



PROTON

Modelling the processes leading
to organised crime and terrorist networks



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Development of Agent Based Simulations of OCTN

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0 Executive Summary

PROTON D5.1 presents two agent-based models (ABMs), one on recruitment in organised crime network and the other on radicalisation and terrorist recruitment. The report presents each model in sequence, addressing the design of the models including their theoretical framework, state of the art, and model overview. It then outlines the calibration, validation, and sensitivity analysis of the models and the policy scenarios and their results.

The PROTON-S models were built in an iterative participatory approach, applying findings from PROTON WP1-3, which included systematic reviews of the literature and provided strong empirical foundations for the models. Selected laboratory experiments have been used to help fill the gaps (see D4.1). Additionally, and unlike many previous ABMs on recruitment into organised crime and terrorism, extensive data are used to calibrate and validate the models. The hypotheses and assumptions underlying the PROTON-S simulations are presented below and discussed in detail in the main text of the report.

The Organized Crime Recruitment (OCR) model

MODEL STRUCTURE

- The agents in this model represent a population of people that live and work in a European community (calibrated to a Southern and Northern European context).
- This ABM models how multiple social relations may influence individuals' involvement into organised crime: family, friendship, school, professional, and co-offending relations.
- The simulations also include relevant individual-level characteristics (age, sex, education, employment, and membership of an organised crime group).
- Based on their relations and individual traits, agents evolve through time. For example, agents grow up, study, marry, get/lose a job, have children, and commit crimes.
- The time scale of the model is that of multiple generations, and each step of the model represents several months.
- The simulations assume that individual and social relations are important drivers of recruitment into organised crime.



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- Agents may commit crimes, either by themselves or together with other criminals.
- Recruitment into organised crime occurs whenever a non-organised crime agent commits a crime with organised crime members.

MODEL CONTEXTS

- The model is calibrated on two different contexts:
 - one referring to Southern Europe, with data from Palermo (being part of the PROTON consortium, the City of Palermo provided privileged access to their official registry);
 - one referring to a prototypical Dutch city, Eindhoven on the other hand in terms of inhabitants and the reality and extent of OC in the city is much more in line with that of other Dutch cities.

CALIBRATION, VALIDATION AND SENSITIVITY

- Calibration is performed in two variants, “standard” and “strong”
 - the standard variant is calibrated on the values obtained from statistics, surveys, and expert opinions;
 - the strong variant employs stronger interventions, more criminals and more law enforcement with respect to the standard variant. This landscape with stronger parameters enables us to reduce some noise present in the standard variant, allowing a significant effect to be observed, if there is one.
- The model measures two main outputs: the number of recruited individuals in the organized crime network and the embeddedness of the crime network in the simulated society, operationalised as the rate of criminal in the social neighbourhood.

POLICY SCENARIOS AND ASSUMPTIONS

PROTON-S simulations on organised crime test two different types of policy interventions:

- the first type of intervention comprises law enforcement disruption strategies and their impact on the recruitment into organised crime. It includes two policy interventions:
 - *Targeting OC Leaders*: convicting and removing the leader of a criminal group can have positive impacts on the way the surrounding social environment perceives the power and strength of the given organized crime group and can also lead to cascade effects within the organisation. We implement this policy in our model by increasing the probability that the OC leader (defined in



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OC networks as the agent that is more central in the criminal organization) of the network is arrested and convicted.

- *Targeting Facilitators*: facilitators are agents that due to their job or social opportunity structure can act as bridges between legal society and criminal groups. This policy scenario tests the effectiveness of increased law enforcement efforts against facilitators to evaluate if these disruption strategies reduce the commission of more complex crimes. We implement this policy in our model by increasing the probability that facilitators are arrested and convicted.
- the second type of intervention comprises preventive measures to reduce recruitment into organised crime. This intervention includes two policy interventions:
 - *Primary Socialisation*: this policy targets juveniles aged 12-18 living in OC families. This intervention tests the effect of breaking the connection between a father convicted for OC offences and his relatives on the chance that those relatives will become involved in OC themselves. We implement this policy by removing the connection with a father convicted for OC offences and OC-involved relatives and providing juveniles with social and welfare support.
 - *Secondary Socialisation*: this policy targeting minors “at risk” in the general population. The policy will provide juveniles aged 6-18 educational and welfare support through the promotion of positive social relations with non-delinquent peers and adults. In the ABM, we target crime-prone children with social, welfare and educational support.

RESULTS

Overview of the main results:



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	Southern European Context		Northern European Context	
	Standard intervention	Strong intervention	Standard intervention	Strong intervention
Targeting OC Leaders	-Recruitment	-Recruitment -Embeddedness		+Recruitment +Embeddedness
Targeting Facilitators	-Embeddedness	-Recruitment -Embeddedness		-Recruitment
Primary Socialisation		-Recruitment -Embeddedness	+Recruitment	+Recruitment +Embeddedness
Secondary Socialisation	-Embeddedness	+Recruitment -Embeddedness	+Recruitment	-Recruitment -Embeddedness

Note: when marked in grey, the intervention shows an effect, but it is not statistically significant.

The policy intervention targeting facilitators results the most effective one, with the only exception of the NE-standard setting. All the other policy interventions show mix of expansion and contraction for the OC. The targeting OC leaders policy intervention favors the OC network in the NE/strong setting, but it compresses it in the SE/strong one. Between the socialization policies, primary socialization is the only effective one, but exclusively in the SE/south scenario.

The Terrorist Recruitment (TR) model

MODEL STRUCTURE

We developed an agent-based model with the purpose of examining what types of interventions would reduce radicalization and recruitment to terrorism. This ABM models the behaviour of heterogeneous agents whose routine activities take place in a neighbourhood of a major European city.

Agents are characterized by a set of socio-demographic characteristics, and opinion based risk and protective factors. Based on the systematic review, these factors are integration/non-integration, institutional trust/legitimacy, and subjective deprivation.

The simulation assumes that the agents' characteristics determine their routine activities, which in turn dictate their patterns of socialization. Socialization, as modelled by opinion-dynamics, consists of interactions between individuals (both in person and on-line).

- Opinions held by agents play a crucial role on the probability of individuals of becoming radicalised, together with other individual



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characteristics like gender, age, employment status, criminal history, and authoritarian personality.

- Once the risk of radicalisation reaches a given threshold, agents can become recruited.
- Recruitment happens after interacting with recruiters in specific locations on the grid for a specific amount of time.
- The time scale of the model is six months and each step of the model represents one hour.
- The model uses the city of Neukölln, Berlin, Germany as a large amount of publicly available data exists for Neukölln. In particular, censuses, polls, and opinion surveys provide the type of data needed for building the model's landscape and initializing the individual-level characteristics of citizen agents. Moreover, Neukölln was selected for its representativeness of boroughs in major western European cities in terms of its makeup, demographics, and experiences with radicalisation and recruitment for right-wing, left-wing, and religious elements.
- The model measures three main outputs, the number of recruited individuals, the number of radicalized individuals, and the status of the opinions on the protective and risk topics.

POLICY SCENARIOS AND ASSUMPTIONS

PROTON-S simulations on terrorism tests two different types of policy interventions. The first type of policy intervention seeks to change the level of unemployment among high risk individuals (employment). The second type of policy intervention involves the deployment of two different types of "special agents" in the modelled environment, namely community workers, and community-police officers. In particular, the PROTON-S simulations addressed three interventions:

- Employment:* the model implements a policy that incentivises employers and would-be employees to hire at-risk individuals. Employment helps to embed individuals in a local network of other employed individuals. The intervention assumes that employed individuals have less time, and are less likely to come into contact with radicalizing influences and recruiters.
- Community workers:* we implement a policy intervention that increases the number of community workers operating at community centres. The intervention assumes that community workers have positive values which will help to prevent radicalization by promoting trust/legitimacy, integration/connectedness, and reducing subjective feelings of deprivation, but that the number of such community workers is conventionally too small to have a major impact on the community.



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- *Community policing*: in this policy intervention the number of trained community police officers is increased. The policy experiment seeks to change the role and effect of police officers in the community, reducing the number of negative interactions between citizens and the police. This intervention is expected to promote integration and trust and reduce feelings of relative deprivation.

RESULTS

- *Employment*. Our results show that, while average radicalization is similar to the base model (i.e., simulation treatment with no intervention), large and strongly statistically significant differences were found in the number of recruited agents. In total, the experiment reduced the number of recruited individuals from about 77 to about 26, or a 66% reduction compared to the based model.
- *Community workers*. Our results show that there were no statistically significant differences between the experimental model in which the policy intervention has been tested and the base model for recruitment, however the mean risk scores (radicalization) of the populations were statistically different. These differences are likely the result of the fact that the experiment also had statistically significant effects on improving all three opinion related factors (integration, deprivation, trust). Accordingly, the community workers model has meaningful impacts on attitudes in the simulated city, but those differences did not lead within the 6-month observation period to significant changes in recruitment.
- *Community policing*. Our results show that there are no statistically significant differences across these two outcomes. However, the experiment did have statistically significant effects on improving trust/legitimacy, as predicted.

Overview of the main results:

	Recruitment	Radicalization	Opinion space
Unemployment	Significant positive effect 66% reduction	n.s.	n.s.
Community workers	n.s.	Significant positive effect 7.8% reduction	Significant effect: Integration 42.11% increase Deprivation



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			32.35% reduction Trust 15.25% increase
Community policing	n.s.	n.s.	Significant effect Trust 5.08% increase

The policy addressing employment is the only one with a statistically significant effect on recruitment. The community workers' intervention had a significant effect on the mean risk of the population (radicalization), as well as on improving overall integration. The community policing intervention policy improved overall trust and legitimacy, but had no significant effect on any of the other outcomes.



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1 Introduction

1.1 Overview

A core aim of PROTON is to develop agent-based models (ABMs) to:

simulate the processes leading to individuals' involvement in OCTNs. Different modelling techniques to assess the risk of the emergence and spread of OCTN groups will enable PROTON to detect the processes of recruitment into different crime careers and the probabilities of crime events in defined conditions. PROTON will adopt a cognitive approach which allows explicit account to be taken of the mechanisms underlying the decision to join OCTNs. The simulation model will represent a region populated by heterogeneous individuals whose decisions to join an OCTN group are influenced by various factors. (PROTON, 2015, p. 46)

We present in the results of this scientific endeavour in the following document.

More precisely, we present the Organised Crime Network (OCN) recruitment model in Section 0 and the Terrorist Recruitment (TR) model in Section 3. Within each model, we describe the theoretical framework driving each of the models (sections 2.1 and 3.1), the state of the art in agent-based models for the relevant domains (sections 2.2 and 3.2), provide an overview of the models (sections 2.3 and 3.3) and their specific contexts (sections 2.4 and 3.4). We then describe the calibration, validation, and sensitivity analysis (sections 0 and 3.5) and the policy scenarios that we test (sections 2.6 and 3.6). Next, we present the results from the policy scenarios (sections 2.7 and 3.7) and discuss these results and draw policy-relevant conclusions (sections 2.8 and 3.8). In the appendices, we include additional calibration details (Section 5) and an exhaustive technical specification of both models (Section 7).

While the structure that we use in D5.1 is somewhat different to that outlined in the PROTON proposal (p. 47, activities 1-3), we cover all of the same material here, and, we believe that we do this in a clearer way. The stylised-facts models and scenarios for PROTON-S are covered in sections 2.1 to 2.4 and sections 3.1 to 3.4, the prototype and technical guide to PROTON-S is in the appendix (Section 7), and the analysis of the impact of different recruitment processes and countering policies on OCTNs are in sections 0 to 2.8 and sections 3.5 to 3.8.



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1.2 The Two Agent-Based Models: Organised Crime Recruitment and Terrorist Recruitment

During the activities that we present in this deliverable, we have designed and implemented two agent-based models. One of these seeks to represent the dynamics of recruitment into Organised Crime Networks (OCN) and the other does the same for recruitment into terrorist groups. While they share some similarities, they are also different and vary in multiple ways because of the specific nature of the phenomena that they are designed to model. At a general level, the OCN model focuses on multiple network structures and how they influence recruitment. The TR model, meanwhile, focuses on opinion dynamics and the role of physical and virtual space on radicalisation and recruitment.

1.2.1 OCN MODEL

The agents in this model represent a population of people that live and work in a European community (calibrated to a Southern and a Northern European context). Some of these people may commit crimes, either by themselves or together with other criminals. The model focuses on relationships between people and how they affect their chances of becoming criminals. The time scale of the model is that of multiple generations, and each step of the model represents several months.

Because the model focuses on relationships, it explicitly represents links between agents. There are five types of links: family, social, professional, criminal, and organised crime. The family links connect agents that are part of the same family. The social links connect agents that are friends or acquaintances. The professional links connect agents that work for the same employer or are in education together. The criminal links connect agents that commit crimes together and the organised crime network those that are connected as part of an OCN.

The networks formed by these links play important roles in the agents' lives: they are how agents find new friends, spouses, jobs and, potentially, opportunities to commit crimes. When two agents share a link with the same person, they have a chance of becoming acquainted with each other. When agents are looking to get married, they try to find a partner within their social network. When employers have positions to fill, they first look for candidates within their current employees and then within the immediate networks of these employees before turning to the general population.



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Even more crucial for the model is the role that networks play in the agents' potential criminal activities. Agents have the possibility of generating criminal opportunities, upon which they can choose to act or not. Sometimes these crimes require the participation of multiple agents, in which case the agent needs to find one or more partners. They first look for partners in their criminal networks but may expand their search to their familial, social and professional networks if needed. Being part of a criminal network greatly increases the number of criminal opportunities available to an agent and thus the probability of being an active criminal.

This model allows us to examine the evolution of criminal networks and criminal activity under various conditions. It also allows us to measure criminal embeddedness by looking at how agents that are not themselves criminals are connected to criminal networks. Consequently, we have the means of testing the effects of different external interventions on these measures.

1.2.2 TR MODEL

The agents in this model represent a population of people that live and work in a European community. These people are embedded in geographical space and gather in various locations: their homes, workplaces, community centres, places of leisure and places of worship. When they get together, they talk to each other and exchange opinions about various topics. Agents can also communicate with each other online. Some opinions contribute to radicalization while others have a protective effect. The time scale of the model is six months and each step of the model represents one hour.

As the model runs, agents go through their daily routines: they go to their work-place at specific times if they have to and are otherwise free to engage in other activities. These activities happen at specific locations. Agents usually prefer to minimize their amount of travel, but they still might try (and potentially adopt) more distant locations that have been suggested to them by other agents.

When agents are at a location, they have a chance of interacting with other agents that are there at the same time. When successful interactions occur, agents move their opinion on a set of different topics slightly closer to the opinion of the agent they were listening to.

Opinions held by agents play a crucial role on their chance of becoming radicalised. Together with other individual characteristics like gender, age employment status, criminal history, and authoritarian personality they form the basis of the algorithm used to calculate the risk of radicalisation. Once the risk of radicalisation reaches a given threshold, agents can become recruited.



1.2.3 MODEL AIMS

These models allow us to simulate impacts of interventions on outcomes. These simulations provide an opportunity to explore whether changes in the real world would be expected to lead to changes in key outcomes of interest given what is known from prior research and theory. We ask a series of key questions: can we develop cost-effective public policies in social, psychological or economic areas that will meaningfully affect recruitment to terrorist groups and OCNs? What policies may prevent or discourage new members from joining? Will programmes that focus on economic issues such as wealth or inequality be more effective than those that, for example, focus on psychological drivers or legitimacy?

For the OCN model we test the effect of four policies. Two aim to disrupt the OCNs themselves directly in order to reduce recruitment. One targets and removes OC leaders—with the idea to remove those with decision-making powers—and the other targets and removes OC facilitators—people who act as bridges between legal society and criminal groups and that can help OCNs. The other two policies focus on the role of socialisation in shaping recruitment into OCNs. The first considers the highly controversial and sensitive policy, albeit one that is already being used in Italy, of reducing the contact between children living in organised crime (OC) families and their families. The idea is to reduce the role of primary socialisation in shaping recruitment. It is important to test this policy precisely because it is already being used and because it is sensitive. The second aims to reduce the role of secondary socialisation in OCN recruitment by increasing support to at-risk youths in school. All of these interventions leverage the network-focused approach of the model.

The TR model tests the effects of three policies: employment, community workers, and community policing. Unemployment, affecting both grievances and subjective deprivation, has long been considered as a risk factor in radicalisation. To test the effect of this variable on radicalisation, the model implements a policy that incentivises businesses to hire at-risk individuals. Increasing the number of community workers at community centres is the second policy we test in this model. The idea is that this increases social cohesion and reduces perceived inequalities and subjective deprivation that in turn reduces radicalisation. Our third policy implements a community policing approach. Community policing—although there are multiple varieties—generally aims to interact more closely with the community that the officers serve. This can occur, for instance, by having specialised units who meet with community members or provide activities for at-risk youth. We test whether this influences radicalisation and recruitment.

It is important to remember, however, that the agent-based models we develop are *models*. They are simplified representations of reality that make a set of assumptions about, among others, how the recruitment and



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radicalisation occur in reality, the interactions between individuals, and how belief change and network formation occur. PROTON has aimed to validate, through internal and stakeholder discussion and data these assumptions, as much as possible. Nevertheless, it is important to consider these factors when evaluating and using the models. We highlight some of the main assumptions of the OCN model in Section 2.6.3 and for the TR model in Section 3.6.5.

While PROTON has made substantial progress in modelling organised crime recruitment and terrorist radicalisation processes, the field more generally is at an early stage (see sections 2.2 and 3.2). This further implies that care should be taken when interpreting and extrapolating from the ABMs. The social process that the models aim to capture are extremely complex.

Following on from these points is an important consequence: the ABMs simulations are not replacements for other methods for understanding and countering organised crime and radicalisation. Instead, they can be seen as additional tools that are available to researchers and practitioners and that should be used in conjunction with other sources of knowledge about OCN and TR.

1.3 Why use agent-based modelling?

Unlike traditional statistical modelling, Agent Based Models (ABM) provide the opportunity to simulate entire social systems and their dynamics whilst simultaneously focus on individual level heterogeneity. The multiple levels that an ABM offers, being able to nest characteristics and decision-making rules within individuals (agents), who are nested within an environment (such as a geographic space), means that they enable the representation of social realities. As such, ABMs offer the opportunity for social scientists to overcome a number of problems, namely that whilst isolating the dynamic of a human system “ethical problems of experimentation are not present when one does experiments on virtual or computational systems” (Gilbert, 2008, p. 3).

But there are other advantages too. The process of creating an ABM implies that implicit assumptions are made explicit, necessitating the discussion and precise specification of the mechanisms and components that generate the social phenomenon of interest. This facilitates the growth of scientific knowledge about a topic—as do the policy tests that can be conducted on the empirically-grounded implementations of the models. From a pragmatic perspective, investigating recruitment dynamics at scale is extremely costly in a real-world setting, involving first and foremost feasibility constraints. Computer simulations, conversely, can overcome these issues.



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For these and other reasons, ABM is becoming increasingly prevalent in criminology where they are used to assess a range of crimes, criminal behaviour, criminal-analogous behaviour, and policing interventions (Brantingham, Glasser, Kinney, Singh, & Vajihollahi, 2005; Groff, Johnson, & Thornton, 2019; Malleson, Heppenstall, & See, 2010; Nardin et al., 2016; Székely, Nardin, & Andrigutto, 2018; Troitzsch, 2016). ABM is especially suited to the study of crime, crime-analogous behaviour and interventions to combat crime because it allows for the simultaneous modelling of places, offenders, targets, and guardians, in which each of these "agents" can have their own set of characteristics, including ones which can be manipulated (Gerritsen, 2015). Although coming from outside of the field of criminology, ABM has also long been touted for its potential applications to the study of terrorism (E. Elliott & Kiel, 2004). While ABM has many distinct advantages, it is important to emphasize that it cannot take the place of field experiments for identifying actual outcomes in the real world (Groff & Mazerolle, 2008). The ABM provides the best possible knowledge given what is known about the phenomenon under study. In this context it suggests what interventions would be most beneficial to implement. But once implemented, those interventions should be evaluated in the real-world setting.

The need to conduct an ABM on recruitment into organised crime and terrorist groups stems from the current policy approaches of western, democratic countries and the European Union and its member states in particular. The approach that has been taken for close to a decade now recognizes that prior approaches are insufficient to deal with these issues. Rather, in order to reduce the OC and the probability of terrorism, policies should be aimed at countering the antecedents to these. Such policies should be aimed at stymieing the underlying risk factors that increase the likelihood of radicalisation and recruitment, whilst also working to bolster the buffering effects of protective factors. However, to date, little empirical evaluation of such policies has been conducted.

1.4 The model building process

The two ABM models we built have strong empirical grounding and were built in an iterative participatory approach. PROTON work packages 1-3 undertook systematic reviews, or meta-analysis, of the literature and provide strong empirical foundations for the models. Selected experiments have been used to help fill the gaps (see D4.1). Additionally, and unlike many previous ABMs on recruitment into organised crime and terrorism, extensive data are used to calibrate and validate the models. For instance, to calibrate the OCN model, extensive data from the Italian National Institute of Statistics (Istat) is used, and, to calibrate the terrorist recruitment model, amongst others, data from the European Values Study are used.



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The other important component of the model building process is that they were developed through a process of participatory modelling with stakeholders and policymakers presented in a series of meetings¹ in which they gave their inputs and their feedback was incorporated into the models accordingly.

Ultimately this means that the research activities inform the theoretical structure and mechanisms of the models, identify the key factors that should be included in the model, and provide the statistical inputs for the model. While the iterative participatory stakeholder process draws on the expertise of stakeholders to build the model.

¹ First PROTON Consortium meeting (October 16th-17th 2017, Jerusalem); PROTON meeting with Practitioners to discuss factors driving Terrorism recruitment processes (5th September 2018, Amsterdam); PROTON meeting with Practitioners to discuss factors driving Italian Organised Crime recruitment processes (20th September 2018, Milan); PROTON meeting with Practitioners to discuss factors driving Dutch Organised Crime recruitment processes (21st September 2018, Amsterdam); Second PROTON Consortium meeting (October 15th-16th 2018, Milan); Third PROTON Consortium meeting (June 17th-18th 2019, Palermo). See Appendix "Stakeholders", for the relevant stakeholders that are involved.



2 Organised Crime Recruitment Model

2.1 Theoretical Framework

The OCN model draws on three theoretical perspectives. Two of these, *differential association theory* (Bruinsma, 2014; Burgess & Akers, 1966; Sutherland, 1937, 1939) and *social learning theory* (Akers, Krohn, Lanza-Kaduce, & Radosevich, 1979), argue that organised crime is embedded in the social environment and that social relations are a crucial factor driving recruitment into organised crime. Both focus on structure—the way in which individuals are organised as opposed to the characteristics of the individuals themselves (Borgatti, Mehra, Brass, & Labianca, 2009)—and how the position that individuals occupy within a criminal network determines their possibilities to commit crimes. The third perspective, the *general theory of crime* (Gottfredson & Hirschi, 1990), argues that individual's low self-control determines their inability to compute the negative consequences of one's criminal behaviour, thereby determining persisting patterns of criminality throughout their life. This perspective focuses on the attributes of individuals to explain criminality. These important criminological theories provide the conceptual foundations of the ABM. By incorporating them, our ABM considers both social structure and individual propensities.

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 (Sutherland, 1939). The theory has nine propositions that taken together argues that crime is learned in social settings and that the people with whom an individual most often interacts (i.e. family, friends, partners) have the greatest impact on this learning process (Bruinsma, 2014; Burgess & Akers, 1966; Sutherland, 1939; Sutherland & Cressey, 1947). The tendency to commit crime increases for those individuals living in an environment where deviance is accepted and the rule of law is discounted (Sutherland, 1939). Thus, if one's community is deviant, an individual is more likely to commit crime. Related to differential association is the argument posited by Akers (1998) stating that when we interact with people, not everyone is equally accessible but there are individuals that we are more likely to interact with than others, especially those in our immediate social surroundings (i.e. family, friends, neighbours etc.).



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Social learning theory complements differential association and stresses the significance of imitation in the learning process and his or her general behavioural evolution (Akers & Jensen, 2011; Akers et al., 1979). The learning process involves the apprehension of techniques, attitudes and rationalisations that are justifying criminal behaviour, as well as the internalisation of criminal identity aspects.

Empirical studies highlight that OC is socially and criminally embedded in their surrounding environment and that the nature and recruitment into organised crime is highly dependent on social relations (Albini, 1971; Blok, 1974; Granovetter, 1985; Haller, 1971; Hess, 1973; Ianni & Reuss-Ianni, 1972; Kleemans & de Poot, 2008; Kleemans & van de Bunt, 1999; McCarthy & Hagan, 1995; Morselli, 2009; Paoli, 2003). The position that individuals occupy within a criminal network determines their possibilities to commit crimes. In this sense, an agent's valuable criminal ties determine his social opportunity structure (Kleemans & de Poot, 2008). Given this, social networks are a core part of our OC model.

The general theory of crime (Gottfredson & Hirschi, 1990) takes a contrasting approach and posits that individuals have a criminal propensity that depends mainly on their level of self-control. If this is low, then it reduces individuals' ability to realise the negative consequences of committing criminal acts—a pattern that can persist throughout individuals' life course. The general theory of crime contends that group crime does not have specific characteristics and that the formation of criminal groups is mostly driven by self-selection processes.

Yet it is clear from the criminological literature that recruitment into organised crime does not merely depend on the criminal propensity of their members but also on their interpersonal relations (Savona et al., 2017). Members of a criminal organisations often share different types of social ties, e.g. kinship, friendship, or work relations, that are defined as the *social embeddedness* (Granovetter, 1985) of organised crime (Kleemans & van de Bunt, 1999). Pre-existing relations are significant for the cohesion of a criminal network and trust between its members, which also implies the importance of social ties for recruitment.

An example of this would be the kinship ties between sons of OC members and their parents, resulting in a high probability to be recruited to the same OC network (Rakt, Nieuwbeerta, & Apel, 2009; Rowe & Farrington, 1997; Thornberry, 2009; van Dijk, Kleemans, & Eichelsheim, 2018). Also work relationships create prospects for being recruited into organised crime networks, especially if people to be recruited demonstrate specific skills through their work experience. For example, customs official, financial and/or legal advisor, book-keeper, tax administrator, or banker, are all occupations with skills and knowledge that can be beneficial for criminal organisations



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(Kleemans & de Poot, 2008). Contacts made at work, or due to the fact that a person is employed in a specific sector, can lead to recruitment into OC (Kleemans & de Poot, 2008). Notably, work and employment relations between people are often closely linked with social ties as they can develop into social relations or they already exist prior to people working together (Kleemans & de Poot, 2008).

Furthermore, being socially embedded within a criminal organisation or having criminal contacts presents an opportunity for tutelage relationships that assist the criminal learning process. This allows individuals to acquire what is known as "criminal capital", i.e. skills, attitudes and assets (McCarthy & Hagan, 1995). Consequently, an individual's criminal relationships determine the social opportunity structure of an agent to commit a criminal act (see Kleemans & de Poot, 2008). Generally, then, the number of criminal ties an individual has, the strength of these ties and their significance for the individual have strong impact in determining the person's OC embeddedness and his or her probability to commit crime.

Although the social relations perspective (social learning and differential association) and the self-control perspective (general theory of crime) generate opposing views about the recruitment into organised crime, we combine elements of both frameworks. With this regard, the development of an agent-based model is a convenient way to do so, since its flexibility can allow to integrate both personal and inter-personal components. In light of this, the OC model operationalizes criminal involvement both as the result of interaction with others and as emerging from agents' individual characteristics pushing towards crime.

2.2 State of the Art

Few studies use ABM in criminology and even fewer apply it to organised crime. Among the handful of relevant studies, there are four broad approaches to ABM in criminology.

First is the environmental approach where simple 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 & Xiao, 2008). The focus here is on the frequency and geographical distribution of criminal activity. However, with exceptions (Agar & Wilson, 2002) social learning theory and a social network approach to crime are not included.

Second is a more complex approach in which agents have more realistic and well-defined roles as well as decision-making options. This approach, which follows the KIDS concept ("keep it descriptive, stupid!") (Edmonds & Moss,



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2005), is to build a rich model and then to gradually whittle it down by removing unnecessary components, leaving only the important factors.

Specifically related to OC these type of models were built as part of the EU project GLODERS (Global Dynamics of Extortion Racket Systems), which analyses highly community-embedded systems of extortion and racketeering (see Elsenbroich, Anzola, & Gilbert, 2016). An example is Nardin et al.'s (2016) case study, which investigates protection rackets by the Sicilian Mafia in Palermo, through the application of legal and social-norm based approaches. Agents in the model are endowed with a set of normative beliefs in order to test what kind of effect different anti-racketeering policies that are based on legal or social norms would have on their decision to pay protection money or not. Székely et al.'s (2018) study again makes use of the ABM presented in Nardin et al.'s (2016) in order to simulate social interactions related to the countering of protection rackets, by testing legal as well as social counter measures. These types of models have the aim of including plausible decision-making rules in the agents and replicating reality as best as possible through the ABM. However, an issue of this approach is excessive granularity, which limits the flexibility and generalizability of the model.

Third is a linear approach that maps the recruitment of agents through social and reinforcement learning rather than individual attributes or environmental opportunities. The social networks in this model are randomised to an extent and pre-established. 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 conceptualisation, 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. An example of such a study is the Seldon project (Berry, Lee, et al., 2004), which aims to model social exchanges between agents for inner city gang recruitment, that uses a three-tier agent architecture made up of simple, abstract and cognitive agents.

The last approach is a variation of the environmental approach where the focus is not only the geographical element of crime but also on the role of social networks on criminal activity. Both components are represented in a multiplex network and agents within the model are not necessarily interested in criminal opportunities that arise but rather in the acquisition of knowledge which they gather from other agents and the environment.

Significant elements of these diverse approaches in relation to organised crime analysis through ABM have been adapted for the current model. The agents are socially embedded and are therefore influenced by their social surroundings. These social surroundings are based on real life demographic, socio-economic and criminological data (see Section 0 for the model calibration). In the current ABM however, agents do not possess different



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decision-making architectures (as in Nardin et al., 2016; Székely et al., 2018) but agents have different personal traits, social positions, economic, education and criminal background and are hence influenced by diverse social environments regarding the choice of joining a criminal group. From, Nardin et al. (2016) and Székely et al. (2018) the current ABM takes on the notion of testing social and legal policies that are, or could be implemented in order to reduce the recruitment into OCNs, in the form of experiments.

None of the prior studies have attempted to combine theories of differential association, social learning and social embeddedness in explaining OC recruitment using a network approach. Thus, by performing such an analysis, our aim is to methodologically innovate the field of computer simulation of organised crime by incorporating the above-mentioned criminological theories within a multiplex dynamic network framework.

2.3 Model Overview

Simulating the dynamics and processes that lead to the recruitment into OC requires us to take into account a wide variety of factors. While certain elements are inherently linked to the individual sphere (e.g. age, gender), others span over the personal characteristics of an agent: making new friends, for instance, is dependent upon the social environment in which an agent is set. Two children at the elementary school are more likely to become friends if they are in the same classroom or if they have the same age, rather than being separate into different classrooms or belong to different years.

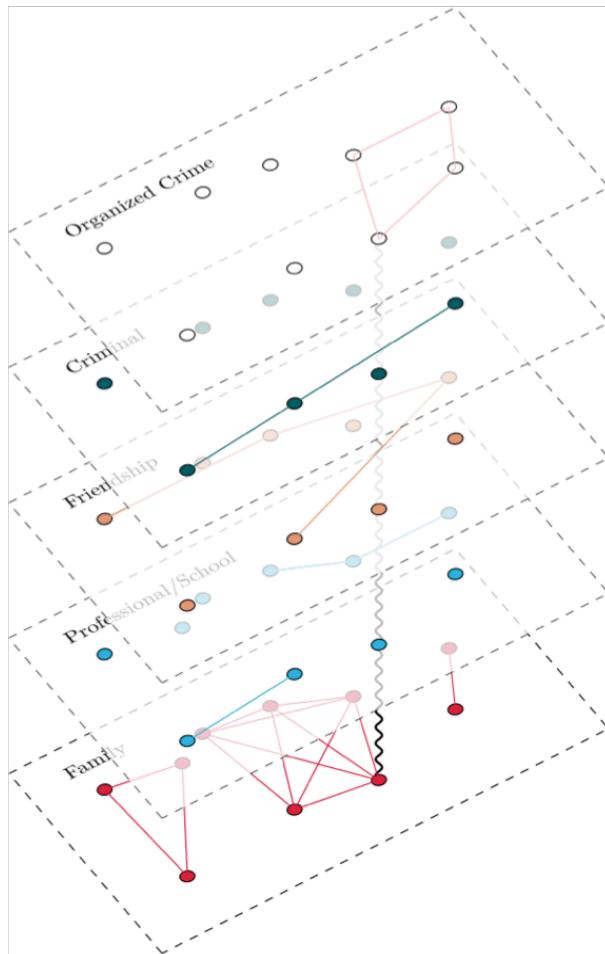
In real life, every person engages in different types of relations, e.g. as part of a family, in friendships, at work, and—if criminals—in co-offending. A member of an OCN is also part of a wider social environment as embedded in multiple social worlds. The literature supports the idea that relations of different types may drive the involvement and recruitment into organised crime (Arlacchi, 1983; Arsovská, 2015; Brancaccio, 2017).

Our model includes both internal attributes and specific social positions within this community. To adequately address the dynamics of individual and social drivers, we opted for an ABM based on a multiplex network. A multiplex network includes several networks, each mapping specific social relations. Five relational layers are modelled in the simulations: Our model contains five types of social networks: (1) *family*, (2) *friendship*, (3) *work and school*, (4) *co-offending*, and (5) *organised crime groups* (Figure 1).

Figure 1. Graphic depiction of the OCN multiplex network structure.



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Apart from the resulting organised crime network, the most important of these is the *co-offending network*. It delineates the set of others that an agent has co-offended with in the past and closely influences recruitment into organised crime. Specifically, if agent i undertakes a criminal activity initiated with another agent, j , who is already part of the OCN, then agent i also becomes part of the OCN. Put differently, if an agent co-offends with another who is part of the OCN, then the first agent also joins the OCN. Taking criminal acts together grows the OCN.

The simulation is initialised with one existing OCN in which the agents are connected via their co-offending network. There is only ever one OCN—we consider a monopolistic situation and exclude for simplicity the possibility of more than one OCN co-existing in a given area, and, again for simplicity we assume that once an agent joins the OCN it will always be part of that group (whether or not the agent commits another crime or not).

In addition to the OCN members, we also consider the role of facilitator agents, or facilitators. By facilitator we mean agents that are not internal to the OCN, but that for some characteristic (skill, rank, network position) are instrumental for the realization of the more complex crimes. Facilitators live on



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the edge of the OCN and might be the target of directed effort from law enforcement, with the purpose of isolating the OCN indirectly, removing the actors the OCN need for carrying out larger scale actions.

The other four networks—family, friendship, work and school, and co-offending—provide the network components upon which the co-offending network is built. Each network has particular features. The family network represents family relationships and is initialized with household data (household data retrieved from the 2011 Census and from data made available by the Municipality of Palermo). Bonds between households are added to represent, for example, relationships brothers living in different households. The friendship network is initialized as a Watts-Strogatz network and it grows as people connected to other ties (work, school, etc.) become friends. The number of friends is limited by Dunbar's number modified by age (see Section 2.5.8; Dunbar, 1992). The work network is created through employment and initialized employment data and the distribution of company size (see Section 2.5.3). School networks create an early foundation for the agents: once agents "leave school" they maintain the friendships they previously created there (see Section 2.5.8). Behind their formation is a general a homophily mechanism (which we call "social proximity factor").

