



# Recruitment into Organized Crime: An Agent-Based Approach Testing the Impact of Different Policies

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## Abstract

**Objectives** We test the effects of four policy scenarios on recruitment into organized crime. The policy scenarios target (i) organized crime leaders and (ii) facilitators for imprisonment, (iii) provide educational and welfare support to children and their mothers while separating them from organized-crime fathers, and (iv) increase educational and social support to at-risk schoolchildren.

**Methods** We developed a novel agent-based model drawing on theories of peer effects (differential association, social learning), social embeddedness of organized crime, and the general theory of crime. Agents are simultaneously embedded in multiple social networks (household, kinship, school, work, friends, and co-offending) and possess heterogeneous individual attributes. Relational and individual attributes determine the probability of offending. Co-offending with organized crime members determines recruitment into the criminal group. All the main parameters are calibrated on data from Palermo or Sicily (Italy). We test the effect of the four policy scenarios against a baseline no-intervention scenario on the number of newly recruited and total organized crime members using Generalized Estimating Equations models.

**Results** The simulations generate realistic outcomes, with relatively stable organized crime membership and crime rates. All simulated policy interventions reduce the total number of members, whereas all but primary socialization reduce newly recruited members. The intensity of the effects, however, varies across dependent variables and models.

**Conclusions** Agent-based models effectively enable to develop theoretically driven and empirically calibrated simulations of organized crime. The simulations can fill the gaps in evaluation research in the field of organized crime and allow us to test different policies in different environmental contexts.

**Keywords** Organized crime · Criminal networks · Embeddedness · Recruitment · Involvement · Multiplex networks · Agent-based model · Generalized estimating equations

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## Introduction

Countries around the world have adopted criminal and non-criminal policies to tackle organized crime including specialized law enforcement, harsh penalties, witness protection, and extensive follow-the-money asset forfeiture policies. Compared to the size of these investments and efforts, however, little attention has been paid to the evaluation of the effectiveness of the different interventions (La Spina 2004; Paoli 2007). The scarce evaluation of most organized crime policies is at least partly due to a lack of reliable data. Organized crime activities are hidden and non-reporting or under-reporting are rife. Even when empirical indications are available at specific geographical aggregations (Dugato et al. 2020), systematic individual-level variables—and particularly those that are time-specific and allow for processes to be identified—are near-impossible to obtain.

Some of the most complex criminal organizations have showed remarkable continuity and, despite intense law enforcement action, they have maintained their operations for decades (Gambetta 1993; Reuter and Paoli 2020; Paoli 2020). Like other organizations, complex organized crime groups must select and admit new individuals to ensure their survival. Consequently, recruitment into organized crime is a crucial process that ensures that criminal organizations are able to withstand law enforcement interventions and survive within a hostile environment (Reuter 1983). Recruitment may thus serve as one key unit of analysis to assess the impact of policies tackling organized crime. Some policies may directly attempt to impair or reduce recruitment, whereas other interventions may merely offset it, e.g., through increased criminal justice measures. Closer attention to recruitment and its dynamics may offer useful information on the impact of policies against organized crime.

The literature on organized crime, while rarely addressing the specific factors leading to involvement into criminal groups, has consistently emphasized the importance of social relations (Savona et al. 2017; Calderoni et al. 2020; Kleemans and Van Koppen 2020). Individuals are recruited through multiple kinds of relations: family, friendship, neighborhood, ethnic and other relations, falling within the broader theoretical frameworks of differential association and social learning (Sutherland 1937, 1947; Akers et al. 1979). At the same time, involvement into organized crime often requires a propensity to commit crimes, which may be driven by individual characteristics such as low self-control (Gottfredson and Hirschi 1990). However, while the literature has suggested that these mechanisms may drive the involvement into criminal groups, it is difficult to translate these intuitions into precise measures that allow researchers to study the impact of organized crime policies on recruitment.

In this study, we use agent-based modelling (ABM) (Gilbert 2007) to overcome the limited available empirical evidence on organized crime recruitment and the impact of policies against it. ABM is a set of computational techniques allowing researchers to reproduce actions and interactions of numerous heterogeneous agents within a built environment, and it is increasingly popular in criminology (Johnson and Groff 2014; Weisburd et al. 2017; Groff et al. 2019; Duxbury and Haynie 2019). In this context, given sufficient real world data upon which to build the model, ABM provides plausible causal estimates of outcomes without actually conducting real world experiments, allowing to identify potentially effective policies which may be subsequently experimented in the real world. Our model draws on different theoretical frameworks pointing to both social and individual drivers of recruitment into organized crime. It combines elements of differential association, social learning and social embeddedness as well as individual propensity in explaining recruitment into

organized crime using a multiplex network approach, thus embedding individuals in multiple social relations which mediate the recruitment into organized crime. Furthermore, and unlike many previous ABMs on organized crime, extensive data are used to calibrate and validate the models based on the social, economic and criminal dynamics of Palermo, Sicily largest city and the main center of Cosa Nostra, the Sicilian mafia (Dugato et al. 2020; Calderoni 2011). The choice of Palermo is due not only to its historic and social relevance for organized crime, but also to the availability of unique socio-demographic data thanks to the cooperation of the municipality of Palermo.

We use the model to examine the specific impacts of four different policy interventions comprising both law enforcement disruption strategies and preventive measures in reducing recruitment into organized crime. The results show that all the tested policies reduce recruitment into organized crime in Palermo, although with different intensities. Interventions targeting organized crime leaders generate, all other things equal, a reduction of about 8–9% in the number of organized crime members across the entire duration of the simulation. Interventions addressing children at risk of recruitment through the family or the school environment and law enforcement actions against individuals who possess skills necessary for the commission of complex crimes (“facilitators”) generate a decrease in organized crime members of around 4–5%. These results, however, are context-specific and should not automatically apply to other cities or countries. The contribution of the study, however, goes beyond the assessment of the impact of the policy scenarios in Palermo. The ABM we have addresses the main challenges for simulations in criminology recently pointed out by Groff et al. (2019). We captured theoretically relevant processes driving the recruitment into organized crime groups across different countries. Resorting to the multiplex network structure enables examination of the complex interactions of relational and individual factors. While we have extensively validated the model in the context of Palermo with detailed information on the data sources and our simulation protocol, our ABM can be used to address multiple theoretical and empirical questions in other contexts. For this, we have made the code and the results freely accessible to use and modify, enabling other researchers to adapt it to other social environments and develop additional features.

## Background

### Theoretical Framework

Understanding the motivations and pathways that lead individuals to join criminal groups has long interested criminologists. One fundamental divide, reflecting a deep and long-standing debate in criminology and the social sciences more broadly, is between explanations that focus on the individual and their dispositions (or psychologies) and those that place the emphasis on social or relational factors (Posick and Rocque 2018). Researchers who adopt the former approach often rely on the general theory of crime to claim that organized crime is a process mainly driven by individual traits and self-selection. Conversely, more socially-oriented criminologists typically draw on differential association and social learning theory to posit that organized crime is embedded in the social environment and that social relations are crucial in driving recruitment.

Differential association theory (Sutherland 1937, 1947; Burgess and Akers 1966) and social learning theory (Akers et al. 1979) suggest that organized crime is embedded in the

social environment and that social relations are a crucial factor driving recruitment into organized crime. Both focus on structure—the way in which individuals are related and organized as opposed to the characteristics of the individuals themselves (Borgatti et al. 2009)—and how the position that individuals occupy within the social structure determines their possibilities to commit crimes. According to the theory of differential association, the tendency to commit crime depends on the social context and the interactions of individuals within that environment. The tendency to commit crime increases for individuals living in social environments where deviance is accepted and the rule of law is discounted (Sutherland 1937, 1947; Burgess and Akers 1966). Social learning points out that not everyone is equally accessible and there are individuals that we are more likely to interact with than others, especially those in our immediate social surroundings (i.e., family, friends, neighbors etc.). It also emphasizes the significance of imitation in the learning process and in the general behavioral evolution (Akers et al. 1979; Akers 1998; Akers and Jensen 2011). The learning process involves the acquisition of techniques, attitudes and rationalizations that are justifying criminal behavior, as well as the internalization of criminal identity aspects.

Disputing the social influences predicated by theories of peer influence, the general theory of crime (Gottfredson and Hirschi 1990) argues that individual's low self-control determines their inability to compute the negative consequences of one's criminal behavior, thereby generating persisting patterns of criminality throughout their life. This perspective focuses on the attributes of individuals to explain criminality. The general theory of crime posits that individuals have different levels of self-control, a trait usually developed since childhood and throughout adult life. Low self-control increases individuals' propensity to commit deviant and criminal acts, intended as opportunistic, short-sighted, and unplanned actions (Pratt and Cullen 2000; Gibbs et al. 2003). According to the theory, crimes occur when individuals with low self-control encounter opportunities for crime. The general theory of crime dismisses the relevance of peer influence and group crime, contending that processes of self-selection are their main drivers. Individuals with low self-control simply tend to associate among themselves.

Studies in the field of organized crime have often disregarded the broader theoretical debate about the social or individual causes of crime. Yet, scholars often pointed out the importance of the social environment and relations (Albini 1971; Haller 1971; Ianni and Reuss-Ianni 1972; Blok and Tilly 1974; Granovetter 1985; Mccarthy and Hagan 1995; Hess 1998; Kleemans and Van de Bunt 1999; Paoli 2003; Morselli 2009). The individuals' position within a society shapes access to criminally exploitable contacts and opportunities and-in turn-their possibilities to be involved in organized crime groups, generating a social opportunity structure (Kleemans and de Poot 2008). Rather than individual propensity, the literature on organized crime focuses on social relations and criminal experience (Savona et al. 2017).

