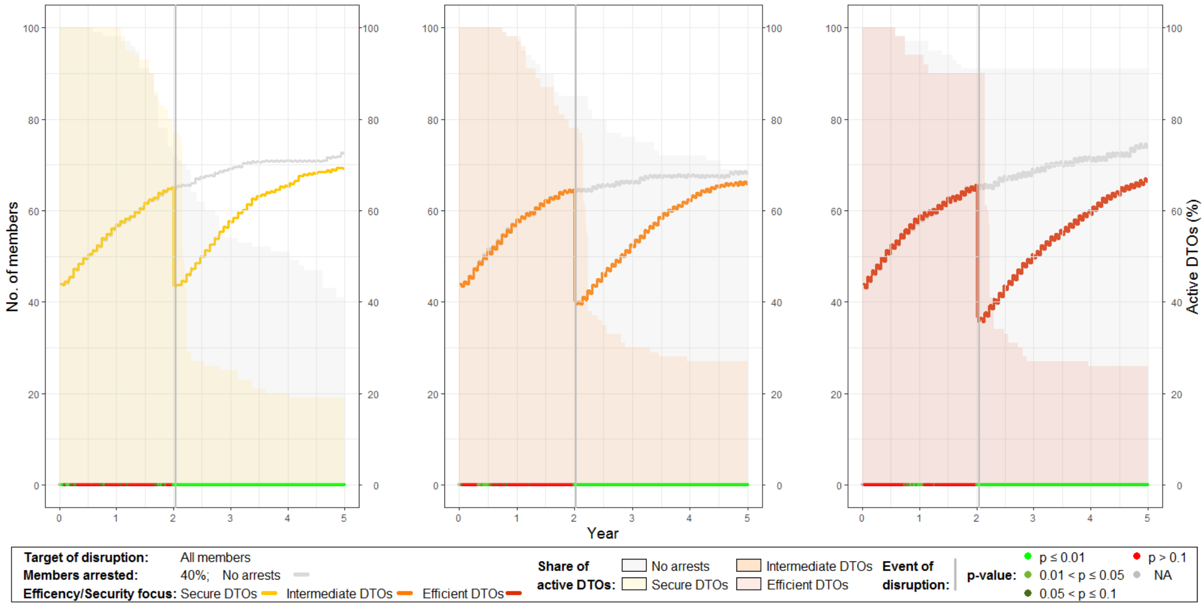
Source: Author's elaboration

4.4.2.2. Second law enforcement intervention scenario

While the second law enforcement intervention scenario produces significant differences in terms of DTOs' persistence over time, there are no remarkable distinctions in the reactions of surviving DTOs.

In the first scenario, DTO members decrease after the attempt at disruption due to the arrests. This reduction is smaller for secure DTOs, which are better able to minimize their visibility and thus the number of members targeted; the reduction is larger for efficient DTOs, which, lacking protective measures for their members, suffer major losses. Shortly after the arrests, DTOs put in place replacement strategies that, however, cannot fully compensate for the impact of the disruptive event (Graph 30 and Table 28).

Graph 30. Number of DTOs members (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)



Source: Author's elaboration

Table 28. Number of DTOs members per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	44	44	44	0	-
	1	98	52	60	56.72	1.80	56.36-57.09
	2	72	61	66	65.08	1.23	64.79-65.37
	3	54	67	70	69.11	0.74	68.91-69.31
	4	51	70	71	70.84	0.37	70.74-70.95
	5	41	71	73	72.44	0.71	72.22-72.66
Secure DTOs	0	100	44	44	44	0	-
	1	100	52	60	56.97	1.71	56.63-57.31
	2	77	40	46	43.62	1.19	43.35-43.89
	3	25	52	61	57.44	1.94	56.64-58.24
	4	20	63	67	65.35	0.99	64.89-65.81
	5	19	67	70	69.21	0.85	68.80-69.62
Baseline, Intermediate DTOs	0	100	44	44	44	0	-
	1	98	53	60	58.03	1.69	57.69-58.37
	2	85	62	65	64.62	0.65	64.48-64.76
	3	76	63	67	65.99	0.96	65.77-66.21
	4	72	65	68	67.47	0.65	67.32-67.62
	5	68	65	69	68.13	0.81	67.94-68.33
Intermediate DTOs	0	100	44	44	44	0	-
	1	97	53	60	58.04	1.67	57.70-58.38
	2	78	37	42	40.01	0.90	39.81-40.22
	3	30	44	58	52.13	2.81	51.08-53.18
	4	27	57	65	62.07	2.30	61.16-62.98
	5	27	62	67	65.81	1.36	65.28-66.35

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Efficient DTOs	0	100	44	44	44	0	-
	1	97	56	60	58.53	1.16	58.29-58.76
	2	91	64	66	65.58	0.63	65.45-65.71
	3	91	66	70	68.25	0.86	68.07-68.43
	4	91	69	72	70.79	0.59	70.67-70.91
	5	91	71	75	73.78	0.79	73.62-73.94
Efficient DTOs	0	100	44	44	44	0	-
	1	94	55	60	58.91	1.10	58.69-59.14
	2	90	35	38	36.76	0.92	36.56-36.95
	3	27	44	54	49.63	2.47	48.65-50.61
	4	26	55	64	59.12	2.23	58.21-60.02
	5	26	60	69	66.27	2.54	65.24-67.29

Randomization-based t tests

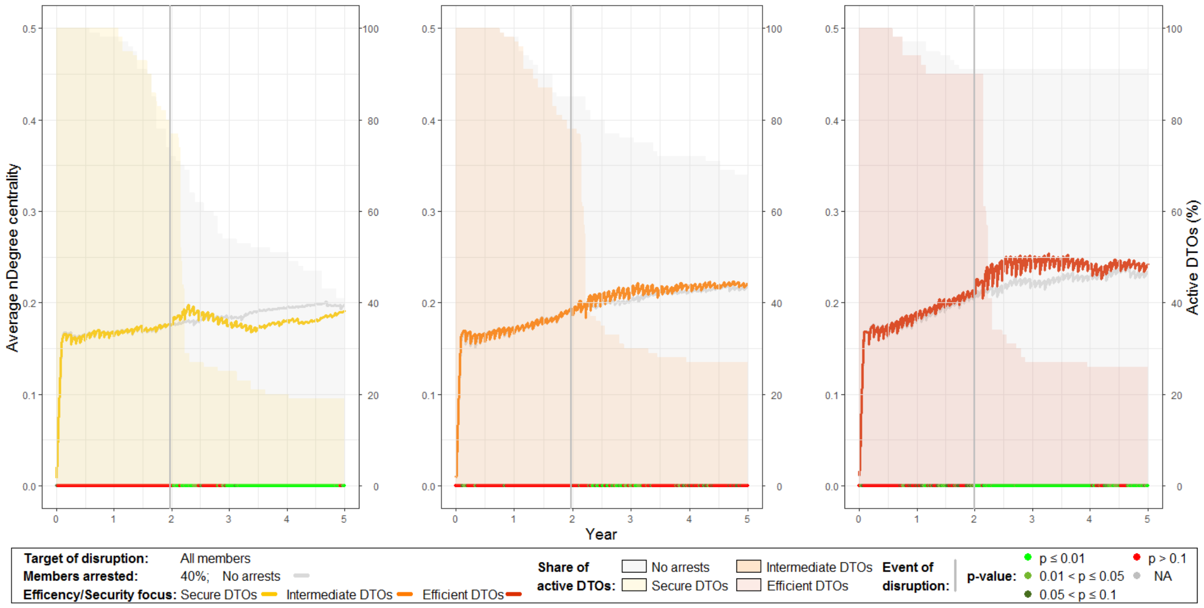
Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	63.86 (8.24)	58.26 (7.86)	***
Baseline – Int. DTOs	62.46 (6.83)	56.04 (7.80)	***
Baseline – Eff. DTOs	64.42 (8.01)	54.95 (8.38)	***
Sec. DTOs – Int. DTOs	58.26 (7.86)	56.04 (7.80)	***
Sec. DTOs – Eff. DTOs	58.26 (7.86)	54.95 (8.38)	***
Int. DTOs – Eff. DTOs	56.04 (7.80)	54.95 (8.38)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

Even in the case of average degree centrality, there are only minor differences compared to the first law enforcement intervention scenario. After the attempt at disruption, members of secure DTOs decrease their connectivity in the long term. Conversely, members of efficient DTOs increase and maintain an augmented level of direct connectivity (Graph 31 and Table 29). However, in the case of attempts at disruption targeting 80% of members, the second law enforcement intervention scenario causes different impacts on surviving secure and efficient DTOs. As in the first scenario, all DTOs, including secure ones, respond to major threats by increasing the direct connectivity among members. Nonetheless, surviving secure DTOs reduce this increase in comparison to the first scenario, signaling the need to put fewer emergency strategies in place. Conversely, efficient DTO members further augment their direct connections, suggesting an escalation in the difficulties experienced (Graph 28, Graph 32, and Annex IV, Graph 61, and Graph 62).

Graph 31. DTOs members average normalized degree centrality (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)



Source: Author's elaboration

Table 29. DTOs members average normalized degree centrality per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	0	0	0	0	-
	1	98	0.130	0.200	0.165	0.013	0.163-0.168
	2	72	0.143	0.198	0.176	0.011	0.173-0.179
	3	54	0.146	0.206	0.184	0.011	0.181-0.187
	4	51	0.177	0.218	0.195	0.011	0.192-0.198
	5	41	0.174	0.217	0.198	0.011	0.195-0.202
Secure DTOs	0	100	0	0	0	0	-
	1	100	0.112	0.188	0.165	0.014	0.162-0.168
	2	77	0.127	0.210	0.176	0.014	0.173-0.179
	3	25	0.132	0.202	0.176	0.015	0.170-0.182
	4	20	0.152	0.206	0.181	0.014	0.174-0.187
	5	19	0.165	0.219	0.191	0.014	0.184-0.198
Baseline, Intermediate DTOs	0	100	0	0	0	0	-
	1	98	0.134	0.197	0.169	0.014	0.166-0.172
	2	85	0.148	0.245	0.191	0.016	0.188-0.195
	3	76	0.158	0.239	0.203	0.016	0.199-0.207
	4	72	0.176	0.262	0.213	0.016	0.209-0.217
	5	68	0.176	0.261	0.218	0.019	0.213-0.222
Intermediate DTOs	0	100	0	0	0	0	-
	1	97	0.129	0.213	0.167	0.015	0.164-0.170
	2	78	0.149	0.231	0.192	0.015	0.189-0.196
	3	30	0.161	0.254	0.211	0.026	0.201-0.220
	4	27	0.173	0.266	0.218	0.022	0.210-0.227
	5	27	0.189	0.262	0.221	0.018	0.214-0.228

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Efficient DTOs	0	100	0	0	0	0	-
	1	97	0.146	0.216	0.181	0.015	0.178-0.184
	2	91	0.171	0.246	0.206	0.014	0.203-0.209
	3	91	0.181	0.255	0.221	0.014	0.218-0.224
	4	91	0.200	0.267	0.229	0.015	0.226-0.232
	5	91	0.201	0.269	0.234	0.015	0.231-0.237
Efficient DTOs	0	100	0	0	0	0	-
	1	94	0.152	0.239	0.183	0.014	0.181-0.186
	2	90	0.173	0.249	0.210	0.014	0.207-0.213
	3	27	0.192	0.287	0.246	0.024	0.236-0.255
	4	26	0.188	0.277	0.242	0.021	0.233-0.250
	5	26	0.223	0.282	0.243	0.017	0.236-0.249

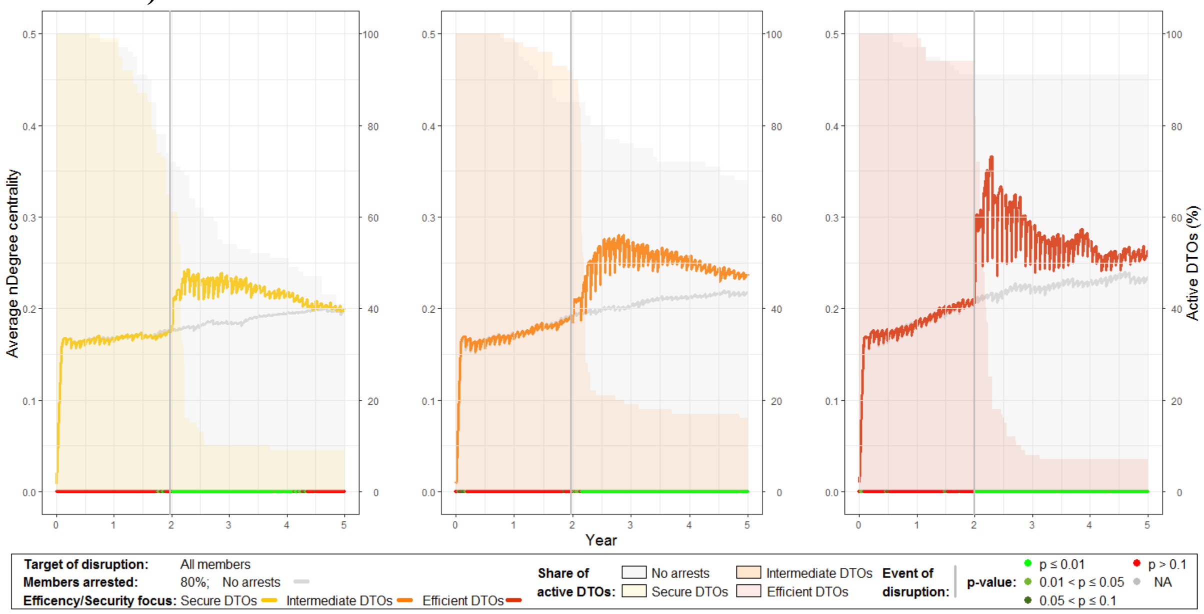
Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	0.179 (0.019)	0.174 (0.016)	***
Baseline – Int. DTOs	0.192 (0.024)	0.196 (0.026)	***
Baseline – Eff. DTOs	0.207 (0.028)	0.218 (0.034)	***
Sec. DTOs – Int. DTOs	0.174 (0.016)	0.196 (0.026)	***
Sec. DTOs – Eff. DTOs	0.174 (0.016)	0.218 (0.034)	***
Int. DTOs – Eff. DTOs	0.196 (0.026)	0.218 (0.034)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

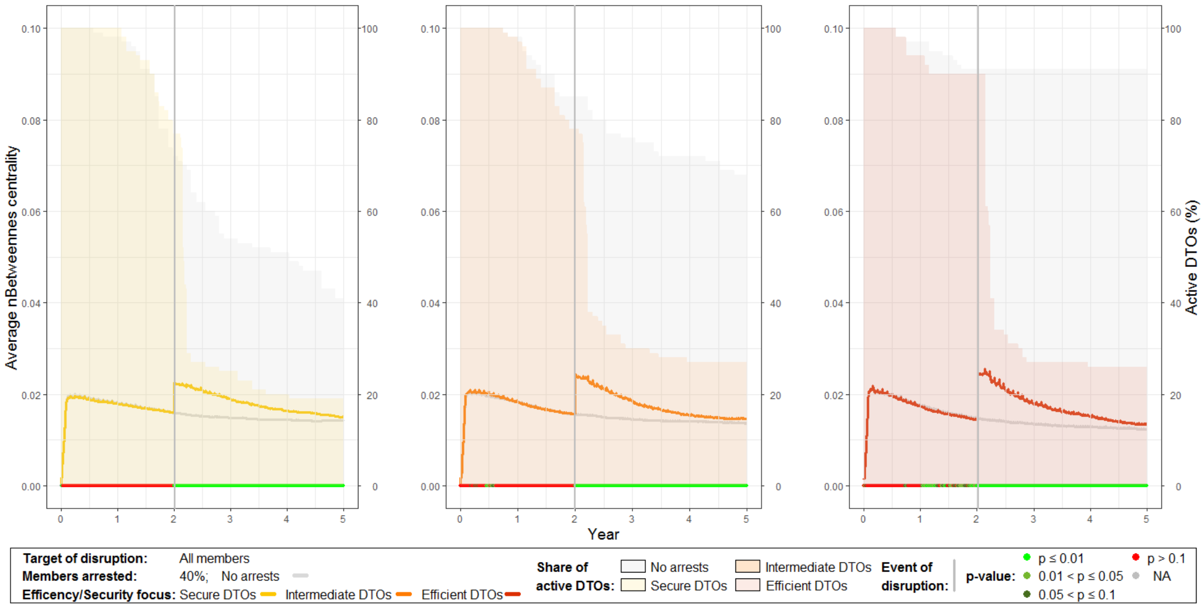
Graph 32. DTOs members average normalized degree centrality (Proportion of members arrested: 80%; Target of disruption: all members; Law enforcement intervention scenario: 2)



Source: Author's elaboration

Average normalized betweenness centrality is the resilience indicator that displays the fewest differences between the first and second law enforcement intervention scenarios. Regardless of DTOs' security vs. efficiency trade-off focus, average betweenness centrality increases immediately after the attempt at disruption and returns to values closer to those of the baseline scenarios over the following years (Graph 33 and Table 30).

Graph 33. DTOs members average normalized betweenness centrality (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)



Source: Author's elaboration

Table 30. DTOs members average normalized betweenness centrality per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	0	0	0	0	-
	1	98	0.011	0.021	0.018	0.002	0.018-0.018
	2	72	0.011	0.018	0.016	0.001	0.016-0.016
	3	54	0.010	0.018	0.015	0.001	0.015-0.015
	4	51	0.010	0.016	0.014	0.001	0.014-0.015
	5	41	0.013	0.016	0.014	0.001	0.014-0.014
Secure DTOs	0	100	0	0	0	0	-
	1	100	0.009	0.021	0.018	0.002	0.017-0.018
	2	77	0.010	0.019	0.016	0.002	0.016-0.016
	3	25	0.016	0.021	0.019	0.001	0.018-0.019
	4	20	0.014	0.019	0.016	0.001	0.016-0.017
	5	19	0.012	0.018	0.015	0.001	0.014-0.016
Baseline, Intermediate DTOs	0	100	0	0	0	0	-
	1	98	0.011	0.022	0.018	0.002	0.018-0.019
	2	85	0.011	0.018	0.016	0.001	0.015-0.016
	3	76	0.012	0.017	0.015	0.001	0.014-0.015
	4	72	0.012	0.016	0.014	0.001	0.014-0.014
	5	68	0.012	0.016	0.014	0.001	0.013-0.014

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Intermediate DTOs	0	100	0	0	0	0	-
	1	97	0.010	0.022	0.018	0.002	0.018-0.019
	2	78	0.010	0.018	0.016	0.001	0.015-0.016
	3	30	0.014	0.021	0.019	0.002	0.018-0.019
	4	27	0.012	0.018	0.016	0.001	0.015-0.016
	5	27	0.011	0.017	0.015	0.001	0.014-0.015
Baseline, Efficient DTOs	0	100	0	0	0	0	-
	1	97	0.013	0.022	0.018	0.001	0.017-0.018
	2	91	0.012	0.018	0.015	0.001	0.015-0.015
	3	91	0.012	0.016	0.014	0.001	0.013-0.014
	4	91	0.012	0.015	0.013	0.001	0.013-0.013
	5	91	0.011	0.014	0.012	0.001	0.012-0.012
Efficient DTOs	0	100	0	0	0	0	-
	1	94	0.013	0.020	0.017	0.001	0.017-0.018
	2	90	0.012	0.017	0.014	0.001	0.014-0.015
	3	27	0.016	0.020	0.018	0.001	0.018-0.018
	4	26	0.013	0.017	0.015	0.001	0.015-0.015
	5	26	0.012	0.015	0.013	0.001	0.013-0.014

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	0.016 (0.002)	0.018 (0.002)	***
Baseline – Int. DTOs	0.016 (0.002)	0.018 (0.003)	***
Baseline – Eff. DTOs	0.015 (0.003)	0.017 (0.003)	***
Sec. DTOs – Int. DTOs	0.018 (0.002)	0.018 (0.003)	n.s.
Sec. DTOs – Eff. DTOs	0.018 (0.002)	0.017 (0.003)	***
Int. DTOs – Eff. DTOs	0.018 (0.003)	0.017 (0.003)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

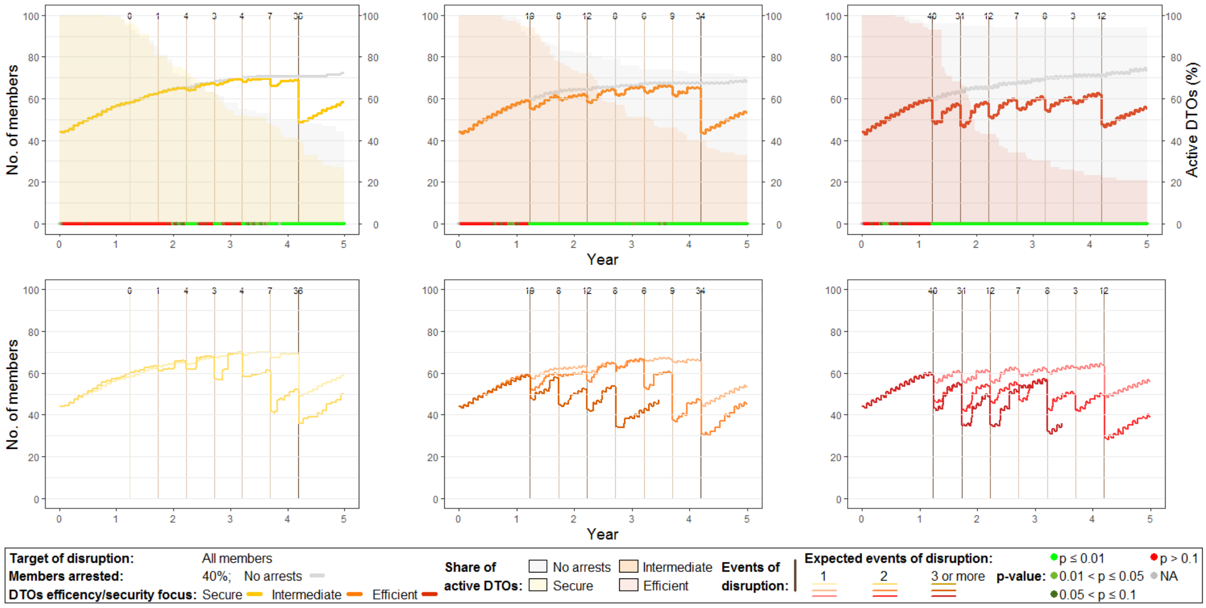
4.4.2.3. Third law enforcement intervention scenario

The third law enforcement intervention scenario, while impacting DTOs' ability to endure disruption, provokes differences in DTOs' reactions that are only slightly different from those of the first and second law enforcement intervention scenarios.

After the attempts at disruption, DTOs try to recruit new members to replace the arrested members (Graph 34and Table 31). In terms of relational strategies, DTO members tend to mildly and temporarily increase both their direct connectivity (Graph 35 and Table 32) and their average brokerage power (Graph 36 and Table 33).

In contrast to the first and second scenarios, in this scenario, the trends of the resilience indicators are affected by the number and timing of the attempts at disruption. Secure DTOs display more regular trends over time, with major modifications from the baseline after the fourth year of criminal involvement due to the delayed interventions. Efficient DTOs present greater variability in both the number and the timing of attempts at disruption over time. The graphs subdividing DTOs according to the number of expected attempts at disruption confirm this assertion, even though the sometimes low number per condition and the possible high fluctuations among single simulations invite caution in the interpretation of the data (Graph 34, Graph 35, and Graph 36).

Graph 34. Number of DTOs members (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)



Source: Author's elaboration

Table 31. Number of DTOs members per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	44	44	44	0	-
	1	100	51	60	56.72	1.86	56.35-57.09
	2	72	61	66	65.01	1.17	64.74-65.29
	3	58	65	70	69.10	0.81	68.89-69.32
	4	49	70	71	70.84	0.37	70.73-70.94
	5	44	70	73	72.39	0.75	72.16-72.62
Secure DTOs	0	100	44	44	44	0	-
	1	99	51	60	56.90	1.95	56.51-57.29
	2	76	46	66	64.46	2.53	63.88-65.04
	3	54	55	70	68.91	2.08	68.34-69.47
	4	41	49	71	68.49	6	66.60-70.38
	5	26	50	68	58.27	3.97	56.67-59.87
Baseline, Intermediate DTOs	0	100	44	44	44	0	-
	1	98	53	60	57.90	1.67	57.56-58.23
	2	82	62	65	64.60	0.68	64.45-64.75
	3	76	63	67	66.14	0.83	65.96-66.33
	4	72	65	68	67.33	0.71	67.17-67.50
	5	71	66	69	68.17	0.74	67.99-68.34

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Intermediate DTOs	0	100	44	44	44	0	-
	1	96	53	60	58.16	1.61	57.83-58.48
	2	73	39	65	61.48	7.50	59.73-63.23
	3	51	38	67	64.9	5.21	63.44-66.37
	4	40	43	68	64.98	7.04	62.72-67.23
	5	33	45	67	53.21	5.41	51.29-55.13
Baseline, Efficient DTOs	0	100	44	44	44	0	-
	1	97	52	60	58.82	1.31	58.56-59.09
	2	95	63	66	65.60	0.64	65.47-65.73
	3	94	67	70	68.35	0.79	68.19-68.51
	4	94	69	72	70.84	0.59	70.72-70.96
	5	94	69	75	73.68	0.91	73.50-73.87
Efficient DTOs	0	100	44	44	44	0	-
	1	96	54	60	58.74	1.25	58.49-58.99
	2	44	36	66	57.18	12.21	53.47-60.89
	3	30	38	70	58.83	10.32	54.98-62.69
	4	23	41	71	61.04	10.51	56.50-65.59
	5	21	39	70	55.14	9.540	50.80-59.48

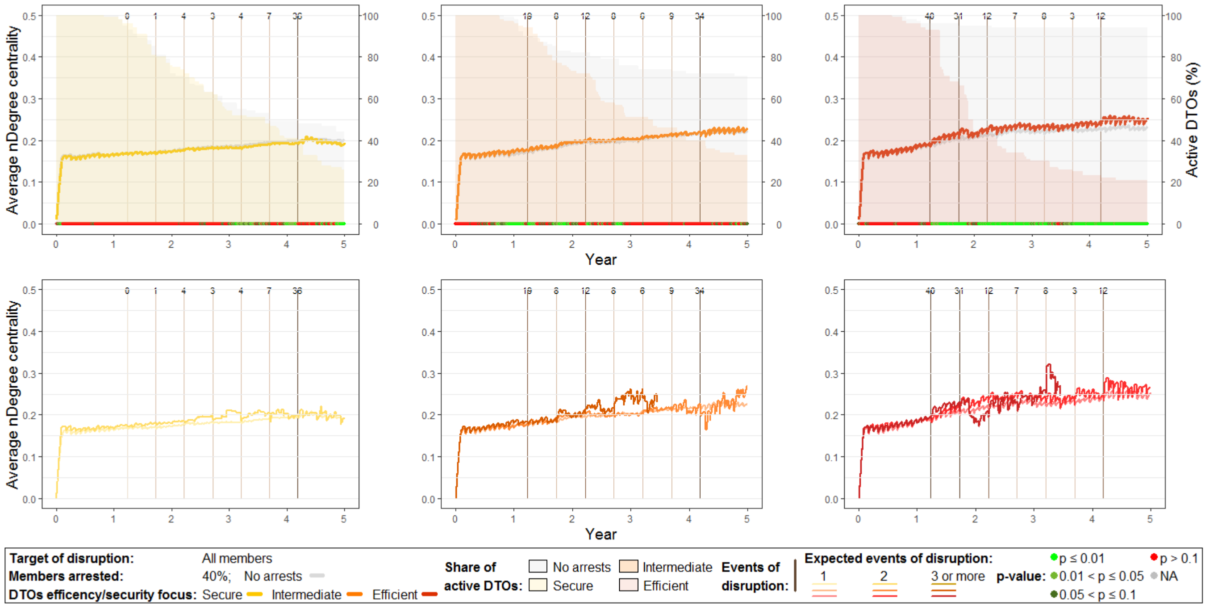
Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	63.85 (8.20)	60.34 (7.70)	***
Baseline – Int. DTOs	62.46 (6.82)	57.59 (6.80)	***
Baseline – Eff. DTOs	64.49 (8.00)	54.67 (4.71)	***
Sec. DTOs – Int. DTOs	60.34 (7.70)	57.59 (6.80)	***
Sec. DTOs – Eff. DTOs	60.34 (7.70)	54.67 (4.71)	***
Int. DTOs – Eff. DTOs	57.59 (6.80)	54.67 (4.71)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

Graph 35. DTOs members average normalized degree centrality (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)



Source: Author's elaboration

Table 32. DTOs members average normalized degree centrality per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	0	0	0	0	-
	1	100	0.109	0.189	0.165	0.016	0.161-0.168
	2	72	0.13	0.204	0.174	0.011	0.171-0.177
	3	58	0.16	0.217	0.186	0.012	0.183-0.189
	4	49	0.171	0.231	0.198	0.014	0.194-0.202
	5	44	0.172	0.236	0.201	0.014	0.197-0.205
Secure DTOs	0	100	0	0	0	0	-
	1	99	0.105	0.189	0.164	0.014	0.161-0.167
	2	76	0.128	0.200	0.173	0.013	0.170-0.176
	3	54	0.147	0.232	0.183	0.017	0.178-0.187
	4	41	0.157	0.231	0.193	0.017	0.188-0.198
	5	26	0.171	0.237	0.193	0.016	0.187-0.200
Baseline, Intermediate DTOs	0	100	0	0	0	0	-
	1	98	0.121	0.195	0.166	0.014	0.163-0.168
	2	82	0.164	0.240	0.192	0.016	0.188-0.195
	3	76	0.174	0.250	0.199	0.015	0.195-0.202
	4	72	0.155	0.264	0.215	0.019	0.210-0.219
	5	71	0.178	0.257	0.222	0.020	0.217-0.227
Intermediate DTOs	0	100	0	0	0	0	-
	1	96	0.138	0.217	0.173	0.015	0.170-0.176
	2	73	0.156	0.251	0.195	0.018	0.191-0.199
	3	51	0.167	0.238	0.203	0.016	0.198-0.207
	4	40	0.171	0.251	0.215	0.019	0.209-0.221
	5	33	0.176	0.272	0.228	0.020	0.221-0.235
Baseline, Efficient DTOs	0	100	0	0	0	0	-
	1	97	0.146	0.223	0.181	0.013	0.178-0.183
	2	95	0.176	0.241	0.208	0.014	0.205-0.211
	3	94	0.178	0.256	0.221	0.016	0.218-0.224
	4	94	0.195	0.260	0.227	0.013	0.224-0.229
	5	94	0.196	0.260	0.232	0.013	0.229-0.235
Efficient DTOs	0	100	0	0	0	0	-
	1	96	0.153	0.245	0.183	0.015	0.180-0.186
	2	44	0.158	0.281	0.215	0.029	0.206-0.224
	3	30	0.182	0.291	0.229	0.027	0.219-0.240
	4	23	0.207	0.294	0.244	0.024	0.233-0.254
	5	21	0.218	0.287	0.253	0.017	0.245-0.261

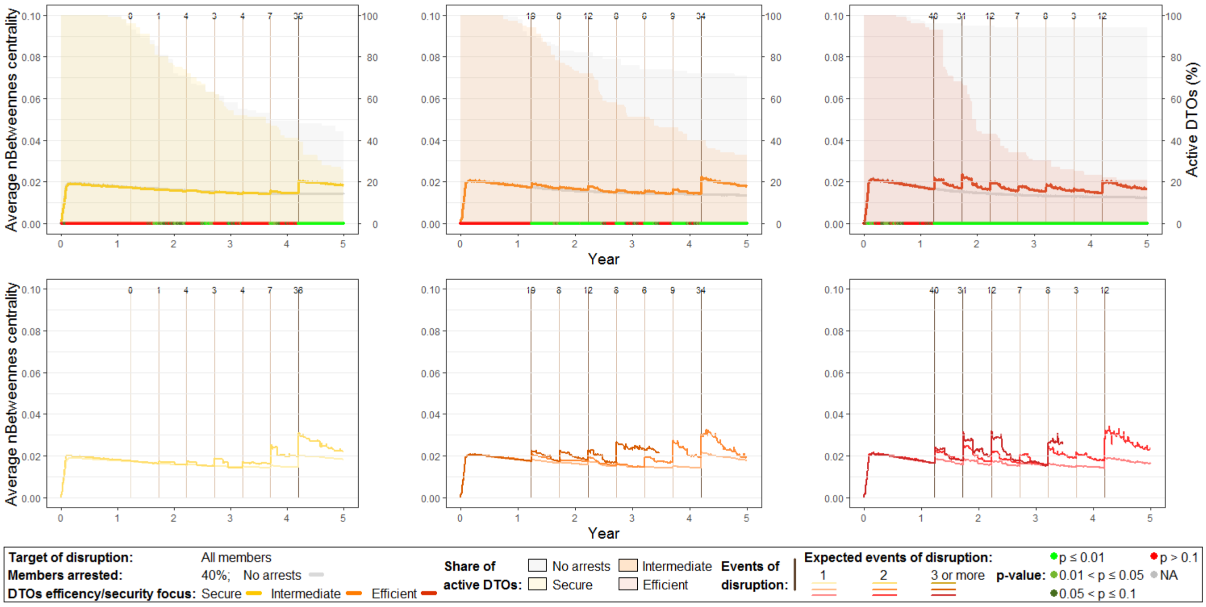
Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	0.180 (0.020)	0.178 (0.019)	***
Baseline – Int. DTOs	0.192 (0.025)	0.195 (0.025)	***
Baseline – Eff. DTOs	0.207 (0.027)	0.217 (0.032)	***
Sec. DTOs – Int. DTOs	0.178 (0.019)	0.195 (0.025)	***
Sec. DTOs – Eff. DTOs	0.178 (0.019)	0.217 (0.032)	***
Int. DTOs – Eff. DTOs	0.195 (0.025)	0.217 (0.032)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

Graph 36. DTOs members average normalized betweenness centrality (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)



Source: Author's elaboration

Table 33. DTOs members average normalized betweenness centrality per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	0	0	0	0	-
	1	100	0.007	0.021	0.018	0.002	0.017-0.018
	2	72	0.008	0.019	0.016	0.001	0.016-0.017
	3	58	0.011	0.018	0.015	0.001	0.015-0.015
	4	49	0.012	0.018	0.014	0.001	0.014-0.015
	5	44	0.012	0.017	0.014	0.001	0.014-0.014
Secure DTOs	0	100	0	0	0	0	-
	1	99	0.010	0.022	0.018	0.002	0.017-0.018
	2	76	0.010	0.022	0.016	0.002	0.015-0.016
	3	54	0.009	0.017	0.015	0.001	0.014-0.015
	4	41	0.012	0.021	0.015	0.002	0.014-0.015
	5	26	0.015	0.022	0.018	0.002	0.018-0.019
Baseline, Intermediate DTOs	0	100	0	0	0	0	-
	1	98	0.013	0.022	0.018	0.002	0.018-0.019
	2	82	0.012	0.018	0.016	0.001	0.015-0.016
	3	76	0.012	0.017	0.015	0.001	0.014-0.015
	4	72	0.012	0.017	0.014	0.001	0.014-0.014
	5	71	0.012	0.017	0.013	0.001	0.013-0.014
Intermediate DTOs	0	100	0	0	0	0	-
	1	96	0.010	0.022	0.018	0.002	0.018-0.018
	2	73	0.012	0.027	0.017	0.003	0.016-0.017
	3	51	0.011	0.024	0.015	0.002	0.014-0.016
	4	40	0.012	0.021	0.015	0.002	0.014-0.015
	5	33	0.013	0.021	0.018	0.002	0.017-0.019

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Efficient DTOs	0	100	0	0	0	0	-
	1	97	0.015	0.022	0.018	0.001	0.017-0.018
	2	95	0.013	0.016	0.015	0.001	0.014-0.015
	3	94	0.011	0.015	0.013	0.001	0.013-0.014
	4	94	0.011	0.015	0.013	0.001	0.013-0.013
	5	94	0.011	0.014	0.012	0.001	0.012-0.013
Efficient DTOs	0	100	0	0	0	0	-
	1	96	0.013	0.021	0.017	0.001	0.017-0.018
	2	44	0.013	0.027	0.017	0.004	0.016-0.019
	3	30	0.012	0.023	0.016	0.003	0.015-0.017
	4	23	0.011	0.022	0.015	0.003	0.014-0.016
	5	21	0.013	0.023	0.017	0.003	0.015-0.018
Randomization-based t tests							
Compared scenarios			**Group 1 Mean (SD)**		**Group 2 Mean (SD)**		**Significance**
Baseline – Sec. DTOs			0.016 (0.002)		0.016 (0.002)		***
Baseline – Int. DTOs			0.016 (0.002)		0.017 (0.002)		***
Baseline – Eff. DTOs			0.015 (0.003)		0.018 (0.002)		***
Sec. DTOs – Int. DTOs			0.016 (0.002)		0.017 (0.002)		***
Sec. DTOs – Eff. DTOs			0.016 (0.002)		0.018 (0.002)		***
Int. DTOs – Eff. DTOs			0.017 (0.002)		0.018 (0.002)		***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

4.4.3. Ability to maintain primary functions and activities unaltered after disruption

To examine DTOs' abilities to maintain their primary functions unaltered despite being targeted by law enforcement interventions, this section investigates the amount of drugs that DTOs store in their warehouses and their revenues from drug trafficking and dealing.

In the baseline scenarios, the focus in the security vs. efficiency trade-off influences the amount of drug stored by DTO members. Secure DTOs adopt the most precautionary behaviors, maintaining the lowest quantities of drugs in stock, 7 kilos on average. In contrast, efficient DTOs store the largest amount of drugs (i.e., 9 kilos on average) and thus have the possibility of best exploiting market opportunities (Table 34, Table 36, and Table 38).

The amount of drug in stock has consequences for the revenues gained by DTOs. DTOs that store more drugs sell more doses and therefore earn more money. Conversely, DTOs that store smaller quantities of drugs in their warehouses make fewer retail sales and thus earn lower profits. Accordingly, efficient DTOs earn the highest profits, with average revenues of almost 2,100-2,200 k€ at the end of the simulated period. In contrast, at the end of the simulated period, on average, secure DTOs have almost half the revenues of efficient DTO (i.e., 1,000-1,100 k€).

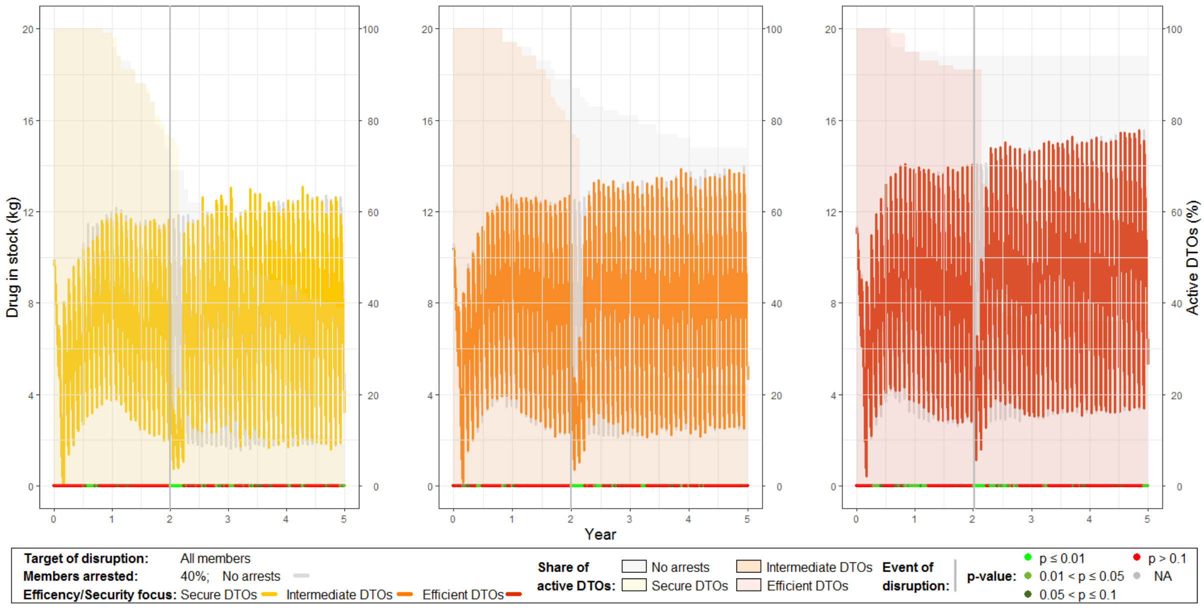
In the same period, intermediate DTOs register revenues that are only slightly higher than those of secure DTOs (i.e., 1,200 k€ on average) (Table 35, Table 37, and Table 39).

4.4.3.1. First law enforcement intervention scenario

The attempt at disruption provokes only minor and short-term impacts on the amount of drugs stored by DTOs. Law enforcement, while arresting DTO members, also seizes the drugs at their disposal. This results in a significant reduction in the amount of drugs in stock immediately after the disruptive event. This reduction occurs regardless of DTOs' focuses in the security vs. efficiency trade-off, and it affects the amount of drugs in DTO warehouses only for less than a semester after the law enforcement intervention (Graph 37 and Table 34).

An interesting pattern emerges in the case of attempts at disruption targeting traffickers. After the steep reduction in the amount of drugs caused by the seizures performed together with the arrests, while no secure DTO survives more than one year after the attempt at disruption, intermediate and especially efficient DTOs significantly increase the quantities of drugs stored in their warehouses for at least one year following the intervention. This behavior supports the risk-taking attitude of organizations favoring the efficiency side of the trade-off that, instead of being worried about the losses experienced, are already projecting into the future and aiming to restart their business as soon as possible (Graph 38 and Annex IV, Graph 79).

Graph 37. Amount of drug in stock (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)



Source: Author's elaboration

Table 34. Amount of drug in stock (in kg) per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	8.70	8.70	8.70	0	-
	1	96	4.75	20.11	10.74	2.45	10.24-11.24
	2	69	4.90	10.14	8.44	1.11	8.17-8.71
	3	56	3.62	8.63	7.05	1.31	6.70-7.40
	4	44	3.39	6.79	5.29	1.03	4.98-5.60
	5	39	1.87	4.90	3.51	0.81	3.24-3.77
Secure DTOs	0	100	8.70	8.70	8.70	0	-
	1	98	5.03	19.30	10.44	2.69	9.90-10.98
	2	76	1.33	7.68	5.17	1.25	4.88-5.45
	3	12	4.55	9.09	7.46	1.17	6.72-8.21
	4	11	2.47	6.39	5.04	1.35	4.13-5.95
	5	9	1.41	4.50	2.81	1.07	1.98-3.63
Baseline, Intermediate DTOs	0	100	8.70	8.70	8.70	0	-
	1	97	6.11	16.71	10.96	2.05	10.55-11.38
	2	87	6.58	10.95	9.41	1.04	9.19-9.63
	3	81	4.04	9.98	8.01	1.29	7.73-8.30
	4	76	2.90	7.79	6.30	1.16	6.04-6.57
	5	74	2.37	5.73	4.38	0.77	4.20-4.56
Intermediate DTOs	0	100	8.70	8.70	8.70	0	-
	1	97	6.70	18.14	11.35	1.98	10.95-11.75
	2	77	2.76	7.45	5.55	0.94	5.34-5.77
	3	25	4.92	10.70	8.16	1.34	7.61-8.71
	4	23	4.53	7.82	6.03	0.91	5.64-6.42
	5	22	2.46	5.72	4.22	0.94	3.80-4.64
Baseline, Efficient DTOs	0	100	8.70	8.70	8.70	0	-
	1	95	6.80	17.01	11.57	1.55	11.25-11.88
	2	94	6.68	11.74	10.62	0.82	10.45-10.79
	3	94	5.43	10.39	9.19	0.74	9.04-9.34
	4	94	3.12	8.62	7.23	0.90	7.04-7.41
	5	94	2.62	6.46	5.18	0.85	5.01-5.36
Efficient DTOs	0	100	8.70	8.70	8.70	0	-
	1	95	8.44	24.50	12.22	2.20	11.78-12.67
	2	91	2.91	8.78	6.38	0.93	6.19-6.57
	3	36	5.09	10.72	8.98	1.11	8.61-9.36
	4	36	3.72	8.47	7.06	1.11	6.69-7.44
	5	36	2.42	6.28	4.84	0.97	4.51-5.17

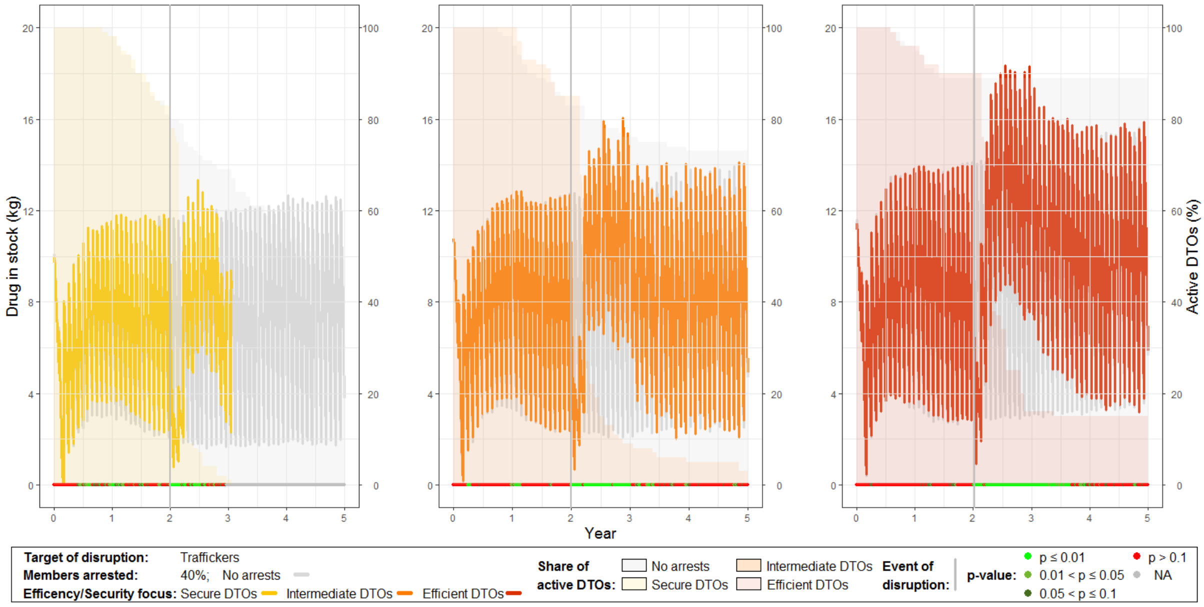
Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	7.13 (3.00)	6.98 (3.08)	*
Baseline – Int. DTOs	7.79 (3.16)	7.68 (3.23)	n.s.
Baseline – Eff. DTOs	8.79 (3.43)	8.79 (3.48)	n.s.
Sec. DTOs – Int. DTOs	6.98 (3.08)	7.68 (3.23)	***
Sec. DTOs – Eff. DTOs	6.98 (3.08)	8.79 (3.48)	***
Int. DTOs – Eff. DTOs	7.68 (3.23)	8.79 (3.48)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

Graph 38. Amount of drug in stock (Proportion of members arrested: 40%; Target of disruption: Traffickers; Law enforcement intervention scenario: 1)

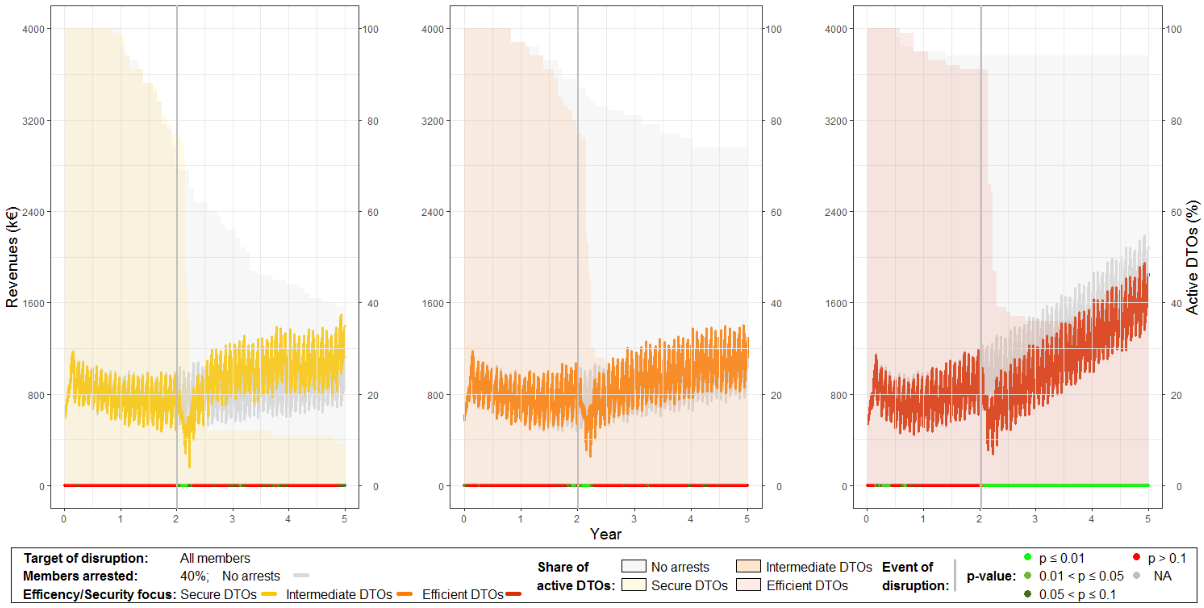


Source: Author's elaboration

The law enforcement intervention has only a limited impact even on DTO revenues and only for DTOs prioritizing the efficiency side of the trade-off. Indeed, arrests always lead to a significant decrease in DTO revenues in the months immediately after the disruptive event. The decrease soon becomes insignificant for secure and intermediate DTOs. Conversely, the reduction in DTOs revenues remains strongly significant until the end of the simulated period for efficient DTOs, with revenues in the fifth year that are approximately 200 k€ lower than in the baseline scenario (Graph 39 and Table 35).

In the case of attempts at disruption targeting DTO traffickers, the choice to incrementally increase drug purchases has negative implications for DTO revenues. In addition to the losses experienced due to the direct impact of the disruptive event, DTOs also must embrace the expenditure for supplementary drug acquisitions, leading to substantially lower revenues over the simulated period (Graph 40 and Annex IV, Graph 108).

Graph 39. DTOs revenues (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)



Source: Author's elaboration

Table 35. DTOs revenues (in k€) per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 1)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	620.77	620.77	620.77	0	-
	1	96	53.69	1432.24	647.04	305.22	585.19-708.88
	2	69	96.71	1924.25	690.98	354.68	605.78-776.18
	3	56	181.74	1947.35	792.85	384.78	689.81-895.90
	4	44	408.87	2067.76	976.37	354.09	868.71-1084.02
	5	39	448.32	1954.25	1172.64	378.46	1049.96-1295.32
Secure DTOs	0	100	620.77	620.77	620.77	0	-
	1	98	34.50	1330.05	608	300.92	547.67-668.33
	2	76	64.95	1607.47	629.63	341.08	551.69-707.57
	3	12	425.76	2209.05	993.8	532.37	655.55-1332.06
	4	11	502.62	2629.74	1178.76	595.84	778.47-1579.05
	5	9	736.11	2681.94	1446.69	536.96	1033.95-1859.43
Baseline, Intermediate DTOs	0	100	620.77	620.77	620.77	0	-
	1	97	35.79	1258.95	595.53	242.82	546.59-644.47
	2	87	227.11	1348.03	642.61	247.79	589.79-695.42
	3	81	196.09	1693.26	840.66	314.93	771.02-910.30
	4	76	357.51	1848.84	1040.01	330.58	964.47-1115.55
	5	74	582.57	2324.99	1267.74	385.06	1178.53-1356.95
Intermediate DTOs	0	100	620.77	620.77	620.77	0	-
	1	97	32.05	1248.87	592.6	265.95	539.00-646.20
	2	77	217.22	1565.22	711.11	283.25	646.82-775.40
	3	25	342.14	1834.12	897.65	379.90	740.83-1054.47
	4	23	502.15	1917.99	1162.41	391.21	993.23-1331.58
	5	22	880.05	2129.02	1340.35	369.99	1176.30-1504.39

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Efficient DTOs	0	100	620.77	620.77	620.77	0	-
	1	95	129.79	926.18	564.88	165.24	531.22-598.54
	2	94	253.15	1274.66	794.58	216.35	750.26-838.89
	3	94	586.73	1740.45	1171.15	269.83	1115.88-1226.41
	4	94	1000.95	2373.37	1624.31	315.06	1559.78-1688.84
	5	94	1249.48	2960.24	2138.70	361.95	2064.57-2212.84
Efficient DTOs	0	100	620.77	620.77	620.77	0	-
	1	95	45.15	1134.13	541.5	217.95	497.11-585.90
	2	91	332.80	1327.98	789.58	207.02	746.46-832.69
	3	36	352.61	1683.13	928.28	380.52	799.53-1057.03
	4	36	630.49	1933.57	1400.79	361.80	1278.38-1523.21
	5	36	877.26	2789.93	1904.02	449.15	1752.05-2056.00

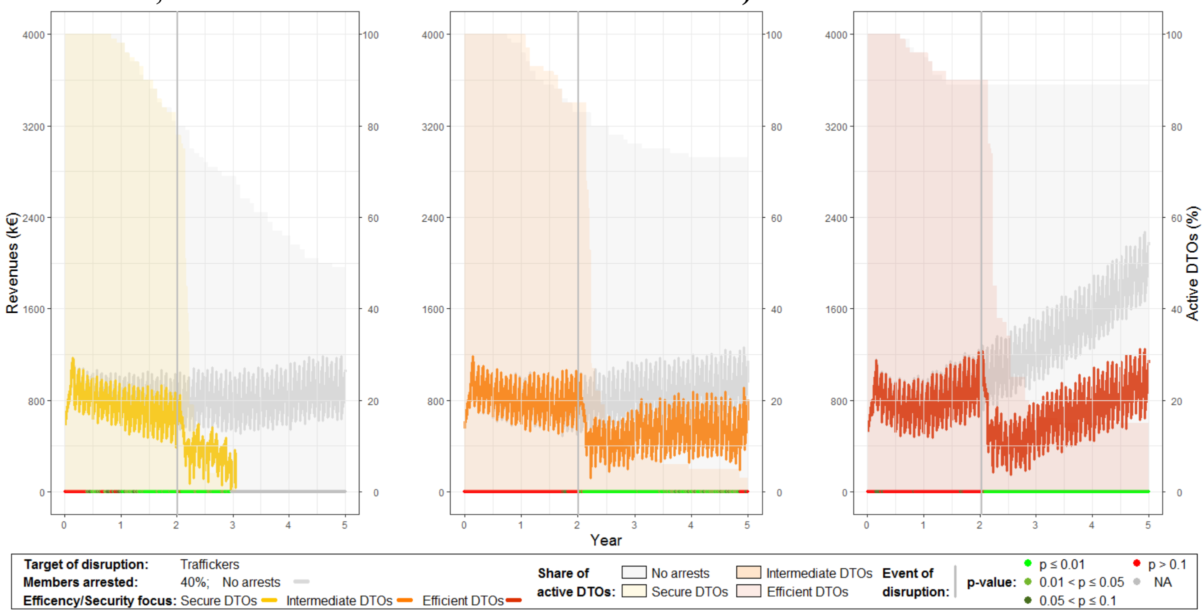
Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	830.14 (144.39)	898.20 (205.71)	***
Baseline – Int. DTOs	847.58 (168.00)	880.66 (193.58)	***
Baseline – Eff. DTOs	1135.01 (390.64)	978.42 (322.75)	***
Sec. DTOs – Int. DTOs	898.20 (205.71)	880.66 (193.58)	**
Sec. DTOs – Eff. DTOs	898.20 (205.71)	978.42 (322.75)	***
Int. DTOs – Eff. DTOs	880.66 (193.58)	978.42 (322.75)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

Graph 40. DTOs revenues (Proportion of members arrested: 40%; Target of disruption: Traffickers; Law enforcement intervention scenario: 1)



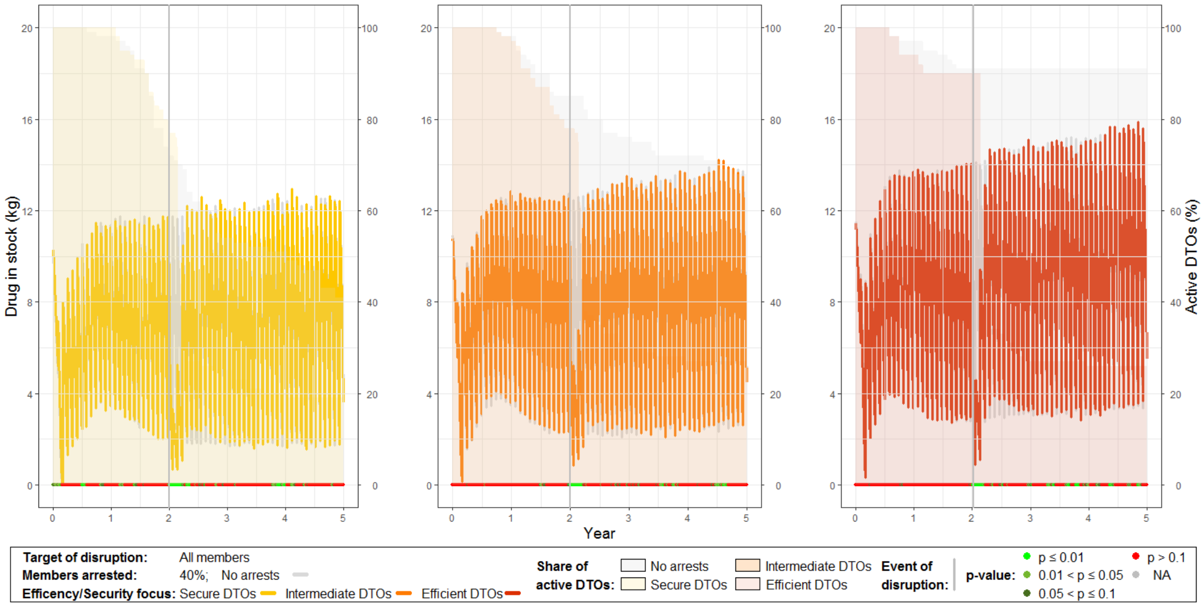
Source: Author's elaboration

4.4.3.2. Second law enforcement intervention scenario

Even in the case of resilience indicators related to DTOs ability to maintain their primary functions unaltered, the impact of the second law enforcement intervention scenario is hardly distinguishable from that of the first scenario.

As in the first law enforcement intervention scenario, the drug seizures performed together with the arrests cause a short-term reduction in the quantities of drugs stored in DTO warehouses. However, in the long term there are no significant effects of the disruptive event (Graph 41 and Table 36).

Graph 41. Amount of drug in stock (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)



Source: Author's elaboration

Table 36. Amount of drug in stock (in kg) per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	8.70	8.70	8.70	0	-
	1	98	2.72	17.30	10.16	2.37	9.68-10.64
	2	72	5.52	11.92	8.74	1.35	8.42-9.05
	3	54	3.64	9.11	7.11	1.27	6.77-7.46
	4	51	2.48	7.04	5.56	1.05	5.26-5.85
	5	41	1.11	4.89	3.41	0.92	3.12-3.70
Secure DTOs	0	100	8.70	8.70	8.70	0	-
	1	100	3.13	18.48	9.98	2.06	9.57-10.38
	2	77	2.31	7.92	5.61	1.14	5.35-5.87
	3	25	4.63	11.18	7.04	1.49	6.42-7.65
	4	20	2.25	6.15	4.78	1.25	4.20-5.37
	5	19	1.25	4.52	3.21	0.83	2.81-3.61
Baseline, Intermediate DTOs	0	100	8.70	8.70	8.70	0	-
	1	98	6.08	18.69	11.15	2.12	10.73-11.58
	2	85	6.37	12.35	9.53	1.03	9.31-9.75
	3	76	4.59	9.35	8.10	1.02	7.86-8.33
	4	72	2.91	7.77	6.23	1.16	5.95-6.50
	5	68	1.66	5.72	4.14	0.98	3.90-4.37

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Intermediate DTOs	0	100	8.70	8.70	8.70	0	-
	1	97	6.63	18.41	11.42	2.30	10.95-11.88
	2	78	3.05	8.80	5.74	1.01	5.51-5.97
	3	30	6.63	11.95	8.38	0.98	8.01-8.74
	4	27	3.68	7.79	6.14	1.18	5.68-6.61
	5	27	1.66	5.72	4.07	1.05	3.66-4.49
Baseline, Efficient DTOs	0	100	8.70	8.70	8.70	0	-
	1	97	8.74	18.10	11.98	1.70	11.63-12.32
	2	91	7.91	12.83	10.59	0.85	10.42-10.77
	3	91	5.58	10.51	9.09	0.98	8.89-9.30
	4	91	4.38	8.61	7.34	0.74	7.18-7.49
	5	91	2.17	6.24	5.07	0.85	4.89-5.24
Efficient DTOs	0	100	8.70	8.70	8.70	0	-
	1	94	8.60	20.01	12.06	1.84	11.68-12.44
	2	90	3.68	7.81	5.71	0.94	5.51-5.90
	3	27	7.63	10.89	9.36	0.69	9.09-9.63
	4	26	4.79	8.32	7.01	0.87	6.66-7.36
	5	26	3.15	6.19	5.06	0.87	4.71-5.42

Randomization-based t tests

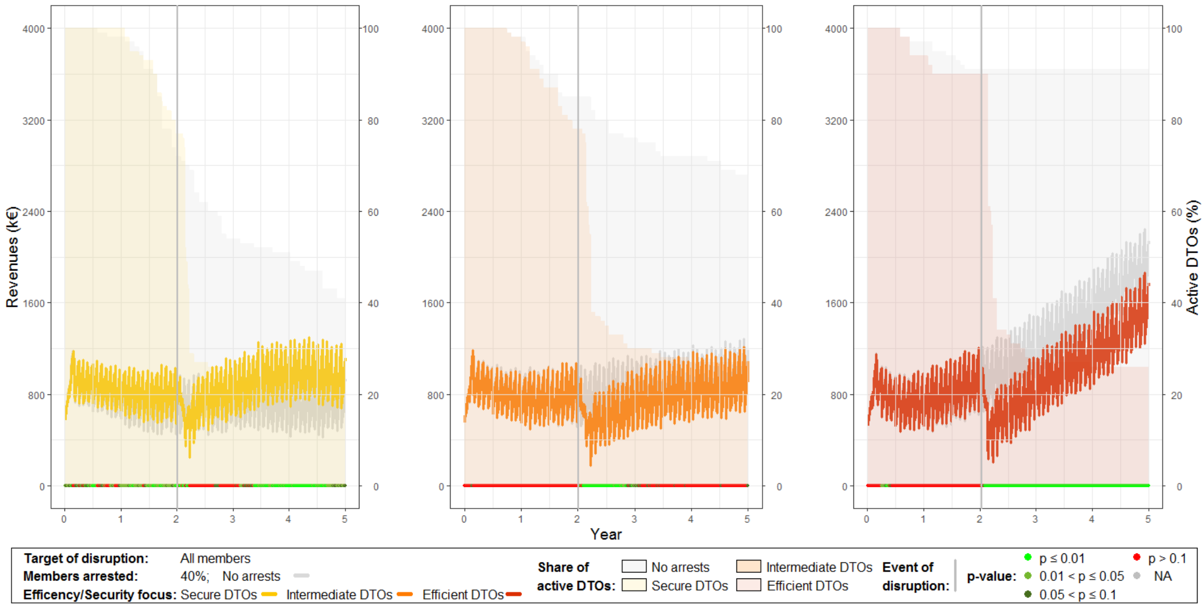
Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	7.06 (2.98)	6.89 (3.06)	**
Baseline – Int. DTOs	7.80 (3.15)	7.70 (3.22)	n.s.
Baseline – Eff. DTOs	8.86 (3.42)	8.68 (3.48)	*
Sec. DTOs – Int. DTOs	6.89 (3.06)	7.70 (3.22)	***
Sec. DTOs – Eff. DTOs	6.89 (3.06)	8.68 (3.48)	***
Int. DTOs – Eff. DTOs	7.70 (3.22)	8.68 (3.48)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

The impact of the second law enforcement intervention scenario on DTOs revenues is equal to that of the first one for efficient DTOs. In comparison to the baseline scenario, the arrests lead to a significant reduction in DTO revenues from the days immediately after the disruptive event until the end of the simulated period. The impact of the second law enforcement intervention scenario is somewhat different from that of the first one for secure and intermediate DTOs. Revenues of secure DTOs decrease in the months after the arrests and then register a moderately significant increase compared to the baseline scenario. For intermediate DTOs, the second law enforcement intervention scenario causes a reduction in the revenues from drug trafficking and dealing that remains significant for almost one year, after which revenues return to levels that are indistinguishable from those in the baseline scenario (Graph 42 and Table 37).