The structure, topology and characteristics of the networks are empirically grounded using official statistics or replicating mechanics found in existing scientific works (see Section 0). Its internal structure, composition (in terms of gender distribution and generation/age distribution) reflects the ones found through analyses of several police investigations on Italian OC networks (OCN).

The multiplex network framework also allows for considering individual-level characteristics as agents attributes, thus making possible to analyse individual and social factors to simulate realistic recruitment dynamics. Agents in the simulation, regardless of being or not part of an OC groups, can be born, get engaged or married, have children, die, create and break relations, and commit crimes.

It is worth mentioning that the model does not consider decision-making process as such. Agents are not called to make actions based on specific evaluation of gains or costs and the simulation does not use reinforcement or learning mechanism. Instead, it is designed to be a probabilistic model in which individual and collective characteristics have the power to either increase or decrease the probability of an event happening. The details of these probabilistic processes are described in the following sections.

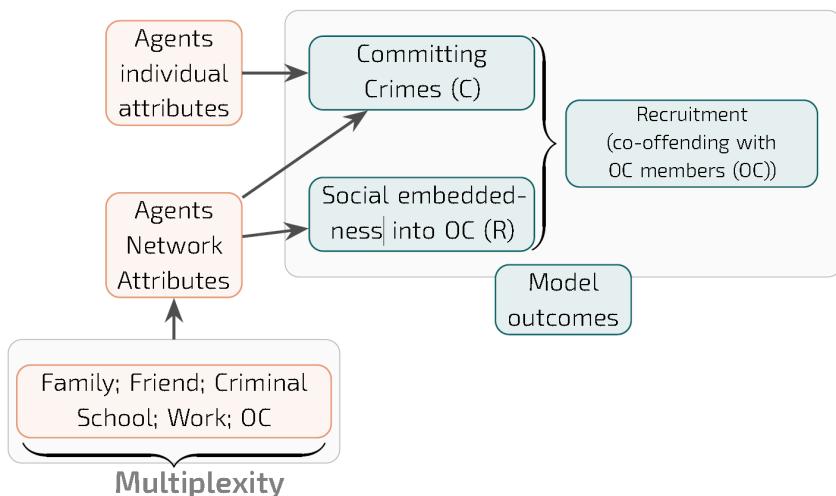


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2.3.1 RECRUITMENT INTO ORGANISED CRIME

Recruitment in our simulation occurs when an agent commits a crime with at least one other agent who is already a member of the OCN and is also the initiator of the crime. This design choice was driven by multiple considerations. First, it is clearly observable in the model and simply to operationalize. Requiring that co-offending happens with an OCN member represents the process of recruitment in a clear and unambiguous way, avoiding subject evaluations. Second, it is broadly consistent with the criminal law approaches across countries that criminalise organised crime (Calderoni, 2010). Two factors contribute to the recruitment process in the model: the probability of committing a crime by an agent (called C) and the embeddedness of an agent in organised crime (called R) (Figure 2).

Figure 2. General structure of the OCN model.



2.3.2 MODELLING CRIMINAL ACTIVITY (C)

The C function models the probability that agent i will attempt to commit a crime at time t . This function primarily represents the attributes of individual agents determining this decision. That this, the combination of their attributes sets the probability with which they start the process towards committing crime. The specific factors, which are based on the systematic reviews, are 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 OC member. The attributes of our agents cover three crucial types of variables: individual-focused ones (e.g. age), socially determined ones (e.g. number of friends who have committed a crime), and habitual ones (e.g. previously committed crimes).



Start with gender and age.² We derived the probabilities associated with committing a crime according to gender and age (split into discrete categories) by estimating the baseline probabilities of committing any crime in Sicily using figures from crimes reported to police and victimisation surveys. Combining these sources allows to minimise the problem of a “dark figure”. The dark figure refers to the difference between the real number of crimes and the actual reported number of crimes (Skogan, 1977). Ultimately, we aimed to estimate the real number of crimes and their association to gender and age that occurred in Palermo in the period 2012-2016. The baseline probabilities are reported in Table 5.

The second set of social and criminal factors we derived from the existing literature. Specifically, we used several systematic reviews that provide information on the association between the relevant factors on the probability of committing a crime (D1.1). These sources provide effect sizes in different forms (e.g. odds ratios) that allow us to determine the different probabilities of coming a crime given an agent’s network and individual characteristics. The list of individual factor-based rules that drive the model rules for committing a crime is presented in Table 1.

Table 1. Individual-level factors (γ) driving criminal activity

Risk factor	Odds ratio	Definition
Unemployment	1.30	Having/not having a job.
Education	0.94	Having/not having a high school diploma.
Natural propensity	1.97	Having a criminal 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 which is higher or equal to 0.5. A criminal family tie is a direct link with a family member which has committed at least one crime in the last 2 years.
Criminal friends and co-workers	1.81	Having a share of criminal friends ties which is higher or equal to 0.5.
OC membership	4.50	Being part of an OC group.

Given the data at our disposal, we model the probability of committing a crime $p(\bar{C})$ for an individual i at time t as

$$p(\bar{C})_{i,t} = \left[(C|\theta(g,a)_{i,t} \left(\sum_{j=1}^m \gamma_{j,i,t} \right)) \right] + \varepsilon \quad (1)$$

² Birth and deaths are included in the model, and, there is a low level of net migration to offset the decreasing population that occurs due to the low birth rate in Italy.



where $(C|\theta(g,a)_{i,t})$ is the baseline probability for individual i given its gender and age and $(\sum_{j=1}^m \gamma_{j,i,t})$ is the summation of the risk factors γ and ε is an error term stochastically distributed in order to bound the individual probabilities of committing a crime to the population average. Specifically, given the odds ratio of a risk factor, we increase or decrease the baseline risk by the percentage provided by the Odd Ratio (OR) itself. For instance, if the OR is equal to 1.41, an individual has this factor among its characteristics, and their baseline is 0.15, it means that the final value has to be the product between the baseline and 0.41, namely the increase of the risk in percentage given that risk factor. Therefore, at each time of reference \bar{t} and for each subset of the population (g, a) of given gender and age class, the following equation shall hold:

$$C(g,a)_{\bar{t}} \approx \frac{1}{n(g,a)} \sum_{i=1}^{n(g,a)} p(\bar{C}) \quad (2)$$

The equation means that at each reference time, the average probability of committing a crime for all individuals belonging to the same gender and age class shall be approximately similar to the fixed average values presented in Table 5, where approximately means that we allow the model to float in a ± 0.1 range to not make the model's mechanics overly deterministic. In other words, we model the distribution of C as a strictly stationary and ergodic random process:

$$F_C[C(g,a)_{t_1}, \dots, C(g,a)_{t_k}] = F_C[C(g,a)_{t_1+\tau}, \dots, C(g,a)_{t_k+\tau}] \forall \tau, t_1, \dots, t_k. \quad (3)$$

C has been computed to provide realistic figures on committed offences within the model, in the form of rates by 100,000 inhabitants, using official statistics for different years (2012-2016, specifically). The calculation relied on the correction of crime figures by the dark number of each crime category. This allowed us to take into account and include also those offences that have not been discovered or prosecuted in the original data at our disposal, thus giving more solid and reliable estimates.

If an agent decides to undertake a criminal act, based on $p(\bar{C})_{i,t}$, then the 'size' of the crime is determined. By size we mean here how demanding a crime is in terms of partners: simple robberies can be sole affairs while robbing a bank is a complex operation with multiple confederates. We base the distribution of crime size based on the literature on co-offending that tells us that most crimes are committed by single offenders and few crimes require more than one offender (Carrington & van Mastrigt, 2013; Stolzenberg & D'Alessio, 2008; van Mastrigt & Farrington, 2009). The "decision" to commit a crime does not have to be considered as a classic decision-making process. As mentioned before, agents do not have the ability to decide to commit a crime or hide from



the police. Contrarily, the commission of a criminal act simply follows a sort of 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 offences 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 to only consider the specific features that we have found in the relevant literature, excluding other social mechanisms that would have been difficult to operationalize and for which it would have been almost impossible to gather empirical real-world data.

Once the size of the crime is determined, the agent looks for partners through all of their social networks (organised crime, co-offending, family, friendship, work, and school). 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 relationship between the number of links between agents and the odds of requesting another agent to co-offend; in other words, having twice as many links makes it twice as likely that the agents will request co-offending. There is one exception to this: previous co-offending together has the highest weight in this decision. Agents with 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 play roles in driving this criminal cooperation (Weerman, 2014). 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.

If agents commit crimes they can be incarcerated. Incarceration is estimated using empirical data retrieved from official statistics and is a fixed probability in each run of the simulation. Apart from family links, agents in prison lose all the ties that they have created during their life (including during their jobs). The mechanism for incarceration is based on a countdown that establishes when the agent leaves prison and returns to be free in the society, recovering part of its ties.

2.3.3 MODELLING ORGANISED CRIME EMBEDDEDNESS (*R*)

R defines the embeddedness into OC and provides the other component of recruitment into an OCN. *R* aims to represent the role of each agent's community in the process of recruitment. The theoretically driven core assumption is that individuals that are embedded in communities (across all the five types of networks considered by our simulation) that are highly populated by OC members face higher risks of being recruited. *R* affects the selection of new OC members in the simulation. For example, among two equally suitable co-offenders, OC members are likely to co-offend with the agent who is more embedded in OC. In a simple form—but coherently with the



differential association and social learning theories as well as the social embeddedness of OC—R is then operationalised as the proportion of OC members among the social relations of each individual (comprising family, friendship, school, working and co-offending relations).

In mathematical notation, a multiplex network $\mathcal{G} = \{G^1, \dots, G^l, \dots, G^M\}$ that resembles our simulated society is a set of M single-layer networks that are dynamically updated at each time unit t . Each single-layer network is denoted as $G^l = (V, E)$, that takes the form of an $N \times N$ matrix. Given this notation, for each G^l , we define an h -hop neighbourhood graph for each node i . The node set of the h -hop neighbourhood graph is defined as the set $N_i^h = \{j | k \in N_i^{h-1}, j \in V, (k, j) \in E\} \cup N_i^{h-1}$ with $h \geq 1$. The set of edges is then formalised as $E_i^h = \{(j, k) | j \in N_i^{h-1}, k \in N_i^h, (j, k) \in E\}$. The local neighbourhood of agent i in the single layer network $G^l = (V, E)$ becomes then a vector $\mathbf{w}_i^{G^l} = [w_{i,l}^{G^l} \dots w_{i,j}^{G^l}]$ where each element represents the weight of the edges included in the h -hop local neighbourhood of the agent. Each value of the vector follows the relation $w \propto h^{-1}$, meaning that the weights are inversely proportional to the distance between the ego i and an agent j included in the h -hop network. At this point, to compute the embeddedness R of an agent i in his local community, we sum over the vectors of each single-layer network:

$$\mathbf{w}^G = [w_{i,l}^{G^1} \dots w_{i,j}^{G^1}] + \dots + [w_{i,l}^{G^l} \dots w_{i,j}^{G^l}] = [w_{i,l}^G \dots w_{i,j}^G]. \quad (4)$$

This equation yields the resultant vector of weights deriving from the complete agent's h -hop network. To calculate the actual OC embeddedness, we derive the resultant vector of weights obtained from the agent's h -hop OC network $\Theta_i^G = [\theta_{i,l}^G \dots \theta_{i,j}^G]$, such that the node set is called $N_{i,OC}^h$, and the set of edges is $E_{i,OC}^h$, where $N_{i,OC}^h \subseteq N_i^h$ and $E_{i,OC}^h \subseteq E_i^h$. R is finally mathematically defined as:

$$R_i = \frac{\sum_{i=1}^{N_{i,OC}^h} \theta_{i,j}^G}{\sum_{i=1}^{N_i^h} w_{i,j}^G} \in [0,1] \quad (5)$$

which is the ratio between the total number of weights in the OC h -hop network and the general h -hop network of agent i . The values of R fall in the range $[0,1]$, with 1 indicating complete overlapping between the general h -hop networks and 0 highlighting total absence of OC members in the local community of the agent. The proposed method implicitly weights the OC embeddedness such that (i) the importance of OC ties is inversely proportional to the distance and (ii) the importance of OC ties (but also of other non-OC ties) is proportional to the number of different ties between any two individuals.



In addition to the contribution in determining recruitment, R provides useful information to analyse the general dynamics of the model. First, it enables us to clearly distinguish between active OC members and pro-OC agents who are not actual members. An agent may be strongly embedded in OC-prone networks but not necessarily be a member. For example, this could be the case of women, among them wives and daughters of OC members, who are certainly living in OC-prone contexts but are rarely charged and convicted as OC members since they generally do not commit offences. Similarly, a juvenile son of an OC member who is just two years old cannot be considered an active member but would still have a very high value of R , making it very likely that he will be recruited in the future. Second, R may contribute to the simulation of prevention policies, especially those on the primary and secondary socialisation. The simulation will need to identify the target population and R could contribute in identifying the population at risk better than merely relying on other indicators e.g. the number of crimes committed by the parents or the involvement of a parent into OC.

In summary, our OCN model represents recruitment as a dynamic and complex interplay between multiple kinds of individuals' attributes and the influence of the social structures—co-offending network, family network, friendship network, work, and school network—within which those agents exist. This interplay coherently mirrors the nature of the theoretical framework that have been selected as the backbone of the simulation. It excludes rational or semi-rational decision-making processes and the presence of values (either positive or negative) as their inclusion would have posed many conceptual issues. These issues regard the availability of data and the subjectivity in designing the formal mechanics behind the virtual society. Nonetheless, our network-based architecture is grounded in literature and built around different information levels and avoids an overly deterministic society.

2.4 Model Contexts

Although our model represents general processes of recruitment into OCNs, there are important differences between OC types that need to be taken into account. In particular, we consider two environments in which distinct forms of organised crime exist and operate: a Southern European city based on Palermo (Italy), which represents recruitment into a more territorially-based and hierarchical OC, and a Northern European city based on Eindhoven (the Netherlands), which captures recruitment in more fragmented OCs that are also less hierarchical and have less territorial control.

2.4.1 SOUTHERN EUROPEAN CONTEXT

We chose Palermo, the capital city of Sicily, as the Southern European city that contains the first kind of OCN for a number of reasons. OC are complex and



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hard to define due to their many types and structures, not only within the European Union but even more so on a global scale. The organised criminal networks that carry out this type of criminal activity can be out on a spectrum from small-scale, fragmented, highly flexible, entrepreneurial groups of individuals to large-scale, hierarchical, rigidly structured groups and many more forms in between. In order to capture this reality and analyse the recruitment of individuals into OCNs, the PROTON project establishes two different OC models. The first one is related to the more traditional form of OC, such as Mafia-type syndicates, which are characterised very generally (but not exclusively) by clans that are aligned in a pyramidal-type structure with bosses at the top and foot soldiers at the bottom. One example of such Mafia-type syndicate and arguably the most widely known is the Sicilian Mafia known as the "Cosa Nostra". The main Cosa Nostra families are situated in the city of Palermo, which represents the context of the first ABM related to OC recruitment. Police records made available to the researchers concerning a specific investigation on the main Mafia families that are operating in Sicily provided the data needed to calibrate the (scaled) amount of already existing organised criminal groups for the model input.

Palermo, with 674,000 inhabitants is big enough as a city to provide sufficient data concerning the city's demography, the socio-economic status of people living in city, the number and types of educational institutions and employers present and also crime-related data (i.e. offences committed in Palermo and type of punishment received as a result). The data could then be easily scaled down to the size of the ABM context. Furthermore, it is worth noting that being part of the PROTON consortium, the City of Palermo provided privileged access to their official registry and thus, made the extraction of data concerning the structure of families living in the city possible in the first place.

2.4.2 NORTHERN EUROPEAN CONTEXT

The second context aims to represent another and common form of organised crime: fragmented, less hierarchical, and flexible OCNs that are not necessarily bound by kinship ties. While the Netherlands was chosen as a context representing this type of OC, the same or at least similar forms are found in many other European countries. Thus, any analysis related to this specific reality might very well be applicable to other contexts.

Amsterdam was specifically not chosen due to the peculiarity of that city in terms of OC, which does not accurately represent the OC reality in the rest of the country as well as the reality of OC in Europe generally. Amsterdam as a city plays a central role when it comes to OC involvement in the trafficking of drugs in and out of the Netherlands. It is a city that favours transit crimes specifically and is hence also a melting pot of various offender types as well as OCNs from all over the world. This makes its OC reality different from any other city in Netherlands.



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Eindhoven on the other hand in terms of inhabitants and the reality and extent of OC in the city is much more in line with that of other Dutch cities.

2.5 Calibration, Validation, and Sensitivity Analysis

So that our OCN recruitment model reflects important aspects of reality, we need to use data from the real-world as inputs into the model, check that the outputs of the model broadly reflect observed real-world patterns, and, we consider the sensitivity of the OCN model to changes in parameter values. For calibration, we use 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. We describe below the source of these data and how they are used in the model³.

The sections below describe the data used for the Southern European Context. In Section 2.5.11 we then outline the data used for the Northern European Context. This builds on the data already outlined but modifies it wherever we indicate. The reason for this is that it was harder to obtain data on OC in the Netherlands than in Italy as there are no official statistics on the distribution or type of OCNs in the country.

We start with the input sources for the Southern European context (based on Sicily and more specifically Palermo wherever possible). Much of this data comes from the Italian National Institute for Statistics (Istat).

We used the findings from the laboratory experiment (T4.3, D4) to provide a broad validation of the approach taken in the OCN model. The experiment demonstrated that in a context, albeit abstract, that captures key elements of the co-offending situation, co-offender selection is driven by social networks and proximity. This buttresses the multiplex network focus of the OCN model.

Table 2. Data for calibrating Southern European OCN model

³ 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 size, we found at 3,000 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.



Variable	Description	Source
Household size	Distribution of household sizes in Palermo, also according household head's age	Istat (2011b)
Age and gender	Distribution of age and gender in Palermo	Istat (2018)
Fertility rate	Distribution of female fertility according to age and conditional on number of children	Istat (2017)
Mortality rate	Probability of living according to age and gender	Istat (2016c)
Employer size	Distribution of employer sizes in Palermo	Istat (2012b)
Socio-economic status	Includes values related to age, gender, wealth level, an education score, a work status and SES-related criminal propensity	Banca d'Italia (2018), Istat (2011a)
Schooling	Number of schools in the city of Palermo by education level	MIUR (2019)
Organised crime network	Distribution of Mafia families in Palermo	Corte d'Appello di Reggio Calabria 2012, Criminal Investigations "Aemilia", "Crimine", "Infinito", "Minotaruo"
Co-offending prevalence		Istat (2016a), cross-checked with literature (Carrington, 2002; Carrington, Brennan, Matarazzo, & Radulescu, 2013; Carrington & van Mastrigt, 2013; Hodgson, 2007; Hodgson & Costello, 2006)
Crime rates	Crime rates corrected for "dark" number	Istat (2012a)
Punishment distribution		Istat (2012a)
Imprisonment length distribution		Istat (2012a)
Friendship networks	Number of meaningful relationships an agent can make	Dunbar (1992)



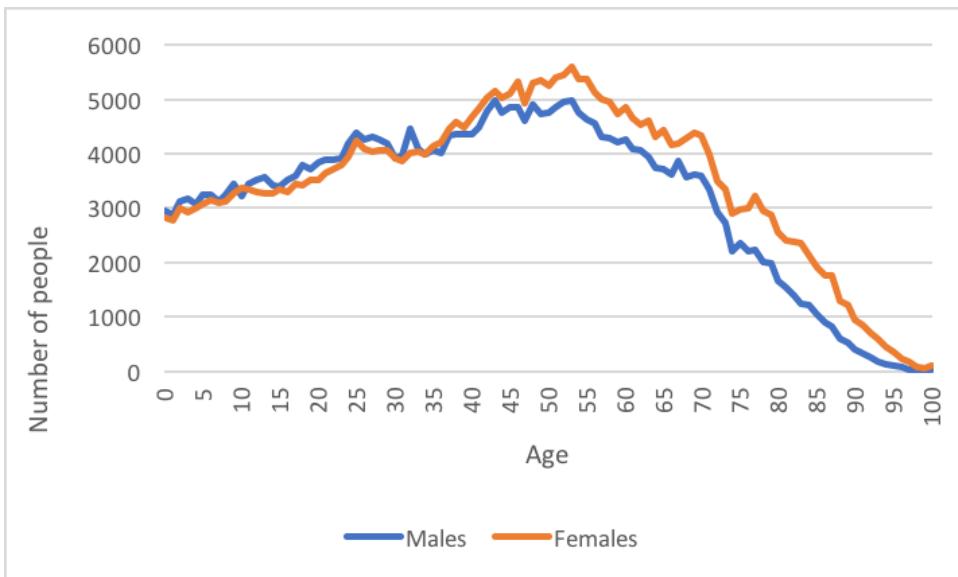
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2.5.1 DEMOGRAPHIC DATA

The population of the model is initialised by implementing different household types. It is important that household structure is based on data as this will influence the demography in our model-city. We follow the procedure from Gargiulo et al. (2010), in which the authors adopt an algorithm that combines different household related data structures (distribution of household type, size, household ages, and household head) to initialise their agent ABM population. See Section 5.1.1 in the Appendix for details about the household algorithm.

We use data about the age and gender distribution in Palermo (Istat, 2018). The different household data structures on the other hand are retrieved from the 2011 Census and from data made available by the Municipality of Palermo (Istat, 2011a). One part of this, the population distribution in Palermo, is shown in Figure 3.

Figure 3. Population distribution by gender in Palermo



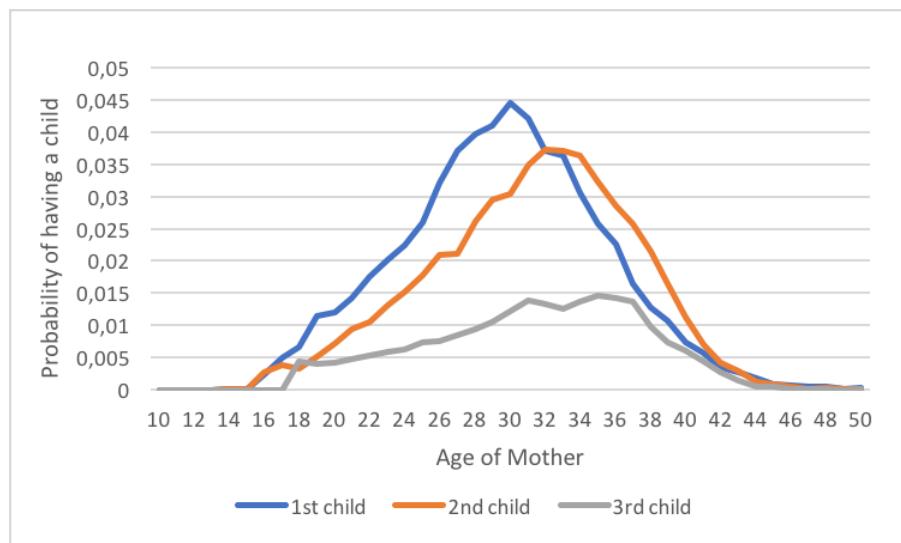
2.5.2 FERTILITY AND MORTALITY RATES

Agents are born and die in the model. To calibrate the birth, we use data on female fertility rates in Sicily (Istat, 2017). This indicates the probability for a woman (married or single) of having a child when she has had previously had no children, one child, two children, and three children—three prior children is the upper limit in the data (Figure 4).



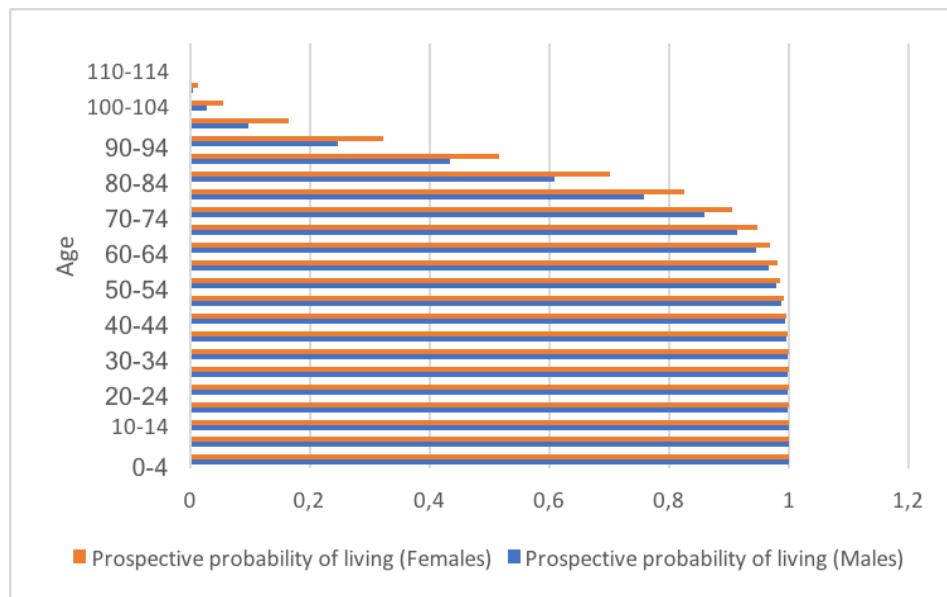
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Figure 4. Fertility rate in Palermo



To calibrate agents' deaths, we use data on people's probabilities of living depending on their age and gender in Palermo (Istat, 2016c) (Figure 5). The age range for this is 0-119 years.

Figure 5. Prospective probability of living by age-group and gender



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2.5.3 EMPLOYERS' NUMBER, SIZE, AND DISTRIBUTION

Employers are vital for the model as they shape the socio-economic status and work relationships of agents in the simulation. Employers are introduced into the ABM based on data on the number of active companies and the number of employees of active companies (plus the owner of the company in question) in Palermo (Istat, 2018). For the employees the age range starts at 15 years as agents do not work before that. This data input differentiates between private and public firms. Each employer has a link to a variety of jobs which in turn have certain education level requirements.

2.5.4 SOCIO-ECONOMIC STATUS (SES)

The SES component includes age, gender, wealth level, education score and work status. When agents are born, they automatically inherit their parents' wealth level, which is then later updated in accordance with the agent's work status. There are five different wealth levels introduced to the model that are based on quintiles of the wealth distribution data. The wealth levels are based on data gathered from the Banca d'Italia (2018) about Sicilian families' income and expenditures.

The SES of each agent is derived from their respective education level. Before the setting up of households in the model, each agent is assigned an education level and after this, other characteristics are added. Four school levels are introduced to the simulation: primary school, 1st level secondary school, 2nd level secondary school, and universities. We obtain data for the distributions of these for Palermo (MIUR, 2019). The absolute numbers are scaled to fit the model population of 10,000 agents (Table 3).

Table 3. Number of schools per education level and age

Education level	Age range	Number of schools
Primary school	6-10 years	202
Secondary school (1 st level)	11-13 years	105
Secondary school (2 nd level)	14-18 years	95
Tertiary education (university)	19-25 years	1

The work status variable of the SES component is related to the agent's actual occupational level and a specific position in work-related networks. It consists of five categories: inactive, unemployed, blue collar worker, white collar worker, and managers⁴. After exiting the education system, active agents look for a job which level is determined by their education score. If they cannot find

⁴ See Bank of Italy study (2018) and Table 4 for data on unemployed individuals, blue collar workers, white collar workers, and managers. Inactive are calculated as a percentage of unemployed individuals, based on data from.



a job, they can also accept a position on a lower level. Agents stay in the workforce until age 65. Once retired, the agents keep their last wealth level.

Table 4. Distribution of work status categories (Bank of Italy 2018)

Blue collar workers (1)	White collar workers (2)	Management (3)	Entrepreneur/ private practitioner (4)	Other self-employed (5)	Other unemployed (7)	Total
n=132 (0.168)	n=126 (0.160)	n=18 (0.023)	n=29 (0.037)	n=39 (0.050)	n=443 (0.563)	n=787 (1.000)

There is also a SES-related criminal propensity that describes an agent's economic stability and satisfaction and therefore, depends on the wealth level of the individual. Consequently, when the wealth level changes, so will the SES-related criminal propensity. The empirically grounded assumption is that less economically stable agents are more open to criminal activities. The SES-related criminal propensity has four levels: the first three represent decreasing degrees of perceived economic instability, whereas the fourth represents the perceived economic stability.

2.5.5 CRIMINAL NETWORK

At the start of the simulation, as part of the population, an already established criminal network is introduced to the environment. This is done by simply introducing a set number of criminals and criminal families to the simulation. The number of families is based on one police operation in Sicily that identifies Mafia families on the island. This number is then expressed as the number of people in the organised criminal network per 10,000 agents, which results in 30 criminals distributed in 8 criminal families being introduced at the onset.

2.5.6 CO-OFFENDING

Criminal links are established between two people through co-offending. If there is a criminal link between two agents, then it implies that they have co-offended at least once. Given the importance of co-offending, a realistic distribution of co-offending rates within the population had to be implemented in the simulation. This was based on data from Istat (2016a) and then validated by comparing it to additional empirical sources gathered from different studies on co-offending rates in Canada, England and the United States (Carrington, 2002; Carrington et al., 2013; Carrington & van Mastrigt, 2013; Hodgson, 2007; Hodgson & Costello, 2006). See Section 5.1.3 for a detailed table of co-offending rates.



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2.5.7 CRIME COMMISSION, PUNISHMENT, AND CONVICTION

The Istat database provides information about the number of reported offences per crime category for the years 2012-2016 in the province of Palermo (Istat, 2016b). This data is used to implement the distribution of crimes committed in the simulation. When implementing crime commission data, it is always vital to not overlook the "dark figure of crime", i.e. the crimes that were committed but not reported. The way this figure was included in the OCN model is through data in relation to specific crime types, provided by the Istat victimisation survey regarding the context of Palermo in 2008-2009 (Istat, 2010). Taking into account this dark figure of crime estimate, an analysis was made to calculate the true number of crimes committed by age and gender, in the region of Sicily, on the basis of Istat data on reported crimes in the region of Sicily for the years 2012-2016 (Istat, 2016a) (see Section 5.1.2). See Table 5 the crime rates after the correction. Overall, a total rate of 2000 crimes has been derived for the model per 10.000 agents.

Table 5. Probabilities of committing a crime in Palermo ((C|θ(g,a))

(Sex, Age group)	Probability	Odds ratio
(Female, < 13 yrs)	0.0004	0.0004
(Female, 14-17)	0.0223	0.0229
(Female, 18-24)	0.0511	0.0538
(Female, 25-34)	0.0634	0.0677
(Female, 35-44)	0.0643	0.0687
(Female, 45-54)	0.0489	0.0514
(Female, 55-64)	0.0308	0.0318
(Female, 65+)	0.0111	0.0112
(Male, <13 yrs)	0.0022	0.0022
(Male, 14-17)	0.1502	0.1767
(Male, 18-24)	0.3019	0.4324
(Male, 25-34)	0.3036	0.4359
(Male, 35-44)	0.2751	0.3795
(Male, 45-54)	0.1996	0.2494
(Male, 55-64)	0.1268	0.1453
(Male, 65+)	0.0537	0.0567

In order to calculate the number of crimes committed on average for OCN members specifically, the Proton Mafia Members dataset was analysed, which was provided by the Ministry of Justice and previously used in WP1.4 (see Deliverable 1.1). This dataset includes all the convictions of Mafia members in Italy from 1982 to 2017, of which only those members were extracted who



were born in Palermo province after year 1960 (n=428). We calculated that OC members commit on average 4.5. times more crimes than normal individuals. This figure can be transformed into a probability and plugged into the C-function to distinguish the crime commission process based on the status of each given individual. However, the crime commission probability is also based on external factors that were established from a systematic review related to fields of delinquency, criminal involvement and peer-influence to obtain odds ratio/probabilities/correlation values to be plugged into the C.

The crime commission distribution naturally has resulting punishment and conviction distribution in real life. This is also included in the simulation through the use of Istat data on punishment related to crimes committed at the national (Italian) level and during the time period from 2012-2016. These numbers had to be scaled down to fit the model population. Data on final convictions was instead calculated by using the before-mentioned data on punishment, by filtering out all sentences that were not resulting in convictions. When filtering out convictions specific attention was paid to the differences in length of sentence involved.

2.5.8 FRIENDSHIP NETWORK

In order to evolve friendship networks in the simulation, new links are created between people according to a random Poisson distribution. The number of friends, or “meaningful connections”, an agent in the simulation 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 relationships with during a lifetime (Dunbar, 1992).

2.5.9 VALIDATION

The model on OC has been developed from the beginning in order to resemble a plausible virtual society. Indeed, it has been fed with real-world data as much as possible, and the mechanics and processes of the model have been designed as to mirror criminological theories and obtain a model providing outcomes adherent with the initial empirical data. As to pursue to this aim, we validate our model results with data retrieved from official open access statistics. In order to avoid overly deterministic simulations, we generally let the results float in a +/- 5% range from the real-world values we set as realistic benchmarks. Specifically, the validation data pertains the number of crimes in each year, the number of arrests per year, 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. Most of the sources have been retrieved from the data available on the website of the Italian Institute of Statistics (Istat), while the number of mafia families and members has been gathered from large-scale criminal investigations on mafia families in Calabria, and the unemployment rate is derived from Eurostat data.



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2.5.10 SUMMARY OF SOUTHERN EUROPEAN CONTEXT

Table 6. Southern European model specification summary.

Variable	Value	Source
N of members OC	30	Corte d'Appello di Reggio Calabria 2012, Criminal Investigations "Aemilia", "Crimine", "Infinito", "Minotauro" Official reports of Italian Antimafia Investigative Division and National Antimafia Directorate
Crime rate (per 10,000 inhabitants)	2000	Crime rates corrected for "dark" number Istat (2012a)
Unemployment rate	16%	Data from (Bank of Italy 2018) applied to the Palermo population age structure
Law enforcement intervention rate	30	Number of convictions divided by 2017 Italian population, per 10000 citizens.
Punishment length	<1 month: 10.71% 1-3 months: 16.19% 3-6 months: 24.93% 6 months -1 year: 22.21% 1-2 yrs: 15.82% 2-3yrs: 4.57% 3-5 yrs: 3.53% 5-10 yrs: 1.55% >10 yrs: 0.49%	(Ministerie van Veiligheid en Justitie, 2018, Table 2.11)

2.5.11 NORTHERN EUROPEAN CONTEXT

To calibrate the model for the Northern European Context, we made the following modifications.

Table 7. Northern European model specification.

Variable	Value	Source
N of members OC	15	No empirical data on the size of OC groups in the Netherlands. We fixed the number to 15 in accordance



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		with the literature explaining that Dutch OC groups are generally of lower size with respect to traditional mafia groups.
Crime rate (per 10,000 inhabitants)	3368.40	Averaging the total number of crimes per 100 inhabitants for the period 2012-2016, and calculating rate for 10,000 (Ministerie van Veiligheid en Justitie, 2017, Table 3.5).
Unemployment rate	6.68%	Average value calculated taking into account the period 2012-2016 (Eurostat, 2019b).
Law enforcement intervention rate	(24,800/17,081,057)*10,000= 14.51	Number of convictions divided by 2017 Dutch population (Eurostat, 2019a; Ministerie van Veiligheid en Justitie, 2017, Table 8.1).
Punishment length	<1 month: 5% 1-3 months: 9% 3-6 mts: 8% 6 mts-1 year: 11% 1-2 yrs: 15% 2-3 yrs: 20% 3-4yrs:7% 4-6 yrs: 7% 6-8 yrs: 4% 8-12 yrs: 5% >12 yrs: 2% Unknown: 6%	(Ministerie van Veiligheid en Justitie, 2018, Table 2.11)

2.6 Policy Scenarios and Assumptions

2.6.1 GROUP DISRUPTION

2.6.1.1 BACKGROUND

New analytical approaches and data in criminology have led to interest in network disruption strategies to tackle clandestine networks such as terrorist and criminal groups (Everton, 2012; Gerdes, 2015). Social network analysis has brought major advancements on this topic: more advanced and



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sophisticated techniques are now available for scholars and analysts, attracting the attention of different academic fields, including statistics and computer science.