The influence of social relations on the recruitment into criminal organization may follow different mechanisms relying on social embeddedness into pre-existing relations (Granovetter 1985; Kleemans and Van de Bunt 1999). First, studies pointed out the role of kinship relations, resulting in a high probability to be recruited into the same organized crime network (Rowe and Farrington 1997; Thornberry et al. 2009; Rakt et al. 2009; van Dijk et al. 2019). The importance of family may appear at odds with the idea of low self-control, often assumed to be the result of the poor supervision of children. Second, work relations generate opportunities of involvement into organized crime, especially for specific skills obtained through their work experience (Steffensmeier and Ulmer 2005; Kleemans and de Poot 2008). Opportunities due to employment contrast with the idea that individuals' low self-control may impair educational and professional attainment. Third,

embeddedness within criminal relations generates opportunities for mentorship allowing individuals to acquire skills and attitudes functional to crime (Mccarthy and Hagan 1995; Kleemans and de Poot 2008). The importance of cooperative social relations contrasts with the arguments that individuals with low self-control are insensitive and lack empathy (Steffensmeier and Ulmer 2005).

The social relations and the self-control perspectives generate opposing views about the processes of recruitment into organized crime. While most organized crime research emphasized its social and relational nature, it is hard to disregard individual level factors. Indeed, there is consistent evidence that members of criminal organizations generally commit a large number of crimes (e.g., Pyrooz et al. (2016); Campedelli et al. (2021); Morgan et al. (2020)), and that low self-control has a positive effect on crime commission and gang membership (Raby and Jones 2016). For these reasons, in our study we rely on both theoretical streams to develop an agent-based model simulating the recruitment into organized crime. The flexibility of an agent-based model offers a convenient way to combine the two perspectives by modeling both personal and inter-personal components. In our ABM, the crime commission process and the recruitment into organized crime are the result of both the agents' social relations and individual characteristics.

### **Agent-Based Models: The State of the Art in Organized Crime Research<sup>1</sup>**

Agent-based models are comprised of three basic components: agents, rules, and an environment. Agents often represent people and are endowed with a set of characteristics. These characteristics can be highly heterogeneous and even unique. Agents in the model have action rules that guide their decision-making. These rules are based on theory or empirical evidence. Agents interact dynamically and the outcomes of agent interactions at one point in time influence agent interaction in subsequent time points. Finally, there is the interaction environment. This can take the shape of a space where agents meet, from a simple grid to a detailed GIS representation of a city, or it can take the shape of a network, with interactions flowing on links, as in the present case (Gilbert and Troitzsch 2005; Gilbert 2007).

A fundamental feature of agent-based models is that, unlike traditional analytical or statistical models, they allow researchers to simulate social systems at multiple levels, nesting characteristics and decision-making rules within individuals (agents) who are located within an environment (such as a geographic space), without forcing unreasonably stringent assumptions about agents and allowing for extensive individual-level heterogeneity. This gives agent-based models the flexibility to represent social realities in detail, and allows researchers to observe the emergent macro-level dynamics that arise from the micro-level interactions of agents. This feature makes ABM especially suited to studying crime and interventions to combat crime because it allows places, offenders, targets, and guardians to be simultaneously modeled (Gerritsen 2015).

Agent-based models also have several other advantages. They avoid ethical and privacy concerns about the use of individuals' personal information and they make it possible to test the impact of policies that cannot be tested "in the wild" due to a lack of data. Furthermore, the process of ABM development makes it necessary to explicate the usually implicit assumptions since creating the ABM requires a precise specification of the

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<sup>1</sup> Parts of this subsection are adapted from Andrighetto et al. (2019).

mechanisms and components that generate the social phenomenon of interest. This facilitates the growth of scientific knowledge and consensus about a topic. Once consensus is reached, policy tests can be conducted on the empirically grounded implementations of the models. From a pragmatic perspective, investigating the dynamics of the recruitment into organized crime at scale is extremely challenging in a real-world setting, involving first and foremost feasibility constraints and also substantial costs and ethical concerns. Computer simulations, conversely, can overcome these issues. Yet, while ABM has multiple strengths, it is not replacement for other approaches—experimental or observational—each of which also have their own advantages (Groff and Mazerolle 2008). ABM may provide evidence about promising interventions given what is known about the phenomenon under study. But once identified, those interventions should be evaluated in the real-world setting.

Given these reasons, ABM is becoming increasingly popular in criminology, with applications across crimes, criminal and deviant behaviors, and policing interventions (Brantingham et al. 2005; Malleon et al. 2009; Troitzsch 2016; Nardin et al. 2017; Weisburd et al. 2017; Székely et al. 2018; Duxbury and Haynie 2019; Groff et al. 2019). Nevertheless, few studies use ABM in criminology and even fewer apply it to organized crime. There are three broad approaches to ABM in criminology. First is the environmental approach, where agents choose the location and time of committing a crime within a simulated environment that is relatively close to reality (e.g., Groff (2007); Johnson (2008); Kim and Xiao (2008); Weisburd et al. (2017)). The focus here is on the frequency and geographical distribution of criminal activity. Second is a more complex approach in which agents have more specific roles as well as decision-making options. This approach, which follows the KIDS concept (“keep it descriptive, stupid!”) (Edmonds and Moss 2005), is to build a rich model and then to gradually whittle it down by removing unnecessary components, leaving only the important factors. Examples are Nardin et al. (2016) and Székely et al. (2018), which investigate the effects of legal and social approaches in countering protection racket (see also Elsenbroich (2016)). These models aim to include plausible decision-making rules in the agents and replicating reality as best as possible. However, an issue of this approach is excessive granularity, which may limit the generalizability of the model. Third is a linear approach that maps the involvement of agents through social relations and learning interactions rather than environmental opportunities or individual decisions (Berry et al. 2004a, b; Duxbury and Haynie 2019). The social networks in this model are pre-established and partially randomized. The environment is reduced to “boxes” in which agents interact with one another and influence each other’s opinion. While this type of ABM application is simple in terms of conceptualization, it is flexible regarding the potential to add complex personality traits and decision-making skills. Even a general political or cultural dimension could be added.

None of the prior ABMs have attempted to combine relational and individual attributes in explaining organized crime recruitment using a multiplex network approach. Unlike standard network theory, a multiplex network provides a more realistic representation of the different and heterogeneous relations that may characterize an entity in the network system in a variety of domains, ranging from biological to technological, and social systems (Mucha et al. 2010; Gómez et al. 2013; Boccaletti et al. 2014; Lee et al. 2015; Klimek et al. 2016).

Our contribution is a theory driven and empirically grounded ABM that represents recruitment into organized crime as a dynamic and complex interplay between multiple individuals’ attributes (i.e., social positions, economic, education and criminal backgrounds) and the influence of the social structures—household, kinship, school, work, friends, and co-offending—in which the agents are embedded. These social environments

are modeled on real life demographic, socio-economic and criminological data from Palermo and Sicily. Similarly to Nardin et al. (2016) and Székely et al. (2018), we use the model to test the effect of different policy scenarios in reducing recruitment into organized crime.

## Policy Scenarios

We assess the effect of four policies using our simulation on recruitment into organized crime groups and the size of the groups. Two policies aim to disrupt the activities of the criminal group by increasing arrest probabilities of organized crime leaders (targeting OC leaders) and facilitators (targeting facilitators), whereas the other two policies focus on socialization mechanisms within the family (primary socialization) and the peer-group (secondary socialization).

Research on criminal networks spurred exploration of effective network disruption strategies (Morselli et al. 2007; Duijn et al. 2014; Wandelt et al. 2018; Duxbury and Haynie 2019; Ren et al. 2019). Despite the growing interest in this field, scholars encounter significant difficulties in obtaining sufficiently detailed data. Analyses often focus on information about events (such as telephone or meeting contacts), rather than long-term states (e.g., enduring social relations). Second, it is difficult to include socio-economic factors on people beyond basic demographic information. The most sophisticated studies on network dismantling have relied on stylized networks (e.g., Erdős–Rényi graphs) or networks with characteristics that may be completely different from the ones of criminal networks (Braunstein et al. 2016; Ren et al. 2019). Third, due to structural data limitations, studies usually rely on short time spans. This reduces the possibility to investigate long-term dynamics and effects following the application of a given disruption strategy. Our ABM model addresses these limitations by modeling stable social relations and not only contacts or co-participation in events. Our approach offers information on criminals' social and economic characteristic and not only their criminal attributes. Finally, we conduct long-term simulations thus allowing us to assess the long-term effects of network disruption policies.

Our *targeting OC leaders* policy aims to disrupt groups by focusing on their leaders. Criminal leaders are generally associated with the idea that criminal groups not only depend on their operational decisions but also on their network position (Morselli 2009; Calderoni and Superchi 2019). Research has focused on lead "k" targeting as the most efficient disruption policy (Alm and Mack 2017; Wood 2017). Scholars offered different views on the effectiveness of targeting strategies against leaders of criminal networks. Our second group disruption policy *targets facilitators*. These are agents that due to their job or social relations can contribute to the commission of complex crimes necessitating several agents. Facilitators can be considered as individuals with specific skills, for instance, chemists for cooking methamphetamine, accountants for money-laundering, safe men for burglary. Criminal facilitators have been studied under many perspectives (for example Levi et al. (2005)). Morselli and Giguere (2006) show that legitimate actors are important for the criminal activities of an illegal drug importation network. Other contributions showed the importance of legitimate actors in shaping the activities of criminal groups (Sanchez 2017; Haller 1971). Kleemans and de Poot (2008) argued that several occupations may offer opportunities and contacts leading to organized crime involvement, as an important demonstration of the social embeddedness of organized crime.