Graph 42. DTOs revenues (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)



Source: Author's elaboration

Table 37. DTOs revenues (in k€) per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 2)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	620.77	620.77	620.77	0	-
	1	98	33.25	1493.12	611.60	291.58	553.15-670.06
	2	72	84.20	1455.45	602.77	318.76	527.86-677.67
	3	54	330.27	1691.02	756.08	290.92	676.68-835.49
	4	51	366.50	1832.70	810.85	322.79	720.06-901.64
	5	41	586.09	1784.03	978.42	321.64	876.89-1079.94
Secure DTOs	0	100	620.77	620.77	620.77	0	-
	1	100	64.78	1411.71	686.25	299.52	626.82-745.68
	2	77	186.34	1586.54	710.65	323.25	637.28-784.02
	3	25	304.74	1762.14	846.32	380.93	689.08-1003.56
	4	20	341.03	2019.93	1106.74	425.52	907.59-1305.89
	5	19	545.33	2171.85	1156.42	520.79	905.40-1407.43
Baseline, Intermediate DTOs	0	100	620.77	620.77	620.77	0	-
	1	98	28.53	1267.03	620.07	265.40	566.86-673.28
	2	85	139.32	1282.88	665.35	279.59	605.05-725.66
	3	76	263.26	1466.57	813.00	295.55	745.46-880.53
	4	72	474.62	1841.44	1015.73	318.50	940.89-1090.58
	5	68	508.63	2090.34	1229.23	314.94	1153.00-1305.47
Intermediate DTOs	0	100	620.77	620.77	620.77	0	-
	1	97	24.87	1244.81	586.88	267.31	533.00-640.75
	2	78	144.77	1442.10	706.91	280.61	643.64-770.18
	3	30	295.27	1685.10	701.30	308.01	586.29-816.32
	4	27	381.81	2240.04	960.41	373.58	812.63-1108.19
	5	27	492.03	2228.71	1132.98	414.31	969.08-1296.87

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Efficient DTOs	0	100	620.77	620.77	620.77	0	-
	1	97	78.39	1064.94	561.67	212.02	518.93-604.40
	2	91	199.79	1505.17	784.40	251.28	732.07-836.73
	3	91	561.99	1983.83	1196.77	306.19	1133.01-1260.54
	4	91	844.83	2524.33	1651.77	356.81	1577.46-1726.08
	5	91	1156.97	2966.32	2184.84	409.19	2099.62-2270.06
Efficient DTOs	0	100	620.77	620.77	620.77	0	-
	1	94	45.40	1013.60	555.38	208.07	512.77-598.00
	2	90	252.56	1373.14	817.07	265.90	761.38-872.77
	3	27	288.53	1490.24	830.02	282.24	718.37-941.67
	4	26	582.68	2020.63	1289.47	335.19	1154.08-1424.85
	5	26	1164.67	2591.21	1821.30	373.64	1670.38-1972.22

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	744.04 (143.16)	861.58 (162.84)	***
Baseline – Int. DTOs	841.91 (151.51)	776.03 (165.08)	***
Baseline – Eff. DTOs	1149.20 (408.69)	930.87 (279.71)	***
Sec. DTOs – Int. DTOs	861.58 (162.84)	776.03 (165.08)	***
Sec. DTOs – Eff. DTOs	861.58 (162.84)	930.87 (279.71)	***
Int. DTOs – Eff. DTOs	776.03 (165.08)	930.87 (279.71)	***

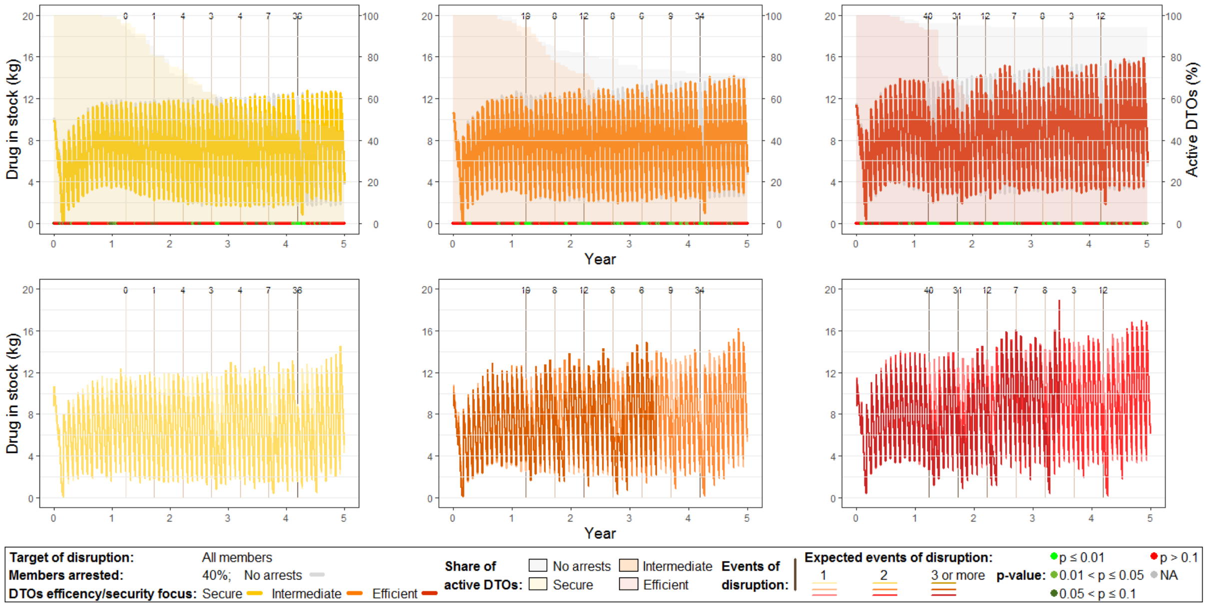
**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

4.4.3.3. Third law enforcement intervention scenario

Even when considering the resilience indicators related to DTOs' ability to maintain their primary functions unaltered, the impact of the third law enforcement intervention scenario is very similar to that of the first and second law enforcement intervention scenarios. The attempts at disruption, even if multiple and differently distributed over time, provoke only minor significant fluctuations in the amount of drug stored in DTO warehouses (Graph 43 and Table 38). While these minor fluctuations in stored drugs do not impact secure DTOs in terms of revenues, efficient DTOs are significantly impacted, with revenues that from the second year of criminal involvement are significantly lower than those in the baseline scenario (Graph 44 and Table 39).

Graph 43. Amount of drug in stock (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)



Source: Author's elaboration

Table 38. Amount of drug in stock (in kg) per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	8.70	8.70	8.70	0	-
	1	100	5.36	18.17	10.54	2.34	10.08-11.01
	2	72	4.94	17.89	9.04	1.85	8.60-9.47
	3	58	3.88	8.70	7.13	1.16	6.83-7.44
	4	49	3.16	7.01	5.32	1.07	5.01-5.63
	5	44	1.13	4.82	3.26	0.79	3.02-3.50
Secure DTOs	0	100	8.70	8.70	8.70	0	-
	1	99	4.72	15.44	10.1	1.95	9.71-10.49
	2	76	0	11.35	8.75	1.61	8.38-9.12
	3	54	4.12	9.93	7.13	1.23	6.79-7.47
	4	41	2.43	8.68	5.32	1.24	4.93-5.71
	5	26	1.20	6.82	3.47	1.45	2.88-4.05
Baseline, Intermediate DTOs	0	100	8.70	8.70	8.70	0	-
	1	98	6.35	17.27	10.83	2.00	10.43-11.24
	2	82	6.38	12.36	9.41	1.18	9.15-9.67
	3	76	4.97	9.39	7.89	1.07	7.64-8.14
	4	72	2.46	7.73	6.00	1.25	5.71-6.29
	5	71	2.51	5.69	4.19	0.86	3.98-4.39
Intermediate DTOs	0	100	8.70	8.70	8.70	0	-
	1	96	6.97	19.80	10.89	2.06	10.48-11.31
	2	73	0.48	15.91	9.40	1.91	8.95-9.850
	3	51	3.17	9.32	7.94	1.27	7.58-8.30
	4	40	3.96	7.54	6.44	0.97	6.13-6.75
	5	33	1.56	9.27	4.44	1.63	3.86-5.02

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Efficient DTOs	0	100	8.70	8.70	8.70	0	-
	1	97	6.72	17.98	11.79	1.69	11.45-12.13
	2	95	8.43	12.66	10.67	0.70	10.53-10.82
	3	94	7.08	10.26	9.27	0.67	9.13-9.41
	4	94	4.48	8.61	7.31	0.86	7.13-7.48
	5	94	2.45	6.22	4.97	0.82	4.80-5.13
Efficient DTOs	0	100	8.70	8.70	8.70	0	-
	1	96	8.94	18.26	12.11	1.61	11.79-12.44
	2	44	0.95	14.17	10.04	2.47	9.29-10.80
	3	30	5.79	15.78	9.28	1.60	8.69-9.88
	4	23	5.00	8.17	7.28	0.92	6.88-7.68
	5	21	2.78	6.24	5.36	0.83	4.98-5.74

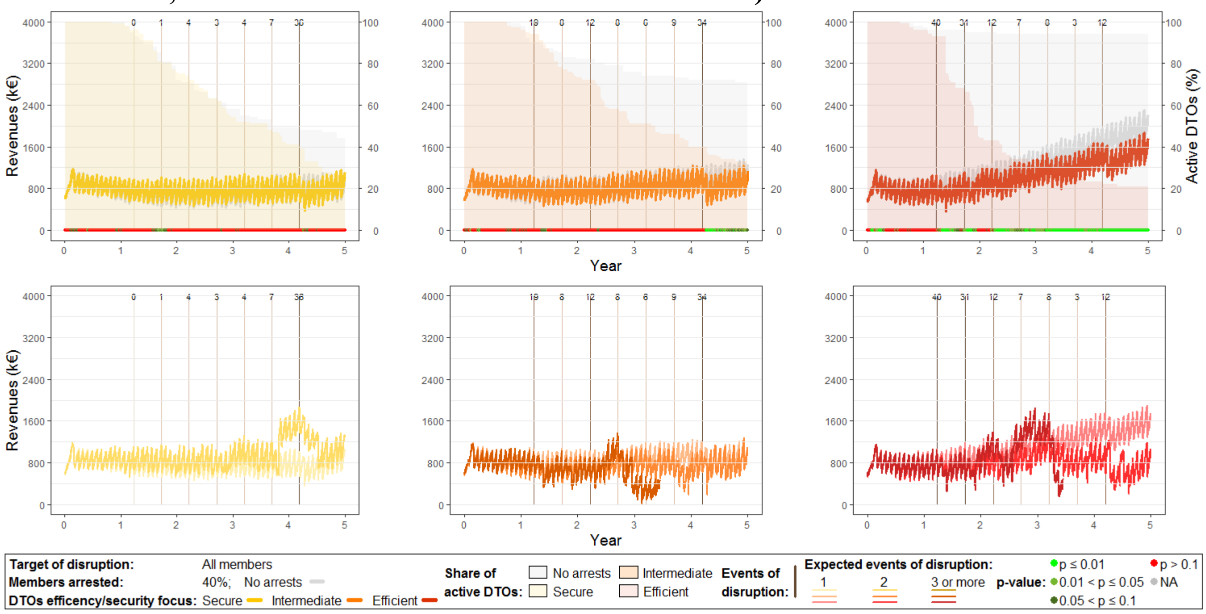
Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	7.12 (2.98)	7.02 (2.96)	n.s.
Baseline – Int. DTOs	7.74 (3.16)	7.61 (3.12)	n.s.
Baseline – Eff. DTOs	8.83 (3.43)	8.55 (3.38)	***
Sec. DTOs – Int. DTOs	7.02 (2.96)	7.61 (3.12)	***
Sec. DTOs – Eff. DTOs	7.02 (2.96)	8.55 (3.38)	***
Int. DTOs – Eff. DTOs	7.61 (3.12)	8.55 (3.38)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

Graph 44. DTOs revenues (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)



Source: Author's elaboration

Table 39. DTOs revenues (in k€) per year (Proportion of members arrested: 40%; Target of disruption: all members; Law enforcement intervention scenario: 3)

DTOs security/efficiency focus	Year	Active DTOs (%)	Min	Max	Mean	SD	Confidence interval
Baseline, Secure DTOs	0	100	620.77	620.77	620.77	0	-
	1	100	28.61	1366.02	606.90	264.39	554.44-659.36
	2	72	157.17	1201.81	602.63	289.08	534.70-670.56
	3	58	269.18	1261.81	713.75	270.56	642.61-784.89
	4	49	424.49	1456.87	879.37	261.36	804.30-954.45
	5	44	570.52	2101.48	1055.7	307.30	962.27-1149.12
Secure DTOs	0	100	620.77	620.77	620.77	0	-
	1	99	95.47	1353.26	658.92	296.71	599.74-718.10
	2	76	48.35	1591.1	634.89	344.20	556.24-713.54
	3	54	252.99	1604.18	765.47	332.13	674.82-856.13
	4	41	312.59	2048.79	905.52	394.85	780.89-1030.15
	5	26	624.30	2222.53	1155.69	424.22	984.35-1327.04
Baseline, Intermediate DTOs	0	100	620.77	620.77	620.77	0	-
	1	98	38.22	1211.86	595.71	282.48	539.07-652.34
	2	82	113.45	1439.53	656.44	286.94	593.39-719.48
	3	76	233.87	1666.73	828.71	313.64	757.04-900.38
	4	72	398.13	1978.95	1047.90	325.62	971.38-1124.41
	5	71	590.68	2192.56	1292.48	336.28	1212.88-1372.08
Intermediate DTOs	0	100	620.77	620.77	620.77	0	-
	1	96	26.01	1144.85	634.14	253.31	582.81-685.46
	2	73	145.18	1229.99	655.83	258.73	595.46-716.20
	3	51	301.55	1439.04	825.17	312.62	737.24-913.09
	4	40	418.03	1744.97	1017.49	353.21	904.53-1130.46
	5	33	499.08	2108.72	1172.64	356.79	1046.13-1299.16
Baseline, Efficient DTOs	0	100	620.77	620.77	620.77	0	-
	1	97	33.05	1135.84	572.12	208.89	530.02-614.22
	2	95	209.88	1361.96	816.28	235.13	768.38-864.18
	3	94	499.10	1971.53	1218.21	299.00	1156.97-1279.46
	4	94	952.13	2382.11	1710.80	326.39	1643.95-1777.65
	5	94	1284.71	3014.02	2257.16	374.18	2180.52-2333.80
Efficient DTOs	0	100	620.77	620.77	620.77	0	-
	1	96	57.53	1067.66	552.16	200.95	511.45-592.88
	2	44	254.62	1420.80	800.34	329.91	700.04-900.64
	3	30	318.56	1654.84	1075.32	360.38	940.75-1209.89
	4	23	567.12	2353.68	1438.18	545.83	1202.14-1674.21
	5	21	1032.13	2762.66	1809.47	480.91	1590.56-2028.37

Randomization-based t tests

Compared scenarios	Group 1 Mean (SD)	Group 2 Mean (SD)	Significance
Baseline – Sec. DTOs	761.09 (145.24)	777.77 (141.13)	***
Baseline – Int. DTOs	848.32 (161.86)	821.50 (150.14)	***
Baseline – Eff. DTOs	1180.9 (420.08)	1008.38 (293.86)	***
Sec. DTOs – Int. DTOs	777.77 (141.13)	821.50 (150.14)	***
Sec. DTOs – Eff. DTOs	777.77 (141.13)	1008.38 (293.86)	***
Int. DTOs – Eff. DTOs	821.50 (150.14)	1008.38 (293.86)	***

**Significance at 95% level, **99%, ***99.9%, n.s Nonsignificant*

Source: Author's elaboration

4.4.4. Research question 3: Summary of the results

The third research question of the study analyses whether DTOs implementing different strategies in relation to the security vs. efficiency trade-off display diversified drug trafficking and dealing *modi operandi* and how they face and react to law enforcement interventions attempting to disrupt their organizations. In doing so, it tests the impact of three scenarios of law enforcement interventions: the first one concerns the arrests of a set proportion of members disregarding DTOs specificities in relation to the security vs. efficiency trade-off; in the second one, secure DTOs are targeted by a lower number of arrests, while efficient DTOs are more heavily targeted; and in the third one, DTOs may be targeted by multiple attempts at disruption differently distributed over time according to their security/efficiency focus.

Under ordinary conditions, with no attempts at disruption, efficient DTOs outperform secure DTOs, with more than 90% vs. almost 40% of DTOs remaining active after five years of criminal involvement, respectively. When DTOs are targeted by law enforcement, their persistence over time is always impacted, with a limited share of organizations surviving disruption. In absolute terms, when considering the impact of a single attempt at disruption, there are more efficient than secure surviving DTOs (i.e., 36-26% as opposed to 9-19% of DTOs remaining active after the first and second law enforcement intervention scenarios, respectively). However, considering DTOs' survival rates in the absence of attempts at disruption, efficient DTOs are more impacted (i.e., -58/-65% from the baseline for efficient DTOs vs. -30/-22% from the baseline for secure DTOs in the first and second law enforcement intervention scenarios, respectively).

The second law enforcement intervention scenario results in fewer disrupted organizations for secure DTOs (i.e., +10% of surviving DTOs). This increase is due to the lesser intensity of the law enforcement interventions experienced. Instead, this scenario results in a significant reduction in efficient surviving DTOs (i.e., -10%) due to the greater intensity of law enforcement interventions. Nevertheless, more efficient DTOs than secure DTOs survive (i.e., 26% vs. 19%, respectively). When considering the 80% arrests scenario, the situation is reversed, with secure DTOs registering more surviving organizations (i.e., 9%) than efficient DTOs (i.e., 7%).

In the third law enforcement intervention scenario, secure DTOs register superior persistence over time for the scenario targeting 40% of members, with 26% as opposed to 21% secure and efficient DTOs surviving, respectively. The 80% arrests scenario further exacerbates this trend (i.e., 12% vs. 4% secure and efficient DTOs surviving, respectively). These trends are due to the different numbers and timing of attempts at disruption experienced by secure and efficient DTOs. Secure DTOs mostly experience only one intervention, often after four years of criminal involvement; this allows them to protract their criminal involvement for a longer time without having to confront threatening situations and to accumulate resources to face future periods of crisis. Efficient DTOs experience more law enforcement interventions (i.e., 2 on average), and these interventions mostly undermine their criminal activities after their second year of criminal involvement, precluding the possibility of being prepared for possible future threats. In contrast, in the softer scenario where only 10% of members are targeted by attempts at disruption, efficient DTOs are better able to endure disruption (56% vs. 18% efficient and secure DTOs surviving, respectively). Nonetheless, this trend is once again affected by the extremely superior performance of efficient DTOs in the absence of disruptive events. Indeed, while efficient DTOs register a -38% decrease in the proportion of surviving DTOs compared to the baseline, secure DTOs register only a -16% decrease.

In protracting drug trafficking and dealing activities, differences in organizational strategies, relational patterns, and *modi operandi* are observable with regard to DTOs' focuses in the security/efficiency trade-off. Both secure and efficient DTOs increase their number of members over time, increasing from 44 to almost 70 members in five years. However, this trend is due to secure DTOs' ability to stay hidden from sporadic law enforcement arrests, while it is motivated by effective recruitment strategies for efficient DTOs. In terms of relational patterns, secure DTOs tend to minimize direct connections among members to reduce the visibility of their members and activities; conversely, efficient DTOs exploit more direct connectivity among members, prioritizing prosperous economic performance. Therefore, efficient DTOs store larger amounts of drug and earn higher profits, while secure DTOs reduce their risks, storing smaller amounts of drugs and are satisfied with lower profits.

Being targeted by an attempt at disruption generates some modifications in the usual behaviors of surviving DTOs. Overall, the arrests cause a steep reduction in the DTO workforce that, despite the recruitment strategies in place, cannot be completely compensated for at the end of the simulated period. Given the threatening event experienced and having to rely on a reduced number of members, DTOs modify their relational patterns as a strategy of reaction and/or as a countermeasure. These approaches differ according to the focus in the security vs. efficiency trade-off. While secure DTOs tend to decrease the direct connectivity among their members to minimize their visibility and try to avoid future attempts at disruption, efficient DTO members increase their direct connections to improve the volume of their business and recoup prior losses. Both approaches result in minor consequences for drug trafficking and dealing activities.

The amount of drugs that DTOs store in their warehouses, as well as the revenues from drug sales are generally reduced only for the months immediately after the arrests. The only exception is that of efficient DTOs' revenues. They continue to earn higher profits than secure DTOs; nevertheless, they cannot reach the expected revenues of the baseline scenario. The second and third law enforcement intervention scenarios do not provoke great differences compared to the first scenario in relation to active DTO adaptation strategies. Secure and efficient DTOs that survive attempts at disruption maintain their relational and operational tactics, displaying substantial levels of resilience.

5. Discussion

The present study aimed to investigate the resistance and resilience of DTOs when confronted with law enforcement interventions attempting to disrupt the organizations themselves and the criminal activities they carry out. To this end, MADTOR was developed. MADTOR is an agent-based model that simulates a DTO and its members in their daily routines of drug trafficking and dealing. During the simulation, the model also emulates some law enforcement interventions that threaten DTOs' criminal involvement. This allowed the exploration of the effectiveness of a variety of law enforcement interventions (e.g., arresting different proportions of members or targeting members performing different tasks) and the related adaptation strategies implemented by DTOs in response to the disruptive events.

MADTOR provided answers to the research questions and tested the hypotheses presented in section 2.2. Specifically, the aim of the study was to assess the impact of arresting different proportions of members, targeting actors in charge of different tasks, and different strategies in relation to the security/efficiency trade-off for DTOs confronting attempts at disruption. The ultimate goal was to improve the knowledge of resilience mechanisms over time across attacks of different intensities and targets and across different organizational configurations as well as to identify eventual recurrent DTO strengths or weaknesses to inform future law enforcement interventions and enhance their effectiveness.

5.1. The impact on DTO resilience of the proportion of members arrested

The first research question of the study considered the impact of arresting different proportions of members from the whole organization on DTO resilience. The hypothesis delineated in section 2.2 was that the higher the proportion of arrested members, the greater the difficulties in rearranging and continuing the criminal activities and thus the lower the resistance and resilience of DTOs.

The proportion of DTO members arrested proved to be a significant factor in terms of impact on DTO resistance and resilience. Increasing the number of actors targeted by law enforcement interventions intensified DTOs' difficulties in surviving and reacting to attempts at disruption, thus confirming the first hypothesis. However, it would be simplistic to believe that aiming at the apprehension of the highest possible number of members is always the best choice. On the one hand, the arrest of a relatively limited proportion of organization members is often challenging for the survival of DTOs; on the other hand, increasing the number of arrests above a certain threshold does not have a directly proportional impact on DTOs' ability to endure disruption.

Attempts at disruption targeting just a few members (e.g., 10% of DTOs members) have remarkable disruptive potential. In the scenario with 10% of arrests, less than 40% of DTOs are still active three years after the attempt at disruption (with a decrease of 36% compared to the baseline) (Table 7). The impact of the arrests in terms of DTO dismantlement is registered a few months after the event, signaling that the remaining DTO members can continue drug trafficking and dealing in the short-term by adopting emergency strategies, but they cannot regain their ordinary sustainability quickly enough to overcome the crisis in the long term. At the same time, DTOs surviving the first months after the attempt at disruption mostly absorb the negative consequences from the event, with the disruption rate decreasing almost to zero a year after the disruptive event (Graph 5). Moreover, DTOs surviving attempts at disruption targeting 10% of members can cope well with the consequences of law enforcement interventions, with no need for particular adaptation strategies in their *modi operandi* to smoothly continue drug trafficking and dealing (Graph 6, Graph 7, Graph 8, Graph 9, and Graph 10).

Greater efforts by law enforcement interventions, such as for the 80% arrests scenario, could also bring suboptimal results in terms of DTO disruption rates that do not compensate for the costs incurred for the intervention. This is observable when comparing the impact of arresting 40% and 80% of members. Indeed, arresting an additional 40% of members reduces the share of active DTOs only by less than 10% (i.e., 25% as opposed to 18% of DTOs remining active one year after the attempt at disruption when arresting 40% and 80% of members, respectively) (Table 7). However, this result may be considered suboptimal only if the main purpose of law enforcement interventions is to disrupt DTOs. In contrast, if the primary law enforcement goal is to deter or incapacitate as many people as possible or merely enforce the law, the arrest of an additional 40% of DTO members doubles the number of actors incapacitated for and distanced from the criminal market, legitimating higher law enforcement expenditures.

Even when considering attempts at disruption alternatively targeting 40% or 80% of DTOs members, the main impact of the arrests is registered a few months after the event and then is mostly digested in the long term (Graph 5). Despite the relatively minor differences in terms of surviving DTOs, arresting 40% or 80% of members has different effects on the strategies and *modi operandi* of DTOs to continue their criminal involvement. While the arrest of 40% of members does not require special adaptation in terms of relational and working schemes, the arrest of 80% of members completely reshapes the organization, at least in the first months after the attempt at disruption. This means that the available workforce is reduced to a minimum, with inevitable consequences for the performance of criminal activities: increased direct reachability and intermediary power of members to assure the best possible operational activity (Graph 6, Graph 7, and Graph 8).

A special reflection should be made when reasoning about the impact and consequences of arresting a large part of an organization, as in the case of targeting 80% of members. In most (i.e., 85%) cases, such a scenario causes the disruption of the organization; in the minority of cases in which the organization survives, substantial recruitment is necessary to rebuild an appropriate workforce. In these cases, two considerations may arise. On the one hand, the environment in which DTOs operate may not always offer the possibility of such heavy recruitment processes. First, replacement workers should be willing to accept the risks related to involvement in an illegal organization. Second, to be recruited, replacements must have skills and criminal abilities that meet DTO expectations. Thus, both being embedded in different environments and the need to replace actors accomplishing specific tasks may compromise the ability to recoup a sustainable workforce (Spapens 2010; Duijn, Kashirin, and Sloot 2014).

On the other hand, if replacements are found, an organization with such a massive turnover rate may not be the same organization as before the attempt at disruption. In the DTOs simulated by MADTOR, the arrest of 80% of members results in DTOs going from having more than 60 members on average to fewer than 15 members. Three years after the attempt at disruption, on average, there are approximately 55 DTO members, meaning that the remaining organization represents only one-quarter of the current members, and the other three-quarters are newcomers. These high turnover rates may lead to significant modifications in DTOs' ambitions, attitudes, and relational patterns, transforming their original distinctive traits. However, ground-breaking transformations are sometimes necessary for the persistence over time of organizations, whether legal or illegal. Indeed, modifications accommodating changing external and/or internal circumstances allow organizations to remain functional over time (Butera 2005). Thus, despite eventual ideological and behavioral changes, as long as an organization maintains its primary functions unaltered, it seems reasonable to consider it the same organization after an attempt at disruption. An alternative would be to consider these organizations newly established entities that supplanted the old ones in the drug market, performing the same tasks. In both circumstances, the overall impact is unchanged: they are still DTOs active in the drug market and posing challenges to law enforcement.

The results for the first research question of the study confirmed the general claims of the literature. Illegal entities tolerate minor adversity well since they consciously operate in a hostile environment and are aware and prepared to accept certain risks (Kleemans 2014; Basu 2014). Indeed, when considering attempts at disruption targeting a small/medium proportion of DTO members (i.e., 10% and 40% arrests scenario), surviving DTOs do not implement major modifications in their *modi operandi* or adaptations strategies in reaction to the disruptive event; they simply continue business as usual. At the same time, it cannot be denied that many DTOs also face important challenges when confronted with these modest adverse events.

In contrast, when considering major attempts at disruption (i.e., 80% arrests scenario), the minority of surviving DTOs must modify their *modi operandi* to maintain their activities, minimizing losses in the short term and foreseeing adaptation strategies for long-term sustainability. As suggested by Butera (2005), in the case of substantial contextual modifications, organizational changes are necessary for DTOs to continue to meet their primary goals.

In general, the results of this study showed that both minor and major attempts at disruption are very often critical events for DTOs. Even when testing the effectiveness of arresting limited proportions of members, more than half of DTOs do not survive attempts at disruption in the long term. This result partially contradicts the claims of the few previous studies on the topic suggesting that criminal organizations have high levels of resilience (e.g., Morselli and Petit 2007; Berlusconi 2013a; Manzi 2019; Diviák et al. 2022). Indeed, these earlier studies focused mostly on peculiar cases and describe exceptional organizations capable of survival and prosperity despite the threats experienced. Unfortunately, until now, there has been no systematic investigation of the impact of major realistic law enforcement interventions on criminal organizations' ability to survive disruptions. At the same time, the results of this study about the minority of DTOs surviving disruptions confirmed the conclusions of previous studies investigating criminal organizations' resilience in terms of their ability to adapt to changing circumstances. Surviving organizations are always highly resilient, being able to continue their criminal involvement whether they do or do not implement reactive strategies (Carley 2006; Berlusconi 2013a; Duijn, Kashirin, and Sloot 2014; Bright et al. 2017; Manzi 2019; Diviák et al. 2022).

Overall, the results for the first research question confirm and suggest the importance of detailed knowledge of the criminal group to be targeted, the expected impact, and the available resources in order to plan efficient law enforcement interventions (Carley 2006; Keller, Desouza, and Lin

2010; Duxbury and Haynie 2019). Indeed, if the aim is to disrupt a DTO, increasing the proportion of members arrested always augments the likelihood of inflicting critical damages; however, in many cases, even a limited number of arrests can lead to the same outcome (i.e., DTO disruption) with considerable savings in the resources needed.

5.2. The impact on DTO resilience of targeting members performing different tasks

The second research question examined the impact of arresting members performing different tasks in the organization on DTOs' resistance and resilience to law enforcement attempts at disruption. According to the hypothesis stated in section 2.2, law enforcement interventions targeting DTO members performing trafficking activities pose the greatest challenges to DTOs, resulting in a lower level of resilience. Conversely, attempts at disruption targeting DTO members involved in retailing activities are easier to face and overcome, resulting in a higher level of resilience.

Diversifying the target of law enforcement attempts at disruption proved to be an element of influence on DTOs' resistant and resilient abilities. However, the results of the study only partially confirm the developed hypothesis. On the one hand, attempts at disruption aiming at neutralizing DTO traffickers are those posing the greatest challenges to the organization; however, on the other hand, it is not true that law enforcement interventions targeting DTO retailers are always easily manageable by the organizations.

Targeting DTO traffickers is by far the attempt at disruption with the worst consequences for DTOs and their criminal involvement. Even though, in absolute terms, it involves a limited number of members (i.e., approximately 5-6 traffickers), it results in less than 10% of DTOs remaining active one year after the attempt at disruption and only 3% of DTOs remaining active three years after it (Table 13). Most difficulties provoked by this kind of attempt at disruption relate to the nonreplaceable tasks performed by traffickers and the correlated complexity of recruiting new collaborators. The traffickers are the only members in charge of drug acquisitions and the only ones who are aware of contacts, channels, and methods of obtaining drugs (Johnson and Natarajan 1995; Calderoni 2012). Their skills are highly strategic, and their tasks are extremely risky; this hinders and delays the recruitment of replacements for the arrested members (i.e., surviving DTOs take almost two years to find replacements for arrested traffickers) (Graph 12). The short-term strategies involve the sales of drugs already in stock to earn the most profits possible while DTO managerial figures strive to recruit new traffickers.

However, in most cases, new recruits are not enough to allow the continuance of drug trafficking and dealing in the long term, thus leading to the dismantlement of the organizations. Even in the exiguous minority of cases in which DTOs survive disruption, the law enforcement intervention maintains a significant long-term impact on DTO revenues, and it is impossible to bridge the gap created by the threatening event (Graph 16).

In contrast to the initial expectation, attempts at disruption targeting DTO members active in street dealing also cause significant obstacles to protracting drug trafficking and dealing. Indeed, while arresting DTO retailers is not as challenging as targeting DTO traffickers, it leads to the dissolution of almost 70% of organizations (Table 13). Unlike traffickers, retailers are usually relatively unskilled; thus, the recruitment of replacements for the arrested actors poses only minor challenges (Johnson and Natarajan 1995; Calderoni 2012). Rather, the relevant impact of arresting DTO retailers relates mainly to their strategic position in the value chain. They are in charge of cashing in the revenues from drug sales; thus, their removal from the organization impedes the ability to earn profits in the short term. Moreover, despite the severe rate of disruption, the still active 30% of DTOs must confront law enforcement intervention impacts that persist in the long term. On the one hand, their revenues significantly decrease over time; on the other hand, the average visibility of DTO members increases as they attempt to return to a sustainable workload and regain the losses generated by the attempt at disruption (Graph 16 and Graph 13). However, this strategy increases DTOs' vulnerability to potential future law enforcement interventions.

In contrast to the hypothesis, the attempts at disruption provoking the least damage are those targeting DTO packagers. The packagers are members of the organization in charge of receiving the drugs acquired by the traffickers, producing saleable unit doses, and delivering those unit doses to the retailers. When law enforcement interventions target these members of an organizations, almost 40% of DTOs can survive the attempt at disruption and continue drug trafficking and dealing until the end of the simulated period (Table 13). Moreover, they seem to do so with relative ease: they do not need to modify their *modi operandi* (i.e., no significant modifications in relational pattern and maintenance of the same business volume), and they have no negative consequences in terms of revenues (Graph 13, Graph 14, Graph 15, and Graph 16).

Overall, the results of the study for the second research question confirmed the findings from the literature that the apprehension of the most strategic players of the organizations (i.e., the traffickers in the case of DTOs) is definitely the most effective strategy of disruption (Johnson and Natarajan 1995; Morselli and Roy 2008; Calderoni 2012; Duijn, Kashirin, and Sloot 2014; Bright et al. 2017; Wood 2017; Castiello, Mosca, and Villani 2017; Duxbury and Haynie 2018; 2019; Villani, Mosca, and Castiello 2019). However, the results partially contradicted previous studies regarding the least effective strategy of disruption. Indeed, while previous studies have stated that interventions targeting grassroots members of criminal groups (i.e., retailers in the case of DTOs) are ineffective (Johnson and Natarajan 1995; Morselli and Roy 2008; Calderoni 2012; Duijn, Kashirin, and Sloot 2014; Castiello, Mosca, and Villani 2017), MADTOR simulations proved that attempts at disruption targeting retailers also have a significant impact on DTOs' resistance and resilience. In contrast, attempts at disruption targeting packagers pose the fewest challenges to DTO resilience. The explanation of this unexpected result relates mainly to the focuses of previous studies. Indeed, as reported in section 3.3.1, the packagers are not recognized figures in the drug market, but they represent a wide range of support figures identified by the literature who in various ways assist and facilitate drug trafficking and dealing. For this reason, previous studies investigating criminal network resilience simply did not focus on these actors, concentrating instead on the most active participants. Nonetheless, when considering the tasks performed by retailers and packagers, the observed impact of law enforcement interventions appears to be plausible. Both oversee tasks that do not require specific skills; thus, they are members who can be replaced with few difficulties. However, the tasks accomplished by arrested packagers can easily be undertaken by the packagers still present in the DTOs since, having a fixed weekly wage unrelated to the performance of specific activities, they are encouraged by DTOs managerial figures to increase their daily workload in the short-term. In contrast, the drug sales performed by the arrested retailers can only partially be covered by other retailers. These actors are paid daily as a percentage of the revenues from their sales; however, their maximum daily earnings are fixed by DTO managerial figures to 500€. Thus, once they have sold a number of doses that would result in that personal profit, they stop selling for the day. Consequently, this negatively impacts on DTOs' profits.

In terms of implications for the planning of future law enforcement interventions, the results related to the second research question suggest that focusing on specific targets may yield positive outcomes. In absolute terms, targeting DTO traffickers would cause the most damage to DTOs and their criminal activities. However, it is likely that traffickers are a difficult target for law enforcement to reach. Indeed, they likely have resources and tactics to conceal themselves from attempts at disruption. In contrast, DTO retailers may lack protective measures since they are considered expendable by the managerial figures of the organization, and the tasks they perform (i.e., street dealing) make them very visible and with limited possibilities of concealment from law enforcement, making them more reachable targets (Morselli 2010a; Calderoni 2014a; 2014b). Considering that interventions targeting DTO retailers are expected to disrupt their organization in almost 70% of cases (Table 13), and imagining a lesser effort for law enforcement to identify, reach, and arrest DTO retailers, attempts at disruption targeting these actors, together with those targeting DTO traffickers, are expected to have high disruptive potential.

5.3. The impact on DTO resilience of a diversified focus in the security vs. efficiency trade-off

The third research question of the study explored the impact of different focuses in the efficiency vs. security trade-off on DTOs' resistance and resilience to law enforcement attempts at disruption. According to the hypothesis presented in section 2.2, efficient DTOs are more resilient to massive attempts at disruption since, compared to secure DTOs, they have more spendable resources for facing and reacting to law enforcement interventions. At the same time, the high visibility of efficient DTOs makes them more exposed to law enforcement interventions (i.e., many attempts at disruption from an early stage of their criminal involvement) with negative consequences for their persistence over time. In contrast, the hypothesis stated that secure DTOs are better able to protect their members and to stay hidden from law enforcement interventions, thus having superior persistence over time.

The positioning in the security vs. efficiency trade-off proved to have a significant impact on DTOs' ability to survive and react to law enforcement attempts at disruption. Confirming the hypothesis delineated in section 2.2, the results of the study demonstrated that efficient DTOs are the most resilient to single massive attempts at disruption (i.e., 9% and 36% of surviving secure and efficient DTOs in the first scenario, respectively). In contrast, secure DTOs are the most resistant; despite operating in a threatening environment, they are proficient in concealing their criminal activities from law enforcement and avoid being targeted for longer periods, thus maximizing their persistence over time (i.e., 26% and 21% of surviving secure and efficient DTOs in the third scenario, respectively).

In line with the hypothesis, efficient DTOs are more resilient than secure DTOs to single massive attempts at disruption, with significantly lower disruption rates (Table 19). Nevertheless, both secure and efficient DTOs remaining active after attempts at disruption need to at least partially modify their *modi operandi* in response to the long-term effects of disruptive events. Efficient DTOs strive to make their *modi operandi* even more effective, increasing the direct connectivity among their members and trying to reduce the losses caused by the law enforcement interventions (Graph 27 and Graph 39). Secure DTOs adopt more precautionary behaviors, at a minimum reducing direct contacts among members to avoid attracting additional law enforcement attention (Graph 27).

However, even though in absolute terms, efficient DTOs display lower disruption rates at the end of the simulated period, this result should be interpreted in light of the disruption rates of the same organizations in the baseline scenarios. The proportion of efficient DTOs remaining active diminished by -58%, while secure DTOs diminished by -30% (Graph 17 and Table 19). Therefore, the basis of secure DTOs with higher disruption rates is the initial weak condition that results in very limited flexibility when confronted with an attempt at disruption. Secure DTOs organize their activities to mitigate the risks of apprehension of their members; this means reducing contacts among members, having strict recruitment requirements, minimizing the quantities of drugs being stored, etc. (Graph 27, Graph 26, and Graph 37). These conditions impact the resources available to secure DTOs (Graph 39) and consequently leave secure DTOs and their members in a condition of fragility when confronted by unexpected attempts at disruption. Without substantial backup resources, secure DTOs can rely on a limited available recovery time, which leads to higher disruption rates. In contrast, efficient DTOs plan their criminal activities with a focus on straight processes and profitability (e.g., members are more connected to each other, recruitment is faster, and quantities of drugs in stock are more consistent) (Graph 27, Graph 26, and Graph 37). This leads to a greater amount of spare resources that can potentially be used in periods of crisis to sustain temporarily inefficient conditions (Graph 39). Nevertheless, the net impact (i.e., considering the disruption rate in the baseline scenario) on efficient DTOs of the attempt at disruption is greater than that on secure DTOs (Table 19). This may suggest that the strategies adopted by secure DTOs are actually more effective in terms of responses and reactions to the disruptive event. Nonetheless, the substantially better performance and resources saved before the attempt at disruption allow efficient DTOs to register lower disruption rates despite the probably fewer and less effective strategies adopted in response to law enforcement interventions.

The second and third law enforcement intervention scenarios, increasing the realism of the simulations, also considered the advantages of secure DTOs' *modus operandi*, that is, the ability to limit the risks of apprehension of their members. The second scenario linked the effectiveness of the law enforcement intervention in terms of the percentage of actors arrested to the DTO security/efficiency focus, with secure DTOs minimizing the arrests and efficient DTOs being more heavily affected. The third law enforcement intervention scenario also included the possibility of multiple attempts at disruption differently distributed over time, with secure DTOs being targeted less and later in time and efficient DTOs experiencing more attempts at disruption from an early stage of their criminal involvement.

In the second scenario, when considering the different levels of intensity of attempts at disruption for secure and efficient DTOs, secure DTOs display a reduction in the disruption rate (i.e., -10% compared to the first scenario), whereas efficient DTOs increase their disruption rate (i.e., +10%) (Table 19 and Table 20). This scenario reflects the enhanced capacity of secure DTOs to protract their drug trafficking and dealing unnoticed by law enforcement, thus minimizing the probability that their members will be targeted by investigations (Morselli, Giguère, and Petit 2007). Experiencing fewer arrests, secure DTOs suffer less damage from attempts at disruption, and as a consequence, more of them survive disruption. In contrast, members of efficient DTOs often disregard protective measures when conducting drug trafficking and dealing, with the consequence of being very visible to law enforcement (Morselli, Giguère, and Petit 2007). This results in more members being arrested and thus in higher disruption rates. The third law enforcement intervention scenario considered the possibility that DTOs may face multiple attempts at disruption over time. Efficient organizations are likely to be the subjects of such interventions more often and from the early stages of their involvement in criminal activities due to their unscrupulousness in conducting drug trafficking and dealing more openly, with few precautions to hide their business. Conversely, secure DTO members are extremely cautious in hiding their drug trafficking and dealing from law enforcement. This leads secure organizations to often experience fewer attempts at disruption, and these attempts at disruption very likely will not endanger their criminal involvement until after many years of activity (Table 22). This scenario results in secure DTOs outperforming efficient DTOs in terms of persistence over time: 26% of secure DTOs, being able to avoid disruption for a long time, maintain their criminal involvement until the end of the simulated period. In contrast, only 21% of efficient DTOs, due to early and repeated interventions, can survive disruption over the five simulated years (Graph 23).

Overall, the results for the third research question of the study suggested that efficient DTOs are more resilient since they are better equipped with the resources needed to sustain the negative impacts provoked by massive attempts at disruption. Differences in the effectiveness (i.e., second law enforcement intervention scenario) and frequency (i.e., third law enforcement intervention scenario) of law enforcement interventions for secure and efficient DTOs impacted this situation. In the second scenario, a larger number of secure DTOs survive disruption, but efficient DTOs still outperform secure ones. In the third scenario, the situation is reversed.

Secure DTOs outperform efficient ones, displaying higher rates of persistence over time (i.e., being more resistant).

The results for the first law enforcement intervention scenario (i.e., equal attempts at disruption targeting both secure and efficient DTOs) are aligned with the claims of the literature on resilience in different fields, which argues the advantages of efficient organizations in reacting to adverse circumstances (e.g., resourcefulness, rapidity, and reactivity) (Carpenter et al. 2001; Tierney 2003; Reghezza-Zitt et al. 2012). However, these results differ substantially from the most accepted criminological studies supporting the advantages of secure organizations in illegal contexts (B. H. Erickson 1981; Reuter 1983; 1985; Morselli, Giguère, and Petit 2007).

A plausible explanation may be partial differences in the points of observation. While the literature on resilience focuses specifically on the reactions and adaptation strategies of organizations confronting major adversity, the criminological literature has to date explored mostly circumstances that allow criminal organizations to perform their criminal activities over time without being targeted and disrupted by law enforcement interventions. Therefore, the criminological literature has addressed criminal organizations' abilities to persist over time, that is, their capacity to resist hostile environments and avoid law enforcement attempts at disruption.

The development of the second and third law enforcement intervention scenarios also enabled the testing of DTO persistence over time. In these scenarios, the model accounted on the one hand for the diversified effectiveness of interventions for secure and efficient DTOs due to different levels of members visibility; on the other hand, it considered that secure and efficient DTOs differ in their ability to avoid attempts at disruption, taking into account the different likelihood of their being targeted by law enforcement interventions. These assumptions are more in line with the criminological literature which argue the advantages of prioritizing security when operating in a hostile environment. Secure DTOs, by minimizing their visibility, protract their drug trafficking and dealing unnoticed for some years before being targeted by law enforcement interventions and, owing to the protection provided to their members, can reduce the impact of the intervention in terms of the number of arrests. In contrast, efficient DTOs disregard protective measures for their members; this attracts law enforcement attention, leading to repeated and heavy attempts at disruption. The consequence is that, despite the extraordinary abilities of efficient DTOs to face law enforcement interventions (i.e., due to their high resilience), most of them cannot cope with the effects of continuous targeting, which in the long run wear down their energies and resources to react to the attempts at disruption.

Conversely, secure DTOs are extremely weak in responding to law enforcement attempts at disruption (as demonstrated by the results of the first law enforcement intervention scenario); however, managing to avoid law enforcement targeting for long periods of time results in high persistence over time. This confirms that, when operating in illegal contexts, the renunciation of the ambition to expand criminal activities, being satisfied with lower profits, facilitates criminal activities over time, and higher rates of resistance in harsh conditions (Eck and Gersh 2000; Benson and Decker 2010; Calderoni 2018).

5.4. Expanding the knowledge of resilience and the security vs. efficiency trade-off

The primary aim of this study was to investigate DTOs' resistance and resilience to law enforcement interventions, examining how these organizations resist and react to attempts at disruption. In doing so, it advances the existing theoretical knowledge of one of the most debated criminological concepts: the security vs. efficiency trade-off (Morselli, Giguère, and Petit 2007).

This study is the first attempt to operationalize the security vs. efficiency trade-off, analyzing how it practically affects drug trafficking and dealing. As discussed in section 3.3.1, MADTOR relates the trade-off to the amount of drugs DTOs acquire and sell (Eilstrup-Sangiovanni and Jones 2008; Morselli 2010b; Bright, Hughes, and Chalmers 2012; Gravel and Tita 2017), DTOs' recruitment strategies (Giménez-Salinas Framis and Fernández Regadera 2017; Duxbury and Haynie 2019), members' retributions (Morselli and Petit 2007; Paoli, Greenfield, and Reuter 2009), and the likelihood and intensity of being targeted by law enforcement interventions (Morselli and Petit 2007; Paoli, Greenfield, and Reuter 2009). This allowed the disentanglement of dynamics that, to date, had mostly been only empirically sensed, with limited possibilities of solid testing.

Previous studies have often interpreted the security vs. efficiency trade-off in terms of criminal organizations' priorities at the group level (e.g., Morselli, Giguère, and Petit 2007; Morselli 2009a; Tenti and Morselli 2014; Gravel and Tita 2017; Duxbury and Haynie 2019; Lawler and Bright 2020). In contrast, this research reveals significant implications of the security vs. efficiency trade-off at the individual level, with direct impacts on individual DTOs members.

The results of this study demonstrate that, from an organizational point of view, efficient DTOs tend to rely on the greater resources generated from rewarding (and risky) attitudes assumed in the drug market. In turn, these resources result in a strategic advantage in periods of crisis. They can be employed during emergencies, when the supply of the usual commodities can be compromised and the reliance on existing assets could be insufficient to promptly overcome threats. Law enforcement interventions attempting to jeopardize DTOs and their criminal activities are precisely one of those situations to which efficient DTOs are better equipped to face and react. In contrast, secure DTOs, being less profit-oriented and favoring *modi operandi* reducing the risks experienced by their members, can count on more limited economic gains. This results in minimal, or no, backup resources to support the organization in the case of unexpected negative events. Thus, secure DTOs must confront more difficulties in rapidly responding to law enforcement attempts at disruption.

At the same time, the more precautionary *modus operandi* of secure DTOs allows minimization of their exposure to and the effectiveness of law enforcement interventions. Indeed, the less pronounced focus on profitability allows secure DTOs to ponder the best strategies of action and evaluate how to minimize the apprehension risk. This results in relevant advantages for secure DTO members in terms of personal protection. In contrast, efficient DTO members are encouraged to aspire to the maximization of DTO profits. However, this often implies having to disregard protective measures when conducting their criminal business and thus often being exposed to greater vulnerability and repeated law enforcement interventions over time, with a significantly higher risk of individual apprehension.

Consequently, efficient DTOs may be very resilient to single attempts at disruption, with extensive capacity to provide continuity for their criminal business; however, on the one hand, their audacity and unscrupulousness in drug trafficking and dealing is likely to lead to multiple law enforcement targeting over time, with the possibility of experiencing a shortage of resources to face and react to these attempts at disruption in the long run. On the other hand, the continuity of the criminal business is not directly related to the permanence of members. Efficient DTOs ability to survive disruption does not imply that individual members do not suffer negative consequences from intense law enforcement targeting. Thus, while efficiency may be beneficial in terms of resilience from the point of view of the organization, the drawbacks for DTO members may be unsustainable. They may be requested to operate in extremely precarious and insecure conditions, with no certainty of personal safety and limited future chances to enjoy the agreed-upon rewards for the risks assumed. Conversely, secure DTO members must be satisfied with lower rewards for their criminal involvement. At the same time, they are offered a more protected environment in terms of where to operate, and they can more confidently expect to protract their criminal activities over time, to maintain their freedom, and to appreciate the compensation for their criminal involvement for longer periods of time. This may compensate for the reduction in the expected profits.

For the reasons expressed above, from an individual point of view, DTO members may prefer operating in secure DTOs despite the lower expected profits. This may pose at least two challenges to efficient DTOs. On the one hand, they may encounter obstacles and difficulties in the recruitment of members (Spapens 2010; Duijn, Kashirin, and Sloot 2014). Indeed, it is possible that no, or only a few, prospective members will be available to tolerate such elevated risks. On the other hand, the expected *modus operandi* of efficient DTOs may be spoiled by the presence of personal interests. Efficient DTO members may in theory accept operating under the risky conditions envisaged by the organization; nevertheless, in practice, they may fail to follow the expected *modus operandi* in favor of protecting their individual interests by minimizing their vulnerability. In turn, these deviations from expected behaviors may lead efficient DTOs to obtain suboptimal results from the organizational point of view.

5.5. Limitations of the study and further research

In addition to the issues discussed in detail in the chapters, this study has several limitations. First, MADTOR provides a simplified representation of DTO drug trafficking and dealing. As discussed in section 3.3.1, ABM calls for a reduction of real-world complexity. This led to the choice to reduce DTOs' drug trafficking and dealing to a few sequential steps (i.e., drug acquisitions, drug processing and packaging, drug sales, and account of expenses.), disregarding other related activities, such as drug production and refining, or the involvement of DTOs in other criminal activities. These simplifications may have impacted the results, since overlooking some processes or DTO specificities may have affected the simulated DTO responses and strategies of reaction to law enforcement attempts at disruption. However, with respect to existing ABMs on the topic (e.g., Dray et al. 2008; Romano, Lomax, and Richmond 2009; Magliocca et al. 2019; 2022; Duxbury and Haynie 2019; 2020), MADTOR already provides an articulated and detailed representation of reality, with a foundation both in empirical evidence and in the literature. Further increasing the complexity of the model would have made the identification of significant patterns and their causes even more difficult. Future research may focus on single niches of the drug market, detailing more specific aspects that have been partially disregarded by this research (e.g., the resilience of organizations involved in drug production and manufacturing, the impact of other drug providers in the same environment, and the role of end-users in the drug market).

A second limitation is the type of drugs trafficked and sold by DTOs in MADTOR. Always following the ABM principle of keeping the model as simple as possible, MADTOR considers only cocaine trafficking and dealing. There are multiple reasons for this choice, as anticipated in section 3.3.1: the impossibility of aggregating DTOs *modi operandi*, the existence of diversified market dynamics, and the diversified availability of input data for different drugs. However, there is evidence of the existence of DTOs involved in the trafficking and dealing of drugs other than cocaine (e.g., Adler 1993; Natarajan 2006; Morselli 2009a) or of multiple drugs at the same time (e.g., Morselli 2009a; Gimenez-Salinas Framis 2011; Hughes et al. 2016; 2016; Hughes, Bright, and Chalmers 2017; Manzi 2019). The focus on cocaine may make it inadvisable to extend the results of this study to DTO trafficking and dealing with drugs other than cocaine or multiple drugs. Indeed, while some general trends may be recurrent and thus generalizable, others may be extremely different (e.g., channels of acquisition, processes of manufacturing, risks in performing the business, costs and revenues). Further MADTOR developments, or future research, may explore the resilience of DTOs trafficking other or multiple drugs.

A third limitation is the input data utilized to calibrate MADTOR. Data on detailed processes of drug trafficking and dealing, costs and prices in the drug market and DTO members' relational patterns are extremely scarce. The author relied mostly on the qualitative literature, and on qualitative and quantitative information retrieved from the Beluga court order, a judicial file reporting a large-scale investigation of an Italian Camorra group. Trusting data related to an investigation targeting a specific DTO to calibrate a model with the ambition of enlarging the knowledge of DTO resilience in general may present some difficulties. Section 3.2.3 thoroughly discusses the similarities between the Beluga group and other DTOs investigated by previous studies, and it shows the reliability and generalizability of the information reported in the Beluga court order. Nevertheless, this may have affected the results, thus reducing their external validity due to the overfitting of the model to the Beluga group. To overcome this potential weakness, future research may follow two complementary directions. On the one hand, it may expand the resources used as a basis for the calibration of the model, modifying, if necessary, the assumptions that prove to be incomplete or incorrect. On the other hand, it is desirable to validate the results of this study through additional case studies investigating how DTOs in different geographical contexts, dealing drugs other than cocaine, with different organizational structures, etc., face and react to law enforcement attempts at disruption. Nevertheless, the value of this study goes beyond its results. This is the first attempt to model DTOs' drug trafficking and dealing dynamics and reactions to law enforcement interventions.

In doing so, it is the first to methodically outline, assess, and operationalize several DTO features and behaviors (e.g., relational patterns, recruitment strategies, and positioning in the security vs. efficiency trade-off). Thus, the potential of the model lies in the possibility of future adapting and advancing it to accommodate DTOs that differ from the Beluga group in size, the distribution of members among tasks, earned revenues, sustained costs, etc.

A fourth limitation is the operationalization of the security vs. efficiency trade-off in MADTOR. The security vs. efficiency trade-off is a widely recognized and supported concept in the criminological literature (e.g., Morselli, Giguère, and Petit 2007; Morselli 2010a; Paoli, Greenfield, and Reuter 2009; Eilstrup-Sangiovanni and Jones 2008; Bright, Hughes, and Chalmers 2012; Gravel and Tita 2017; Giménez-Salinas Framis and Fernández Regadera 2017; Calderoni 2014b; 2018; Duxbury and Haynie 2019; Berlusconi 2021). However, almost no studies have tried to operationalize it by methodically assessing how it affects the *modi operandi* of criminal organizations in general and of DTOs specifically. Section 3.3.1 details all the aspects of the model influenced by this trade-off; nonetheless, some issues and challenges may arise from its operationalization. First, MADTOR may overlook the influence of the trade-off on some aspects of DTOs' *modi operandi* (e.g., workload sustained by DTO members and wholesale prices of drug acquisitions) or it may tie other aspects of DTOs *modi operandi* to the trade-off (e.g., wholesale quantities of drugs acquired or the size of drug packages) even though they are not connected. Certainly, this could bias some of the obtained results. Second, this study is the first attempt to directly link DTOs' performance in drug trafficking and dealing with the security vs. efficiency trade-off. For this reason, there is no possibility of corroborating the reliability of the parametrization of the elements influenced by the trade-off for secure and efficient DTOs. It may be that the thresholds set to modulate the different aspects of DTOs' *modi operandi* have a low level of accuracy and coherence with those of real organizations. To minimize this risk, the author operationalized the security/efficiency trade-off as an indicator on a continuum of values, augmenting the confidence in capturing dynamics similar to reality. Third, MADTOR operationalizes the security vs. efficiency trade-off mostly by considering its implications for DTOs on the whole, disregarding its implications for DTO members. Further research could address the issues expressed above. On the one hand, additional case studies may be relevant to better understanding all the aspects of DTOs' *modi operandi* impacted by the security vs. efficiency trade-off, allowing for specifications of MADTOR. On the other hand, MADTOR could be further refined, including DTOs' individual decision-making processes. Both implementations, without overlooking the need to keep the model as simple as possible, would allow a better representation of DTOs' drug trafficking and dealing and their reactions to law enforcement attempts at disruption.

The last limitation is the choice of resilience indicators employed to assess DTOs' resistance and resilience. MADTOR allowed the storage of a wide array of resilience indicators previously identified by the literature (see "The compute-statistics procedure" section in Annex II) (e.g., Bright et al. 2017; Wood 2017; Castiello, Mosca, and Villani 2017; Duxbury and Haynie 2019). After a preliminary examination of all the indicators, the author selected a battery of only six indicators for the final analyses. The motivations behind this selection were many: the need to have indicators vastly supported by the literature, to rely on indicators focused on the three dimensions of the definition of criminal network resilience, and to limit the number of indicators in favor of unambiguous results. The reliance on this set of indicators may have affected the results of this study. Indeed, exploring different or additional indicators may have resulted in at least partially different findings, which may be further investigated by future research.

Conclusions

The study of the resilience of criminal networks has only recently attracted the attention of criminologists. The negative societal and economic impacts attributed to criminal organizations and their illegal activities have encouraged scholars to explore the *modi operandi*, structures, strategies, strengths, and weaknesses of these organizations. In turn, this better picture has led to the ambition to identify strategic points of intervention to inform law enforcement investigations aiming at jeopardizing criminal organizations and their criminal businesses.

Nonetheless, to date, the criminological literature has often mixed theoretical ambitions with the desire to enhance the planning of effective investigation techniques. Most studies have suggested as a disruption strategy the targeting of actors with very specific features (e.g., those with the highest number of contacts with other members, playing brokerage roles in the organization, owning significant social or human capital, or possessing key resources for the group) who are extremely difficult, or impossible, for law enforcement to identify. In addition, many previous studies have disregarded criminal organizations' flexibility and dynamism, with the consequence of ignoring the adaptation strategies that they implement in response to law enforcement interventions.

This study advances the literature in several directions. First, it offers a precise and comprehensive definition of criminal network resilience. After an examination of resilience definitions in a variety of domains, it selected the most appropriate features providing information about groups' resilience abilities. Three aspects were identified as the most relevant: the ability to endure disruption, react quickly and efficiently to threats, and maintain primary functions unaltered. The possibility of relying on a universally accepted definition allows a starting point for progress in this still underinvestigated field of research to be identified. Second, it provides realistic expectations of DTOs' reaction strategies to plausible law enforcement interventions. Based on the Beluga court order's detailed empirical information on DTO structure and criminal activities, it developed an empirically calibrated ABM simulating the daily routine of DTO drug trafficking and dealing being endangered by different types of attempts at disruption that can potentially be implemented by law enforcement (i.e., planned based on information available from the preliminary stages of police investigations). The results of the study allowed the proposal of strategies of intervention in relation to the optimal number of DTO members and the most vulnerable stages and actors in the drug market, revealing the best balance between the resources employed by law enforcement and the expected impact of the intervention. Law enforcement attempts at disruption, even when arresting few members or when targeting grassroots members, always pose considerable challenges to the survival of DTOs. Therefore, this study has significant operational implications since it provides evidence that it is not always necessary to allocate and expend extremely large resources in investigations against criminal organizations. Indeed, even more limited resources, if they support well-planned investigations, can result in great damage to DTOs' drug trafficking and dealing. Third, this study advances the theoretical knowledge in relation to the security vs. efficiency trade-off. It is the first attempt to operationalize the security vs. efficiency trade-off by analyzing how it practically affects the performance of drug trafficking and dealing and DTOs' reactions to law enforcement attempts at disruption.

This study aimed to improve the knowledge of an underresearched topic. It did so by developing the first agent-based model specifically addressing the resistance and resilience of drug trafficking organizations to law enforcement attempts at disruption. Simulation models, if built on reliable and accurate assumptions, have the merit of providing valuable insights when real data cannot be directly accessed. The model allowed the investigation of the effectiveness of a variety of disruption strategies, providing evidence of DTOs' levels of survival and response tactics. Despite the value of this study, there is still room for advancements. Further research should rely on additional literature and case studies to validate both the assumptions and the findings obtained from the model. In addition, this model could become the basis for a plethora of future specifications that can add or improve a variety of model aspects, such as DTO structures and *modi operandi*, types of drugs trafficked and sold, and prices and costs in specific geographical areas. Each of these specifications would enrich the available knowledge of DTO resistance and resilience, advancing the literature and providing valuable material for planning informed future law enforcement interventions.