One of the first applications of social network analysis to assess the strength and structure of a covert network, in the aftermath of 9/11, used open source information to re-create the jihadist network of hijackers and collaborators in the attempt to map the whole set of connections (Krebs, 2002). This important article triggered dozens of works to come.

The specific nature of criminal organisations, and especially organised crime groups, implies that they must conceal their activities to survive. This pressure shapes their network structure and topology. Compared to licit entities (e.g. legitimate companies), criminal networks have different characteristics that are related to the well-known “security-efficiency” trade-off: the need for these groups to protect their activities from the spotlight of law enforcement agencies while running either ideological or profit-oriented activities (Morselli, Giguère, & Petit, 2007).

Research on the way in which agents in criminal groups are connected quickly led to the investigation of effective targeting strategies to assess the degree of resilience and to understand how to inflict the highest damage in terms of human and economic resource to these entities (Duijn, Kashirin, & Sloot, 2014; Duxbury & Haynie, 2019; Leuprecht, Aulhouse, & Walther, 2016; Morselli & Petit, 2007; Ren, Gleinig, Helbing, & Antulov-Fantulin, 2019; Wandelt, Sun, Feng, Zanin, & Havlin, 2018). However, nearly twenty years after the 9/11 attacks, the sophistication of methods has not been followed by a parallel increase in quality of data. Although more information on criminal networks exist with respect to 2002, it is still difficult for academics to obtain sufficiently detailed data. For example, few works use longitudinal information, making it difficult to reliably evaluate the effects of potential dismantling strategies. Additionally, the most sophisticated studies on network dismantling have proposed methodological frameworks experimenting techniques using stylized networks (e.g. Erdős-Rényi graphs) or other social networks that are not criminal in their very nature, and therefore are likely to have very different characteristics from the ones of our interest (Braunstein, Dall'Asta, Semerjian, & Zdeborová, 2016; Ren et al., 2019).

In relation to these aspects, no comprehensive agreement exists on the effectiveness of disruption strategies for clandestine networks. Particularly, no “one size fits all” solution has been found, as each action is intrinsically dependent on the groups’ topology and resources and the attacker’s aims. Although the literature provides contrasting evidence regarding certain dismantling strategies, we will show in the following subsection the potentials of our modelling approach.



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We test two commonly proposed policies for reducing recruitment through law enforcement intervention. The first targets criminal leaders to weaken the criminal group and reduce recruitment. Criminal leaders are generally associated with the idea that criminal groups not only depend on their operational decisions but also on their network position. Specifically, scholars have argued that in clandestine groups, leaders act as central nodes, meaning that they are the most connected actors. Building from this assumption, the majority research has focused on lead "k" targeting as the most efficient disruption policy (Alm & Mack, 2016; Wood, 2017). The second, instead of acting on prominent criminal members, targets criminal facilitators with the same aim. Studies have shown how focusing on "brokers" (those agents with access to heterogeneous sub-groups of other members) can have better performance in terms of group disruption. We partially model this alternative strategy in our second hypothesis where we indeed focus on a specialized form of brokers, namely "facilitators".

Criminal facilitators have been studied under many perspectives (for example Levi, Nelen, & Lankhorst, 2005). Morselli and Giguere (2006) show that legitimate world actors are important for the criminal activities of an illegal drug importation network because legitimate world agents (1) are able to attract others into the network and (2) are influential in maintaining relationships with traffickers and non-traffickers. Following this study, other articles showed the importance of legitimate actors in shaping the activities of criminal groups (Hall, Koenraadt, & Antonopoulos, 2017; Sanchez, 2016). Specifically, Kleemans and De Poot (2008) demonstrate that the social opportunity structure of an individual—defined as social ties giving access to profitable criminal opportunities—is decisive for evaluating the risk of becoming part of a group. Their study shows how non-criminal individuals are involved in organised crime due to their specific jobs and skills. Jobs that can either get access to critical infrastructures, as transport (e.g. working for maritime shipping companies) or that are intrinsically related to qualified expertise (e.g. tax experts, bankers) can make the business of organised crime groups much easier.

While methodological developments and changing interests have led to an increase in research on criminal network disruption, multiple issues remain in the studies on this topic. First, analyses often focus on information about events (such as telephone or meeting contacts), rather than long-term states (e.g. enduring social relations). This limitation can lead to substantial under- and over-estimation of meaningful connections; considering that telephone contacts or co-attending a meeting are not representative of real-world importance and connection strength. This applies especially to criminal networks that deliberately hide their actions and relations from law enforcement agencies. Second, it is difficult to gather comprehensive information on people in these networks. This means that knowledge concerning the criminal agents' socio-economic conditions or about their social



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relations besides criminal ones is limited. Third, due to structural data limitations, studies usually rely on short timespans. This reduces the possibility to investigate long-term dynamics and effects following the application of a given disruption strategy.

Our ABM model overcomes, or at least mitigates, each of these limitations. Our criminal networks are modelled on enduring relations—representing meaningful permanent or semi-permanent connections between individuals and not only digital contacts or co-participation in events. The data we use from official sources gives us information on criminals' social and economic characteristics and not only their criminal attributes. Finally, we conduct long-term simulations that cover one or more generations (e.g. 50 years) allowing us to assess the long-term effects of policies aimed at disrupting or damaging organised crime groups. In light of these aspects and following two of the most prominent approaches found in the literature, we use our model to test the effects of targeting OC leaders and facilitators external to OC groups.

2.6.1.2 TARGETING OC LEADERS

Scholars do not universally agree on the effectiveness of targeting strategies against leaders of criminal networks: the positive effect of these contrasting actions is generally dependent upon the topology of the specific network. However, from a practical and law enforcement point of view, convicting and removing the leader of a criminal group can have positive impacts on the way the surrounding social environment perceives the power and strength of the given OCG and can also lead to cascade effects within the organisation. For this reason, we test a disruption policy directed against OC leaders.

This policy is designed to evaluate how much the removal of the leader has an impact in both the overall number of crimes committed by the group and the recruitment dynamics. While it is expected that the criminal strength of the group will be diminished, it may also be that a reduction of the probability of being convicted for all the other OC members and criminals acts has a spill-over effect in the increase of the overall number of offences occurring in the model.

We implement this policy in our model by increasing the probability that the OC leader of the network is arrested and convicted. The probability is proportional to the number of OC members' neighbours that we consider as a proxy of their importance in the network.⁵ Leaders are defined in OC networks as agents that are more central in the criminal organization. The proposed policy will be kept in place from round 12 until the end of the simulation.

⁵ To isolate the effect of targeting OC leaders, we keep the mean probability that an OC member is arrested across the model constant.



2.6.1.3 TARGETING FACILITATORS

While disruption policies that target OC members in central roles are important for investigating the direct effects on the OC group present in our model, we were also interested in developing policies directed to agents acting in more hybrid contexts. In light of this, and consistently with different works in the literature, we propose a policy against “facilitators”.

Facilitators are agents that due to their job or social opportunity structure can act as bridges between legal society and criminal groups and can be exploited by OCGs due to their specific position in a network or because of their skills and jobs. This policy scenario tests the effectiveness of increased law enforcement efforts against facilitators to evaluate if these disruption strategies reduce the commission of more complex crimes (i.e. crime involving a higher number of co-offenders) and if they have a subsequent impact in the recruitment mechanisms present in the model. Under this intervention, a facilitator committing a crime will have a higher probability (twice as much as a normal citizen) of being apprehended. Because arrests are kept constant, this also reduces by a small amount the probability that a normal citizen will be apprehended. Like for the OC leader disruption scenario, this policy will remain in place from round 12 until the end of the simulation.

2.6.2 PRIMARY AND SECONDARY SOCIALIZATION

2.6.2.1 BACKGROUND

Different academic disciplines (e.g. paediatrics and psychiatry, psychology, sociology, criminology) have long investigated the origins and development of aggressive, antisocial, and delinquent behaviour. While aggressive behaviour has been associated with human instinct by some scientists (e.g. Lorenz, 1966), much research in the last century has embraced the social learning paradigm that highlights the importance of social factors.

Several studies have addressed physical aggression among preschool children and adolescents with the aim to understand the age of onset of physical aggression and its development over time (e.g. Brame, Nagin, & Tremblay, 2001; Tremblay et al., 1999).⁶ Physical aggression has been reported during infancy, though only a small proportion of youths have onset at a very young age; most juveniles have onset of aggression during early teenage years (D. S. Elliott, 1994; Loeber & Stouthamer-Loeber, 1998). It has also been observed that during adolescence there is an increase in delinquent behaviour, with a subsequent sharp decline beginning from the early 20s. This trajectory of

⁶ “From a developmental perspective the word ‘onset’ generally refers to the age at which an individual first starts to engage in a type of behaviour that will persist for a relatively long period of time” (Tremblay, 2000, p. 132).



offending, commonly referred to as the age-crime curve (Farrington, 1986), shows that criminal involvement takes place mostly among juveniles, who may be vulnerable to exposure to negative influences as deviant family members and friends.

In criminology, the influence of the social environment and the learning mechanisms of crime have been postulated by the differential association theory and social learning theory (see Burgess & Akers, 1966; Sutherland, 1937; Sutherland & Cressey, 1947). In the differential association theory, Sutherland described the dynamics through which individuals become involved in crime, pointing out that: criminal behaviour is learned as law-abiding behaviour and through social interactions and communications with others; learned deviance occurs within intimate groups as family, peers, and friends; leaning includes the techniques and attitudes, and that "a person becomes criminal because of excess of definitions favourable to the violation of law over definitions unfavourable to the violation of law" (see Antwi Bosiakoh, 2012, p. 991). Akers (1973, 1998, 2001) further expanded these notions with the social learning theory, which includes the influence of the imitation of peer behaviour and the importance of reinforcement for repeating delinquent acts in the future. According to these theories, therefore, crime is learned through social interactions, in which definitions and reinforcement of criminal behaviours play a central role for individuals' involvement in offending.

These concepts have not remained merely theoretical contributions but have received empirical support (see Cao, 2004). Such support has not only emerged from single studies, but has also been provided by narrative reviews (see Akers & Jensen, 2006; Akers & Sellers, 2009) and systematic reviews with meta-analysis (Pratt et al., 2010). Pratt and colleagues (2010), found that peers' behaviour is the single strongest predictor of delinquency and offending behaviour (p. 783). Though with less strength, also parents' behaviour has been found to be a significant predictor of offending. Ultimately, this literature points out the influence that that primary and secondary ties have on individuals' deviant behaviour.

Peer and family risk factors have also been studied in relation with involvement in criminal groups, as gangs. Raby and Jones (2016) conducted a systematic review with narrative synthesis on risk factors for male street gang affiliation. The review included 102 observational studies and results showed that family, school, peers, and community were among the main domains associated with gang affiliation. Parents' gang membership, criminal history, and school issues were found to be factors associated with risk of gang affiliation, though the research design of the studies did not allow to determine the directionality of the relationship (Raby & Jones, 2016, pp. 611–612). As for peers and community, relations with antisocial peers and residing in antisocial and socioeconomic disadvantaged urban communities impact juveniles' involvement into gangs. Similarly, a systematic review conducted by Higginson



and colleagues (2018) on risk factors for gang membership in low- and middle-income countries (e.g. Turkey, El Salvador, China, Brazil) found that socialisation with delinquent peers, lack of parental monitoring, and negative family environments were positively associated with involvement into gangs.

Most of the empirical studies have focused on juvenile youth groups and gangs, and less on organised crime groups (OCGs). Over the last decades, however, scholars have investigated the processes related with involvement into organised crime (OC), pointing out the social embeddedness of OC (Kleemans & de Poot, 2008; Kleemans & van de Bunt, 1999). Van Dijk et al. (2018) investigate the intergenerational transmission of OC through the enquiry of children of OC offenders and find that transmission of involvement in OC across generations was, among other aspects, related with deviant social learning and the violent reputation of fathers. Factors leading to involvement into OC were also analysed by Savona and colleagues (2017), who conducted a systematic review of literature on OC recruitment as part of PROTON project. In line with literature on juvenile offending and gang membership (Gilman, Hill, Hawkins, Howell, & Kosterman, 2014; Raby & Jones, 2016), the authors find that criminal social relations with family members (i.e. kinship and blood ties) favour involvement into OC (Savona et al., 2017, p. 30).

These results inform—together with other data collected—our agent-based model simulating recruitment into OC. The following sections present the primary and secondary socialisation policies which aim to prevent youth involvement into OC by decreasing the influence that OC-prone social relations have on juveniles.

2.6.2.2 PRIMARY SOCIALIZATION

The primary socialisation policy targets juveniles aged 12-18 living in OC families, intended as families where at least one parent is an OC member. Studies on juvenile development and behaviour have shown that parents' criminal history predict future involvement in offending, because of the social learning of crime and impact that bad influences have on youths (e.g. Farrington, 1989; Farrington, Jolliffe, Loeber, Stouthamer-Loeber, & Kalb, 2001). With regard to involvement into gangs, the literature highlights that poor family relationships are associated with gang membership. In particular, difficult relationship with parents and parents' deviance (Raby & Jones, 2016), as well as living with a gang member constitute favourable conditions leading adolescents to gang joining (Gilman et al., 2014). As for involvement into OC, recent studies investigate family risk factors for offending behaviour of individuals living in families with OC members. Van Dijk and colleagues (2018) have argued in favour of deviant social learning and violent reputation of the father as factors associated with intergenerational continuity of offending in criminal families. Similarly, Spapens and Moors (2019) have investigated the relation between intergenerational transmission and OC through the study of seven criminal families in the Netherlands. Using a variety of data sources



(e.g. court records, interviews) to reconstruct family compositions across three to four generations, the authors have found support for the notion that criminal behaviour is learned within criminal family contexts. The intergenerational transmission of OC seems to occur through the older generations functioning as an example for the younger ones, as “growing up in a family in which crime is accepted as a way of life, and where illegal activities contribute functionally to wealth and independence, does have an educational influence” (2019, p. 10). Living in criminal families therefore has a great impact on youths’ future offending, with intergenerational transmission being particularly problematic for individuals growing up in families with OC members (Spapens & Moors, 2019).

The intergenerational transmission of crime poses important challenges for implementing effective intervention programs to reduce the risk of offending for juveniles living in criminal families. Yet there is lack of studies on intervention policies addressing youth involvement in OC, mostly because such programs have been designed and implemented only very recently. For instance, in 2017 the Juvenile Court of Reggio Calabria (Italy) signed a cooperation protocol with national and local authorities to potentially limit the parental responsibilities of children living in OC families. The aim of the project is to protect minors and decrease their exposure to mafia indoctrinations (see Di Bella, 2016), though this approach has been criticised with the argument that the mere belonging to a mafia family does not constitute a sufficient reason for such restrictive measure. Despite critical issues, this approach provides valuable inputs for the ABM simulating recruitment into OC.

The ABM incorporates findings from the literature and the experience of recent intervention programs simulating a primary socialisation policy that targets young people at risk of involvement into OC. In the simulation, it will be possible to identify a group of juveniles at risk that will be subjected to intervention measures aimed at reducing OC parental ties. The ABM therefore will be able to model cases in which court orders limit the contacts between people involved in OC and their families or cases of OC members’ conviction and imprisonment. In such cases, the ABM will temporarily (until children turn 18 years old) decrease the relation that OC members have with their families and children while also providing juveniles at risk and their mothers with social and welfare support. Alternative approaches aimed at secondary socialisation settings (e.g. school support, employment support) are indeed complementary to policies intervening on OC-prone primary ties of vulnerable young people. Like for the other policy interventions, this policy will remain in place from round 12 until the end of the simulation.

2.6.2.3 SECONDARY SOCIALIZATION

The secondary socialisation policy targets juveniles aged 6-18 who are in school. Youth students would benefit from enhanced training programs, developed in the school environment, that provide additional support and may



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result in decreasing dropouts, especially in socially disorganised areas affected by OC presence. Intervention programs as the project promoted by the Juvenile Court of Reggio Calabria in Italy highlighted also the relevance of counselling services with experts (e.g. psychologists, social educators) in school premises in disadvantaged areas (see Cascini & Di Bella, 2017). Approaches intervening on 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 (Higginson et al., 2015; Hodgkinson et al., 2009), though the reviews have pointed out the difficulty of drawing unique conclusions on the effectiveness of such preventing interventions.

In the ABM, it will be possible to target crime-prone children, i.e. those with higher criminal propensity C , with increased social support and/or increased welfare support. Increased social support will be related, as outlined by the literature, with better educational support. In the ABM, this will be translated in having targeted agents completing high school and/or achieving a higher level of education. The ABM may also include the support of psychologists and social workers. The promotion of pro-social relations and inhibition of anti-social relations will be simulated by randomly creating friendship ties with non-deviant peers and adults. Finally, social support includes the enhancement of social activities between children, by the random creation of new friendship ties and/or by moving them to new school classes.

Increased welfare support instead may include providing a job to the juvenile's mother, resulting in diversification of her network. When young people turn 18, they can also benefit from welfare support policies, which may lead to a reduction of the criminal involvement through a diversification of juveniles' social networks. Like for the other policy interventions, this policy will remain in place from round 12 until the end of the simulation.

2.6.3 MODEL ASSUMPTIONS

In this section, we highlight some of the important assumptions of the OCN model (Table 8). For the motivation and support behind these assumptions, see sections 2.1, 2.2, 0, and 2.6.

Table 8. Selected assumptions of the OCN model

Assumption	Details
Networks influence OCN recruitment	<ul style="list-style-type: none"> Four networks are important in OCN formation: (1) family, (2) friendship, (3) work and school, and (4) co-offending. Co-offending is a necessary condition for an agent to join an OCN. Co-offending occurs with someone already in an offender's networks.



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Individual factors affect the probability of committing a crime (C)	<ul style="list-style-type: none"> Age, gender, unemployment, education, natural propensity, criminal history, criminal family, criminal friends and co-workers, and OC membership. The distributions for the above factors (e.g. mean, upper and lower limits, and standard deviations) and their association with the probability of committing a crime. Uses a probabilistic and non-strategic approach to decision-making. Does not consider the role of values in decision-making.
Modelling organised crime embeddedness (R)	<ul style="list-style-type: none"> Importance of OC ties is inversely proportional to the distance. Importance of OC ties (but also of other non-OC ties) is proportional to the number of different ties between any two individuals.
Targeting OC leaders	<ul style="list-style-type: none"> It is possible to capture and imprison OC leaders. OC leaders are identified by their centrality in a network.
Targeting facilitators	<ul style="list-style-type: none"> Facilitators important in the criminal activities of OCNs.
Primary socialisation	<ul style="list-style-type: none"> It is possible to identify children living in OCG families. Possible to limit identified OCG parental ties to children.
Secondary socialisation	<ul style="list-style-type: none"> Support in school leads to increased level of education and larger, more diverse, network connections than without the support.

2.7 Results

The simulations were used to test the impact of four interventions (presented above): primary socialization, secondary socialization, targeting OC leaders, and targeting facilitators. The interventions were tested in two contexts, one simulating a Southern European city (with empirical data drawn from Palermo and Sicily) and the other simulating a Northern European city (with empirical data based on Eindhoven and the Netherlands). Overall, this resulted in ten possible combinations. These combinations were prioritized compared to the exploration resulting from the changes in some of the main parameters, due to available computational capacity.



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For each of the contexts, we conducted simulations with both “standard” and “strong” variants of interventions. The standard interventions rely on the parametrization described in the prior sections. We find that these standard interventions have no significant effects on the outcomes of interest (sections 2.7.1 and 2.7.2). To understand what would happen if the interventions were made more stringent, we conducted additional simulations, this time with more extreme parameters to implement the strong variant (sections 2.7.3 and 2.7.4). The parameters of the standard and strong variants of the interventions are presented in Table 9 for the Southern European Context and in Table 10 for the Northern European Context.

Simulations are populated with 3000 agents. Each simulation runs for a total of 360 ticks, representing 30 years of simulated time. We then repeat the simulations at least 25 times for each treatment to give us a robust average of the results. Each simulation needs between 6 and 22 hours to complete. The results for the standard interventions needed 3500 hours computing hours; while the results for the strong interventions needed 5340 computing hours.

Table 9. Parameters of the standard and strong interventions for the Southern European Context. All values refer to 10K agents.

Parameter		
	Standard	Strong
# OC members	30	100
Number of law enforcement interventions	30	300
Targeting OC leaders	Depends on same degree	
Targeting facilitators	x3 multiplier	X10 multiplier
Primary socialisation	10% of targets addressed once a year	100% of targets addressed every month
Secondary socialisation	10% of targets addressed once a year	100% of targets addressed every month

Table 10. Parameters of the standard and strong interventions for the Northern European Context. All values refer to 10K agents.

Parameter	
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	Standard	Strong
# OC members	15	50
Number of law enforcement interventions	15	150
Targeting OC leaders	Depends on same degree	
Targeting facilitators	x3 multiplier	X10 multiplier
Primary socialisation	10% of targets addressed once a year	100% of targets addressed every month
Secondary socialisation	10% of targets addressed once a year	100% of targets addressed every month

We focus on four outcomes for each of the treatments: the number of OC members, recruitment into OC per tick, average criminal propensity, and average organised crime embeddedness.

To analyse the overall treatment differences, we calculate the average of each outcome for each run of the simulation (to create independent observations) and then compare the averages using t-tests. To consider the differences in dynamics between treatments, we calculate significant differences tick by tick and show these on the figures.

2.7.1 SOUTHERN EUROPEAN CONTEXT: STANDARD INTERVENTIONS

2.7.1.1 TARGETING OC LEADERS

Results from our statistical analysis highlight no substantial difference between Baseline and Leaders treatments in the observed outcomes (Table 11). Reported t-tests suggest that the average values of each of the four outcomes in Baseline and Leaders are statistically indistinguishable.

Table 11. Comparison of outcome averages for Baseline and Leaders

Outcome	Treatments		Significance
	Baseline (n=60)	Leaders (n=60)	
# OC members	9.743 (3.076)	8.969 (2.726)	$t(118) = -1.459^{n.s.}$

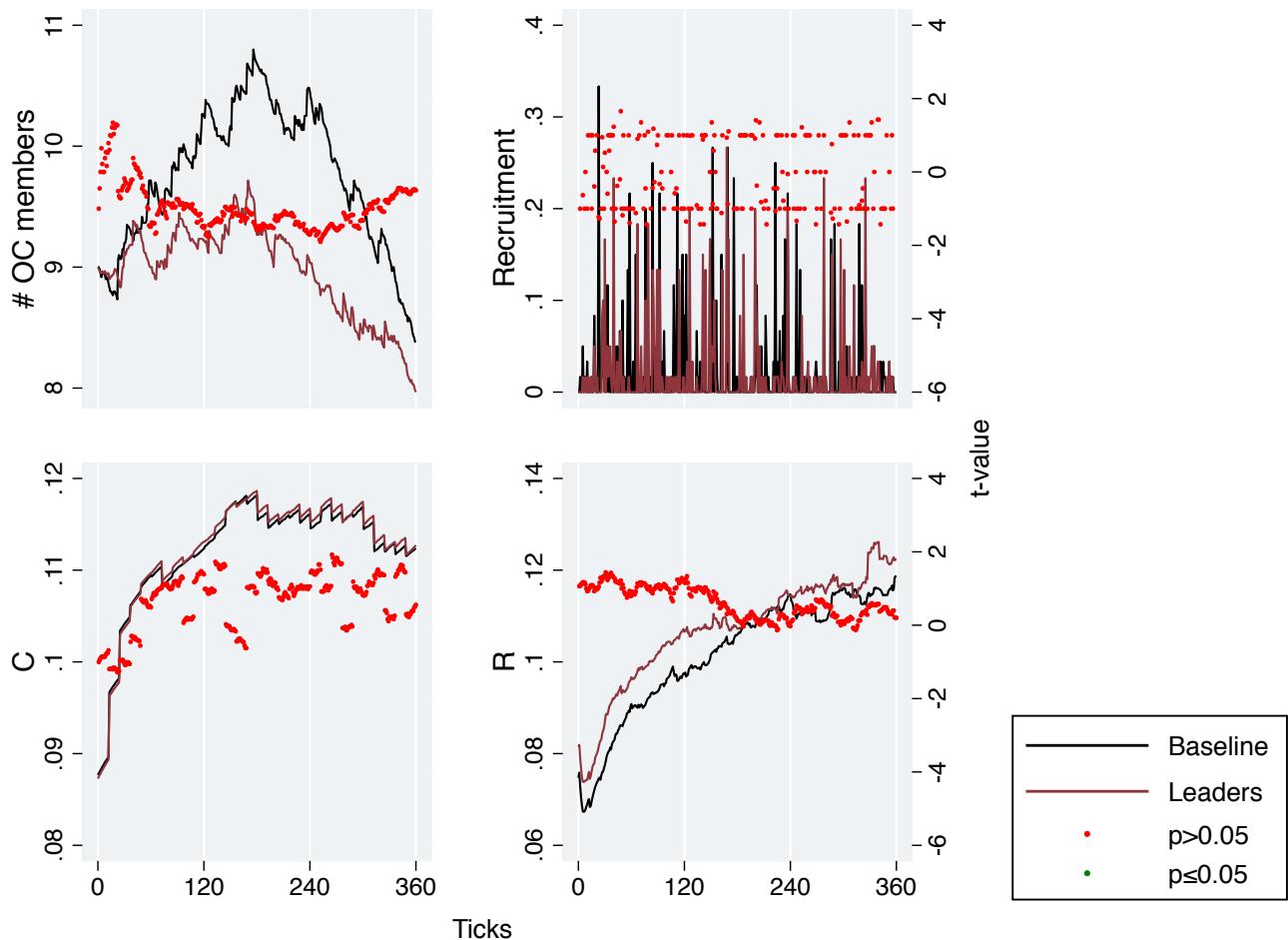


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Recruitment into OC per tick	0.023 (0.019)	0.020 (0.016)	$t(118)=-1.173^{\text{n.s.}}$
C (Criminal propensity)	0.112 (0.002)	0.112 (0.002)	$t(118)=1.079^{\text{n.s.}}$
R (Organised crime embeddedness)	0.102 (0.046)	0.107 (0.046)	$t(118)=0.644^{\text{n.s.}}$

Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$).

Figure 6. Comparison of outcome dynamics for Baseline and Leaders



The lack of statistical difference between conditions becomes clearer when analysing each outcome dynamics over runs. Outcomes display similar patterns under both Baseline and Leaders conditions (Figure 6).

The number of OC members under the Baseline condition displays a more marked inverted-U trend, qualitatively different from the dynamic observed in the Leaders condition, albeit not statistically different.



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2.7.1.2 TARGETING FACILITATORS

The results from Facilitators treatment follow the same caveat as the one in the treatment analysed before. Average values of our four outcomes are not statistically different from the Baseline. While values are similar in both Baseline and Facilitators across all the outcomes, we notice a substantial increase in standard deviations values of most of the outcomes.

Table 12. Comparison of outcome averages for Baseline and Facilitators

Outcome	Treatments		Significance
	Baseline (n=60)	Facilitators (n=60)	
# OC members	9.743 (3.076)	9.444 (3.305)	$t(118)=-0.513^{\text{n.s.}}$
Recruitment into OC per tick	0.023 (0.019)	0.021 (0.017)	$t(118)=-0.846^{\text{n.s.}}$
C (Criminal propensity)	0.112 (0.002)	0.113 (0.002)	$t(118)=1.706^{\text{n.s.}}$
R (Organised crime embeddedness)	0.102 (0.046)	0.095 (0.034)	$t(118)=-0.831^{\text{n.s.}}$

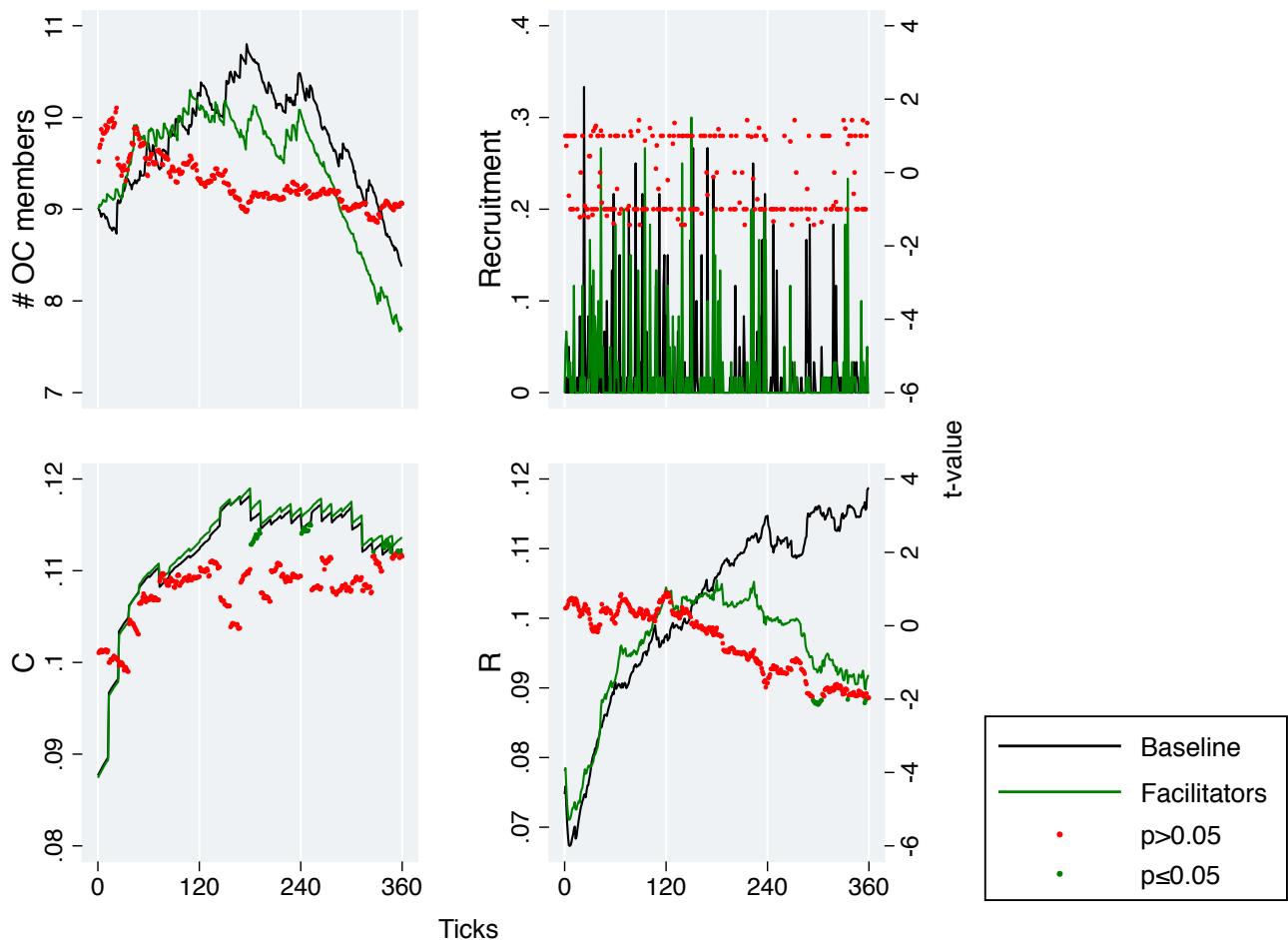
Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$).

Dynamics in Figure 7 depict a similar scenario as the one seen in the previous section. The number of OC members still display an inverted-U shape dynamic over time. Yet, differently from what observed in the previous section, the gap between Baseline and Facilitators is more attenuated.

What is more, the trend of outcome “Level of organised crime embeddedness (R)” inverts upon achieving half of the total number of ticks (around tick 180). Despite the larger gap with the Baseline, most of the per-tick t-test report no statistical difference in the second-half of the graph.



Figure 7. Comparison of outcome dynamics for Baseline and Facilitators



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2.7.1.3 PRIMARY SOCIALIZATION

Results remain roughly unchanged compared to previous conditions even in the Primary Socialisation treatment. All the outcome variables in this treatment do not display any statistical difference from the baseline according to our t-tests.

Table 13. Comparison of outcome averages for Baseline and Primary socialisation

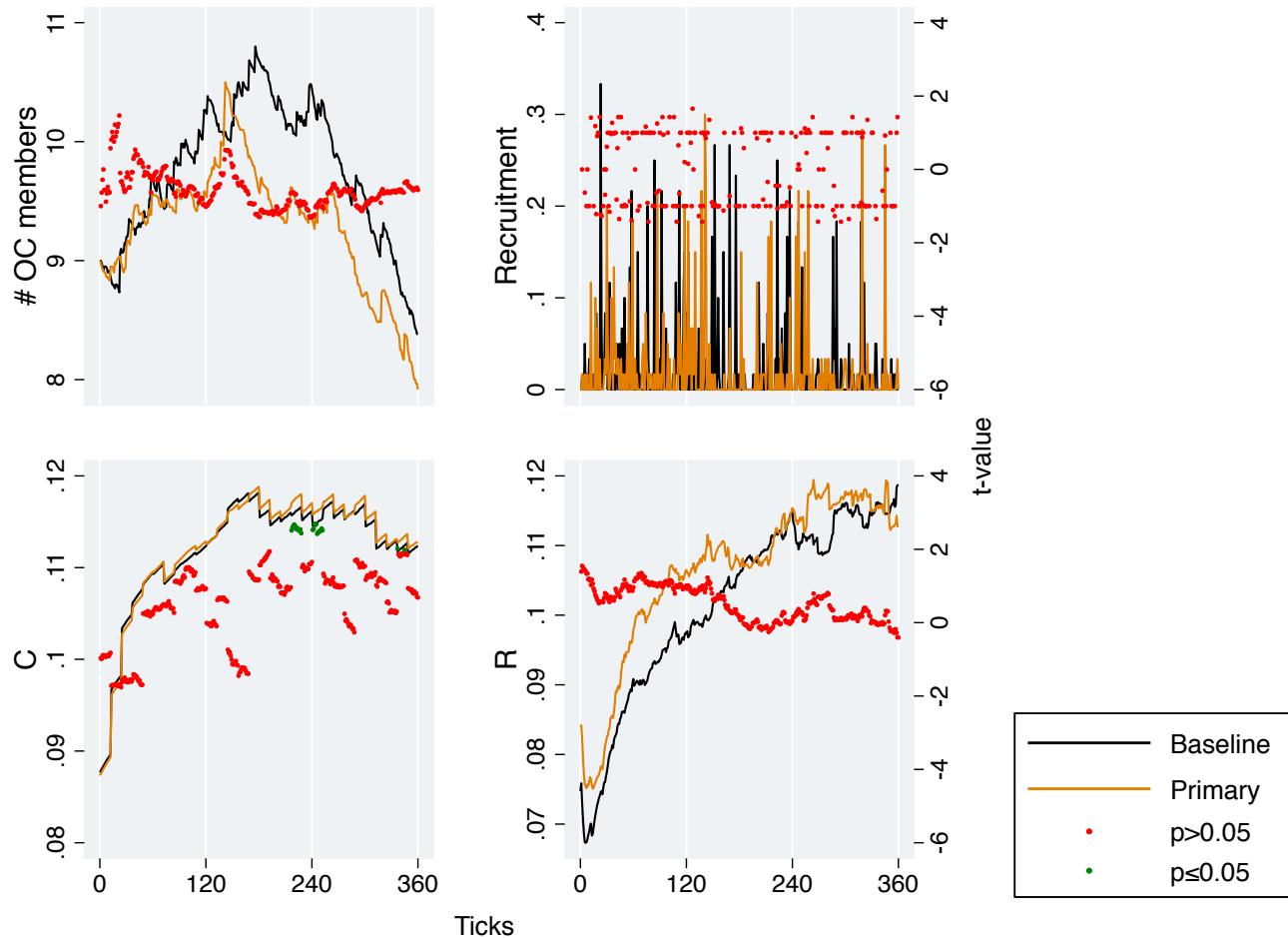
Outcome	Treatments		Significance
	Baseline (n=60)	Primary (n=60)	
# OC members	9.743 (3.076)	9.291 (2.867)	$t(118)=-0.832$ ^{n.s.}
Recruitment into OC per tick	0.023 (0.019)	0.021 (0.018)	$t(118)=-0.643$ ^{n.s.}
C (Criminal propensity)	0.112 (0.002)	0.112 (0.002)	$t(118)=1.013$ ^{n.s.}
R (Organised crime embeddedness)	0.102 (0.046)	0.106 (0.051)	$t(118)=0.509$ ^{n.s.}

Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$).