The role of family and friends in the differential association and social learning theories received empirical support from narrative reviews (see Akers and Jensen (2006); Akers

and Sellers (2009)) and systematic reviews with meta-analysis (Pratt et al. 2010). Peer and family risk factors have also been studied in relation to involvement in criminal groups, as gangs. Raby and Jones (2016) showed that family, school, peers, and community were among the main domains associated with gang affiliation. Similarly, a systematic review conducted by Higginson et al. (2018) on risk factors for gang membership in low- and middle-income countries found that socialization with delinquent peers, lack of parental monitoring, and negative family environments were positively associated with involvement into gangs. van Dijk et al. (2019) found that inter-generational transmission of organized crime was related to deviant social learning and the violent reputation of fathers. Spapens and Moors (2019) argued that criminal behavior is learned within criminal family contexts in the Netherlands. A systematic review by Savona et al. (2017) also indicated that relations with criminal family members (i.e., kinship and blood ties) favor involvement into organized crime.

Using one policy, we consider the possible influence of fathers (and other relatives) who are members of organized crime on their children (*primary socialization*). For instance, in 2017 the Juvenile Court of Reggio Calabria (Italy) signed a cooperation protocol with national and local authorities to limit the parental authorities of fathers as well as the influence of other relatives involved in organized crime. The aim of the policy is to protect minors and mothers and decrease their exposure to mafia indoctrination (see Di Bella (2016); Sergi (2018)). In the final policy, we test whether providing children at risk of delinquency with enhanced training programs developed in the school environment can reduce organized crime involvement. As such, this policy focuses on the role of *secondary socialization*. Intervention programs such as the project promoted by the Juvenile Court of Reggio Calabria in Italy highlighted also the relevance of counseling services with experts (e.g., psychologists, social educators) in school premises in disadvantaged areas (see Cascini and Di Bella (2017)). Approaches intervening upon educational opportunities, as well as recreational activities (e.g., sport, dance), have also been reported by systematic reviews of intervention programs for reducing gang membership and criminal involvement (Hodgkinson et al. 2009; Higginson et al. 2015), though the reviews have pointed out the difficulty of drawing unique conclusions on the effectiveness of such preventing interventions.

## Methodology

### Structure of the Agent-Based Model

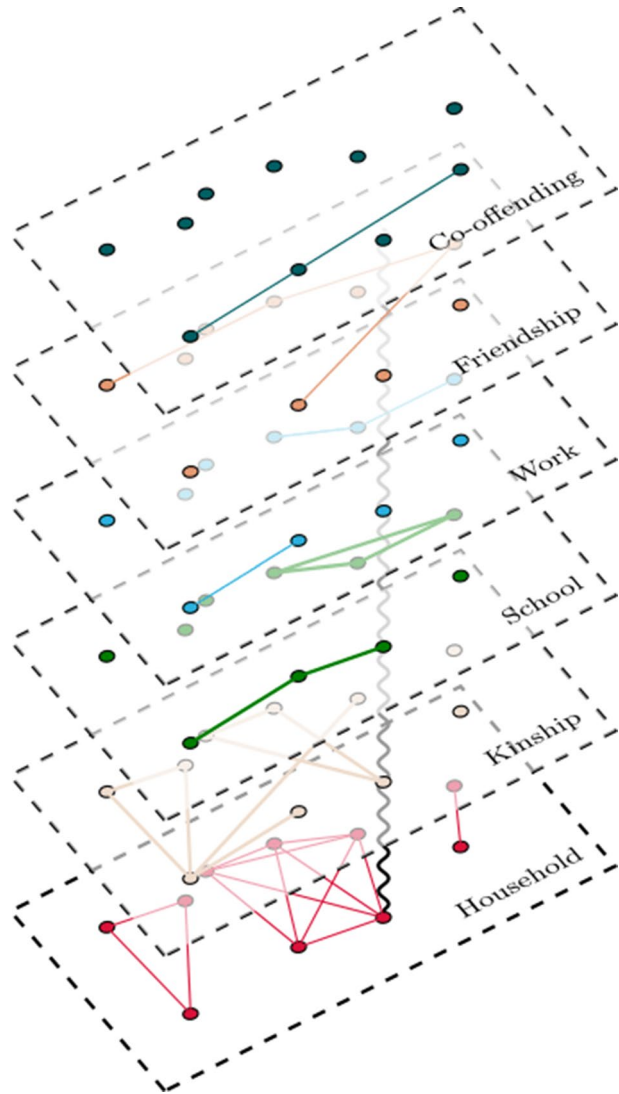
#### Overview

We model both social relations and individual attributes within a multiplex network framework. A multiplex network includes several networks, each mapping specific social relations. Our ABM includes six networks: (1) household, (2) kinship, (3) school, (4) work, (5) friends, and (6) co-offending (Fig. 1 offers a schematic representation). We summarize each of these below, whereas the Supplementary Materials provide additional information, and the Appendix includes the ODD+D protocol (Müller et al. 2013).

Start with the co-offending network. It comprises the set of others that an agent has co-offended with in the past and its dynamics closely influence the recruitment into organized crime. Specifically, if an agent co-offends with another who is part of the organized crime group, then the first agent also joins the group. The simulation is initialized with



**Fig. 1** The multiplex network structure for the organized crime model



one existing organized crime group, in which the agents are connected via their co-offending network. In other words, organized crime members are a subset of the co-offending network.<sup>2</sup>

The other five networks, household, kinship, school, work, and friendship, provide the foundations upon which the co-offending network is built. Each network has particular features (more details in the Supplementary Materials). The household network represents family relationships and is initialized with household data (household data retrieved from

<sup>2</sup> We consider a single-group situation and for simplicity exclude the possibility of multiple organized crime groups. We also assume that once an agent joins, it will always be part of that group irrespective of whether or not the agent commits another crime.

the 2011 Italian Census and from data made available by the Municipality of Palermo). Bonds between households are added to represent kinship, e.g., brothers living in different households. The friendship network is initialized as a Watts–Strogatz network (Watts and Strogatz 1998) and it grows as people connected via other ties (e.g., work, school) become friends. The number of friends is limited by Dunbar's number modified by age (Dunbar 1992). The work network is created through employment and initialized based on employment data and the distribution of company sizes. School networks create an early foundation for the agents: once agents "leave school" they maintain the friendships they previously created there. Behind their formation is a general homophily mechanism (which we call "social proximity factor").

The multiplex network framework also allows us to consider individual-level characteristics as agents attributes. Agents in the simulation can be born, get engaged or married, have children, die, establish and break social relations, and commit crimes. We also include facilitator agents, who are like other agents, except that they possess generic skills that are necessary to undertake more complex crimes that require several co-offenders. Facilitators are not necessarily members of the organized crime group, but they represent a range of individuals who collaborate and contribute to the activities of organized crime groups (e.g., accountants for money-laundering, politicians for protection, custom officers for smuggling) (Van Koppen and De Poot 2013; Catino 2019).

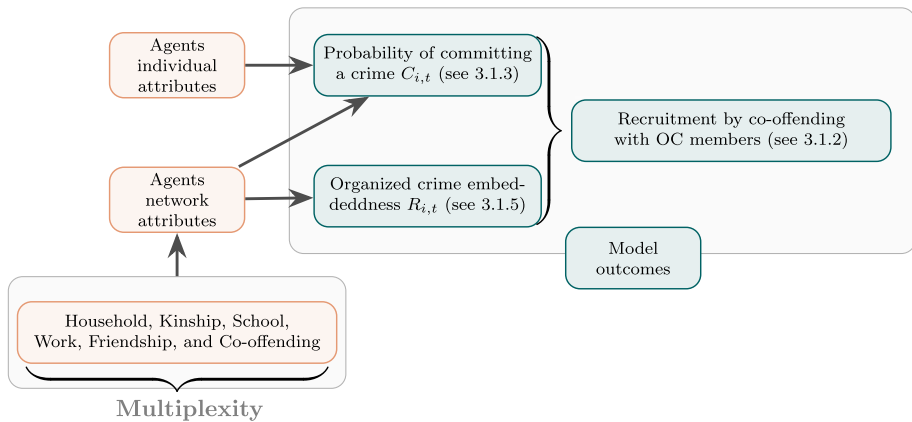
The model refrains from including explicit rational or semi-rational decision-making processes and the presence of values. Agents are not called to make actions based on specific evaluation of costs or benefits and the simulation does not use reinforcement or learning mechanism. We adopt this approach because there is a dearth of detailed evidence about individual-level decisions regarding the involvement and recruitment into organized crime. Rather than including an arbitrary set of values, or costs and benefits, into the formal dynamics of the model, we opted for a probabilistic model in which individual and social characteristics either increase or decrease the probability of an event happening. The details of these probabilistic processes are summarized in the following sections with additional information in the Supplementary Materials and the ODD+D protocol in the Appendix.