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Annex I
The NetLogo software

The ABM developed for this research was implemented in NetLogo (Wilensky 1999). NetLogo is a programmable modelling environment developed in 1999 by Uri Wilensky at the Center for Connected Learning and Computer-Based Modeling within the Northwestern University. Since its release, it has been continuously updated, with the latest available version at the time of conducting the present research being the 6.2.0, issued in September 2019 (Wilensky 2021).

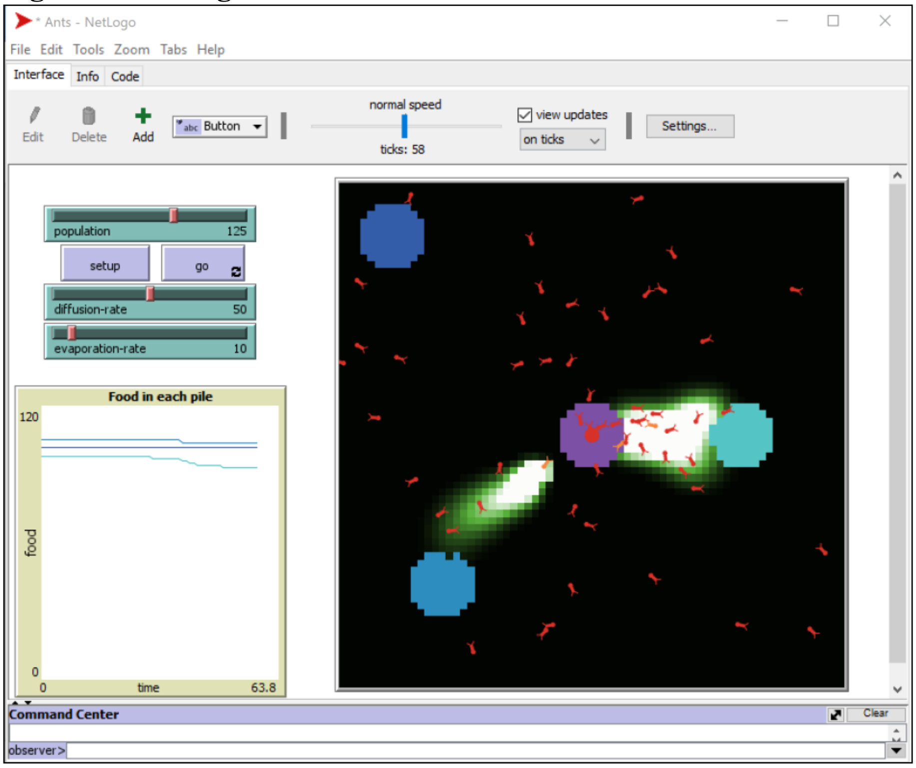
NetLogo allows modelers to give instructions up to thousands agents that, operating independently, enables the possibility of developing complex systems with evolving dynamics over time (Wilensky 2021). NetLogo is an open-source software, and it is downloadable and usable free of charge by any user. It is the latest of a series of software developed for running agent-based simulations, such as StarLogo and StarLogoT. It is written in Java, allowing the reproducibility on all major platforms (i.e., Microsoft Windows, Mac OS X, and Linux), and it has its own desktop application (Tisue and Wilensky 2004; Sklar 2007; Wilensky 2021). In contrast with other ABM tools (e.g., Swarm, RePast, AgentSheets, etc.), NetLogo is relatively simple to use and accessible to developers without an extensive programming background. The computer language used to programme agents is a variant of the Seymour Papert's LOGO, thus making NetLogo particularly suited for non-programmer users (Sklar 2007). In addition, the availability of extensive information, documentation, and sample models, freely accessible, makes NetLogo extremely approachable and user-friendly to beginners. Despite being relatively simple and intuitive to use, NetLogo offers to its users a complete and advanced simulation environment, being a tool particularly suitable for researchers operating in a wide array of fields (Tisue and Wilensky 2004; Sklar 2007; Wilensky 2021).

The graphical interface of NetLogo includes three tabs: the "Interface", the "Info", and the "Code" (Sklar 2007). The "Interface" is the tab where the programmer builds and edits the visual and graphical elements of the model (Figure 3). In this tab, the programmer has the possibility of adding buttons, sliders, choosers, or switches to initialize the model, and setting some variables to specific values. In the "Interface" the programmer can also see the model while running and eventually monitor some preliminary statistics thanks to monitors and/or plots. The "world" is initially set by default as a black square of 35x35 units (easily modifiable by the modeler), called "patches", where the agents, called "turtles", can move and perform their actions (Tisue and Wilensky 2004; Sklar 2007; Wilensky 2021).

The "Info" tab is dedicated to model documentation (Figure 4). Here the author can provide a series of information about its model. By default, the sections present in the "Info" tab are the following: *What is it?*, *How it works*, *How to use it*, *Things to notice*, *Things to try*, *Extending the model*, *NetLogo features*, *Related models*, and *Credits and References*. The modeler has anyways the possibility of adding or removing sections, providing the most suitable information for the specific model (Wilensky 2021; Sklar 2007).

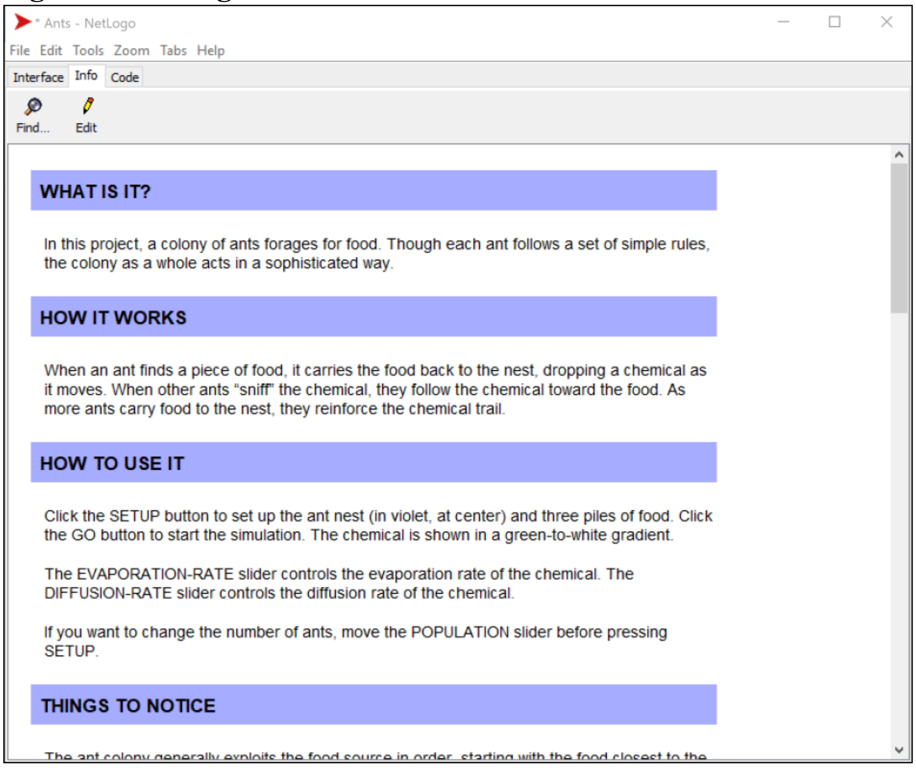
Finally, the "Code" tab stores the code of the model (Figure 5). In this tab, the modeler sets the rules governing the simulated world and instructs the agents on how to behave. The "Code" tab must include at least two procedures, but it usually contains several ones. The first indispensable procedure is the "setup procedure" that sets the initial features of the world, and it initializes some variables. The second indispensable procedure is the "go procedure" that is the piece of code where the modeler explicates the actions to be performed by the agents during the simulation. In extremely simple models, these can be stand-alone procedures; however in most models, where some degrees of complexity exist, the setup and the go procedures call several other procedures that details specific processes to be performed by the model (Wilensky 2021; Sklar 2007).

Figure 3. NetLogo Interface tab



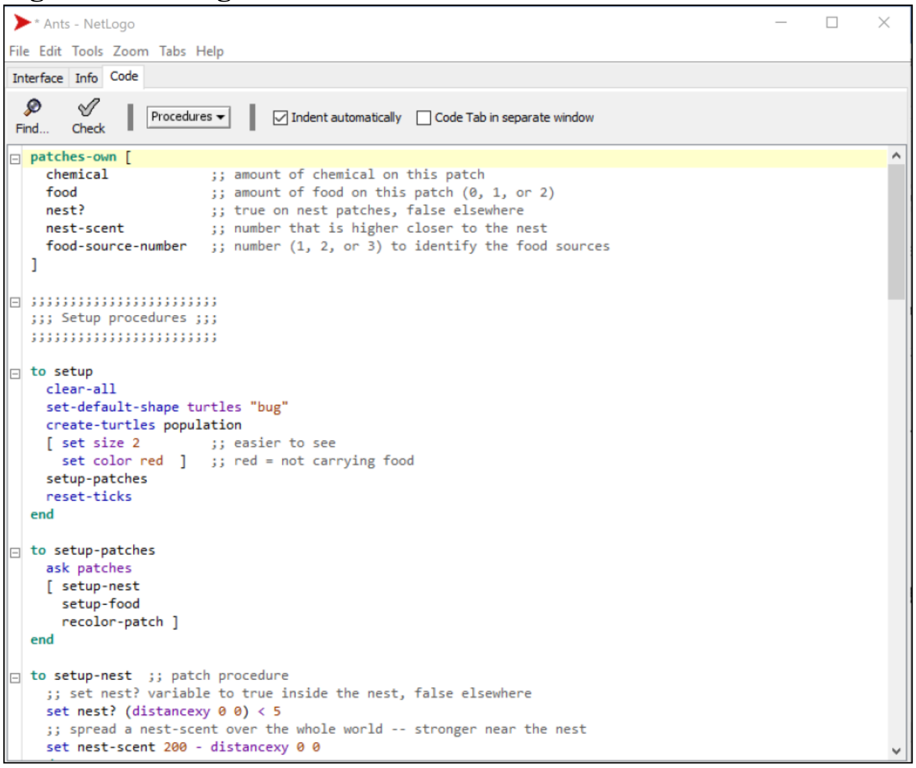
Source: Ants model, available in NetLogo Model Library (Wilensky 1999)

Figure 4. NetLogo Information tab



Source: Ants model, available in NetLogo Model Library (Wilensky 1999)

Figure 5. NetLogo Code tab



Source: Ants model, available in NetLogo Model Library (Wilensky 1999)

This section has provided an overview of NetLogo to give the reader the general understanding of the software and of the functioning of the ABM developed for this research. However, one of the advantages of NetLogo is the availability of extensive documentation about the software itself and its usage. Complete and accurate information can be found in the NetLogo User Manual (Wilensky 2021), and in additional publications, among the others those by Wilensky and Rand (2015), Tisue and Wilensky (2004), and Sklar (2007).

Annex II

MADTOR and its procedures

Figure 6 displays the NetLogo “Interface” tab of MADTOR after running the *setup* procedure. The top-left part of the interface includes two buttons, the “setup” button that performs the related *setup* procedure, and the “go” button that starts the simulation. Below the “setup” and “go” buttons there are a switch and some choosers that allow to personalize some settings before running the simulations.

The “AtomaticicRun” switch is a service command that enables and disables the display of an array of messages and summary statistics during the running of the model. The switch is set to off when the simulations are run manually. Conversely, the switch is set to on when the simulations are run automatically through an experiment, allowing computational time saving.

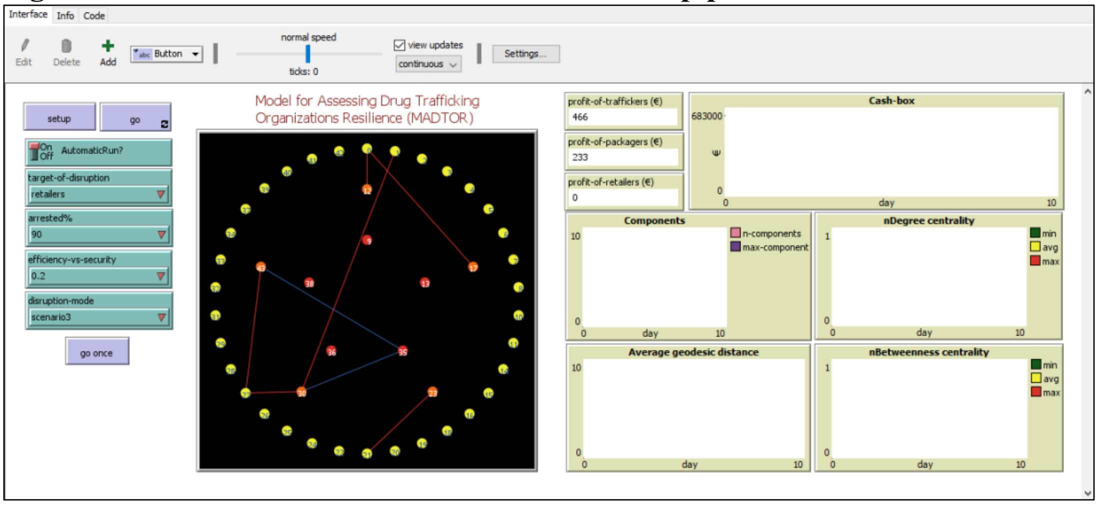
The choosers are related to the disruptive events the DTO will have to face and to its positioning in the security vs. efficiency trade-off. With respect to the attempt at disruption, it is possible to select the target of the intervention (i.e., all members, traffickers, packages, retailers) but also the proportion of members to be arrested. In addition, the “disruption-mode” chooser allows to select which law enforcement intervention scenario is going to be tested (see 3.3.2, and section below “The periodically-arrests and attempt-at-disruption procedure”).

Lastly, the “efficiency-vs-security” chooser allows to test how the performance of DTOs with a different focus in the security vs. efficiency trade-off is affected by law enforcement interventions; the chooser ranges from 0 to 1, with 0 standing for a DTO prioritizing security at the maximum and disregarding instead the efficiency side of the trade-off, and 1 standing for a DTO not being concerned about the security of its activities and favoring its efficiency at the maximum.

The central part of the interface displays the environment and the agents present in the world, allowing to watch the model while running. In the present model, the dots represent the agents (i.e., DTO members), and the lines stands for the working connections among them.

Finally, the right side of the interface presents some preliminary statistics accounting for DTO performances while the model is still running. There are three monitors and five plots. The monitors display the wages earned by DTO members (distinguishing among traffickers, packagers, and retailers) in the current tick of the simulation. The plots report the money the organization has in its cash-box (i.e., Cash-box plot) and the trends of a number of SNA statistics, particularly: the number of components in the network and the size of the largest component (i.e., Components plot); the minimum, maximum and average normalized degree centrality of DTO members (i.e., nDegree centrality plot); the minimum, maximum and average normalized betweenness centrality of DTO members (i.e., nBetweenness centrality plot); and their average geodesic distance (i.e., Average geodesic distance plot).

Figure 6. MADTOR "Interface" tab after the setup procedure



Source: Author's MADTOR model

The sections below present and explain in detail the pieces of code developed (i.e., model procedures) to run MADTOR. Each procedure is functional for a specific purpose, from the initialization and setting some variables, to the simulation of some activities performed by DTOs members, or the reporting of some statistics related to DTO performances.

The setup and update-parameters procedures

The *setup* and the *update parameters* procedures are sections of the code initializing most of the variables in the model. The *setup* is the first procedure of the model, it defines the features of the simulated world and its agents. The *update-parameters* procedure is performed every 30 ticks of simulation (i.e., once a month) to modify the values of some variables according to changing circumstances of the environment. In tracing the variable trends over time, the author relied on some functional forms. The choice of specific functions for different variables relates to their capability of best fitting the empirical data of the Beluga court order.[39]

Members of the drug trafficking organization

Three types of agents exist in the model and they are differentiated by the tasks they accomplish in the DTO. Traffickers oversee drug acquisitions, packagers are involved in the processing and packaging of drugs, and retailers are the DTO members selling the drugs to end users.

The agents present in the model at tick 0 and their tasks mirror the Beluga group at the initial stage of the investigation. The author entirely read and coded relational information about communications among members reported in the Beluga court order.[40] The whole investigation and related relational data were split in four timeslots (from T1 to T4, corresponding to years from 2008 to 2012), including approximately one year of investigation each.[41] In addition, the

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[39] The author chose the most appropriate functional forms during the model calibration process. Since there was neither information in existing literature, nor specific mathematical assumptions providing guidance on the choice of the equations, after the examination of several functional forms, the ones that best fitted the empirical data were employed.

[40] The analysis of the Beluga court order allows to obtain information on 189 individuals heavily involved in the Di Lauro clan criminal activities and on 516 communications among them (i.e., personal meetings and phone conversations).

[41] The analysis of the Beluga court order allows to gather information from October 2003 to April 2013; the whole timespan was divided into six timeslots. The rationale behind the construction of the timeslots was that of having periods of time sufficiently long to include a substantial number of communications allowing to presume robust

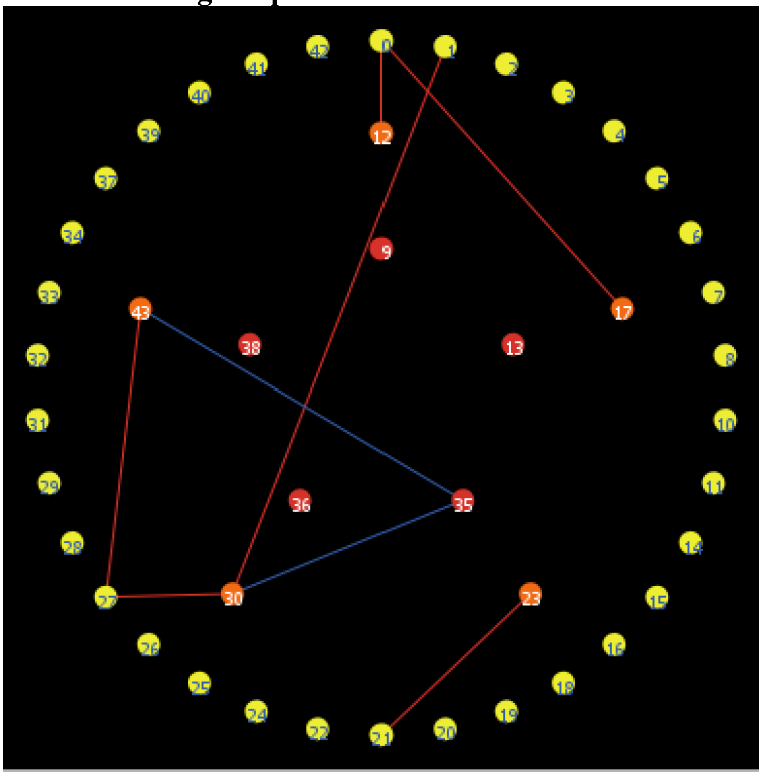
author performed a task analysis, assigning to each member a specific task according to its contribution to the criminal activities of the DTO.[42] The agents imported in the model are those active in the drug trafficking and dealing activities of the group and being present in the T1 timeslot. DTO members that were present in T1 but that were not assigned with a task in the drug trafficking and dealing were not imported in the model. This resulted in a DTO initially comprising 5 traffickers (red dots in Figure 7), 5 packagers (orange dots in Figure 7) and 34 retailers (yellow dots in Figure 7).

The original relational data was imported to account for existing links among DTO members. Considering the purpose of the model, only the ties functional to the performance of drug trafficking and dealing were maintained (i.e., links between traffickers and packagers, and links between packagers and retailers), disregarding instead ties among actors accomplishing the same tasks that reflected family or friendship relations unrelated to the performance of drug trafficking and dealing. This resulted in 8 links, 2 between traffickers and packagers (blue lines in Figure 7) and 5 between packagers and retailers (red lines in Figure 7).

dynamics (i.e., not driven by chance). At the same time, having a reasonable number of timeslots was also essential to investigate possible modifications over time. Two out of the six timeslots, the initial and the final one, were excluded from the analyses; the cut-off results to be necessary because information included in those timeslots was not comparable to that in the remaining timeslots (i.e., T1-T4). The initial timeslot covered a larger period of time compared to the others and it includes only few extracts from previous investigations on the same Camorra clan and some depositions of collaborators with justice. These contents were excluded because they do not refer to Operation Beluga, and they did not reflect the complete structure and features of the Di Lauro clan in the period of interest. The final timeslot covered a similar period of time to T1-T4, nonetheless the included events and the involved actors were definitely less than in the other timeslots, probably signaling that the major investigative activities had already ended, and law enforcement was mainly concluding its activities; thus, it was excluded from the analyses either.

[42] To obtain information on the main task of each individual in activities of the organization, the 189 actors were classified based on information from the court order and on previous studies (Natarajan 2000; 2006; Calderoni 2012; Bright, Hughes, and Chalmers 2012). The main tasks identified by the analysis of the literature were adapted to accommodate the specificities of the examined network. The tasks were selected relying on a top-down approach; the author, relying on the literature and on general information provided by the court order, established a set of task categories for each of the activities in which the clan was involved. As a second step, to assign tasks to each individual the author with the help of a colleague read all the extracts of the court order providing detailed information about activities carried out and expected mansions of each individual. Few actors were assigned with discordant tasks by the coders; in these cases, they examined and discussed together evidence provided by the court order to establish a single task unanimously. Since the Beluga group includes individuals involved in the organizational management of the clan, drug trafficking and dealing, illicit arms trade, and illegal gambling activities, and due to the existence of overlapping tasks performed by the members of the organizations, each actor was assigned with a task for all the four activities (with those actors not being involved in a specific activity being assigned as N/A). For this study, only information on the drug trafficking and dealing was considered.

Figure 7. DTO at the initial stage imported in the model



Source: Author's MADTOR model

The *update-parameters* procedure updates the actors present in the organization according to the evolution of the DTO reported by the Beluga court order. Specifically, the traffickers of the organization in 2008 were 5, becoming 13 in 2009, and 16 in 2010. The packagers present in 2008 were 5, becoming 13 in 2009, and not registering an increase nor a decrease in 2010. The retailers of the organization were 34 in 2008, 33 in 2009, and 37 in 2010.

These trends were traced thanks to the following logarithmic function computed for each category of actors (i.e., traffickers, packagers, and retailers):

$$Y = Y_{2008} + \log_{(Y2010 - Y2008)+1} (1 + x_{tick} * (Y_{2010} - Y_{2008}) / x_{tick2010}) * (Y_{2010} - Y_{2008})$$

In the function the x variable is the tick of simulation and $x_{tick2010}$ is the tick 730 of the simulation, corresponding to the end of the second year of simulation, namely the end of 2010. The Y variable is the number of actors present in the organization in a specific tick and the Y_{2010} and Y_{2008} variables are the number of actors present in the organization in 2008 and 2010, respectively. Even though the functions rely on data from 2008 to 2010, they are used also to compute and update the number of DTO members for ticks of simulation corresponding to years after 2010.

After attempts at disruption, the following inverse exponential function is used:

$$x_{tick} = [(Y_{2010} - Y_{2008}) + 1]^{\{[(Y - Y2008) / (Y2010 - Y2008) - 1] * xtick2010 / (Y2010 - Y2008)\}}$$

It identifies the correspondent x_{tick} when considering the number of actors present in the simulation. Since the number of actors can also go below the 2008 thresholds, the x_{tick} can be negative. The computed x_{tick} is stored in a specific variable for each category of actors (i.e., *ticks-traffickers*, *ticks-packagers*, *ticks-retailers*) and it governs the trends of DTOs members.

After the identification of the optimal number of actors that should be present in a specific tick thanks to the logarithmic and exponential functions, some checks are made to determine the eventual recruitment of new actors. Firstly, only one actor at the time accomplishing the same task can be recruited; this means that every run of the *update-parameters* procedure no more than one trafficker, one packager and one retailer can enter the organization. Secondly, a new actor is recruited only when the DTO has resources enough to afford the payment of its wage; if the recruitment of a new actor would result in lowering the profits of current members below their minimum threshold, the actor is not allowed to enter the organization. Thirdly, a randomized factor is introduced to consider possible challenges in the recruitment of criminal actors. This randomized factor operates in two directions: on the one hand, it makes more or less difficult for the DTO to recruit actors in charge of different tasks; on the other hand, it relates the recruitment of new actors to the DTO security/efficiency focus.

In relation to the first aspect, there is evidence attesting that the recruitment of actors in charge of operational tasks is easier than the recruitment of managerial figures. Protracting operational tasks is far less sensitive for the organization; the actors involved in these tasks can be relatively unskilled, and they only need to be aware of minimal aspects of the activities performed; this missing the whole figure of the criminal business reduces the risk of betrayals. Conversely, actors involved in the trafficking stages need specific skills to perform their task and they need to be aware of very sensitive issues for the DTO. For these reasons, they need to be fully trusted by the organization (Spapens 2010; Johnson and Natarajan 1995; Desroches 2007; Calderoni 2012). Therefore, in the model the recruitment of traffickers is the most difficult, that of retailer is the easiest, and the recruitment of packagers has an intermediate level of difficulty.

In relation to the second aspect, the randomized factor also makes the recruitment of new actors more difficult for organizations prioritizing the security of their activities, and it makes it easier for organizations prioritizing the efficiency of their activities. This is because organizations prioritizing security are stricter in relation to the requirements in terms of trust and skills of their members and this leads to the decision of waiting for the most appropriate person before recruiting a new member. Conversely, organizations prioritizing efficiency are laxer in relation to the requirements to be satisfied by newly recruited actors. This allows to be always ready to accommodate, in terms of workload, the existent demand for their activities (Giménez-Salinas Framis and Fernández Regadera 2017; Bright, Hughes, and Chalmers 2012; Eilstrup-Sangiovanni and Jones 2008).

Once members are recruited, according to their task, they are assigned with a link with a DTO member. Newly recruited traffickers are assigned with a link to a random packager, newly recruited packagers are assigned alternatively with a link to a random trafficker or retailer, and newly recruited retailers are assigned with a link to a random packager.[43]

Drug quantities parameters

The *unit-dose* variable is the amount of drug doses the DTO sells in one day. The Beluga court order reports information about maximum, minimum and average daily doses and this informs the model. The organization sold 1,498 doses on 16 June 2010, an average of 2,340 doses per

[43] Due to the necessity of keeping the model feasible, MADTOR simulates recruitment processes in a simplified manner. In the model there is not a pool of prospective members with their own characteristics; instead, when the conditions for a recruitment are met, the new actor is introduced in the model and he/she is assigned with specific features. Despite this simplification, the model still captures the main aspects of real recruitment processes. The newly recruited actor is assigned with a contact with an actor already active in the DTO. This contact represents the relational channel enabling the recruitment (Gambetta 2009; Granovetter 1985). In addition, patterns of interaction (i.e., working relations) in the organization consider also prior contacts among members. According to DTOs security/efficiency focuses, members select their criminal partners favouring already known and trusted members if they are most interested in their protection (Gambetta 2009; Granovetter 1985); in contrast, members aiming at maximizing their profits, favor criminal partnership with members that may be less trusted but that have excellent criminal abilities (Weerman 2003; Clarke and Cornish 1985).

day in the weekend of 11-13 June 2010, and an average of 1,370 doses per day in May 2010. In the model for the year 2010, 1,500 is set as the reference average value of doses sold, 1,370 is set as the minimum value of doses sold, and 2,340 is set as the maximum value of doses sold.

The average, minimum and maximum number of doses in 2008 is reparametrized starting from the 2010 values and considering the workforce the organization could rely on in 2008. The ratio between the number of packagers in 2008 and in 2010 is used as a reference value for the DTO workforce. This results in an average of 580, a minimum of 530 and a maximum of 900 doses sold. Following the same logic used to compute the trends of the actors present in the organization, three logarithmic functions simulate the trends of the doses sold by the DTO over time. In the function below the x variable is the tick of simulation and $x_{tick2010}$ corresponds to the tick ending the second year of simulation. The Y variable is the average, minimum and maximum number of doses in a specific tick, respectively and the Y_{2008} and Y_{2010} variables stand for the average, minimum and maximum doses in 2008 and 2010. The functions also compute and update the number of doses the DTO sold for ticks corresponding to years after 2010.

$$Y = Y_{2008} + log_{(Y2010 - Y2008)+1} (1 + x_{tick} * (Y_{2010} - Y_{2008}) / x_{tick2010}) * (Y_{2010} - Y_{2008})$$

To account for uncertainties in the drug market and for the variability in the daily demand of drug by end users, the variable *unit-dose-now* is computed. This variable randomly ranges between the minimum and the maximum number of doses computed by the logarithmic functions and it corresponds to the actual number of doses the DTO sells each day.

Each dose includes 0.25 grams of cocaine (*gram-per-dose* variable). This amount of drugs is computed as the ratio between the UNODC cocaine wholesale price per gram in Italy in 2010,[44] and the retail price reported by the Beluga court order. The *drug-package-of-retailers* variable accounts for the quantity of drugs included in the packages of drug delivered to retailers and, following the Beluga court order, it includes 23 doses (i.e., 5.75 grams). The *drug-package-of-packagers* and the *drug-package-of-traffickers* variables account for the drugs included in packages processed by packagers and traffickers, respectively. They are computed as the ratio between the average number of doses daily sold and the number of packagers and traffickers in the DTO. These amounts are then adjusted according to the DTO security/efficiency focus. Efficient organizations process larger drug packages, allowing for easier flows of drugs in the case of higher demand, but also producing greater losses in the case of attempts at disruption. Conversely, secure organizations process smaller drug packages, preventing huge losses in the case of attempts at disruption but also precluding the possibility of accommodating unexpected higher demand of drug.

Costs of drug trafficking and dealing

The *cost-per-day* variable accounts for the average daily costs the DTO incurs for drug trafficking and dealing activities. It is computed according to information reported by the Beluga court order. In May 2010 the costs of the DTO are reported to be 68% of its revenues (i.e., Revenues: 2,685,475.00€; Costs: 1,814,680.00€). The daily costs are then elaborated considering the revenues from cocaine sales registered on 16 June 2012 (i.e., 39,800€). This results in daily costs of 26,900.00€ in 2010. Following the same logic adopted for the computation of the doses in 2008, the costs of the DTO in 2008 are a reparameterization of the 2010 values according to the DTO workforce in 2008. This results in 10,300.00€ of costs each day in 2008. A logarithmic function simulates the trends of the DTOs daily costs over time. In the function, the x variable is the tick of simulation and $x_{tick2010}$ is the tick 730 of the simulation. The Y variable is the daily costs in a specific tick and the Y_{2010} and Y_{2008} variables are the daily

[44] In 2010, in Italy 1 gram of cocaine had a wholesale price of 43.90€ (UNODC 2010).

costs in 2008 and 2010. The function also computes and updates DTO daily costs for ticks after 2010. These costs are updated once every 30 ticks in the *update-parameters* procedure.

$$Y = Y_{2008} + \log_{(Y2010 - Y2008)+1} (1 + x_{tick} * (Y_{2010} - Y_{2008}) / x_{tick2010}) * (Y_{2010} - Y_{2008})$$

The daily costs are used to compute the *start-up-money* variable. This variable informs about the amount of money the DTO has at the beginning of the simulation and it is set to the amount of money covering two months of the 2008 daily costs. Differently, the *cash-box* variable accounts for the money available to the DTO. At the beginning of the simulation, it corresponds to the *start-up-money* variable; it is then augmented and/or decreased according to the costs and revenues of drug trafficking and dealing.

The *weekly-profit* variable is complementary to the *cost-per-day* variable; it accounts for the total profits the DTO earns from drug trafficking and dealing. It is computed according to the trends reported by the Beluga court order, with the monthly profits of the DTO in May 2010 being 32% of its revenues (i.e., Revenues: 2,685,475.00€; Profits: 870,795.00€). The daily profits are elaborated from the cocaine revenues on 16 June 2010. This results in a daily profit of 12,900€, that means a weekly profit of 90,300€ in 2010. As for the computation of the *unit-doses* and the *cost-per-day*, the 2008 DTO *weekly-profit* is a reparameterization of the 2010 values relying on the proxy for the workload the organization could sustain at that time and it results in 35,000.00€. Even for the weekly profits, a logarithmic function simulates the trends of the variable over time. The x is the current tick and $x_{tick2010}$ is the tick 730. The Y variable is the *weekly-profit* in the current tick and the Y_{2010} and Y_{2008} variables are the *weekly-profit* in 2008 and 2010. The function is used also in computing profits related to years after 2010. The initial profits are updated in the *update-parameters* procedure.

$$Y = Y_{2008} + \log_{(Y2010 - Y2008)+1} (1 + x_{tick} * (Y_{2010} - Y_{2008}) / x_{tick2010}) * (Y_{2010} - Y_{2008})$$

The ratio between the UNODC wholesale and retail prices for cocaine in Italy allows calculation of the *supply-costs* variable. It estimates the proportion of the DTO daily costs devoted to drug acquisition. Considering UNODC wholesale and retail prices from 2008 to 2010 (UNODC 2008; 2009; 2010), this percentage ranges from 57.22% to 58.25% of the daily costs. The supply costs are updated in the *update-parameters* procedure according to the year being simulated. Since this variable is computed from static values (i.e., UNODC prices), for ticks going beyond 2010, the computation always relies on 2010 UNODC prices. This does not affect the results of the simulation overall because UNODC prices for years after 2010 do not differ much from those of the previous years. The *supply-costs* variable is used only to manage marginal aspect of the model.

The wages of the packagers and traffickers are a consistent expense for the DTO. The *profit-of-traffickers* and the *profit-of-packagers* variables account for these expenses for a single day. The overall profits of traffickers and packagers are the proportion of the daily costs that is not covered by the supply costs. It has been arbitrary decided that 70% of this amount accounts for the profits of traffickers, while the remaining 30% accounts for the profits of packagers (*traffickers-share-of-profits* variable).[45] These profits are then split among the traffickers and packagers in the DTO. To avoid too high or too low wages, and considering the expected profits between 2008 and 2010, maximum and minimum thresholds are established. These thresholds also consider the DTO security/efficiency focus; members of efficient DTOs, when compared

[45] The arbitrary choice of traffickers and packagers share of profits gives a sense of what could be a reasonable wage for these DTO actors but it has not an empirical nor theoretical basis. However, this does not affect the predictive power of the model since these variables are only used in their aggregate format to account for the total DTO expenses. In this format the profit of traffickers and packagers are computed thanks to the *cost-per-day* and *supply-costs* variables, that have instead a strong empirical basis.

to members of secure DTOs, have the possibility of receiving higher wages as a reward for the greater risk assumed.

In contrast, retailers are daily paid as a percentage of the revenues from what they sell. According to the Beluga court order, retailers earn 18% of the price of each dose (i.e., *retailers-share-of-profits* variable). Thus, the *profit-of-retailers* variable is computed as 18% of the number of doses sold in a day at the retail price and it is then divided by the number of DTO retailers.[46] Following the Beluga court order, retailers cannot earn more than 500€ per day (i.e., *profit-of-retailers-max* variable). Differently from traffickers and packagers, they do not have a minimum daily profit.

Stocks of drug

The *target-stock-drug* variable reports the desired quantity of drug the DTO wants to have in stock. It corresponds to the amount of drug covering the doses sold by the organization in two months, coherently with the *start-up-months* setting.

The *stock-drug* variable informs about the amount of drugs available to the DTO in a specific tick. At the beginning of the simulation, it corresponds to the *target-stock-drug* variable; it is then augmented and/or decreased according to the acquisitions and sales performed by the DTO. The *stock-drug-traffickers*, *stock-drug-packagers* and *stock-drug-retailers* variables account for the amount of drugs stored by the different categories of actors. These variables monitor the flows of drugs within the organization. Their sum is equal to the *stock-drug* variable.

The *drug-max-of-packagers* and *drug-max-of-retailers* variables define the maximum quantity of drugs single members can store and process in a day. The *drug-max-of-packagers* variable is arbitrarily set to 500 grams and it is an estimate of the maximum workload a single packager can sustain in a day. The *drug-max-of-retailers* variable is set as the quantity of drug that would allow a single retailer to reach 500€ of daily profits (i.e., *profit-of-retailers-max* variable).

Drug prices

DTO traffickers acquire the drugs according to UNODC wholesale prices (UNODC 2008; 2009; 2010). The *wholesale-price* variable is initially set at the 2008 value (i.e., 40.20€/kg); in the *update-parameters* procedures, at tick 365 it is updated at the 2009 value (i.e., 40.68€/kg), and at tick 730 it is updated at the 2010 value (i.e., 43.90€/kg). For ticks beyond 730, the model continues to use 2010 prices. This does not affect the results of the simulation because the fluctuation of UNODC prices over years is limited and because the *wholesale-price* variable is used after introducing a randomized factor accounting for price variability.

The UNODC retail prices are also imported in the model (UNODC 2008; 2009; 2010). However, they are employed only to compute the proportion of the daily supply costs on the overall daily costs. The accounting of drug sales revenues is instead computed relying on the Beluga court order. The *price-per-dose* variable is the price at which a single dose is sold, and it corresponds to 32.00€. This price states the cost for one dose for the end user, it also includes 18% of the *retailers-share-of profits* that, for instance, earn 5.76€ for each dose they sell.

[46] The *profit-of-retailers* variable considers as each retailer of the DTO sells the same number of doses, thus having exactly the same profit. This is not the case in the model; the division of the profits for each retailer only gives a sense of a reasonable wage for these actors. This does not affect the predictive power of the model since the profits of retailers are used in their aggregate format to account for the total expenses of the DTO. In this format the variable accounts for the profits from the number of doses sold in the day, disregarding the actors selling them.

Members of the organization's attributes

Each actor of the DTO has some personal attributes (Table 40).

Table 40. Attributes of DTO members

Attribute	Definition
Drug	Amount of drugs stored by each DTO member in a specific tick.
Attractiveness	Differentiated criminal abilities of each actor. It is assigned making random draws from a normal distribution normalized between 0 and 1. The mechanism for updating actors' attractiveness differs according to the task accomplished.
Familiarity	Number of times each pair of actors in the DTO has already been in touch with each other. During the simulation, every contact between two actors increases their familiarity by 1.
Availability	Possibility of each actor to receive some drugs in a specific tick of simulation.

Source: Author's elaboration

The *attractiveness* attribute draws from a normal distribution. This choice is consistent with prior research and it accounts for the differences in skills and criminal abilities of the actors (Duxbury and Haynie 2019; Weisburd et al. 2017a; Birks, Townsley, and Stewart 2012). The mechanism for updating actors' attractiveness differs according to the task accomplished:

- Traffickers scores are updated after every attempt of acquisition with an exponential criterium. If the acquisition is successful, the trafficker attractiveness score is increased; the lower the score before the acquisition, the higher the increase and vice versa. If the acquisition failed, the trafficker attractiveness score is decreased; the higher the score before the acquisition, the higher the decrease and vice versa (see "The acquire-drug procedure" section in Annex II for details).
- Packagers and retailers scores are updated every tick of simulation and they can randomly result to be slightly higher or lower than the value in the previous tick. This is because, differently from traffickers, the work of packagers and retailers is not strictly linked to the performance of a single activity (i.e., a drug acquisition) but it consists of more continuous tasks, leading to quite stable levels of performance over time.

The *familiarity* attribute considers existent working relations among DTO members. At tick 0 most pairs of actors have a 0 familiarity, apart from those eight pairs of actors being tied by the initial links mirroring the relational information from the Beluga group. During the simulations, every contact (i.e., drug exchange) between two actors increases their familiarity by 1.

The *availability* attribute informs about DTO members ongoing workload. Members are available if they can still perform some tasks for the organization in the current tick, otherwise they are unavailable. Packagers are available if they have not received yet a quantity of drug that is equal or higher to their maximum workload in a day. Retailers are set as available if they have not received yet a quantity of drug that, when sold, would result in exceeding their maximum daily profit. Traffickers do not need to have the *availability* attribute.

The go procedure

The *go* procedure is the piece of code that defines the processes performed by the model. Each of the outlined processes is then detailed in a separate procedure.

Figure 8 summarizes the processes included in the *go* procedure and performed by the model; orange boxes represent operational activities performed by the DTO, whereas the grey box represents a service procedure necessary for the proper functioning of the model but unrelated to the tasks performed by the DTO.[47]

Figure 8. Steps of the go procedure

Source: Author's elaboration

Considering the operational activities, firstly, every month, DTO traffickers have the possibility of acquiring some large quantities of drugs to refill their warehouses. As a second step, the traffickers deliver the acquired drug to the packagers; these members pack-up the drugs in doses and deliver them to DTO retailers. As a third step, every day, the retailers engage in street drug dealing, cashing in the revenues from the drug trafficking activities. As a fourth step, once a week, DTO managerial figures distribute the wages to DTO members and they account for some expenses. The DTO members cyclically perform the above-mentioned activities every established tick of simulation. During the simulated period, the DTO faces attempts at disruption performed by law enforcement.

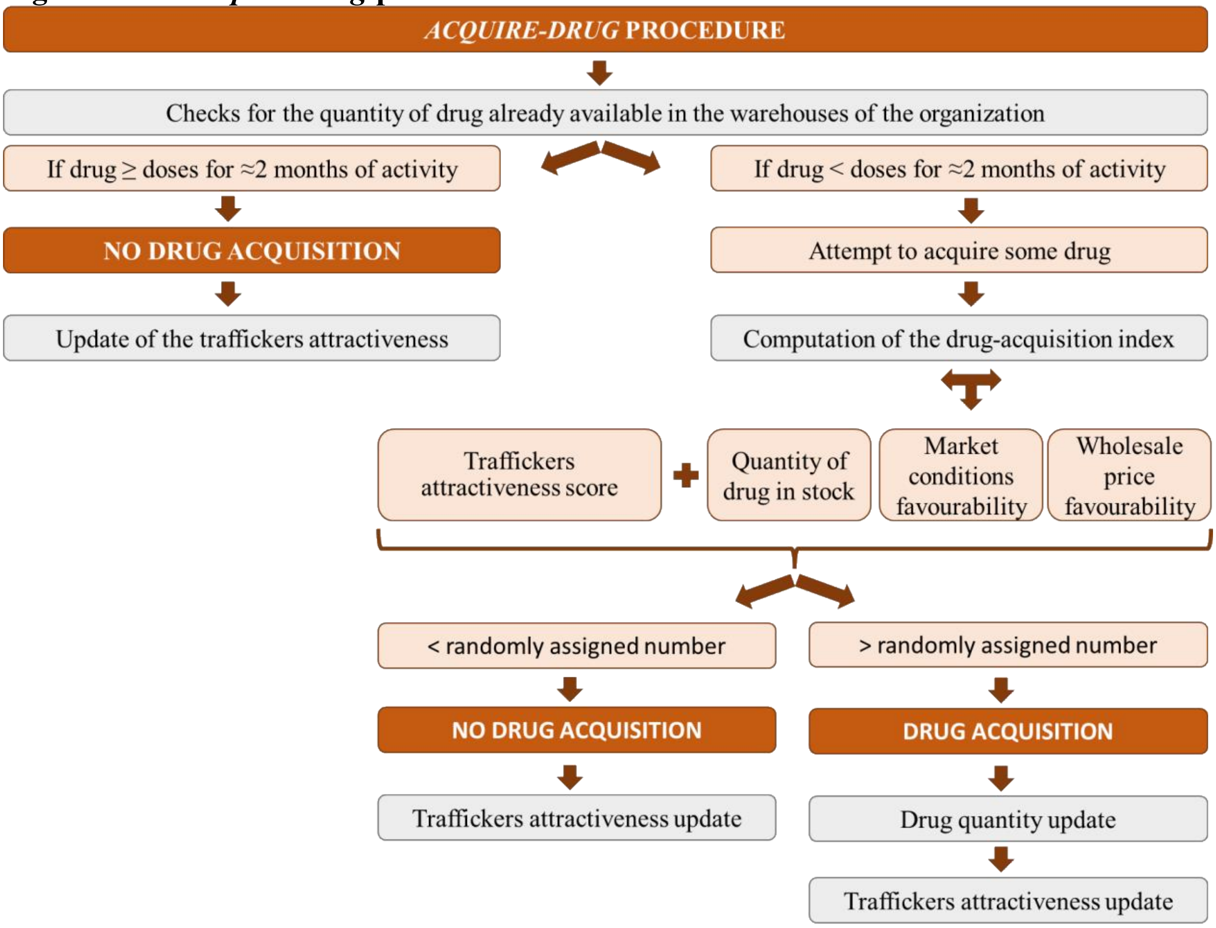
Considering the service procedure, the *compute-statistics* procedure allows to keep track, at every step of the model, of some SNA statistics (e.g., degree and betweenness centrality, components in the organization, etc.) to monitor the structure of the DTO over time.

[47] The *updated-parameters* procedure described in the previous "The setup and update-parameters procedures" section is a service procedure included in the *go-procedure*. Since it is an additional *setup-procedure*, for the clarity of exposure, it was presented together with the *setup-procedure*.

The acquire-drug procedure

The *acquire-drug* procedure accounts for the decision-making processes behind DTO drug acquisitions (Figure 9).

Figure 9. The *acquire-drug* procedure



Source: Author's elaboration

When the DTO already has a large quantity of drug in stock (i.e., twice the *target-stock-drug* variable), the traffickers do not perform new drug acquisitions. This is because having too many drugs in stock creates an array of problems to the organization: it is very risky in case of police interventions, it requires to have secure warehouses where to store the drug, etc. Instead, when the DTO has a modest amount of drug in stock, the decision on whether to acquire some more drugs or not relates to the computation of a composite index.

The composite index includes three indexes evaluating: the amount of drugs the DTO already has in stock, the market conditions, and the drug wholesale price at the moment of the possible acquisition.

The index for the amount of drugs already in stock (i.e., *stock-drug-index*) ranges from 0 to 1, where 0 stands for no drug available and 1 stands for the organization already having its warehouses full of drugs.

The index accounting for the market conditions (i.e., *market-condition-index*) follows a normal distribution ranging from 0 to 1, where 0 stands for favorable market conditions and 1 stands for adverse market conditions. This index includes many not explicitly identified factors that may affect the possibility of acquiring drugs, such as the availability of drugs in the market and perceived or actual risks in the acquisition process. After its computation, the *market-condition-index* is weighted according to the DTO security/efficiency focus; this is because organizations favoring security will have a more precautionary behavior when performing drug acquisitions, while organizations favoring efficiency will tolerate higher levels of risk.

Lastly, the index for the wholesale price (i.e., *wholesale-price-index*) ranges from 0 to 1, where 0 stands for a convenient wholesale price and 1 stands for an expensive wholesale price. Wholesale prices correspond to the *wholesale-price-now* variable. This variable is a randomization of UNODC wholesale prices performed before every attempt of acquisition. The randomization follows a normal distribution ranging from the minimum and the maximum European UNODC wholesale prices in the year of interest (UNODC 2008; 2009; 2010). This accounts for the possibility that wholesale prices may vary over time or according to the channels of acquisition exploited by each trafficker.

The composite index ranges from 0 to 1 and it is the product of the three above-mentioned indexes: the *stock-drug-index*, the *market-condition-index*, and the *wholesale-price-index*.

DTO traffickers perform a drug acquisition when the sum between their attractiveness score and a randomly assigned number ranging from 0 to 1 is higher than the computed composite index. When an acquisition is performed, the quantities of drug available to the DTO and stored by the actor involved in the acquisition are updated (i.e., the *stock-drug*, *stock-drug-traffickers* variables and the *drug* attribute of the trafficker are augmented of the quantity of drug included in the *drug-package-of-traffickers* variable).

After every attempt of acquisition, the attractiveness scores of the traffickers are exponentially increased or decreased according to the outcome of the acquisition (i.e., successful or failed) and the prior attractiveness scores (i.e., high or low). For successful acquisitions, traffickers' attractiveness is increased as follows:

$$Attr_{\text{new}} = Attr_{\text{old}} + 0.0001 \wedge {}^{Attr_{\text{old}}}$$

Instead, for failed acquisitions, the following formula is used to decrease the attractiveness scores:

$$Attr_{\text{new}} = Attr_{\text{old}} - 0.0001 \wedge {}^{(1\text{-}Attr_{\text{old}})}$$

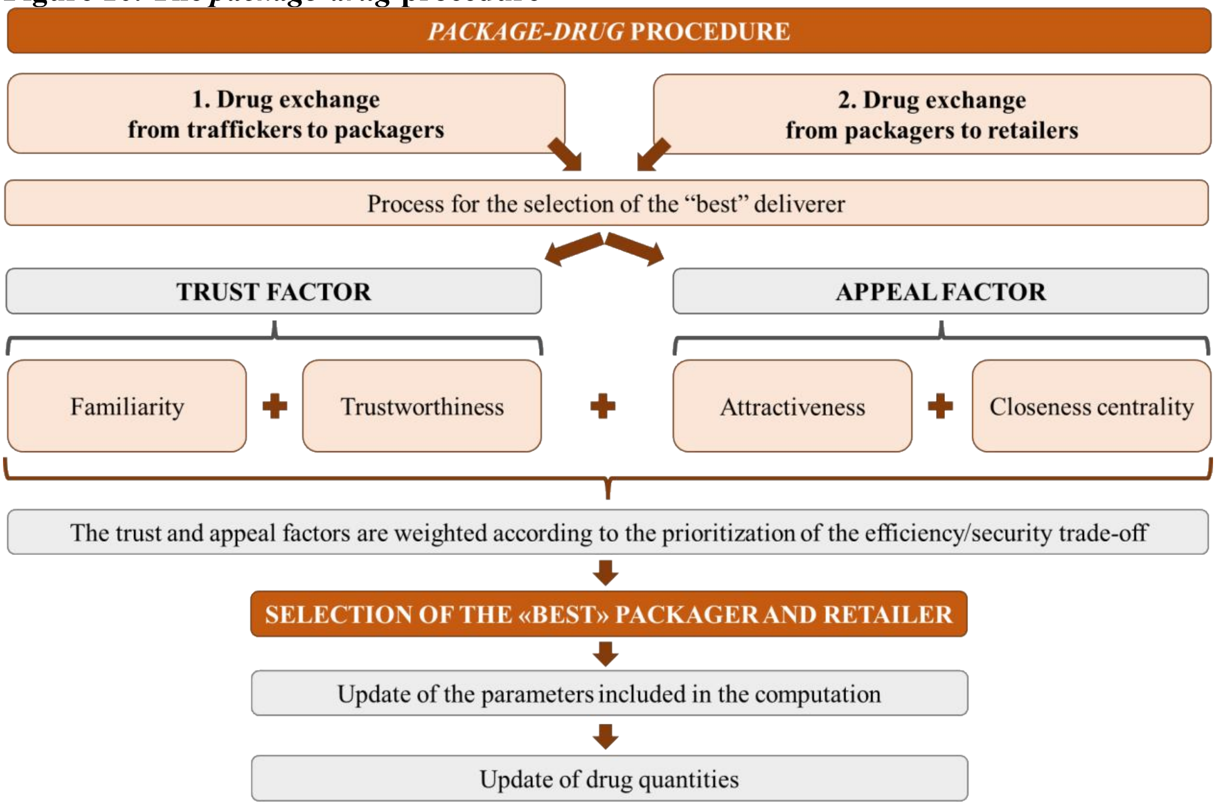
where $Attr_{\text{new}}$ is the updated attractiveness score of traffickers after having performed an acquisition and $Attr_{\text{old}}$ is the traffickers' attractiveness score before performing the drug acquisition. The value 0.0001 is set to calibrate the inclination of the exponential curves. These formulas are not used in case of successful acquisitions for the lowest attractiveness scores (i.e., <0.2), where the attractiveness score is set to 0.2 and in the case of failed acquisitions for the highest attractiveness scores (i.e., >0.8), where the attractiveness score is set to 0.8.

The decision of relying on an exponential criterium is related to the computation of the composite index itself. For traffickers having higher attractiveness scores, it is easier to perform successful acquisitions, since attractiveness concurs to the overcoming of the composite-index threshold; thus, a bad performance impact more on the score rather than a successful one. The same logic, in the opposite direction, works for traffickers scoring low in their attractiveness.

The package-drug procedure

The *package-drug* procedure links the drug acquisition phase to the drug sale phase. It accounts for two exchanges of drugs: the first from traffickers to packagers, the second from packagers to retailers (Figure 10).

Figure 10. The *package-drug* procedure



Source: Author's elaboration

The trafficker-packager exchange

In the exchange of drugs from traffickers to packagers, as initial step, traffickers check which packagers are available to receive some drugs; the available packagers are those that in the current tick have not received yet the maximum quantity of drug storable and processable by a single packager in one day. Among the available packagers, traffickers decide the packager to who delivering the drug evaluating two elements: the level of trust with and the appeal of the packagers. Both trust and the appeal scores of packagers are normalized values ranging from 0 to 1.

Two factors influence packagers' level of trust. The first factor informs about the familiarity between the two actors (i.e., the number of contacts between the trafficker delivering the drug and the prospective packager). The second factor evaluates the trustworthiness of actors. Duxbury and Haynie (2019) first use trustworthiness as a factor to account for the visibility of the actor in the whole network; it considers the difference between the number of contacts of the actor in relation to the number of contacts of the actor having the highest number of contacts in the organization. Indeed, actors with a smaller number of contacts offer securer and more trusted connections. Duxbury and Haynie (2019) use this metric, together with a randomly assigned trust score. The present model advances their metric by replacing the randomly assigned score with the familiarity score that considers the actual closeness in terms of working relations between two actors. A second advantage of this metric is that it combines an actors' attribute (i.e., familiarity) with a network metric (i.e., visibility), allowing traffickers to evaluate both their personal relations with packagers and how packagers are strategically positioned in the network.

The appeal of packagers also evaluates two factors. The first factor is the packagers attractiveness score, signaling their level of criminal abilities. The second factor is the closeness centrality of the actor. Closeness centrality is a measure assessing how much an actor is close to the other actors in the network (Giménez-Salinas Framis and Fernández Regadera 2017; Mainas 2012). Actors that are closer to others are critical to rapidly interact, give and receive information (Catanese et al., 2013).

The trafficker delivers the drugs to the packager being available and having the highest sum of the trust and appeal scores. This sum is weighted according to the DTO security/efficiency focus. Organizations favoring security give more relevance to actors' levels of trust. This is because cooperating with already well-known members and being unnoticeable reduce the risk of being discovered by law enforcement. Conversely, organizations favoring efficiency give more importance to actors' levels of appeal. An actor having crucial criminal abilities and being strategically positioned in the network allows to better perform criminal activities.

This selecting process relies on the formula below:

$$P^* = max\ [\ s_{DTO}\ (\ nFam_{pt} + nVis_p\ ) + e_{DTO}\ (\ nAttr_p + nClos_p\ )\ ]$$

where s_{DTO} and e_{DTO} are complementary 0-1 indexes informing about the prioritization of the security (s_{DTO}) and efficiency (e_{DTO}) of the DTO. $nFam_{pt}$ and $nVis_p$ are the factors included in the trust score: the normalized familiarity among the trafficker and the packager involved in the drug exchange ($nFam_{pt}$), and the normalized visibility of the prospective packager ($nVis_p$). In contrast, $nAttr_p$ and $nClos_p$ are the factors included in the appeal score: the normalized attractiveness of the prospective packager ($nAttr_p$), and the normalized closeness centrality of the prospective packager ($nClos_p$). The packager selected to receive the drug (P^*) is the one scoring the highest value in the formula.

Once the trafficker has selected the best packager, the drugs are delivered to that packager. The quantity of drugs available to the actors involved in the exchange are updated, the familiarity between the two actors is incremented by 1 and the attractiveness scores of the packagers are updated.

The packager-retailer exchange

The second exchange of drugs in the *package-drug* procedure accounts for the delivery from packagers to retailers. This exchange largely follows the same logic of the trafficker-packagers exchange.

As first step, the packagers check which retailers are available to receive some drugs. Available retailers are those that in the current tick have not sold yet a quantity of drugs exceeding the maximum amount storable and saleable by a single retailer each day. Among the available retailers, packagers decide the retailer to whom delivering the drug evaluating their level of trust and appeal. The formula below informs about the retailer receiving the drugs, that is the one having the highest sum of the trust and appeal scores weighted according to DTO the positioning in the security vs. efficiency trade-off.

$$R^* = max\ [\ s_{DTO}\ (\ nFam_{tr} + nVis_r\ ) + e_{DTO}\ (\ nAttr_r + nClos_r\ )\ ]$$

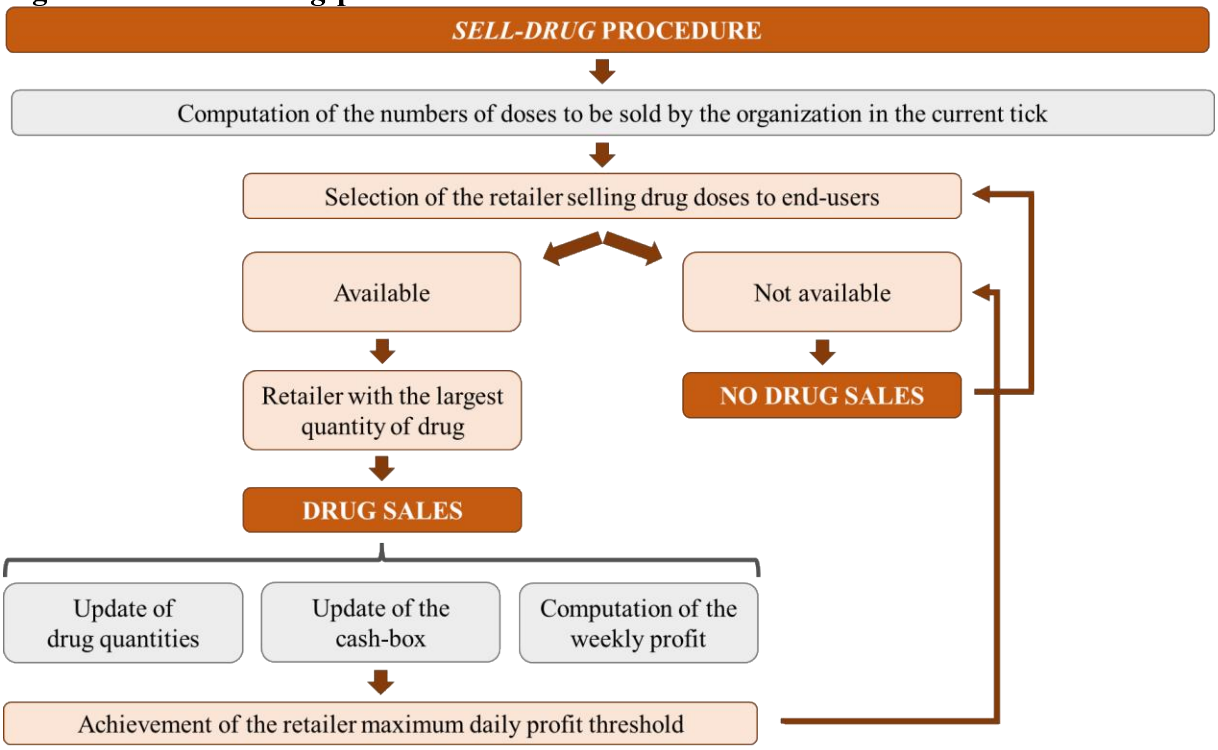
where s_{DTO} and e_{DTO} are the security (s_{DTO}) and efficiency (e_{DTO}) indexes of the DTO. $nFam_{tr}$ and $nVis_r$ are the factors included in the trust score (i.e., the normalized familiarity among the actors involved in the drug exchange and the normalized visibility of the prospective retailer). $nAttr_r$ and $nClos_r$ are the factors included in the appeal score (i.e., the normalized attractiveness and the normalized closeness centrality of the prospective retailer). The retailer selected to receive the drugs ($R*$) is the one scoring the highest value in formula.

Once the packager has selected the best retailer, the delivery is performed and the quantities of drugs available to the actors involved in the exchange are updated. After this, the familiarity between the two actors is incremented by 1 and the retailers attractiveness scores are updated.

The sell-drug procedure

The *sell-drug* procedure is the piece of code used to account for the sale of drug doses to the end users by retailers (Figure 11).

Figure 11. The *sell-drug* procedure



Source: Author's elaboration

As a first step, the number of doses the DTO is going to sell in the specific tick is computed (i.e., *unit-dose-now* variable). This variable randomly ranges between the minimum and the maximum number of doses the organization can sell in that moment of the simulation (i.e., *unit-dose-min* and *unit-dose-max* variables). Based on the actual number of doses, the model computes the profits of the retailers for the specific tick.

As a second step, the retailer having the largest quantity of drugs in stock and being available (i.e., not having exceeded yet the daily profits of 500€) begins to sell the doses to the end users. Each retailer having drugs in stock sells some doses in each tick; the retailer having the largest quantity is that selling first but this does not affect in any way the results of the model. If a retailer, while selling, reaches the maximum profit threshold, it becomes unavailable and it stops selling for the current tick.

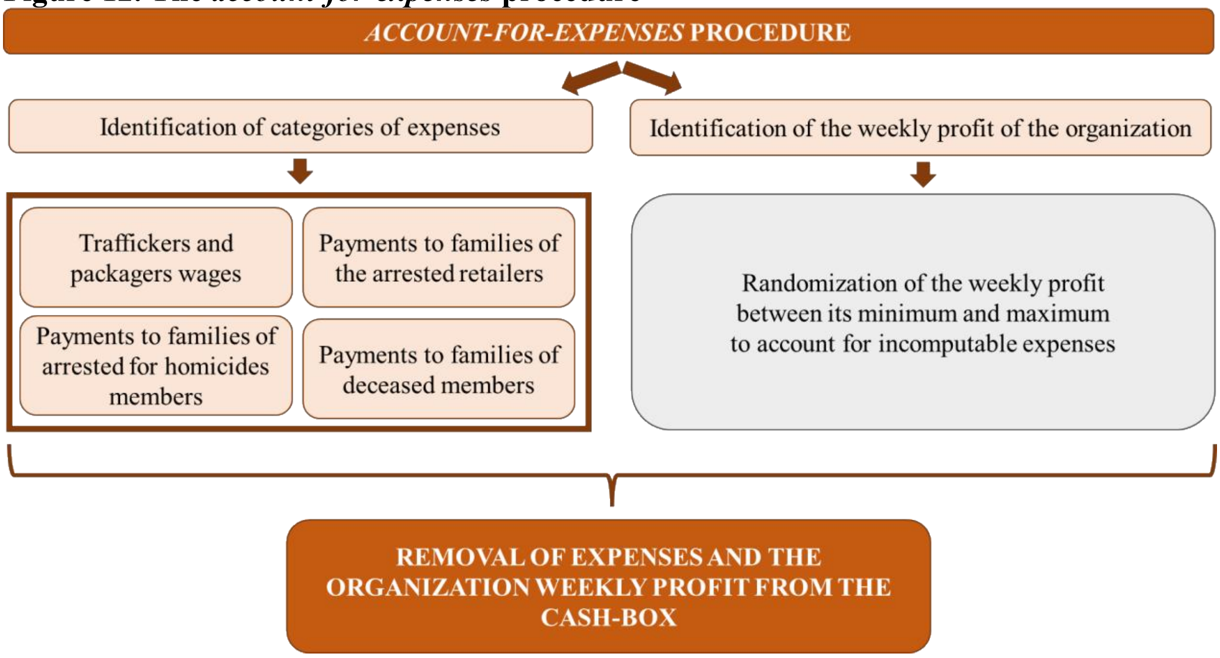
Every sale of drug doses, the model updates the amount of drugs available to the DTO. The amount of drugs stored by the retailer selling and the drug in the warehouses are reduced of the quantity of drugs included in a dose (i.e., 0.25 grams). The *cash-box* of the DTO increases by the revenues of the sale of that dose, that is the price consumers pay for a dose, minus the retailers' percentage of profit.