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Figure 8. Comparison of outcome dynamics for Baseline and Primary socialisation



Outcome series reported in Figure 8 confirm the fact that dynamics are not statistically distinguishable between baseline and primary treatments.

2.7.1.4 SECONDARY SOCIALIZATION

Finally, outcomes from the Secondary Socialization treatment do not differ from the Baseline condition (Table 14). The estimated average number of OC members is lower in the Secondary Socialization treatment compared to the Baseline. Although such difference is far from being significant at any conventional level.

Table 14. Comparison of outcome averages for Baseline and Secondary socialisation

Outcome	Treatments		Significance
	Baseline (n=60)	Secondary (n=60)	
# OC members	9.743	9.545	$t(118) = -0.339^{n.s.}$



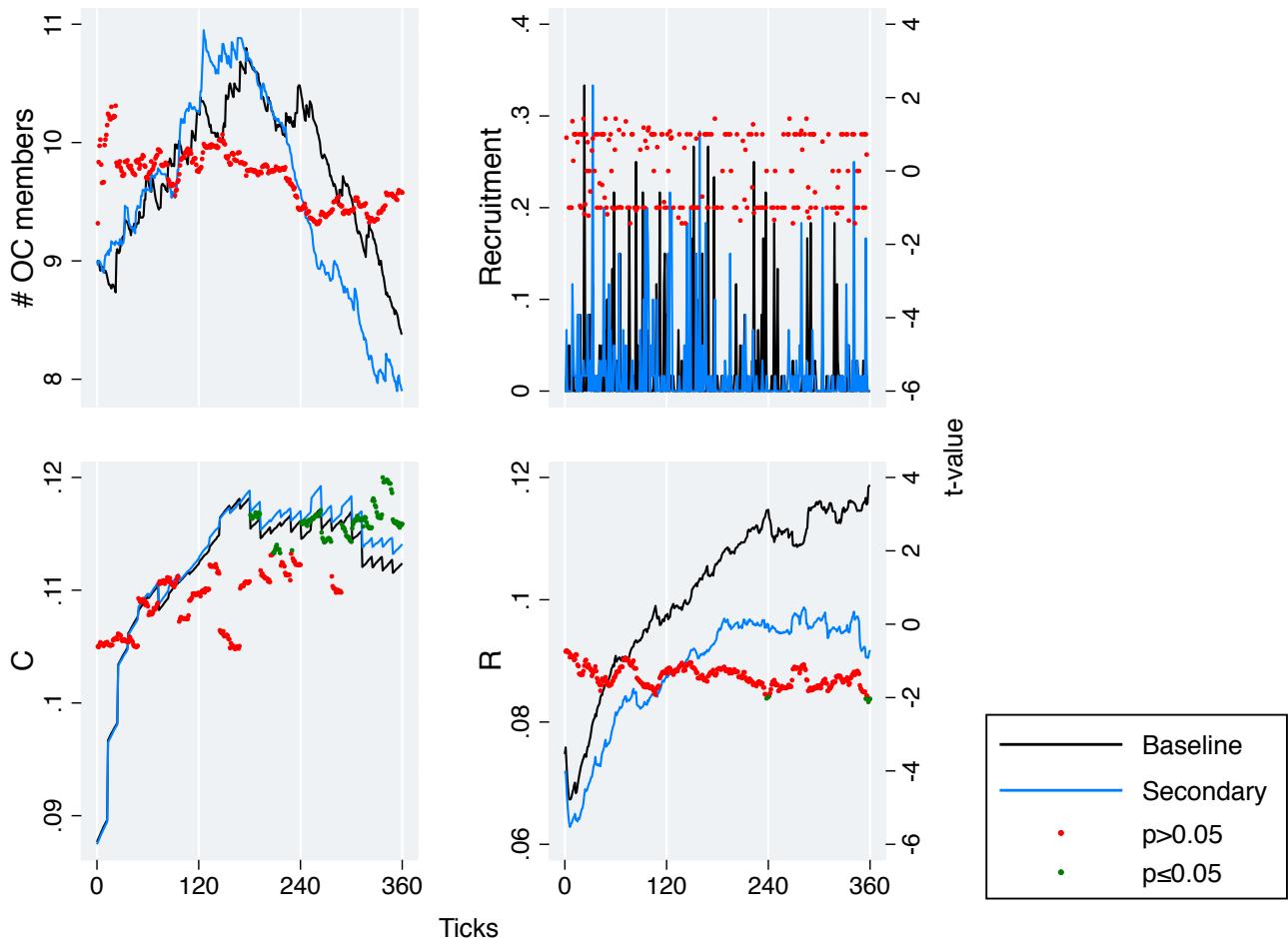
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	(3.076)	(3.314)	
Recruitment into OC per tick	0.023 (0.019)	0.022 (0.018)	$t(118)=-0.547^{\text{n.s.}}$
C (Criminal propensity)	0.112 (0.002)	0.113 (0.002)	$t(118)=2.392^*$
R (Organised crime embeddedness)	0.102 (0.046)	0.089 (0.036)	$t(118)=-1.717^{\text{n.s.}}$

Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$), * $p<0.05$.

Consistently to our estimates, dynamics of our variables of interest are similar between treatment conditions (Figure 9). We can notice a flatter trend of the outcome "Organised crime embeddedness" starting from tick 180-200. The two series, Baseline and Secondary Socialization, end up in the last tick with statistically significant values. Yet overall uncertainty remains in previous ticks which makes one rather cautious before drawing any inference.

Figure 9. Comparison of outcome dynamics for Baseline and Secondary socialisation



2.7.2 SOUTHERN EUROPEAN CONTEXT: STRONG INTERVENTIONS

2.7.2.1 TARGETING OC LEADERS

Also in the strong intervention, there are no significant differences between three out of the four outcomes in the Baseline as compared to the Leaders treatment (Table 15). That is, over the course of the simulation, both the Baseline and Leaders end up with substantively similar outcomes that are statistically indistinguishable for the number of OC members recruited, recruitment into OC at each tick, and average criminal propensity in the simulation. The embeddedness of organised crime, however, is significantly lower in Leaders relative to Baseline ($p=0.035$).

Table 15. Comparison of outcome averages for Baseline and Leaders

Outcome	Treatments		Significance
	Baseline (n=42)	Leaders (n=30)	
# OC members	27.429 (3.971)	27.402 (3.854)	$t(70)=-0.029$ ^{n.s.}
Recruitment into OC per tick	0.034 (0.019)	0.039 (0.021)	$t(70)=1.001$ ^{n.s.}
C (Criminal propensity)	0.114 (0.002)	0.115 (0.002)	$t(70)=1.134$ ^{n.s.}
R (Organised crime embeddedness)	0.125 (0.026)	0.114 (0.016)	$t(70)=-2.151^*$

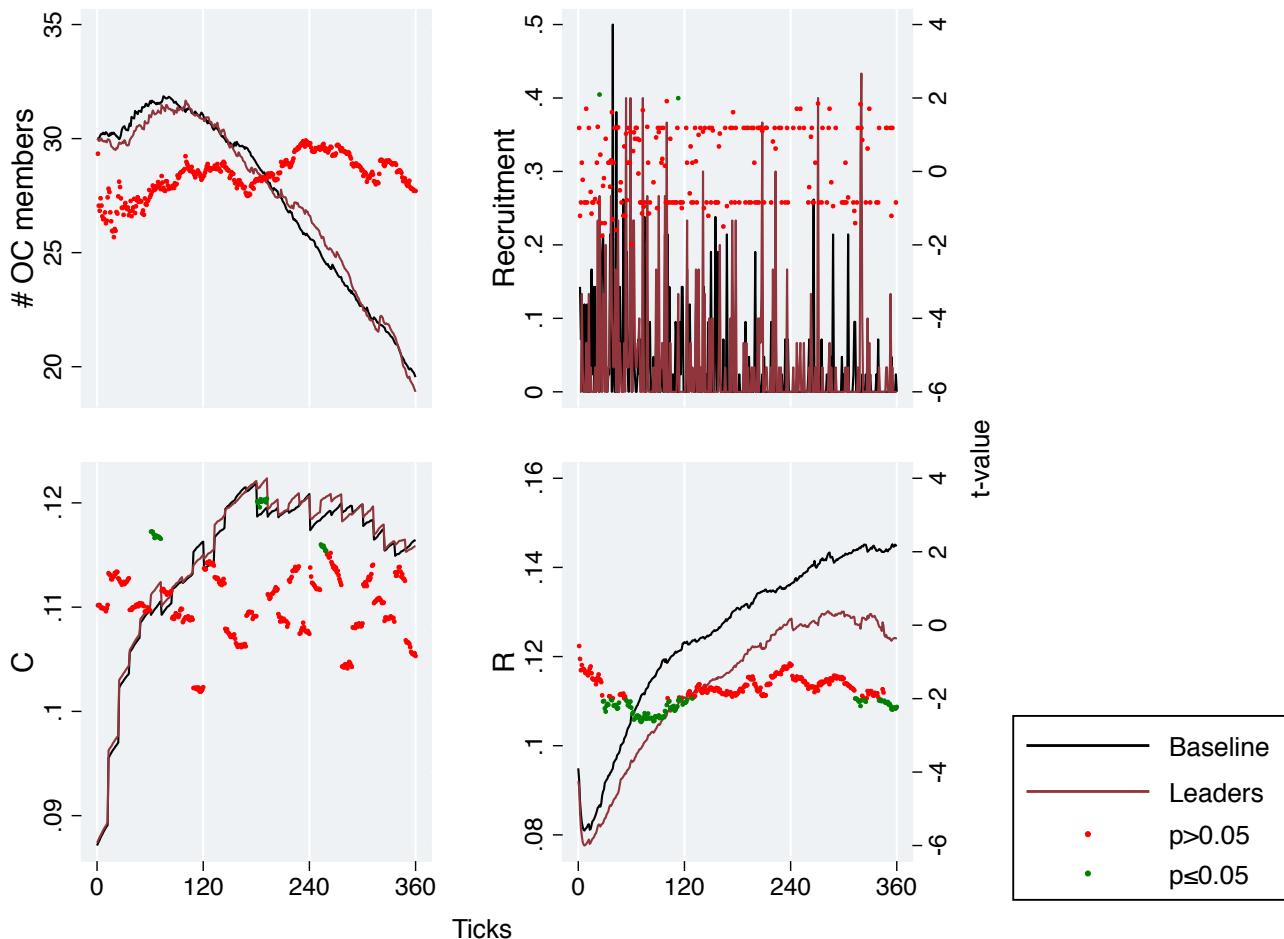
Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$), $*p<0.05$.

In terms of dynamics, we see that the targeting OC Leaders treatment leads to similar dynamics than the Baseline for most of the outcomes: number of OC members, recruitment per tick, and C (Figure 10). Concerning R, however, the dynamics appears to be different to the Baseline, increasing at a slower rate.

Figure 10. Comparison of outcome dynamics for Baseline and Leaders



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2.7.2.2 TARGETING FACILITATORS

In the strong intervention, the targeting facilitators treatment, in contrast to targeting OC leaders treatment, has a strong and substantive effects on two important outcomes (Table 16). It reduces the number of OC members that are recruited into the simulation ($p<0.001$), and, the rate at which recruitment occurs is also slower in the targeting facilitators treatment relative to the Baseline ($p=0.003$). The other two outcomes, C and R , are not significantly nor substantively different in Facilitators relative to the Baseline.

Table 16. Comparison of outcome averages for Baseline and Facilitators

Outcome	Treatments		Significance
	Baseline (n=42)	Facilitators (n=42)	
# OC members	27.429 (3.971)	24.444 (3.559)	$t(82)=-3.628^{***}$
Recruitment into OC per tick	0.034 (0.019)	0.022 (0.016)	$t(82)=-3.094^{**}$
C (Criminal propensity)	0.114 (0.002)	0.114 (0.002)	$t(82)=-0.282^{n.s.}$
R (Organised crime embeddedness)	0.125	0.117	$t(82)=-1.404^{n.s.}$



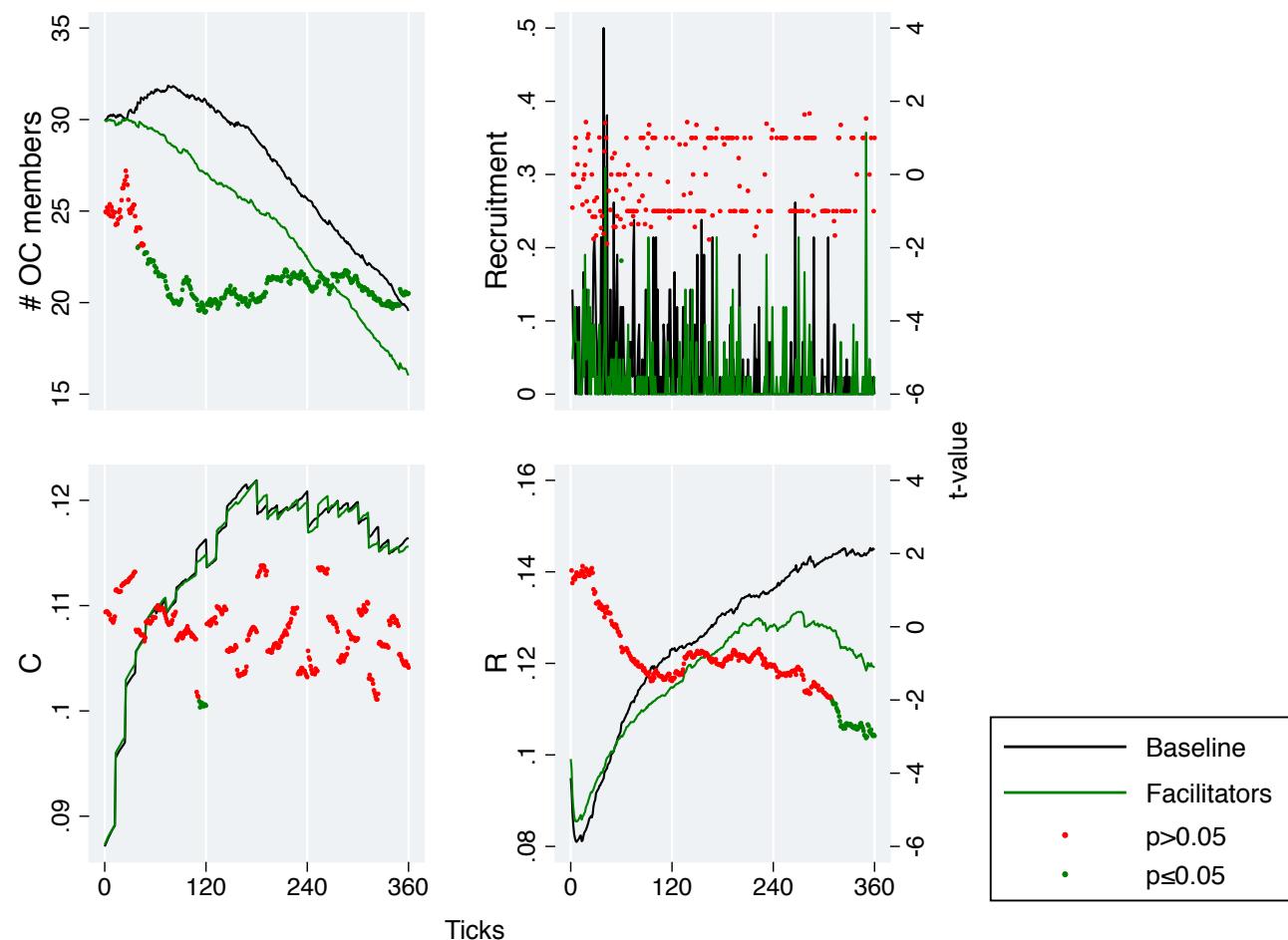
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(0.026) (0.026)

Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$), ** $p<0.01$, *** $p<0.001$.

The dynamics about the number of OC members recruited confirm the importance of the difference (Figure 11). There are consistently fewer OC members in the Facilitators treatment than in the Baseline. In terms of recruitment in each tick, the difference is difficult to see, however, cumulatively the small reduction in the Facilitators adds up to a significantly lower rate of recruitment overall than in the Baseline treatment. There is no difference in the dynamics concerning C , while, there is evidence that R is lower in Facilitators than in the Baseline towards the end of the simulation (from about tick 300 onwards). This suggests that if the simulation were to be run for longer, there would also be overall reductions in R due to the targeting of facilitators.

Figure 11. Comparison of outcome dynamics for Baseline and Facilitators



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2.7.2.3 PRIMARY SOCIALIZATION

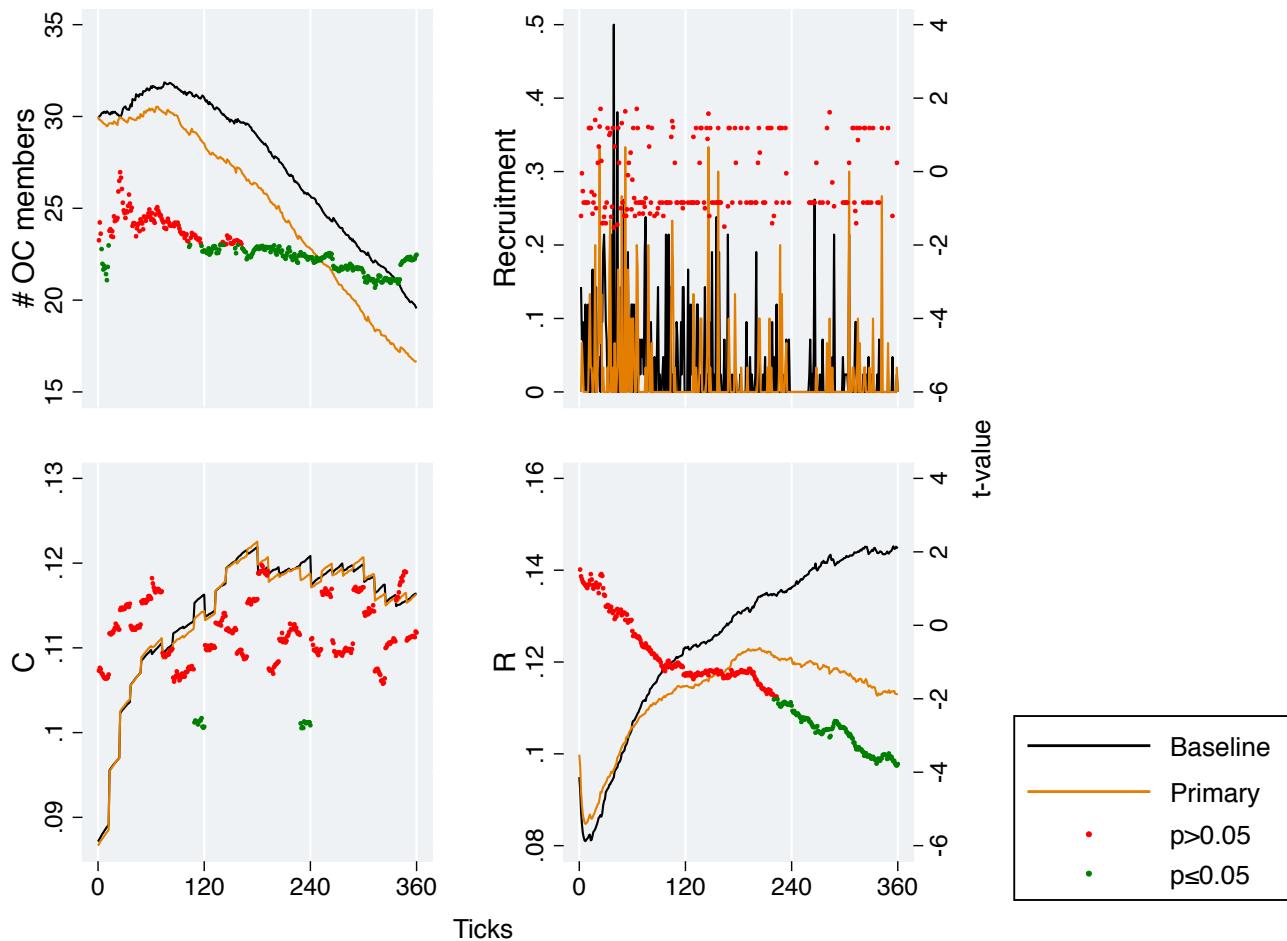
In the strong version, the primary socialisation intervention leads to a reduction in the number of OC members ($p=0.010$), recruitment into OC per tick ($p=0.014$), and a decrease in R ($p=0.035$), relative to the Baseline (Table 17). Criminal propensity meanwhile does not differ between the two.

Table 17. Comparison of outcome averages for Baseline and Primary socialisation

Outcome	Treatments		Significance
	Baseline (n=42)	Primary (n=30)	
# OC members	27.429 (3.971)	25.045 (3.475)	$t(70)=-2.642^*$
Recruitment into OC per tick	0.034 (0.019)	0.023 (0.017)	$t(70)=-2.513^*$
C (Criminal propensity)	0.114 (0.002)	0.114 (0.001)	$t(70)=-0.586^{n.s.}$
R (Organised crime embeddedness)	0.125 (0.026)	0.113 (0.021)	$t(70)=-2.150^*$

Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$), * $p<0.05$.

Figure 12. Comparison of outcome dynamics for Baseline and Primary socialisation



The fewer OC members in the primary socialisation treatment can be seen in the dynamics (Figure 12). The difference arises early in the simulation and slowly grows wider as the model progresses. Regarding C , there is no difference in dynamics between the Baseline and primary socialisation, while R is substantively lower in the Facilitators than in the Baseline.

2.7.2.4 SECONDARY SOCIALIZATION

In the strong version, the secondary socialisation intervention does not lead to differences in the number of OC members, nor in the rate of recruitment to OC (Table 18), relative to the Baseline. However, this treatment leads to an increase in criminal propensity (C) ($p<0.001$) and a decrease in organised crime embeddedness (R) ($p=0.001$).

Table 18. Comparison of outcome averages for Baseline and Secondary socialisation

Outcome	Treatments		Significance
	Baseline (n=42)	Secondary (n=78)	
# OC members	27.429 (3.971)	28.133 (4.573)	$t(118)=0.841^{\text{n.s.}}$
Recruitment into OC per tick	0.034 (0.019)	0.039 (0.023)	$t(118)=1.063^{\text{n.s.}}$
C (Criminal propensity)	0.114 (0.002)	0.116 (0.002)	$t(118)=5.793^{***}$
R (Organised crime embeddedness)	0.125 (0.026)	0.110 (0.017)	$t(118)=-3.952^{***}$

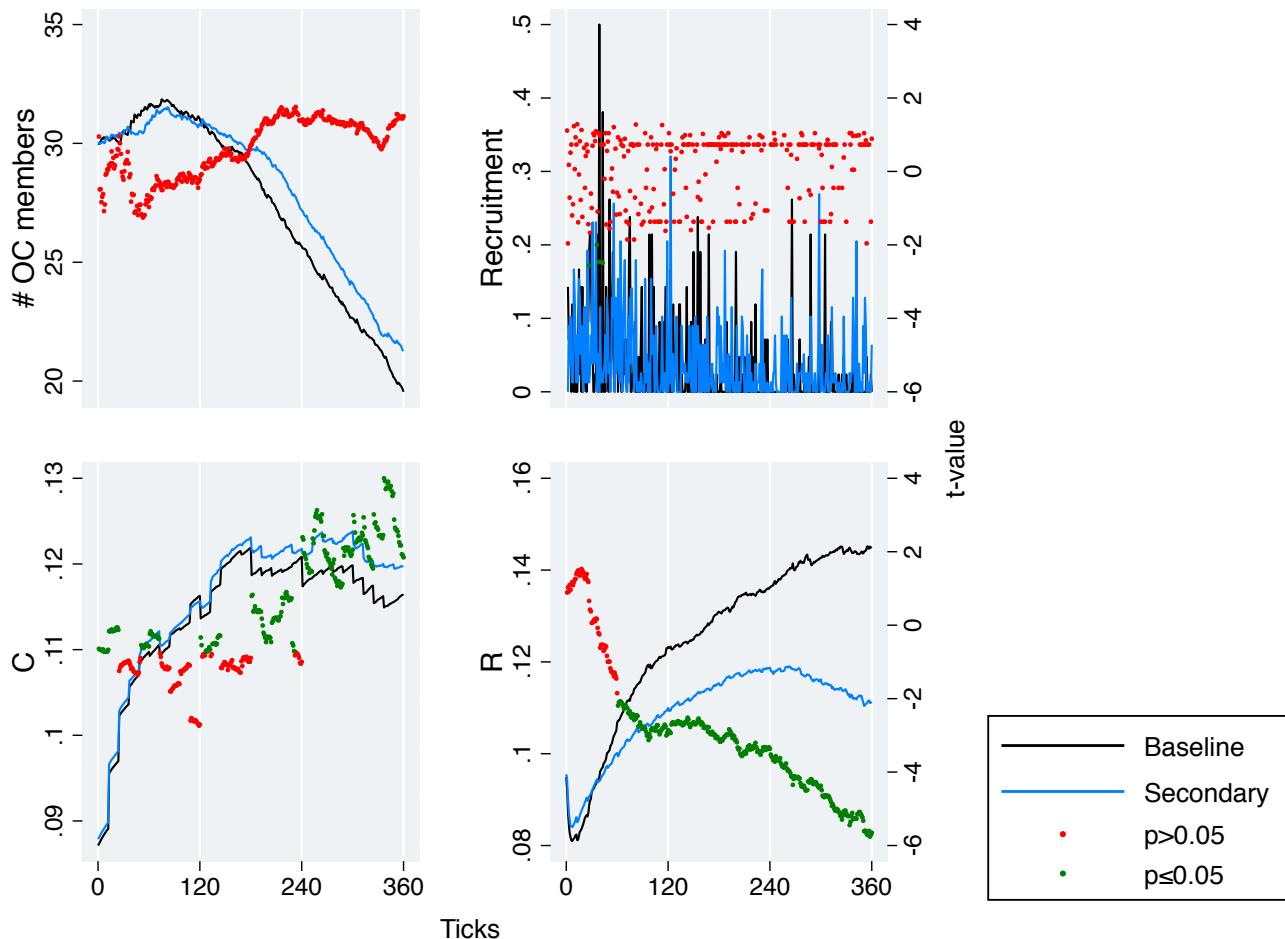
Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$), *** $p<0.001$.

In terms of dynamics, there are no differences at any point in the number of OC members and in recruitment per tick between the Baseline and the Secondary socialization treatments (Figure 13). There is a small positive effect of the Secondary socialization intervention on C , however, this difference is substantively small. While the reduction in R caused by the Secondary socialization intervention is large and, past around tick 60, remains consistently and significantly lower than R in the Baseline.

Figure 13. Comparison of outcome dynamics for Baseline and Secondary socialisation



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2.7.3 NORTHERN EUROPEAN CONTEXT: STANDARD INTERVENTIONS

2.7.3.1 TARGETING OC LEADERS

Results show no statistical difference between Baseline and Leaders in our observed outcomes (Table 19). Estimates from t-tests report no significant effect of the Leaders treatment compared to the Baseline condition.

Table 19. Comparison of outcome averages for Baseline and Leaders

Outcome	Treatments		Significance
	Baseline (n=60)	Leaders (n=60)	
# OC members	10.341 (4.192)	10.852 (5.758)	$t(118)=0.557^{\text{n.s.}}$
Recruitment into OC per tick	0.029 (0.020)	0.033 (0.025)	$t(118)=0.950^{\text{n.s.}}$
C (Criminal propensity)	0.022	0.022	$t(118)=-0.262^{\text{n.s.}}$



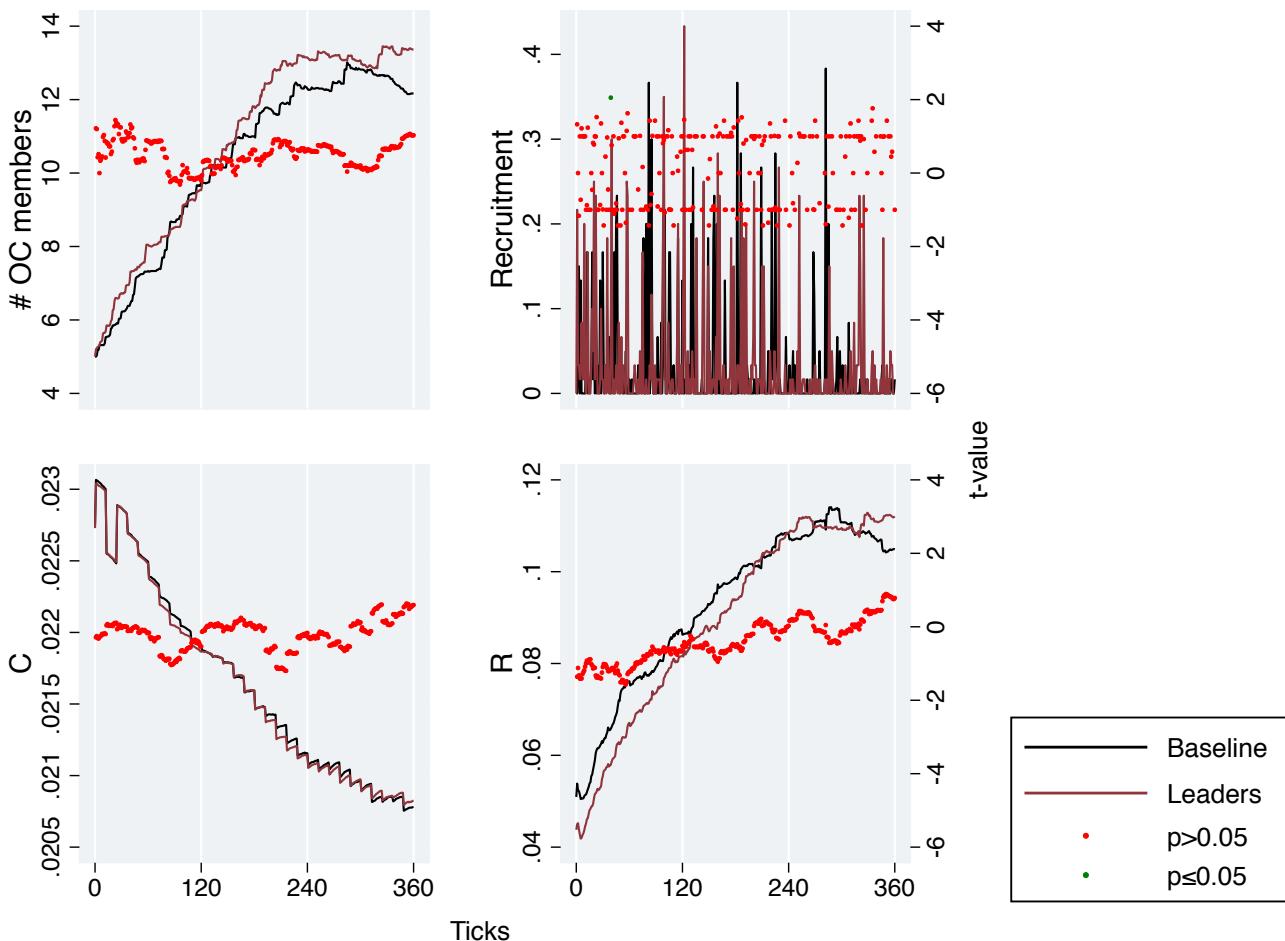
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	(<0.001)	(<0.001)	
R (Organised crime embeddedness)	0.093 (0.042)	0.090 (0.036)	$t(118)=-0.410^{\text{n.s.}}$

Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$).

Dynamics over ticks in the Leaders treatment does not differ from those observed in baseline treatment across all the outcomes (Figure 14). Most of estimated per-tick t-test do not reject the null hypothesis.

Figure 14. Comparison of outcome dynamics for Baseline and Leaders



2.7.3.2 TARGETING FACILITATORS

Results of the Facilitators treatment show no significant difference from the Baseline (Figure 20). Estimates from our t-tests across all the four observed outcomes report evidence indicating that Baseline and Facilitators average values are statistically indistinguishable.

Table 20. Comparison of outcome averages for Baseline and Facilitators

Outcome	Treatments		Significance
	Baseline (n=60)	Facilitators (n=60)	
# OC members	10.341 (4.192)	10.930 (4.719)	$t(118)=0.723^{\text{n.s.}}$
Recruitment into OC per tick	0.029 (0.020)	0.032 (0.021)	$t(118)=0.656^{\text{n.s.}}$
C (Criminal propensity)	0.022 (<0.001)	0.022 (<0.001)	$t(118)=-1.871^{\text{n.s.}}$
R (Organised crime embeddedness)	0.093 (0.042)	0.088 (0.043)	$t(118)=-0.630^{\text{n.s.}}$

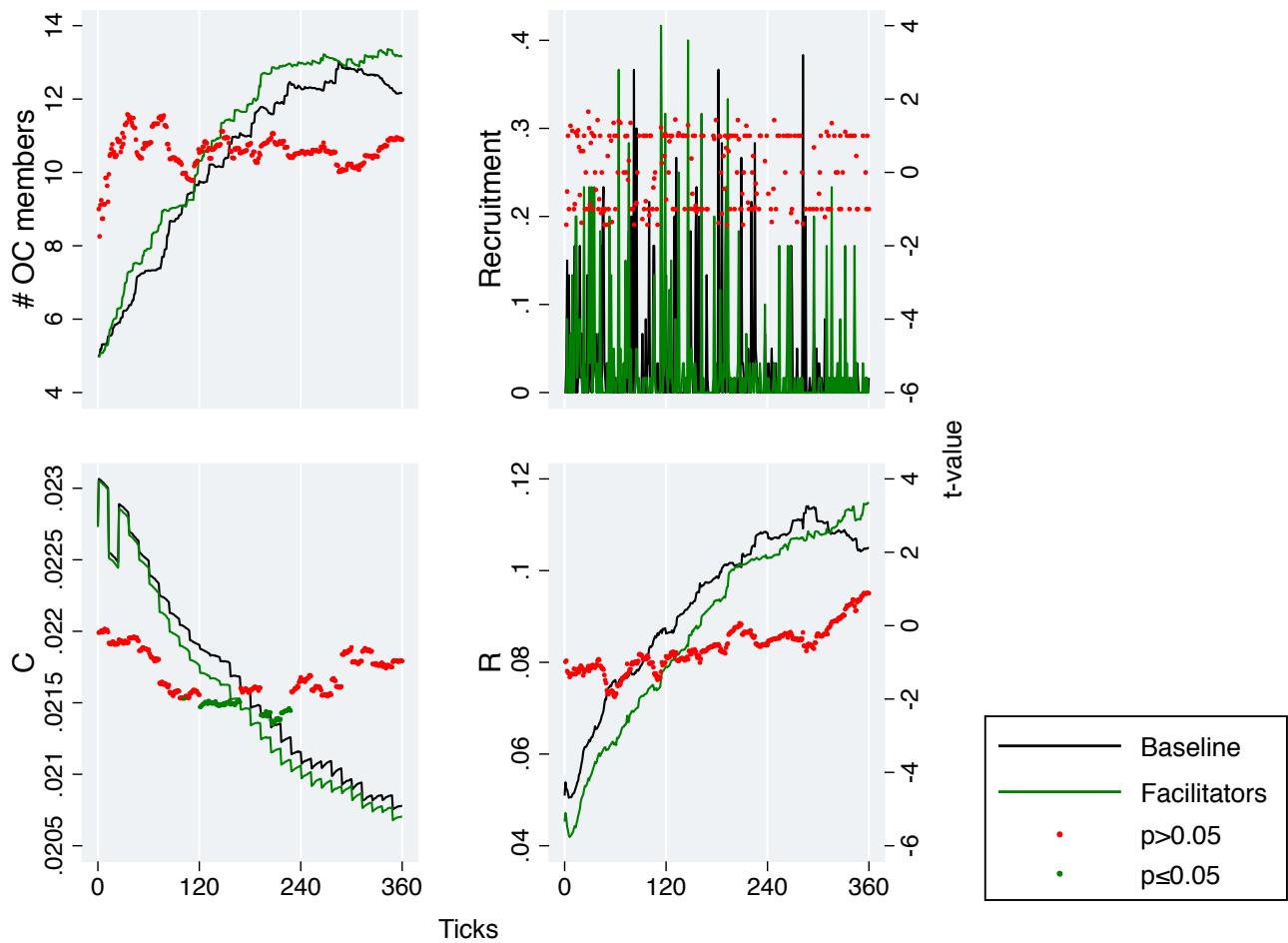
Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$).