## Recruitment into Organized Crime

Recruitment occurs when an agent commits a crime with at least one other agent who is already a member of the organized crime group and is also the initiator of the crime. This design choice was driven by multiple considerations. First, it is broadly consistent with the legal requirements for the participation in a criminal organization across a number of countries (Calderoni 2010). Second, it is clearly observable in the model and simple to operationalize; it identifies the moment of recruitment in a clear and unambiguous way, avoiding subjective evaluations or discretionary thresholds often observed in other studies. Two factors contribute to the recruitment process in the model: an agent's probability of committing a crime (called  $C$ ) and an agent's social embeddedness in organized crime (called  $R$ ) (Fig. 2). We turn to these next.

## Modeling Criminal Activity: The Probability of Committing a Crime ( $C$ )

The  $C$  function is the probability that agent  $i$  will commit a crime at time  $t$ . The function comprises specific agents' attributes such as individual characteristics (e.g., sex, age),



**Fig. 2** General Structure of the Organized Crime Model

socially determined ones (e.g., number of friends or parents who have committed a crime), and criminal ones (e.g., previously committed crimes). The specific factors included in  $C$  are based on systematic reviews: age, gender, employment, education, criminal propensity, criminal history, the number of friends, family members and co-workers who have committed a crime, and whether the agent is an organized crime member (Farrington et al. 2017; Calderoni et al. 2020; Pratt and Cullen 2000; Pratt et al. 2010). The combination of these attributes sets an agent's probability to commit a crime. As the agent's attributes change in time,  $C$  is updated as the simulation proceeds.

Considering the consolidated evidence about the crime-age curve (Farrington 1986; Nagin and Land 1993; Stolzenberg and D'Alessio 2008; Loeber et al. 2012), which indicates that most crimes are committed by young males between their teens and young adulthood, the  $C$  function includes a baseline probability condition on agent's age and sex. We derived the probabilities associated with committing a crime according to sex and age (split into discrete categories) by estimating the probabilities of committing any crime, including unreported crime, or the dark figure (Skogan 1977; Groff et al. 2019). This correction is driven by the consideration that the recruitment into an organized crime group is largely independent on whether a crime is discovered, reported, investigated and prosecuted. We estimated the total number of crimes starting from the average reported crimes in Palermo between 2012 and 2016 (Istat 2016b). Averages by type of crime were corrected by the propensity to report by crime type from the Istat national victimization survey (Istat 2010). The total crimes were then distributed across age classes and gender through available data on known offenders (Istat 2012a). The baseline probability was computed as a ratio between the total crimes and the total population by age class and gender (Table 1). Consistent with the evidence about the age-crime curve, the probability of committing a crime is always higher for males and peaks for both sexes during teenage and young adulthood. Furthermore, in line with some studies arguing the extension of adolescence and youths periods in contemporary developed societies, we observe a high probability also at age 35–44 (Jolliffe et al. 2017).

Other factors modify each agent's baseline probability. Based on systematic reviews on the association between the relevant factors on the probability of committing a crime (Pratt and Cullen 2000; Pratt et al. 2010), we included further factors that are compatible and

**Table 1** Baseline probability of committing any crime each year (including unreported crime) by sex and age class

Age class	Female Baseline probability	Male Baseline probability
≤ 13 years	0.0004	0.0022
14–17	0.0223	0.1502
18–24	0.0511	0.3019
25–34	0.0634	0.3036
35–44	0.0643	0.2751
45–54	0.0489	0.1996
55–64	0.0308	0.1268
≥ 65	0.0111	0.0537

measurable in the simulation. The systematic reviews provide effect sizes in different forms (e.g., odds ratios) allowing us to modify each agent's baseline probability whenever one or more of such factors are present. Table 2 presents the list of individuals factor-based rules modifying the baseline probability of committing a crime.

Put simply, committing a crime follows an assignment procedure inherently present in the model architecture. This procedure works based on the value of  $C$ : the higher the value, the higher the probability that, out of the number of offenses that occur in the model at each time step, a given number (one or even more) is committed by that agent. This stochastic process allows us to focus on the specific relational and individual features found in the relevant literature and avoid any arbitrary cut-off value or discretionary threshold. For details about the equation for estimating  $C$ , see the Supplementary Materials.

Agents committing crimes can be incarcerated. Incarceration occurs with a fixed probability in each round of the simulation, based on data retrieved from official statistics. Apart from family links, agents in prison temporarily lose all the ties that they created during their life (including during their jobs). The mechanism for incarceration relies on a countdown that establishes when the agent leaves prison (based on the empirical evidence about the length of imprisonment sentences) and returns to be free in the society, recovering part of its ties.

### Modeling criminal activity: co-offending

When, based on each agent's  $C_{i,t}$ —i.e., the value of  $C$  at time  $t$ —a crime is due to take place, the ABM also determines the "size" of the crime (put another way the number of required co-offenders). We base the distribution of crime size on the literature on co-offending showing that most crimes are committed by single offenders and few crimes require two or more offenders (Stolzenberg and D'Alessio 2008; van Mastrigt and Farrington 2009; Carrington and van Mastrigt 2013).

Once the model probabilistically establishes that an agent commits a crime as well as the size of the crime, the agent looks for partners through all of their social networks (household, kinship, school, work, friends, and co-offending). They look through their networks in such a way that they are likelier to ask other agents with whom they have more links to be co-offenders. More specifically, there is a direct positive relation between the number of links between agents and the probability of requesting another agent to co-offend. Furthermore, previous co-offending relations have the largest weight in this process; agents with

**Table 2** Individual-level factors modifying the probability of committing any crime—odds ratios

Risk factor	OR	Definition
Unemployment	1.30	Having/not having a job
Education	0.94	Having/not having an high school diploma
Natural Propensity	1.97	Having a crime propensity higher than a certain value $x$ (log-normally distributed in the population)
Criminal history	1.62	Having/not having committed a crime in the past
Criminal family	1.45	Having a share of criminal family ties (kinship and household) which is higher or equal to 0.5.*
Criminal friends and Co-Workers	1.81	Having a share of criminal friends and work ties which is higher or equal to 0.5.**
Organized crime membership	4.5	Being part of an organized crime group

\* A criminal family tie is a direct link in the kinship or household networks with an agent who has committed at least one crime in the last 2 years.

\*\* A criminal friendship/co-worker tie is a direct link in the friendship or work networks with an agent who has committed at least one crime in the last 2 years

whom an agent has already committed a crime are likelier to be selected for future crimes. This reflects the idea that peer, and more generally social, influence drives criminal cooperation (Weerman 2011). The model thus matches co-offenders based on mechanisms of social proximity: the closer two agents are in terms of social relations across network layers and the higher is the value of  $C$  of both individuals, the higher the probability of becoming co-offenders.

### Modeling organized crime embeddedness ( $R$ )

As summarized above, recruitment into a criminal group is mediated by other, often non-criminal, social relations. In other words, people embedded in networks including organized crime members have higher probabilities of being recruited. We model the social embeddedness in organized crime by adding one element to the selection of co-offenders whenever crimes requiring two or more co-offenders are initiated by organized crime members. In addition to social proximity and  $C$ , a third element contributes to the selection:  $R$ . Function  $R$  measures the proportion of organized crime members among the social relations (comprising household, kinship, school, work, friends, and co-offending) of agent  $i$  at time  $t$  (for more detail on  $R$  computation, see the Supplementary Materials).  $R$  operationalizes each agent's social distance from the existing organized crime members (across all the six types of networks) and affects the selection of co-offenders by organized crime members, i.e., the recruitment of new agents. For example, among two equally suitable co-offenders (both socially close and with similar  $C_{i,t}$ ), organized crime members are likely to co-offend with the agent who is more socially embedded in organized crime relations, i.e., with the higher  $R_{i,t}$ , where  $i$  refers to the agent and  $t$  to the present time unit. Furthermore,  $R$  enables clear distinction between active organized criminals and agents socially close to organized crime but who are not actual members. An agent may be strongly embedded in organized crime-prone relations, but not be involved in organized crime activities. For example, mothers, partners, and daughters of organized crime members are socially close to organized crime although rarely involved in criminal activities. Similarly, children of organized crime members cannot be considered active members but would still have a very high value of  $R$ , increasing the probability of recruitment in the future.

Our simulation models recruitment into organized crime as a dynamic and complex interplay between multiple individual attributes and the influence of the social structures—household, kinship, school, work, friends, and co-offending networks—in which the agents are embedded. This accurately models the dynamics formulated by theories such as differential association, social learning, and social opportunity structure, also including the effect of individual traits and characteristics.

## Data and simulation

### Data

We put extensive efforts in developing the model exclusively on real-world data. All the inputs of the simulations are calibrated through empirically observed distributions and values in the city of Palermo or in Sicily generally. The choice of Palermo is based on its historical and social role for organized crime. Capital of Sicily and center of the Sicilian Mafia, the city has witnessed the recruitment of thousands of organized crime members. Furthermore, cooperation of the Municipality of Palermo allowed to obtain unique data

on its socio-economic structure. Specifically, we retrieved and use in the simulation, data on (i) demography and households, (ii) fertility and mortality rates, (iii) employers and employment, (iv) socio-economic status and education, (v) criminal networks, (vi) co-offending, and (vii) friendship networks. Most of the data are from the Italian Institute of Statistics (Istat), the European Statistical Office (Eurostat), and the Bank of Italy, while the number of mafia families and members has been gathered from large-scale criminal investigations on mafia groups. We summarize the source of the data and how they are used in the model in Table 3.<sup>3</sup> Additionally, we validate our model results on the annual crime rate, the annual arrest rate, the number of mafia families and members, the punishment length, the unemployment rate, the age and gender distribution and the associated probabilities to commit a crime (the *C* function), and the co-offending prevalence. In other words, we have ensured that these parameters stay within a reasonable, empirically observed, range of values throughout the simulations. This also allowed us to evaluate the sensitivity of the model to changes in the parameters (see 3.2 and Supplementary Materials).