This procedure accounts also for the weekly net profits of the DTO (i.e., *weekly-profit-now* variable). This variable corresponds to the price at which the doses are sold, minus the retailers' percentage of profit and the wholesale price at which the doses were acquired. The following *account-for-expenses* procedure explains the meaning and the application of this variable.

The account-for-expenses procedure

The *account-for-expenses* procedure concerns the wages and expenditures of the organization. Following the Beluga court order, the DTO pays for these expenses once a week (i.e., every 7 ticks) (Figure 12).

Figure 12. The *account-for-expenses* procedure



Source: Author's elaboration

In addition to the cost of purchasing the drugs, the main expenses of the DTO relate to the wages and the payments to families of DTO members in specific conditions. The first category of expenses includes the wages for traffickers and packagers; they correspond to the daily profits of traffickers and packagers (i.e., *profit-of-traffickers* and the *profit-of-packagers* variables) multiplied for the seven days of the week and for the number of members in each category.

The second category of expenses pertains to payments to the families of some DTO arrested or deceased members. According to the Beluga court order, the families of arrested retailers receive between 200€ and 250€ weekly (the model relies on an average of 225€); the families of members arrested for committing homicides receive between 3,000€ and 4,000€ weekly (the model uses an average of 3,500€); and the families of deceased members receive 500€ weekly. Data elaborations from the Beluga court order allow to establish the number of the families in these conditions.[48] The families of arrested retailers are 56% of the retailers currently present

[48] The identification of the number of families receiving DTO weekly payments relies on elaborations on data portraying the organization at the end of the Beluga investigations. However, the model uses this information since

in the DTO; this is because during the Beluga investigations, among the charged retailers, the police arrested and remanded in custody 56% of them. Similarly, the families of deceased members are 10% of the current DTO members since, according to the Beluga court order, 10% of individuals identified as members of the DTO was deceased. Finally, the families of DTO members arrested for homicides are two since, among the members being responsible for committing killings and other violent actions for the organization, during the Beluga investigations, the police arrested two of them.[49]

As a second step, the model removes the amount of money corresponding to the identified expenses from the cash-box and from the DTO weekly profit.

As a third step, the model randomly modifies by +/-10% of its current value the DTO weekly profit to account for possible miscalculations due to lack of available data. The model also sets the DTO maximum and minimum weekly profit. These values correspond to the DTO weekly profit without the two abovementioned categories of expenses with an addition of 10% (*weekly-profit-max*) and to 50% of the DTO weekly profit always without the two abovementioned categories of expenses (*weekly-profit-min*). Subsequently, the model removes the weekly profit from the DTO cash-box. If the computed weekly profit is higher or lower than the set thresholds, it removes only the maximum and minimum weekly profits.

This removal accounts for the net profits the managerial figures of the DTO keep for themselves as a reward for the involvement in the trafficking and dealing. According to the Beluga court order, this mainly includes personal expenditures (e.g., luxury goods or lifestyle). In MADTOR, this amount of money also accounts for other variable incomputable expenses excluded from the categories mentioned above (e.g., briberies to corrupt public officials, payments to lawyers in charge of defending members of the organization in trials, expenditure for renting warehouses where to store drug).

The periodically-arrests and attempt-at-disruption procedure

The *periodically-arrests* and *attempt-at-disruption* procedures simulate two different types of law enforcement interventions targeting the DTO.

The *periodically-arrests* procedure is executed once a month starting from day 15 of the simulation and it reproduces minor occasional arrests performed by law enforcement (Figure 13).

According to the DTO security/efficiency focus, this procedure sets some probability thresholds regulating the periodical attempts at disruption. Secure organizations have the lowest probability of being targeted by periodical arrests (i.e., organizations scoring 0 in the *efficiency-vs-security* variable have 1% probability of being targeted, organizations scoring 0.2 in the *efficiency-vs-security* variable have 5% probability of being targeted, and organizations scoring

---

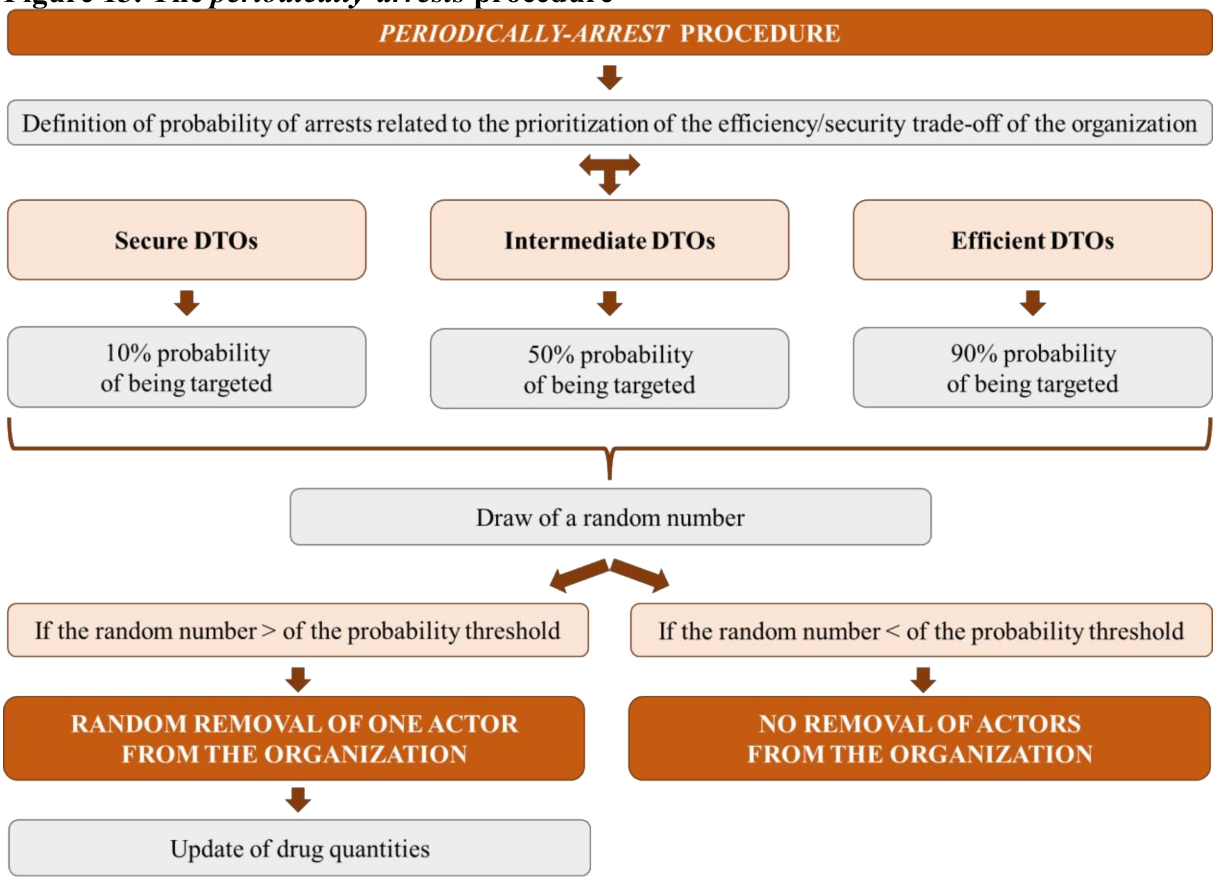
the beginning of the simulations. The intuition is that previous investigations on the same DTO could possibly have led to similar outcomes, in terms of arrests and deaths of members, to the ones reported by the Beluga court order. The author decided to use these data because there was not more reliable information available and the only alternative would have been to use arbitrarily set values. Despite the abovementioned limitations, the reliance on these values as proxies for the actual number of families receiving DTO weekly payments does not preclude the accuracy of the model since these expenses are then aggregated to other variable expenses; thus, it could be that the repartition of different categories of expenses is inexact but the total amount is still robust.

[49] Considering expenses related to the payments of the families of members arrested for committing homicide offences, the model utilizes the absolute number because using the percentage, considering the total number of members in the simulation, would have resulted in numbers always below 1. In addition, DTO members charged with this task were not replaced during the whole Beluga investigations. Thus, it is reasonable to expect that this number is quite stable over time.

0.4 in the *efficiency-vs-security* variable have 10% probability of being targeted). Organizations prioritizing in the same manner both efficiency and security (i.e., those scoring 0.6 in the *efficiency-vs-security* variable) have 50% probability of being targeted by periodical arrests. Conversely, efficient organizations have the highest probability of being targeted (i.e., organizations scoring 0.8 in the *efficiency-vs-security* variable have 90% probability of being targeted, and organizations scoring 1 in the *efficiency-vs-security* variable have 100% probability).

When a randomly drawn number overcomes the probability thresholds, a DTO member selected by chance is arrested and removed from the organization. Since the amount of drugs available to the arrested member is seized during the simulated law enforcement intervention, after the arrest, the amount of drugs available to the organization is updated.[50]

Figure 13. The *periodically-arrests* procedure

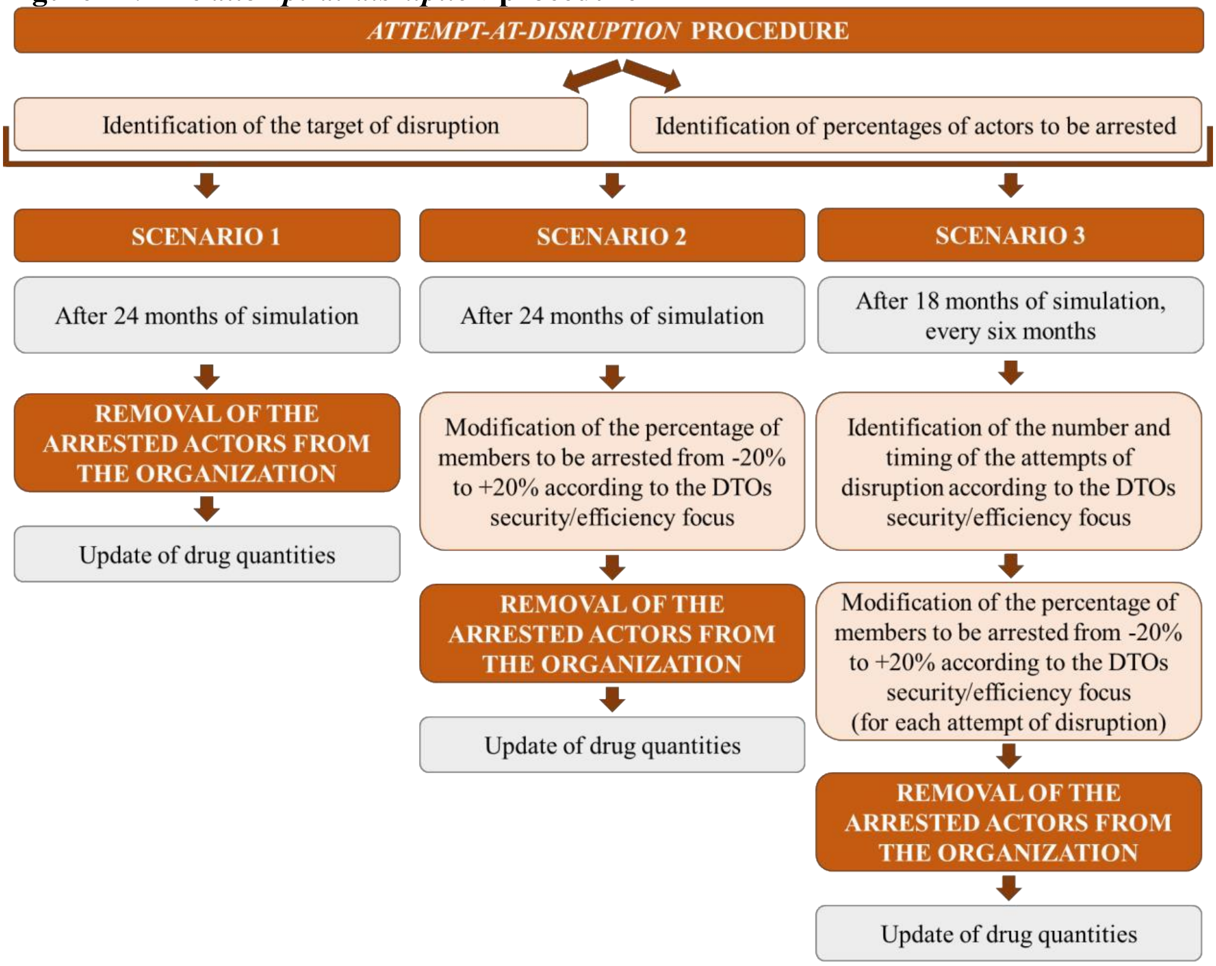


Source: Author's elaboration

[50] The main goal of the *periodically-arrests* procedure is that of accounting for the differentiated probabilities of DTOs with a different security/efficiency focus of being subjected to sporadic minor arrests by law enforcement. Nonetheless, this procedure can also reflect dynamics of DTO members abandonment unrelated to police interventions, such as the personal choices of leaving the organization or the deaths of some members. Indeed, DTO security/efficiency focus also influences these two additional motivations for defections (e.g., efficient DTOs may face more defections due to the choices of members to leave the organization since relations among members are mostly based on business activities with lower levels of trust, members of efficient DTOs may be more at risk when conducting criminal activities, thus having higher probabilities of being involved in deathly incidents).

The *attempt-at-disruption* procedure simulates the major events of disruption targeting DTOs during the simulations. It consists of three scenarios with an increasing level of complexity (Figure 14).

Figure 14. The *attempt-at-disruption* procedure



Source: Author's elaboration

In the first scenario, the *attempt-at-disruption* procedure is executed once in the whole simulation, exactly at tick 730 that, considering the timeframe of the Beluga court order, corresponds to the end of 2010. The reason behind this choice is twofold. Firstly, for validation purposes, it enables the possibility of simulating an attempt at disruption that is as similar as possible, also with respect to the timing, to the one actually experienced by the Beluga group. This allows to verify if the ABM realistically simulates the reactions of DTOs to law enforcement attempts at disruption.

Secondly, the choice of disrupting the DTO after two simulated years of criminal involvement increases the robustness of the results. As an example, Duxbury and Haynie (2019) simulate an attempt at disruption at tick 1 of their model; this precludes the possibility of understanding if the cause of the identified trends is the attempt at disruption or they could have been observed also without any intervention. Conversely, observing the behaviors of the organization in the two years before the attempt at disruption, it is possible to determine which is the usual DTO *modus operandi* and the trends of some variables accounting for its status of well-being. This allows to detect eventual significant modifications after the law enforcement intervention.

In this scenario, the procedure removes from the organization a selected number of actors, those established before starting the simulation. In particular, the model allows to select the target of disruption (i.e., randomly all DTO members, traffickers, packagers, or retailers) and the proportion of the targeted actors to be removed. Secondly, the procedure removes from the DTO the targeted actors and it updates the quantities of drugs available to the organization. This is because, during the attempt at disruption, law enforcement arrests the members and seizes the drug they have in stock in that moment (Figure 14).

In the second scenario, DTO members still have to confront with an attempt at disruption after two years of criminal involvement but its effectiveness is influenced by the DTO security/efficiency focus. Law enforcement aims at arresting a determinate proportion of members and seizing the drugs at their disposal; however, according to the DTO security vs. efficiency focus, the results are dissimilar. For secure DTOs (i.e., 0.0, 0.2, and 0.4 *efficiency-vs-security* categories) the selected proportion of arrests is diminished of a random 10-20%, for DTOs with an intermediate focus in the security vs. efficiency focus (i.e., 0.6 *efficiency-vs-security* category) the selected proportion of arrests is randomly modified by +/-5%, and for efficient DTOs (i.e., 0.8, and 1.0 *efficiency-vs-security* categories) the selected proportion of arrests is augmented of a random 10-20%.[51] Table 41 reports how the model modifies the percentage of arrests when considering DTOs with different security/efficiency focuses for 10, 40 and 80% categories of arrests (Figure 14).

Table 41. Percentage of arrests in the second scenario of law enforcement intervention

Selected % of arrests	Modified % of arrests for secure DTOs	Modified % of arrests for intermediate DTOs	Modified % of arrests for efficient DTOs
10%	8-9%	9.5-10.5%	11-12%
40%	32-36%	38-42%	44-48%
80%	64-72%	76-84%	88-96%

Source: Author's elaboration

In the third scenario, the number and timing of law enforcement interventions may vary according to the DTO security/efficiency focus. This scenario departs from the second one (where the magnitude of the attempt at disruption after two years varies according to the security/efficiency focus) and it introduces the possibility of multiple attempts at disruption at different moments during the five years. After the first 15 months of criminal involvement, DTOs may face law enforcement interventions every six months, for a total of 7 timeslots in which attempts at disruption may occur. Secure DTOs (i.e., 0.0, 0.2, and 0.4 *efficiency-vs-security* categories) face on average 1 attempt at disruption over the five years, DTOs having an intermediate focus in the security/efficiency trade-off (i.e., 0.6 *efficiency-vs-security* category) face on average 1.5 attempts at disruption, and efficient DTOs (i.e., 0.8, and 1.0 *efficiency-vs-security* categories) on average face 2 attempts at disruption. Disregarding DTOs security/efficiency focuses, each organization faces 1 attempt at disruption at minimum and 5 attempts at disruption at maximum (Table 42).[52]

[51] When considering efficient DTOs in the 90% of arrests scenario, the author calibrated the model to have increases in the percentages of arrests that do not exceed 99%, since this would result in an immediate disruption of the DTO.

[52] Considering the arbitrarity of choosing some thresholds for the average number of attempts at disruption targeting DTOs with different focuses in the security/efficiency trade-off (i.e., there is no indication in previous literature, nor in the Beluga court order), the author selected the values utilized for the final version of the model after the testing and evaluation of several combinations.

Table 42. Percentage of expected attempts at disruption per DTO security/efficiency focus in the third scenario of law enforcement intervention

Average attempts at disruption	Secure DTOs	Intermediate DTOs	Efficient DTOs
	1.043	1.463	2.105
No. of attempts at disruption	**Secure DTOs (%)**	**Intermediate DTOs (%)**	**Efficient DTOs (%)**
1	96.50	63.25	33.75
2	2.75	28.50	34.50
3	0.75	7.00	21.25
4	0.00	1.25	8.50
5	0.00	0.00	2.00
Total	**100.0**	**100.0**	**100.0**

Source: Author's elaboration

The DTOs security vs. efficiency focus also affects the timing of the attempts at disruption, with secure DTOs being more likely targeted in the last timeslots (i.e., after four years of criminal involvement) and efficient organizations being more likely targeted already from the first timeslots (i.e., starting from the second year of criminal involvement) (Figure 14).

The compute-statistics procedure

The *compute-statistics* procedure computes several network statistics at every tick of the simulation. This allows to monitor the structural features of the DTO over time. The computed statistics include: the number of components in the network and the size of the largest component; the minimum, maximum, and average degree centrality of DTO members; the degree centralization of the organization; the minimum, maximum, and average betweenness centrality of DTO members; the betweenness centralization of the organization; and the average geodesic distance among actors in the network.

The components of a network are subgroups of actors connected to each other through one or more paths but who cannot reach the actors in other subgroups of the network. The more the components in a network, the more the network is fragmented since there are some actors that cannot be in contact with others belonging to the same network. The largest the size of the main component in the network, the more cohesive the network is (Hanneman and Riddle 2005; Mainas 2012).

Degree centrality is a measure at node level that indicates the extent to which the actors within the network are strictly connected to each other. This measure reveals the total number of direct connections each actor in the network has, showing how many actors are directly connected with a specific node (Baker and Faulkner 1993; Cordeiro et al. 2018; Hanneman and Riddle 2005; Mainas 2012; Morselli 2010a). In the model, the normalized degree centrality is computed by dividing the actual value for the maximum possible value. This results in the percentage of the whole network to which an actor is directly connected (Hanneman and Riddle 2005).

Degree centralization, that varies from 0 to 1, attests if the nodes of a network differ in the number of direct contacts they have. High degree centralization means that the network is centralized around some nodes that have a disproportioned number of direct contacts in comparison to the others. On the contrary, low degree centralization means that there are not many differences in the number of direct contacts among the nodes in the network and so the network on the whole is not dependant on a specific actor (Baker and Faulkner 1993; Bichler, Malm, and Cooper 2017; Hanneman and Riddle 2005; Robins 2009).

Betweenness centrality is a measure at node level that indicates the number of times a specific node lies in the shortest path between two other nodes. Like degree centrality, betweenness centrality has been normalized by dividing the actual value for the maximum possible value to have the possibility of comparing networks different in size. Normalized betweenness centrality shows the percentage of cases in which a node lies in the shortest path in a dyad (Baker and Faulkner 1993; Hanneman and Riddle 2005; Mainas 2012; Morselli 2010a).

Betweenness centralization, that varies from 0 to 1, attests if in the network there are a number of actors playing strong brokerage roles. If betweenness centralization is high, it means that in the network there are some nodes that control the flows of communication; whereas if betweenness centralization is low, it means that in the network there are not nodes in stronger brokerage positions rather than the others, with all the actors having almost the same control on the flows of communication (Baker and Faulkner 1993; Bichler, Malm, and Cooper 2017; Hanneman and Riddle 2005).

Average geodesic distance asserts the average distance among actors in terms of paths. It is computed as the average of the shortest distances among all possible pairs of actors in the network. The shorter is the path tying two actors, the more efficient their relation can be. Average geodesic distance helps to understand how and in how much time information spreads across the network. Reaching actors in the network passing through a lower number of others avoids the need of intermediaries, increasing the efficiency of communication and resources flows in the network (Cordeiro et al. 2018; Hanneman and Riddle 2005; Mainas 2012).

Annex III

MADTOR ODD+D protocol

The ODD+D (Overview, Design Concepts, Details, and Decision-making) is the protocol developed by Müller and colleagues (2013) to define the design of decision-making processes, specifically human decision-making processes. It is suited to detail modelers choices in ABM simulations; the precise information provided in the protocol facilitate the possibility of model replication by other researchers.

ODD+D protocol (protocol from Müller et al. 2013))

Structural elements		**Guiding questions**	**Model description**
I) Overview	I.i Purpose	I.i.a What is the purpose of the study?	To understand DTOs resistance and resilience to law enforcement attempts at disruption. Specifically, the study investigates: I. Whether and how arresting different proportions of DTOs members affects the organization's resilience to law enforcement attempts at disruption. II. Whether and how arresting DTOs members performing different tasks affects the organization's resilience to law enforcement attempts at disruption. III. Whether and how a different focus in the efficiency vs. security trade-off affects DTOs resilience to law enforcement attempts at disruption.
		I.ii.b For whom is the model designed?	The model is designed for researchers and policy makers.
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	There is only one type of entity in the model, the members of a DTO. These members are grouped into different breeds according to the tasks they accomplish in the organization. The breeds are the following: • **Traffickers**: in charge of acquiring drug for the DTO; • **Packagers**: in charge of packaging the drug in unit doses; • **Retailers**: in charge of selling the unit doses to end users.
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	The agents of the model are characterized by the following attributes: • **Drug**: quantity of drugs at disposal of each agent in a specific tick. • **Availability** (for packagers and retailers only): dummy variable standing for the availability of each actor in a specific tick to package or sell some drugs.

			• **Attractiveness**: randomly attributed value from a normal distribution signaling the skills and criminal abilities of each actor in a specific tick. • **Familiarity**: level of familiarity among pairs of actors in the DTO. It counts the number of working relations occurred between each pair of actors. • **Trust-appeal**: aggregate attribute accounting for the level of trust of specific actors (familiarity with a determined other actor in the network + visibility in the network) and the level of appeal of specific actors (attractiveness + closeness centrality).
		I.ii.c What are the exogenous factors / drivers of the model?	In the model there are three categories of exogenous factors: I. Amounts of initial resources (in terms of money and drugs) the DTO can rely on at tick 0; II. Features of law enforcement attempts at disruption (task of the actors subjected to the intervention, proportion of members targeted, law enforcement intervention scenario); III. DTOs positioning in the security vs. efficiency trade-off (related to the contextual environment in which the DTO is embedded).
		I.ii.d If applicable, how is space included in the model?	Space is not included in the model.
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	Temporal resolution: One tick in the simulation represents one day.
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	Agents act at every tick performing their tasks. More specifically, the activities performed in the model are the following: I. DTO traffickers try to acquire some drugs for the DTO (every 30 ticks, corresponding to one month); II. DTO traffickers deliver to DTO packagers some of the drugs acquired to be packed-up in unit doses (every tick, corresponding to one day); III. DTO packagers deliver to DTO retailers the unit doses to be sold (every tick, corresponding to one day); IV. DTO retailers sell the unit doses of drug to end users (end users are not explicitly modelled) (every tick, corresponding to one day). Every week (i.e., 7 ticks) DTO managerial figures distribute the wages to DTO members, and they deal with some other expenses (managerial figures are not explicitly modelled).

			During the simulated period, according to the selected law enforcement intervention scenario, the DTO is subjected to one or more attempts at disruption.
II) Design Concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	• Rational-choice theory (Clarke and Cornish 1985); • Social embeddedness theory (Granovetter 1985); • Complexity theory of strategy (Pina e Cunha and Vieira da Cunha 2006); • Transaction cost model applied to the illicit supply chain (Basu 2014); • The security vs. efficiency trade-off (Morselli, Giguère, and Petit 2007)
		II.i.b On what assumptions is/are the agents' decision model(s) based?	The core assumptions are related to the theoretical frameworks of the model: • Traffickers decide whether to acquire or not some drugs based on the expected affordability of the acquisition but also considering the perceived risk of the transaction. These elements have their foundation in the rational-choice theory (Clarke and Cornish 1985). • Traffickers and packagers decide the actors to whom delivering drugs based on different factors: the trust between themselves and the selected actor (Granovetter 1985); the visibility of the selected actor in the DTO (Morselli, Giguère, and Petit 2007); the attractiveness of the selected actor in terms of criminal abilities (Weerman 2003; Clarke and Cornish 1985); and their closeness to other actors in the network, granting the efficient flows of resources (Catanese et al., 2013).
		II.i.c Why is a/are certain decision model(s) chosen?	The focus on rational-choice theory, social embeddedness theory and on the security vs. efficiency trade-off is chosen because it is largely supported by empirical literature. In addition, the events portrayed in the Beluga court order support the validity of these theories in the explanation of drug trafficking and dealing. The model relies on a probabilistic approach instead of explicit decision-making processes due to the lack of empirical evidence on such decision-making processes.
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	The model builds on theoretical knowledge and on empirical data from qualitative criminological literature and from a detailed court order against a large-scale Italian DTO (i.e., the Beluga court order). Quantitative data used in the model are retrieved from the Beluga court order (Tribunale di Napoli 2013). In addition, data related to cocaine wholesale and retail prices is retrieved from UNODC (UNODC 2008; 2009; 2010).

		II.i.e At which level of aggregation were the data available?	Data were mostly available at an aggregate level (information on DTOs). Some information was available at individual level, but this was used as insights to deduct general patterns for the entire organization.
	II.ii Individual Decision Making	II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included?	The subject of decision-making are the agents of the model, but they do not have specific decision-making mechanisms. Their decisions are guided by probabilistic computations that imply different outcomes based on their personal and relational characteristics. The objects of decision-making are: the decision whether to acquire or not some drug (performed by traffickers); and the decision about the DTO member to whom delivering a certain quantity of drugs (performed by traffickers and packagers).
		II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	Agents decision-making accounts for the decision whether to acquire or not some drug and the interactions among DTO members. The decision whether to acquire or not some drugs is based on rational-choice theory; traffickers decide to acquire some drugs when and if the market conditions are favorable (Clarke and Cornish 1985). The decision of interacting with a specific agent is based on: the level of trust among agents (Granovetter 1985); the visibility of actors within the DTO (Morselli, Giguère, and Petit 2007); the actors skills and criminal abilities (Weerman 2003; Clarke and Cornish 1985); and the actors structural position in the DTO (Catanese et al., 2013).
		II.ii.c How do agents make their decisions?	Decisions are based on multiple conditional probabilities derived from exogenous factors and from the individual and relational characteristics of each agent.
		II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	Yes, agents adapt their behaviors (acquisition, delivering, and selling of drug) based on external environmental conditions (i.e., favorability of market conditions during drug acquisitions), their criminal abilities, the quantity of drugs at their disposal, but also based on other agents' characteristics (e.g., trust, visibility, criminal abilities, etc.).
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	No.
		II.ii.f Do spatial aspects play a role in the decision process?	No, since space is not included in the model. However, "distance" intended as a network-driven concept (e.g., number of ties that separate two or more agents) partially influences the selection of the actors to whom delivering the drug (closeness centrality is an element considered by agents).

		II.ii.g Do temporal aspects play a role in the decision process?	No.
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	Decisions of DTO members are driven also by specific probability distributions (e.g., randomized external environmental conditions during drug acquisitions; randomized actors' attractiveness scores to choose the actor to whom delivering the drug).
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?	Learning processes are not included in the model.
		II.iii.b Is collective learning implemented in the model?	No.
	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?	Individuals do not perceive any of their own characteristics. However, their characteristics directly affect the probability of events (e.g., probability of receiving some drugs by other agents). The traffickers of the organization are assumed to perceive the exogenous external environmental conditions, these conditions affect their decision to acquire some drug for the DTO.
		II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?	Agents do not perceive state variables of other agents directly. However, their decision-making considers other agents' personal and relational features.
		II.iv.c What is the spatial scale of sensing?	Space is not included in the model.
		II.iv.d Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?	There are no mechanisms to diffuse information.
		II.iv.e Are costs for cognition and costs for gathering information included in the model?	No.
	II.v Individual Prediction	II.v.a Which data uses the agent to predict future conditions?	Agents do not predict any future condition.

		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	None.
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?	Prediction processes are not included.
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	Interactions among agents are modelled through probabilistic rules and are direct.
		II.vi.b On what do the interactions depend?	Interactions depend on the individual and relational characteristics of each agent.
		II.vi.c If the interactions involve communication, how are such communications represented?	There is no explicit communication between agents.
		II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?	The DTO is a coordination network; in addition, the breeds of agents (i.e., traffickers, packagers, and retailers) can be considered other coordination networks. The structure of these networks is imposed at t_0 but then it changes over time (i.e., recruitment and defection of DTOs members). New structures adopted by these coordination networks are therefore emergent in the model. Nonetheless, new coordination networks cannot emerge during the simulations.
	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?	Individuals belong to a specific breed of agents (i.e., traffickers, packagers or retailers). This aggregation affects the activities performed by the agents. It is imposed at the beginning of the simulation (or when an agent is introduced in the simulation) by the modeler. It cannot change during the simulation.
		II.vii.b How are collectives represented?	Collectives are represented in the model as actors accomplishing different tasks in the organization. These collectives affect the activities performed by the agents.
	II.viii Heterogeneity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?	All agents are heterogeneous differing in their individual and relational characteristics (stochastically set). Agents differ in the tasks they accomplish in the organization, the level of criminal abilities (i.e., attractiveness score), the structural position in the network and the relations they have with other agents.

		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	Agents are not heterogeneous in their decision-making. However, decision-making is based on probability. This means that identical agents (that are very unlikely) will take different decisions even if following the same decision-making process.
	II.ix Stochasticity	II.ix.a What processes (including initialization) are modelled by assuming they are random or partly random?	All processes are assumed to be, at least in part, random. Stochasticity is included in assigning individual and relational characteristics to agents at the beginning of the simulation, but also in the processes leading to actors' decision-making.
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analysing it, and how and when are they collected?	The results recorded from the simulations are: • Number of DTO members (and their distribution over time); • Number of arrested members (and their distribution over time); • Revenues from drug trafficking and dealing (and their distribution over time); • Steps needed to DTO disruption (# of members=0). • Distribution of members among tasks (i.e., traffickers, packagers, and retailers) over time; • Number of components and size of the largest component in the network over time; • Average, minimum and maximum degree centrality of actors over time; • Average, minimum and maximum betweenness centrality of actors over time; • Degree centralization; • Betweenness centralization; • Average geodesic distance among actors in the DTO. This data is collected at each tick of the simulation performing an experiment through the NetLogo BehaviorSpace.
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	Resilience, resistance, or vulnerability of DTOs. Eventual capacity of withstanding or avoiding attempts at disruption and strategies and reactions in response to threatening situations.
III)	II.i Implementation Details	III.i.a How has the model been implemented?	The model has been implemented in NetLogo (version 6.2.0).
		III.i.b Is the model accessible and if so where?	The complete code of the model in available here: https://www.comses.net/codebase-release/a5543b7a-8ed1-413b-88b8-5a44aed06c0d/

	III.ii Initialization	III.ii.a What is the initial state of the model world, i.e. at time t=0 of a simulation run?	The initialization of the model at t_0 depicts the status of the DTO portrayed in the Beluga court order in terms of actors and links imported, but also considering the volume of the DTOs drug trafficking and dealing.
		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	Each initialization produces unique patterns. Agents' individual features (e.g., attractiveness score), and some variables affecting the volume of drug trafficking and dealing activities (e.g., number of doses to be sold, wholesale prices) are stochastically assigned at the beginning of every simulation and they are modified at each tick of the simulation.
		III.ii.c Are the initial values chosen arbitrarily or based on data?	Initial values and parameters are calibrated based on empirical data from the Beluga court order. When this document could not provide the necessary information to calibrate the model, theoretical knowledge and existing qualitative research have been used.
	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?	Input data are used only in the *setup* and *updated-parameters* procedure. The *setup* procedure initializes most variables in the model. The *update-parameters* procedure is an additional *setup* procedure performed every 30 ticks to account for variations in the model conditions that change over time.
	III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?	The submodels tested derive from the intersection of three experimental conditions: (i) the target of the attempt at disruption; (ii) the proportion of members belonging to the target category that are arrested during attempts at disruption; and (iii) DTOs positioning in the security vs. efficiency trade-off. The *target-of-disruption* variable assumes four values: all members, traffickers, packagers, and retailers. The *arrested%* variable assumes eleven values: 0%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90%. The *efficiency-vs-security* variable assumes six values: 0, 0.2, 0.4, 0.6, 0.8, and 1. These experimental conditions result in a total of 264 combinations (i.e., 4*11*6). Three law enforcement intervention scenarios are tested, and for each one these 264 combinations are repeated 100 times. The three law enforcement intervention scenarios are the following: 1. Equal single attempt at disruption: each DTO, disregarding its focus in the efficiency/security trade-off is targeted by an equal attempt at disruption. 2. Diversified effectiveness of attempts at disruption targeting DTOs with a different focus in the efficiency/security trade-off. The effectiveness of the attempt at disruption (i.e., proportion of members arrested) is modified of +/-10/20% of the target value according to the DTO efficiency/security focus (see table below).

<table>
<tr>
<td></td>
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<table>
<tr><th>% arrests</th><th>Secure DTOs</th><th>Intermediate DTOs</th><th>Efficient DTOs</th></tr>
<tr><td>10%</td><td>8-9%</td><td>9.5-10.5%</td><td>11-12%</td></tr>
<tr><td>40%</td><td>32-36%</td><td>38-42%</td><td>44-48%</td></tr>
<tr><td>80%</td><td>64-72%</td><td>76-84%</td><td>88-96%</td></tr>
</table>
3. Diversified timing and frequency of attempts at disruption targeting DTOs with a different focus in the efficiency/security trade-off. According to their efficiency/security focus, DTOs have diversified probability of being targeted by one or more attempts at disruption and of being targeted earlier or later during the simulated time (see table below).
<table>
<tr><th>Average attempts at disruption</th><th>Secure DTOs</th><th>Intermediate DTOs</th><th>Efficient DTOs</th></tr>
<tr><td></td><td>1.043</td><td>1.463</td><td>2.105</td></tr>
<tr><th>No. of attempts at disruption</th><th>Secure DTOs (%)</th><th>Intermediate DTOs (%)</th><th>Efficient DTOs (%)</th></tr>
<tr><td>1</td><td>96.50</td><td>63.25</td><td>33.75</td></tr>
<tr><td>2</td><td>2.75</td><td>28.50</td><td>34.50</td></tr>
<tr><td>3</td><td>0.75</td><td>7.00</td><td>21.25</td></tr>
<tr><td>4</td><td>0.00</td><td>1.25</td><td>8.50</td></tr>
<tr><td>5</td><td>0.00</td><td>0.00</td><td>2.00</td></tr>
<tr><td>Total</td><td>100.0</td><td>100.0</td><td>100.0</td></tr>
</table>
The first scenario is used to test the resilience of DTOs; the second and third scenarios are used to test DTOs resistance.
</td>
</tr>
<tr>
<td></td>
<td></td>
<td>III.iv.b What are the model parameters, their dimensions and reference values?</td>
<td>Each submodel is initialized with the same calibration as the main model. They are based on quantitative and qualitative data from the Beluga court order, theoretical knowledge, and empirical qualitative research.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?</td>
<td>The submodels were designed based on theoretical assumptions in the field of criminal network resilience. The changing parameters in the submodels have been chosen because they may be factors affecting DTO resistance and resilience.</td>
</tr>
</table>

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Annex IV

Supplementary material

The graphs below report the trends of the resilience indicators presented in in Table 1 of section 3.5.1 and utilized to assess DTOs' resistance and resilience to the simulated law enforcement attempts at disruption. The graphs compared the baseline scenario in which no arrests are performed (i.e., grey lines), and some alternative scenarios in which the DTOs are targeted by the arrests of some members. The alternative scenarios are the following:

- 10% of arrests: green lines (left graphs);
- 40% of arrests: blue lines (middle graphs);
- 80% of arrests: red lines (right graphs).

The trends of the resilience indicators for DTOs with differentiated focuses in the security vs. efficiency trade-off are reported from the top to the bottom. Specifically:

- Yellow dot in the graph (top graphs): secure DTOs;
- Orange dot in the graph (middle graphs): organizations not having a preference neither for security, nor for efficiency (i.e., intermediate DTOs);
- Red dot in the graph (bottom graphs): efficient DTOs.

Conditions in which the attempt at disruption targets different DTOs members according to the tasks accomplished in the organizations are reported in graphs in subsequent pages following this order:

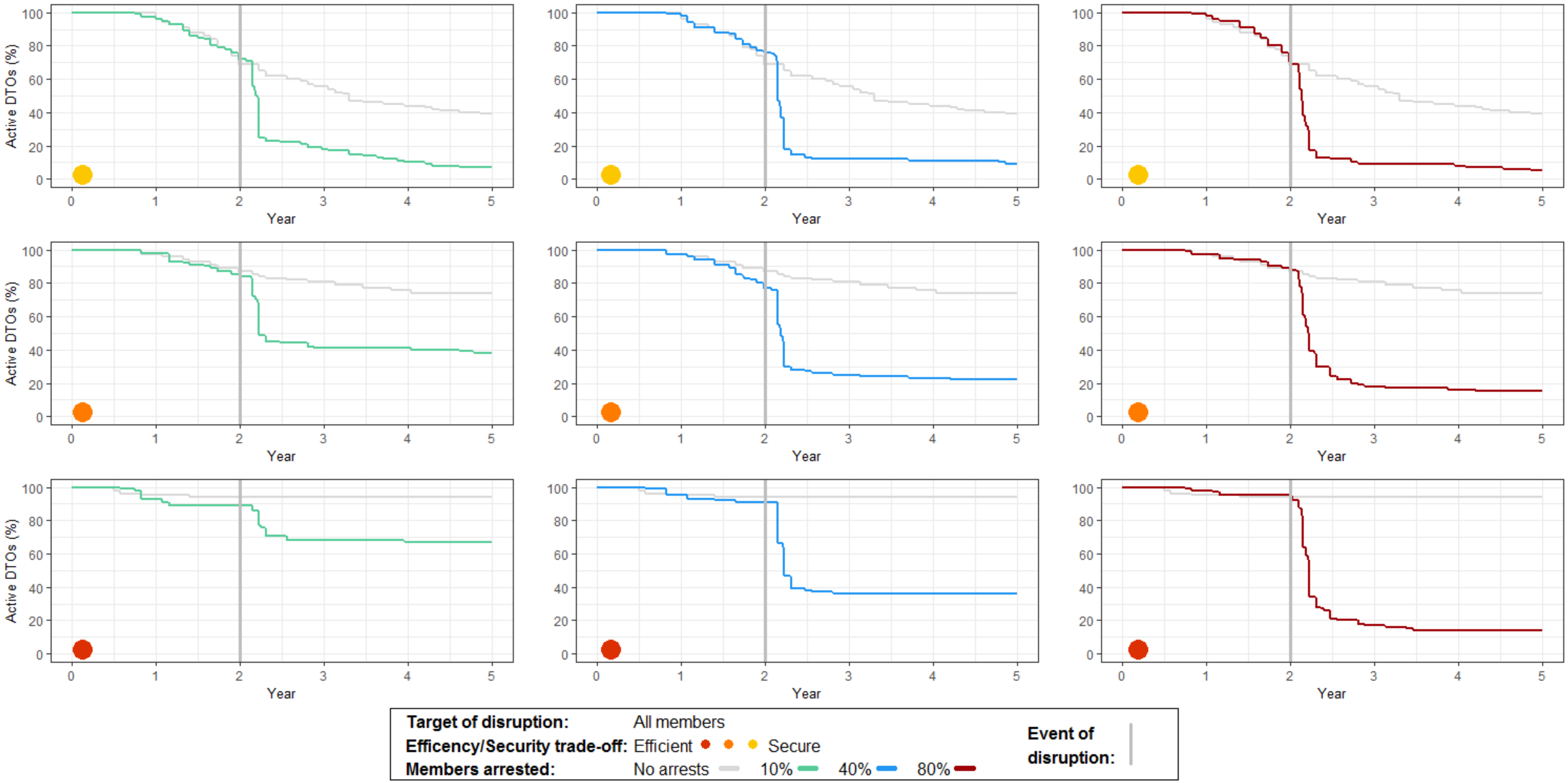
- All members;
- Traffickers;
- Packagers;
- Retailers.

The three law enforcement intervention scenarios are presented for each target in subsequent pages.

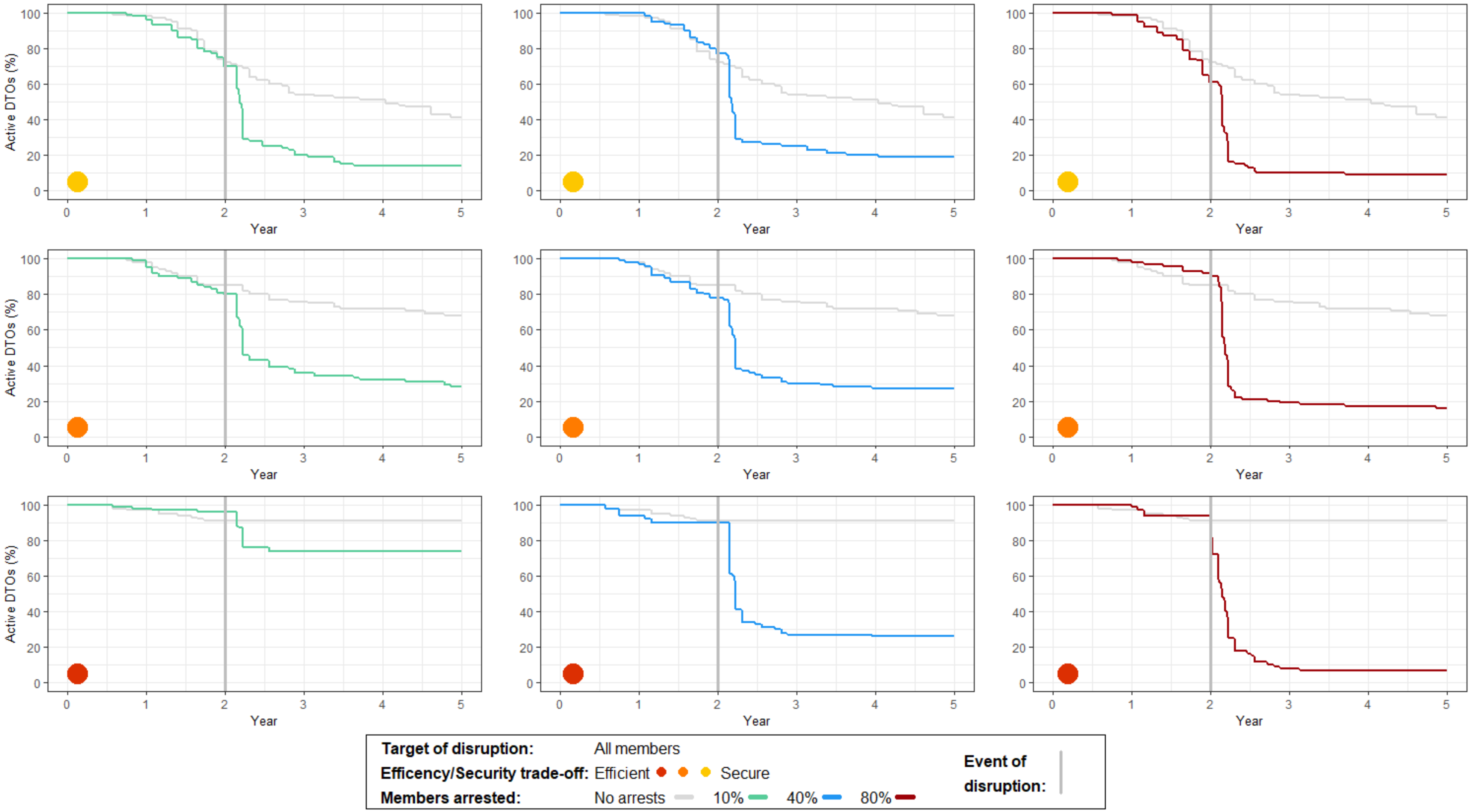
Apart from the graphs related to the share of active DTOs, each point in time represents the average of the resilience indicator for active DTOs (i.e., at year 0 the average is computed with the values of 100 organizations; at year 5 the average may be computed with less than 100 values because of disrupted DTOs). For the same set of graphs, the colored areas report the share of active DTOs over time in each scenario. The red and green dots inform about the significance levels of the t tests performed in each point in time between the baseline and the alternative scenario (red= nonsignificant, green=significant).

Share of active DTOs

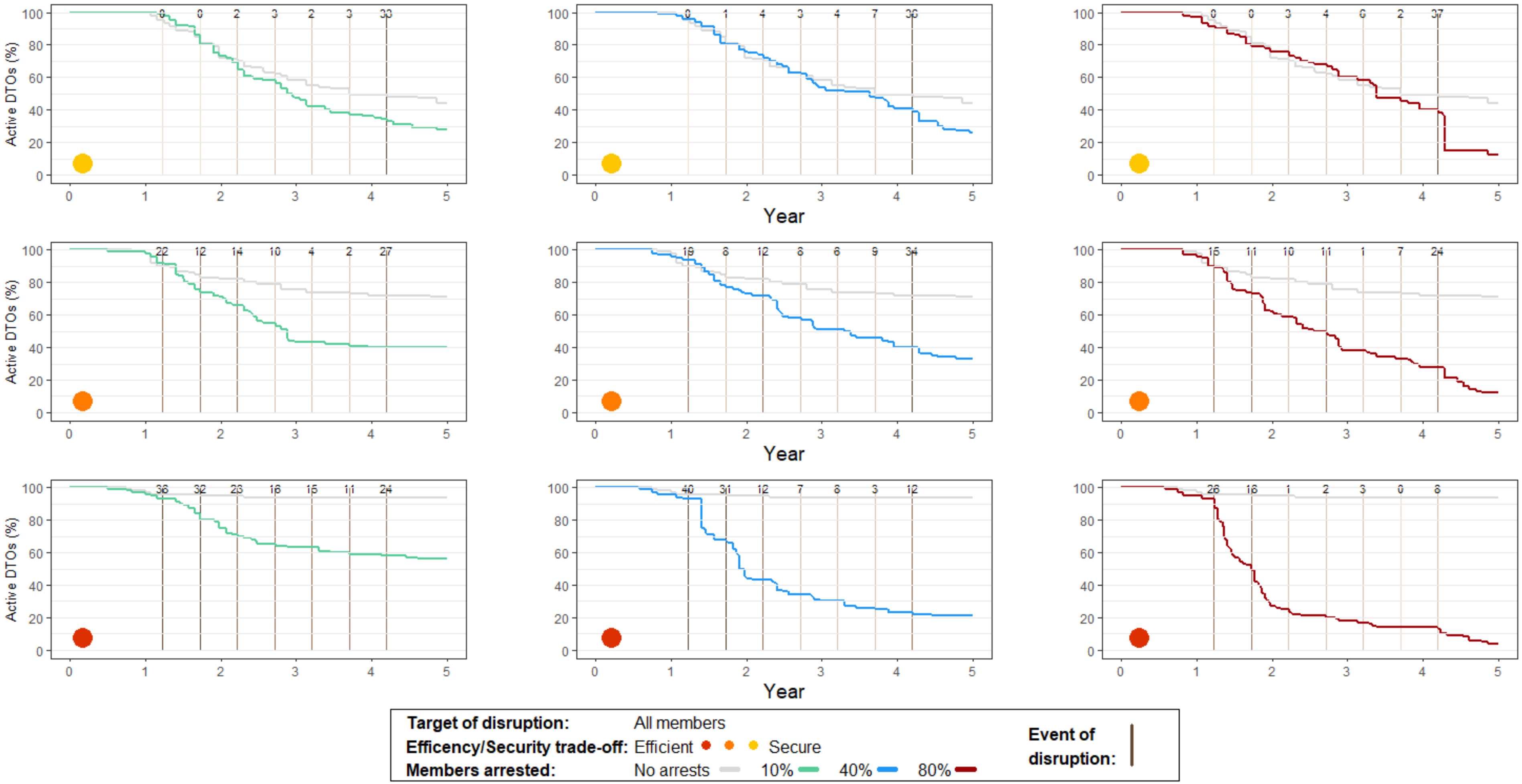
Graph 45. Share of active DTOs (Target of disruption: All members; Law enforcement int. scenario: 1)



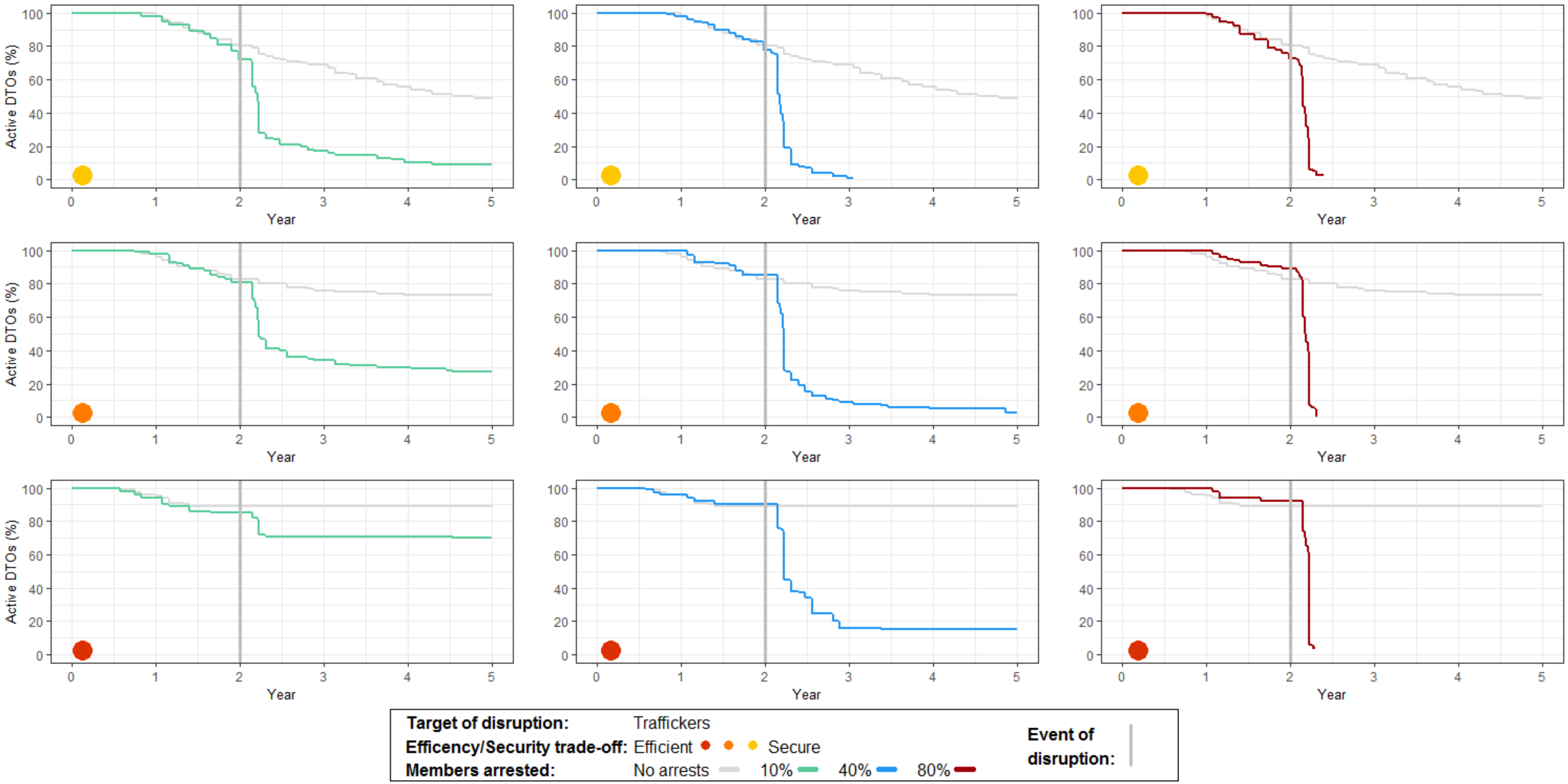
Graph 46. Share of active DTOs (Target of disruption: All members; Law enforcement int. scenario: 2)



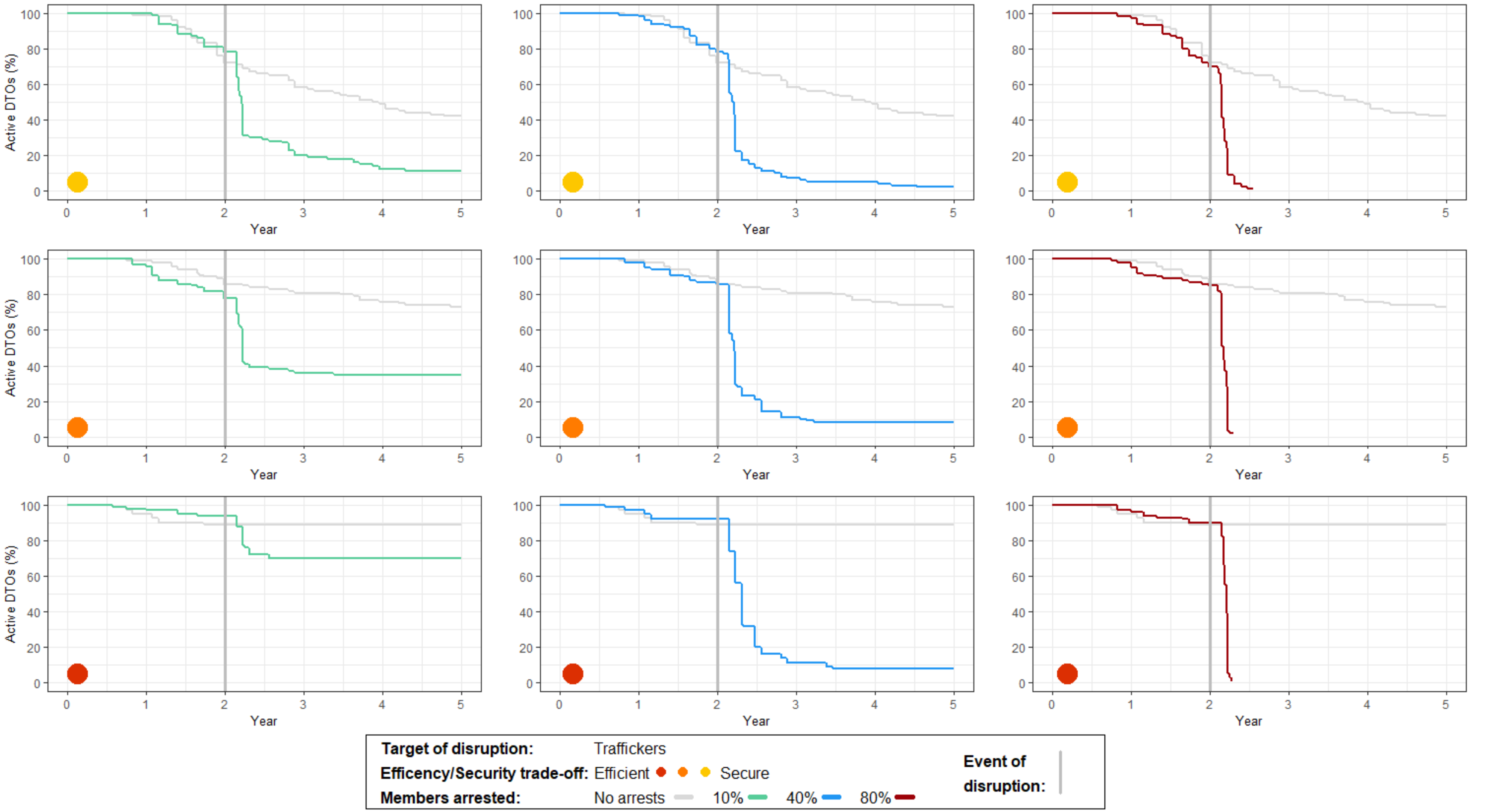
Graph 47. Share of active DTOs (Target of disruption: All members; Law enforcement int. scenario: 3)



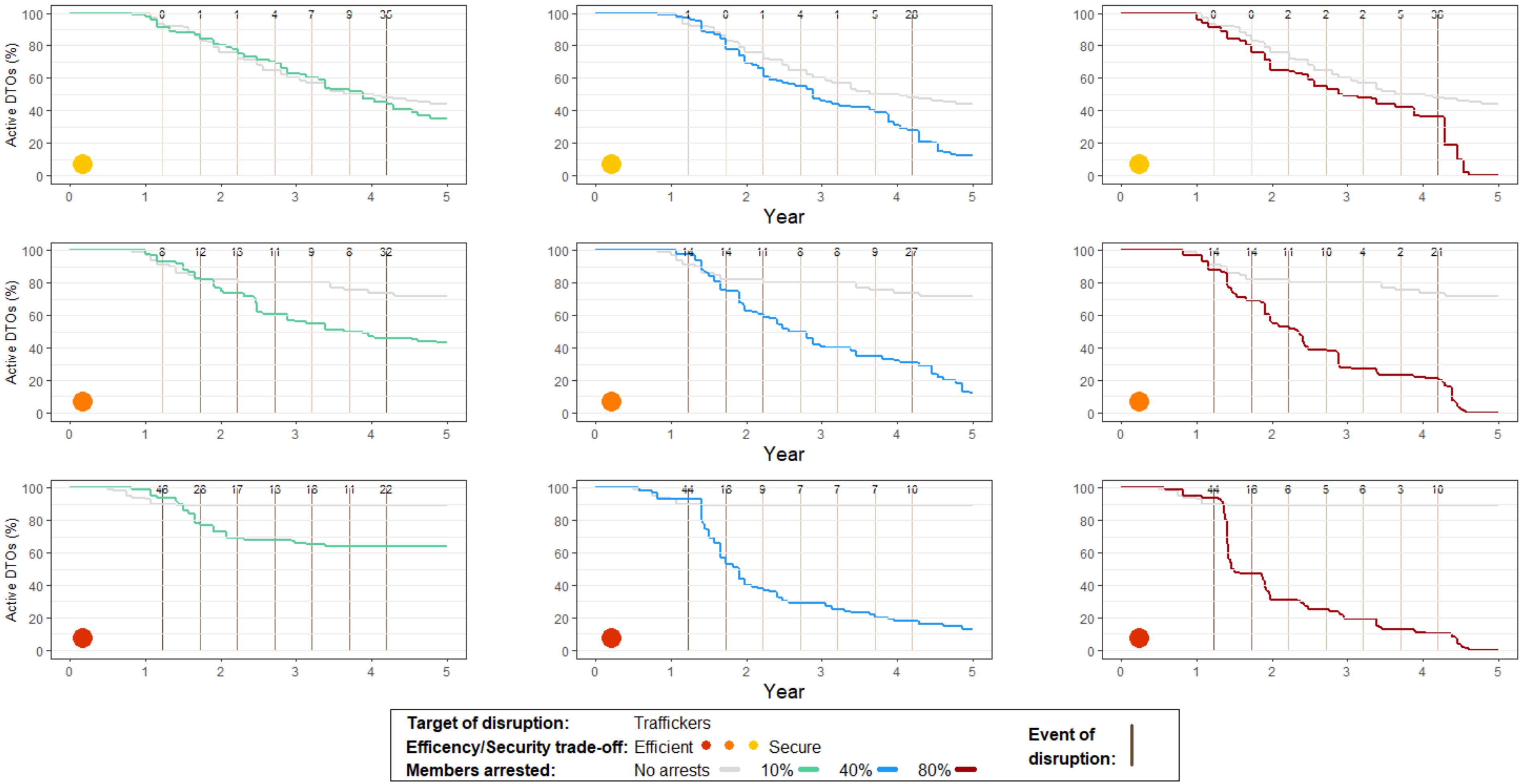
Graph 48. Share of active DTOs (Target of disruption: Traffickers; Law enforcement int. scenario: 1)