In terms of dynamics, outcomes follow almost identical patterns under both treatments (Figure 15). There is mild evidence showing that the Criminal propensity series is significantly lower in most of the ticks in the middle-part of the graph (ticks 120-240). However, the gap between the two series dramatically decreases as the series approach towards the end.



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Figure 15. Comparison of outcome dynamics for Baseline and Facilitators



2.7.3.3 PRIMARY SOCIALIZATION

Results of the Primary Socialization Treatment seems not to be affecting outcomes, as it can be seen from t-test results (Table 21). Significance levels of the test are far from any rejection threshold.

Table 21. Comparison of outcome averages for Baseline and Primary socialisation

Outcome	Treatments		Significance
	Baseline (n=60)	Primary (n=60)	
# OC members	10.341 (4.192)	10.509 (5.379)	$t(118)=0.191^{\text{n.s.}}$
Recruitment into OC per tick	0.029	0.029	$t(118)=-0.070^{\text{n.s.}}$



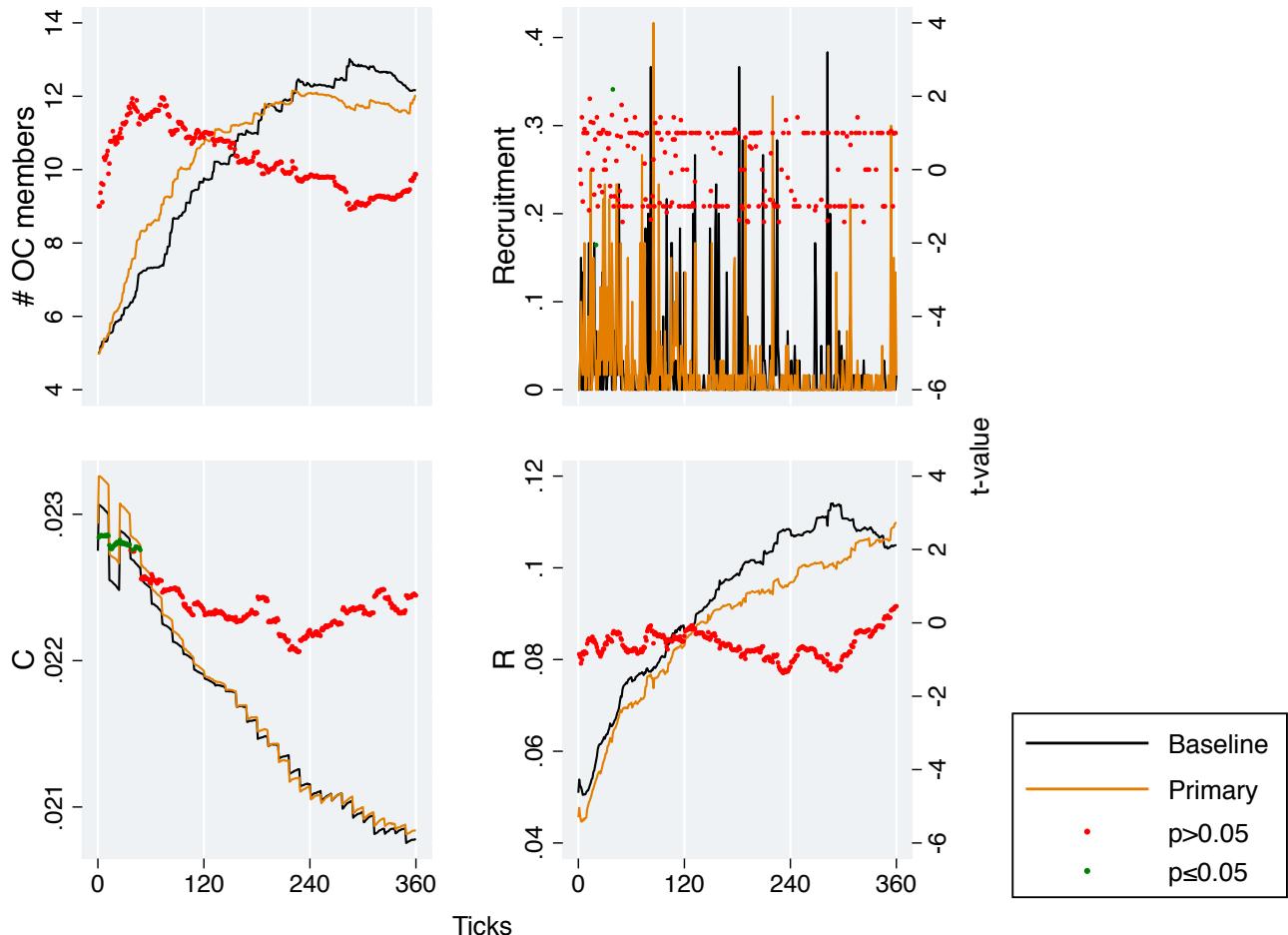
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	(0.020)	(0.024)	
C (Criminal propensity)	0.022 (<0.001)	0.022 (<0.001)	$t(118)=0.784^{\text{n.s.}}$
R (Organised crime embeddedness)	0.093 (0.042)	0.087 (0.039)	$t(118)=-0.724^{\text{n.s.}}$

Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$).

Dynamics of the outcomes examined reflect the results from the previous paragraph (Figure 16). No statistical, nor qualitative, difference arises from a dynamics comparison of the data from the Baseline and Primary Socialization treatment.

Figure 16. Comparison of outcome dynamics for Baseline and Primary socialisation



2.7.3.4 SECONDARY SOCIALIZATION

Finally, in the Secondary Socialisation treatment, we observe a significant increase in the level of Recruitment into OC per tick compared to the baseline (Table 20, $p<0.05$). We report no significant difference in the average values of the remaining outcome variables.

Table 22. Comparison of outcome averages for Baseline and Secondary socialisation

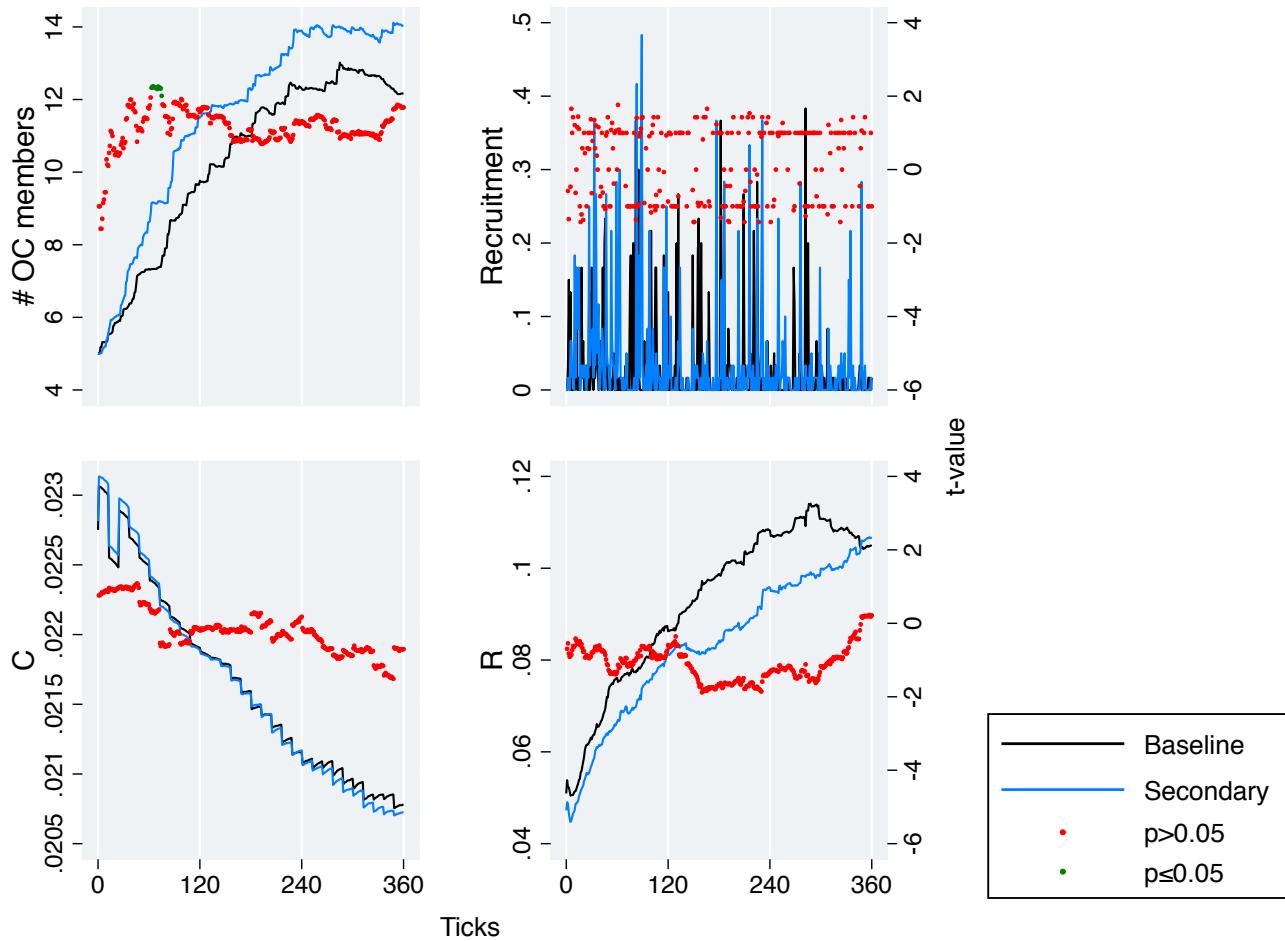
Outcome	Treatments		Significance
	Baseline (n=60)	Secondary (n=60)	
# OC members	10.341 (4.192)	11.576 (5.056)	$t(118)=1.457^{\text{n.s.}}$
Recruitment into OC per tick	0.029 (0.020)	0.037 (0.021)	$t(118)=2.127^*$
C (Criminal propensity)	0.022 (<0.001)	0.022 (<0.001)	$t(118)=-0.232^{\text{n.s.}}$
R (Organised crime embeddedness)	0.093 (0.042)	0.083 (0.031)	$t(118)=-1.385^{\text{n.s.}}$

Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$), * $p<0.05$.

As a result, the dynamics of all of the three outcomes are similar across the two treatments (Figure 17). As for outcomes “Number of OC members” and “Organised crime embeddedness”, we observe a larger gap between the Baseline and Secondary Socialization treatment as they unravel over runs. The former outcome is on average higher in the treatment Secondary compared to the Baseline in every tick, albeit there is no evidence for statistical significance of these differences. Secondary treatment, on the other hand, reduces the average values of outcome R, particularly from the tick 120 ahead. Yet, as expected from our estimates, the decrease observed in the outcome at hand is far from being significant at our adopted threshold (5%).



Figure 17. Comparison of outcome dynamics for Baseline and Secondary socialisation



2.7.4 NORTHERN EUROPEAN CONTEXT: STRONG INTERVENTIONS

2.7.4.1 TARGETING OC LEADERS

Table 23. Comparison of outcome averages for Baseline and Leaders

Outcome	Treatments		Significance
	Baseline (n=43)	Leaders (n=43)	
# OC members	17.206 (3.830)	17.894 (4.451)	$t(84)=0.768^{\text{n.s.}}$
Recruitment into OC per tick	0.036 (0.020)	0.042 (0.024)	$t(84)=1.259^{\text{n.s.}}$

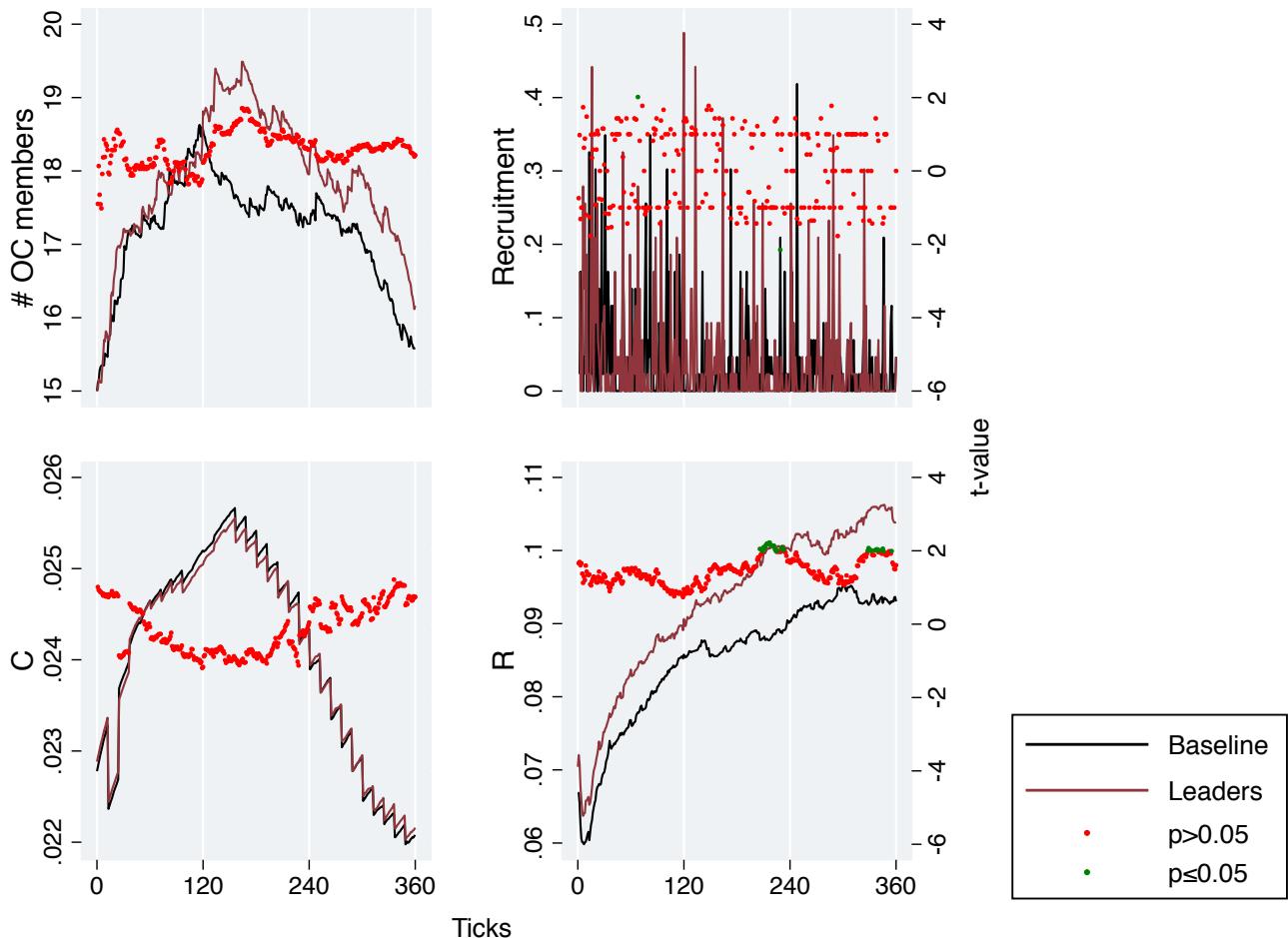


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C (Criminal propensity)	0.024 (<0.001)	0.024 (<0.001)	$t(84)=-0.266^{n.s.}$
R (Organised crime embeddedness)	0.085 (0.018)	0.093 (0.022)	$t(84)=1.830^{n.s.}$

Standard deviations in parentheses, $n.s.$ =not significant ($p>0.05$).

Figure 18. Comparison of outcome dynamics for Baseline and Leaders



With strong intervention, the targeting OC leaders treatment in the Northern European context has no effect on any of the outcomes (Table 23). There is some indication, albeit not significant at the 5%-level ($p=0.071$), that this treatment increases R .

Reflecting the averages, the dynamics indicate that the targeting OC leaders intervention in the Northern European context has little effect on the three outcomes (Figure 18). The outcome that this treatment may affect the most is R , slightly increasing it; however, the evidence for this is unclear also in the dynamics.



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2.7.4.2 TARGETING FACILITATORS

With strong intervention, the targeting facilitators treatment, in contrast to the targeting OC leaders intervention, does lead to reductions in key outcomes. Relative to the Baseline, fewer OC members are recruited on average ($p=0.002$) and at a slower rate ($p<0.001$) in the targeting facilitators treatment. The other outcomes, of C and R , do not differ between the Baseline and Facilitators.

Table 24. Comparison of outcome averages for Baseline and Facilitators

Outcome	Treatments		Significance
	Baseline (n=43)	Facilitators (n=43)	
# OC members	17.206 (3.830)	14.733 (3.200)	$t(84)=-3.250^{**}$
Recruitment into OC per tick	0.036 (0.020)	0.021 (0.016)	$t(84)=-3.776^{**}$
C (Criminal propensity)	0.024 (<0.001)	0.024 (<0.001)	$t(84)=-0.571^{\text{n.s.}}$
R (Organised crime embeddedness)	0.085 (0.018)	0.086 (0.024)	$t(84)=0.264^{\text{n.s.}}$

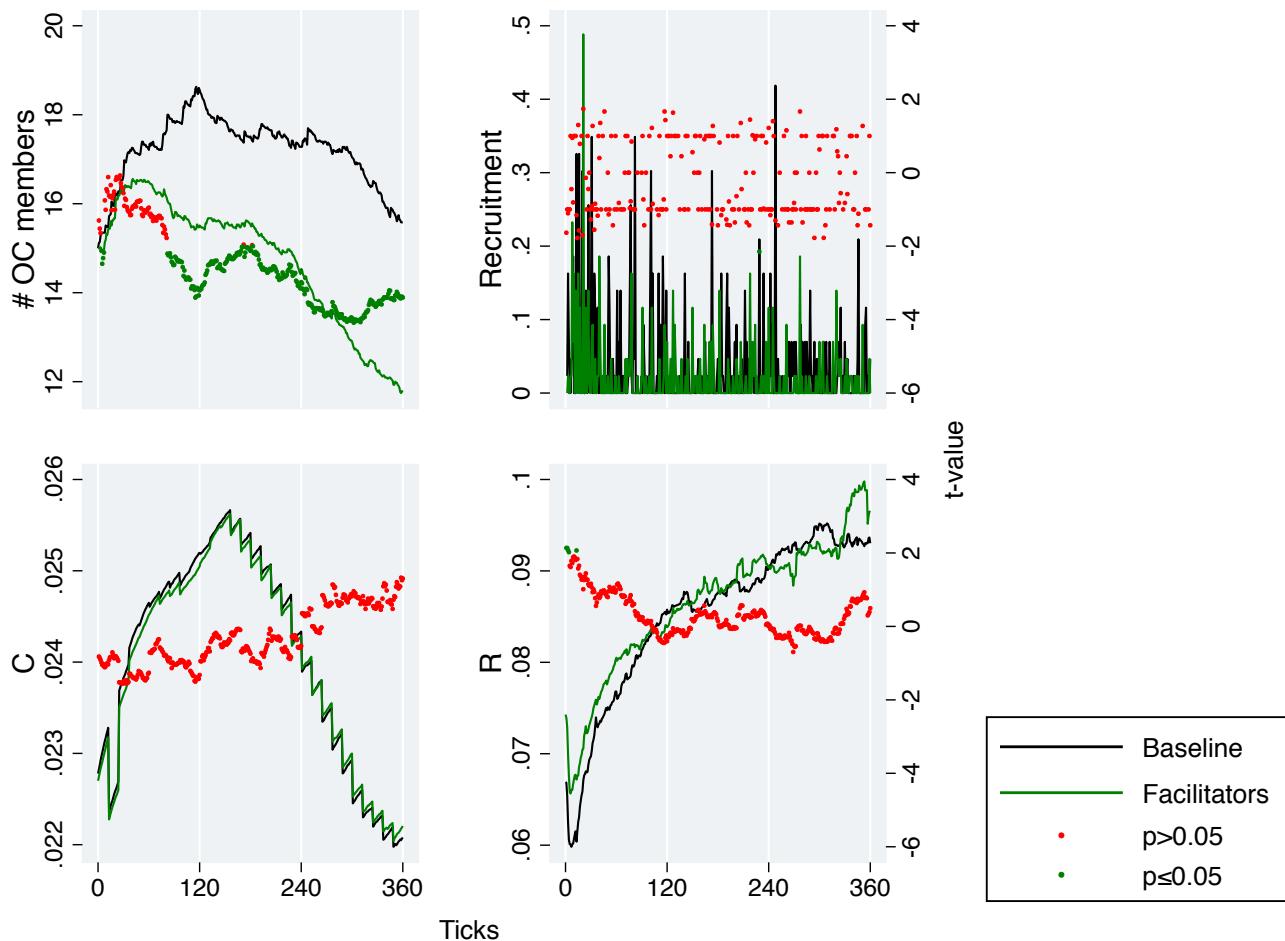
Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$), $^{**}p<0.01$.

These differences between Facilitators and the Baseline can also been seen in the dynamics (Figure 19). From early on in the simulation and until the end, there is a clear and substantive reduction in the number of OC members. There is a slightly lower rate of recruitment also (not significant at each tick but significant overall) in Facilitators. As in the averages, there are no differences between Facilitators and Baseline regarding C and R



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Figure 19. Comparison of outcome dynamics for Baseline and Facilitators



2.7.4.3 PRIMARY SOCIALIZATION

With strong intervention, primary socialisation has no effect on any of the four outcomes in the Northern Europe context relative to the Baseline. This contrasts with the same treatment in Southern Europe setting which reduced the number of OC members, the rate of recruitment, and R (Table 25).

Table 25. Comparison of outcome averages for Baseline and Primary socialisation

Outcome	Treatments		Significance
	Baseline (n=43)	Primary (n=43)	
# OC members	17.206 (3.830)	17.890 (3.411)	$t(84)=0.874^{\text{n.s.}}$
Recruitment into OC per tick	0.036 (0.020)	0.035 (0.017)	$t(84)=-0.111^{\text{n.s.}}$
C (Criminal propensity)	0.024 (<0.001)	0.024 (<0.001)	$t(84)=0.928^{\text{n.s.}}$
R (Organised crime embeddedness)	0.085 (0.018)	0.090 (0.020)	$t(84)=1.245^{\text{n.s.}}$

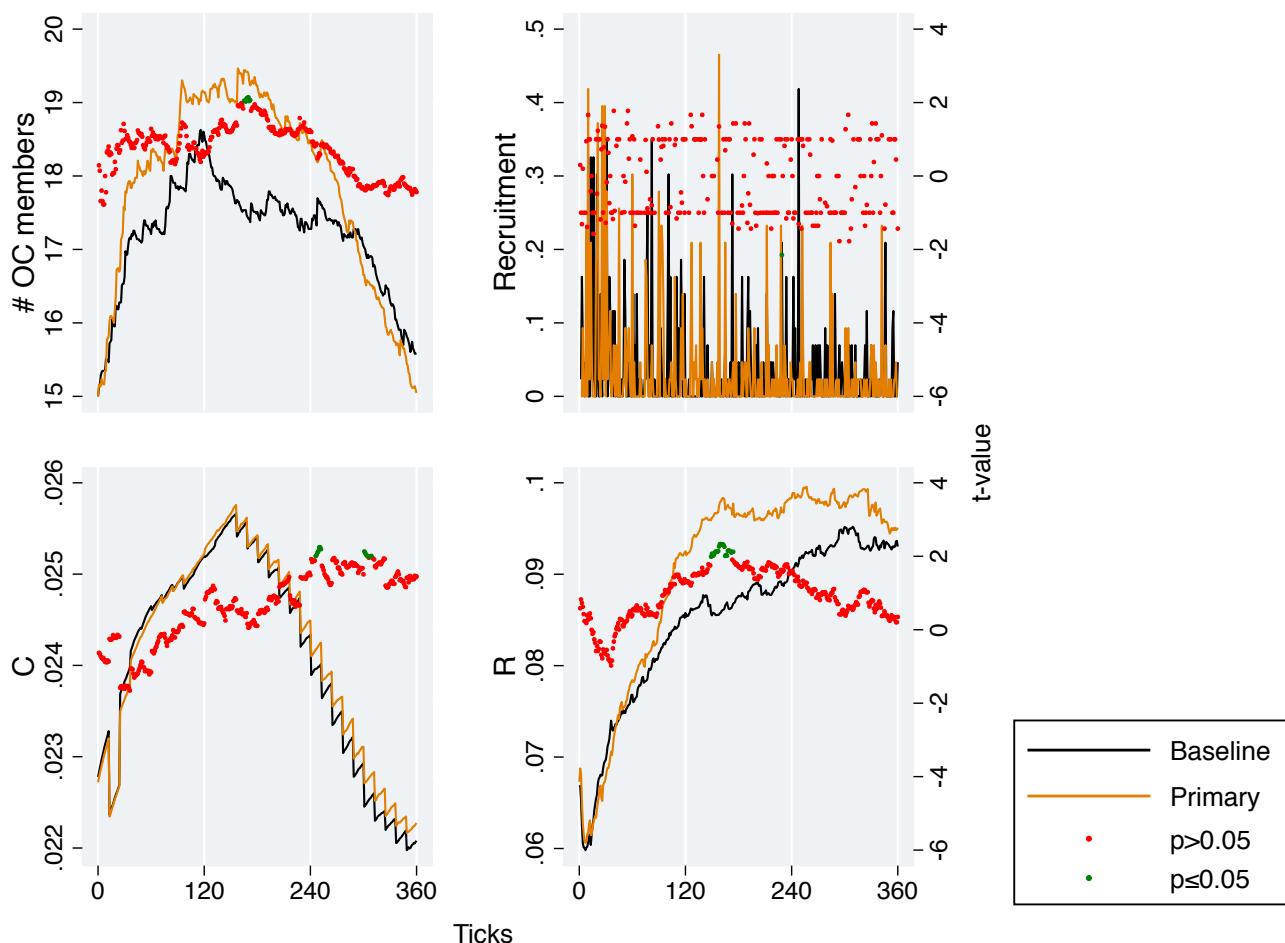
Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$).



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There are some indications of differences in the dynamics between the Baseline and the Primary Socialisation treatment (Figure 20). In the number of OC members, in C , and in R , the averages of these outcomes in the Primary treatment are somewhat higher than they are in the Baseline. However, these differences are only significant in a few ticks and, on average, they are not different (indeed all the t-values are quite far from significance).

Figure 20. Comparison of outcome dynamics for Baseline and Primary socialisation



2.7.4.4 SECONDARY SOCIALISATION

With strong intervention, on average, secondary socialisation does not lead to changes in the four outcomes (Table 26).

Table 26. Comparison of outcome averages for Baseline and Secondary socialisation

Outcome	Treatments		Significance
	Baseline (n=43)	Secondary (n=25)	
# OC members	17.206 (3.830)	16.597 (5.103)	$t(66)=-0.558^{\text{n.s.}}$
Recruitment into OC per tick	0.036	0.037	$t(66)=0.112^{\text{n.s.}}$



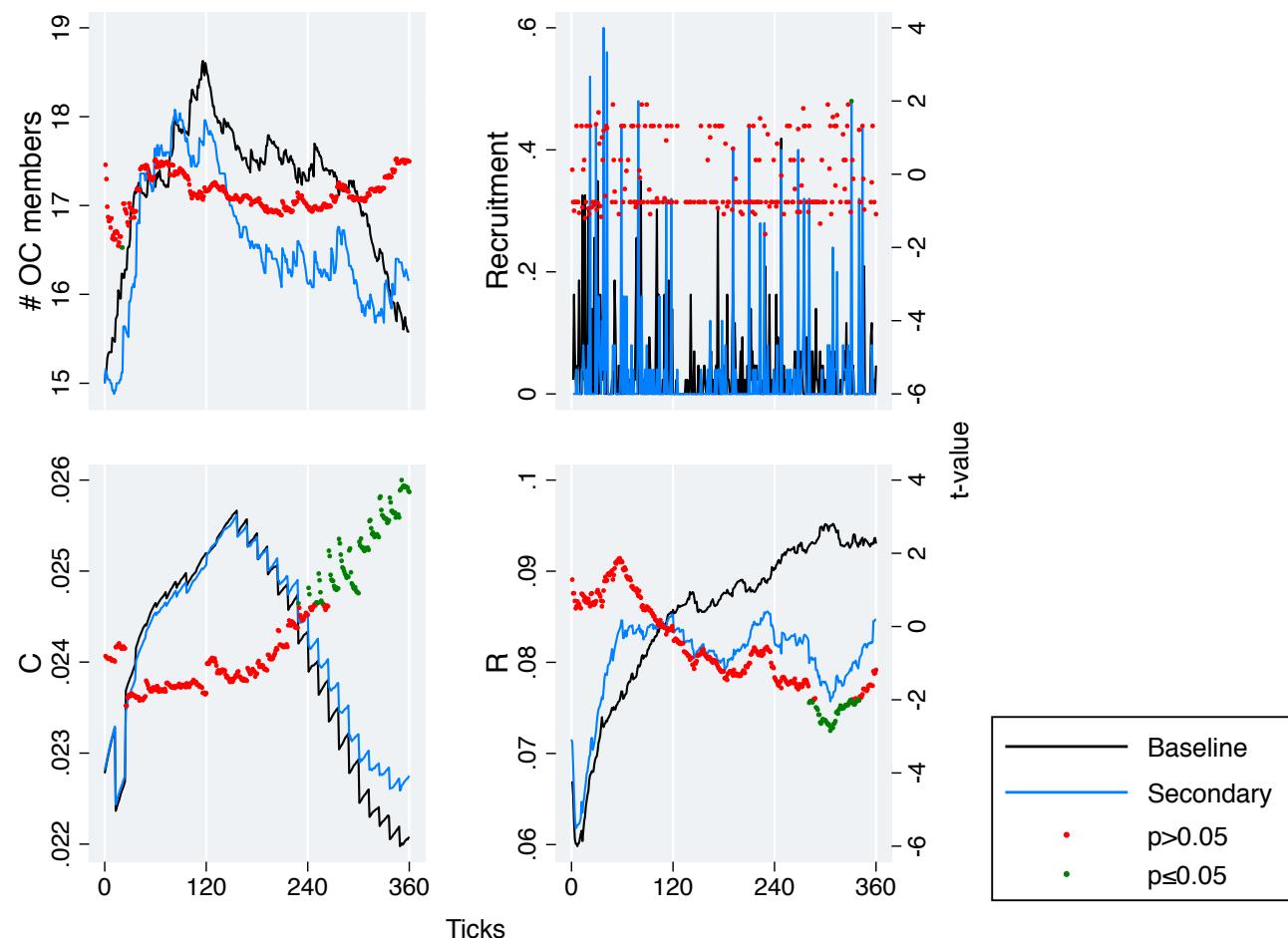
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	(0.020)	(0.030)	
C (Criminal propensity)	0.024 (<0.001)	0.024 (<0.001)	$t(66)=1.250^{\text{n.s.}}$
R (Organised crime embeddedness)	0.085 (0.018)	0.080 (0.016)	$t(66)=-1.093^{\text{n.s.}}$

Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$).

While the averages do not differ, there are some suggestions that Secondary socialisation has an effect on the outcome (Figure 21). The number of OC members is lower in the Secondary socialisation treatment than in the Baseline throughout the simulation although not significantly so in any tick. R is also slightly lower in the Secondary socialisation treatment than in the Baseline and significantly so in some ticks. While C is slightly higher in Secondary socialisation treatment than in the Baseline towards the end of the simulation.

Figure 21. Comparison of outcome dynamics for Baseline and Secondary socialisation



2.8 Discussion and conclusions

The simulations on the recruitment on organised crime focused on the interaction between individual traits and social relations as drivers of the recruitment into organised crime. The decision on the structure of the simulations were based on the evidence derived from the D1.1, where specific criminal skills and background and social relations were identified as the main drivers of the recruitment into organised crime.

Overall, the results of the simulations yield realistic outcomes. For example, in the standard interventions in the Southern European context, the number of organised crime members starts at 9 members and ranges between approximately 8 and 11 for the entire simulation. In the Northern European context, the simulations show more variability, with the number of members starting at 5 and growing until approximately 13-14. Turning to the strong interventions, the size of OC groups is also very stable. The number of organised crime members in the Southern European simulations starts from 30 members and generally remains in the range of 15-35 members across the simulation. The Northern European setup exhibits similar stability, with OC members starting at 15 and mostly remaining in the 15-20 range. The growth observed in the standard interventions in the Northern European context may be due to the very small number of starting members, which may force existing OC agents to find co-offenders among non-OC agents.

Furthermore, the total number of crimes in the simulations is stable across different runs and exhibits a slowly declining trend across time (not shown in the above figures), which is generally comparable to the declining crime rates experienced across Europe in the last decades. These results show that the simulations are generating a realistic environment where some of the main parameters are stable and consistent with empirical evidence. The realistic and reliable structure of the simulations can be considered the first important outcome of PROTON-S, considering that the application of ABMs to complex societal dynamics is still in its infancy. Compared to the existing literature on simulations of organised crime the PROTON simulations are certainly more complex, sophisticated and empirically sound.

The simulations were used to test the impact of four interventions (presented above): targeting OC leaders, targeting facilitators, primary socialization, secondary socialization. The interventions were tested in two contexts, one simulating a Southern European city (with empirical data drawn from Palermo and Sicily) and the other simulating a Northern European city (with empirical data based on Eindhoven and the Netherlands). The results present also a strong and a standard level of intervention. Overall, this resulted in twenty possible combinations. These combinations were prioritized compared to the exploration resulting from the changes in some of the main parameters, due to



available computational capacity. The results show different effects and statistical significance for the strong and standard interventions.