### Simulation Execution

We model the agents, rules and environment in a simulation platform built on NetLogo (Wilensky 1999).<sup>4</sup> The ABM is initialized with 30 organized crime members and an annual crime rate equal to 2,000 offenses per 10,000 inhabitants. Simulations are populated with 3000 agents and run for a total of 360 steps, representing 30 years of simulated time. Each policy scenario (presented above in Sect. 2.3) starts at round 12 and is maintained until the end of the simulation. We repeated each policy scenario 60 times with different pseudo-random seed initialization to account for the stochasticity of the models and reach sound aggregate statistics.<sup>5</sup>

We used the ABM to test the impact of the four simulated policy scenarios on recruitment into organized crime groups and the size of the groups against a baseline (no intervention) scenario (Groff et al. 2019). Two policies try to disrupt the activities of the criminal group by increasing arrest probabilities whereas the other two policies focus on socialization mechanisms within family and peer-group. Andrighetto et al. (2019) provide detailed discussion of the simulated policies and of the related assumptions (see also the Supplementary Materials and the ODD+D protocol in the Appendix). Table 4 summarizes the operationalization of the policies in the ABM.

In addition to testing the proposed policies, we undertook a set of sensitivity tests focusing on a subset of five key parameters (number of organized crime members, crime rate, unemployment rate, law enforcement intervention rate, imprisonment length) (Groff et al. 2019). We explore the effect of proportional changes, one at a time, for each of those parameters, using multipliers of 0.5 for low values and 1.5 for high values for the baseline

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<sup>3</sup> The calibration is made with statistics calculated for 10,000 citizens, as it is customary for relatively rare events. These values are imported in the simulation and then scaled down or up to the actual number of agents. After exploring several simulation sizes, we found at 3000 agents an ideal compromise between completeness of exploration and execution speed; thus, several of the calibration figures declared in this section will be scaled at 3/10 inside the simulation.

<sup>4</sup> The simulation model is available at <https://github.com/LABSS/PROTON-OC>.

<sup>5</sup> Given the size of the simulation and the complex network-based calculations, the average time for one repetition was approximately 20 h on specially-dedicated computers. The total computing time for the entire project (including additional analyses not presented here), amounted to approximately 14,000 h. The full set of results are available on Zenodo at <http://doi.org/...> link removed for anonymization.

**Table 3** Data for calibrating the organized crime model

Variable	Description
Household size	We used 2011 Census and data specifically provided by the municipality of Palermo to derive the distribution of household sizes in Palermo, also considering the age of the household head to reconstruct the family structure of the city. Source: Istat (2011b)
Age and gender	The population is modeled following the age and gender distribution of citizens living in Palermo, according to official statistics. Source: Istat (2018)
Fertility rate	Fertility rate is derived from official statistics to model plausible reproduction patterns within the society. The fertility rate is calculated according to the age and conditioned upon the number of children. It indicates the probability for a woman of having a child when she had previously had no children, one child, two children, and three children. Source: Istat (2017)
Employers' size	To realistically model the economic dimension and the generation of the work network, we have estimated the distribution of the employer size using official data on the city of Palermo. Each employer has a link to a variety of jobs that have in turn certain education requirements. Source: Istat (2012b)
Socio-economic status	We have estimated the socio-economic status of each individual, by including information on age, gender, wealth level, educational attainment and work status. At birth, agents inherit their parents' wealth status which is later updated based on the agent's work status. There are five wealth levels introduced into the model based on quintiles of the wealth distribution data gathered from Banca d'Italia on Sicilian families' income and expenditures. Source: Banca d'Italia (2018); Istat (2011a)
Unemployment rate	We derived the labor status of agents (employed, unemployed, and inactive) by gender and age class from Eurostat's data on Sicily. The unemployment rate is the share of unemployed individuals out of the economically active population (empl. + unempl.) Source: Eurostat (2019)
Friendship networks	New friendship links are created between agents according to a random Poisson distribution. The number of friends an agent can have is limited by Dunbar's number modified by age, which is the average of 150 persons that an agent can maintain stable social relations with during a lifetime. Source: Dunbar (1992)
Schooling	Four school levels are included in the model: primary school, 1 <sup>st</sup> level secondary school, 2nd level secondary school, and universities. Schooling also determines the socio-economic status of each agent. Data for Palermo are obtained from the Ministry of Education, University and Research. Source: MIUR (2019)
Organized crime group structure	The size of the organized crime group is based on estimates on the number of individuals affiliated to mafia organizations, suggesting a rate of 30 members per 10,000 inhabitants Sources: Corte d'Appello di Reggio Calabria (2012); Paoli (2003); Direzione Investigativa Antimafia (2017). The group is made agents from different households and ages, derived from qualitative analysis of large-scale investigations on mafia organizations. Source: operations "Montagna" (Tribunale di Messina 2007), "Aemilia" (Tribunale di Bologna 2015), "Crimine" (Procura di Reggio Calabria 2010), "Infinito" (Tribunale di Milano 2011), and "Minotauro" (Tribunale di Torino 2011)

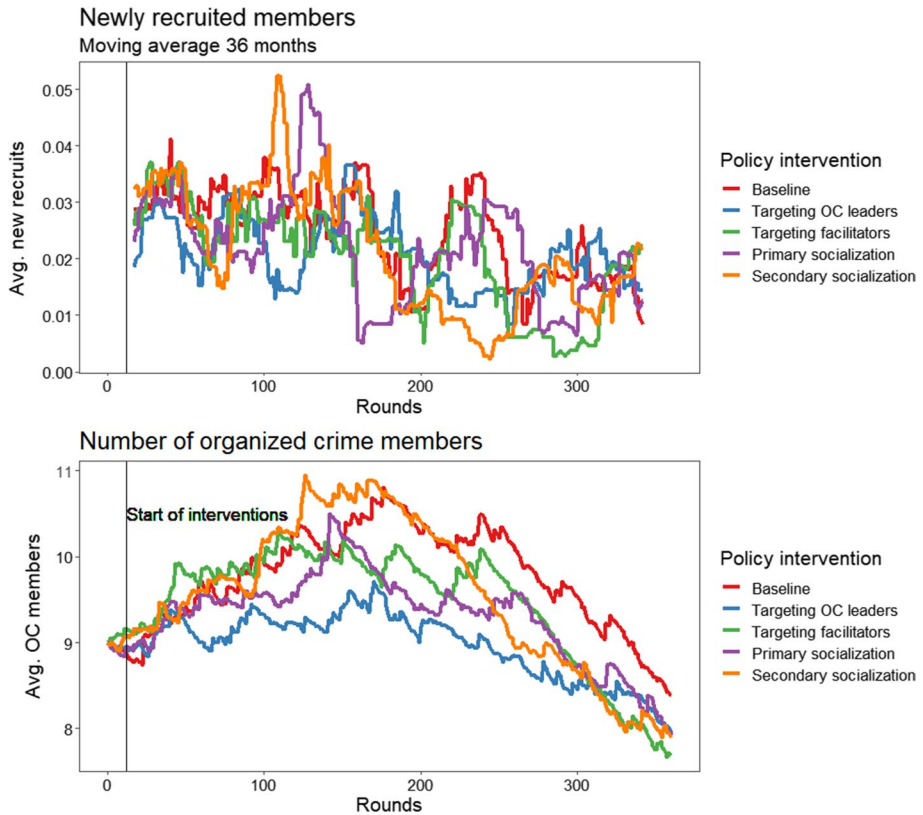


**Table 3** (continued)

Variable	Description
Co-Offending prevalence	The distribution of co-offending has been derived from Istat data and validated by comparing it to empirical studies in the literature. Source: Istat (2016a), cross-checked with the literature Carrington (2002); Hodgson (2007); Hodgson and Costello (2006); Carrington et al. (2013); Carrington and van Mastrigt (2013),
Crime rate	We have calculated crime rates for Palermo without discriminating between crime types and including unreported crimes. Unreported crimes were estimated by correcting the distribution of reported crimes by type through the propensity to report by crime type from the Istat national victimization survey. This resulted in an annual crime rate (incl. unreported crimes) of 2000 crimes/10,000 inhabitants. The rates of crime by age class and gender were estimated through available data on known offenders. Source: Istat (2010, 2012a, 2016b)
Law enforcement intervention rate	Official data provide information on the type of penalties imposed on convicted offenders. By solely focusing on convictions to imprisonment, we have estimated the law enforcement intervention rate. This results in approximately 30 annual imprisonment convictions per 10,000 inhabitants. Source: Istat (2012a)
Imprisonment length distribution	Official data on the length of imprisonment sentences enabled to compute the following imprisonment length distribution: <1 month: 10.71% 1–3 months: 16.91% 3–6 months: 24.93% 6 months–1 year: 22.21% 1–2 years: 15.82% 2–3 years: 4.57% 3–5 years: 3.53% 5–10 years: 1.55% >10 years: 0.49% Source: Istat (2012a)

**Table 4** Operationalization of the simulated policies

Simulated policies	Operationalization
Targeting organized crime leaders	Increases the probability of arrest of a leader whenever it commits a crime, while keeping the overall number of arrest constant across the simulation. Organized crime leaders are the agents member of the organized crime group with the highest degree in the multiplex network
Targeting facilitators	Increases (*3) the probability of arrest of a facilitator agent whenever it commits a crime, while keeping the overall number of arrest constant across the simulation
Primary socialization	The policy targets agents between age 12 and 18 with one parent agent (normally the father) who is an organized crime member. The ties between the father agent (as well as other family agents who are organized crime members) and the mother and children agents are severed. The mother and children agents receive welfare, psychological and educational support: the mother has a higher probability to find a job, the children achieve a higher educational degree. Once the children reach age 18, the ties with the father are re-established
Secondary socialization	The policy targets schoolchildren at risk by selecting school aged agents with a higher probability to commit a crime (function C). These agents are provided with increased social and welfare support: they will complete high school or higher levels of education and random links with non-delinquent peers and adults will be created



**Fig. 3** Dependent variables. Average values per round of simulation and per policy scenario

scenario and the four policy scenarios. In no case do the results change dramatically and these changes generally confirmed our intuition about the parameters (more organized crime members at the simulation onset, causing mode growth overall) or failed to reach significance. Additional information and results of the sensitivity tests are reported in the Supplementary Materials.