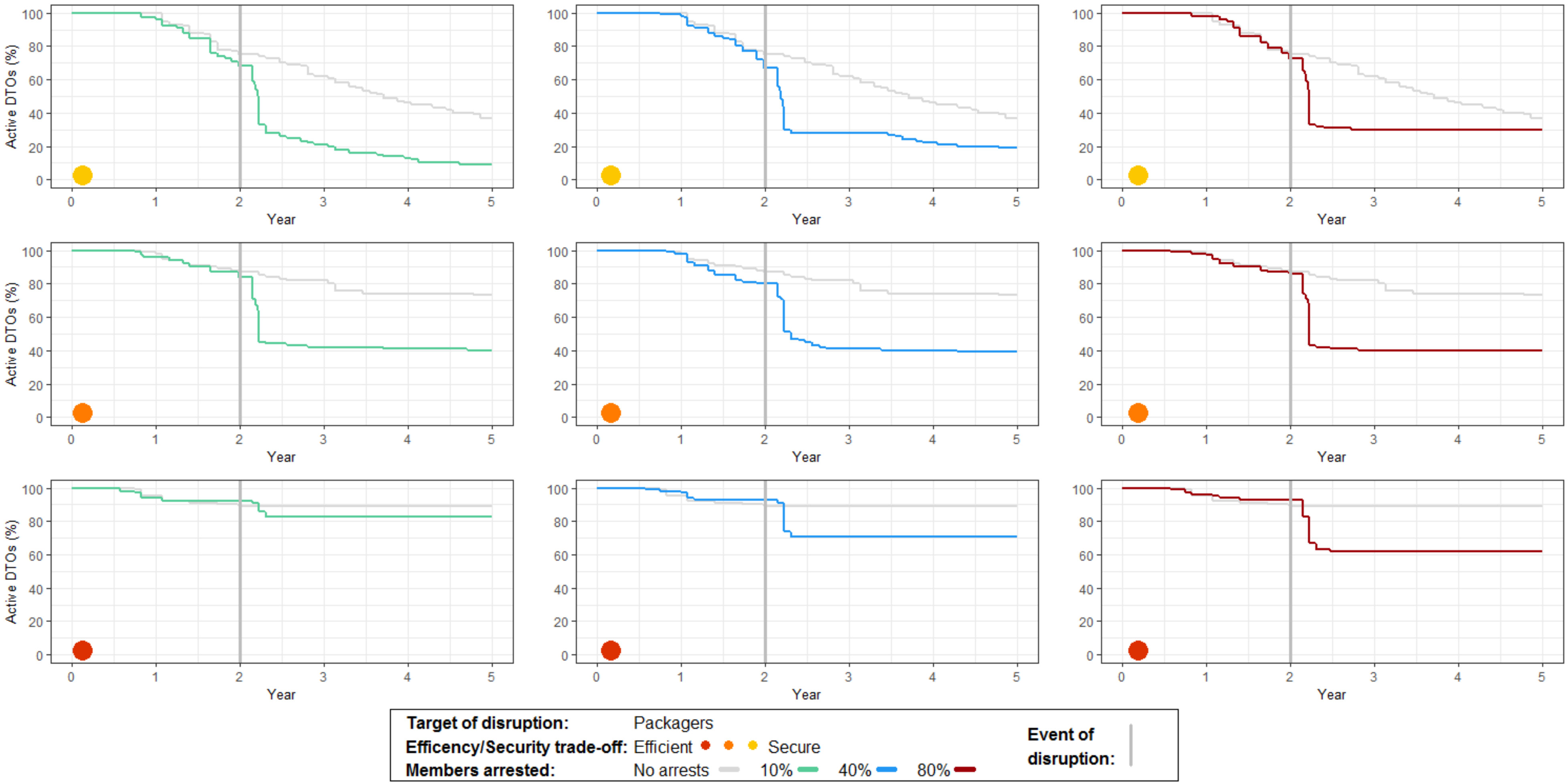
Graph 49. Share of active DTOs (Target of disruption: Traffickers; Law enforcement int. scenario: 2)



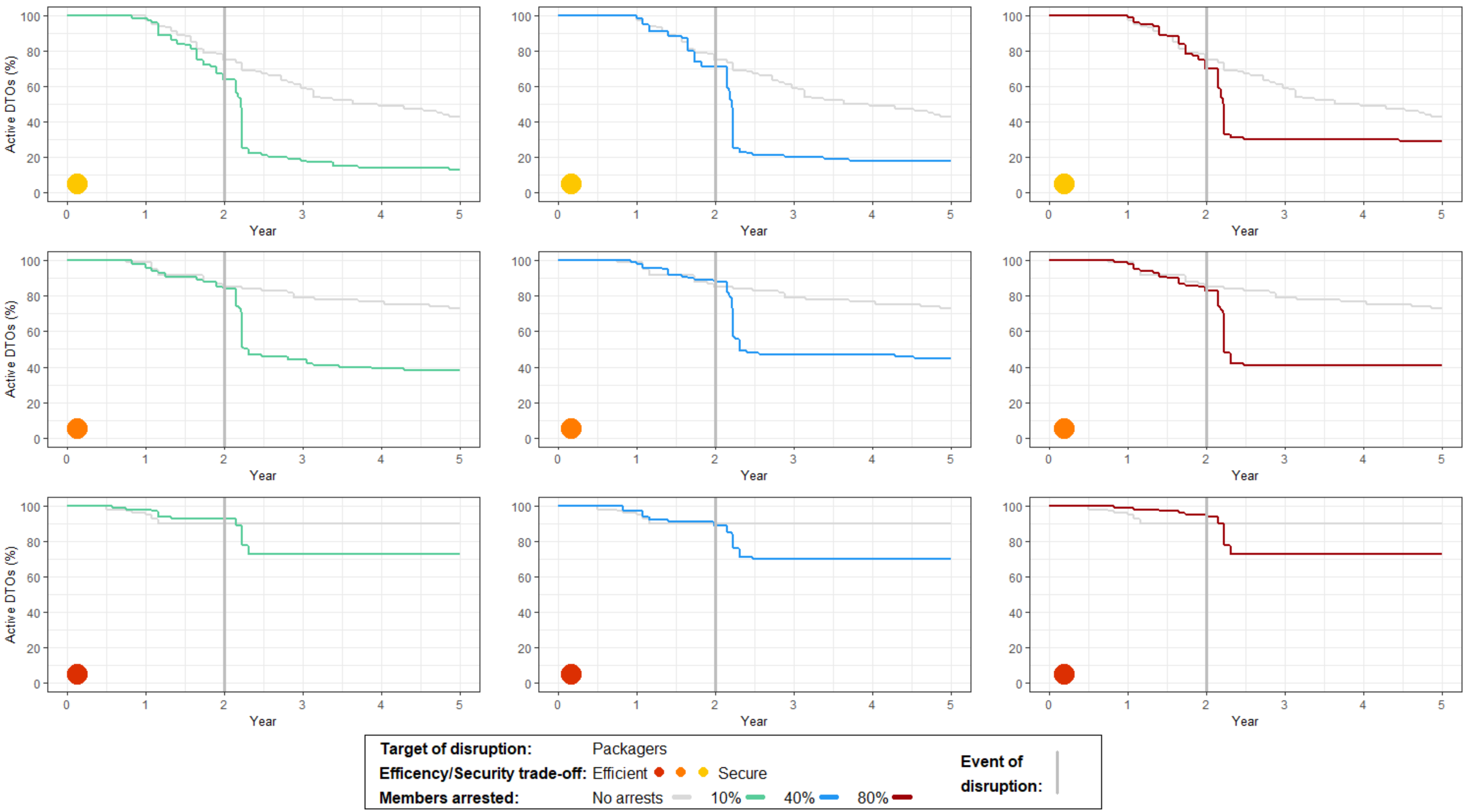
Graph 50. Share of active DTOs (Target of disruption: Traffickers; Law enforcement int. scenario: 3)



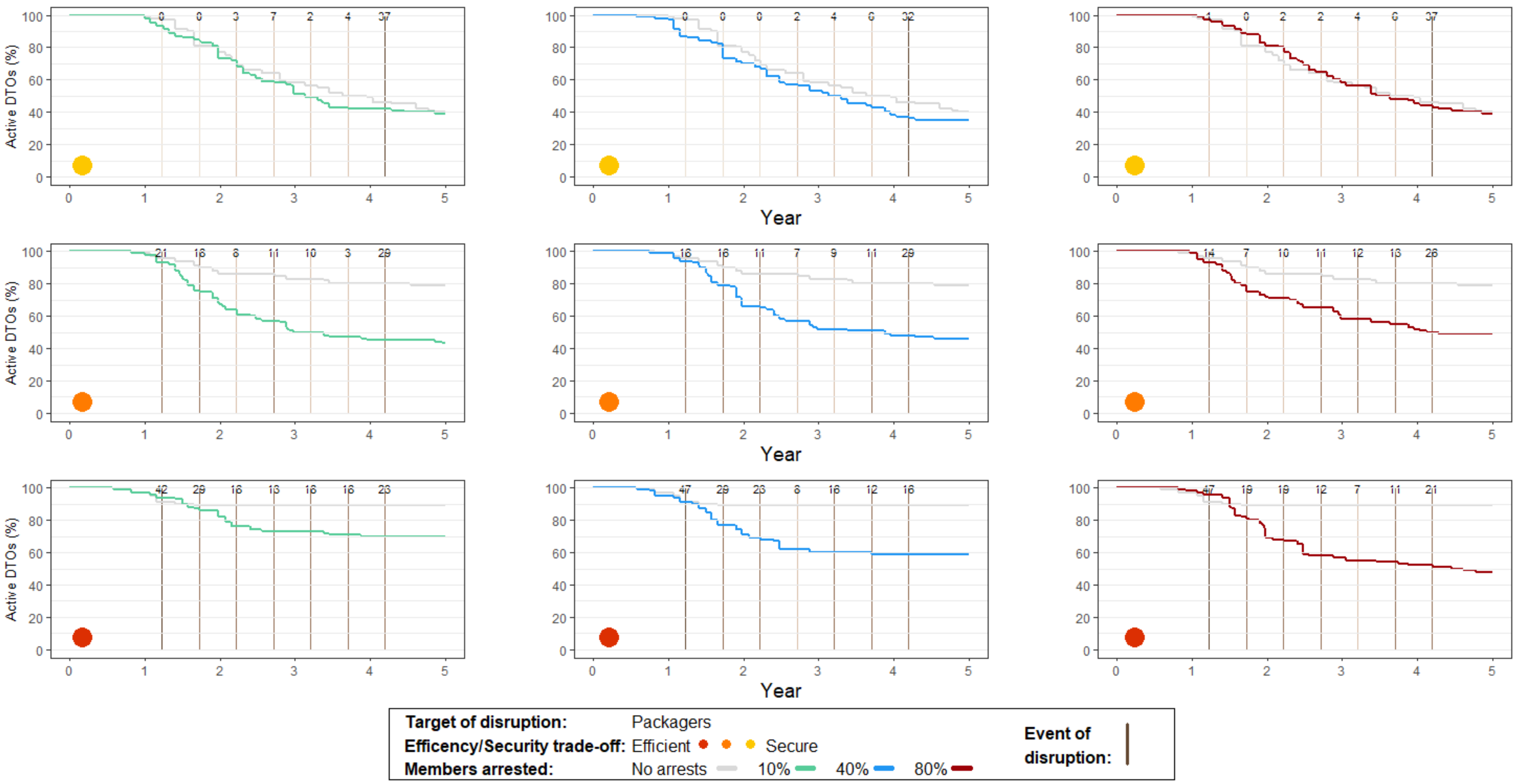
Graph 51. Share of active DTOs (Target of disruption: Packagers; Law enforcement int. scenario: 1)



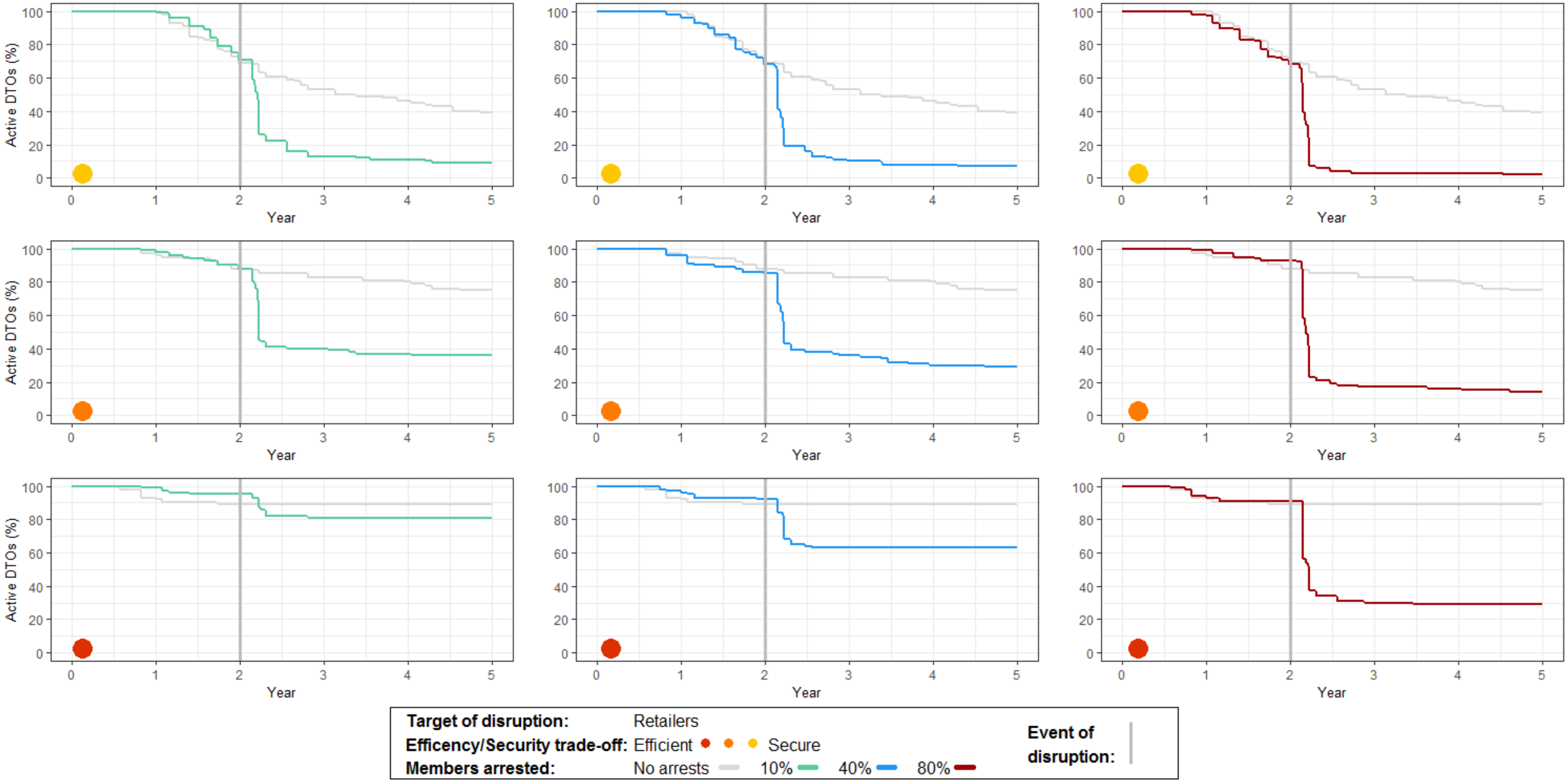
Graph 52. Share of active DTOs (Target of disruption: Packagers; Law enforcement int. scenario: 2)



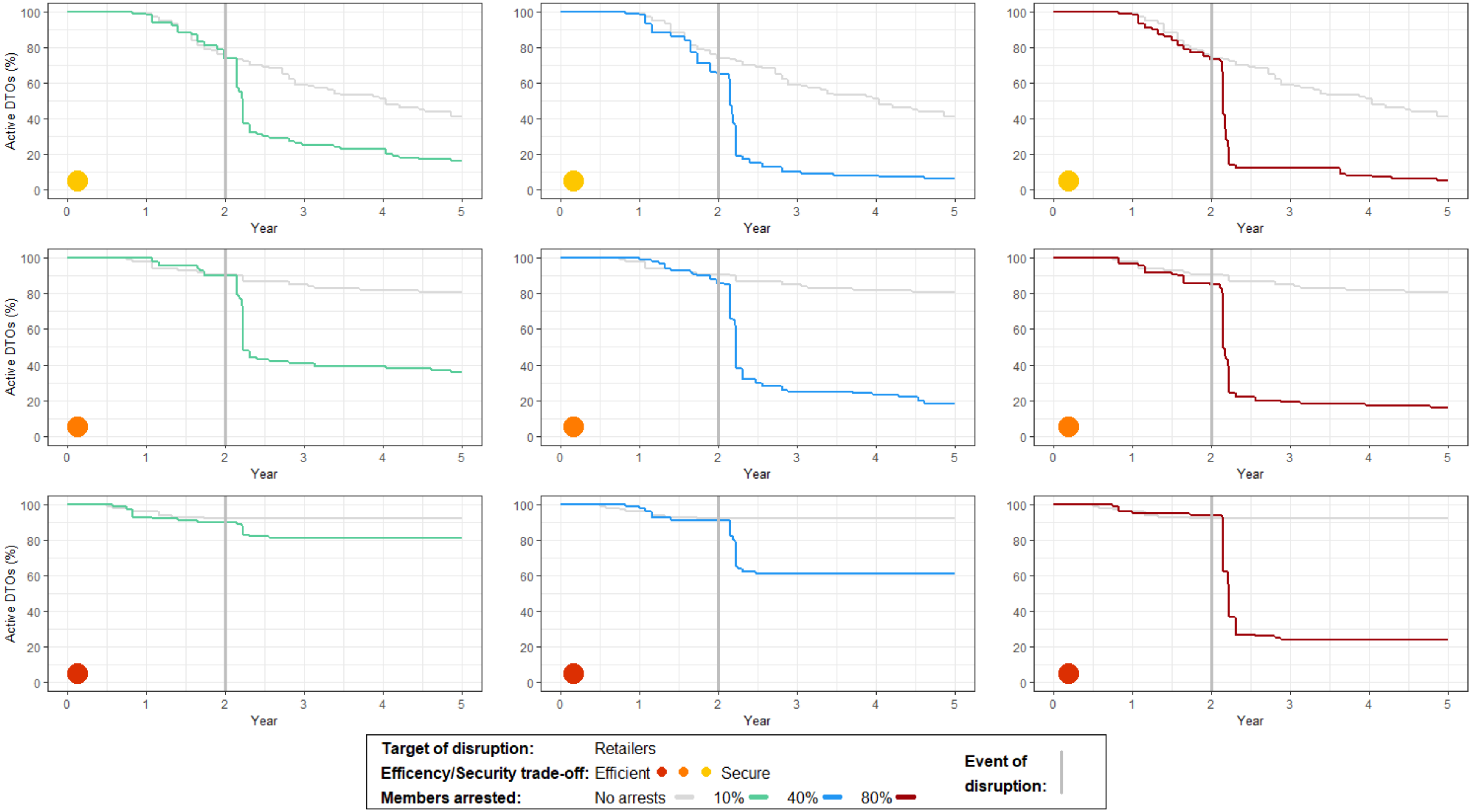
Graph 53. Share of active DTOs (Target of disruption: Packagers; Law enforcement int. scenario: 3)



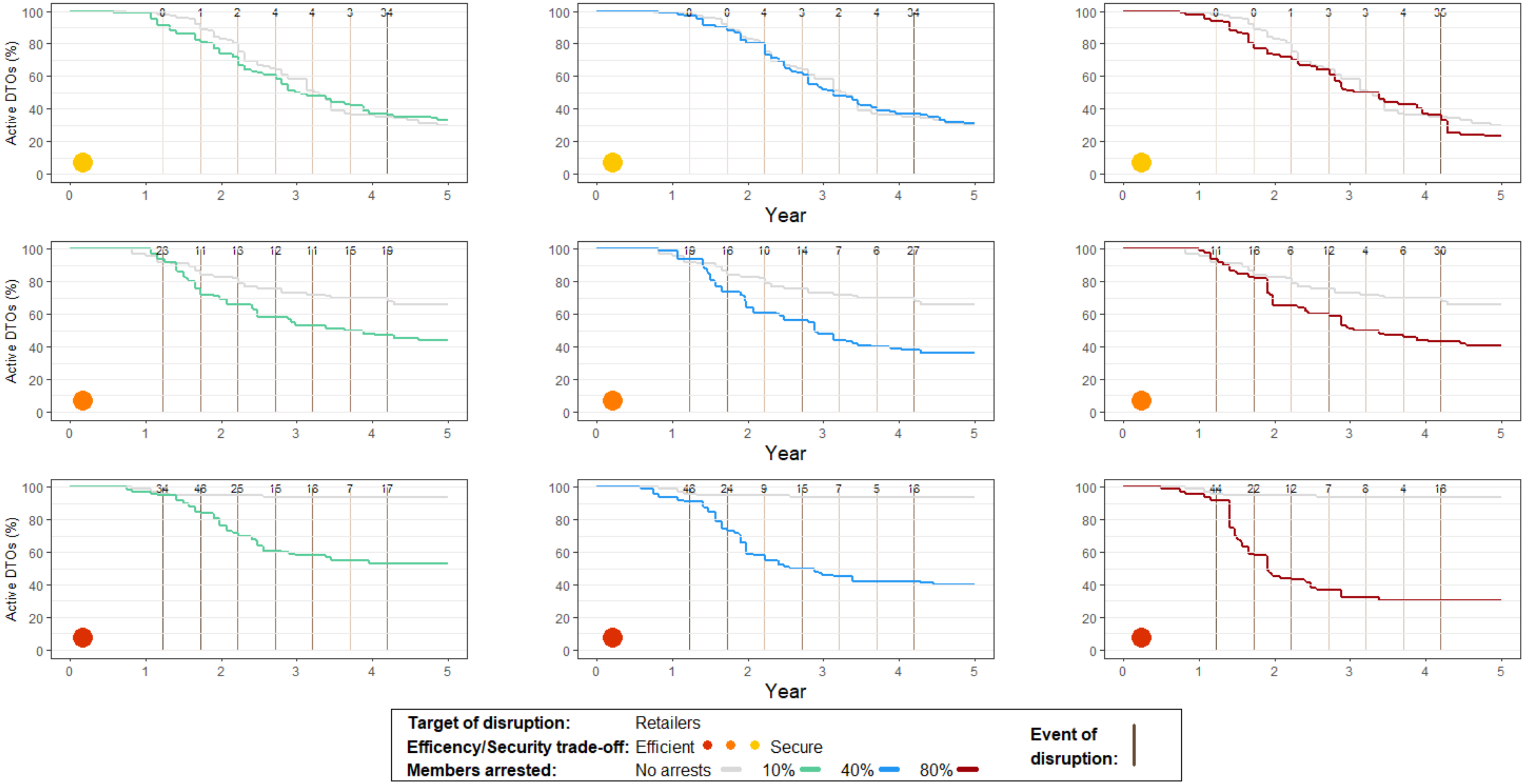
Graph 54. Share of active DTOs (Target of disruption: Retailers; Law enforcement int. scenario: 1)



Graph 55. Share of active DTOs (Target of disruption: Retailers; Law enforcement int. scenario: 2)

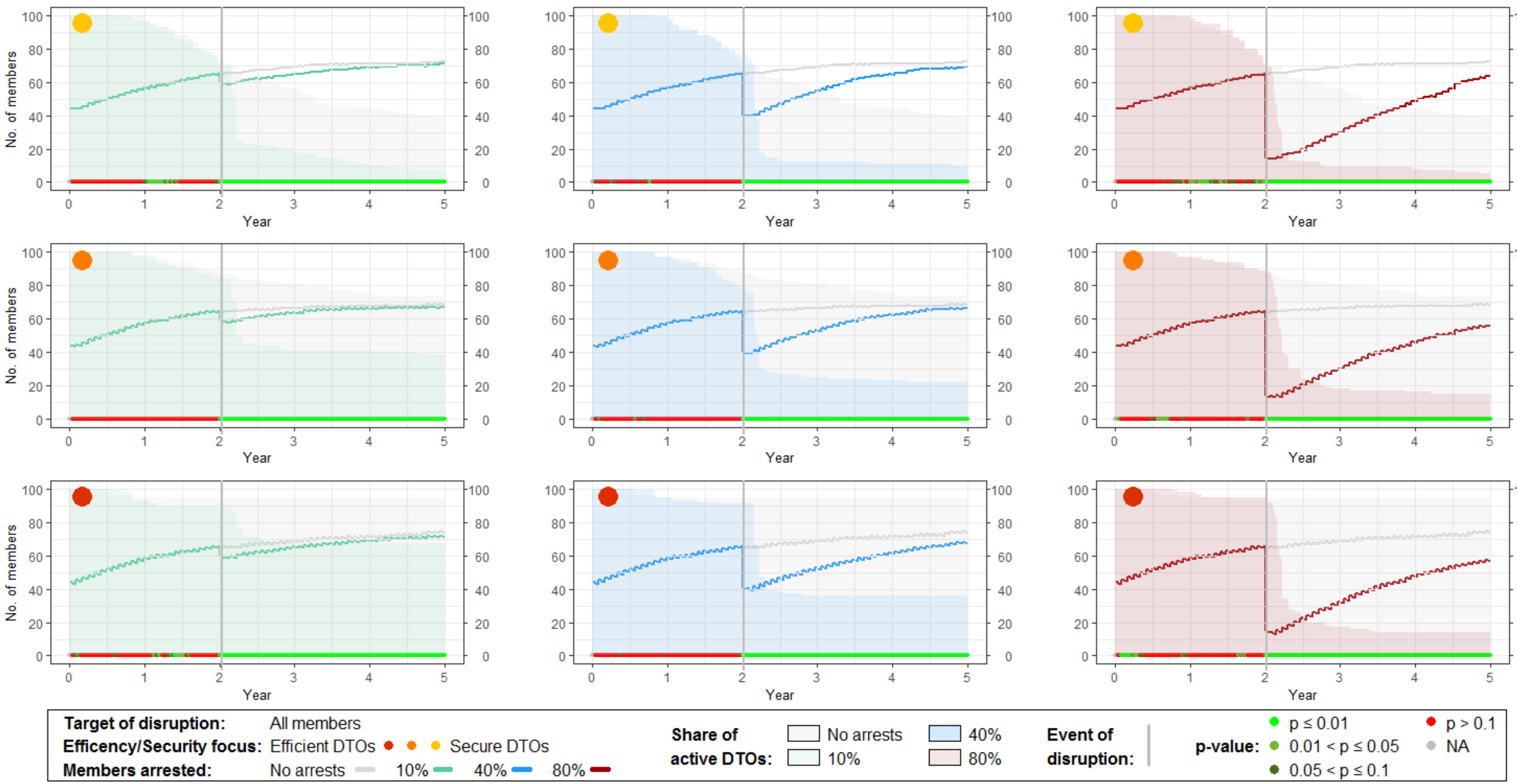


Graph 56. Share of active DTOs (Target of disruption: Retailers; Law enforcement int. scenario: 3)

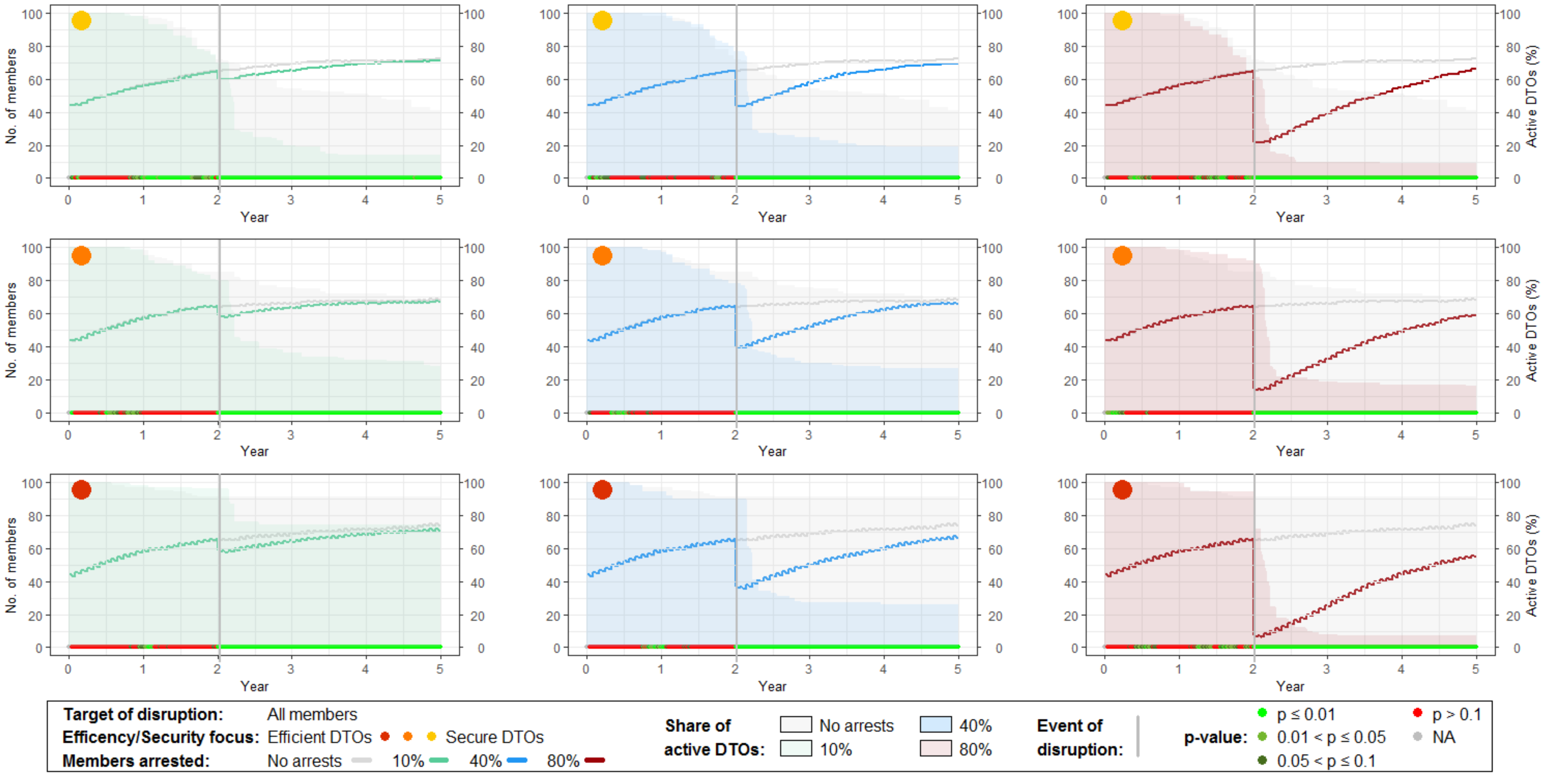


Number of DTOs members

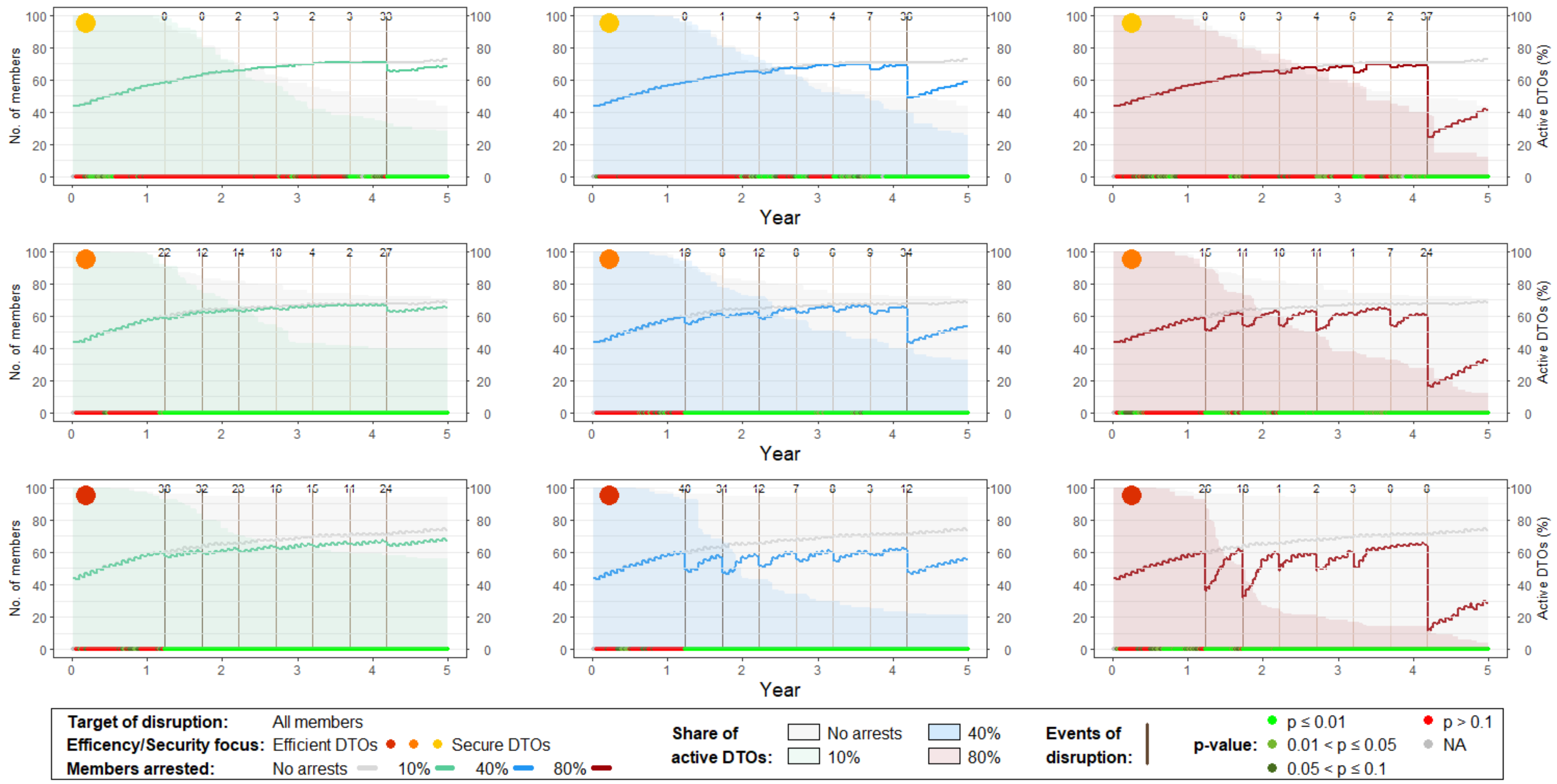
Graph 57. Number of DTOs members (Target of disruption: All members; Law enforcement int. scenario: 1)



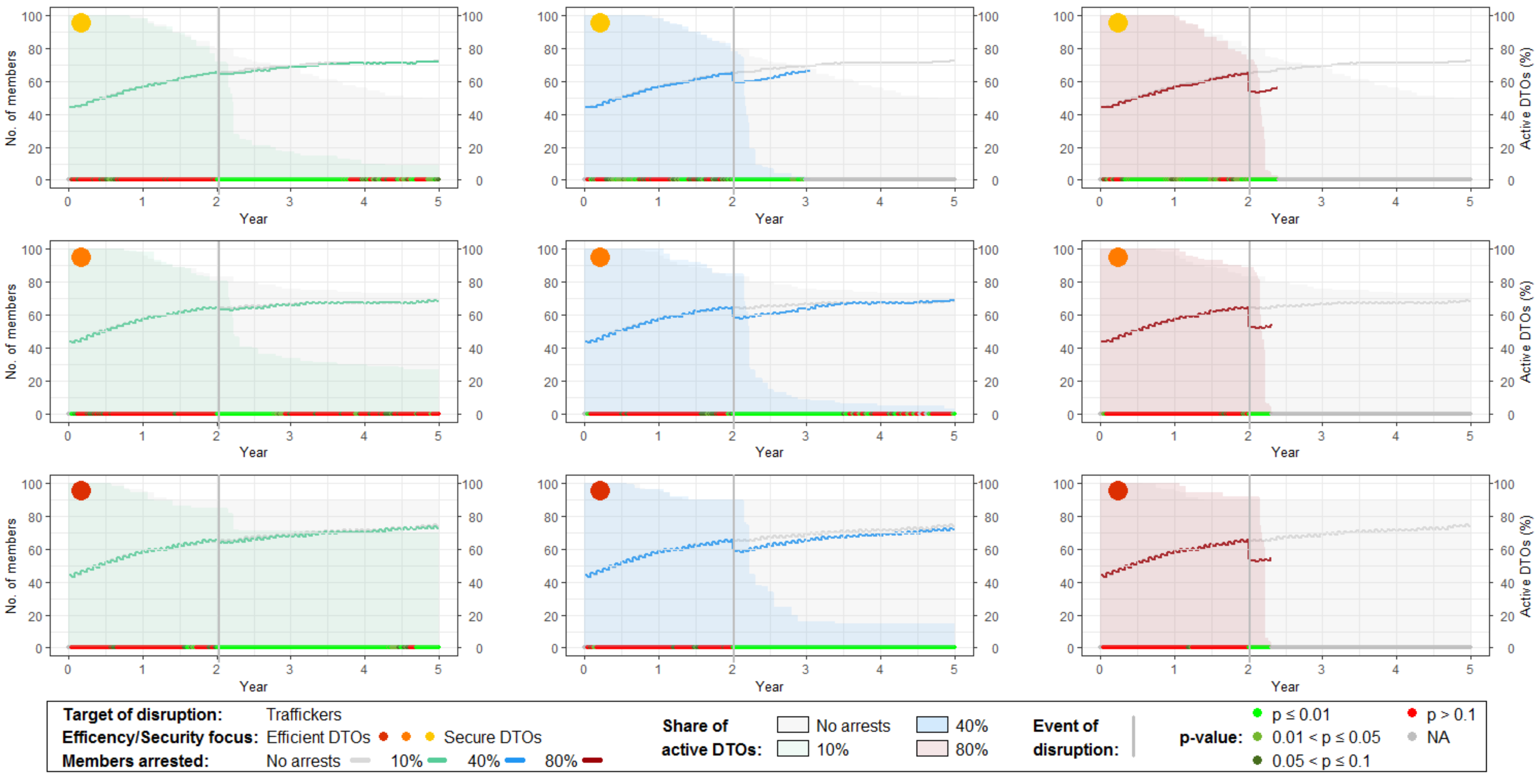
Graph 58. Number of DTOs members (Target of disruption: All members; Law enforcement int. scenario: 2)



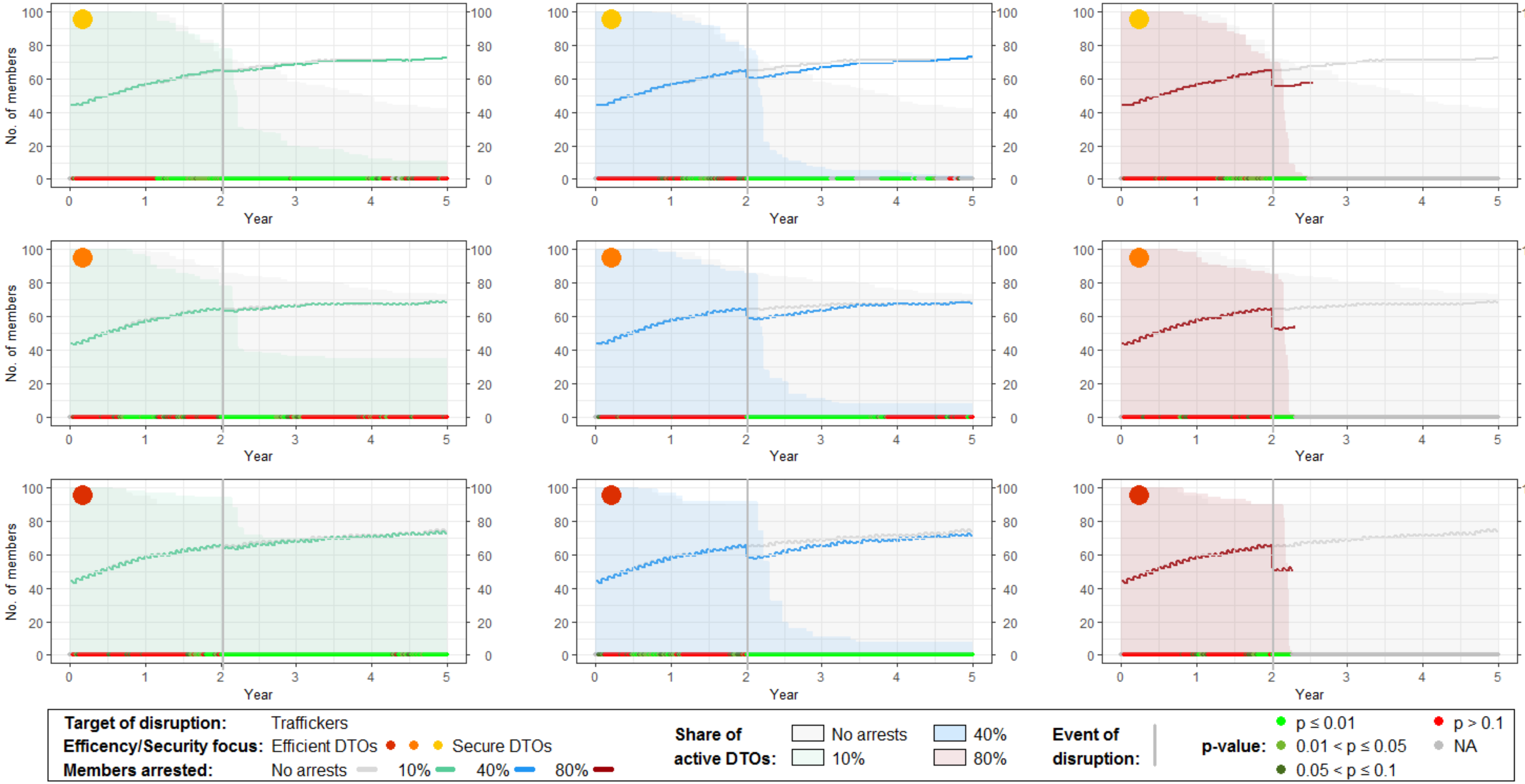
Graph 59. Number of DTOs members (Target of disruption: All members; Law enforcement int. scenario: 3)



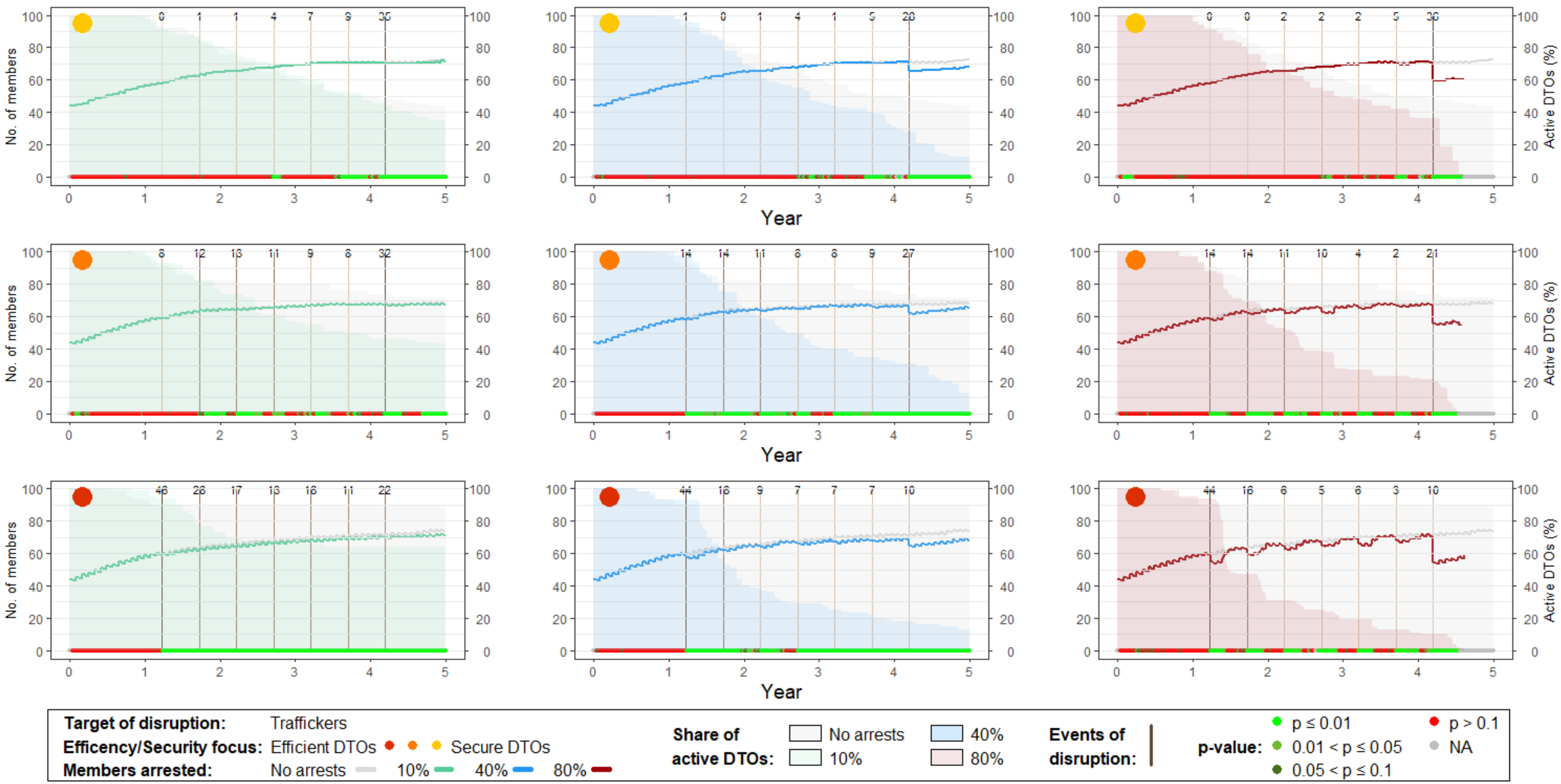
Graph 60. Number of DTOs members (Target of disruption: Traffickers; Law enforcement int. scenario: 1)



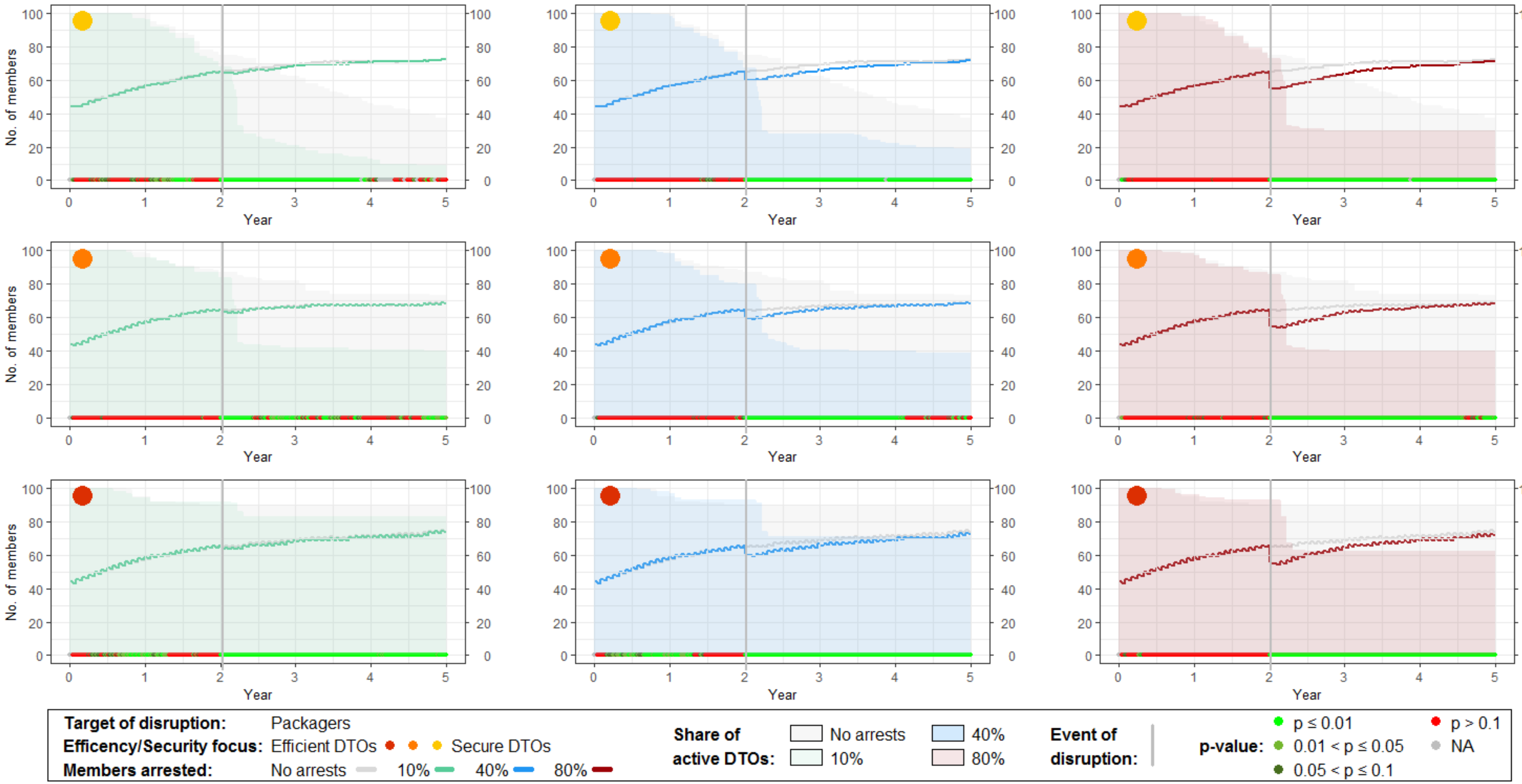
Graph 61. Number of DTOs members (Target of disruption: Traffickers; Law enforcement int. scenario: 2)



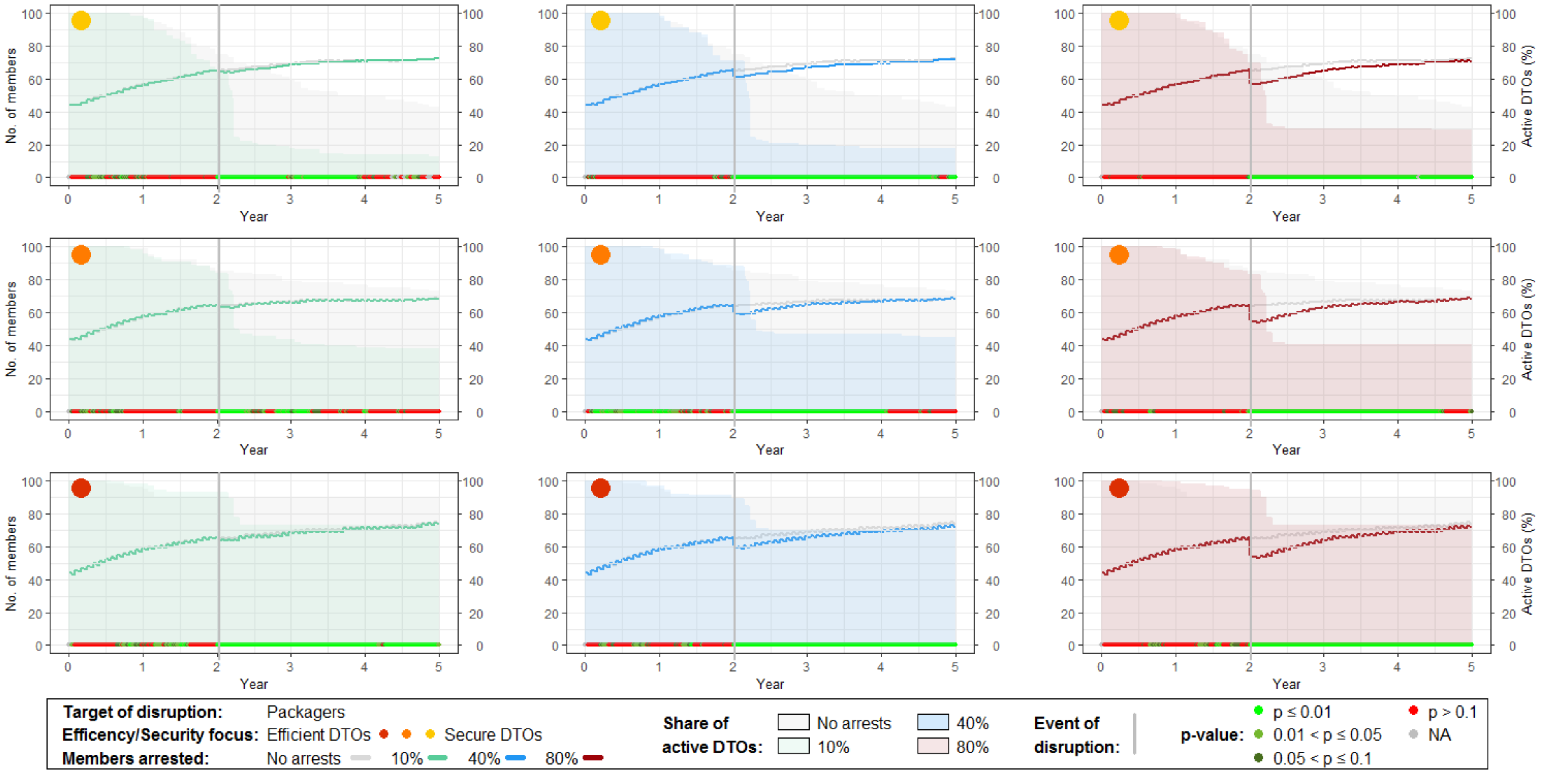
Graph 62. Number of DTOs members (Target of disruption: Traffickers; Law enforcement int. scenario: 3)



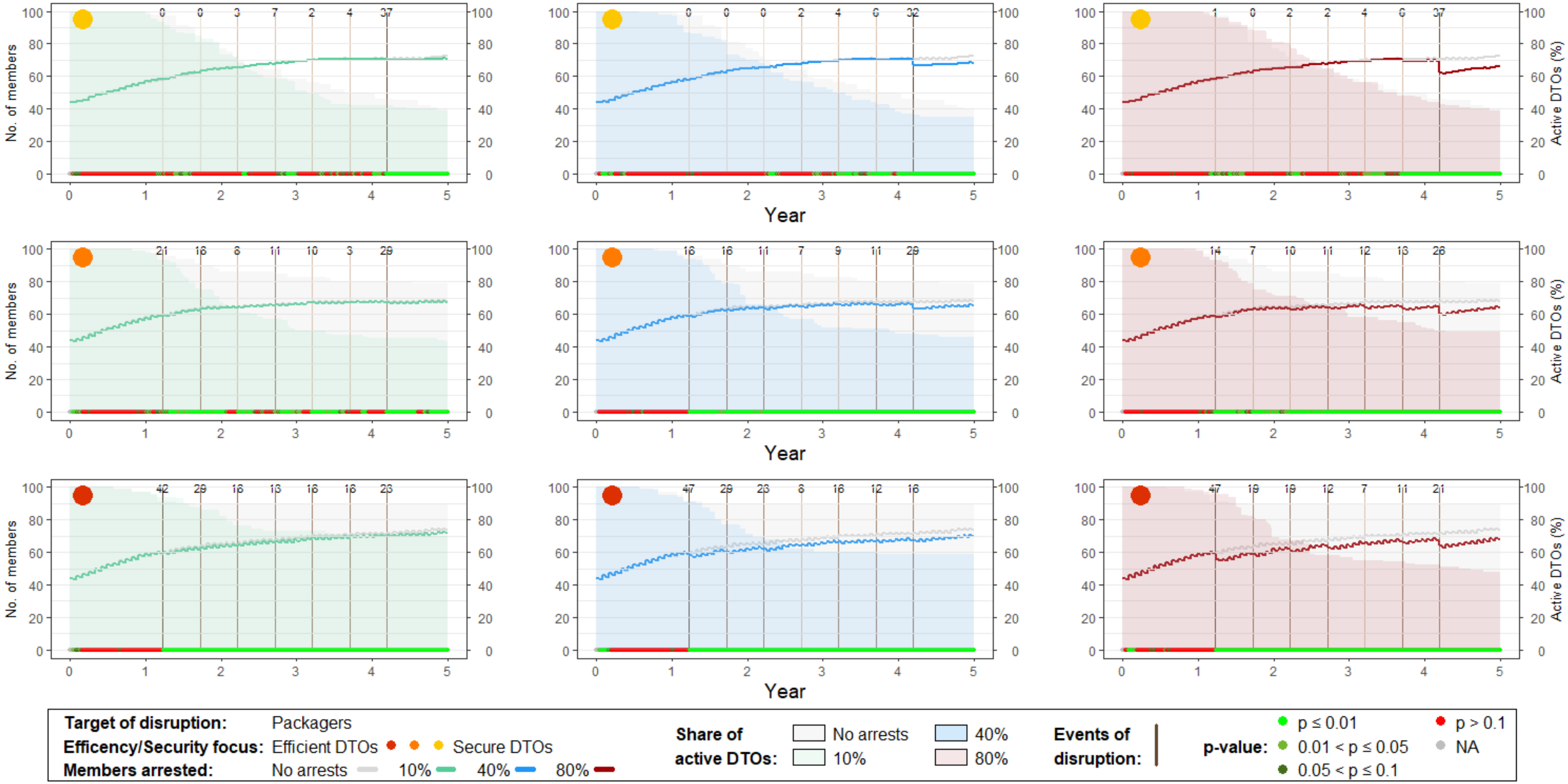
Graph 63. Number of DTOs members (Target of disruption: Packagers; Law enforcement int. scenario: 1)



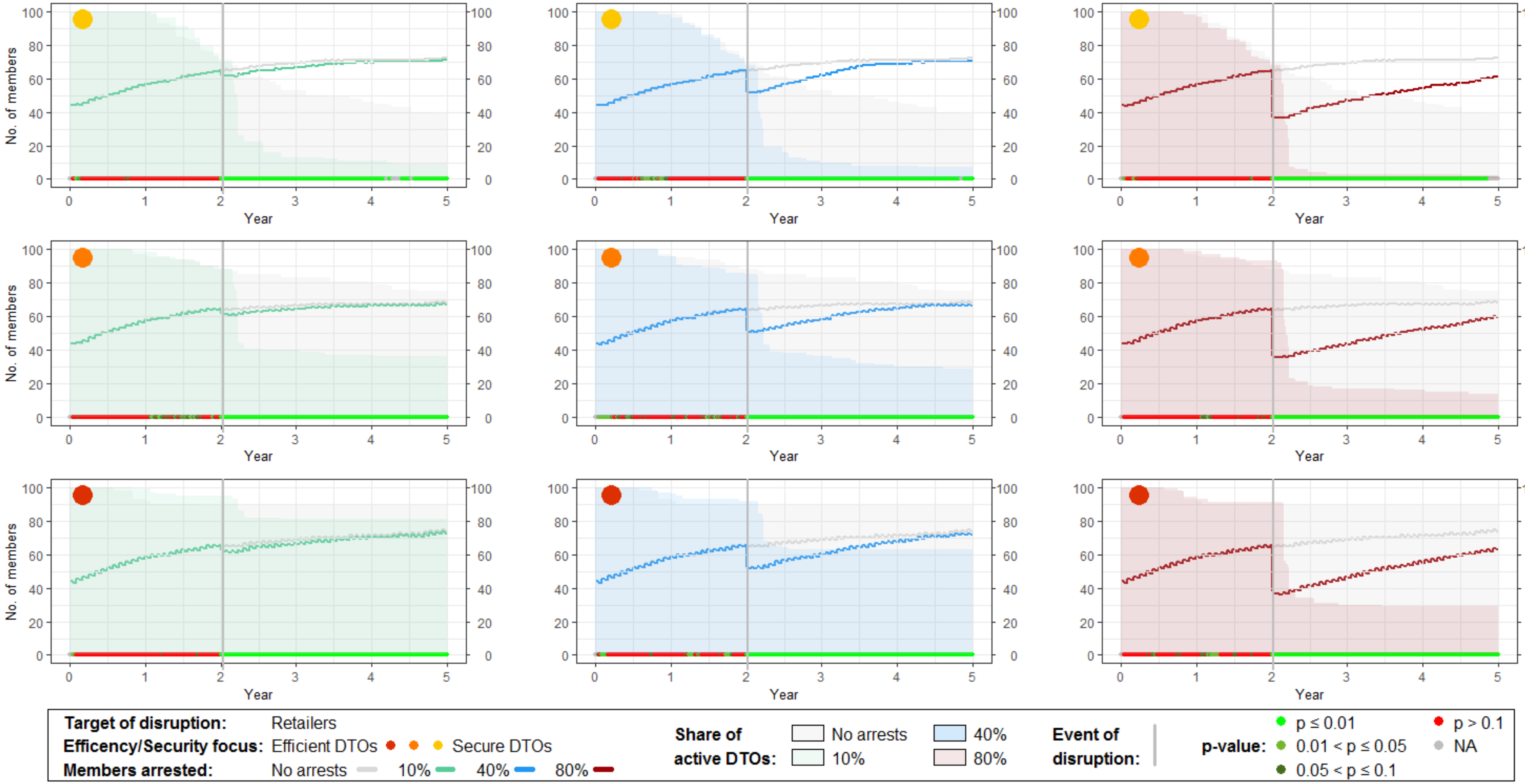
Graph 64. Number of DTOs members (Target of disruption: Packagers; Law enforcement int. scenario: 2)