Regarding the strong interventions, for the Southern European context, the interventions targeting facilitators and primary socialization report a statistically significant effect on the number of recruited individuals, whereas the interventions targeting OC leaders and secondary socialization do not report an effect statistically different from the baseline. In particular, an increase in the risk of arrest for facilitators results in a reduction in the number of recruited OC members which is statistically significant from approximately tick 60 (5 years from the start of the simulation) until tick 360 (30 years). The intervention on primary socialization shows a statistically significant effect from tick 120 (10 years from the start of the simulation) until the end. The lag in the appearance of the effect may be due to the fact that the intervention targets children of OC members aged 12-18 and thus the effect on the recruitment dynamics may require a few years to show.

In the Northern European context, the only intervention reporting a statistically significant effect is the one targeting facilitators. The other three interventions do not report a statistically significant effect. In particular, Figure 19 and Table 24 show that targeting facilitators decrease the number of recruited individuals compared to the baseline simulation starting around tick 80 (during the seventh year) until the end of the simulation.

Regarding the standard interventions, no intervention shows a statistically significant effect on the recruitment into OC groups. However, in the Southern European context, the Figures 6 to 9 show that the intervention lines are below the baseline in the number of OC members for all or part of the simulated period. This indicates that, on average, the interventions report an overall lower level of OC members, although it is too small to be statistically significant. The findings are encouraging as they show that even in a more realistic social environment the tested interventions may impact on the recruitment process in the expected direction. It may be possible that with a higher number of repetitions the effect may become statistically significant, although its size would still be small.

Overall, the results of the simulations show that the strong version of two types of interventions may have an effect on the recruitment into organized crime. Contrarily, standard interventions do not report any statistically significant effect. As a consequence, the differences between strong and standard interventions are the likely cause of the differences in the impact on the recruitment into organised crime. Closer inspection of these differences provides additional insights into the simulations and the results. In particular, the differences between the strong and standard interventions comprise two main types of modifications.



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The first type of modifications regards the simulation environment and namely the number of OC members and the law enforcement intervention rate. Regarding the number of OC members, empirical evidence and experts' opinions pointed out that there may be approximately 30 OC members and 15 OC members per 10,000 inhabitants in Palermo and Eindhoven, respectively. The simulations of strong interventions have increased the number of OC members to 30 and 15 per 3,000 agents in the Southern and Northern European contexts, respectively. Similar number of organised crime membership are likely higher than those empirically observed in larger territories (regions or provinces), but they may realistically represent specific, extreme, situations characterized by a heavy presence of organized crime in a specific social environment. For example, according to the Court of Appeal of Reggio Calabria (Italy) some small cities of Southern Calabria (pop 10-15,000), OC members may range between 300 and 400 (Corte d'Appello di Reggio Calabria, 2012, p. 94). In a 3,000-agent simulation this would correspond to about 90 members. The strong interventions may thus simulate conditions where organised crime presence is more pervasive and intense. Regarding the rate of law enforcement interventions, the empirical data show that the number of yearly convictions leading to imprisonment penalties are about 30 and 15 per 10,000 inhabitants in Italy and the Netherlands, respectively. In simulations with 3,000 agents these law enforcement interventions would have decreased to negligible levels. In the simulations for strong interventions, the number of yearly law enforcement interventions was increased to 100 and 50 for the Southern and Northern European contexts, respectively. This modification was driven by the need to test the functioning of the simulations in more extreme scenarios, since at least two interventions are strictly associated to a change in the probability of being arrested of OC leaders and facilitators, respectively. However, such high rates of convictions may hardly represent the real rate of imprisonment convictions in a Western European country. These considerations suggest to interpret with caution the effect of the interventions based on higher probabilities of arrests (targeting OC leaders and facilitators), since these are likely to be affected by the inflated law enforcement intervention rates of the strong interventions. Future extensions of this work may consider additional simulations to assess what levels of law enforcement intervention are required for these interventions to show statistically significant results.

The second type of modifications concerned the operationalization of the interventions. As already mentioned at the beginning of the Results section, the strong interventions assumed that the targeting facilitators, primary socialization and secondary socialization interventions were particularly intense, i.e. with extreme parameter values. In particular, the probability of arresting a facilitator was increased by ten times (vs an increase by three times in the standard intervention) whereas the number of children targeted in the both the primary and secondary socialization was set at 100% (vs. 10% in the standard interventions). There is insufficient empirical evidence on the



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actual intensity of similar interventions in the real world. In other words, it is still unknown what is the share of potential targets which is actually reached in similar policies in the EU. For example, there is no available evidence about the share of children of mafia members currently enrolled in the programme developed by the Juvenile Court of Reggio Calabria (see above **Errore. L'origine riferimento non è stata trovata.**). Thus, the selection of the parameters for the standard and strong interventions tested how the variations in the intensity of the interventions may affect the results in two opposite situations. Future extensions of this work may include additional simulations to assess the impact of all possible levels of interventions (e.g., targeting 10%, 20%, 30%, ... of organised crime children) to establish the necessary intensity that potential interventions should achieve to have a statistically significant impact on the recruitment into organized crime.

In conclusion, PROTON-S simulations on the recruitment into organized crime were successful in the development of agent-based simulations of complex social dynamics leading to the recruitment into organized crime. The simulations are stable and yield realistic results. The design of the simulation and the code are publicly available and will enable interested researchers and policy makers to further develop simulations addressing specific regional and policy environments.

Furthermore, the results of the simulations show that some of the tested interventions may cause a statistically significant reduction in the number of organized crime members over the years under specific circumstances. Nevertheless, these interesting outcomes relied on simulations of strong interventions. Standard interventions, while showing lower averages of organized crime members for the Southern European context, did not meet the threshold for statistical significance. The current results may suggest that these policies may be particularly suitable for territories where organised crime presence is particularly strong and embedded in the society. The interpretation is in line with the evidence from policies currently implemented in the EU. For example, the interventions on the children of mafia members in Italy is currently implemented only in the Juvenile Court of Reggio Calabria, one of the areas with the highest mafia presence in Italy (Calderoni, 2011; Sergi, 2018; Dugato, Calderoni, & Campedelli, 2019).

While the results offered relevant insights, caution is invited when interpreting the findings of the interventions. As discussed above, the positive effects were found only in the strong version of two types of interventions. Although PROTON-S simulations on organized crime have generated some of the most sophisticated agent-based simulations in the literature, the simulation of complex social dynamics is still in its infancy. Additional tests and explorations can potentially run for several years and the consortium is currently exploring possible cooperation with other interested stakeholders in the EU and beyond. The research team plans to continue the simulations in several directions. First, further tests and parameters variations may enable a better operationalisation of the interventions. Second, in both the Southern and



Northern European contexts, we will simulate different combinations of the five parameters (number of OC members, crime rate, unemployment rate, law enforcement intervention rate, and length of punishment) to provide input for the PROTON Wizard and to further explore the robustness and variation of the results in different contexts. Third, additional simulations may test the sensitivity of the results to small variations in the operationalization of the interventions, thus enabling to identify minimum intensity levels which may positively impact on the recruitment.



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3 Terrorist Recruitment Model

3.1 Theoretical Framework

The European Union (2005) defines radicalisation as "the development of opinions, ideas etc. that could lead to acts of terrorism". According to this definition there are two outcomes to radicalisation. First is opinions, ideas, and attitudes towards terrorism, and second is the acts of terrorism. The EU also distinguishes radicalisation from recruitment, with the latter being when someone has been solicited to "commit or participate in the commission of a terrorist offence, or to join an association of group, for the purpose of contributing to the commission of one or more terrorist offences by the association or the group" (Council of Europe, 2005). Whether or not an individual has yet successfully carried out a terrorism offence has no bearing on their status as having been recruited. In fact, the majority of individuals prosecuted and convicted for terrorism-related offences in Europe, and in the US, have yet to actually carry out terrorism offences.

These definitions correspond closely with important distinctions made by researchers who distinguish between the *cognitive and behavioural dimensions* of radicalisation and the *outcomes* of radicalisation (McCauley & Moskalenko, 2017). Such an approach to radicalisation accounts for the fact that only a small percentage of radicalised individuals ever turn to violence. However, as has been noted in the literature, while not all of those who are recruited to terrorism are necessarily especially radicalised, most are. Even in cases in which recruited individuals are not "especially radicalised", they are generally radicalised to some degree or another. As Taarnby (2005, p. 6) describes it, "Recruitment is the bridge between a personal belief and violent activism". Recruitment occurs when radicalised individuals come into contact with other radicalised individuals who are specifically soliciting others to participate in terrorism offences, or otherwise lead them to be convinced to join in, or otherwise engage in such activities (Della Porta, 1988).

Explaining why only a small percentage of radicals turn to violence, and identifying what factors differentiate non-violent from violent radicals, remains the primary concern of radicalisation research and interest of policy makers. According to Stern (2016), "there must be individual risk factors that explain why some members of an aggrieved group join terrorist groups while most do not" (p. 104). Identifying these factors has been hampered by a lack of data and studies that compare violent with non-violent radicals (Sageman, 2014). Nevertheless, leading scholars believe that a risk-protective factor paradigm, as used in the study of criminal attitudes and behaviours, may still be the most



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appropriate framework for identifying the factors relevant for effective intervention and policy (Bhui, Hicks, Lashley, & Jones, 2012; P. Gill, 2015). Heeding this call, PROTON's WP2 identified a large number of risk and protective factors, as well as their relative weights, enabling the development of a risk-protective factor framework for the issue of radicalisation and recruitment to terrorism.

3.1.1 A RISK-PROTECTIVE FACTOR FRAMEWORK

While the study of risk factors for radicalization and recruitment to terrorism has been arguably slow, the risk-protective factor paradigm, that is well established in criminology, has a high level of applicability to these outcomes (Bhui et al., 2012). Broadly speaking, the risk-protective factor paradigm holds that "Offending is more likely to occur when risk factors outweigh protective factors, and offending is less likely to occur when protective factors outweigh risk factors" (Taylor, Friday, Ren, Weitekamp, & Kerner, 2004, p. 24). It is therefore the cumulative weight and interaction between risk factors—in the absence of or when they outweigh protective factors—that increases the risk of offending (Assink et al., 2015; Farrington, Ttofi, & Piquero, 2016; Pollard, Hawkins, & Arthur, 1999). While a close relationship exists between many risk and protective factors, protective factors are not simply the reverse of risk factors. For example, for ordinal factors such as high and low integration, "the exact meaning of a risk or protective factor refers not to the particular variable in general but to different poles or different degrees of a continuous variable" (Lösel & Farrington, 2012). Similarly, for categorical or dichotomous factors, the protective effects of one pole are likely to be different than the risk effects of the other. For example, employment does not necessarily have a protective factor of a similar magnitude to the risk effect of unemployment.

Beyond criminal offending, more recent research has sought to identify risk and protective factors for criminal attitudes. Generally speaking, the risk and protective factors for criminal attitudes are similar to those for criminal offending, albeit with different effect sizes (Ramsay, Steeves, Feng, & Farag, 2017). The rationale for investigating risk and protective factors for criminal attitudes is quite intuitive. Prior studies have found that criminal attitudes are one of the greatest predictors of criminal behaviours (Bowes & McMurran, 2013; Pratt et al., 2010), whereas normative attitudes and beliefs have been found to be among the most important protective factors (Walters & Bolger, 2018). A further extension of the risk-protective framework to the study of criminal attitudes and criminal behaviours holds that the cumulative and interactive effects of risk and protective factors in both totality and strength may explain why criminal attitudes lead to behaviours for only a small proportion of people (Folk et al., 2018; Tuck & Riley, 1986).

To date, there is little understanding of how risk and protective factors operate with regards to radicalisation and recruitment. This is in part because little is



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known about the relative weights, magnitudes, and clustering of the different factors (P. Gill, 2015). However, the results of PROTON's WP2 have established weights for a large number of risk and protective factors, whilst also identifying the relative weights of related risk and protective factors (see D2.1). Using this data, the current study is able to, for the first time, model the dynamics of key risk and protective factors and conduct experiments that seek to assess the impact of policies that aim to target such factors.

3.1.1.1 TYPES OF RISK AND PROTECTIVE FACTORS

While a host of putative risk and protective factors exist, they can generally be split into two main categories of static and dynamic. A simplistic translation is that static risk factors indicate the propensity of who is or will be at risk of radicalisation, whereas dynamic factors dictate when individuals of varying propensities will be at risk. This is the difference between propensity (risk status) and risk state (level of risk at a given point in time) (Douglas & Skeem, 2005). Generally speaking, interventions seek to target dynamic risk factors as they are considered to be malleable. Changes in dynamic factors, especially cognitive related factors, have been provided the most successful outcomes in terms of reducing the risk of criminal and criminal-analogous behaviours (e.g. Assink et al., 2015; Hanson & Morton-Bourgon, 2005). Indeed, research has found that targeting such factors can also lead to desistance from terrorism and even de-radicalisation (Altier, Leonard Boyle, Shortland, & Horgan, 2017).

With regards to risk state, many of the commonly examined risk factors are socio-demographic factors that are not open to change. These factors can be said to influence an individual's propensity. For example, age and being male are better characterized as markers of propensity, or risk state, than risk factors per se. Research on criminality, recidivism, and desistance from crime has repeatedly found that by targeting dynamic factors such as attitudes and orientations, significant reductions in risk can be achieved. But perhaps more importantly, many static risk factors are simply unchangeable. For example, someone either has a criminal history or doesn't; or they suffer from a psychological disorder or they don't. Dynamic factors on the other hand are seen to be malleable to some degree and therefore offer the opportunity for targeting by intervention. As has been pointed out in the literature, it is necessary to identify which risk and protective factors can be best targeted by interventions (Bhui et al., 2012). While any simulation must take both propensity and risk factors into account, it is the dynamic risk factors which in our model are able to be targeted by interventions (see Section 3.3).

In assessing the results of WP2 and T2.1 in particular, of the 62 risk and protective factors for radical attitudes, only about 15 can be classified as dynamic, attitudinal related factors. For protective factors these are general trust, high integration, institutional trust, law legitimacy, and law obedience. While for risk factors these are perceived injustice, relative deprivation (individual and collective), anger/hate, low integration, legal cynicism, moral



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neutralization, and law legitimacy. There are important overlaps between many of these factors and they can generally be placed into three main domains of *trust/legitimacy*, *integration*, and *subjective deprivation*.

With regards to trust/legitimacy, the literature emphasizes that elements such as perceived injustice, legal cynicism, and moral neutralizations are also important risk factors. Similarly, with regards to integration, elements of societal connectedness and identity. What all of these factors share in common is that research has found each of them to be conditioned by differential associations, that is socialization and social learning from others. In this regard, the results of WP2 also indicate that differential associations (e.g. radical peers) are a key risk factor for radicalisation in and of itself.

3.1.2 DIFFERENTIAL ASSOCIATIONS (SOCIAL LEARNING)

In addition, the theoretical framework we adopt for the terrorist recruitment model draws on differential associations and social learning theories and routine activity theory.

The development of radical attitudes occurs primarily through socialization, in which individuals are exposed to different radicalising messages from peers, family, members of the community, and the internet (Hamm & Van de Voorde, 2005; Hegghammer, 2013; Holt, 2012; Holt, Freilich, Chermak, Mills, & Silva, 2019). As the results of T2.1 highlighted, having radical peers is an important risk factor for radical attitudes and behaviours. Similarly, out-group friendships can serve as a protective factor for both radical attitudes and intentions. But differential associations and social learning are not limited to the learning of attitudes directly related to deviance, or as in our case, radical attitudes such as the justification of terrorism. As originally stated, the learning of deviant attitudes and behaviours is the same as the learning of normative attitudes and behaviours, or any other attitude or behaviour (Sutherland & Cressey, 1947).

Research has found that many of the subjective opinion-based risk-protective factors for radicalization and recruitment identified in T2.1 are also primarily conditioned by differential associations and social learning (Walters, 2016; Wolfe, McLean, & Pratt, 2017). For example, attitudes towards the legitimacy of the law and legal institutions are influenced by friends, neighbours, and family members (Fagan & Tyler, 2005), in addition to one's own experiences, such as negative encounters with the police (Sampson & Bartusch, 1998). Similarly, there is an extensive literature that highlights the relationship between social integration/connectedness and differential associations. Specifically, those with higher levels of social integration are not only less likely to hold deviant attitudes or engage in deviant behaviours but are also less likely to socialize with associations who hold such attitudes (Thorlindsson & Bernburg, 2004).



Similarly, changes in feelings and perceptions of relative deprivation are said to also be the result of learning and socialization (Burchardt, 2005; Folger & Kass, 2000). As has been pointed out in the literature, there is a significant amount of overlap between classic relative deprivation theory and the more criminologically oriented strain theory. According to both theories, one does not need to individually, directly, or objectively suffer from strains in order for them to have an impact. Individuals may "suffer" from indirect forms of strain, including vicarious strains, and attachment to group-based strains and deprivations. When an individual perceives her own situation, or that of a group with whom she identifies as being underdeveloped or being worse off compared to some other individual or group, this can engender feelings of anger, hate, resentment, and importantly injustice (Agnew, 2010, 2016; Rice, 2009). These types of social comparisons are a key element of some social learning perspectives that also include components of subjective forms of deprivation as increasing deviance justifying definitions (Bandura, 1986).

According to social learning theory, differential associations vary in terms of their degree of "intensity". That is, some differential associations carry more weight in influencing a given attitude or behaviour. Certain figures, such as opinion-leaders, individuals in a community who maintain a high-status, are more likely to be successful in influencing attitudes and behaviours than lower-status individuals (Bandura, 1977). The literature on radicalisation and counter-radicalisation highlights the role of both Imams and community workers as opinion-leaders. Imams have been found to have a significant effect on radicalisation specifically (e.g. Berger, 2016). Police as well have been found to have differential effects on attitudes pertaining to trust and legitimacy (Cherney & Murphy, 2019; e.g. Jackson, Huq, Bradford, & Tyler, 2013).

Generally speaking, differential associations in the form of radical peers or other contacts have been found to be an important predictor of both radicalisation and recruitment to terrorism (WP2). However, chance encounters between radicalised individuals can also underpin recruitment, and in fact this has been the case for many recruited individuals (Sageman, 2004; Taarnby, 2005).

3.1.3 ROUTINE ACTIVITIES

Differential associations, as well as chance encounters, must be contextualized within the context of space, movement, and the routine activities in which they occur. While routine activities generally refers to the necessary components for the commission or prevention of a criminal act (Felson & Cohen, 1980). At a more basic level, it refers to the "generalized patterns of social activities in a society (i.e. spatial and temporal patterns in family, work, and leisure activities)" (Wikström, 2018, p. 1). Routine activities and differential



associations are mutually dependent and conditioning. This is because routine activities determine the availability of differential associations and opportunities for social learning, whereas differential associations play a role in determining routine activities (Akers, 1998; Bernburg & Thorlindsson, 2001; Sampson & Laub, 2009). Indeed, there is substantial overlap between routine activities and social learning theories. Studies analysing delinquency and crime from both perspectives have found, for example, that more time "hanging out" outside of the home increases the likelihood of deviant behaviour. Moreover, studies show that differential routine activities, specifically regarding the amount of leisure time, characterize differences between offenders and non-offenders (Riley, 1987). Changes in routine activities are determined by life changes, such as employment, which as a result of changing routine activities in turn create new opportunities for socialization, or differential associations. Such changes to routine activities (e.g. employment, marriage, children) reduce the time available for leisure activities, which also thereby changes differential associations (Laub & Sampson, 2003, pp. 38–42).

All of this is relevant to the mechanisms underpinning radicalisation and recruitment to terrorism. Beyond changes to routine activities and differential associations, life changes such as employment can also have a direct effect on risk factors such as relative deprivation and societal connectedness, as well as overall violent propensity. In turn, employment can reduce the risk of radicalisation as it serves to target multiple risk and protective factors simultaneously (Feddes, Mann, & Doosje, 2015).

Additionally, research has found that interactions with radicalising influences, regardless of how contact occurs, occur within built environments and locations; such as a mosque, pub, community centre, or virtual environment (Bouhana & Wikström, 2011). Some areas are more likely to be home to such "risky" places or nodes than others. Like in the study of crime concentration, which builds on routine activities perspectives, "risky" places may concentrate even to the level of specific addresses (e.g. actual buildings) (Sherman & Weisburd, 1990). The European Commission (2005) has already identified some "the phenomenon of violent radicalization concentrating on recruitment hotspots" that include a range of different places. These hotspots tend to develop due to differential associations through bottom-up processes of collective radicalization. It is in these hotspots where recruitment is most concentrated and successful (Vidino, Marone, & Entenmann, 2017).

It should also be noted that while recruitment usually occurs at such places, it also happens through chance encounters during routine activities (Sageman, 2004; Taarnby, 2005).



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3.2 State of the Art

Agent Based Model (ABM) applications to the study of terrorism have generally expanded on the social networking approaches that were popular in the early days of terrorism research. As such, terrorism ABMs can generally be found to study the emergence of terrorist networks (Ko & Berry, 2004), the disruption of terrorist networks and their logistics (Keller, Desouza, & Lin, 2010; Latora & Marchiori, 2004), and the spatial distribution of terrorist network (Moon & Carley, 2007). A small number of ABMs have also been used to model radicalisation, building upon the traditional social network modelling approaches, and more recently, on opinion-dynamic models.

Despite the prevalence of ABMs in the broader field of terrorism research, radicalisation models have been quite general, and can be described as being theoretically and methodologically underdeveloped. This is not a criticism as much as it is simply a reflection of the fact that radicalisation research is still a young and developing field (Neumann & Kleinmann, 2013). It is also a reflection of a lack of collaboration between computer science experts and criminologists.

Early applications of ABM to terrorism related phenomena primarily focussed on the emergence and disruption of terrorism networks. These models generally relied upon social network-based approaches (e.g. MacKerrow, 2003) (e.g. MacKerrow, 2003). Unfortunately, as trends in terrorism have changed, especially in the West, traditional applications of network disruption may be less relevant. Moreover, with the exception of experimenting with changes to a population's demographic makeup, these models provide little in the way of policy experimentation. One model that did explore some experimental changes was Berry et al. (2004), however this model assessed general group recruitment, using theoretical models of gang recruitment and only made a theoretical connection to terrorism.

In more recent years a small number of ABMs have been carried out to model radicalisation. For the most part, these models have included opinion dynamics to model the development and transfer of radical opinions between agents, and a variety of approaches have been taken. Galam and Javarone (2016), for instance, used a mathematical model as a proxy for the initialization of the distribution of radical opinions. Unfortunately, this model lacked geography, place, and movement. Another model by Genkin and Gutfraind (2011) included opinion dynamics to model the transmission of radical attitudes and key places where agents could meet. However, this model did not include movement, and was not built on any real distributions of opinions. Importantly, neither of these models included any risk factors for radical attitudes and only modelled the transmission of radical attitudes themselves. As Thornton (2015) notes,



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using opinion dynamics to model the transference of radical attitudes through socialization itself is also problematic since this dynamic is not well understood.

Another study, carried out by Pruyt and Kwakkel (2014), did examine an attitudinal risk factor for radical attitudes, namely uncertainty. The model used a variant of opinion dynamics in which agents sought to convince others of grievances and thereby increase the likelihood of radicalisation. However, this model did not include any physical environment or movement. Moreover, as T2.1 demonstrated, uncertainty is a putative risk factor with an exceptionally small effect size. In another study, Cioffi-Revilla and Harrison (2011) used opinion polarization dynamics to model the spread of radical attitudes. The model also included “demagogues”, or extremist preachers, whose pre-set opinions could be broadcasted to other agents. While the specific opinions chosen as proxies for radical attitudes can be seen as being theoretically grounded, the model was based on a social-network platform and primarily focused on the role of the spread of grievances as the independent factor predicting radicalisation. This means that the model had no geography or movement. Additionally, the spread of grievances was based purely on a computational dynamic rather than any real-world data.

In a recent review of the ABM literature pertaining to radicalisation, recruitment, and terrorism, Thornton (2015) identifies that with few exceptions, prior studies have failed to use real world data to initialize and validate. Additionally, she finds that most models are not grounded in the theoretical literature and do not use established theories to set the mechanisms of the simulations. Beyond these issues, we believe that prior studies have also been underdeveloped due to 1) the limited number of factors they include, 2) their limiting to only one mechanism (e.g. geography, movement, and places, or opinion dynamics), 3) their limit to only one outcome (e.g. they do not include recruitment), and 4) a lack of testing of the effects of counter-radicalisation policies. In fact, the only study that we are aware of which includes each of these elements is the PhD thesis of Thornton (2015) herself.

The terrorist recruitment model developed in PROTON seeks to fill these gaps in the body of knowledge by constructing an ABM that is both theoretically and empirically driven, drawing on the results of WP2. The current ABM builds on the opinion dynamics models used in prior studies but includes a number of non-radical attitudinal risk and protective factors that increase or decrease the likelihood of radicalisation. Moreover, the current study also models the recruitment of radicalised agents. Additionally, we move beyond the mere modelling of radicalisation and conduct simulation experiments on the impact of three key counter-radicalisation policies that are in line with current approaches undertaken in EU member states and mimic feasible and realistic policy options for reducing the risk of radicalisation and recruitment to



terrorism. Compared to previous ABMs the current ABM can be considered as being based on an especially rich source of data.

Prior ABMs on radicalisation have been built on theoretically driven parameters. However, these parameters, whilst perhaps in line with computational theories, are not necessarily in line with the radicalisation and recruitment literature. This disconnect is likely to be a reflection of the lack of collaboration between computer science and social science more generally. While using abstract empirical data is not an unheard-of approach in criminological application of ABM, studies using real data, but which can be generalized to broader settings are generally considered to be of higher quality and reliability (Bosse & Gerritsen, 2010; Malleson & Brantingham, 2009). Models that take this approach calibrate according to data from a particular context but define the mechanisms and parameters in a way that the model and its outputs can be connected to empirical data from other contexts (Gerritsen, 2015).

3.3 Model Overview

Drawing on the results of T2.1, the modelling of the dynamics and processes of radicalization and recruitment to terrorism is by no means an easy task. This is because there is a large spectrum of factors that can and do affect these two interrelated outcomes. While the findings of T2.1 identified a large number of *individual* level and *meso-level factors* affecting both of these outcomes, only a few of them are open to change. That is, only certain factors are dynamic, or are malleable. For example, individual characteristics such as age and gender, or experiential factors such as exposure to violence, are not open to change. On the other hand, other factors such as socio-economic conditions, and subjective beliefs and values, can possibly be changed.

In the real world, individuals do not exist in isolation. Humans are both active and socially inclined creatures. All individuals possess their own characteristics with respect to how they conduct their daily lives, including their activities and movements, as well as the social relationships and interactions they hold. Together with the factors that shape and determine these things, routine activities and socialization are the primary mechanisms through which individuals become more likely to fall within a spectrum of normative and conforming belief and behaviour, or by which they will deviate from the norm.

The literature supports the idea that *socialization* is the primary mechanism by which both radicalization and recruitment occur. However, rather than radical beliefs being transmitted in a direct way, individuals are at a greater risk for harbouring such beliefs when other subjective beliefs are negative. Moreover, socialization is dependent on the individual's routine activities, which are



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structured around their commitments, such as employment. As such, while unemployment can certainly affect the risk of radicalization and recruitment directly, it also affects routine activities, and thereby socialization. Radicalized individuals are at the highest risk of recruitment, as these individuals may seek out like-minded individuals, seek out to be recruited, be targeted by recruiters themselves, or a combination of these (Veldhuis & Bakker, 2007; Veldhuis & Staun, 2009).

Given the complexity of modelling individual and environmental conditions and heterogeneity, the radicalization and recruitment to terrorism model includes a number of attributes, achieving a high degree of detail, whilst maintaining an acceptable level of parsimony. In order to achieve this, the current model includes 1) a physical landscape representing a borough of a major European city, 2) places that are characteristically neutral, risky, or protective by way of the types of individuals who frequent these places 3) citizen agents with a heterogeneous set of characteristics, 4) static and dynamic risk and protective factors, 5) risk and protective agents, and 6) recruiter agents.⁷

At initialization, the model includes a built landscape with neutral places (e.g. residences, places of business/employment, parks, public spaces), protective places (e.g. community centres), and risk places (e.g. propaganda places and cafes), split up into four adjacent neighbourhoods that differ in their makeup in terms of places and socio-demographics. The model also includes a heterogeneous set of citizen agents who each have their own individual-level characteristics that include static factors affecting their radicalization propensity, namely, two demographic factors (age and gender), an economic factor (employment), a psychological factor (authoritarian personality), and an experiential factor (criminal history). Agents also hold opinion-based risk/protective factors that are socially related, namely, trust/legitimacy of authorities, integration/non-integration, and subjective deprivation. These factors are then combined to create overall risk and propensity (Figure 22).

Figure 22. Calculation of propensity and risk scores.

⁷ Research indicates that major European cities have to contend with radicalization and recruitment to terrorism as it pertains to a range of extremist ideologies and doctrines, including right-wing, left-wing, and religious ideologies. Major European cities likely differ in the proportion of instances of radicalization and recruitment that can be attributed to individuals ascribing to these different ideologies. While many counter-radicalization policies and programs are directed at, or tailored towards specific groups, others are more general. Of course, it would be ideal that policies could have an appreciable effect on all forms of radicalization and recruitment. Findings from WP2 support qualitative research that suggests that the risk factors for radicalization and recruitment for different ideologies are more similar than they are different (Valk, 2012). Indeed, WP2 found few statistically significant differences exist between risk and protective factors as they relate to radicalization and recruitment to terrorism based on these different ideologies. As such, in this model, agents are not identified by race, ethnicity, religion, or ideological affiliation. Rather, just like ordinary citizens, radicalized and recruited agents can represent individuals adhering to any of the primary extremist ideologies that are the target of counter-radicalization policies.



$$\begin{aligned}
 \text{propensity} &= \underbrace{\left(\frac{\text{factor}}{\text{weight}} \right)}_{\text{Stochastic factor}} + \underbrace{\left(\frac{\text{factor}}{\text{weight}} \right)}_{\text{Social Factors}} + \cdots + \underbrace{\left(\frac{\text{factor}}{\text{weight}} \right)}_{\text{Psychological Factors}} + \cdots + \underbrace{\left(\frac{\text{factor}}{\text{weight}} \right)}_{\text{Economic factors}} \\
 \text{risk} &= \underbrace{\left(\frac{\text{propensity}}{\text{weight}} \right)}_{\text{Propensity}} + \underbrace{\left(\frac{\text{factor}}{\text{weight}} \right)}_{\text{Social Factors}} + \cdots + \underbrace{\left(\frac{\text{factor}}{\text{weight}} \right)}_{\text{Psychological Factors}} + \cdots + \underbrace{\left(\frac{\text{factor}}{\text{weight}} \right)}_{\text{Economic factors}}
 \end{aligned}$$

There are three categories of agents in the model: citizens, broadcasting agents, and recruiters. While agents from all categories share a primary set of common rules that govern their decision-making, there are some key differences. All agents engage in routine activities—moving around the landscape and visiting different “places”—and differential associations—interactions with other agents that may impact opinion-related factors. However, broadcasting agents and recruiters have more rigid routine activities. Additionally, they are only “speakers” and not “listeners” during interactions. Unlike citizen agents, broadcasting agents and recruiters have fixed objectives as will be described below.

Citizen agents share a common set of rules that govern their decision making and behavioural options. These agents have the opportunity to update and change the decisions that they make at each step of the model (one hour). At each step of the model, an agent can choose to remain in the patch in which they were already located in at the previous step, or to move to a new patch that is within their activity radius. Agents are required to spend a fixed amount of time “sleeping” (8 hours) during which they make no decisions. Additionally, agents who are employed spend a fixed amount of time at their place of employment “working” (8 hours) and are unable to move to a different patch during this time.

When an agent is located in a given patch they may or may not share that patch with other agents. If there are at least two agents in a given patch, they are presented with the opportunity to decide to interact with each other. As such, as described above, whilst “working”, agents are able to decide, at each step of the model, to engage in conversation with other agents located at the place of work at the same time. All such interactions similarly follow the opinion-dynamics model and the rules that govern it. At each step of the model, agents’ opinion-related scores are updated based on the interactions that have occurred during the previous step. Agents also develop memory and preferences for certain other agents. Based on the successfulness of prior interactions, agents may prefer to engage in further interactions with the same agents. That is, when presented with the opportunity to interact with a new agent, or an agent with whom unsuccessful, or less successful interactions have previously been had, or an agent with whom there is a shared history of



successful interactions, the agent has the ability to decide to whom preference will be given, thus determining with which agent the interaction is more likely to be had.

Among the potential cells to which agents can decide to traverse are certain cells that contain places. Agents are able to decide to visit these places when they are within the same cell. If an agent decides to visit a place, they then have the opportunity to decide whether to engage in conversation with another agent who is also located at the place at the same time. The ensuing conversation then operates according to the opinion-dynamics model and the rules that govern it. Agents also develop memory and preferences for certain places. If an agent has had successful interactions at certain places, or if other agents for whom the agent has developed a preference tend to be located at certain places, an agent may give preference to returning to this place over another possible option that may be available.

Certain places are staffed by broadcasting agents, who are able to interact with multiple agents that are located at the same place simultaneously. Agents located at such a place may or may not decide to be receivers of this broadcasted interaction. Similarly, when agents are located at a patch that does not contain any place, they may have a chance encounter with a police officer. Police officers also broadcast in that they can interact with multiple agents that are located in the same patch simultaneously. Similarly, an agent can decide to be a receiver of this broadcasted interaction. Both of these are one-way interactions, in which only the receiving agents' opinions can be updated, that operate according to the adjusted opinion-dynamics model and the rules that govern it.

Based on the above, at each step of the model each agent's risk score is recalculated and updated. Agents therefore may, over time, pass the risk (radicalization) threshold and become open to recruitment, or may drop below the threshold and thereby make them closed to recruitment. As agents traverse the model's landscape, they may come into contact with a recruiter agent. Recruiter agents are able to sense which agents are above the risk threshold and they also give preference for an interaction with such an agent over an agent who is below the threshold if both types of agents are located in the same patch at the same time. Recruiter agents develop a memory and preference for high-risk agents with whom they have had prior successful interactions. Similarly, these agents develop memory and preference for the recruiter agent as they do for other agents more generally. Once a recruiter has successfully interacted with a high-risk agent for a given number of steps—using a normal distribution where 500 steps is the mean—then the high-risk agent becomes recruited. These agents remain in the model and do not carry out any specific functions expressing their recruitment, rather recruitment is a categorization of the outcome of interest.



Both broadcasting agents and recruiters differ from normal citizen agents in three ways. Firstly, their routine activities include less free time, and they are situated at the places to which they are assigned for longer periods of time. Nevertheless, these agents do have some free time, where they visit other places, and they are also required to sleep. These agents also differ in that they have fixed values on opinion-related factors which are not open to change. Consequently, the third difference is that these agents are unable to be receivers in opinion-dynamics.

As the model runs, agents carry out daily routine activities, including going to work, visiting different places (parks, cafes, etc), sleeping. Agents spend also some of their time on the internet. As they engage in these activities, they come in to contact with and socialize with other agents and they exchange opinions about different topics. Within the model also exist agents with special functions, namely: community workers, police officers, risk promoters, and recruiters. Each of these agents have an impact on citizen agents via the opinion-dynamics mechanism, albeit they are each assigned specific tasks and abilities as will be detailed below.