## Analytical Strategy

To evaluate the impact of the proposed policies on organized crime, we run two sets of regressions focusing on different dependent variables: the number of newly recruited individuals and the number of active organized crime members at each time step (Fig. 3). The two different dependent variables capture the complexity of our ABM. While newly recruited agents are the most straightforward measure of the recruitment process, we also consider the total number of members to encompass the complex dynamics underlying our multiplex network model. For each policy scenarios, we performed 60 simulations with 360 monthly-sampled time units. This modeling structure allows us to treat the time-stamped outcomes of the simulations as a panel dataset at the societal level. To estimate the effects of the policies compared to the baseline scenario (in which no policies are applied), we have thus run two sets of generalized estimating equations models (GEE) (Liang and Zeger 1986).

**Table 5** Descriptive statistics of variables included in the regression models—per policy scenario

	N agents (/100)	N edges (/100)	Avg C ( $\times 100$ )	N of newly recruited OC members	N of OC members
Baseline					
Mean	22.82	334.63	11.19	0.02	9.74
SD	3.43	67.86	0.68	0.41	4.12
Min	16.78	192.21	8.25	0.00	0.00
Max	30	556.34	12.56	16	28
Targeting OC leaders					
Mean	22.78	337.21	11.23	0.01	8.96
SD	3.45	68.30	0.71	0.36	3.77
Min	16.25	188.1	8.35	0.00	2
Max	30	531.4	13.10	16	26
Targeting facilitators					
Mean	22.77	339.96	11.25	0.02	9.44
SD	3.50	70.59	0.71	0.38	4.22
Min	16.36	185.5	8.30	0.00	0.00
Max	30	529.38	12.95	16	26
Primary socialization					
Mean	22.77	330.42	11.22	0.02	9.29
SD	3.43	65.01	0.72	0.38	3.96
Min	16.68	191.83	8.41	0.00	1
Max	30	509.34	12.82	18	23
Secondary socialization					
Mean	22.98	354.57	11.27	0.02	9.54
SD	3.18	60.12	0.72	0.38	4.18
Min	17.52	218.98	8.31	0.00	0.00
Max	30	545.05	13.17	17	24

GEE are an extension of the popular generalized linear models (GLM), explicitly designed to analyze longitudinal or clustered data (Zorn 2001; Ballinger 2004; Hardin 2005). One of the main advantages of GEE is the unbiased estimation of the population-averaged coefficients in spite of potential misspecification of the correlation structure.<sup>6</sup> In fact, compared to classic panel models, GEE does not estimate subject-specific effects. Instead, it provides average predictions for the entire population. This makes GEE particularly fitting for our simulations. Given the virtual nature of our societies (and experiments), we are not concerned about the individual effects that each policy has on each simulation run. Instead, we aim to understand the significance and magnitude of the average effect that a given intervention has on a set of simulations that share that same intervention. The two sets of models each comprise four specifications where, besides the factor-shaped variables

<sup>6</sup> The quasi information criterion (QIC) Pan (2001) and Cui (2007), a method developed to select the working correlation structure that best fits the data under analysis, suggested the use of an independent matrix specification. Further information and results are available in the Supplementary Materials.

**Table 6** GEE Models results—number of newly recruited members

	Model (1)	Model (2)	Model (3)	Model (4)
	IRR (SE)	IRR (SE)	IRR (SE)	IRR (SE)
Targeting OC leaders	0.8369** (0.0550)	0.8319** (0.0546)	0.8272** (0.0543)	0.8213** (0.0540)
Targeting facilitators	0.8802* (0.0570)	0.8748* (0.0567)	0.8523* (0.0553)	0.8451** (0.0548)
Primary socialization	0.9057 (0.0582)	0.9008 (0.0579)	0.9419 (0.0607)	0.9301 (0.0601)
Secondary socialization	0.9214 (0.0590)	0.9079 (0.0581)	0.8307** (0.0537)	0.8268** (0.0534)
N Agents (/100)		1.0587*** (0.0063)	0.9489*** (0.0120)	0.9821 (0.0160)
N Edges (/100)			1.0064*** (0.0006)	1.0057*** (0.0007)
Average C (×100)				1.1543*** (0.0485)
Intercept	0.0235*** (0.0010)	0.0063*** (0.0009)	0.0086*** (0.0013)	0.0010*** (0.0007)
Obs	108300	108300	108300	108300
Wald Chi2	8.0924	100.5179	210.2549	218.1236
Model p-val	0.0883	0.0000	0.0000	0.0000

\*Significance at 95% level, \*\*99%, \*\*\*99.9%

capturing policy effects, we include controls to ensure the robustness of the results (Table 5 reports summary statistics for the variables included in the models).

As we designed our simulations including time-varying demographic and social components a first control, named “N Agents(\100)”, simply measures the number of agents divided by 100 (for ease of interpretation) to take into account the role of the evolution of the population during the 360 monthly time steps (given the unbalance between births and deaths in today’s Palermo, the population declines throughout the simulation). The second one (“N Edges(\100)”) measures the number of edges across all social relations divided by 100, to control for the degree of social connectivity in the virtual experiments. Lastly, we include “Average C (×100)” to control for the effect of the average individual probability of committing a crime (C).

## Results

Table 6 shows the results for the models on newly recruited individuals at every round. *Targeting OC Leaders* decreases newly recruited agents, incidence rate ratio (IRR) range between 0.8213 and 0.8369, and is statistically significant at 99% level. This means that the policy intervention decreases newly recruited members across the entire simulation by approximately 17–18% compared to the baseline. *Targeting facilitators* also shows a negative effect on new members, although effect is smaller, ranging between approximately –12% and –14.5%, and statistical significance is at 95% level in models 1 to 3. *Secondary socialization* exhibits a different trend. While the coefficients of the first two specifications are not statistically significant, in the last two specifications the policy produces an average reduction of newly recruited members in the range 17–18% (IRR 0.8307 and 0.8268, respectively). Finally, *primary socialization* does not provide any significant reduction in newly recruited members, with coefficients are always under the 95% threshold.

**Table 7** GEE Models results—number of organized crime members

	Model (1)	Model (2)	Model (3)	Model (4)
	IRR (SE)	IRR (SE)	IRR (SE)	IRR (SE)
Targeting OC leaders	0.9206*** (0.0029)	0.9200*** (0.0029)	0.9185*** (0.0029)	0.9159*** (0.0029)
Targeting facilitators	0.9693*** (0.0030)	0.9687*** (0.0030)	0.9619*** (0.0030)	0.9588*** (0.0030)
Primary socialization	0.9536*** (0.0030)	0.9531*** (0.0030)	0.9640*** (0.0030)	0.9591*** (0.0030)
Secondary socialization	0.9797*** (0.0030)	0.9778*** (0.0030)	0.9513*** (0.0030)	0.9493*** (0.0030)
N agents (/100)		1.0065*** (0.0003)	0.9746*** (0.0006)	0.9884*** (0.0008)
N edges (/100)			1.0019*** (0.0000)	1.0015*** (0.0000)
Average C (×100)				1.0612*** (0.0021)
Average R (×100)				
Intercept	9.7428*** (0.0212)	8.4166*** (0.0585)	9.3021*** (0.0672)	3.8984*** (0.1183)
Obs	108300	108300	108300	108300
Wald Chi2	779.0155	1271.6542	5038.6141	5872.5386
Model <i>p</i> -val	0.0000	0.0000	0.0000	0.0000

\*Significance at 95% level, \*\*99%, \*\*\*99.9%

Except for *Secondary socialization*, the inclusion of the controls does not affect the direction and significance of the effects, suggesting that the results are stable to the addition of further variables.

The second set of models assesses whether the different policy interventions affect the overall number of active members of the organized criminal group (Table 7). GEE models show that all the policies contribute to a statistically significant reduction in the number of organized crime members and the results are unaffected by the inclusion of controls. *Targeting OC Leaders* yields the largest reduction overall IRR in the range 0.9206–0.9159. This means that, compared to the baseline, the policy reduces active organized crime members by 7.9–8.7%, all other variables constant. *Targeting facilitators*, *primary socialization*, and *secondary socialization* also provide statistically significant reductions and are invariant to the addition of further variables.