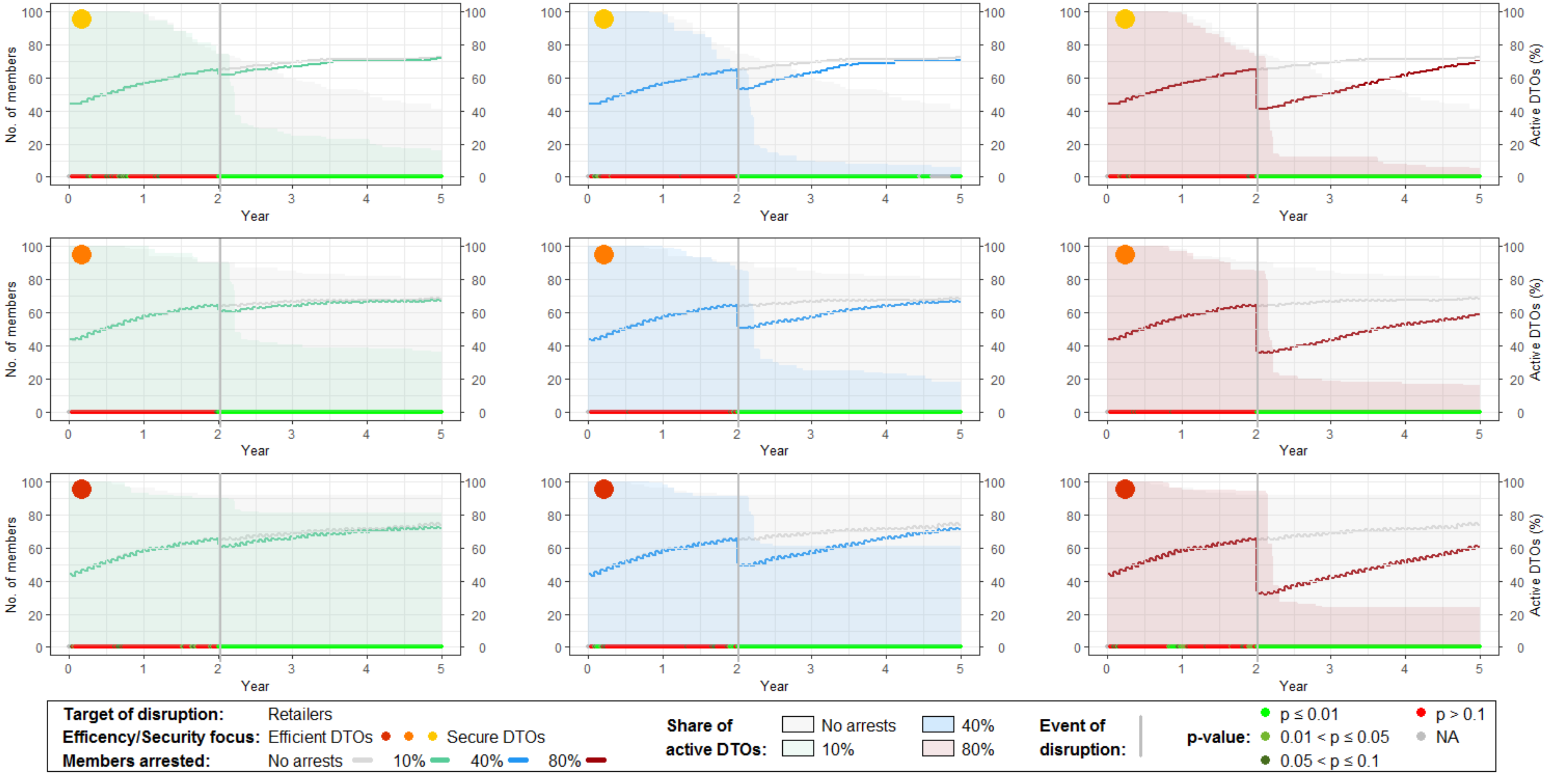
Graph 65. Number of DTOs members (Target of disruption: Packagers; Law enforcement int. scenario: 3)



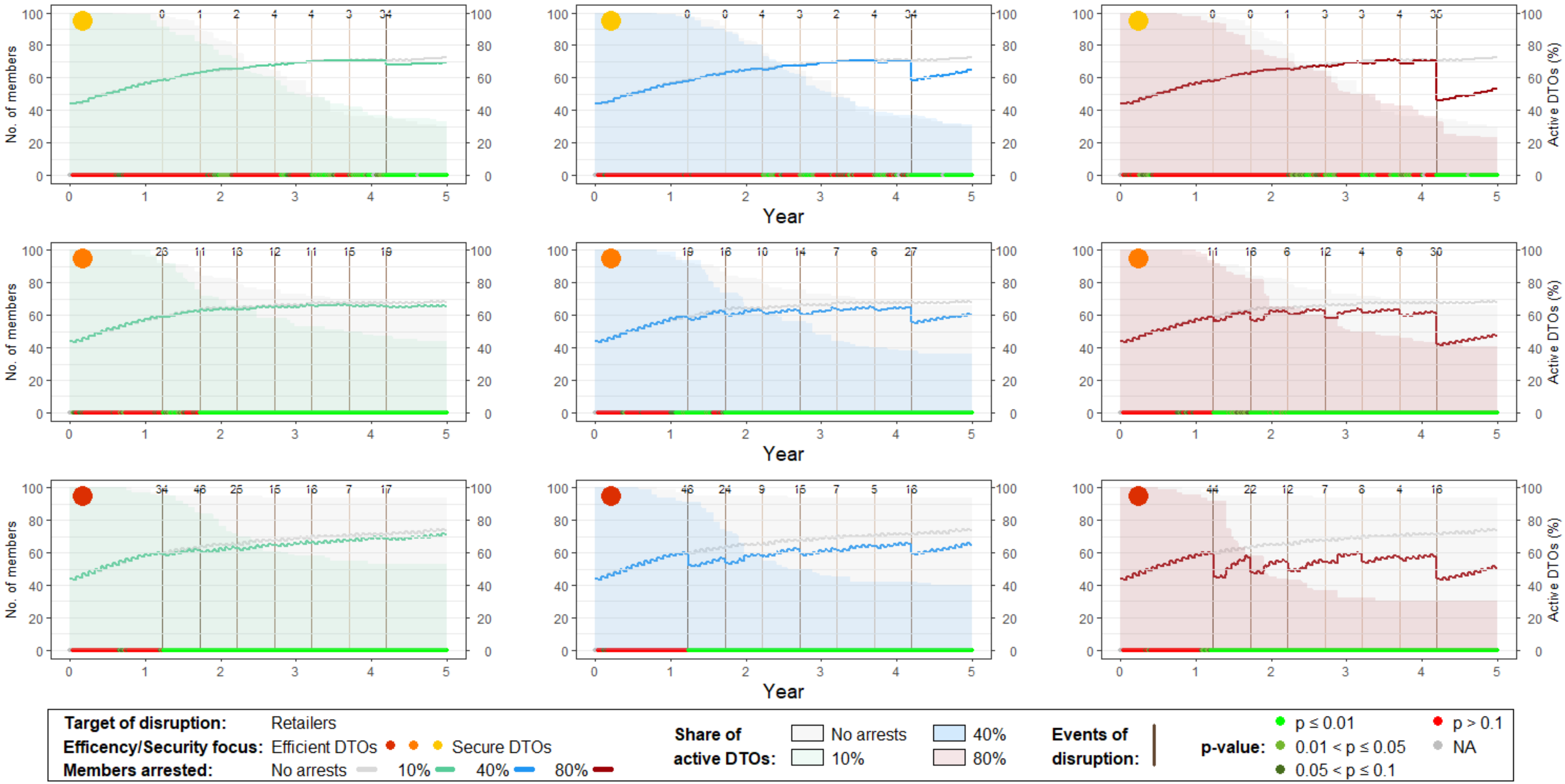
Graph 66. Number of DTOs members (Target of disruption: Retailers; Law enforcement int. scenario: 1)



Graph 67. Number of DTOs members (Target of disruption: Retailers; Law enforcement int. scenario: 2)

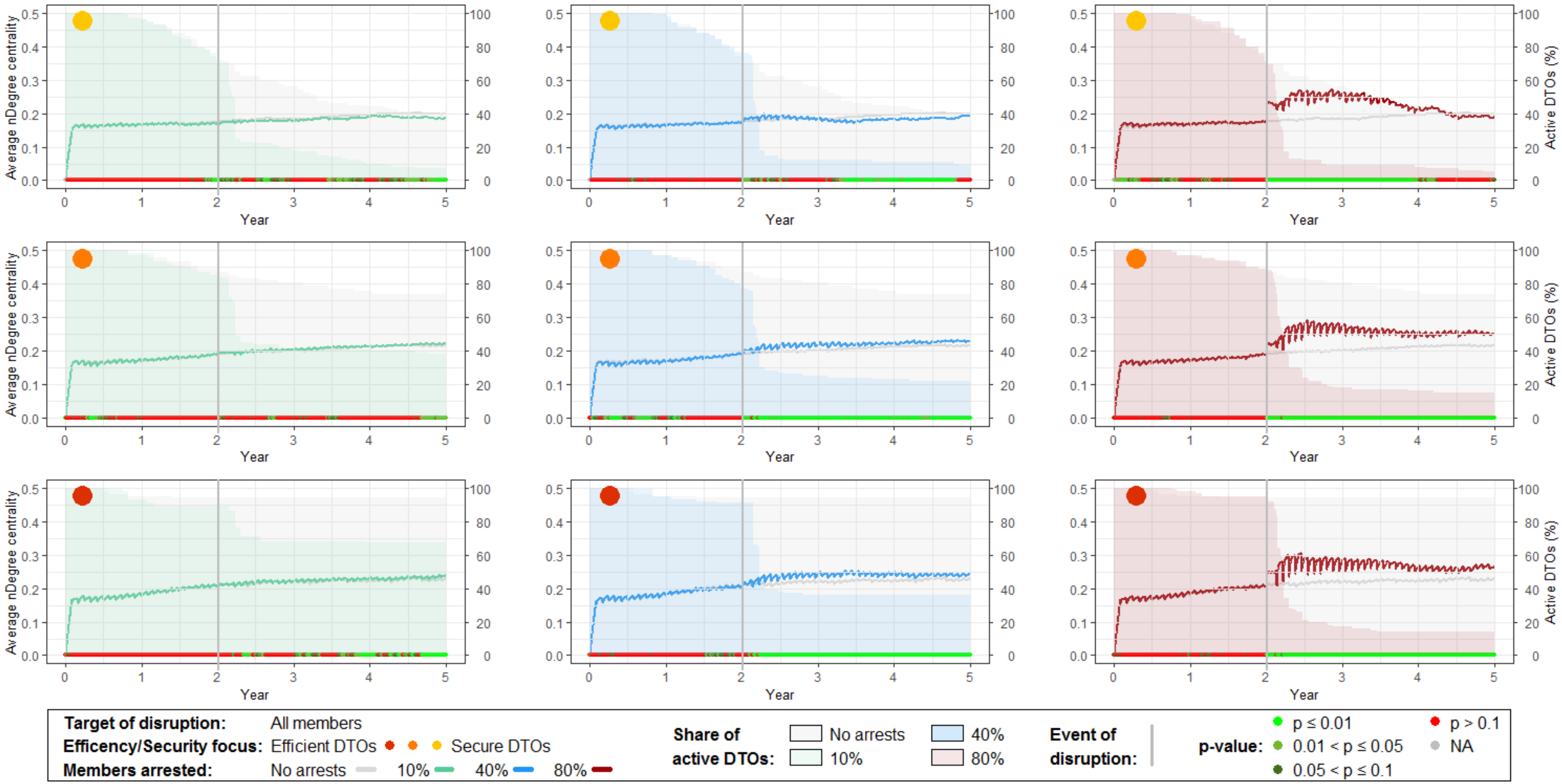


Graph 68. Number of DTOs members (Target of disruption: Retailers; Law enforcement int. scenario: 3)

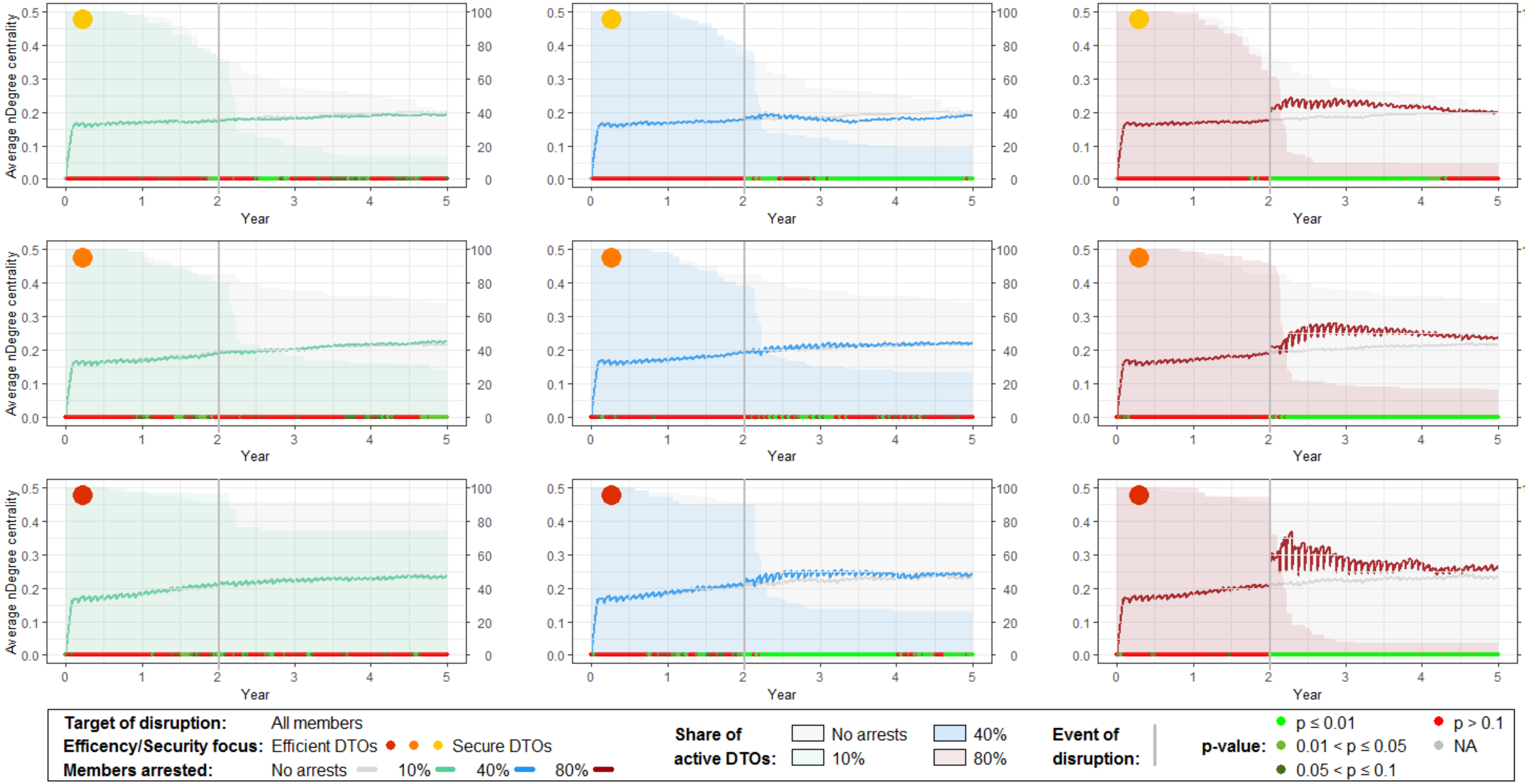


DTOs members average normalized degree centrality

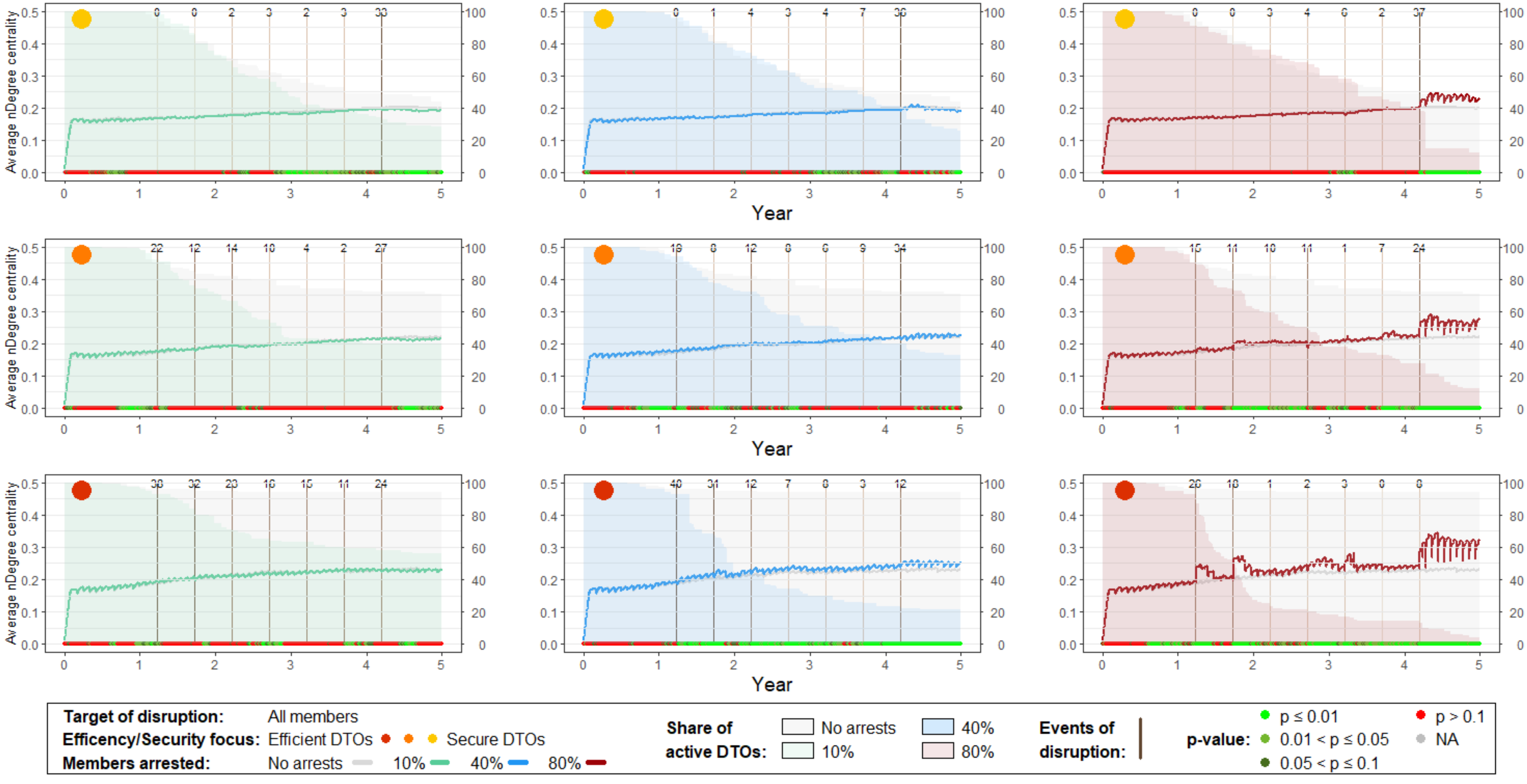
Graph 69. DTOs members average normalized degree centrality (Target of disruption: All members; Law enforcement int. scenario: 1)



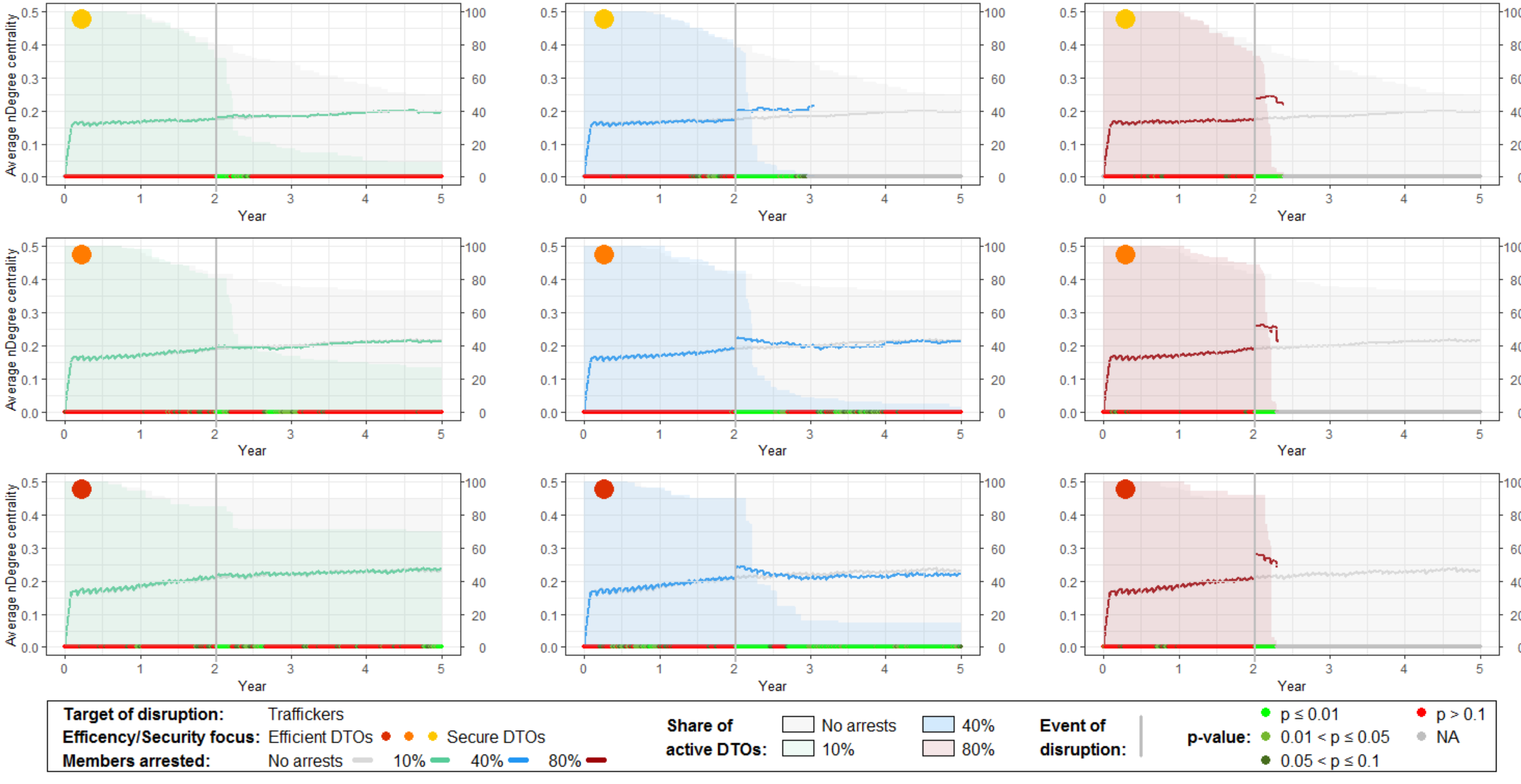
Graph 70. DTOs members average normalized degree centrality (Target of disruption: All members; Law enforcement int. scenario: 2)



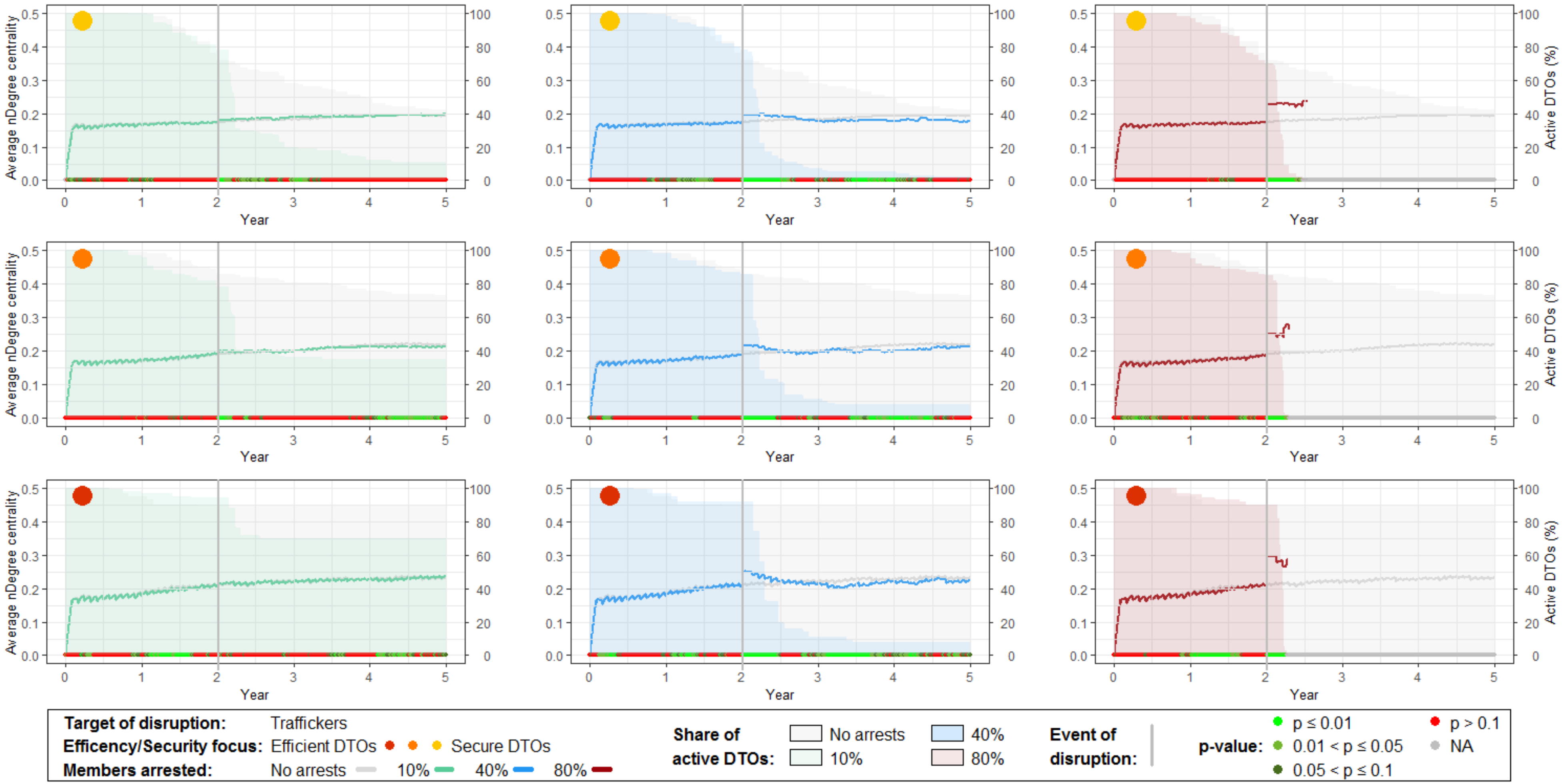
Graph 71. DTOs members average normalized degree centrality (Target of disruption: All members; Law enforcement int. scenario: 3)



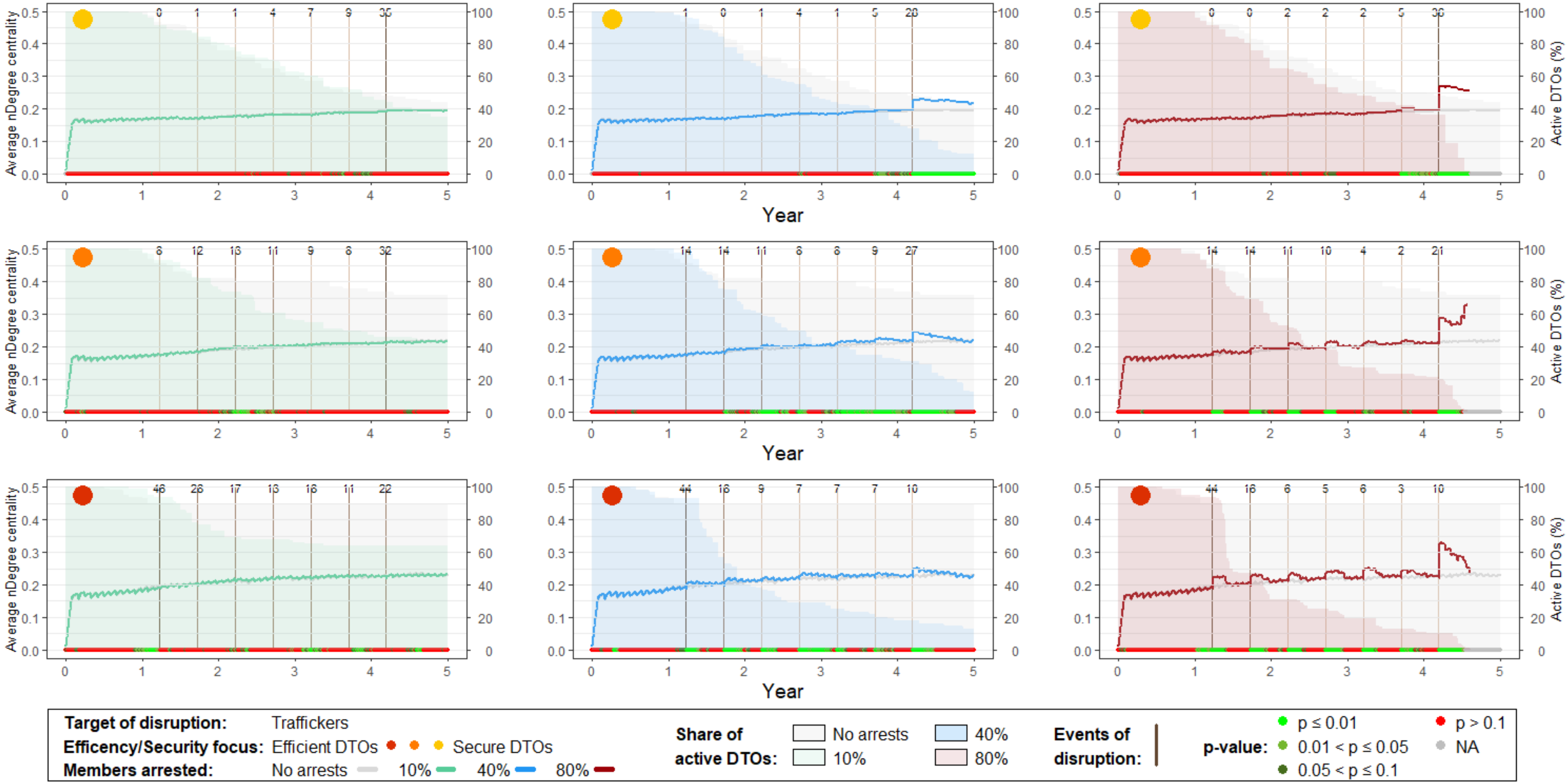
Graph 72. DTOs members average normalized degree centrality (Target of disruption: Traffickers; Law enforcement int. scenario: 1)



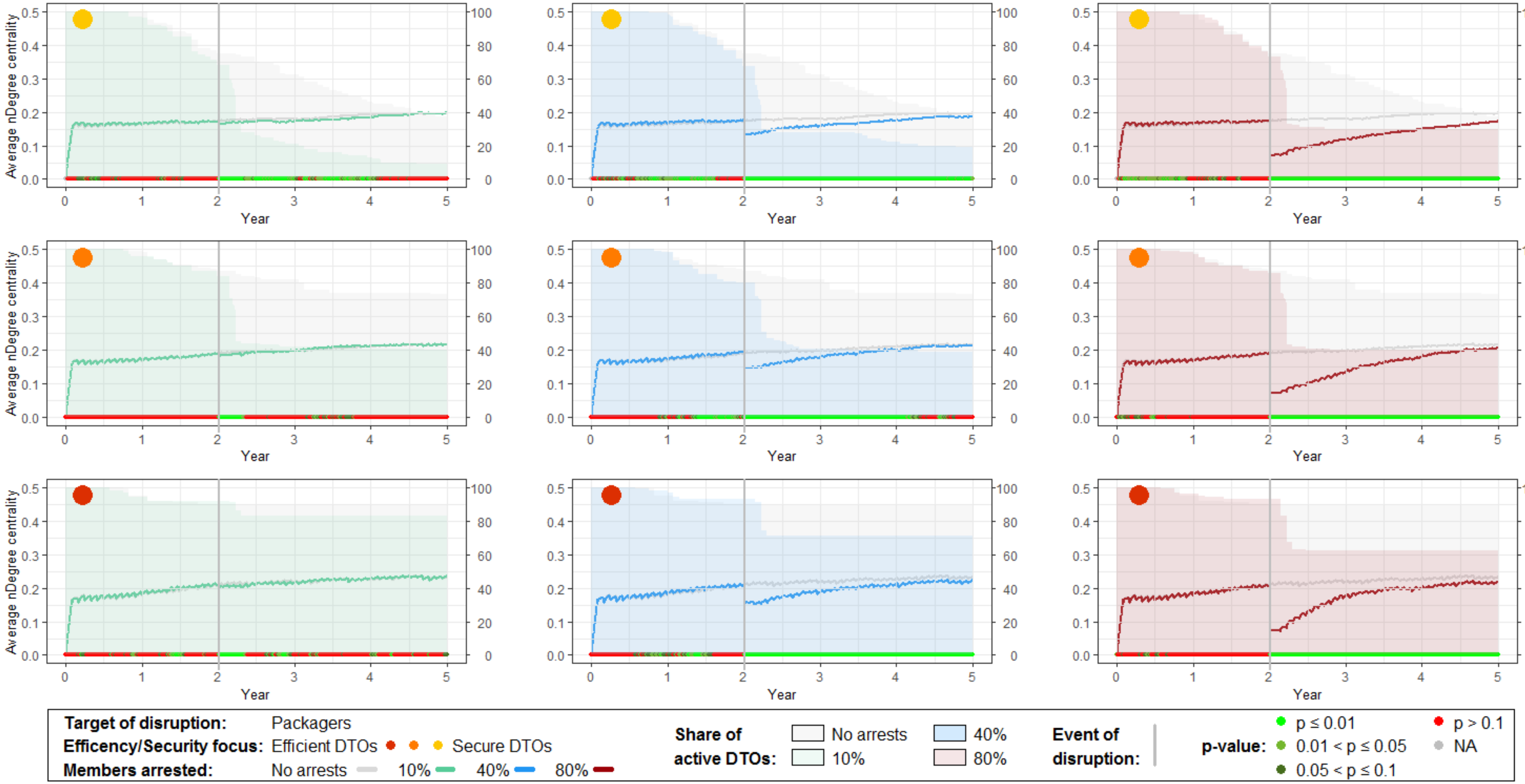
Graph 73. DTOs members average normalized degree centrality (Target of disruption: Traffickers; Law enforcement int. scenario: 2)



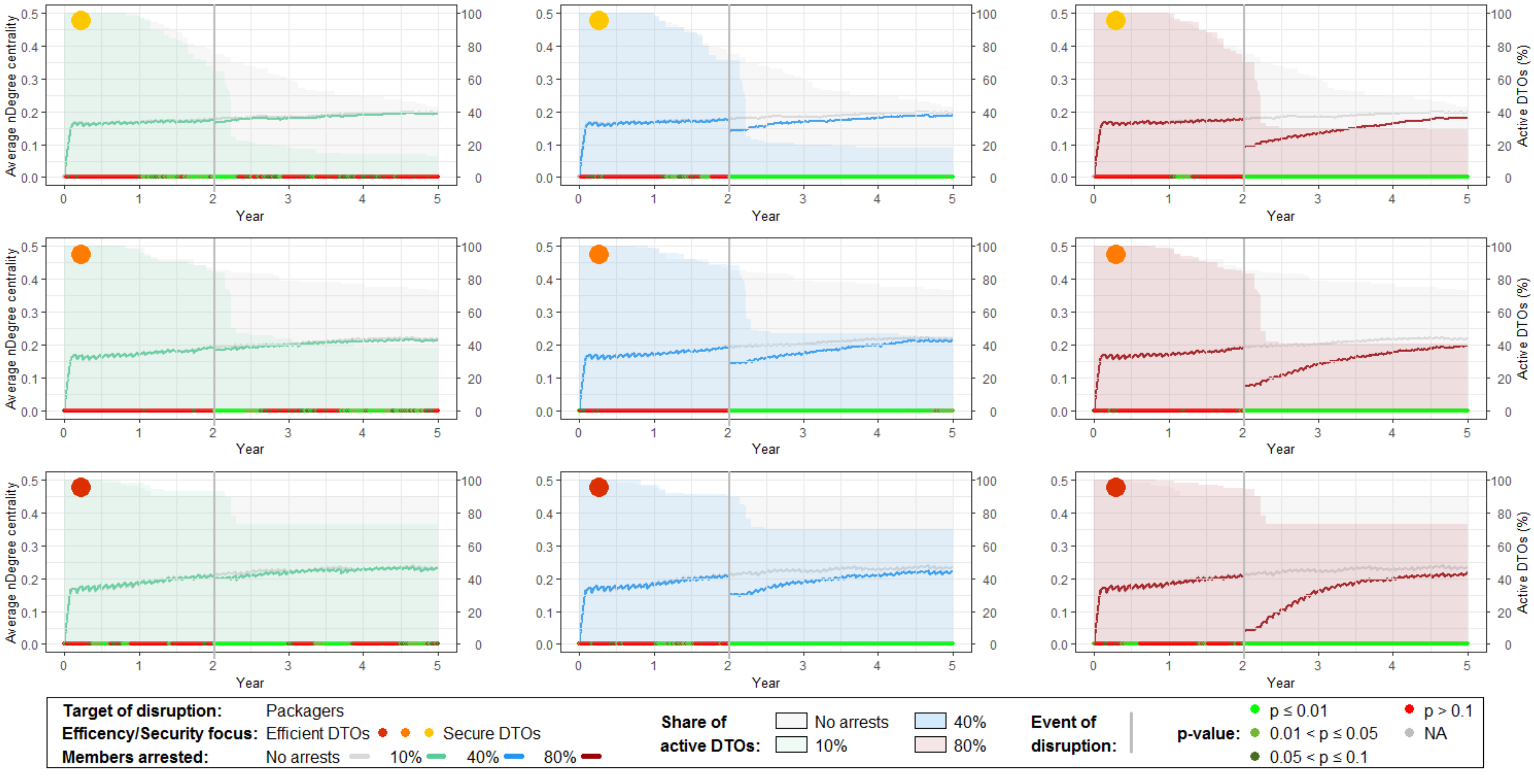
Graph 74. DTOs members average normalized degree centrality (Target of disruption: Traffickers; Law enforcement int. scenario: 3)



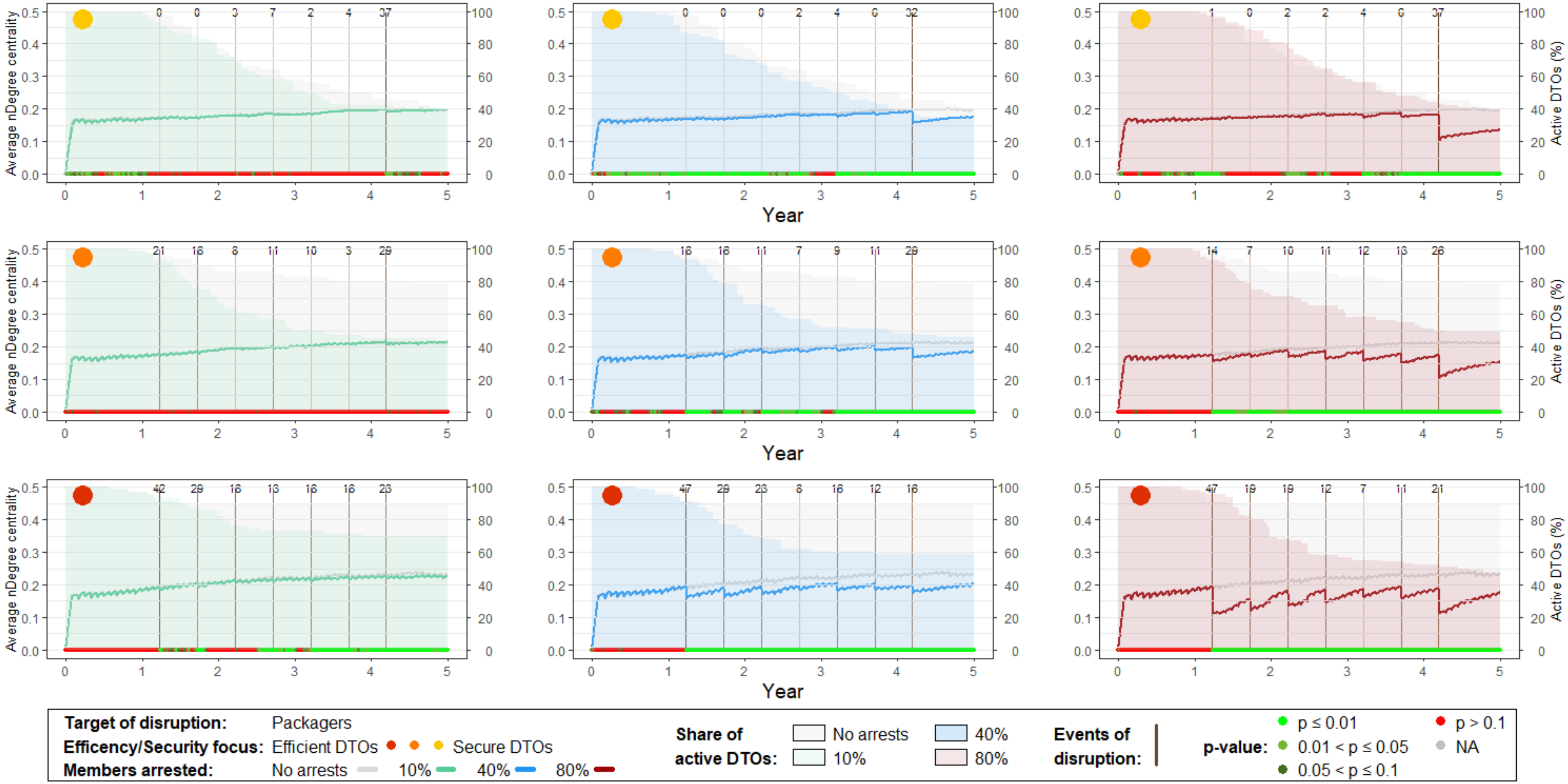
Graph 75. DTOs members average normalized degree centrality (Target of disruption: Packagers; Law enforcement int. scenario: 1)



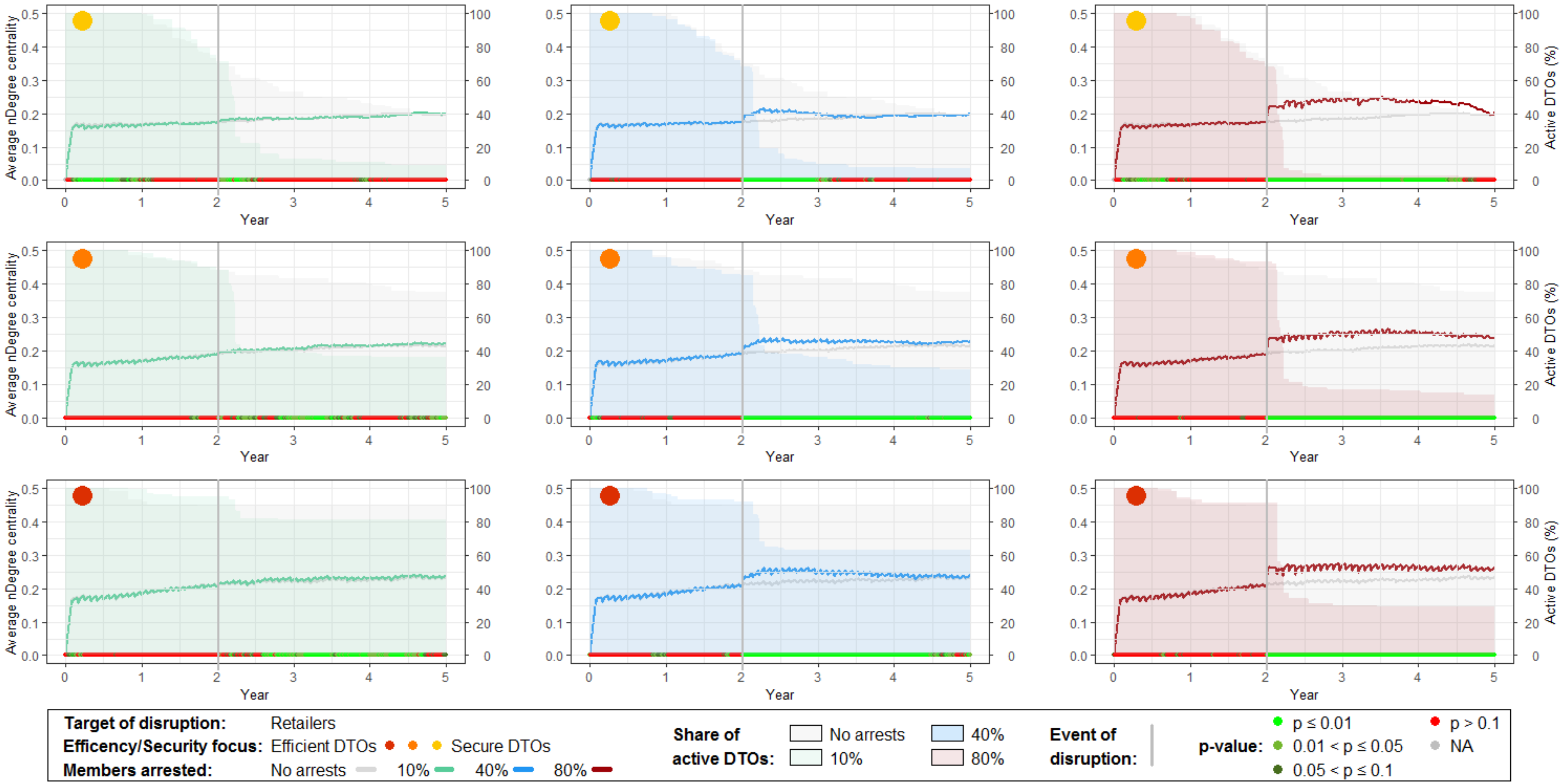
Graph 76. DTOs members average normalized degree centrality (Target of disruption: Packagers; Law enforcement int. scenario: 2)



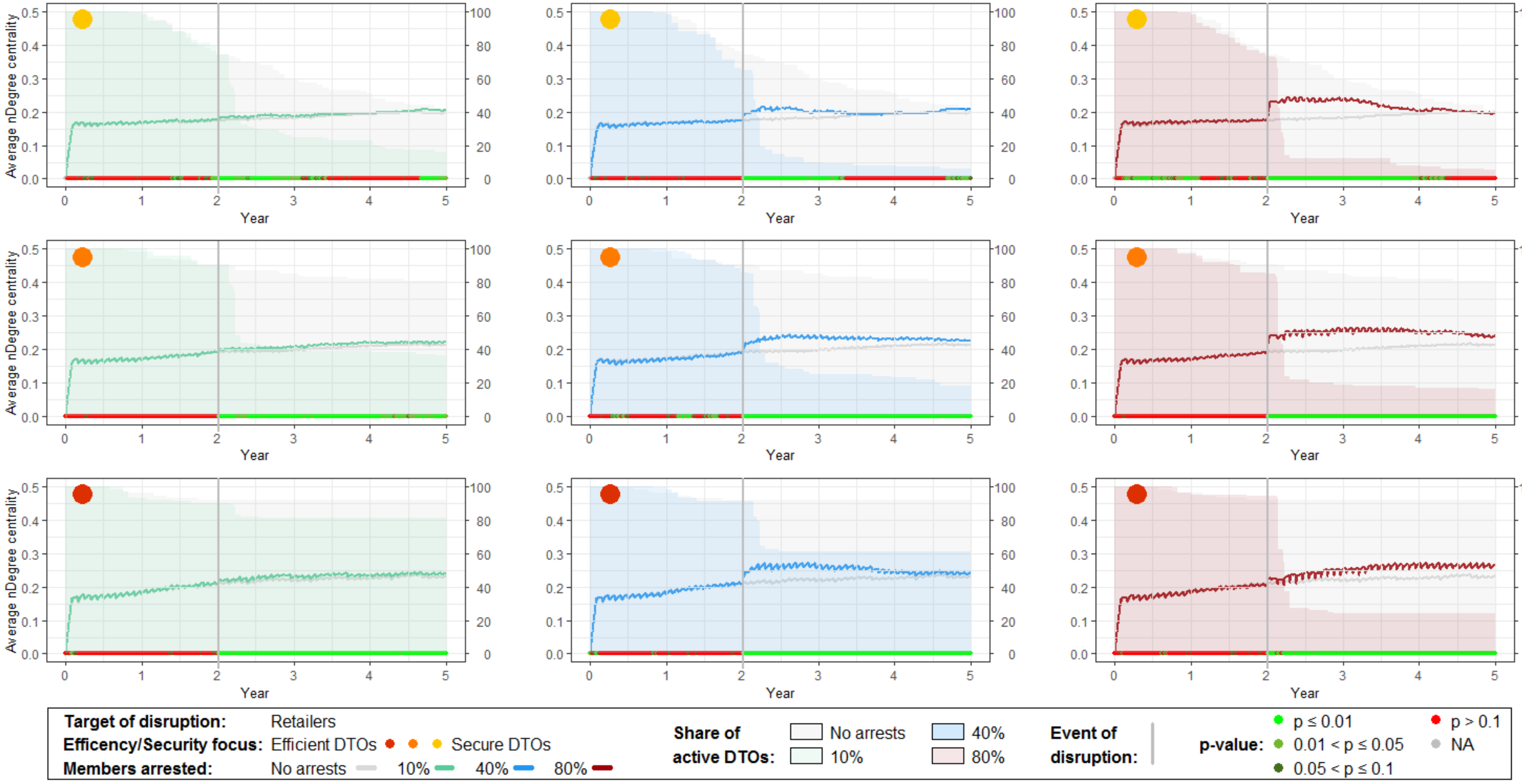
Graph 77. DTOs members average normalized degree centrality (Target of disruption: Packagers; Law enforcement int. scenario: 3)



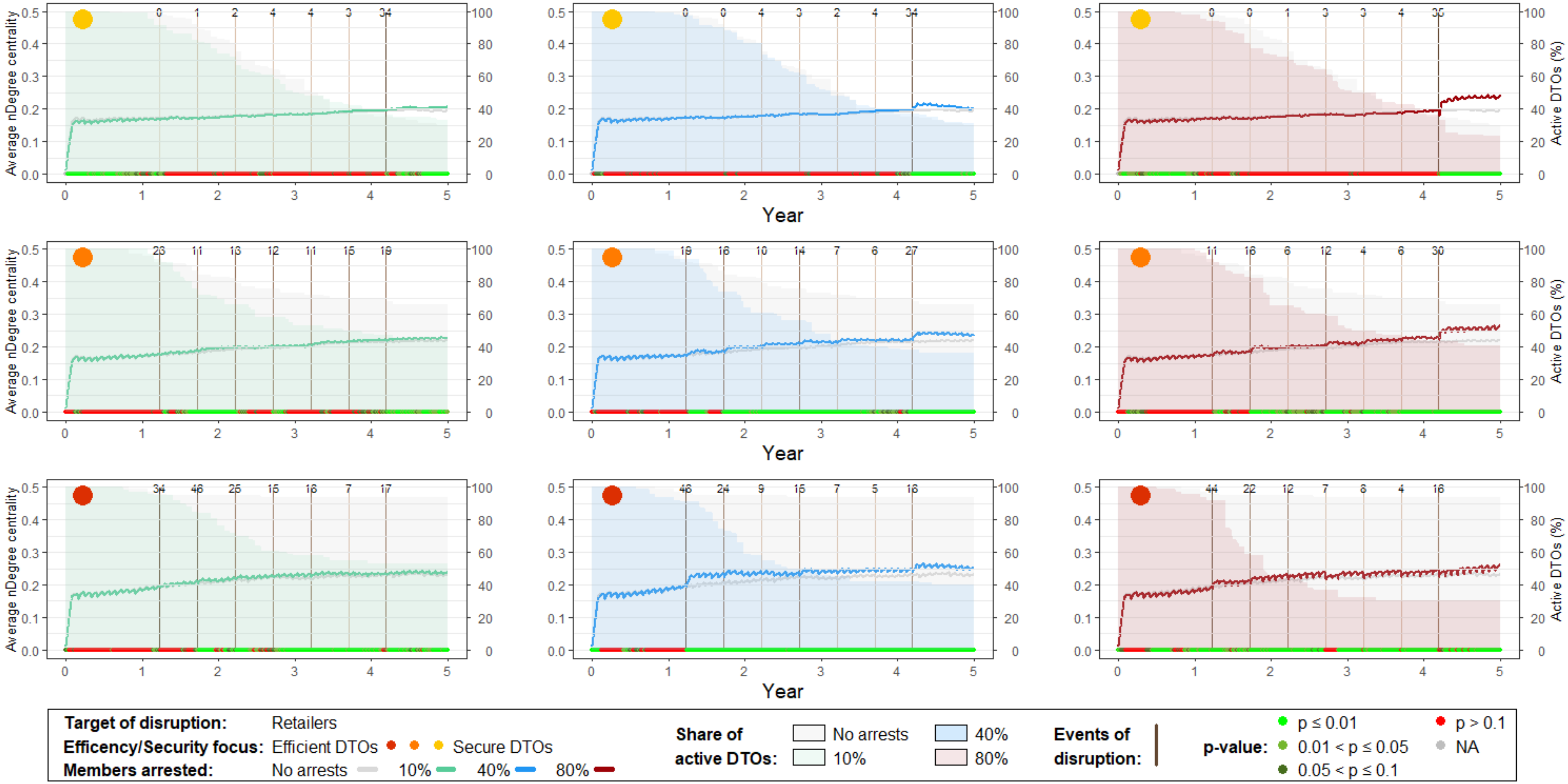
Graph 78. DTOs members average normalized degree centrality (Target of disruption: Retailers; Law enforcement int. scenario: 1)



Graph 79. DTOs members average normalized degree centrality (Target of disruption: Retailers; Law enforcement int. scenario: 2)

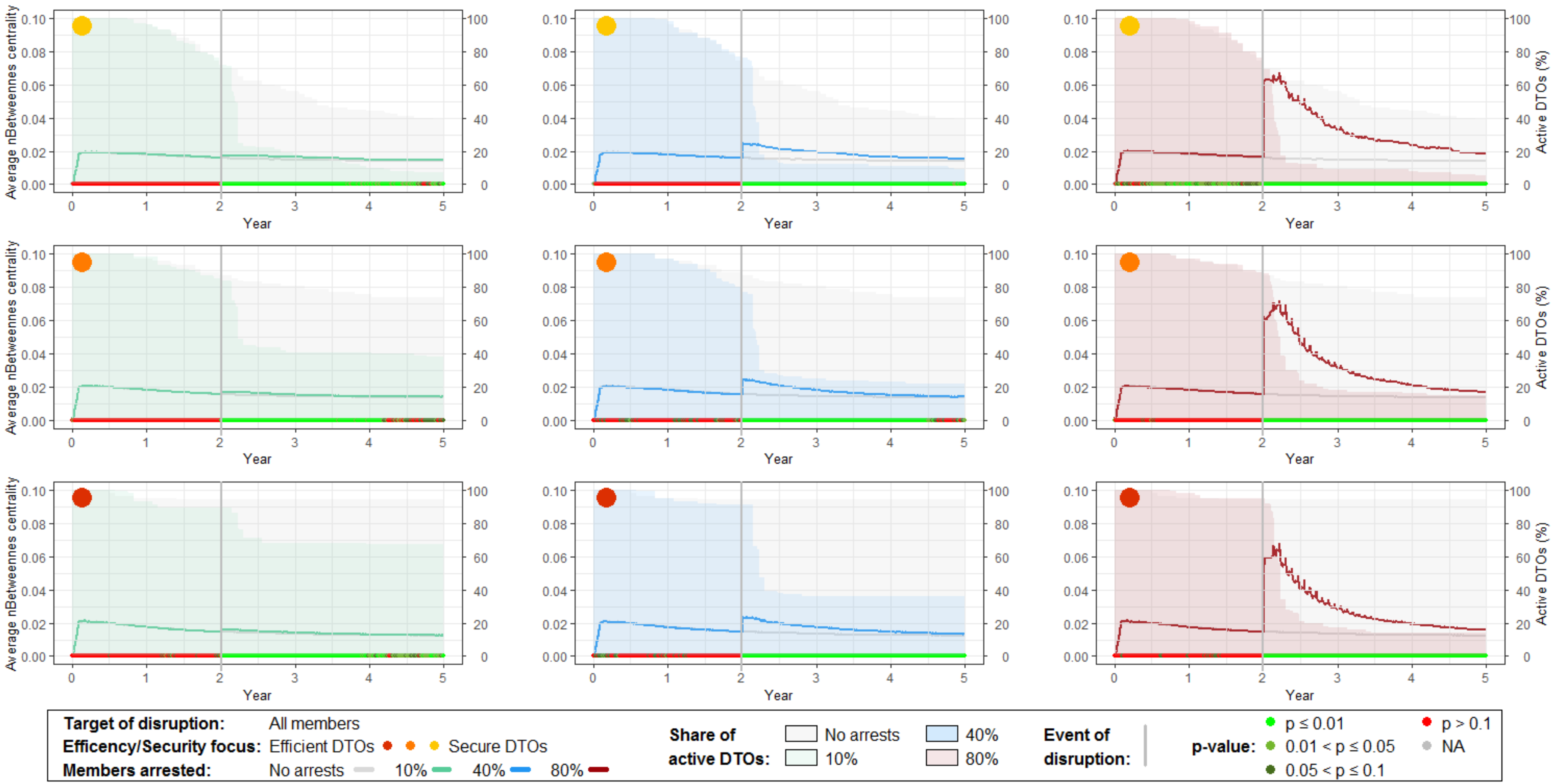


Graph 80. DTOs members average normalized degree centrality (Target of disruption: Retailers; Law enforcement int. scenario: 3)

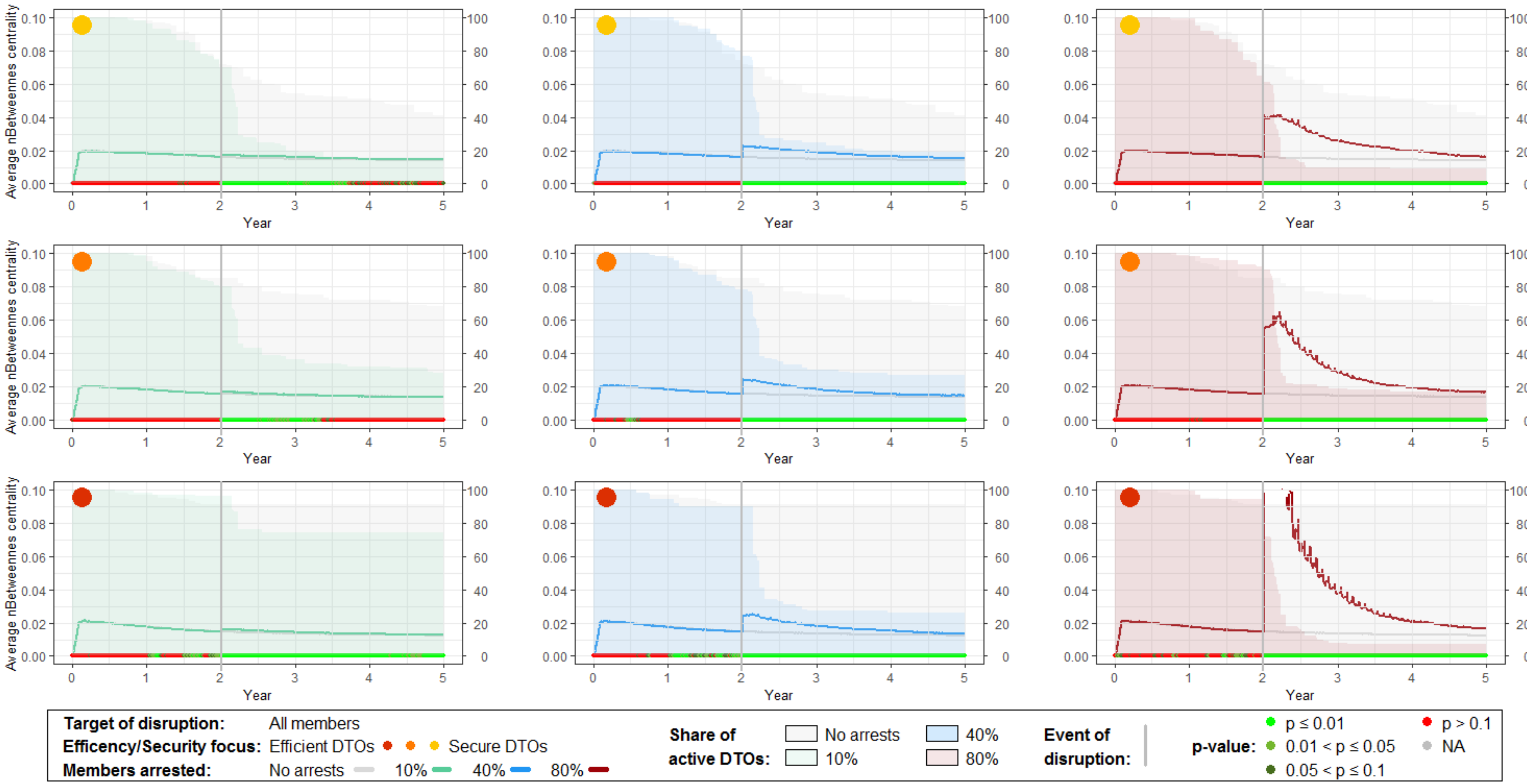


DTOs members average normalized betweenness centrality

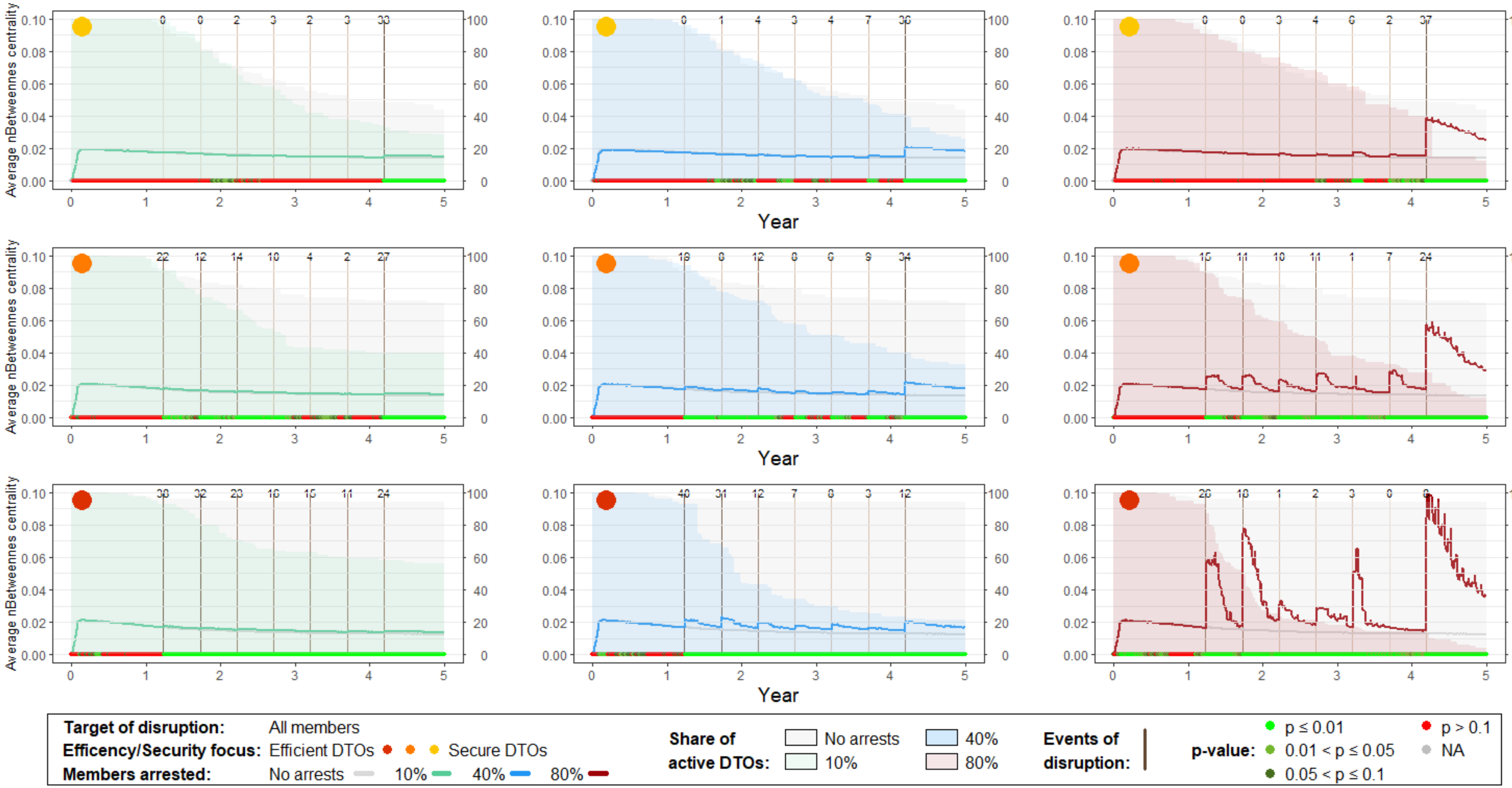
Graph 81. DTOs members average normalized betweenness centrality (Target of disruption: All; Law enforcement int. scenario: 1)