Opinions held by agents play a crucial role on their chance of becoming radicalised. Together with fixed individual characteristics (age, gender, employment, authoritarian personality, and criminal history), they form the basis of the equation used to calculate the risk of radicalisation. Once the risk of radicalisation reaches a given threshold, agents are considered to be vulnerable to recruitment. Recruiter agents are more attractive to radicalized agents, and recruiter agents are able to sense who is radicalized and seek out interactions with them. Following a normal distribution of the amount of time required from radicalization to recruitment, once a radicalized agent has spent a certain amount of time with a recruiting agent, the agent is classified as having been recruited, according to the working definition of recruitment noted above.

3.3.1 ROUTINE ACTIVITIES

Each agent has routine activities that include time they spend at home, at their places of employment, at different “places”, and time they spend travelling. Each activity lasts for a minimum of 1 tick of the model, which is equivalent to 1 hour, but can last longer. At the outset of the model, citizens are identified as either being employed or unemployed. For employed agents, their need to be at work for 8 ticks, and at home for 8 ticks each day are considered mandatory activities which occur at the same time each day. For unemployed agents, their only mandatory activity is remaining at home for 8 ticks each day. In both cases agents are able to spend more time at home as part of their free activity. Rather than travelling between different places based on a street or other type of geographic network, agents are “teleported” between the patches.



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At the outset of the model, citizens' free time activities are concentrated nearby the locations of their mandatory activities: home and work. However, as the model progresses over time, agents can learn about other possible activities through discussions with other citizens. Depending on individual routines, "activity links" are created and agents will begin to develop preferences for certain places over others based on their past routines and proximity.

Reflecting this, at each tick of the model, each agent's "Current task" is updated. Each current task is governed by a number of parameters, as outlined below (Table 27).

Table 27. Agents' current tasks.

Variable	Type	Description
is-job?	Boolean	TRUE/FALSE is place of work or not
is-mandatory?	Boolean	TRUE/FALSE if free activity
location-type	String	Type of location where activity is performed
Max-agents	Integer	Max. # of agents who can perform activity
Start-time	Integer	Time when activity starts
Duration	Integer	Fixed for mandatory activities only
Criteria	Reporter	TRUE when agent allowed to perform activity
Task	Command	What agents do at each tick during activity
Activity-radius	Integer	Radius of activity space-possible places

3.3.2 MODEL DYNAMICS

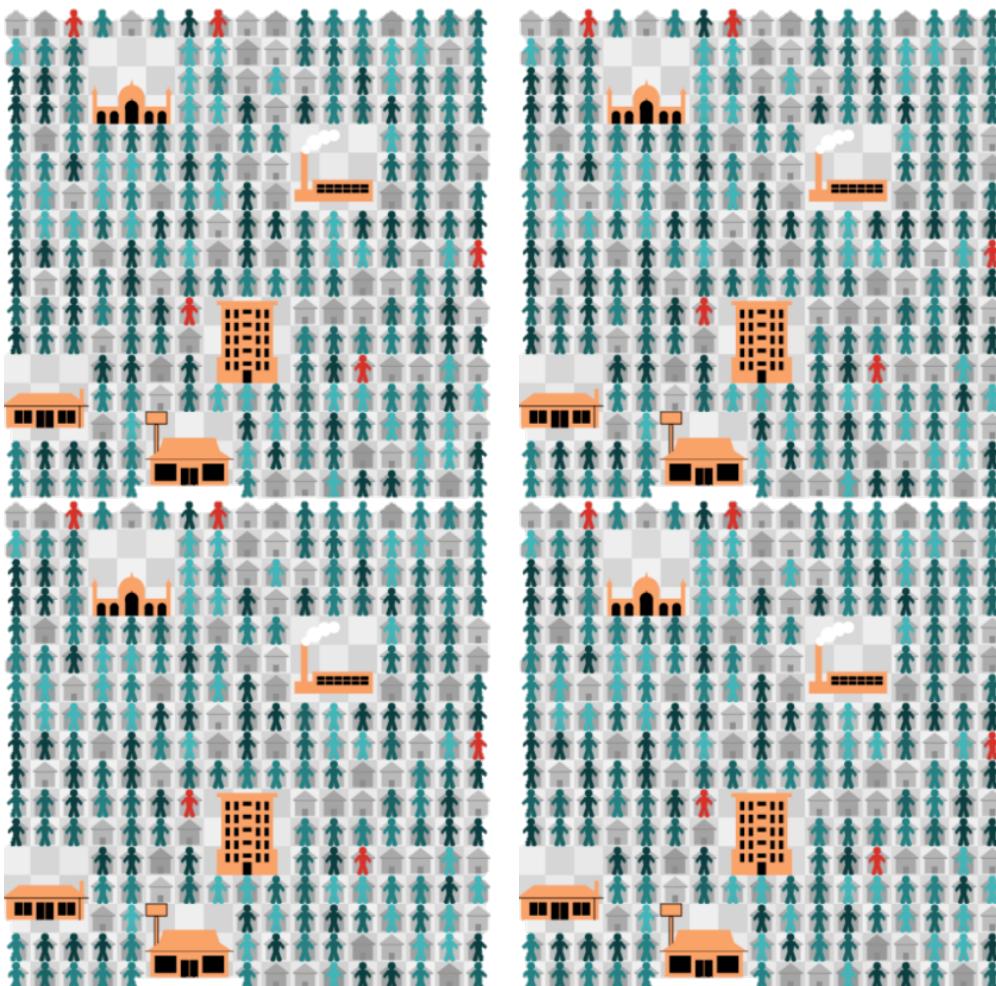
Following from the above, the model's dynamics can be described as follows. The model is based on a 2D environment that represents a borough in a European city which is made up of four adjacent but distinct neighbourhoods. The borough is an ideal unit of analysis because its size limits the effects of confounding variables, helps address issues of computational complexity, and allows for generalizations to be inferred with regards to upscaling (Weisburd, Braga, Groff, & Wooditch, 2017; Weisburd, Wooditch, Weisburd, & Yang, 2016). These neighbourhoods differ in terms of their socio-demographic makeup (including population size), as well as the number of different places (e.g. residences, workplaces, parks, propaganda places, community centres etc.). Each agent carries on daily routine activities in this environment which include certain mandatory activities such as returning home and remaining (to simulate sleeping), and going to work (for employed individuals), as well as free-time activities in which agents are free to choose where they go and what



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they do. Agents spend also some of their time on internet (50% of the time agents spend at home when they are not sleeping).

Figure 23. Four adjacent communities with differing characteristics



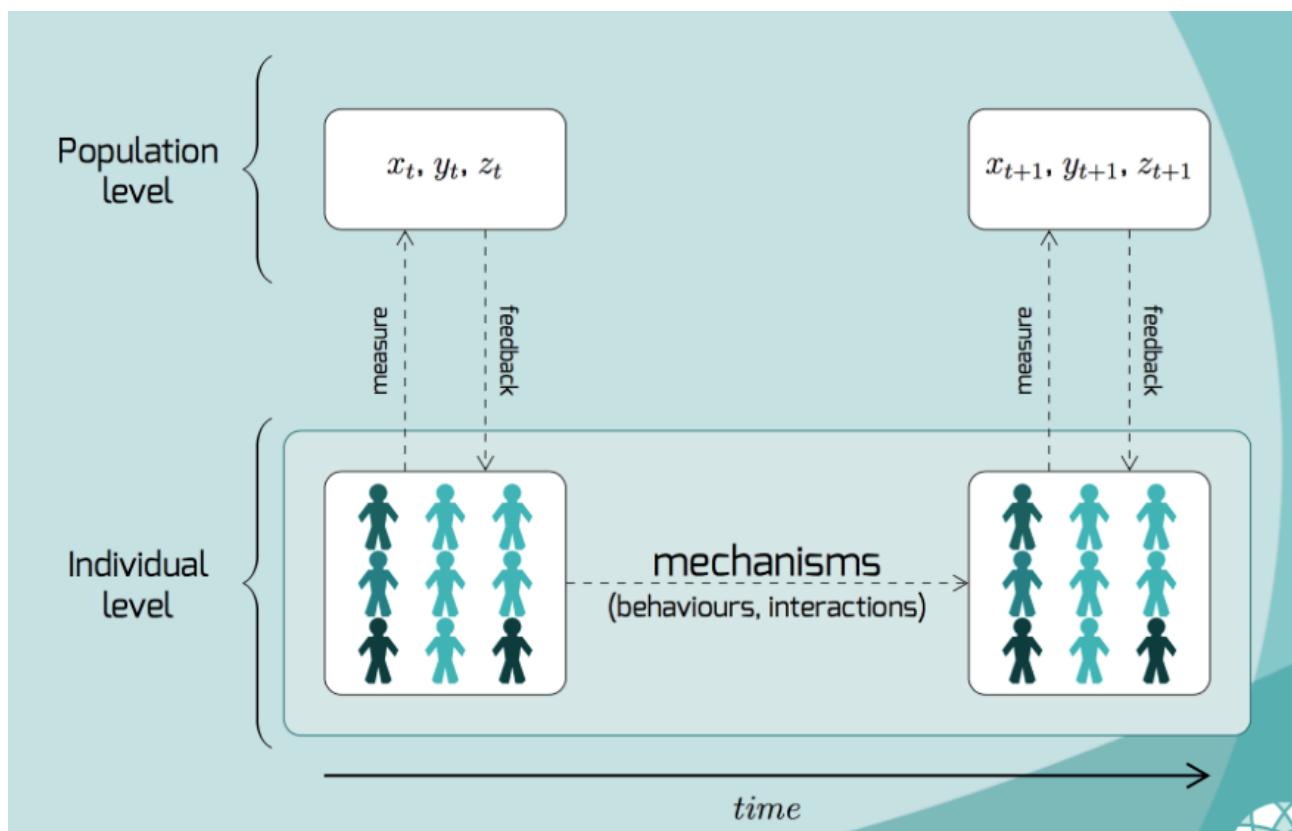
At initialization each agent has both a propensity and a risk score which is calculated based on the characteristics assigned to him/her. Most agent-based models in criminology use routine activities to determine when individuals will converge in time and space in order for a specific event to occur. For example, the convergence of a potential offender and potential victim, or police and offender (e.g. Weisbord et al., 2017, 2016). In this model, routine activities determine when and where agents will converge in time and space to enable differential associations, or interactions to occur. Through these interactions, agents' opinion-topic scores can change in either direction. In addition to face-to-face interactions, agents are able to interact via online communications. These changes affect their dynamic risk score. Agents that are high-risk are those agents who are in the top 5.6% of risk scores at any given tick of the model. These agents are considered to be radicalised *and* at high-risk for recruitment. In order for one of these agents to become recruited, they must interact with a recruiter agent, who is essentially an already recruited



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individual. While recruiters can and do interact with any agent in the model, they are only able to recruit radicalised agents who have reached the radicalisation threshold. In fact, recruiter agents “target” radicalised individuals and “go out of their way” to interact with them specifically. After a certain number of hours of interacting with a recruited agent, a radicalised agent may be recruited, although it is not necessary that they will be. In order to account for the differential outcomes, a normal distribution of the number of hours needed for a radicalised agent to be recruited was constructed based on a mean of 500 hours.

Figure 24. Model overview.



Every time that an agent meets another agent in the simulation in a specific location and they interact, these agents choose from a list of topics to talk about. An agent will be most likely to talk about the topic he or she feels most strongly about.

The three topics which agents discuss when they interact are the following: (i) trust in/legitimacy of institutions, (ii) integration, and (iii) subjective deprivation. These topics were chosen on the basis of an exhaustive literature review regarding the factors that lead to the recruitment into terrorist groups (see D2.1). These factors apply to both right-wing terrorist groups and Islamic extremist terrorist groups. In WP2, a number of individual variables were measured in terms of their effect size regarding their impact on recruitment



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into terrorist groups. The results were that the three mentioned variables (i.e. trust in/legitimacy of institutions; integration, and subjective deprivation) were most significant and had the greatest effect size on an individual level across the literature.

3.3.2.1 DIFFERENTIAL ASSOCIATIONS AND OPINION FORMATION

The mechanism of differential associations, or socialization, is common in ABM. Social influence is recognized as an important part of human interactions more generally. It is recognized that interpersonal encounters are primarily responsible for the development of, and changes to individuals' opinions, attitudes, and beliefs. It is through interpersonal encounters that opinions, attitudes, and beliefs change, moving towards greater agreement or opposition to those of the individuals with whom an individual interacts (Flache et al., 2017) (Figure 25).

Figure 25. Opinion dynamics.



While previous models of radicalisation have sometimes included, or even been based on opinion dynamics, they are typically quite specific and examine only radical attitudes (radical cognitions). But there are other relevant antecedents to cognitive and behavioural outcomes of interest in ABMs such as social norms (Andrighetto, Campennì, Conte, & Paolucci, 2007; Conte, Andrighetto, & Campennì, 2013; Székely et al., 2018). As Conte and Castelfranchi (1995) explain, in ABM, social norms can increase or reduce the likelihood of a behavioural outcome, and, or serve as outcomes in and of themselves. This perspective is directly in line with differential associations and social learning theory which holds that the balance of definitions that one receives that are supportive are oppositional vis-à-vis a given behaviour is what increases or decreases the likelihood that the individual will engage in the given behaviour (Sutherland & Cressey, 1947).

Following from this, the current model focuses on the holding of, and changes to attitude-based risk and protective factors as increasing or decreasing risk of radicalisation (belief) and recruitment (behaviour). Changes to these factors



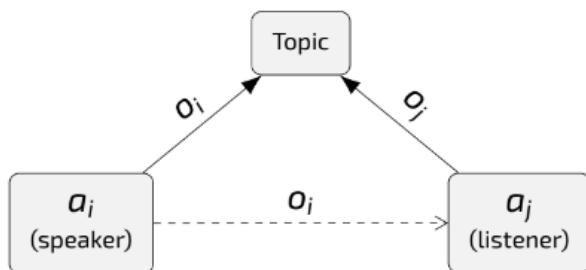
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occur through a variant of the similarity biased influence opinion dynamic model. In this model, only opinions that are sufficiently similar can influence each other, bringing the opinions to be closer to each other. Unlike other model options, the similarity-based model is useful for avoiding situations in which consensus can be theoretically achieved. In fact, this model provides the possibility that where similarity bias is sufficiently strong, multiple homogenous, distinct clusters of individuals emerge, but remain within the relative range of the initialization of the opinions' distribution (Deffuant, Neau, Amblard, & Weisbuch, 2000; Flache et al., 2017; Hegselmann & Krause, 2002).

Influencing the opinion of agents regarding their trust in institutions and their legitimacy, is the interaction of the agents with the police in the simulation. This interaction is based on data regarding the number of people who interact with the police in Neukölln, taken from the Neukölln criminality report (2016).

The opinion dynamic function is based on the following process (see Deffuant et al., 2000; Flache et al., 2017; Hegselmann & Krause, 2002):

Figure 26. The opinion dynamic process.



Each interaction is governed by the level of tolerance of each agent which is calculated as: $t_j = 1 - \alpha|o_j|$. Interactions are classed as "successful" when the initial difference in opinions is below the level of tolerance, as indicated by: $|o_j - o_i| < t_j$. In this successful interaction, o_j 's opinion is updated in the direction of o_i 's to a degree dependent upon t_j as defined by: $\Delta o_j = t_j \times \frac{o_i - o_j}{2}$. This approach to update opinions therefore allows for the possibility that a successful interaction can be related to only one or two topics. The same function is used for the "broadcasting" of opinions by "special" agents, namely, community workers and propaganda agents.

In addition to face-to-face interactions, agents are able to interact via online communications. Prior studies have shown that social media is primarily used as a tool to maintain and further offline connections. That is, the primary people with whom individuals interact with online are those who they also know offline. However, as demonstrated by T2.1, the effects of online engagement are about half the size as offline peers/friendship. As such, we applied the same opinion-dynamics model to online communications, whilst



reducing the overall effects by half. Each agent is able to spend up to 25% of their free, leisure time using the internet, in line with the average amount of time spent on social media in Germany (Global Web Index, 2018).

As opposed to ordinary citizen agents and opinion-leader broadcasting agents (such as, propaganda agents and community worker), ordinary police agents have either a neutral or negative impact on citizen agents' trust/legitimacy score. In a typical German city, about 23% of citizens have police contacts in a year, with young, migrant males being more likely to have a police contact (Oberwittler & Roché, 2013). Research from the "Zusammenleben in Nord-Neukölln" (Hirseland & Lüter, 2014) report indicates that about 19.3% of police-citizen interactions have specifically negative effects on opinions pertaining to trust and legitimacy, as well as relative deprivation (in the form of perceived discrimination). The overall effect of negative police encounters on trust/legitimacy was calculated from an internal meta-analysis using the data from T2.1, with an effect of Cohen's $d = -.691$.

Following from this, these special agents spread their opinions through the same opinion-dynamics function, albeit that instead of communicating only with a_j , they communicate with a set (either limited or unlimited) of receiving agents who each represent a_j in parallel and simultaneously.

3.4 Model Context

3.4.1 NEUKÖLLN (BERLIN, GERMANY)

The radicalisation and recruitment literature highlights that in the West, radicalisation and recruitment generally occur within individuals' immediate communities. In fact, a handful of communities and neighbourhoods in Europe have been found to produce a disproportionate amount of radicalisation and number of recruited individuals (Innes, 2006; Kenney, 2011; Slootman & Tillie, 2006; Van Vlierden, 2016). Indeed, counter-radicalisation initiatives in Europe are often taken at the city, and borough levels. Whilst cities and neighbourhoods vary widely, boroughs across western European contexts tend to share much in common. This is because boroughs are more homogenous than cities are (albeit still quite heterogeneous). As described in D4.1, using boroughs as a size for modelling has a high level of parsimony in addressing the needs of both computational capacity, scalability and generalizability.

The city borough chosen to serve as the basis for our model was Neukölln, Berlin, Germany. It is certainly advantageous that as a borough of Berlin, a large amount of publicly available data exists for Neukölln. In particular, censuses, polls, and opinion surveys provide the type of data needed for building the model's landscape and initializing the agents. A number of studies



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have also described the nature of radicalization in Neukölln, and the characteristics of different places relevant to radicalization, recruitment, and counter-radicalization. But more importantly, Neukölln was selected for its representativeness of boroughs in major western European cities in terms of its makeup, demographics, and experiences with radicalisation and recruitment for right-wing, left-wing, and religious elements. Many parts of Neukölln share characteristics with other European boroughs—such as Anderlecht in Brussels, the 20th arrondissement of Paris, and Feyenoord in Rotterdam—in which radicalization can flourish (Husbands, 2002). Neukölln has been referred to as a “high risk” borough with the potential for radicalization to be much worse than what it currently appears to be (Shoshan, 2008; Soederberg, 2017).

Neukölln is one of Berlin's largest districts/boroughs, home to about 350,000 residents and has been home to a highly multicultural population for the last few decades. The number of poor, immigrant and ethnic minority families has increased in recent decades, leading to a downturn in the social and quality of life in the area. However, in recent years, the area has also become quite popular among students and has undergone a period of gentrification. The borough has also absorbed a large number of immigrants from the middle east since 2011, which increased its proportion of immigrants to over 20% in total.

Whether on account of, or despite its multicultural makeup, Neukölln has unfortunately seen its fair share of extremism from all sides of the spectrum. In recent years the borough and its residents have suffered from violent riots and attacks carried out by right-wing, left-wing, and Islamic extremists. Security forces have paid close attention to specific mosques for promoting extremism, as well as certain locations around the city where individuals have been arrested for planning attacks based on both right-wing and left-wing ideologies. But located around Neukölln are also places that actively work against different forms of extremism. For example, while certain mosques are known for promoting extremism, others, such as the Şehitlik mosque operates a community centre and community-oriented programs that seek to prevent extremism (OSCE, 2018).

In fact, a number of community-oriented programs exist in Neukölln working against both Islamic and Nationalist forms of extremism, borrowing from approaches already implemented against right-wing extremism. These programs exemplify the community-based approaches that have been undertaken in other European cities (Berczyk, 2013). In addition to community-oriented initiatives, initiatives to promote public and social services, as well as employment, have already been implemented to varying degrees with a view to combatting radicalization (OSCE, 2018). Nevertheless, it remains unknown if these initiatives have any effect (Buschkowsky, 2013).

Neukölln is composed of four adjacent but distinct communities: Neukölln, Britz/Buckow, Gropiusstadt, and Buckow Nord/Rudow. Each of area has its



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own distinct characteristics, and research has found that places of recruitment are dotted around the different neighbourhoods. For example, the Al Nur mosque is widely known for promoting extremism. An anarchist housing project was previously raided in Neukölln and firearms and other weapons, as well as a terrorist plot were uncovered there. On the other hand, the areas of Gropiusstadt and neighbouring Buckow Nord/Rudow are known for their right-wing extremist presence. Gropiusstadt is known to be home to neo-Nazi gangs as well as Muslim-Arab gangs.

To maintain order and a safe environment, between 2017-2018 a large number of individuals were arrested in Neukölln on charges related to politically motivated crimes. The numbers show however a relatively steady stream of individuals engaging in illegal behaviours and being arrested by the police, with little signs of a drop in these numbers.

According to official data, the communities of Neukölln, Britz/Buckow, Gropiusstadt, and Buckow Nord/Rudow differ in terms of their socio-demographic makeup and other socio-economic characteristics. For example, the population is youngest in Neukölln, followed by Britz-Buckow, with considerably older populations residing in Gropiusstadt and Buckow Nord-Rudow. The areas also differ in terms of their inner-area population mobility. Neukölln has the highest rate of residents moving within the area, followed by Gropiusstadt, Britz/Buckow, and Buckow Nord/Rudow having the lowest. However, the picture of overall population growth is more difficult to dissect given that official data split up these four areas into smaller geographic units. Nevertheless, Neukölln and Buckow Nord/Rudow have similarly high levels of population growth, followed by Gropiusstadt, and Britz/Buckow with the lowest.

The number of individuals living in single family dwellings is highest in Neukölln, followed by Gropiusstadt and Britz/Buckow that have similar levels, and Buckow Nord/Rudow with the lowest. The levels of population density also follow this order, with Neukölln and Gropiusstadt at about 13,000 inhabitants/km², Britz/Buckow at about 6000, and Buckow Nord/Rudow at about 3000. In fact, Neukölln has the highest population density area in all of Berlin.

Levels of unemployment among the populations are by far the lowest in Neukölln, which also showed a worsening trend in the period of 2009-2014. The area of Gropiusstadt is home to the second largest population of unemployed residents, while unemployment is considerably lower in Britz/Buckow, and lowest in Buckow Nord/Rudow. The level of dependence on welfare and social services follows the same pattern. In fact, Neukölln may have the largest proportion of residents on social services than any other locale in Berlin. While in Neukölln and also Britz/Buckow the number of people



dependent on these services was improving over the period between 2011-2014, they worsened somewhat in Gropiusstadt during the same period.

During the period of 2011-2014, the largest proportion of planning and development was in the area of Neukölln, followed by Gropiusstadt, Britz/Buckow, and Buckow Nord/Rudow. According to social-inequality indexes, Neukölln is the worst of the four areas in terms of relative deprivation, followed by Gropiusstadt, Britz/Buckow, and Buckow Nord/Rudow. Between 2008-2013 however, the direction of these measures was showing an improvement in most of Neukölln, although a decline in the area that comprises the border between Gropiusstadt and Britz/Buckow. In Buckow Nord/Rudow some areas showed an improvement whilst others experienced a decline. Nevertheless, over the entire period this area remained the strongest relative to the other three areas.

Overall, the top 5 "high risk" places identified by the social-inequality reports as being most in need of support and development in 2013 were all located in the northern section of Neukölln, even though all of them had experienced improvement between 2008-2013.⁸

We believe that the chosen borough represents a prototypical layout, which only differs marginally from other places in terms of its socio-demographics and environment. Large boroughs in other major European cities are also made up of adjacent neighbourhoods which can differ greatly in their socio-demographic makeup and other characteristics. Similarly, certain neighbourhoods are more likely than others to be home to hotspots of recruitment and concentrations of extremism. Like other boroughs of major European cities, there is a lot of mobility by residents between the neighbourhoods, especially for routine activities such as school, shopping, leisure, travel, and employment etc.

3.5 Calibration, Validation, and Sensitivity Analysis

The current study builds on the theoretical and quantitative outputs of PROTON's WP2 and models individual level radicalisation and recruitment to terrorism as it occurs within a borough of a major European city. It draws on official survey data to create the population and the individual-level characteristics of citizen agents. The use of survey data for populating ABMs has been widely used in geography and other fields but has rarely been used in

⁸ The information described in the above section was derived from the data presented in Sozialbericht Neukölln zur sozialen Lage der bevölkerung (Berlin, 2016).



sociology and the modelling of social processes more generally. We follow the general guidelines set for by Williams, O'Brien and Yao (2017) for applying survey-level data to the populating of the ABM. Additionally, unlike ABMs based entirely on theoretically driven characteristic distributions, survey-based ABMs are more useful for the testing of experimental conditions and the identification of causal chains and mechanisms (Williams et al., 2017). The primary difference between our approach and that of Williams et al. (2017) is that rather than using regression equations on the original survey data to establish probability weights, the weights for the different factors derived from the surveys are drawn from the results of T2.1.

3.5.1 MODEL PARAMETERS

The model runs for a duration of time that represents a 6 months period, for a total of 3060 steps (ticks), where each step represents an hour, and hours in which agents "sleep" not being counted as steps. The parameters of the model therefore update at each tick of the model (Table 28).

Table 28. Terrorist recruitment model parameters

Variable	Value	Total
Number of communities	$\{n^2 (n \in \mathbb{N}_{>0}) \wedge (n^2 \bmod 2 \neq 0)\}$	4
Community side length	$\mathbb{N}_{>0}$	30
Citizens per community	$\mathbb{N}_{>0}$	10,000
Activity radius	$\mathbb{N}_{>0}$	
Tolerance (Alpha)	[0,1]	
Shape (Places)	String	
# of agents	40,000	40,000
Tick	1 hour	3060

The current ABM relied on a number of different data sources for calibrating the model. Data was needed to calibrate the environment, its places, the population, the population's characteristics and opinions, the number of radicalised individuals, the number of recruited individuals, and the effects of different types of agents and encounters. In addition to the data provided by WP2, the model includes a large amount of real data derived from a combination of official data sources and existing quantitative literature (Table 29).

Table 29. Summary of factors and their data sources

Factor	Source
Individual-level factors	
Demographic data Age, Gender, Employment status, religion,	Statistik Berlin-Brandenburg (2017)



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migrant status	
Criminal history	Camino (2017)
Psychological characteristics	European Values Study (2008)
Authoritarianism	
Opinion dynamics factors	European Values Study (2008)
Trust, integration, subjective deprivation	
Weights for individual-level factors	T2.1
Environmental factors	
Size and density of neighbourhoods	Statistik Berlin-Brandenburg (2017)
Number of police	Berlin Police (2018b)
Proportion of radicalised individuals	European Values Study (2008)
Number of recruiters and recruited individuals	Berlin Police (2018b)
Types and number of places (e.g. cafes, parks, community centres)	Google Earth
Characteristics of risky places	Becker (2017, 2019)
Experiential factors	
Time spent online	Global Web Index (2018)
Weight of online communication	T2.1
Recruitment time	Klausen et al (2016)
Police-citizen encounters	Oberwittler & Roché (2013)
Proportion of negative encounters	Hirseland and Lüter (2014)
Weight of negative police encounters	T2.1
Weight of positive police encounters	Gill et al (2014)

The process of calibrating the model with the above data was carried out in three stages. In the first stage, the layout of the environment needed to be calibrated, primarily with respect to its overall size, the size of each of its four areas, as well as the number and types of places located within the overall area. Secondly, each area was assigned a population of agents who possessed socio-demographic characteristics. Thirdly, each agent was assigned with a number of opinions pertaining to different topics.

3.5.2 ENVIRONMENT AND POPULATION

For the first stage, we utilized statistics from the Berlin Central Bureau of Statistics (CBS) for Neukölln. The CBS statistics are split into Neukölln's four neighbourhoods: Neukölln, Britz/Buckow, Gropiusstadt, and Buckow Nord/Rudow. As described in Section 3.4.1, each of these areas differ substantially in terms of their spatial characteristics and the socio-demographic characteristics of the population. As such, the number of agents and their socio-demographics were assigned to residence in each of these four areas



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according to the official statistics, including the number of males and females, their ages and their employment status.⁹ The data appears to provide a picture that reflects the description of the different neighbourhoods and their populations as discussed above in Section 3.4.1.

The number and types of places (e.g. community centres, parks, public spaces and workplaces, propaganda places, and cafes) for each of the four communities was determined based on data obtained from Google Earth and Google Maps. We subsequently carried out extensive searches to identify the proportion of these places that could be characterized as normative meeting places or “risky” places, and their locations, for Islamic (Becker, 2017, 2019), right-wing (Lewek, 2016), and left-wing forms¹⁰ of radicalism.

Subsequently, using data from the Neukölln Criminality Report (Camino, 2017), we estimated that 2% of the population have a criminal record. We subsequently assigned criminal histories to 2% of the population based on their socio-demographics and areas of residence according to the report’s statistics that broke down the number and proportion of offenders for each of the four areas (Table 30).

Table 30. Neukölln Environment and Population data.

Factor	Area 1 (Neukölln)	Area 2 (Britz/Buckow)	Area 3 (Gropiusstadt)	Area 4 (Buckow Nord/Rudow)
Population size	155,950	35751	38219	29029
Population density	13000	13000	6000	3000
% of males	51.2	47.3	48.1	49.1
# of immigrant Muslims	31316	8120	6573	10107
% 0-17	16%	16%	15.00%	16.00%
%18-64	74%	55%	58.00%	63.00%
%65+	10%	28%	27.00%	21.00%
Unemployment males	12%	12%	7.50%	6.50%
Poverty rates	30%	35%	15.00%	13.00%
Collective relative dep. rating (avg. from 1-7)	5	5.5	3	1.5

At initialization the model includes five recruited/recruiting agents. These agents are positioned in four risky places and one neutral place for a

⁹ The data also included individuals’ estimated religion and immigrant status but these factors were not included in the model as the interest was in general radicalization and recruitment.

¹⁰ Due to a lack of studies we relied on a number of different media reports which detailed known “squatting” places of anarchists who have been raided by police, as well as other places associated with left-wing extremism and recruitment, such as a bookstore. These raids have led to the arrests of individuals involved in terrorism activities, including arson, as well as planning, and the uncovering of weapon caches.



proportion of their day in addition to their routine activities. They engage in recruiting activities for an average of 3 hours per day, based on a normal distribution.

3.5.3 OPINION INITIALIZATION

In the second stage, we utilized the European Values Study (2008) (EVS) for Germany to create four variables: one for the propensity score (authoritarianism/fundamentalism) and the three-dynamic opinion-based risk-protective factors, namely integration, trust/legitimacy, and subjective deprivation. The inter-reliability for the four created variables (authoritarianism, integration, trust, and subjective deprivation) remained relatively stable compared with the initial values. We subsequently used propensity score matching to identify the opinion profile cases that had the highest propensity matches to the agents in the model. We then distributed the opinion profiles from this sample to the 40,000 agents based on their individual characteristics (age, gender, criminal history, and employment status).

3.5.3.1 AUTHORITARIANISM

Authoritarianism is a personality trait that is characterized by submission to a higher authority, moral absolutism, racial/ethnic prejudice, and disdain for "deviants". Right-wing authoritarianism and religious authoritarianism or fundamentalism are virtually indistinguishable from each other (Altemeyer & Hunsberger, 1992, 2004). There is however a debate as to whether authoritarianism is an innate personality trait or a learned set of attitudes (Adorno, Frenkel-Brunswik, Levinson, & Sanford, 1950; Altemeyer, 1996). This mirrors the debate about innate criminal propensity more generally. Prior research on religious authoritarianism has actually found it to be a predictor of other criminal propensity factors, such as low self-control (Schils, 2014). The results of T2.1 highlight that authoritarianism/fundamentalism is a key risk factor for radicalization and recruitment to terrorism.

The measure for authoritarianism from T2.1 consisted of 30 items (Chronbach's alpha=.847, M=5.012, SD=.918). The first set of items consisted of three pro-authoritarian and three anti-authoritarian measures concerning the rearing of children. The use of these factors in the EVS as proxies for authoritarianism has precedence in the literature which finds that views on child rearing have a high level of inter-reliability with authoritarianism (Feldman, 2003). Following the approach of Tillman (2013), we added three additional variables related to religious authority being mixed with political authority, as well as an additional measure assessing respondents' views that the state's primary role is to maintain order. We subsequently added 20 measures assessing tolerance for a range of deviant-normative behaviours related to political decisions.



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3.5.3.2 INTEGRATION

Integration/non-integration, or acculturation, or social connectedness relates to the degree that an individual feels they are a part of the society in which they exist. Feeling that one is not integrated in their society, or is otherwise disconnected from it, can lead to alienation and is a key risk factor for radicalization (Doosje, Loseman, & Bos, 2013). The results of T2.1 found that among dynamic factors for which independent effects exist for both protective and risk dimensions, integration had a stable and modest effect in both directions. As detailed in D2.1, integration's role in radicalisation and recruitment has been considered for both its risk and protective potential (Ellis, Sideridis, Miller, Abdi, & Winer, 2019; Ventriglio & Bhugra, 2019).

The variable for integration consisted of 6 items (Chronbach's alpha=.69, M=1.85, SD=.503). The items included assessed how much weight respondents attributed to being proud of being from their country of residence, speaking the local language, respecting the local country's values and laws, being born in the country, being part of the country's ethnicity, and living in the country for a long time.

3.5.3.3 TRUST/LEGITIMACY

Institutional trust and legitimacy relate to the degree to which individuals view the state and its institutions as having the authority to govern them. Low levels of trust and legitimacy have been found to be correlated with radicalization and recruitment outcomes (T2.1). The results of T2.1 found that among dynamic factors, factors relating to institutional trust and legitimacy of the law had exceptionally large effects as both risk and protective factors. As detailed in D2.1, institutional trust and legitimacy have often been considered in the literature as factors which can promote radicalisation, or act as a buffer against it (Ellis et al., 2019).

With regards to trust/legitimacy we combined 8 items (Chronbach's alpha=.849, M=2.71, SD=.526). The items assessed to what extent the respondents had confidence in the Education system, Police, Parliament, Civil Service, Social Security system, Judicial System, Government and Political parties.

3.5.3.4 SUBJECTIVE DEPRIVATION

Relative, or subjective forms of deprivation refer to situations in which individuals view themselves or their in-group as being less well off than a reference group, often as the result of systematic discrimination. Subjective deprivation has long been to radicalization and recruitment outcomes. The results of T2.1 highlighted that objective socio-economic status had an exceptionally weak connection with radicalisation. While it is still popular to discuss the role of socio-economic status and radicalisation, the literature is



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quite clear that its correlation with radicalisation is poor. However, as the results of T2.1 identified, and in line with theoretical perspectives, individual and collective forms of subjective deprivation can represent an important risk factor for radicalisation. The literature also highlights that subjective deprivation can be affected by perceptions of legitimacy of authorities and vice versa (Tyler, 2006).

Unfortunately, the EVS (2008) does not include data that would allow us to assess the full spectrum of relative deprivation. As such, whilst an imperfect measure, we follow prior studies that have used EVS data as a proxy for subjective deprivation by combining measures of subjective satisfaction with relative income (Lepiaska, Gelissen, & van Oorschot, 2010). As such, we combined 5 items (Chronbach's alpha=.69, M=5.316, SD=.998) that includes measures assessing life satisfaction, life happiness, life self-control and job satisfaction, as well as purchasing power parity adjusted income.