## Discussion and conclusions

Our study developed an ABM comprising individual and relational dynamics that influence the recruitment into organized crime. All inputs were based on empirically observed data from the contemporary context of Palermo, or Sicily in general. We used this synthetic society to test the impact of four different policy scenarios on the recruitment into organized crime compared to a no-intervention scenario. The simulations generate realistic outcomes, particularly in terms of total crimes and number of organized crime members, and sensitivity tests indicate that the results are robust to relatively large variations in several parameters. The results of GEE models show that two of the policies, Targeting OC leaders and targeting facilitators, yield statistically significant reductions in the number of newly recruited individuals. Additionally, Secondary socialization shows a negative effect after the number of edges are accounted for while primary socialization shows

small non-significant reductions. All policy interventions decrease the average number of organized crime members with targeting organized crime leaders generating the largest reduction.

Targeting organized crime leaders leads to a statistically significant decrease in both the newly recruited members and the total number of organized crime members, reporting the largest reduction in both dependent variables. The results are consistent with studies showing the pivotal brokering role of leaders in sophisticated organized crime groups (Calderoni and Superchi 2019). Removal of these central agents may substantially disrupt these groups, not only directly by removing these key players, but also indirectly by impairing their capacity to involve new recruits (Bright et al. 2017; Duxbury and Haynie 2019; Bright et al. 2019). Some studies contended that leader removal may generate more violence due to increased competition within and among groups (Dickenson 2014; Vargas 2014). This may be a possible outcome in competitive contexts with multiple groups, unclear territorial boundaries, fast-changing affiliations, and overall high levels of violence. Against this argument, last years' Palermo showed low homicide numbers and a clear division of territories among mafia families and years of law enforcement interventions against Cosa Nostra leadership have hardly caused a fresh outbreak of violence (Direzione Investigativa Antimafia 2019; Dugato et al. 2020).

Targeting facilitators reduces both new recruits and total number of members. A marginal growth in the probability of arrest for facilitators committing any crime may make it harder to find offenders with certain skills for complex crimes, thus increasing the costs also for organized crime groups (Bullock et al. 2010). In turn, this affects the group capacity to recruit of new members. The dynamics are coherent with research emphasizing the social embeddedness of organized crime and the need for external, additional, co-offenders with specific skills and competences (Morselli 2009; Van Koppen and De Poot 2013; Catino 2019).

We also found support for policy interventions addressing socialization mechanisms. The underling mechanisms of these policies leverage on the social embeddedness of organized crime, contrasting or offsetting the formation of social ties with agents who are members of, or socially close to, organized crime groups. In turn, this decreases the relations, interactions and social learning processes that lead to recruitment. The results are coherent with the studies pointing out the social opportunity structure of organized crime as one of the main pathways for involvement (Kleemans and Van de Bunt 1999; Steffensmeier and Ulmer 2005; Kleemans and de Poot 2008), and the inter-generational transmission of criminal behavior in the context of organized crime (Sergi 2018; van Dijk et al. 2019; Spapens and Moors 2019). Interestingly, primary and secondary socialization show different impacts on new recruits and on the overall number of members: secondary socialization—focusing on offering pro-social relations to children-at-risk—decreases both overall membership and new recruitment. The intervention has a general scope (targeting a relatively large share of juvenile agents in the simulation) and this may effectively reduce the number of newly recruited agents. Yet, it should be noted that the effect on new recruitment becomes statistically significant only once we control for the number of edges in the simulation (Table 6). This is likely due to the policy design, which randomly creates pro-social ties to the targeted agents. While linking to non-delinquent agents, these ties make the network denser (as shown in Table 5), that may ultimately facilitate recruitment, all other things equal. Simultaneously, the policy improves the educational attainment of the children, which may trigger several positive effects on the targeted agents, well beyond their probability to commit a crime and the recruitment into criminal organizations. Conversely, primary socialization targets the very specific recruitment channel of involvement through

family relations. While the intervention effectively reduces the overall number of members, it lacks statistically significant impact on new recruits. This is likely due to its exclusive focus on the family recruitment, the reduction of which may partially be offset by recruitment through other dynamics. Also, the effect of this intervention are likely delayed in time, affecting the recruitment into organized crime only once the children grow up.

As a further contribution, the findings of the study show that we were able to develop theoretically and empirically grounded ABM simulations about recruitment into organized crime. Starting from popular theoretical frameworks about crime commissioning and involvement into organized crime, such as differential association, social learning and social embeddedness, we grounded our simulations on extensive empirical data (primarily) on the city of Palermo. As discussed in the background, the existing literature on ABMs of organized crime typically relies on purely theoretical assumptions, limited empirical evidence, and discretionary thresholds. While the focus on Palermo enables us to overcome these limitations, it also invites caution in the generalization of the findings to other contexts. The model itself, however, could be applied to other geographical and social contexts pending on the use of correct context-specific input data, as already shown by Andrighetto et al. (2019) who modeled recruitment in a Dutch scenario. The code and further information is freely accessible and we encourage other scholars to further develop the simulation and its applications.

While attempting to address many of the theoretical, empirical, and computational gaps in previous research, our study is not exempt from limitations. First, our models rely on several assumptions, extensively discussed in Andrighetto et al. (2019). In particular, we operationalized recruitment as the commission of an offense in cooperation with at least one organized-crime agent. While this is generally consistent with legal requirements in most jurisdictions, for more elaborate forms of organized crime, where the process of recruitment may require vetting and observation of prospects, our operationalization may be excessively broad. At the same time, arbitrarily setting a high number of offenses above which recruitment occurs would have introduced a discretionary threshold that has limited empirical support. To address this, we required that co-offending leading to recruitment is initiated by the organized crime members, and also included the  $R$  function to specifically proxy the selection processes adopted by some criminal groups. Scholars interested in replicating or expanding our work may be able to change or remove this parameter to mirror different recruitment practices. We also assume that the probability of committing a crime is influenced by both individual and social-relational factors, based on evidence from narrative and systematic reviews (Akers and Jensen 2006; Akers 2009; Pratt et al. 2010) and that, in line with the literature, co-offender selection is driven by mechanisms of social proximity (Weerman 2003; Carrington and van Mastrigt 2013; Van de Bunt et al. 2013). Second, while we tried to minimize assumptions unsupported by research evidence, the elaboration of computational models inevitably requires simplifications. For example, we had to limit the size of the simulation to 3,000 agents due computational costs. This warrants caution in extending the validity of our results to larger social environments, due to possible non-linearity problems such as allometric scaling (Alves et al. 2014). Also, we refrained from including more than one organized crime group, thus our results should not be simply extended to contexts with multiple competing groups, which are likely to generate additional dynamics (e.g., inter group conflicts, membership shifting). Furthermore, our simulation takes a relatively neutral stance regarding the effect of imprisonment. Arrested agents are merely removed from the simulation and re-enter after serving their time. Depending on the social and legal contexts, imprisonment of organized crime members could actually sever the ties with the organization or promote the establishment of new

criminally exploitable contacts. Future research may further expand the scope of the simulation to address the above issues and assess their impact on the recruitment into organized crime.

## Appendix 1

The ODD+D (Overview, Design Concepts, Details, and Decision-making) is a protocol developed by Müller et al. (2013) to expand the classic ODD (Overview, Design Concepts and Details) protocol (Grimm et al. 2006) adding a specific dimension on Human decision-making processes. The ODD+D protocol better suits models addressing individual and collective decisions made by human-like agents and also addresses theoretical and empirical information to better present the model itself.

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

Structural elements	Guiding Questions	Description
I) Overview		
I.i Purpose	I.i.a What is the purpose of the study?	The main research question addressed by the study is: <i>What is the impact of different policy interventions on the recruitment into organized crime?</i> Different policy scenarios will be tested into the model against a baseline (no intervention) scenario
	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?	Entities include agents (that hold individual and relational attributes), network layers (namely household, kinship, school, work, friends, and co-offending) and also entities that drive network formation (e.g., households, firms, or schools)



Structural elements	Guiding Questions	Description
	I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	<p>Agents are characterized by two functions <math>C</math> and <math>R</math>, that will drive their actions and behaviors in the model.</p> <p><math>C</math> is the individual probability to commit a crime at any round and is based on individual-level agent attributes including:</p> <ul style="list-style-type: none"> <li>Age</li> <li>Gender</li> <li>Number of friends</li> <li>Number of committed offenses / criminal history</li> <li>Wealth level</li> <li>Education score</li> <li>Work status</li> </ul> <p><math>R</math> measures the extent to which an agent is embedded in organized crime-prone social relations. <math>R</math> is operationalized as the proportion of organized crime members across the multiplex <math>k</math>-step local networks</p>
	I.ii.c What are the exogenous factors / drivers of the model?	<p>Exogenous factors take the form of law enforcement strategies or preventive policies. For example: testing law enforcement policies, where the law enforcement intervention in the model vary, e.g., by increasing the probability of arrest of leaders or facilitators. testing prevention policies aiming at reducing the negative influence on children in organized crime families or on schoolchildren at risk in general</p>
	I.ii.d If applicable, how is space included in the model?	Space is not included in the model, only network proximity
	I.ii.e What are the temporal and spatial resolutions and extents of the model?	Temporal resolution: each round represents a month

Structural elements	Guiding Questions	Description
I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	<p>Agents act at every round of the model with no determined order. For example, agents grow older, find jobs, go to school, and establish or loose social relations of different types. Agents may commit crime</p> <p>Regarding the mechanisms of co-offending, a simple multi-step procedure models the creation of new co-offending ties:</p> <ol style="list-style-type: none"> <li>a. Identification of all nodes who commit a crime in a time period (based on empirical evidence of crime frequencies)</li> <li>b. Identification of the share of all nodes who a) co-offend (based on empirical evidence of co-offending frequencies)</li> <li>c. Based on b), identification of the number of co-offenders per crime (based on empirical evidence of co-offending size)</li> <li>d. Matching of co-offenders based on social proximity</li> <li>e. Establishment of new ties in the co-offending network</li> </ol> <p>Law enforcement may arrest agents who have committed a crime, based on empirical evidence on the frequency of imprisonment</p>