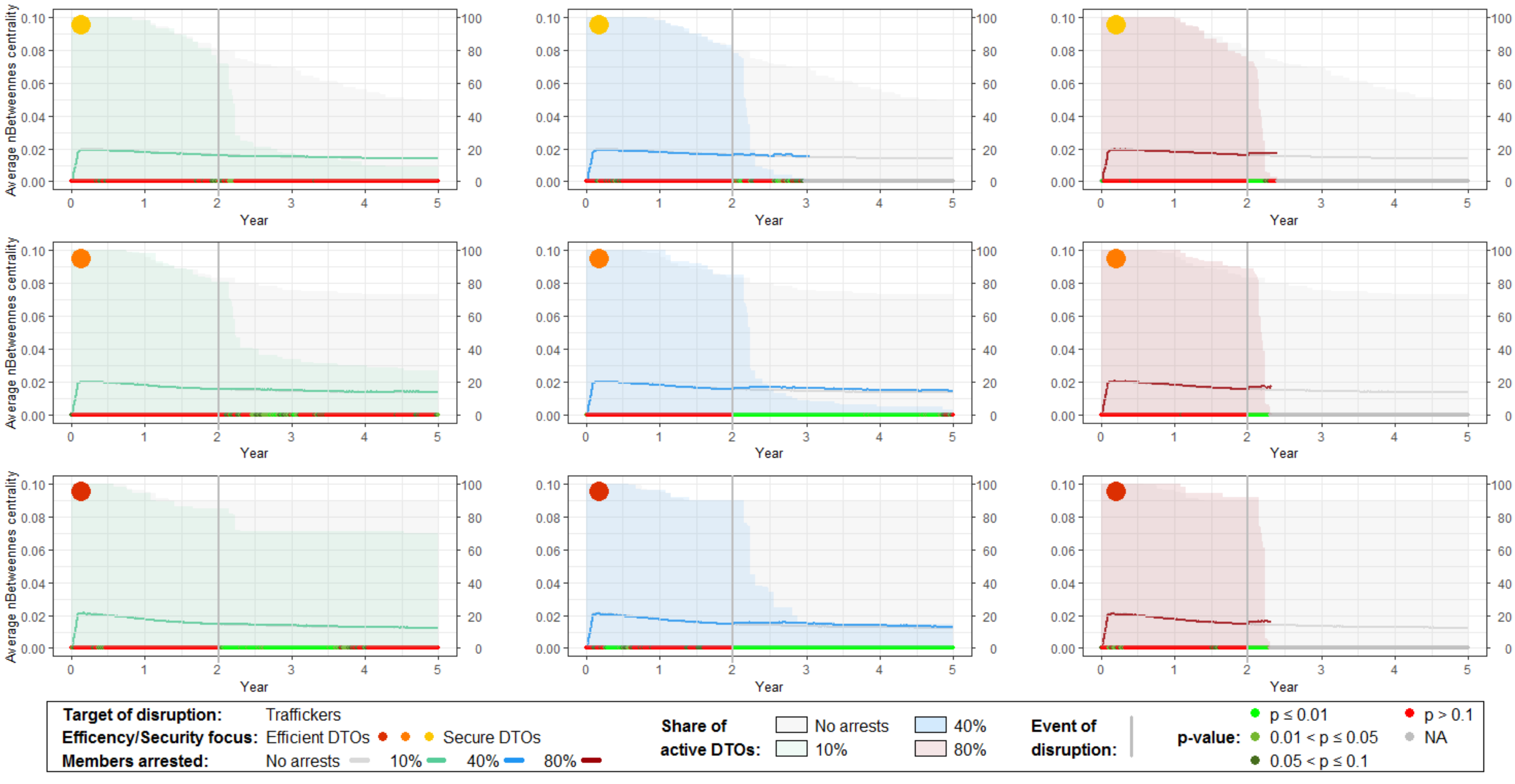
Graph 82. DTOs members average normalized betweenness centrality (Target of disruption: All; Law enforcement int. scenario: 2)



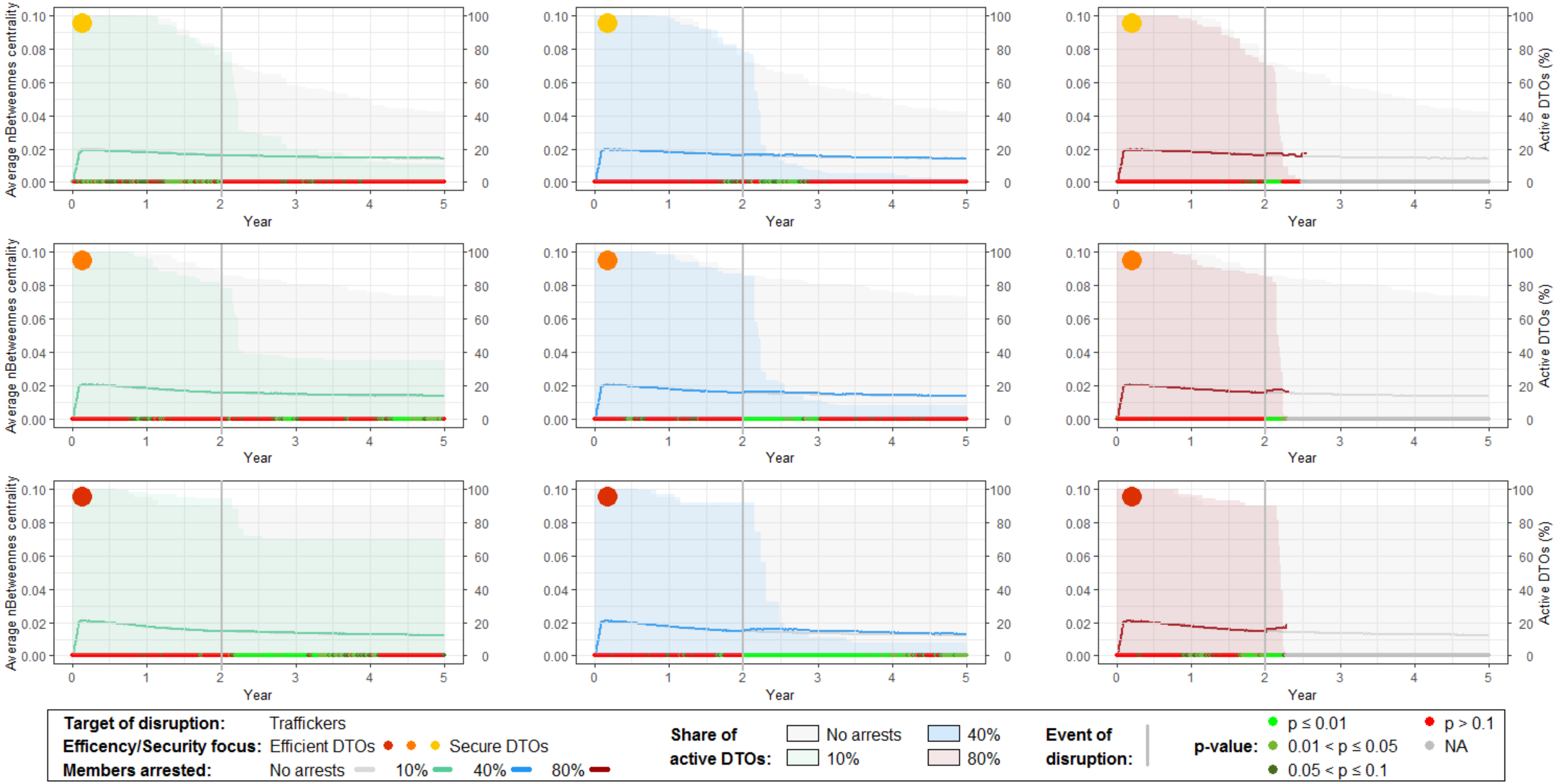
Graph 83. DTOs members average normalized betweenness centrality (Target of disruption: All; Law enforcement int. scenario: 3)



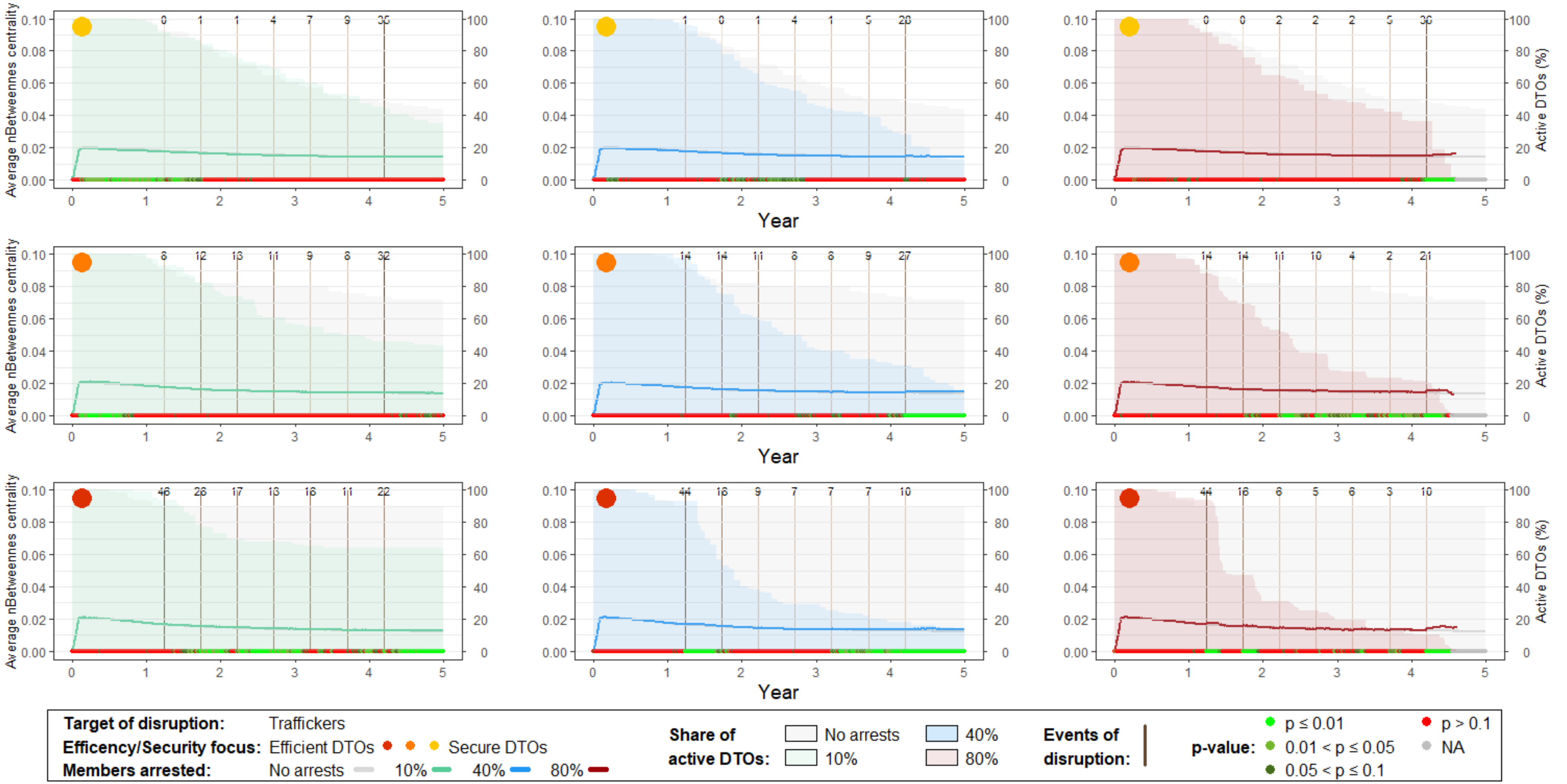
Graph 84. DTOs members average normalized betweenness centrality (Target of disruption: Traffickers; Law enforcement int. scenario: 1)



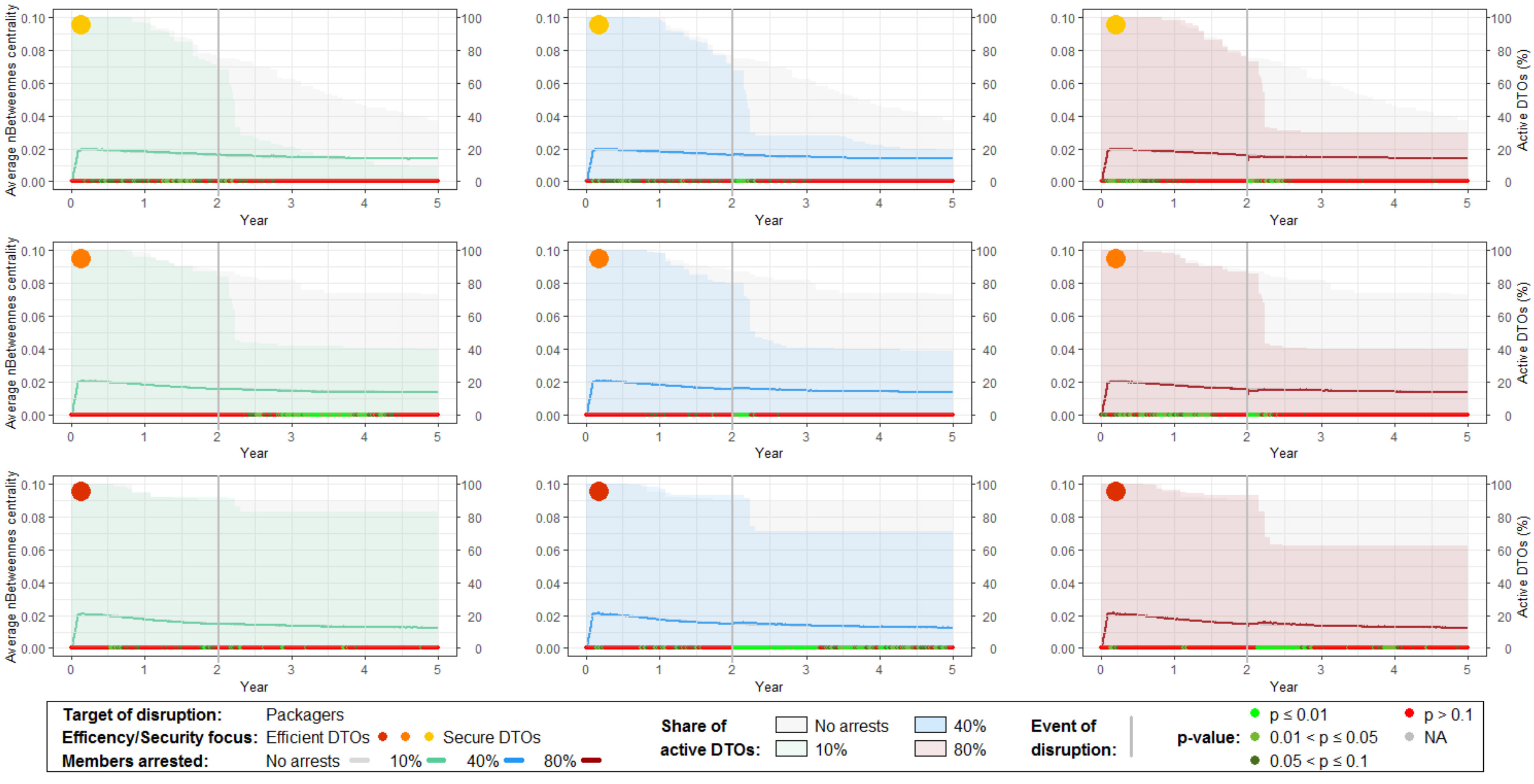
Graph 85. DTOs members average normalized betweenness centrality (Target of disruption: Traffickers; Law enforcement int. scenario: 2)



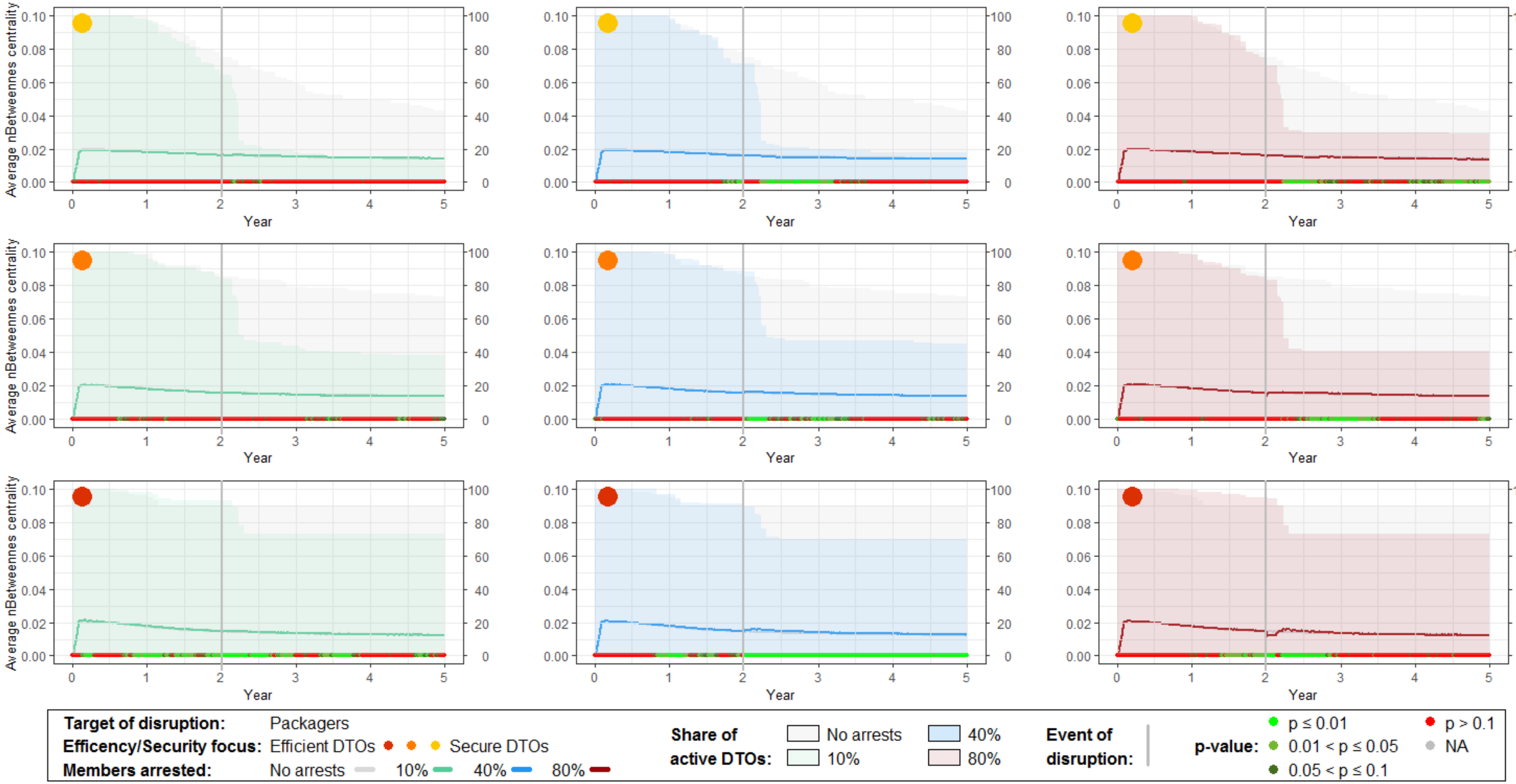
Graph 86. DTOs members average normalized betweenness centrality (Target of disruption: Traffickers; Law enforcement int. scenario: 3)



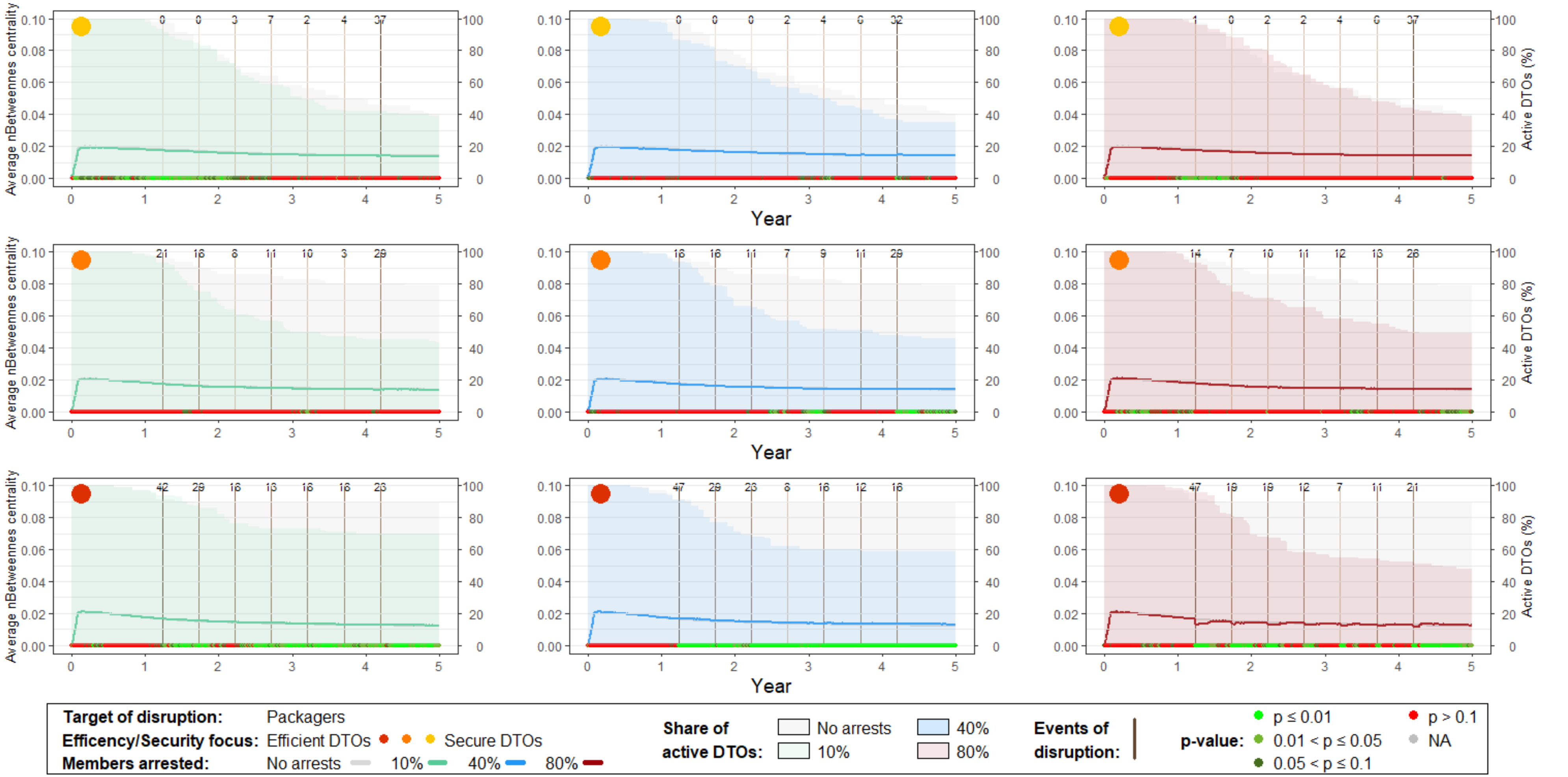
Graph 87. DTOs members average normalized betweenness centrality (Target of disruption: Packagers; Law enforcement int. scenario: 1)



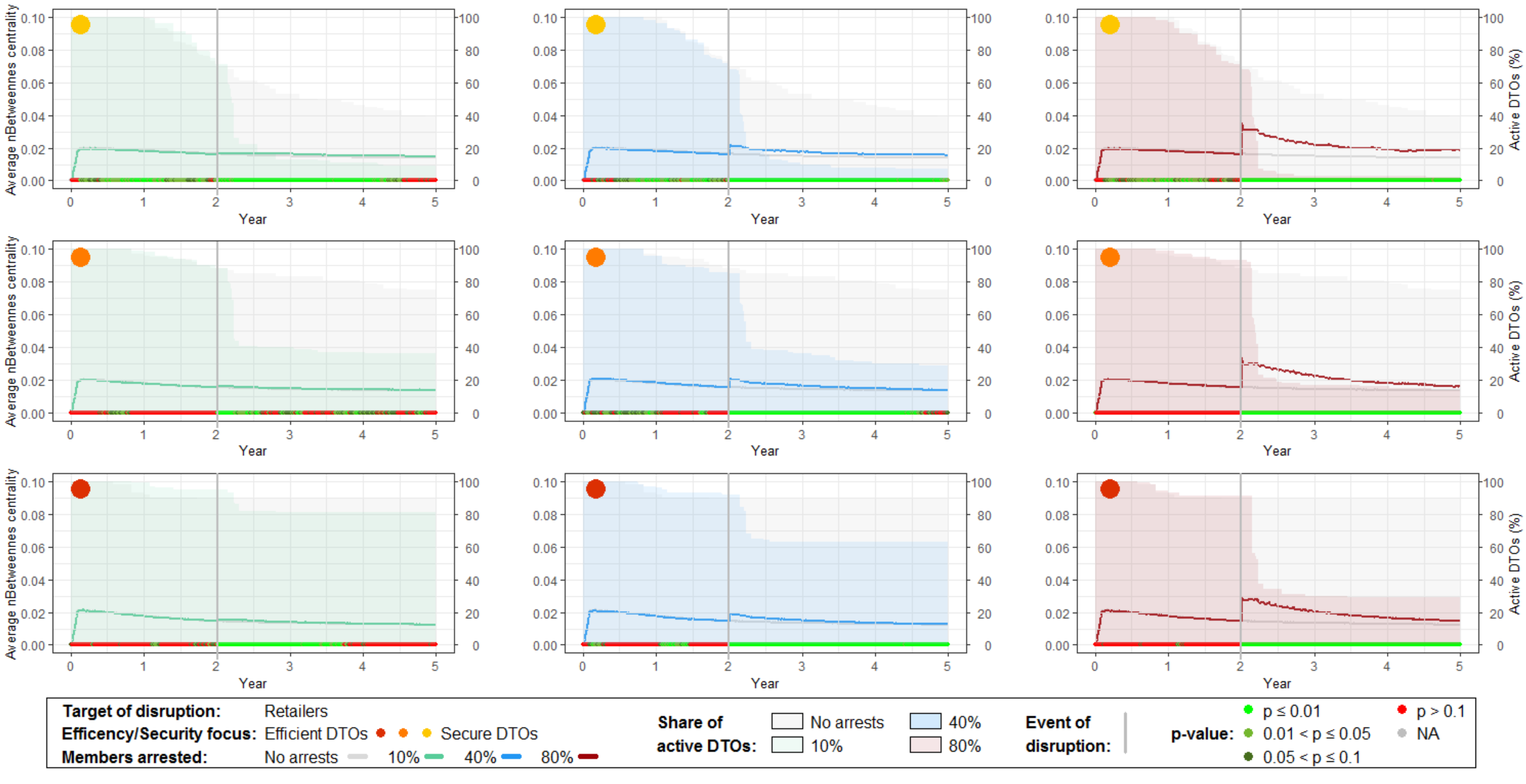
Graph 88. DTOs members average normalized betweenness centrality (Target of disruption: Packagers; Law enforcement int. scenario: 2)



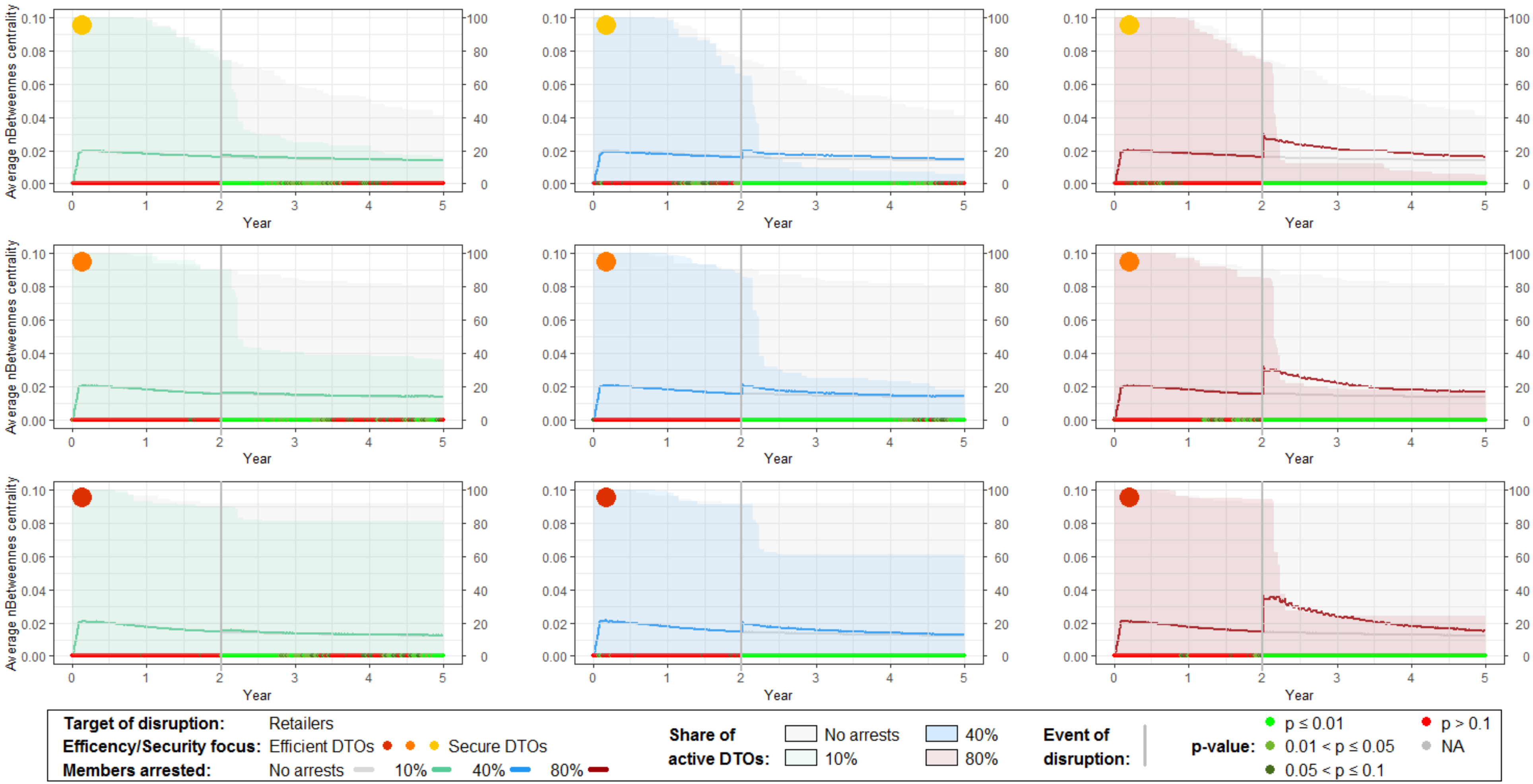
Graph 89. DTOs members average normalized betweenness centrality (Target of disruption: Packagers; Law enforcement int. scenario: 3)



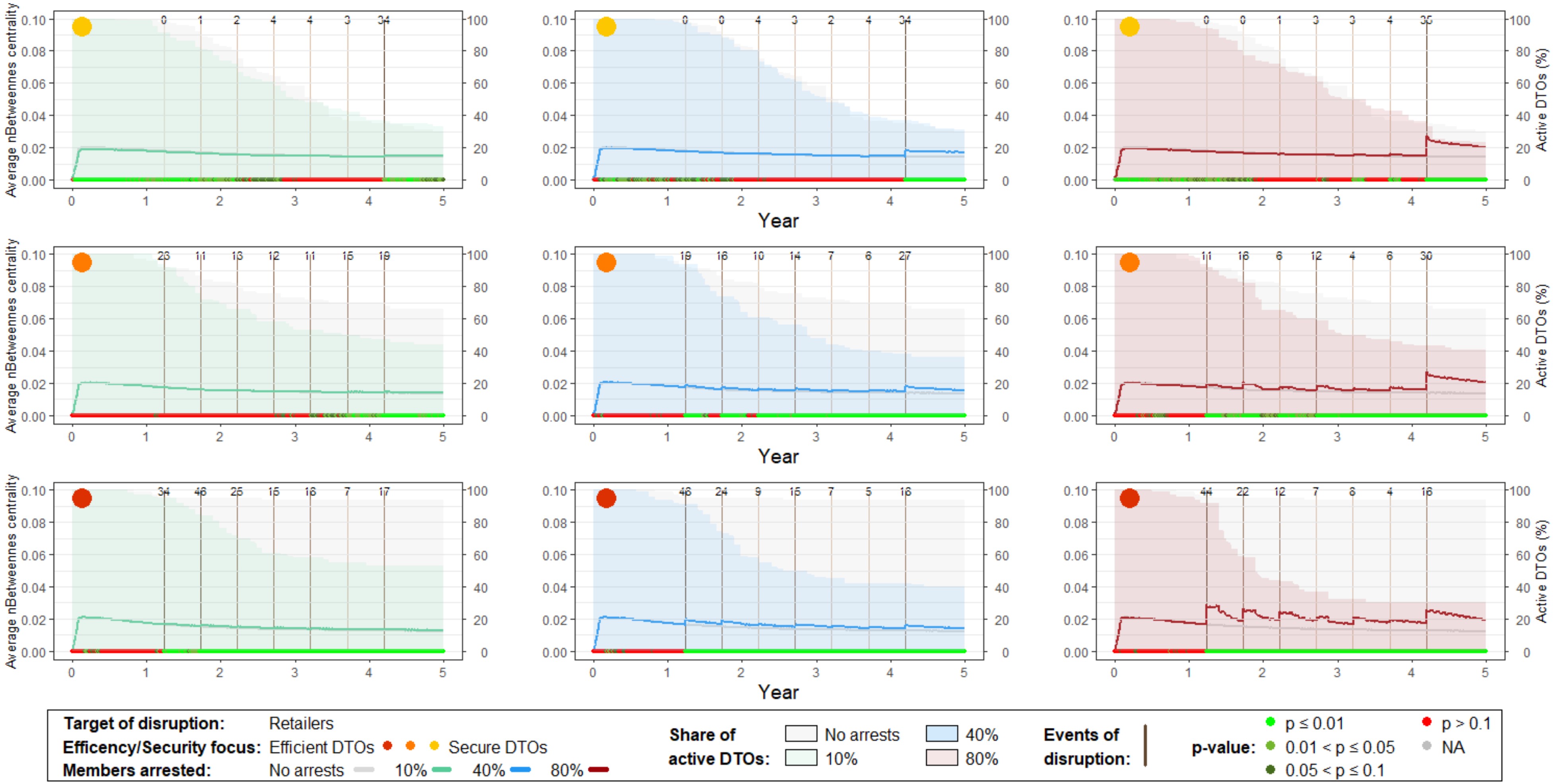
Graph 90. DTOs members average normalized betweenness centrality (Target of disruption: Retailers; Law enforcement int. scenario: 1)



Graph 91. DTOs members average normalized betweenness centrality (Target of disruption: Retailers; Law enforcement int. scenario: 2)

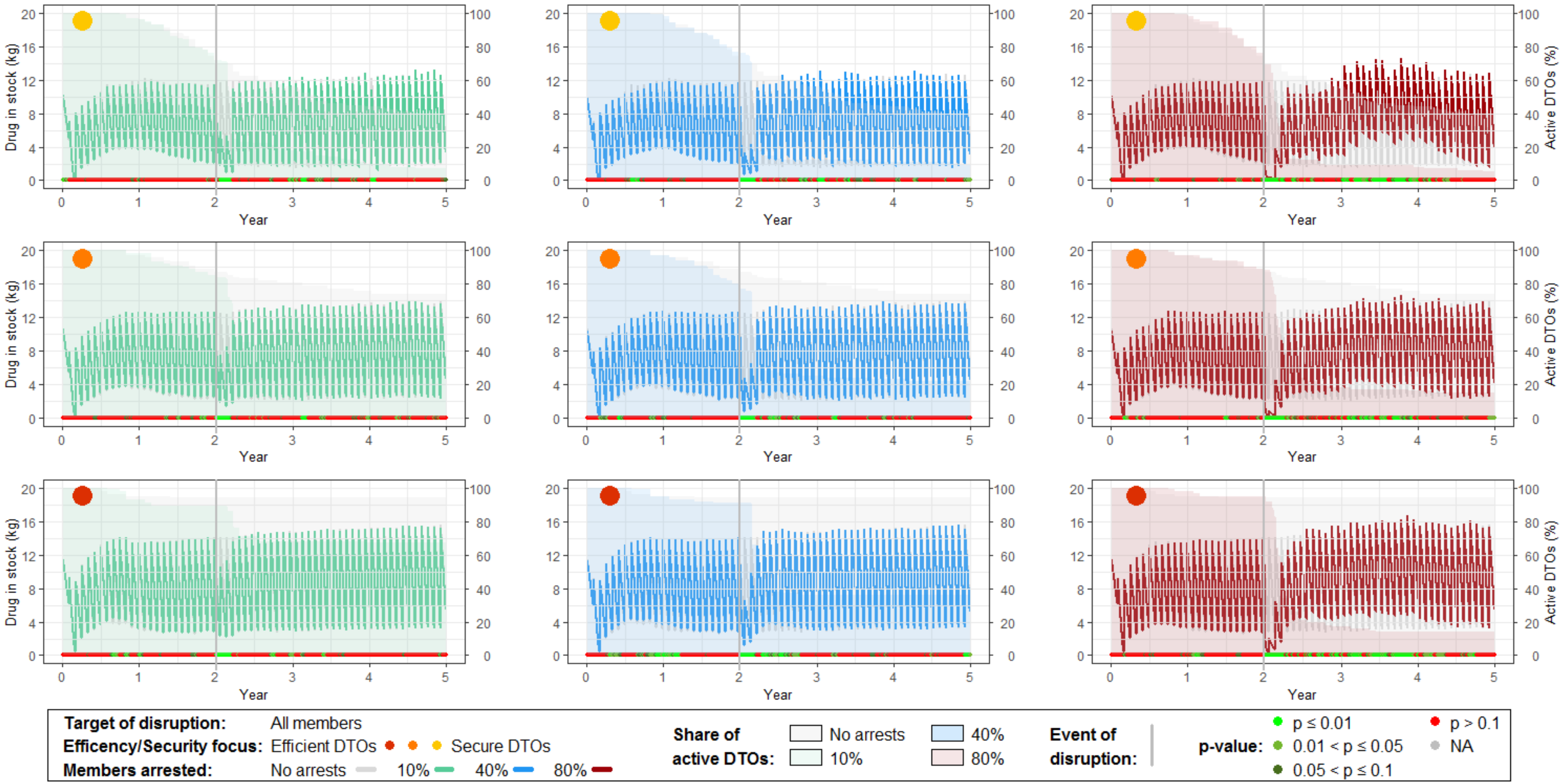


Graph 92. DTOs members average normalized betweenness centrality (Target of disruption: Retailers; Law enforcement int. scenario: 3)

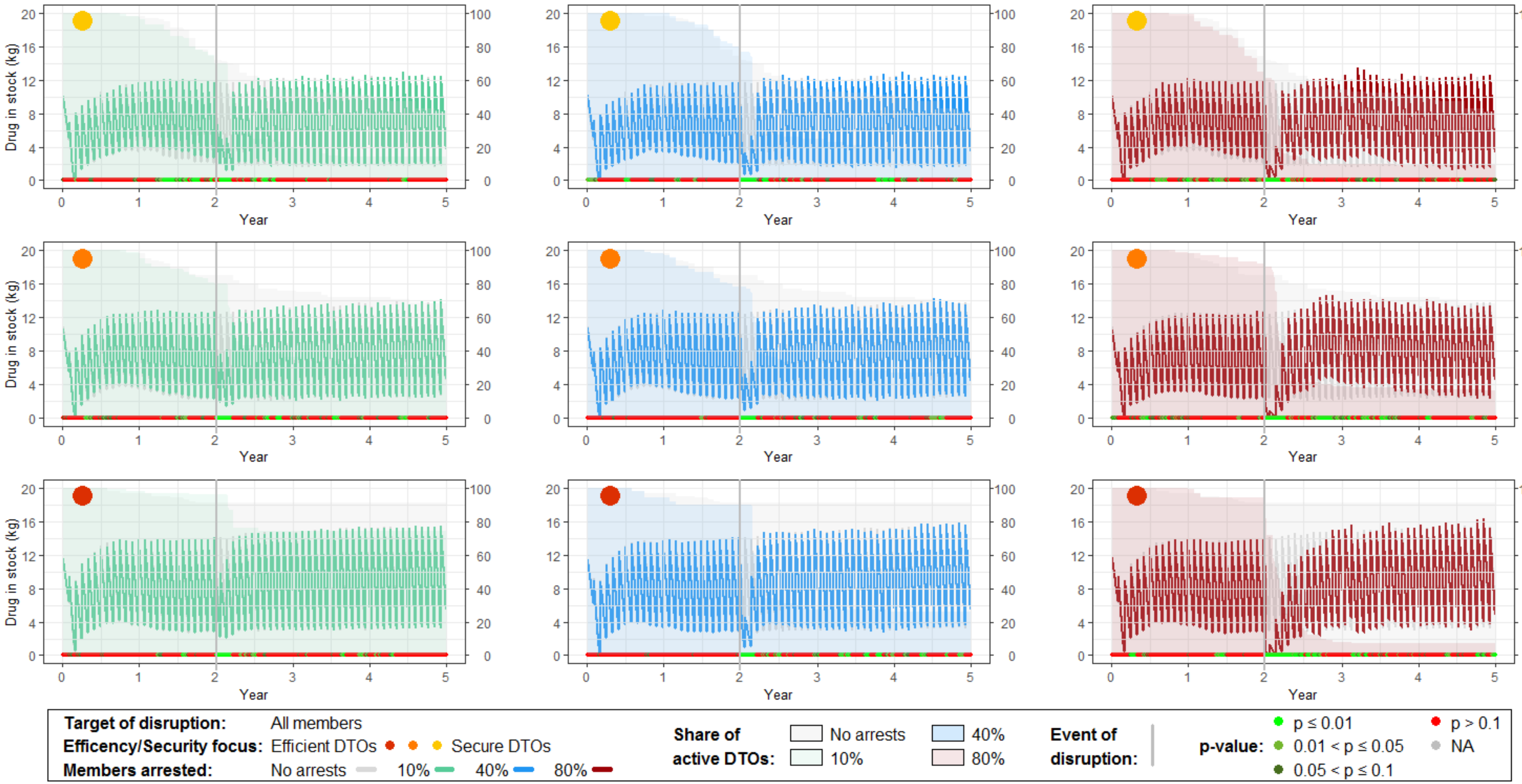


Amount of drug in stock

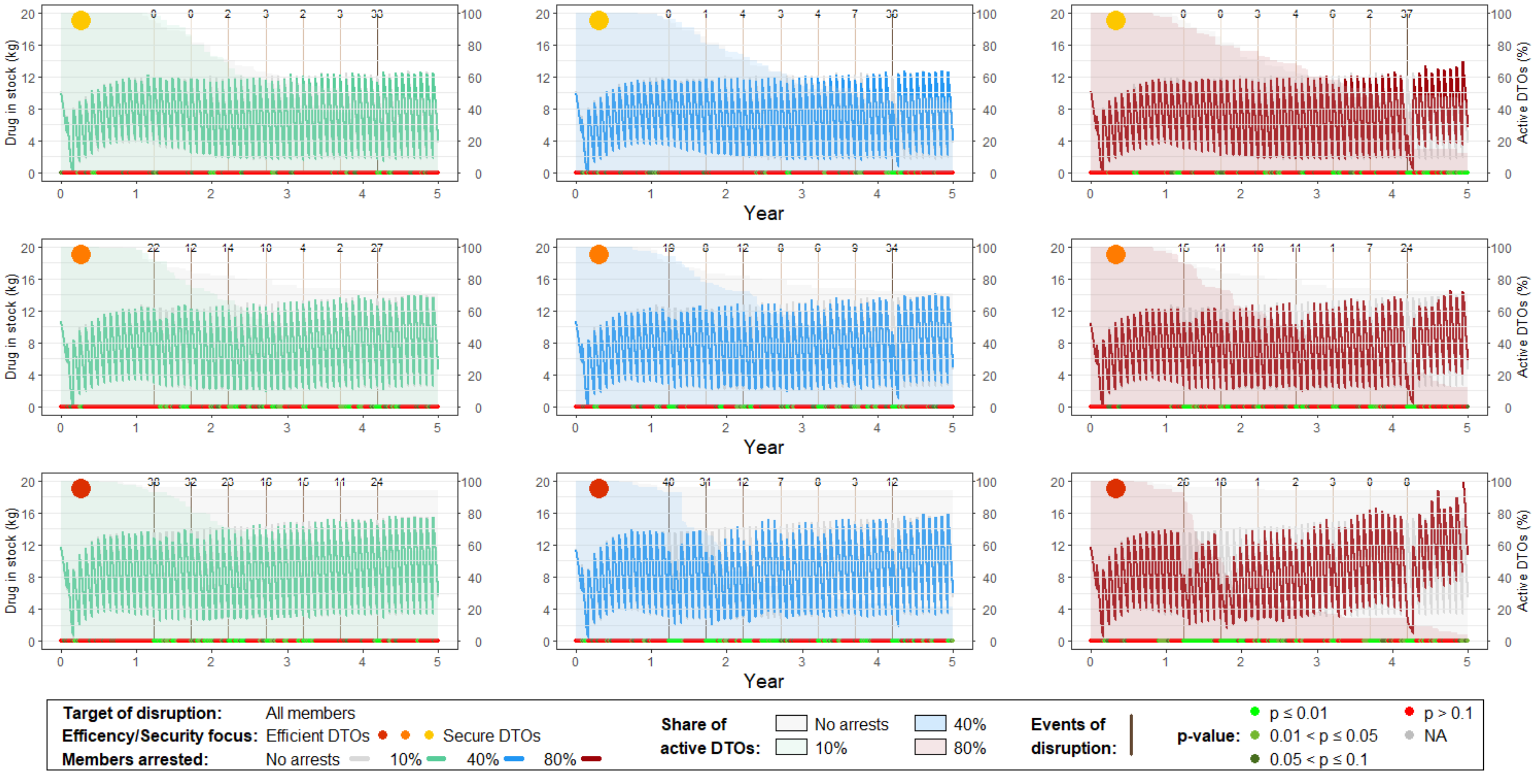
Graph 93. Amount of drug in stock (Target of disruption: All members; Law enforcement int. scenario: 1)



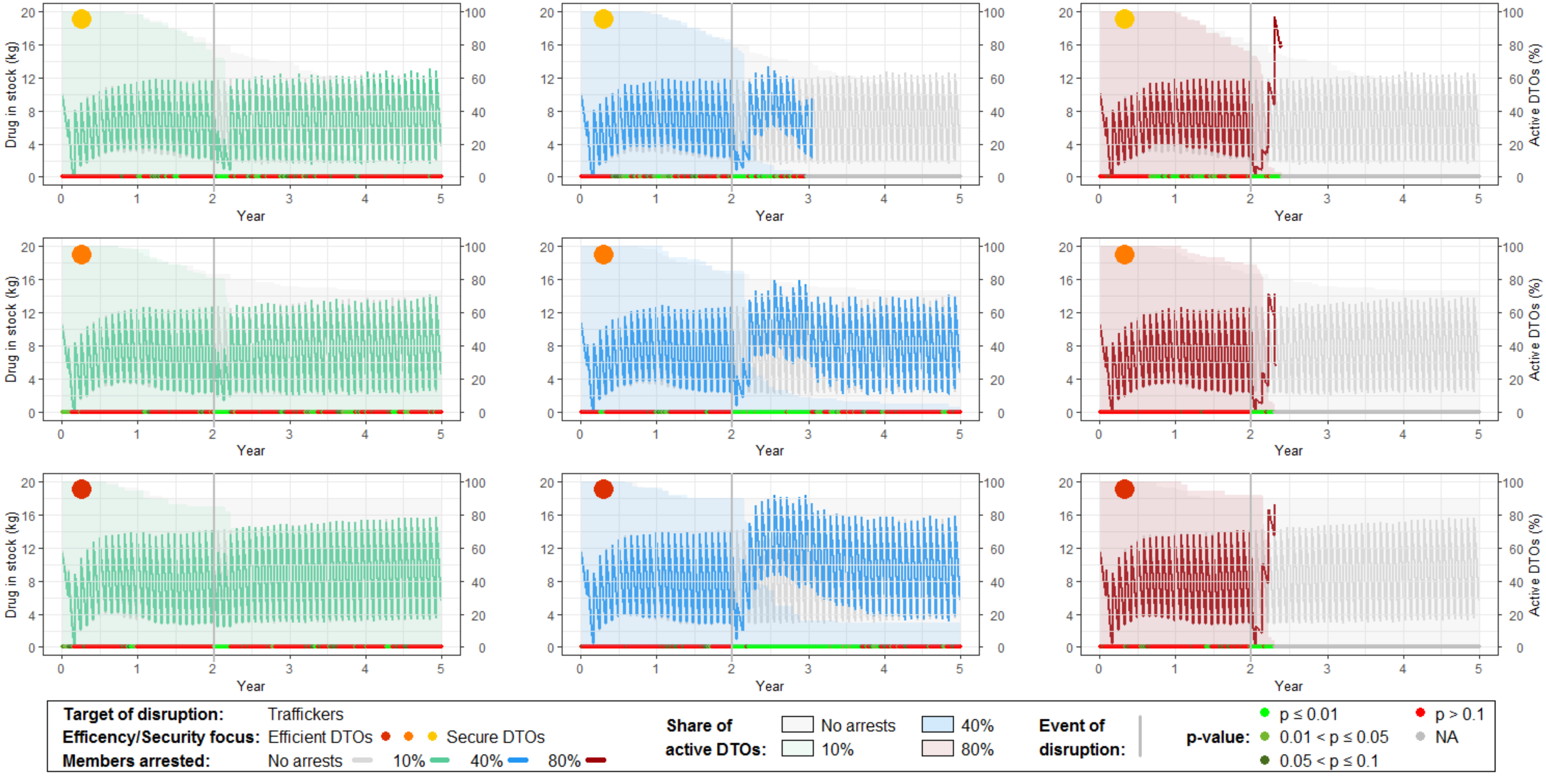
Graph 94. Amount of drug in stock (Target of disruption: All members; Law enforcement int. scenario: 2)



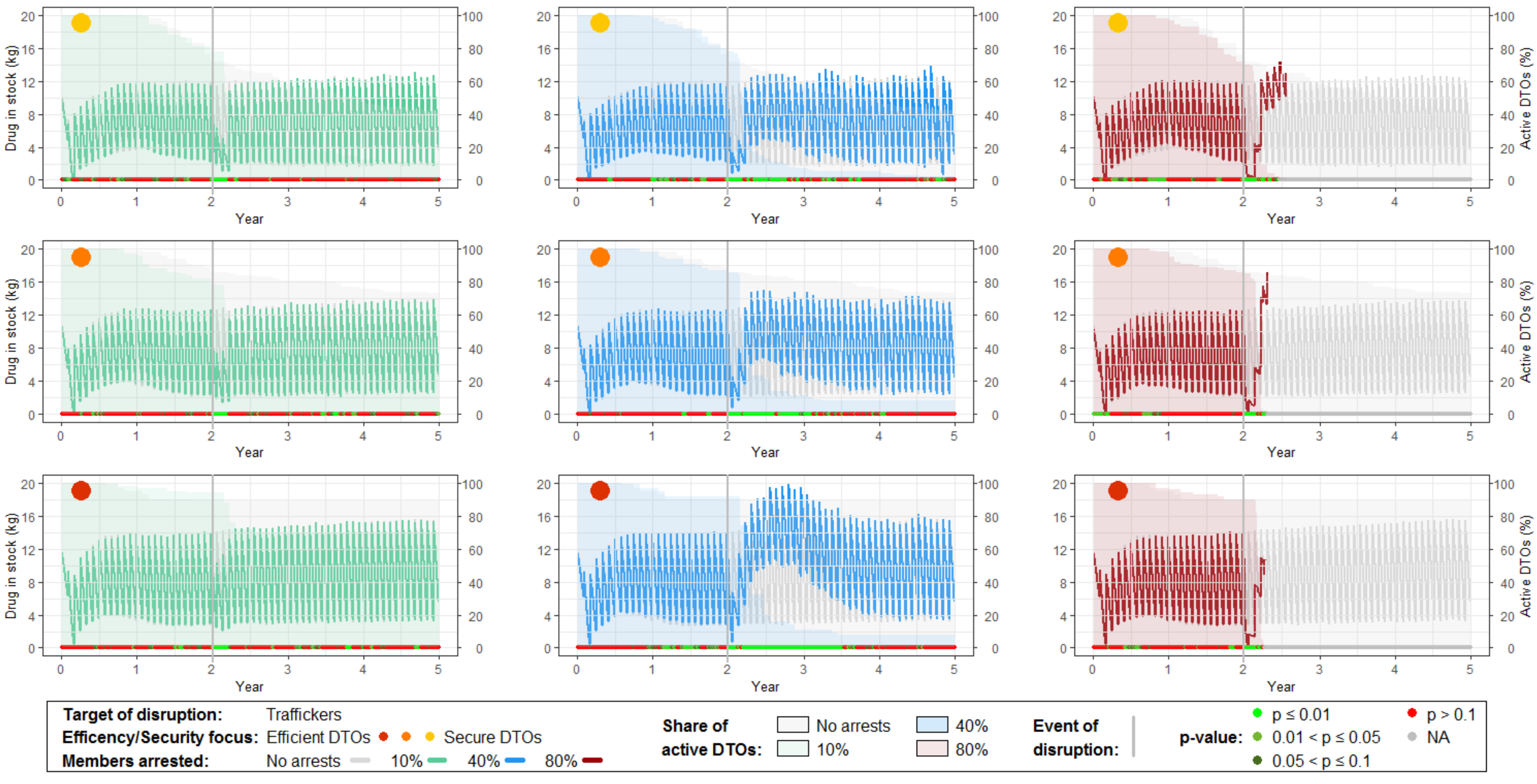
Graph 95. Amount of drug in stock (Target of disruption: All members; Law enforcement int. scenario: 3)



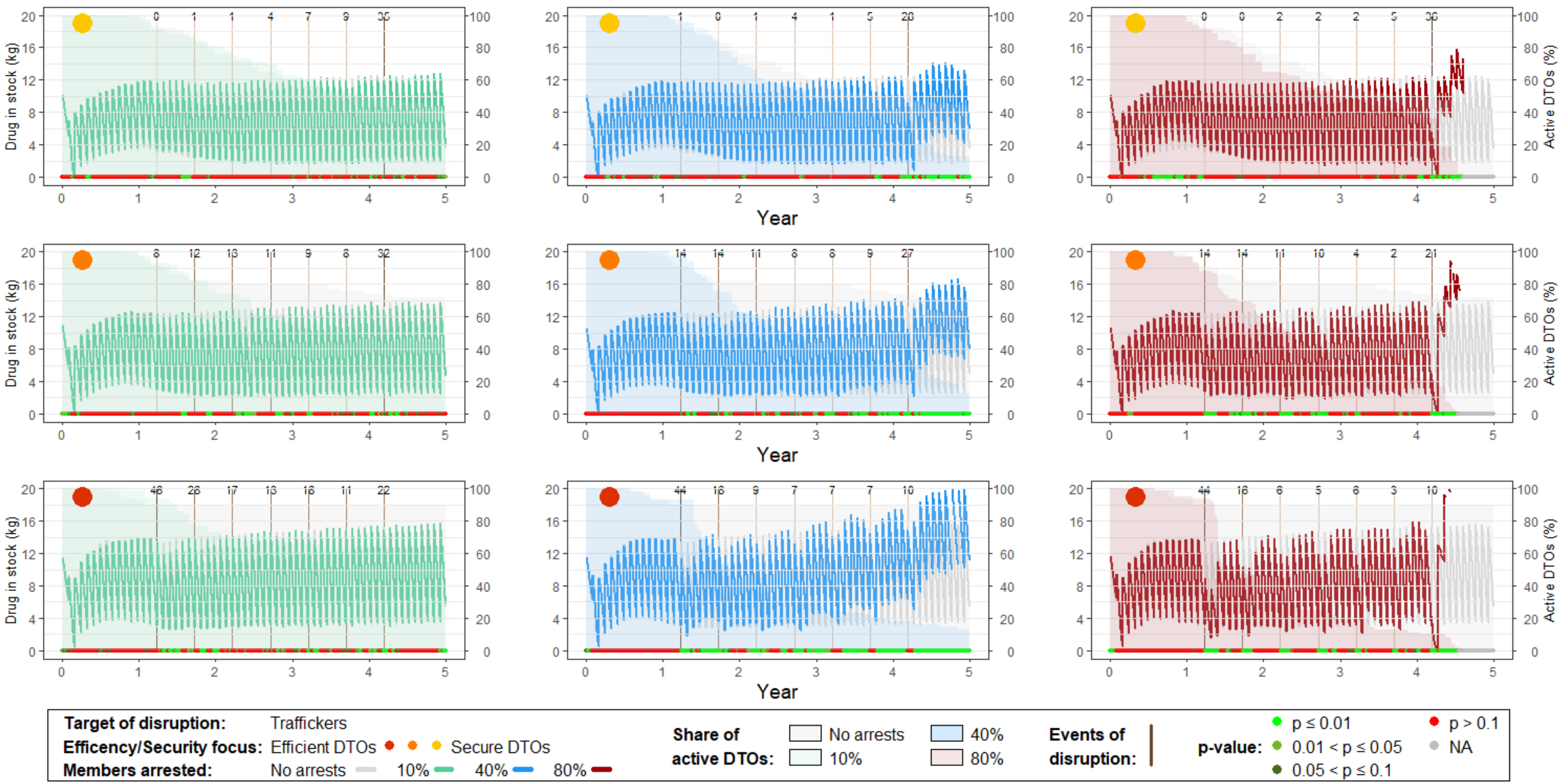
Graph 96. Amount of drug in stock (Target of disruption: Traffickers; Law enforcement int. scenario: 1)



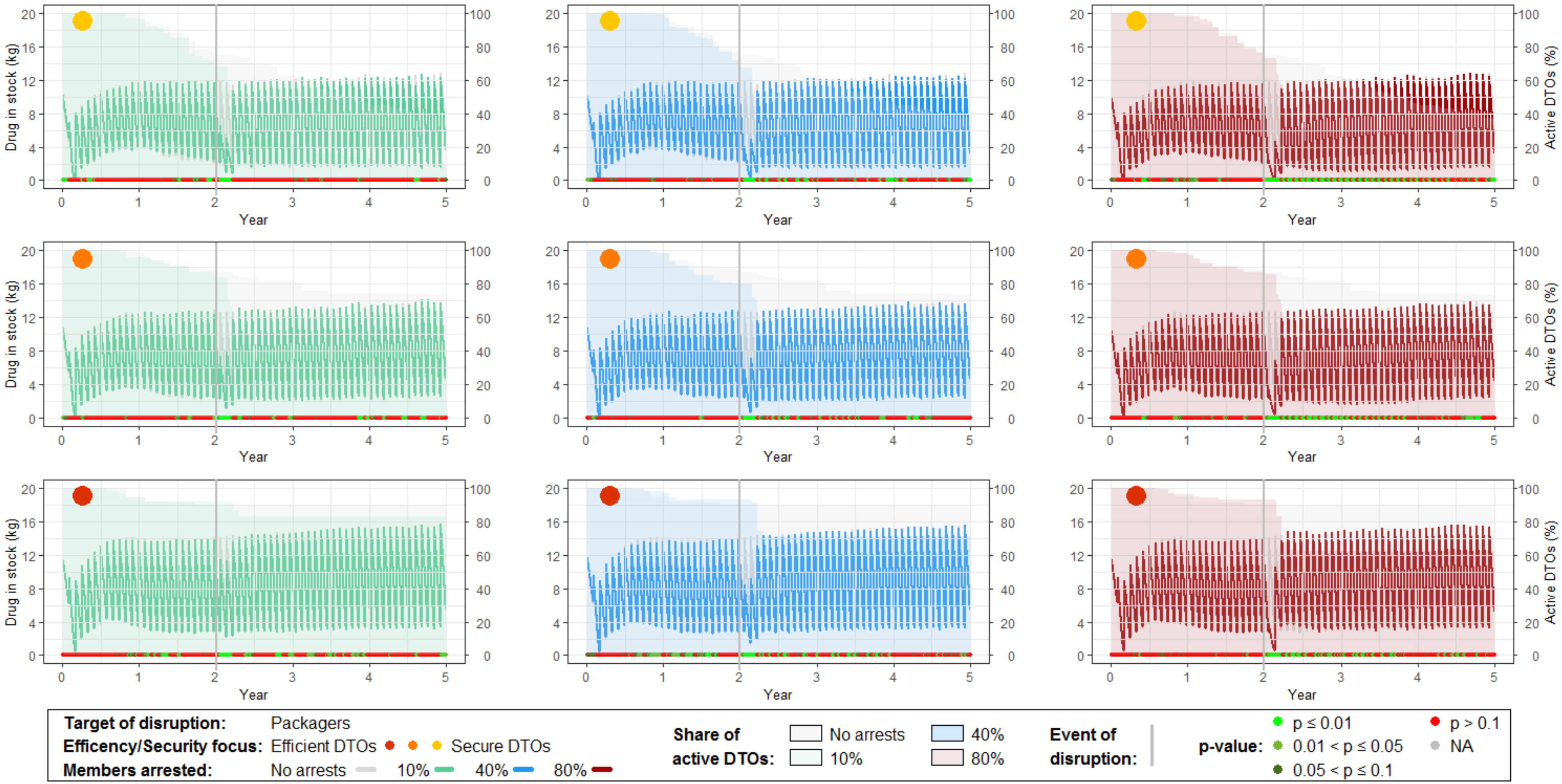
Graph 97. Amount of drug in stock (Target of disruption: Traffickers; Law enforcement int. scenario: 2)



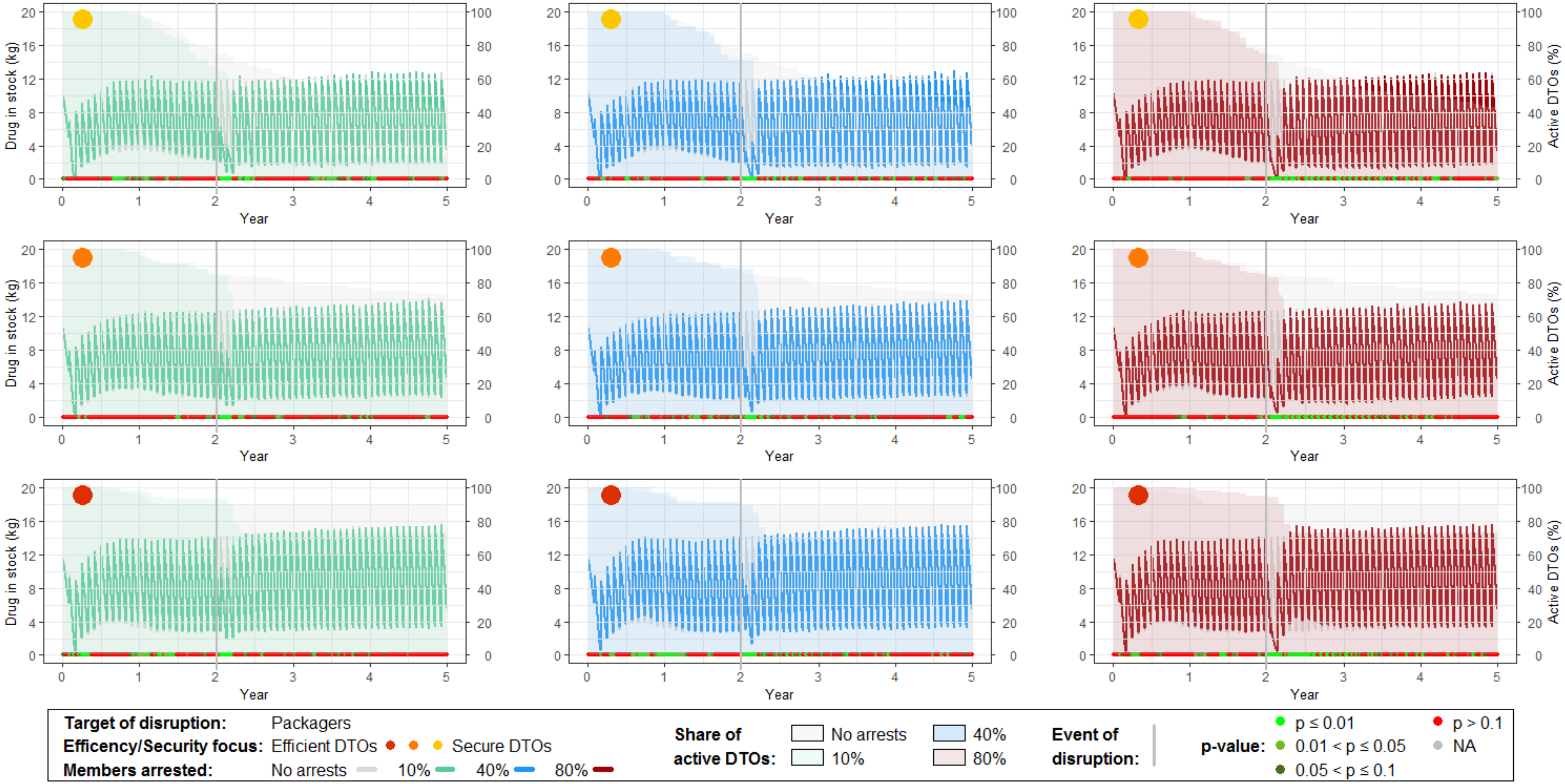
Graph 98. Amount of drug in stock (Target of disruption: Traffickers; Law enforcement int. scenario: 3)



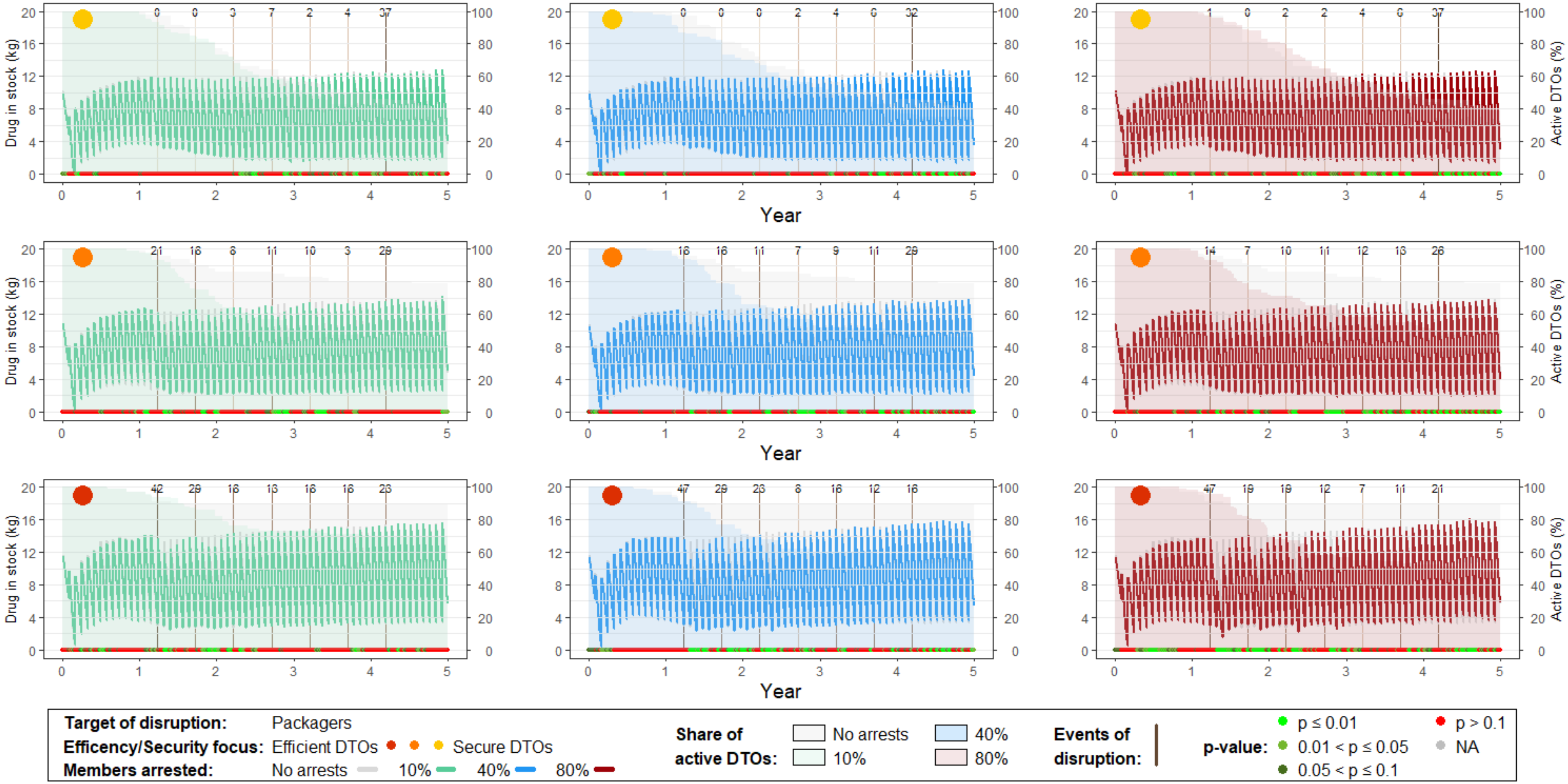
Graph 99. Amount of drug in stock (Target of disruption: Packagers; Law enforcement int. scenario: 1)



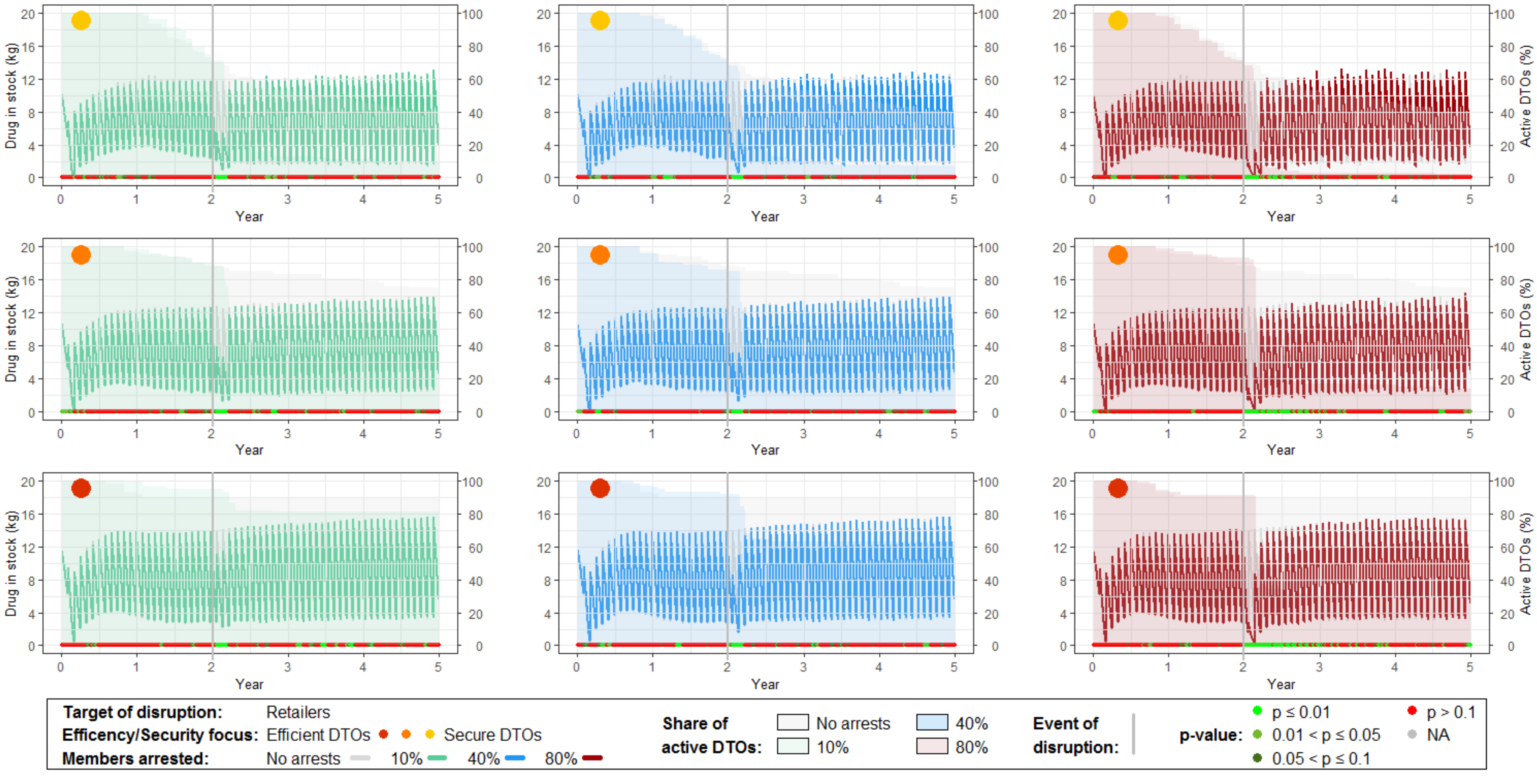
Graph 100. Amount of drug in stock (Target of disruption: Packagers; Law enforcement int. scenario: 2)



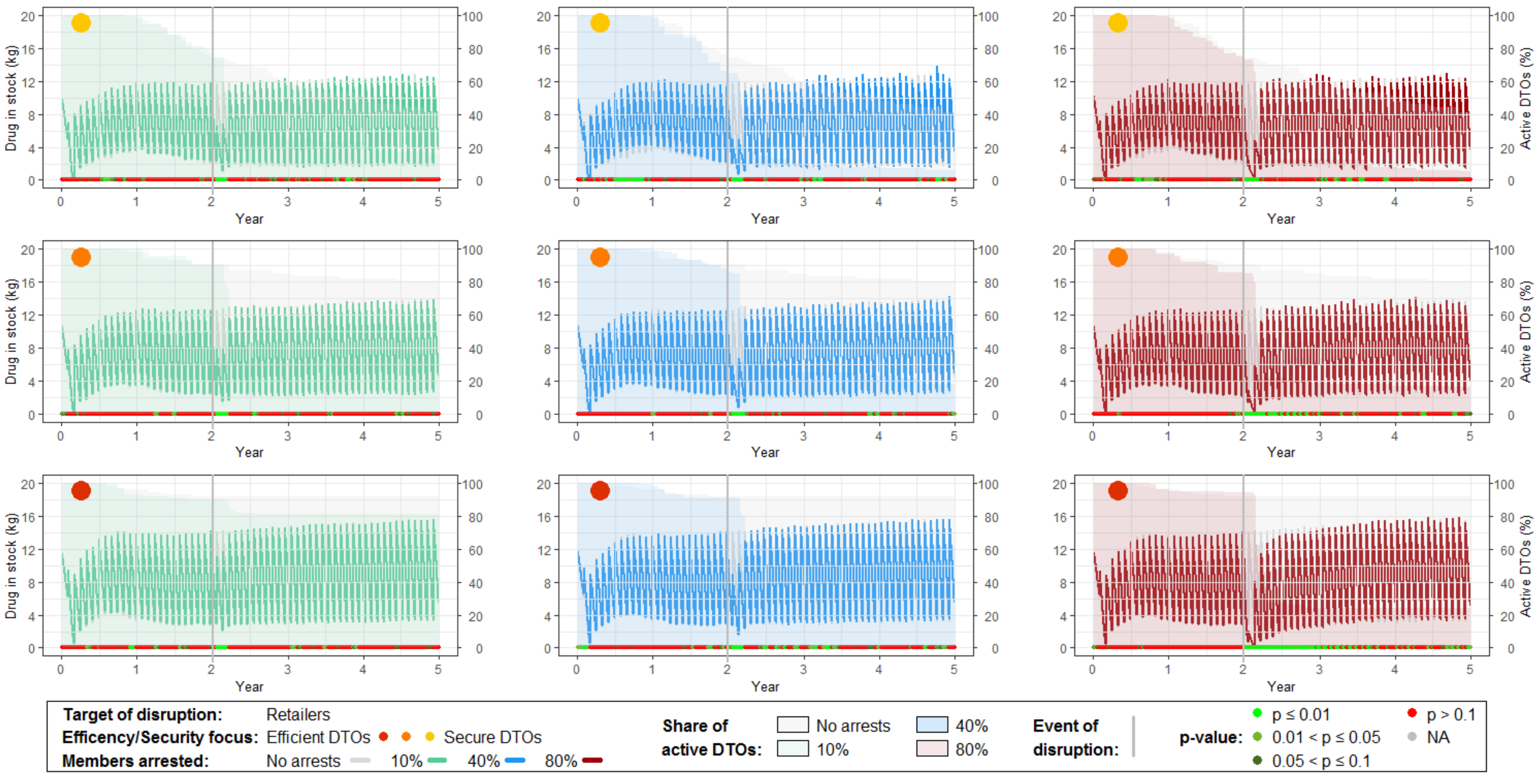
Graph 101. Amount of drug in stock (Target of disruption: Packagers; Law enforcement int. scenario: 3)



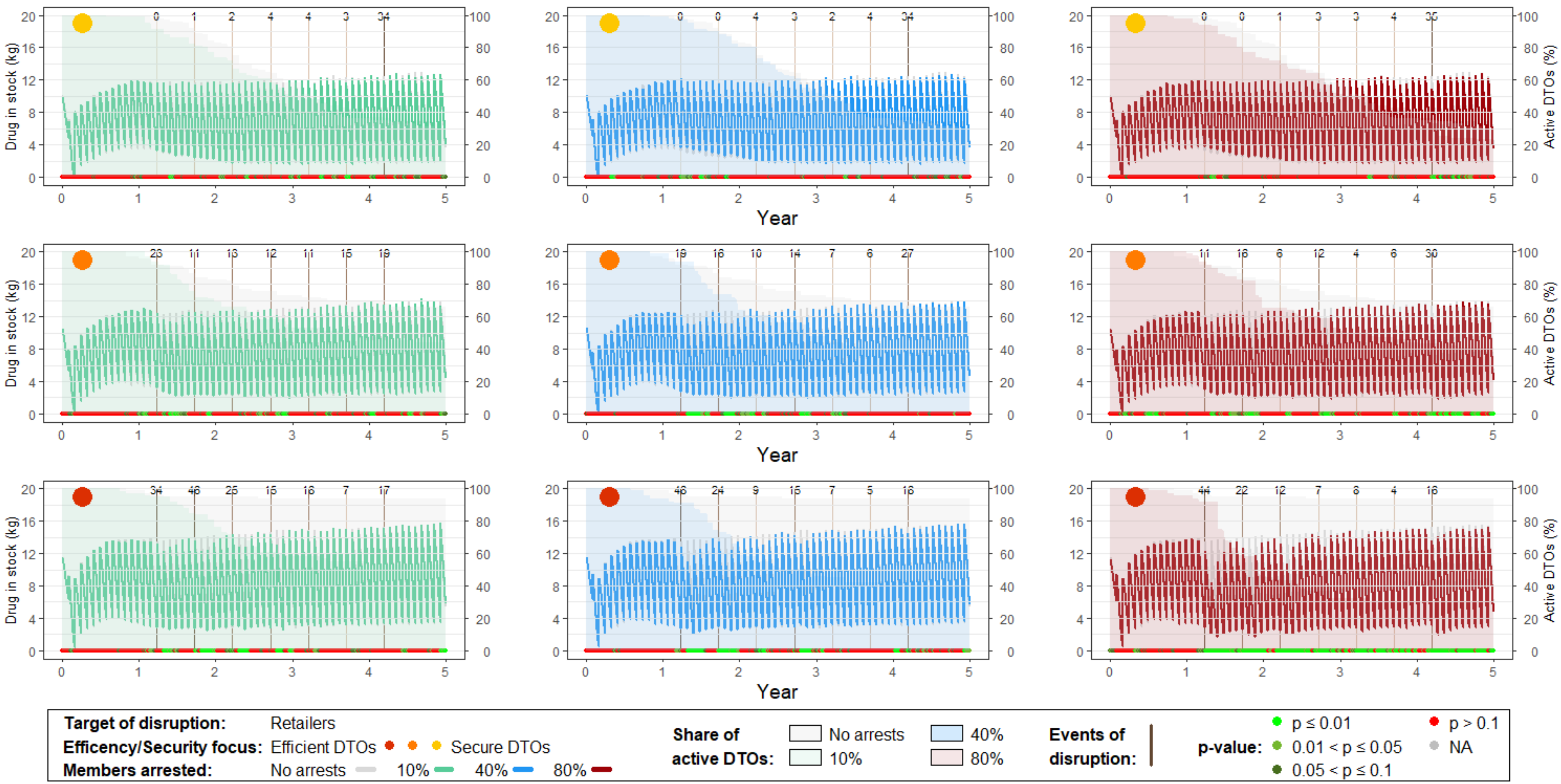
Graph 102. Amount of drug in stock (Target of disruption: Retailers; Law enforcement int. scenario: 1)



Graph 103. Amount of drug in stock (Target of disruption: Retailers; Law enforcement int. scenario: 2)

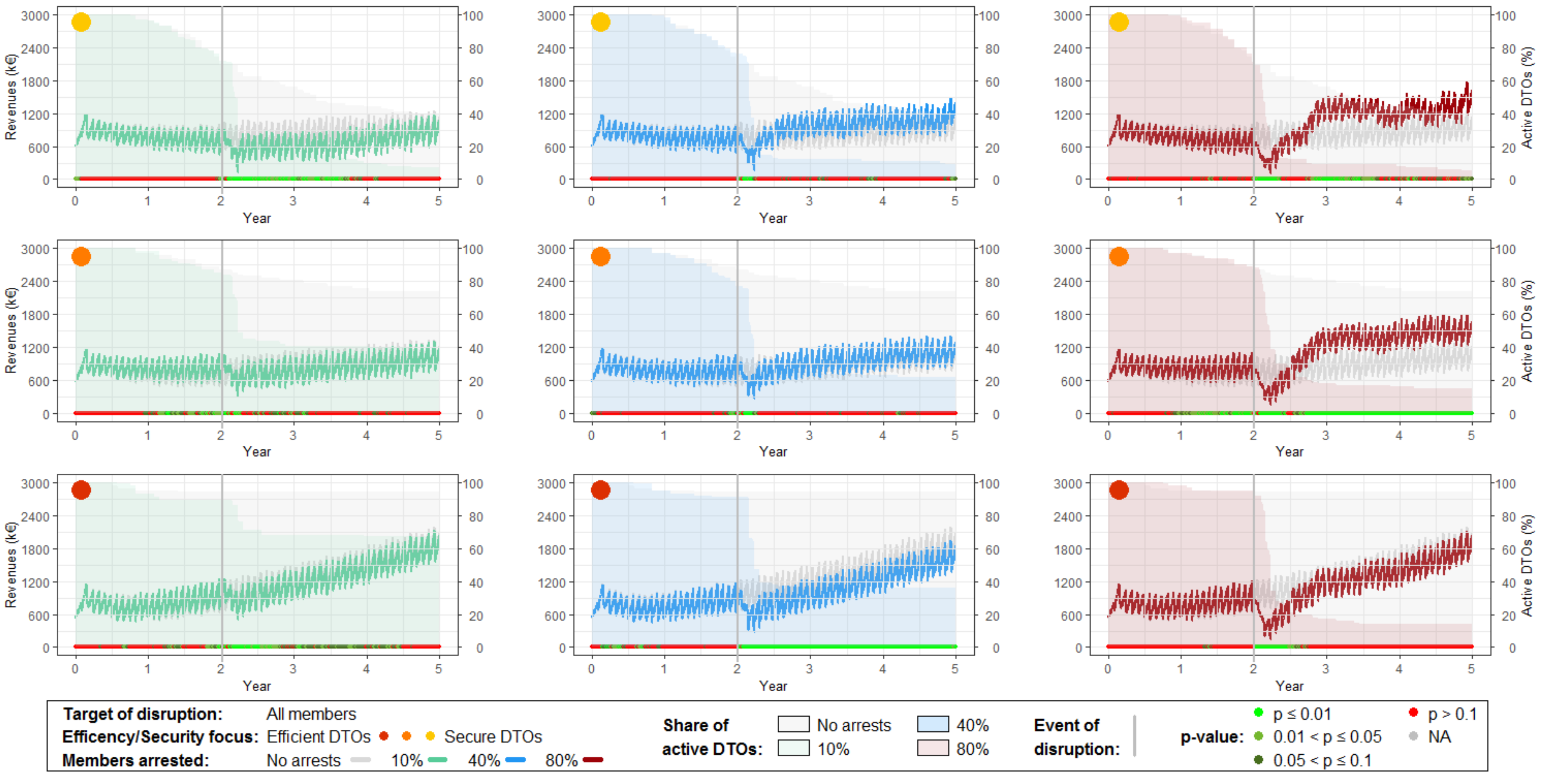


Graph 104. Amount of drug in stock (Target of disruption: Retailers; Law enforcement int. scenario: 3)

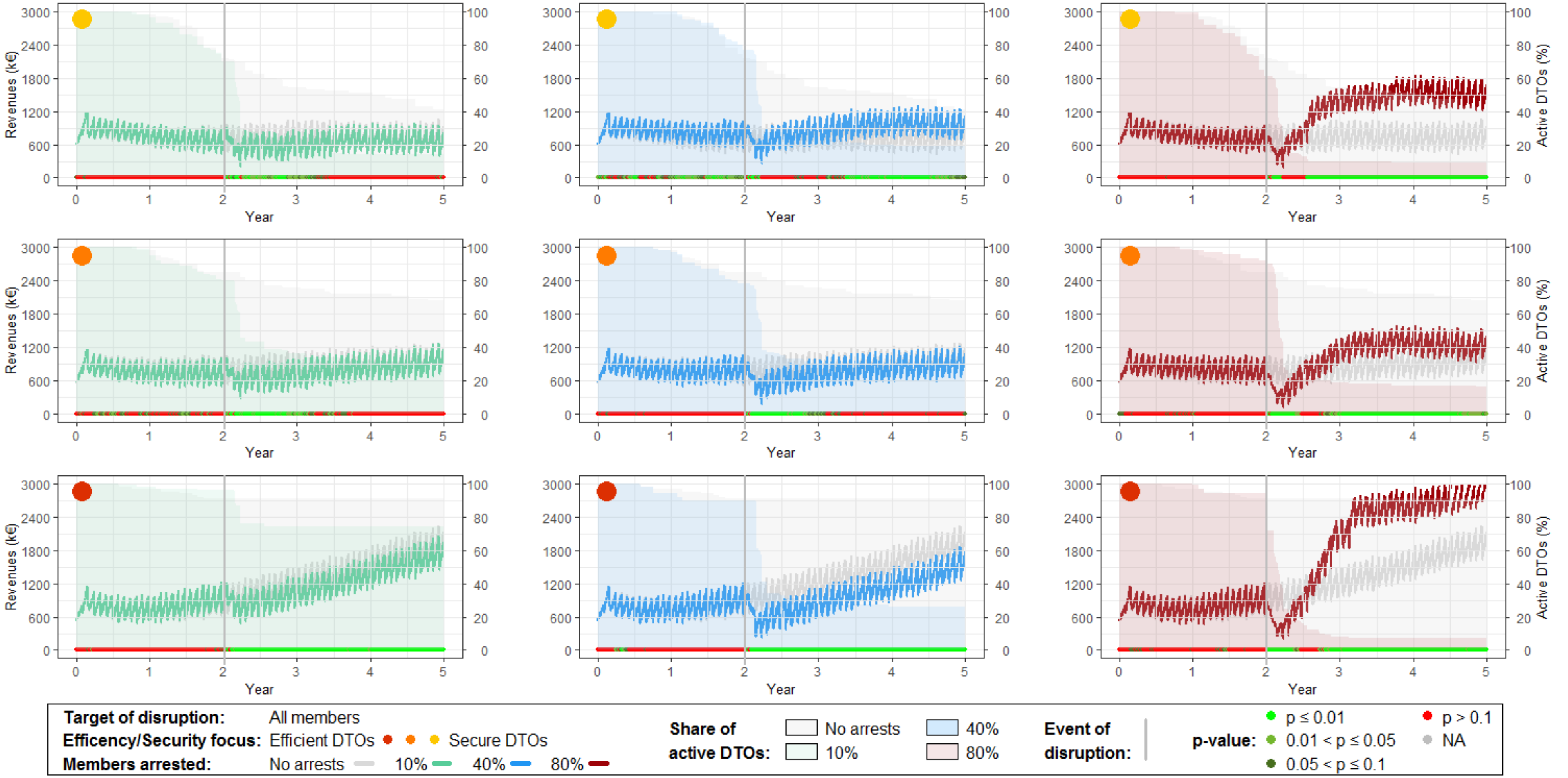


DTOs revenues

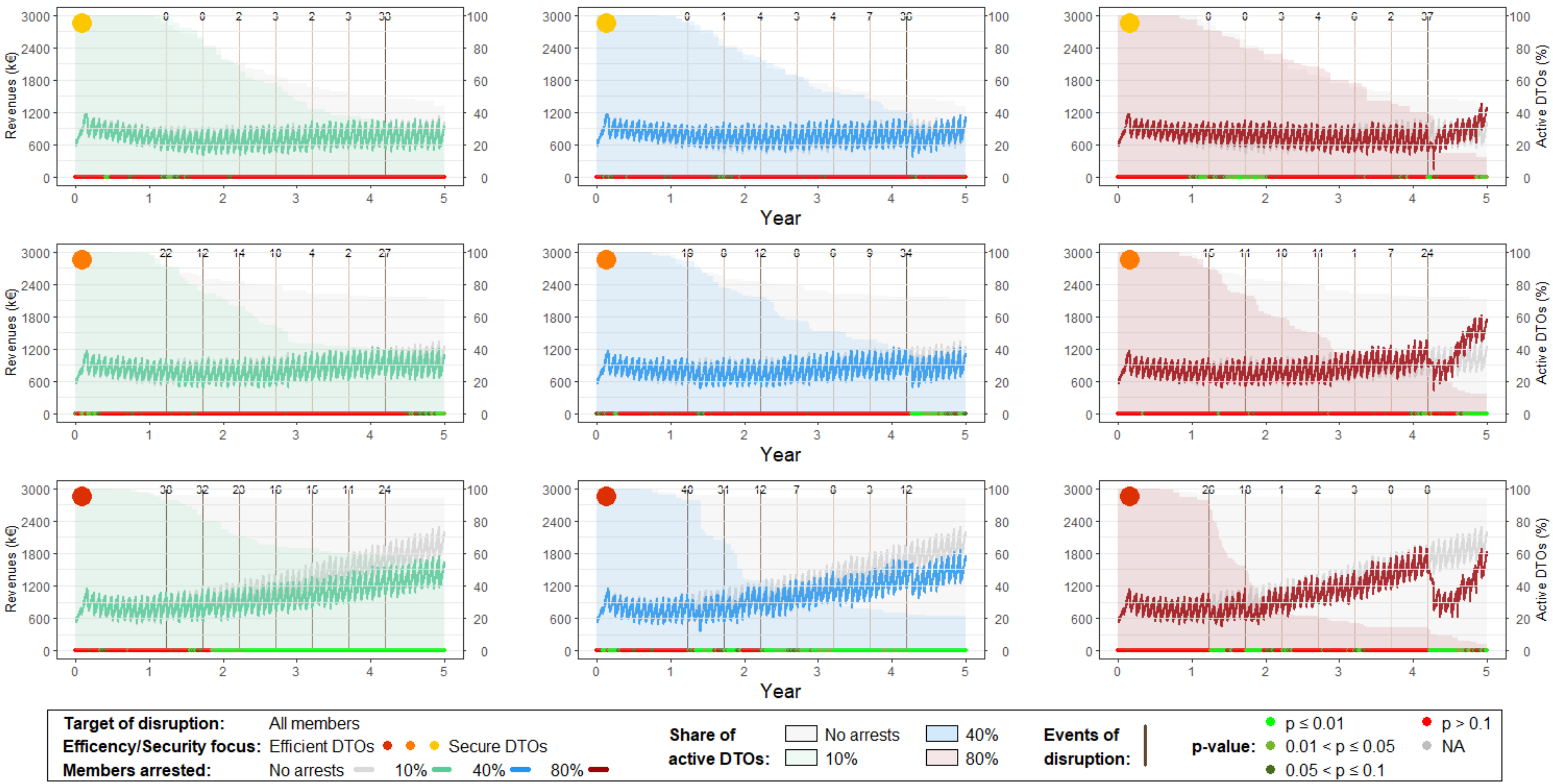
Graph 105. DTOs revenues (Target of disruption: All members; Law enforcement int. scenario: 1)



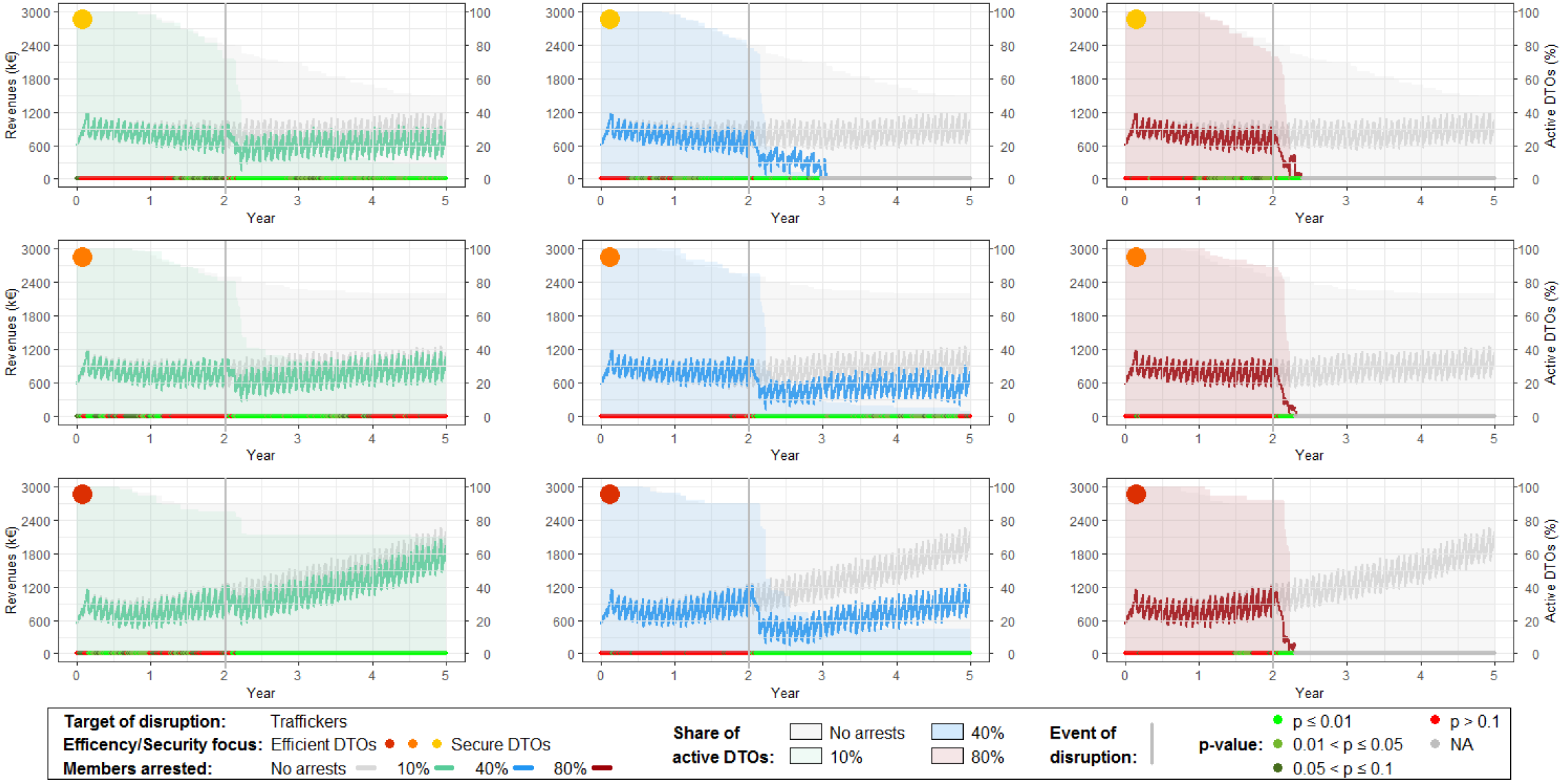
Graph 106. DTOs revenues (Target of disruption: All members; Law enforcement int. scenario: 2)



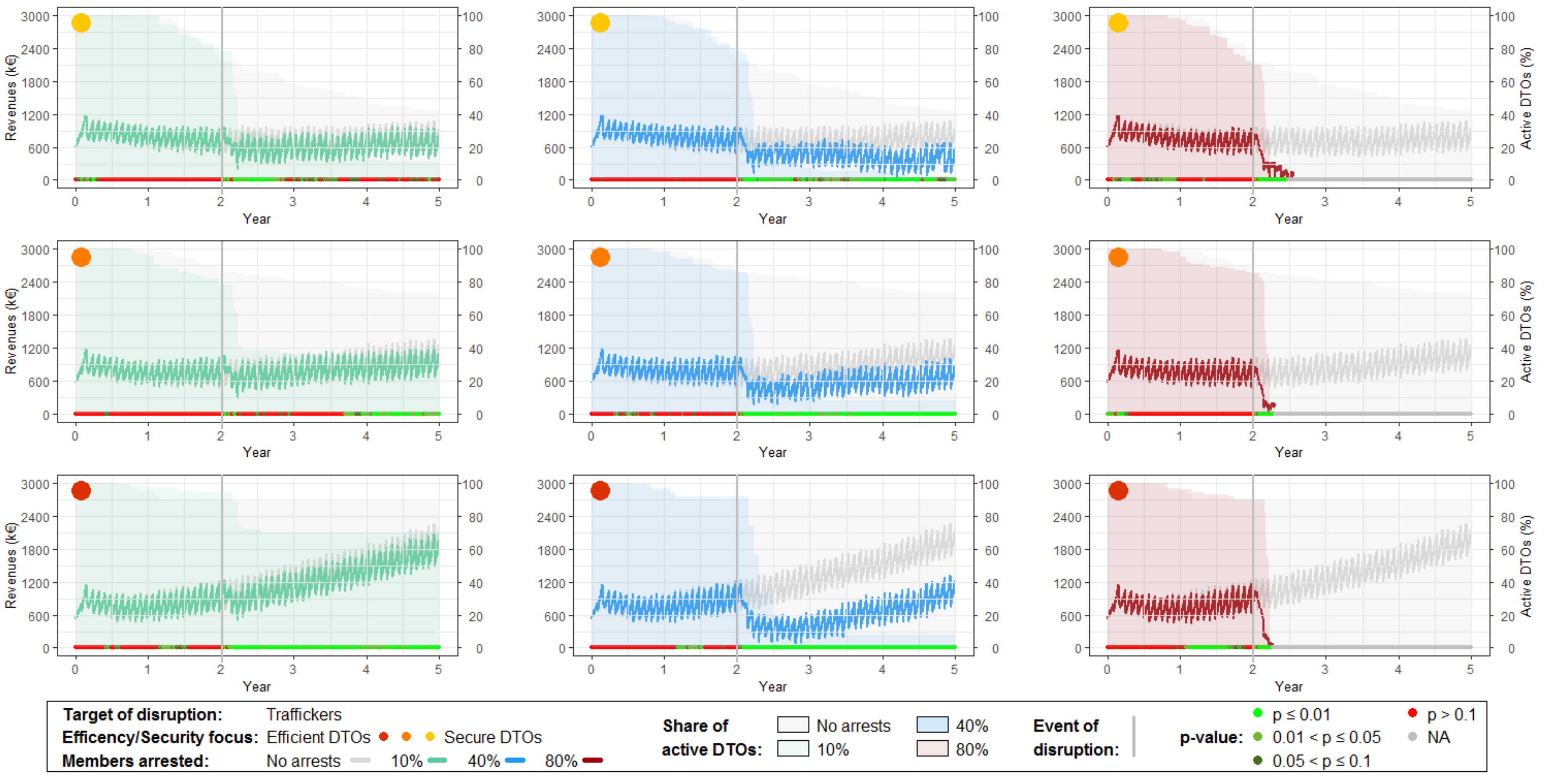
Graph 107. DTOs revenues (Target of disruption: All members; Law enforcement int. scenario: 3)



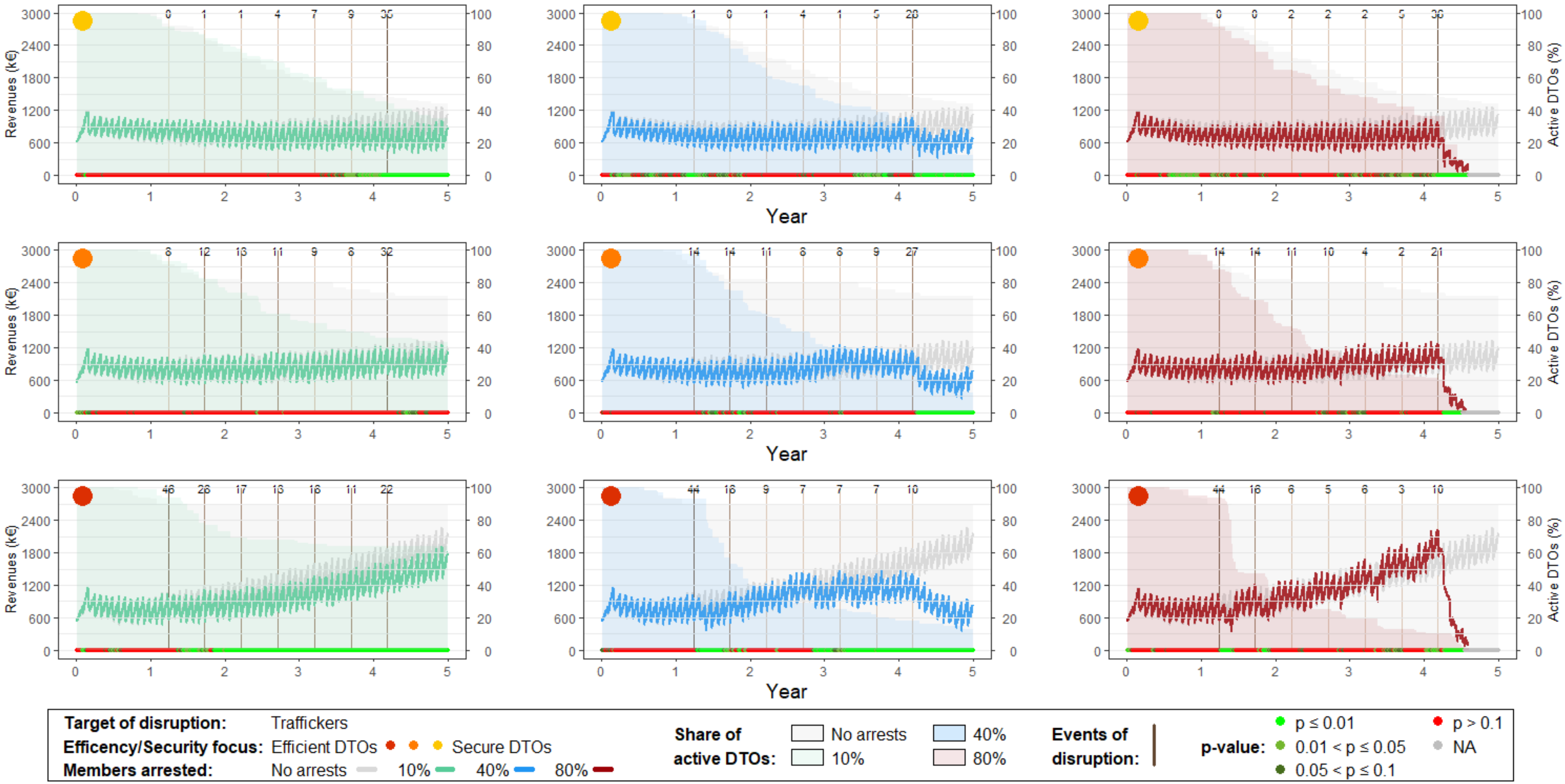
Graph 108. DTOs revenues (Target of disruption: Traffickers; Law enforcement int. scenario: 1)



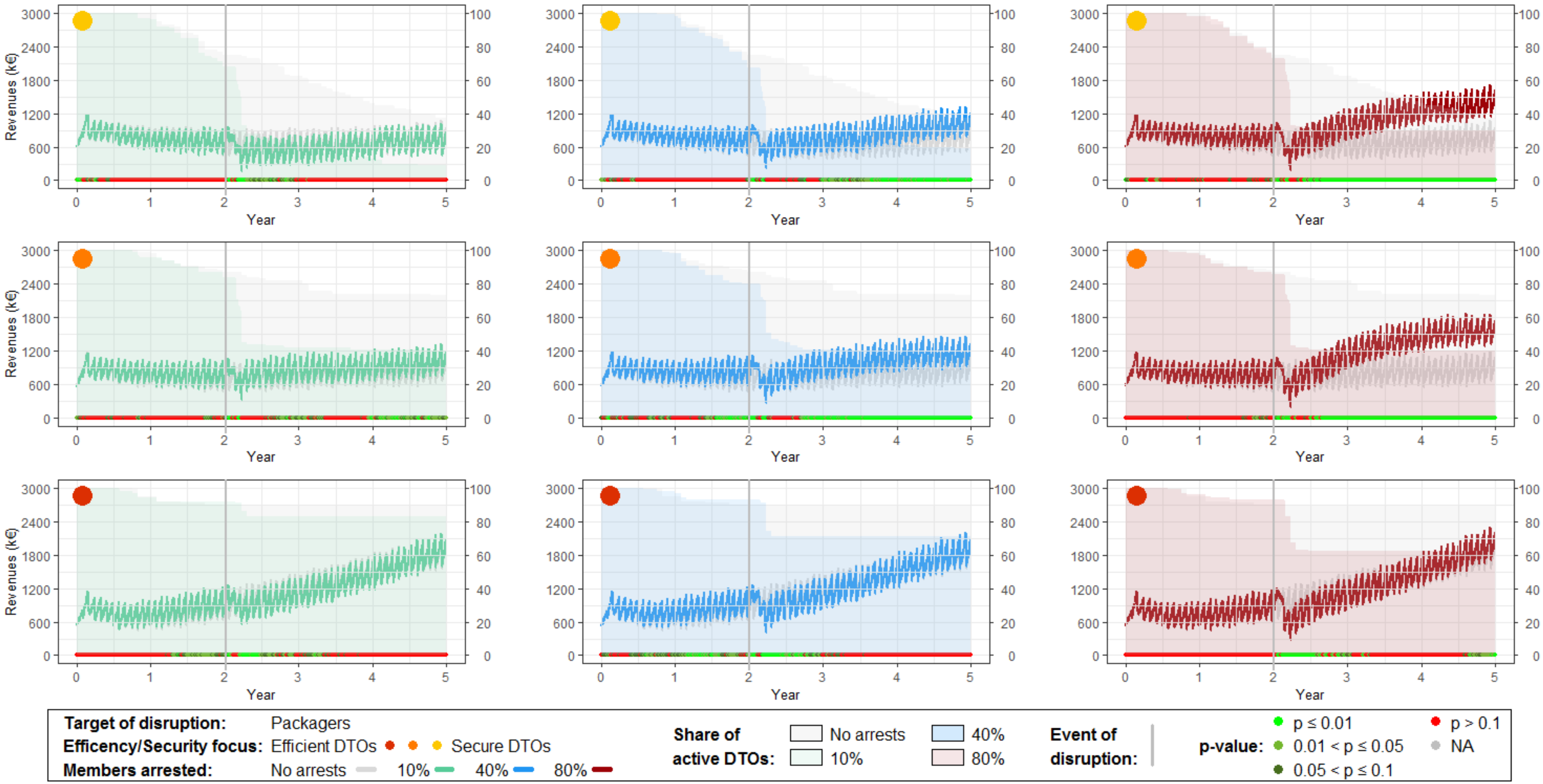
Graph 109. DTOs revenues (Target of disruption: Traffickers; Law enforcement int. scenario: 2)



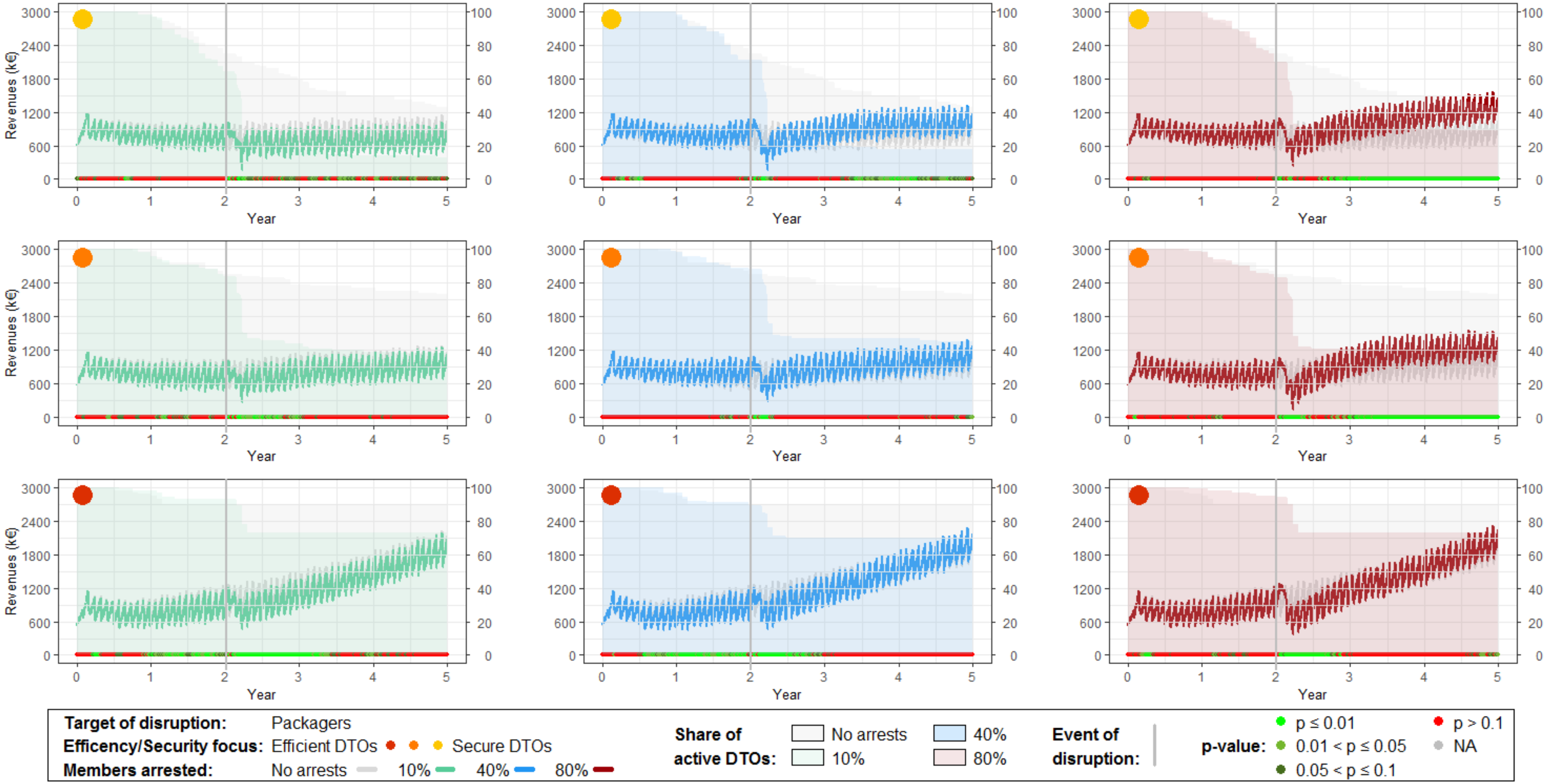
Graph 110. DTOs revenues (Target of disruption: Traffickers; Law enforcement int. scenario: 3)



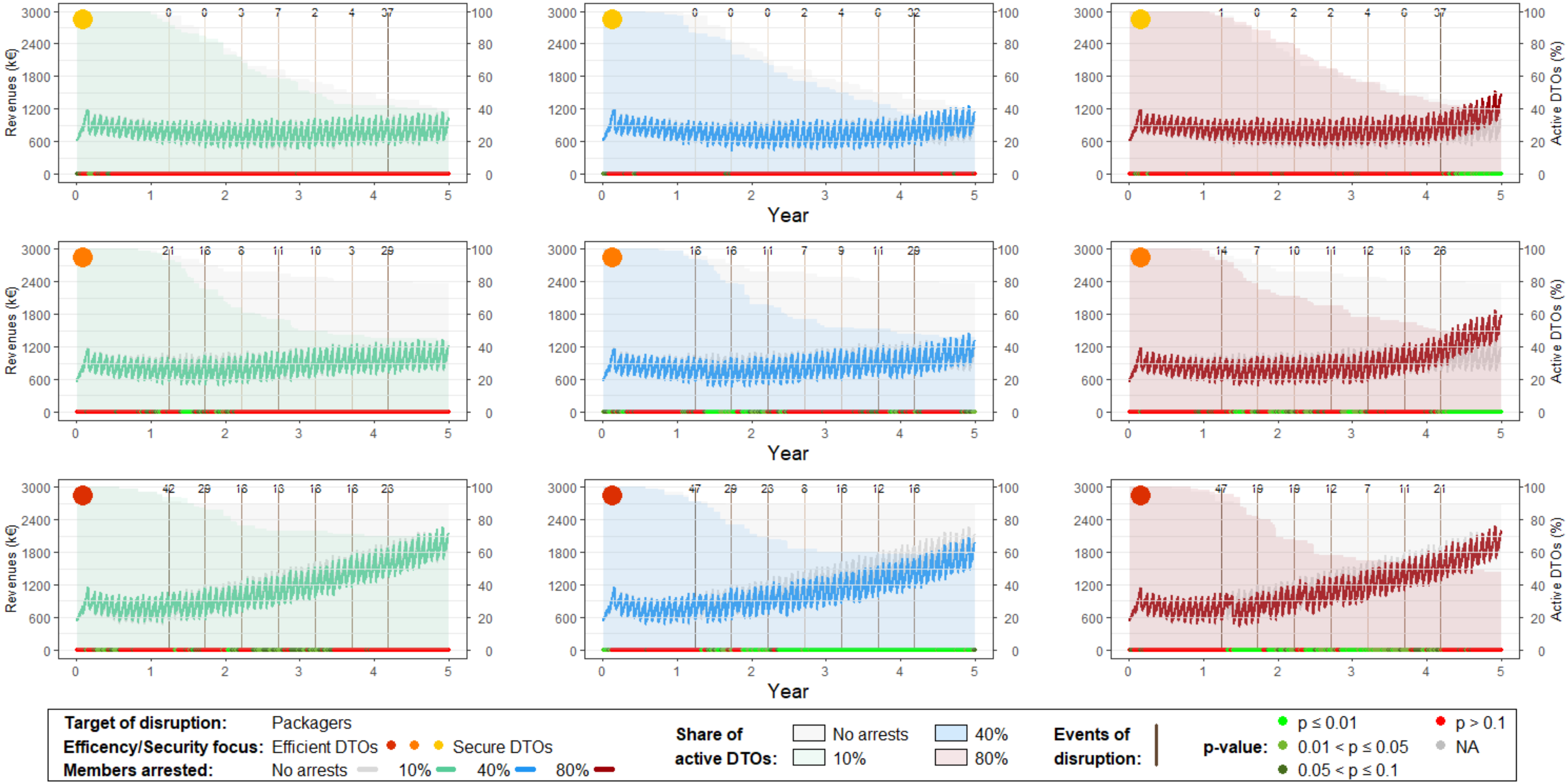
Graph 111. DTOs revenues (Target of disruption: Packagers; Law enforcement int. scenario: 1)



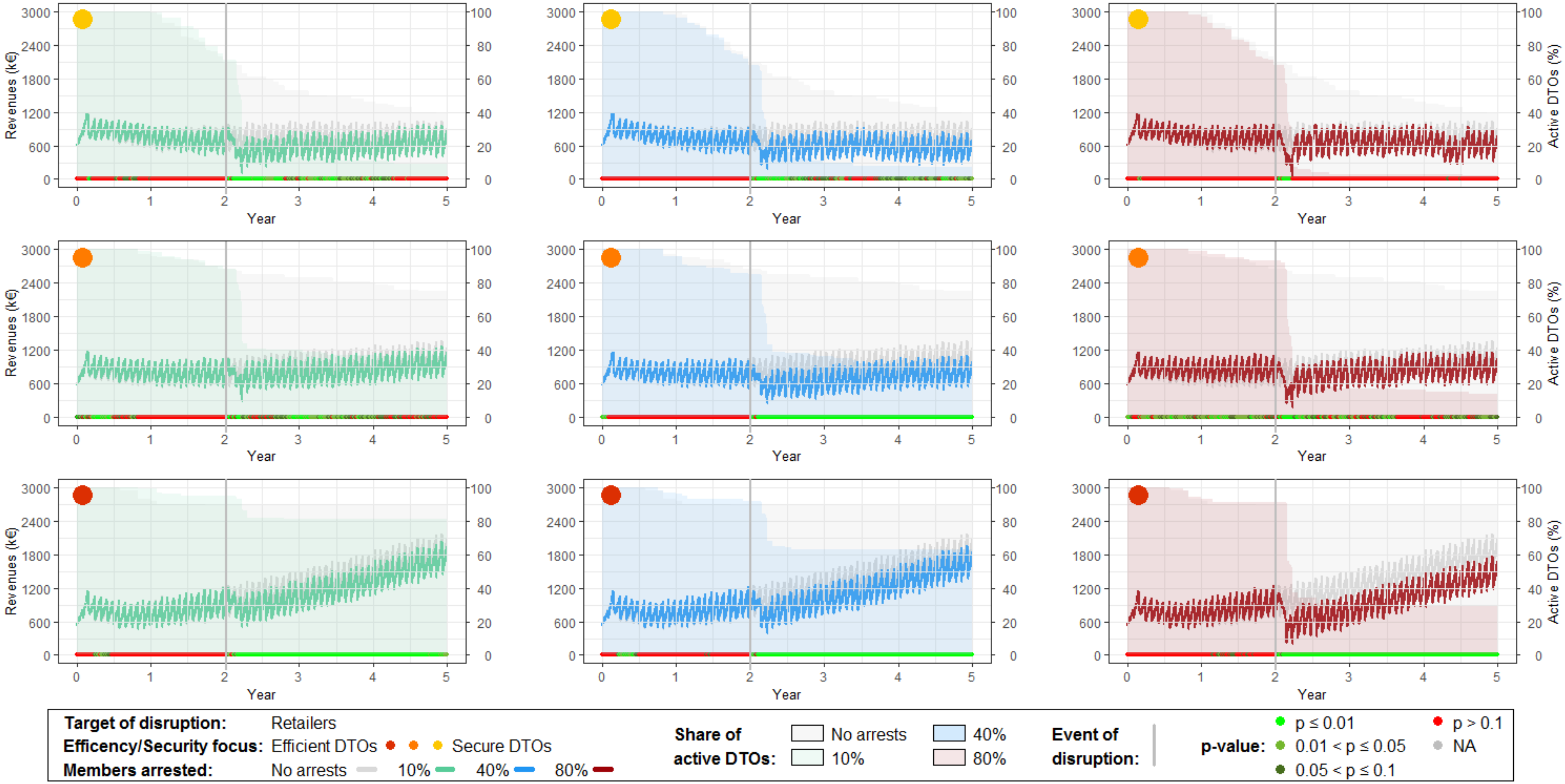
Graph 112. DTOs revenues (Target of disruption: Packagers; Law enforcement int. scenario: 2)



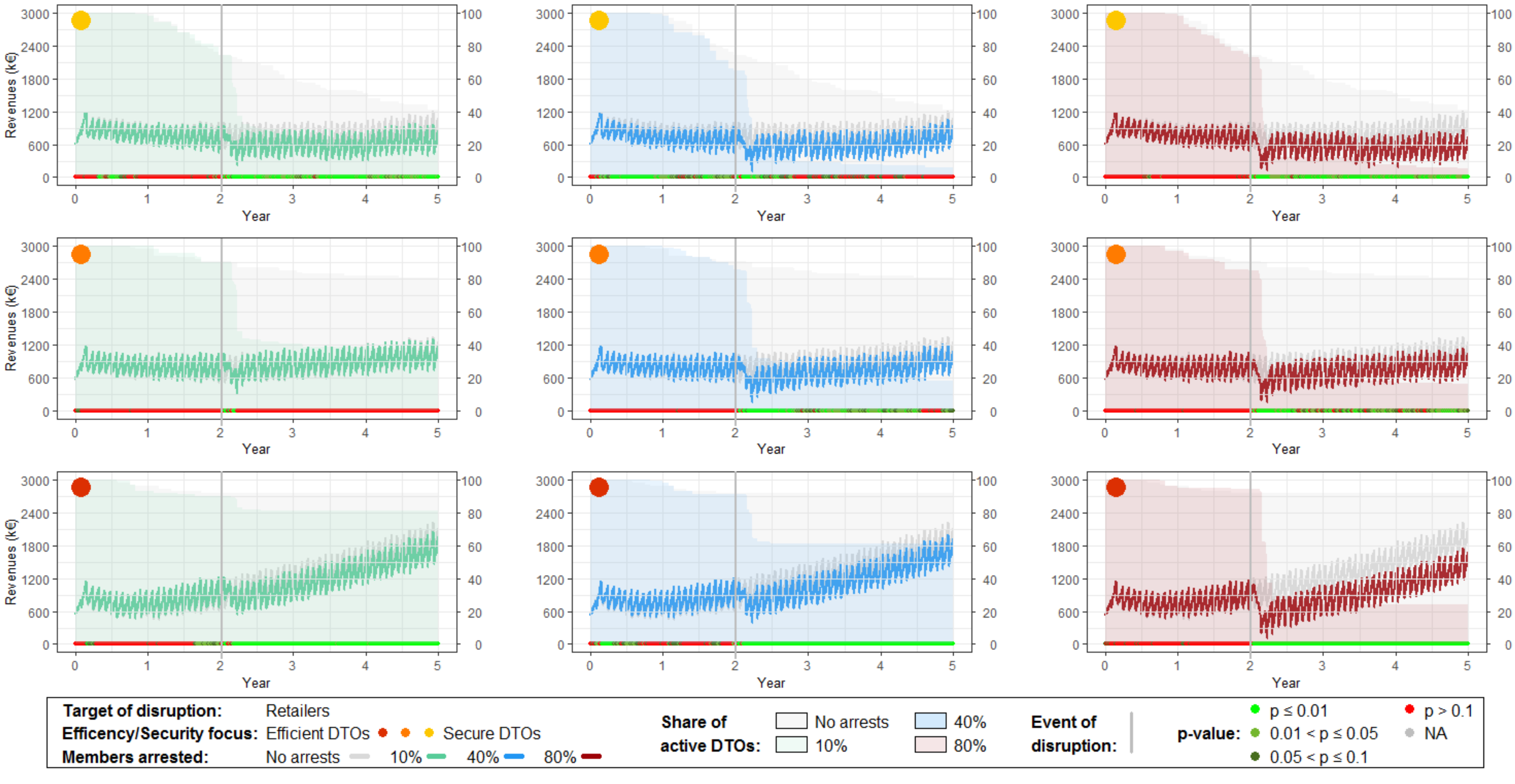
Graph 113. DTOs revenues (Target of disruption: Packagers; Law enforcement int. scenario: 3)



Graph 114. DTOs revenues (Target of disruption: Retailers; Law enforcement int. scenario: 1)



Graph 115. DTOs revenues (Target of disruption: Retailers; Law enforcement int. scenario: 2)



Graph 116. DTOs revenues (Target of disruption: Retailers; Law enforcement int. scenario: 3)