Structural elements	Guiding Questions	Description
<b>II) Design concepts</b>		
<p>II.i Theoretical and Empirical Background</p>	<p>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?</p>	<p>The literature on organized crime argues the importance of social relations for involvement into organized crime groups (Calde-roni et al., 2020; Kleemans &amp; Van Koppen, 2020). Individuals are recruited through multiple kinds of relations: family, friendship, neighborhood, ethnic and other relations, falling within the broader theoretical frameworks of differential association and social learning (Sutherland, 1937, 1947; Akers, 1973). At the same time, involvement into organized crime often requires a propensity to commit crimes, which may be driven by individual characteristics such as low self-control (Gottfredson &amp; Hirschi, 1990). The model combines elements of differential association, social learning and social embeddedness as well as individual propensity in explaining recruitment into organized crime using a multiplex network approach. Agents have individual characteristics and are embedded in multiple social relations, and both mediate the recruitment into organized crime</p>

Structural elements	Guiding Questions	Description
	<p data-bbox="432 208 718 278">II.i.b On what assumptions is/are the agents' decision model(s) based?</p> <p data-bbox="432 1143 718 1195">II.i.c Why is a/are certain decision model(s) chosen?</p>	<p data-bbox="739 208 1048 278">The core assumptions are related to the theoretical framework of the model. In particular:</p> <p data-bbox="739 278 1048 478">An agent's probability of committing a crime is influenced by individual and relational attributes including age, sex, employment status, education, wealth status, criminal history, criminal relations and organized crime membership.</p> <p data-bbox="739 478 1048 575">Agents' crime commission can be modeled as a probabilistic approach based on agents' individual probabilities</p> <p data-bbox="739 575 1048 672">Co-offender selection is driven by social proximity and the potential co-offenders' probability to commit crimes</p> <p data-bbox="739 672 1048 843">Recruitment into organized crime is influenced by social relations and namely the six relations of household, kinship, friends, school, work, and co-offending as well as by the probability of committing a crime</p> <p data-bbox="739 843 1048 989">Recruitment into organized crime occurs when a non-organized-crime agent co-offends with at least one organized-crime agent and the latter is the initiator of the crime</p> <p data-bbox="739 989 1048 1143">When selecting potential co-offenders, organized-crime agents also consider their embeddedness into organized crime social relations (operationalized through function R)</p> <p data-bbox="739 1143 1048 1342">The focus on multiplex social relations aims at modelling the social and relational nature of organized crime widely observed in empirical research, while allowing to control also for individuals-level factors relevant for crime commission in the general population.</p> <p data-bbox="739 1342 1048 1511">The model relies on a probabilistic approach instead of explicit decision making processes due to the lack of empirical evidence on such decisions within organized crime and also to avoid discretionary cut-off thresholds</p>

Structural elements	Guiding Questions	Description
	II.i.d If the model / a submodel (e.g., the decision model) is based on empirical data, where does the data come from?	Most of the data are from the Italian Institute of Statistics (Istat), the European Statistical Office (Eurostat), and the Bank of Italy, while the number of mafia families and members has been gathered from large-scale criminal investigations on mafia groups. The source of the data and their use is summarized in the main text as well as in the Supplementary Materials
	II.i.e At which level of aggregation were the data available?	Although with some limitations (and relying on theory- or empirical-driven theories), data for the organized crime population were available at individual level/family level. Other data comes in variously aggregated forms. These enabled us to derive distributions and frequencies used in the model
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 modelled dynamics are not properly of explicit decision making. At the agent-level, agents are guided by complex probabilistic computations that imply different outcomes based on their personal characteristics and social relations. Agents thus act (or make “decisions”) in the model regarding to link formation or disruption (e.g., making new friends, getting married, finding a job), and on committing crime
	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 come into contact with other agents based on individual attributes and the multiplex network. These processes are variously informed by patterns of homophily and social proximity. Based on social relations and personal characteristics and background, agents can commit crimes and, eventually, be recruited into organized crime groups
	II.ii.c How do agents make their decisions?	The decision to commit a crime is based on multiple conditional probability distributions derived from the individual characteristics of each agent, with an additional complementary stochastic component

Structural elements	Guiding Questions	Description
	II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	Yes. Agents adapt their behaviour based on e.g., economic conditions, role changing, number and nature of relations and criminal background. The most important adaptations are the changes that these elements cause in the probability of committing a crime
	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 in the strict sense is not included. However, “distance” intended as a network-driven concept (e.g., number of ties that separate two or more agents) can be seen as a non-physical derivation of space. The assumption is that members of the same community (e.g., school) share a common social environment modelled as network proximity
	II.ii.g Do temporal aspects play a role in the decision process?	Yes. Agents live for a finite number of years (empirically derived from a data on life expectancy). Moreover, agents’ age influence individual attributes, social relations, and the probability of committing a crime
	II.ii.h To which extent and how is uncertainty included in the agents’ decision rules?	Every agent decision is driven by specific probability distributions
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 is 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 such as weddings, employment, and crime. For example, the probability of committing a crime generally declines with age
	II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?	Some of the agents’ actions are driven by variable comparison with others (social proximity)

Structural elements	Guiding Questions	Description
	II.iv.c What is the spatial scale of sensing?	As pointed out in II.ii.f, space is not included, although network distances among nodes maps, in a certain sense, the “social” or community distance. Therefore, “spatial sensing” here can be thought as the threshold to which individuals (e.g., organized criminals) select nodes for certain actions. That distance is the $k$ that bounds the capacity to look for patterns or new recruits when a certain radius is exceeded
	II.iv.d Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?	There is no information diffusion in the model
	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?	It does 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?	Not applicable
II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	Interactions are direct and modify the whole state of the model. These interactions are mediated by behavioral dynamics modelled through probabilistic rules
	II.vi.b On what do the interactions depend?	Interactions depend on the individual characteristics of each agent. Individual characteristics that can influence the interactions include e.g., wealth, education, criminal background, and age
	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?	Coordination networks, in this model, are more than one and are modelled as groups of different size and nature (e.g.: criminal/non-criminal, families, professional communities). The structure of the network is imposed at $t_0$ but then it changes over time. New structures are therefore emergent in the model

Structural elements	Guiding Questions	Description
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?	They form and belong to aggregations that affect and are affected by the individuals. Aggregations emerge during the simulation
	II.vii.b How are collectives represented?	Different types of collectives are represented, mirroring the different explicit and non-explicit networks within the model (e.g., household, kinship, friends, schools, work, and co-offending)
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 across a variety of individual and relational characteristics. The simulation starts with some agents who are already members of the organized criminal group. This only affects (increases) their probability to commit a crime and the possibility to recruit new members by initiating co-offending with non-members
	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 heterogeneous in their decision making only in the selection of co-offenders. Non-organized-crime agents select co-offenders based on a social proximity score derived by their social networks and the probability of committing a crime. Organized-crime agents select their co-offenders by a social proximity weighted by R, a score assessing how any agent is embedded in social relations with organized crime agents
II.ix Stochasticity	II.ix.a What processes (including initialization) are modeled by assuming they are random or partly random?	Stochasticity is included in the emerging dynamic processes at different stages. First, it influences the probability of creating a link between two agents. Second, it drives the uncertainty in whether committing an offense or not. Stochasticity also affects the probability of being alive or dead at a certain point in time. Essentially, all processes are assumed to be at least partly random



Structural elements	Guiding Questions	Description
II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?	The main results are the number of organized crime members and the number of new recruits per round (month). Average values of C (criminal tendency) and R (OC embeddedness) are recorded too. Other recorder values (the runs reported in the paper have a total of 57 variables saved, some of which saved in the form of histograms). They are documented in the code and in the XML file that defines the experiments. Some of them are: * Total number of friends * Total number of offences, arrest and conviction rate
	II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	<i>Not applicable</i>
III) Details		
II.i Implementation Details	III.i.a How has the model been implemented?	The model has been implemented in NetLogo. Unit tests were ran in Scala
	III.i.b Is the model accessible and if so where?	The open access code of the model is accessible on GitHub: <a href="https://github.com/LABSS/PROTON-OC">https://github.com/LABSS/PROTON-OC</a>
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 is randomized on the base of the statistical data collected during the PROTON project
	III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	Each initialization will produce unique agents, whose characteristics combined will respect the distributions according to the aggregate statistics used inputs. Networks will be initialized on the basis of existing evidence (OC), official statistics (households) and mechanisms from the literature (friendship)
	III.ii.c Are the initial values chosen arbitrarily or based on data?	All initial values and parameters of the simulation are carefully calibrated, based on empirical data based on the social and criminal environment of Palermo, Sicily
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?	No, input data are used only on setup

Structural elements	Guiding Questions	Description
III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes listed in ‘Process overview and scheduling’?	The four policies implemented, to be compared to a business-as-usual baseline, can be seen as four submodels. They are grouped as Group Disruption policies, the first targeting organized crime leaders, the second aiming at facilitators, and Socialization policies, targeting the offspring of imprisoned organized crime members (primary socialization), or aiming at increasing the non-criminal connection of school-children (secondary socialization)
	III.iv.b What are the model parameters, their dimensions and reference values?	The submodels are initialized with the same kind of calibration as the main model. They are based on official statistics and literature review
	III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	The policy submodels were selected by PROTON stakeholders

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