3.5.4 PROPENSITY AND RISK SCORES

After every agent is assigned each of the characteristics described above, a propensity and risk score were calculated for each of them. While other survey based ABMs have used regression-based methods to estimate the weights for independent variables (e.g. Gore, Lemos, Shults, & Wildman, 2018; Williams et al., 2017), in this study the weighting for each of the variable was based on the results of T2.1, using the Cohen's *d* statistic (Table 31).

Table 31. Propensity and risk scores.

Factor	Risk effect	Protective effect
Propensity score		
Age (Under 25)	.10	
Male	.113	-.065
Unemployed	.171	-.176
Criminal history	.678	
Authoritarianism	.857	
Risk score		
Integration	.376	-.355
Trust/legitimacy	.554	-.678
Subjective deprivation	.285	

Note: Empty cells indicate that the factor has no specific protective effective.

3.5.5 ANALYTIC STRATEGY

In order to calibrate the ABM, a series of tests were conducted at each stage of the building of the model. In the final version of the model, a base model was



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run for a total of 40 runs to ensure stability. Following these runs, the results of the base model were averaged to create the baseline statistics. Subsequently, the selected experiments (see Section 3.6) were conducted, with a total of 40 runs per experiment, for which the results were averaged. Comparisons were then made between the results of the base model and the experimental condition models in order to assess effect of the experiments on the primary outcomes of interest.

3.5.6 VALIDATION

In addition to the base model, we ran a series of sensitivity tests. In this stage, it is necessary to assess whether the model is operating and predicting as expected, and that it is accurately reflecting the setting and dynamic that it represents. This type of internal validation was conducted by manipulating key factors in the model—such as the proportion of females and unemployed (Gerritsen, 2015). Extreme manipulations of these variables should result in extreme changes to the model's outcomes. When the models perform as expected, given these changes, they can be said to have an acceptable degree of internal validity.

External validation was conducted by comparing the output opinion distributions and risk scores at the end of the models with data derived from the recent release of the European Values Study (2017) for Germany. All the primary variables used in the initial set up of the model, which were derived from the 2008 survey, have remained the same. The only differences between the 2008 and 2017 surveys pertains to the proxy used to set the cut-off level for radicalization. The 2008 version of the survey used a dichotomous measure assessing justification of terrorism, in which 5.6% indicated that it can sometimes be justified. The 2017 version of the survey however replaced this question and instead used a 1-10 Likert scale measuring justification of politically motivated violence. According to this scale, any selection above 1 (never justifiable) indicates some level of justification for politically motivated violence. However, given the distribution of responses to this variable, we selected 3 as being the cut-off. Accordingly, 5.9% of respondents indicated that politically motivated violence can sometimes-often be justified. This number represents a small increase from the 5.6% of respondents to the 2008 survey who indicated that terrorism can sometimes be justified. The highly similar proportion is in line with the hypothesis that across populations, levels of radicalization have remained relatively stable over the last decade. The similarities also indicate that the cut-off selection of "3" from the 2017 survey is theoretically justified.

In order to assess stability of the output of mean recruitment, we used statistics from the "Lagedarstellung politisch motivierte kriminalität in Berlin" (Polizei Berlin, 2018b). These statistics include the number of individuals arrested and charged with politically motivated crimes in Berlin annually. The



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data includes separate measures for Neukölln, for each ideology (e.g. left-wing, right-wing, religious), the proportion of the types of offences (e.g. violent and non-violent offences), and a bi-annual breakdown by these categories. This project follows the EU's definition of recruitment, which considers that someone who has been solicited to commit a terrorism-related offence can be said to have been recruited.

These two data sources provide for the ability to gauge the degree of external validity of the model. If the outcomes of the model are within a reasonable range of similarity to these real-world data, then the model can be said to have an acceptable level of external validity.

3.5.6.1 THE DARK FIGURE OF RADICALIZATION AND RECRUITMENT

Our ABM is intended to predict the number of recruited individuals in a population. One issue that exists in terms of validation for ABMs of this nature is that the output ought to include measures of the outcome which can be validated, but which also include the so called "dark figure", which is difficult to validate (Troitzsch, 2017). A dark figure exists for every type of crime but there is great variation between different crimes. For example, while the dark figure for homicide is believed to be quite low, for other crimes the dark figure can rise to as high as 95% (Roberts, 1995).

With respect to terrorism itself, in terms of attacks, the dark figure should be quite low, since terrorism attacks are generally public knowledge. The dark figure of terrorism therefore generally refers to the idea that official statistics do not include all instances of terrorism, both successful and unsuccessful (Decker & Pyrooz, 2015; Falkenrath, 2001). Included in this dark figure would be attacks that were aborted for a variety of reasons and which may or may not have come to the attention of authorities (Anarumo, 2005). While the number is thought to still be quite small, for some terrorism-related crimes, such as kidnappings, the dark figure could be as high as 90% (Zuccarello, 2011). For hate crimes, which have often been referred to as being closely related to terrorism, the dark figure hovers around 60% (Bowling & Phillips, 2003).

In discussing the dark figure of terrorism, Kellett et al.'s (1991) report for the Government of Canada highlights some of the key issues. Terrorist attacks, for the most part, will be public knowledge, and while some analysts believe that a small proportion may be kept secret from the public, the dark figure is likely to be quite small. However, the majority of terrorism offences are non-violent offences, as identified by a number of studies. The dark figure is likely to be much higher for the undetected population of non-violent terrorism offenders, such as those providing material support, or who are engaged in planning activities (Kellett et al., 1991). Indeed, external validation data Berlin confirms that the majority of terrorism-related offences by residents of Berlin, and Neukölln specifically, were non-violent (Polizei Berlin, 2018b, 2018a). As such,



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the issue of the dark figure of recruitment to terrorism is more complex than the dark figure of crime since it pertains to the underestimation of the number of individuals involved, or active, and not to events that have merely gone unreported by victims. The dark figure therefore relates more to the size of a "hidden population". It could also be, that similar to other conflict related crimes and offenders, terrorism offending could be a case in which this "dark" figure is a "doubly-dark figure" (Bijleveld, 2007). As such, methods such as using victimization surveys to estimate dark figures are not applicable, which in any case are lacking in Germany and other European countries (Leitgöb-Guzy, Birkel, & Mischkowitz, 2017).

The literature highlights that it is notoriously difficult to estimate the scope and size of membership in terrorist organizations, networks, and groups. Traditional methods for identifying these "hidden populations" are especially difficult with respect to this phenomenon (Davies & Dawson, 2014). In a study of 499 organizations, Asal and Rethemeyer (2008) had "low confidence" in the number of members from 77 organizations. A recent study that attempted to estimate the number of terrorists in ISIS-affiliated groups in Africa highlights that even between different official intelligence agencies, estimates can differ by up to 50% (Warner & Hulme, 2018). The case of foreign fighters also highlights discrepancies in official and non-official statistics, highlighting the definite presence of a dark figure. While in some cases estimates from official data can be somewhat higher, non-official data are more likely to have identified larger numbers. For example, in the case of Australia, the number of reported foreign fighters as of 2015, was only 120 according to official data but 255 according to reliable, non-official data. Similar rates of discrepancy were found for Spain (Benmelech & Klor, 2018).

Another factor that must be taken into consideration is the way that official statistics are recorded. For example, depending on the nature of the offence, prosecutors may prefer to apply only ordinary criminal charges, for which the likelihood of conviction is higher. Indeed, in the U.S., the FBI has stated that only 25% of terrorist offenders were being charged with terrorism related offences, mostly on account of such considerations (Mueller & Stewart, 2012, 2014).

A possible indicator of the extent of the dark figure may be gauged from gangs and gang members, who have often been likened to terrorist groups and terrorists. Some have estimated that gang membership may be as much as two and even three times higher than official estimates (Pyrooz & Sweeten, 2015).

Official statistics therefore provide an "at least this much" estimate of the crime-related phenomena being examined (Flyghed, 2013). Based on the above, we believe that the best "at least this much" estimates of recruitment among radicalized individuals represent only about 25-50% of those actually



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recruited. The remaining 50-75% are made up of individuals who may already have been included among those arrested or charged on non-terrorism related charges, who are under surveillance, or who remain entirely unknown to authorities.

The nature of our external validation data supports the bottom-line estimate of a dark figure of 50%. For example, if we accept the widely held conservative estimate that only 1% of radicalized individuals will ever act upon their radicalized beliefs (McCauley & Moskalenko, 2017), and according to the EVS data 2008 5.6% of individuals are “radicalized”, we would expect 1922 cases of “recruitment” in Berlin. According to the data from the Berlin politically motivated crimes, the number of arrests for the first half of 2018 was 1646. Scaling down to the level of Neukölln, if 1% of radicalized individuals were to be recruited, we would have 179 cases of recruitment, whereas the official statistics for the first half of 2018 put the number at 154. As such, these estimates are fairly accurate in terms of what is known but do not include the dark figure.

According to the definition of recruitment, another proxy for gauging the extent of recruitment is expressed intentions, or admission to willingness to engage in radical violence. According to findings from studies included in T2.1, which assessed “radical intentions”, an average of 2% of respondents indicated a willingness or intentions to engage in radical violence. This number is essentially double that of McCauley and Moskalenko’s 1% estimate.

Additionally, according to a 2017 report (Senatsverwaltung für Inneres und Sport, 2017), Neukölln is one of Berlin's three centres for Salafists and Jihadists. According to the report, there are 850 known Salafists, of which 470 are potentially violent and under surveillance. Of those for whom place of residence is known, 145 (20%) reside in Neukölln. A total of 201 are members or frequent visitors to a known radical mosque located in Neukölln. In total, 88 of these are known Salafist Jihadists, which the report describes as being those known to exercise violence, who “are willing to use force or support acts of violence. e.g. acts of violence are considered supportive of logisticians to procure weapons and clothing, as transporters of materials in combat zones abroad or by collecting money for Terror organizations” (Translated from German). As per the report, the above number does not include those already arrested or incarcerated (see Senatsverwaltung für Inneres und Sport, 2017). We can estimate, scaled down to our ABM's population of 40,000, at least 12 known Jihadists. If similar numbers of right-wing and left-wing extremists were to be included, then the number of “recruited” individuals from this category would reach 36. If we assume that 50% of recruited individuals are unknown, then we would expect about 72 individuals overall. As described below our base model produces 77 recruited subjects, which is very close to this number and suggests that our model is producing a realistic landscape for the experiments that we run.



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3.6 Policy Scenarios and Model Assumptions

3.6.1 BACKGROUND

Since researchers and policy makers have adopted the term “radicalisation”, there has been a growing focus on counter-radicalisation and de-radicalisation policies and initiatives. While the literature on counter-radicalisation strategies is now quite rich, there is little empirical evidence, and a near absence of experimental evaluation of policies (Marret, Feddes, Mann, Doosje, & Griffioen-Young, 2013). For the most part, policies aim to change the attitudes and beliefs of individuals, promoting the legitimacy of democratic values and institutions, and delegitimizing illegal, and non-normative values and behaviours.

From a criminological perspective, promoting accepted norms, normative values, and societal connectedness has long been viewed as a protective package against criminal attitudes and behaviours. These components can all be placed within the Social Bond and Social Control theory frameworks (Hirschi, 1969). As has been identified in the literature, there is a significant overlap between the protective factors for general youth delinquency and violence and radicalisation, and factors derived from social bond and control theories figure prominently (Lösel, King, Bender, & Jugl, 2018).

Indeed, most counter-radicalisation initiatives in western, and especially European countries, implicitly seek to target familiar risk and protective factors, although different policies give different weight to different domains. For example, many policies focus on integration, referred to seemingly interchangeably as societal connectedness, cohesion, and acculturation (Rahimi & Graumanns, 2015). Other policies place a greater emphasis on developing trust and legitimacy towards societal norms, values, and institutions (Lindekilde, 2012). Yet other policies focus more on the empowering of individuals through the provision of skills training, education and employment opportunities. While each European country may place a greater emphasis on one focus over another, for the most part, all countries have policies that deal with each of these domains in some way (Council of the European Union, 2004).

Despite the differences in their primary focuses, these policies share an important commonality, namely that they do not challenge radicalisation, or radical attitudes head-on. Rather, they seek to tackle underlying risk and protective factors, especially attitudinal antecedents. In the case of policies like employment, they may seek to reduce the likelihood of, or opportunities for individuals coming into contact with radicalizing influences through changes to routine activities (Simi & Windisch, 2018), whilst increasing the likelihood of them coming into contact with protective influences. As noted above however,



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to date, there is little if any evaluation of the effectiveness of such programs. In fact, according to measures derived from the European Values Study, the proportion of European residents who justify politically motivated violence has increased over the last decade. Additionally, the number of citizens and residents involved in terror attacks at home, as well as abroad, has increased during this period. It is therefore necessary to identify the effectiveness of different counter-radicalisation strategies, as well as their relative effectiveness when compared with each other (Pratchett, Thorp, Wingfield, Lowndes, & Jabbar, 2009).

In a rare experiment, Amjad and Wood (2009) conducted an empathy-based training among a group of Pakistani males. The orientation of the intervention was to affect normative beliefs of aggression. Those who went through the training were significantly less likely to subsequently express a willingness to join a violent, anti-Semitic organization.

In a recent study, Feddes et al. (2015) focussed on a self-esteem and empathy training that sought to specifically impact subjective deprivation and feelings of societal connectedness with a view to reducing radical attitudes and intentions. While the study found that there were some changes in these variables following the intervention, the differences were not statistically significant.

These interventions are actually quite representative of the general policy approaches taken towards counter-radicalisation in the West and Europe in particular. That is, rather than engaging in traditional counter-radicalisation interventions, which seek to directly engage with and change radical attitudes and ideologies, they seek to tackle "risk factors" for radical attitudes and ideologies. These programs therefore generally focus more on issues like promoting integration for "at risk" populations (Pettinger, 2017).

The focus on tackling issues like societal connectedness and integration to counter radicalisation have become central components of many policies. While integration is certainly not the only, or even the most important factor in radicalisation, experts generally agree that it plays a fundamental role (Archick, Belkin, Blanchard, Ek, & Mix, 2011). In part, the change in focus was prompted by criticisms of earlier policies and strategies that they were having a negative impact on cohesion and integration, and thereby even potentially contributing to radicalisation (Kundnani, 2009). Today, policies and strategies seek to include a wide spectrum of stakeholders in promoting cohesion, integration, values and norms. In addition to members of the community, education staff, community workers (including social workers), and police, have become important deliverers of these new policies (Beider & Briggs, 2010). However, different countries place a different amount of weight on each of these actors. For example, the UK places more responsibility for the delivery of counter-radicalisation interventions on the police, and some Scandinavian countries place more emphasis on community workers (Haugstvedt, 2019).



Another interesting component of these types of interventions is that they almost all take a theoretical premise that their effectiveness is reliant upon a trickle-down effect. That is, by reducing radicalisation, or the risk of radicalisation in one individual, that individual will go on to positively affect others, and they others, and so on (Pratchett et al., 2009). In a systematic review of counter-radicalisation initiatives, Pratchett et al (2009) found only 18 studies. As all the studies were qualitative, they were only able to employ a qualitative content analysis to assess effectiveness. Despite the admitted limitations, the study found that initiatives focussed on capacity building and empowerment were the most effective.

The trickle-down perspective, as well as the reliance on key stakeholders and opinion-leaders and facilitators that lay at the basis of current policies, inherently acknowledged that factors such as integration, trust, and legitimacy are affected through socialization. Indeed, the criminological literature provides evidence to support such a premise, having found that for each of these factors, interpersonal relationships and interactions are the key mechanisms through which changes to subjective values on such topics are changed.

From a theoretical perspective, differential associations and social learning theory perspectives hold that both normative and deviant attitudes and behaviours are learned in the same way. In line with perspectives from behavioural psychology regarding the attitude-behaviour consistency, whether an individual holds normative or deviant attitudes towards a given behaviour will determine the likelihood of involvement in the given behaviour. Attitudes are learnt from differential associations, who provide a balance of definitions in support of, or against the given behaviour, which determine the individual's own attitude.

This perspective is also in line with social bonding/social control theory (Hirschi, 1969). While social bonds/social control theory has previously been criticized for failing to explicitly acknowledge its inclusion of differential associations, the overlap is quite clear. According to the social bonds/social control perspective, it is the different social bonds, such as parents, teachers, friends, community members, and institutions, who promote norms and values.

For the purposes of modelling social phenomena, such as in the case of agent-based modelling, it has been argued that opinion-dynamics cannot properly model the transference and development of radical attitudes specifically. However, they can model the change and development of other attitudes and beliefs, such as those noted above. Since, as described above, most policies seek to tackle these attitudinal-related factors rather than radical attitudes themselves, it makes sense that these are the types of factors that should be modelled in simulating the effects of counter-radicalisation policies.



ABMs provide key benefits for experimenting with different policy interventions and options. Of note, "A major advantage of agent-based modelling is that the difficulties in ensuring isolation of the human system and the ethical problems of experimentation are not present when one does experiments on virtual or computational systems" (Gilbert, 2008, p. 3). Additionally, policy interventions are often quite costly. Especially in light of the fact that quantitative evaluation has been mostly absent with respect to counter-radicalisation policies, and such evaluations should inform the priority given to a particular policy or set of policies, ABM provides an ideal environment for carrying out such evaluation. As such, in the current ABM we seek to test key policy interventions that are representative of the types of initiatives either currently being employed in EU member states, or which have been discussed in the literature as possible strategies. In particular, we test the effect of community workers, community policing, and employment initiatives on radicalization and recruitment. Each of the chosen interventions focus on the trickle-down approach as well as the targeting of attitudinal risk and protective factors, whilst accounting for individual level propensity and heterogeneity.

We take the following approach in carrying out experiments and populating the information for the Wizard. First, we carry out experiments for high dosage interventions. What we aim to achieve with these experiments is to identify whether the interventions at a high but realistic level of dosage can be seen to have impacts on recruitment and radicalization. If we find significant impacts (at $p < .05$) we then include combinations for that intervention and the specific outcomes where significance is observed in the Wizard.

3.6.2 EMPLOYMENT

It has long been observed that among radicals of all persuasions, unemployment is a common characteristic (de Witte, 1992; El-Said, 2015). Early research found that higher-educated, unemployed individuals were more likely to hold radical left and radical right-wing attitudes (de Witte, 1992). Even in cases where radicals and terrorists have not experienced unemployment themselves, they often emerge from places and communities which are characterized by high unemployment (El-Said, 2015). As such, grievance, subjective deprivation, and perceived injustice can develop, whether the individual themselves is unemployed, or whether their community suffers from high unemployment. For this reason, a number of policies in the EU have focused specifically in increasing employment opportunities for university students and graduates.

Among the many obvious benefits of employment, when it comes to counter-radicalisation, employment helps to embed individuals in a local network of other employed individuals. Employment also provides the individual with the opportunity to become involved with established institutions and society as a



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whole. Additionally, employment changes the balance of structured and unstructured socialization in a direction that is generally associated with a reduction in risk for deviant attitudes and behaviours. As such, employment can reduce the number of, or effects of risk factors, and act as an important protective factor both directly and indirectly through the mechanisms of individual propensity, routine activities, and differential associations.

In order to test the effects of a policy that provides employment high-risk individuals, we simulate the effects of increasing employment among high-risk individuals (the top 5.6%) to 75%. This scenario could serve to model a range of possible policy initiatives. For example, the government could provide incentives to employers to hire high-risk, unemployed individuals. Initiatives of this nature may include training programs and providing additional incentives to the prospective employees.

As per the results of T2.1, employment reduces agents' propensity scores by $d=-.176$. Additionally, the agents' routine activities are altered as a result of their employment, limiting the amount of free time that they have compared to the base model. Moreover, agents are able to spend up to 25% of their time at their place of employment socializing with other co-worker agents, which may impact their opinion-related risk-protective factor scores.

3.6.3 COMMUNITY WORKERS

As previously described (Section 3.6.1), community workers (including social workers) have become important stakeholders and deliverers of counter-radicalisation initiatives. A number of initiatives currently in use focus on the promotion of community centres and the variety of activities and services they offer to the local community. However, as has been noted in the literature, the opening of community centres on its own is unlikely to lead to lower risk of radicalisation in local communities. In order to accomplish this, community centre's must be staffed by highly trained, motivated, and well-funded staff (Mucha, 2017). This is especially important given that community centres have sometimes been known to be taken over by radical elements, and even used as bases of recruitment to terrorism.

The view of researchers and policy makers is that when properly implemented, community centres and their staff have the ability to increase social cohesion, connectedness and integration, as well as improve trust and legitimacy. They may also provide assistance as well as work opportunities, thereby reducing perceived inequalities that underpin subjective deprivation. Community workers play an important role in counter-radicalization initiatives in a number of countries already, including the UK and Ireland, Germany, the Netherlands, and Israel.



To test the effects of additional community workers on radicalization and recruitment, we simulate a policy that increases the number of community workers operating at community centres from 1 worker per community centre to 4 workers per community centre. Community workers are able to broadcast their opinions to all citizen agents that are located at the community centre simultaneously. In addition, community workers are also members of the community, and they may interact with other agents during routine activities. As such, this policy scenario primarily seeks to reduce radicalisation by improving agents' scores on the opinion-topics that affect the risk score calculation. All community centre workers in this model have positive scores in terms of the opinion dynamics function and so have a positive impact on the opinion of agents they interact with within the community centre, regarding topics of integration, institutional trust and subjective deprivation. This scenario increases the number of social works at community centres by one or two and is compared to the baseline setup.

3.6.4 COMMUNITY POLICING

Prior research has found that the police play an important role in counter-radicalization and counterterrorism. Police engage in routine activities, either as part of their patrol or other activities. A surprisingly large number of terror attacks have been disrupted by routine stops by the police (Dahl, 2011; Strom et al., 2010). Police are well positioned to identify potentially high-risk individuals through their familiarity with the local community in which they operate. They are also well positioned to build positive relationships in communities that may produce radicalized individuals, or in which such individuals reside and leverage these relationships to prevent radicalization and recruitment (Bayley & Weisburd, 2011; Weisburd, Jonathan, & Perry, 2009). However, encounters with the police also run the risk of contributing to radicalization, by weakening legitimacy, trust, and increasing feelings of discrimination or injustice (see T2.4, Donohue, 2008). In order to capitalize on the many advantages that police have in the fight against radicalization and recruitment, and reduce the potential negative backlash of policing on radicalization, many scholars have suggested that community policing strategies are the most ideal approach (Innes, Roberts, Innes, Lowe, & Lakhani, 2011; Innes, Roberts, & Lowe, 2017; LaFree & Bersani, 2014; Schanzer, Kurzman, Toliver, & Miller, 2016). Indeed, western countries such as Australia (Dunn et al., 2016), the Netherlands (Open Society Institute, 2010), and the UK (Spalek, 2010) place community policing as a central feature of their counter-radicalization policies.

Whilst less popular in Europe than in the US, efforts have been made to implement different aspects of community policing, sometimes with an openly expressed intent towards counter-radicalisation. Community policing focusses on building partnerships between the police, the community, and its members. The goal is to promote legitimacy, trust and willingness to cooperate with the



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police. Community policing strategies seek to identify and address public safety concerns and other issues that are important to the community. Additionally, community-policing approaches seek to improve the level of procedural justness in their routine activities. When activities are more procedurally just, the potential negative impacts of police-citizen interactions are minimized and the police, as an institution, are perceived as being more legitimate (C. Gill et al., 2014; Jonathan-Zamir & Weisburd, 2013; Weisburd & Eck, 2004; Weisburd, McElroy, & Hardyman, 1988). Community policing strategies can also be implemented in conjunction with hot-spot policing, where police focus their attention on specific areas or places that are known to attract deviants and deviant activities (Braga & Weisburd, 2010). Evidence suggests that community policing is successful in achieving these goals when implementation includes specific community-policing training for ordinary officers, as well as officers who are dedicated solely to community policing activities (National Academies of Sciences & Medicine, 2018).

As such, the implementation of community policing strategies can fall under two broad approaches. The first approach is a more institutional one, in which the entire institution of the police takes on a more community-policing orientation and culture. This approach is one that often includes the decentralization of the police structure, enabling greater levels of discretion for front-line officers, and embedding the police as an organization within the community, such as with the opening of new field offices. The second approach involves the creation of specialized community-policing units and officers who engage specifically in community policing activities, whilst the majority of the force maintain their normal operations. For these officers there is a reorientation in the activities that they undertake, including patrol activities, visiting specific places, and engaging in community activities such as workshops, meetings, and other events (C. Gill et al., 2014; Weisburd et al., 1988). In many western countries, such as Australia, the latter approach has been taken within the framework of counter-radicalisation. Dedicated community police officers, often from the communities in which they operate, engage in community-policing activities, and position themselves as the representative of the police in the community. These officers may run additional programs within the framework of community-policing, such as with Australia's Police-Community-Youth-Clubs and their boxing programs for youth at risk of radicalisation (Bull, Hogg, & Harvey, 2011).

In either form, community police officers engage in foot or vehicle-based patrols but their overall approach towards citizens, and the types of interactions they hold with them are different; both in terms of their approach, as well as the fact that these interactions occur on the back of pre-existing relationships and rapport. A small number of studies have found that elements of community policing are directly correlated with a reduced likelihood of attitudes relevant to radicalisation, such as the acceptance of violence as a legitimate means of social change (e.g. Jackson et al., 2013; Tyler, Schulhofer,



& Huq, 2010). PROTON's T2.4 found that police-stops were viewed by members of the Muslim community as possibly contributing to radicalization when they lacked elements of procedural justice. These findings support a wide literature that holds that community policing is an ideal tool to counter radicalisation and recruitment to terrorism.

To test the effects of a community-policing policy on radicalization and recruitment to terrorism, we model a scenario in which 50 percent of police officers are trained in community policing. We assume that the introduction of trained community police officers has a positive impact, concerning the agents' interaction with the police in the simulation. The effect of community policing on legitimacy is derived from a systematic review and meta-analysis conducted by Gill, Weisburd, Telep, Vitter and Bennett (2014) who found that the overall effect of community policing officer interactions on legitimacy was $d=.134$. This figure can be seen to be much smaller than the size of the effect of routine, negative police encounters on legitimacy which have an effect of $d=-.691$.

This implies that the interaction with the police in the model is altered, in that each new community police officer generates a positive influence on the opinion dynamic of each agent he or she interrelates with, concerning an agent's attitude towards topics of institutional trust or legitimacy and integration. The new community police officers do not have an impact on opinion dynamics related to the topics of subjective deprivation, and they do not generally produce negative influences on agents' opinion dynamics. In the model, 90% of the interactions between the police and citizens are positive.

Community police officers are located on a specific patch, where they stay for one hour (one simulation tick). With each tick of the model, they move to a new patch, where at least one citizen agent has to be located at that point in time for the police officer to interact with. Unlike ordinary citizen agents, police officers can broadcast their opinions to multiple agent simultaneously. However, community police officers differ from other broadcasting agents, such as community workers, in two ways. First, community police officers are limited with regards to how many agents they can broadcast to simultaneously; they are limited to a maximum of four citizen agents on a specific patch before the agent moves on. If only one to three citizen agents are located on a given patch, all three of these agents are influenced by the community police officer interacting with them. Instead, if there are more than four citizen agents, it is random selection that determines which agents are positively influenced by the community police officer on their patch. Secondly, unlike other broadcasting agents in which the citizen agent's decision to listen is voluntary, community-policing agents force the interaction to occur. This dynamic resembles the way in which police-citizen interactions tend to occur during the course of routine patrols.



3.6.5 MODEL ASSUMPTIONS

In this section, we highlight some of the important assumptions of the TR model (Table 32). For the motivation and support behind these assumptions, see sections 3.1, 3.2, 3.5, and 3.6.

Table 32. Selected assumptions of the TR model

Assumption	Details
Physical landscape	<ul style="list-style-type: none"> Landscape through which agents move important component of radicalisation process.
Routine activities	<ul style="list-style-type: none"> The routine activity of agents is important in their interactions with others and consequently opinion formation.
Differential associations	<ul style="list-style-type: none"> Agents interact face-to-face and online with particular weights assumed for both.
Opinion formation	<ul style="list-style-type: none"> Specific approach for updating opinion formation. Opinions can have both risk and protective effects, increasing or decreasing radicalization (risk) and risk of recruitment. The opinion-related risk-protective factors are institutional trust, integration, and subjective deprivation.
Neutral, risky, or protective place	<ul style="list-style-type: none"> Locations on landscape which have a tendency to house or attract broadcasting agents. Places have differential effects on the opinions of agents depending on the influences and opinions of other agents who at those places at the same time.
Providing employment	<ul style="list-style-type: none"> It is possible to identify and provide employment to high-risk individuals. Employment reduces agents' propensity scores for radicalisation. Employment alters routine activities and reduces the amount of free time an agent has.
Increasing community workers	<ul style="list-style-type: none"> Community workers have a positive effect on the opinions of other agents they interact with. Community workers can broadcast to multiple agents simultaneously.
Adopting community policing	<ul style="list-style-type: none"> Community police officers have a positive impact on the opinion of other agents in 90% of their interactions.



3.7 Results

The main outcomes of interest for the simulations were radicalization and recruitment, as well as the three opinion-based risk-protective factors; integration, trust/legitimacy, and subjective deprivation. To analyse the overall treatment differences, we calculate the average of each outcome for each run of the simulation (to create independent observations) and then compare the averages using t-tests. The only exception to this is the number of recruited agents, which analyse in the final step (at step 3060). To consider the differences in dynamics between treatments, we calculate significant differences tick by tick and show these on the figures.

The baseline model consisted of 40 runs for a duration of 3060 steps (equivalent to 6 months of activity). Simulations were populated with 40000 agents. We then repeat the simulations 40 times for each of treatments, for a total of 160 simulations. Each simulation needed about 8 days to be completed, for a total of 1280 computation hours. The average risk score (radicalization) was 0.50 (SD=.01) and the number of recruited citizens at the end of the simulation was 77.20 (SD=8.42). Scores for the three opinion-based risk-protective factors remained relatively stable throughout the model (see e.g. Figure 27), as predicted.

3.7.1 EMPLOYMENT

The experimental model for employment of high-risk citizens consisted of 40 runs for a duration of 3060 steps (equivalent to 6 months). While the average radicalization was similar to the base model, large and strongly statistically significant differences were found in the number of recruited agents. In total, the experiment reduced the number of recruited individuals from about 77 to about 26, or a 66% reduction compared to the based model.

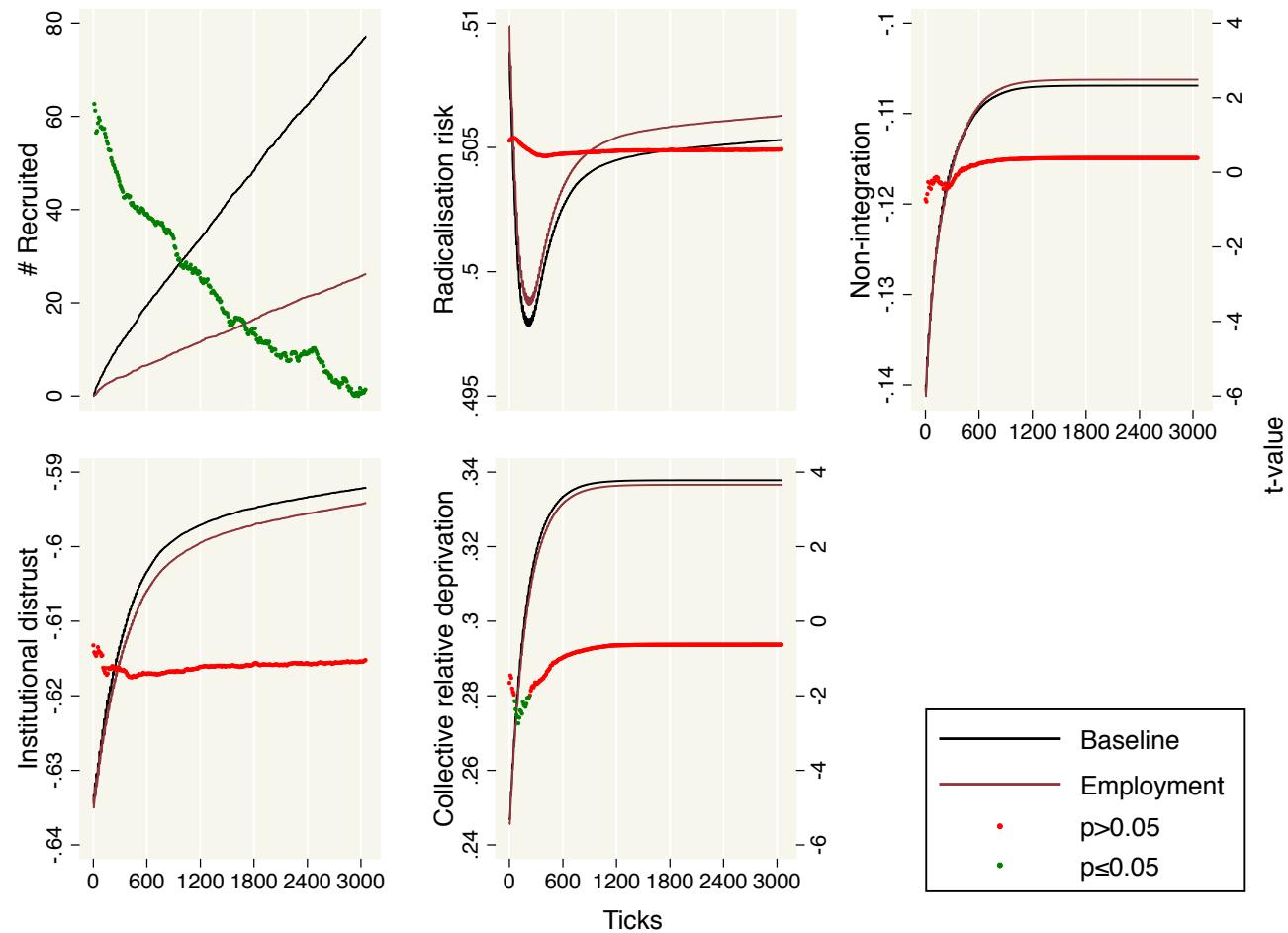
Table 33. Comparison of outcome averages for Baseline and Employment

Outcome	Treatments		Significance
	Baseline (n=40)	Employment (n=40)	
Recruited agents	77.200 (8.422)	26.200 (5.823)	$t(78)=-31.502^{***}$
Average risk of citizens (radicalization)	0.504 (0.006)	0.505 (0.007)	$t(78)=0.585^{n.s.}$
Opinion: Non-integration	-0.109 (0.007)	-0.109 (0.008)	$t(78)=0.306^{n.s.}$
Opinion: Institutional distrust	-0.599 (0.008)	-0.602 (0.008)	$t(78)=-1.231^{n.s.}$
Opinion: Subjective rel. deprivation	0.332 (0.009)	0.330 (0.007)	$t(78)=-0.819^{n.s.}$



Standard deviations in parentheses, ^{n.s.}=not significant ($p>0.05$), *** $p<0.0001$.

Figure 27. Comparison of outcome dynamics for Baseline and Employment



3.7.2 COMMUNITY WORKERS

In the experimental model for community workers, the average risk score was 0.47 ($SD=0.01$) and the number of recruited citizens was 80. There were no statistically significant differences between the experimental model and the base model for recruitment, however the mean risk scores (radicalization) of the populations were statistically different ($p<0.0001$). These differences are likely the result of the fact that the experiment also had statistically significant effects on improving all three opinion related factors (Figure 28). Accordingly, the community worker model has meaningful impacts on attitudes in the simulated city, but those differences did not lead within the 6-month observation period to significant changes in recruitment.

Table 34. Comparison of outcome averages for Baseline and Community workers

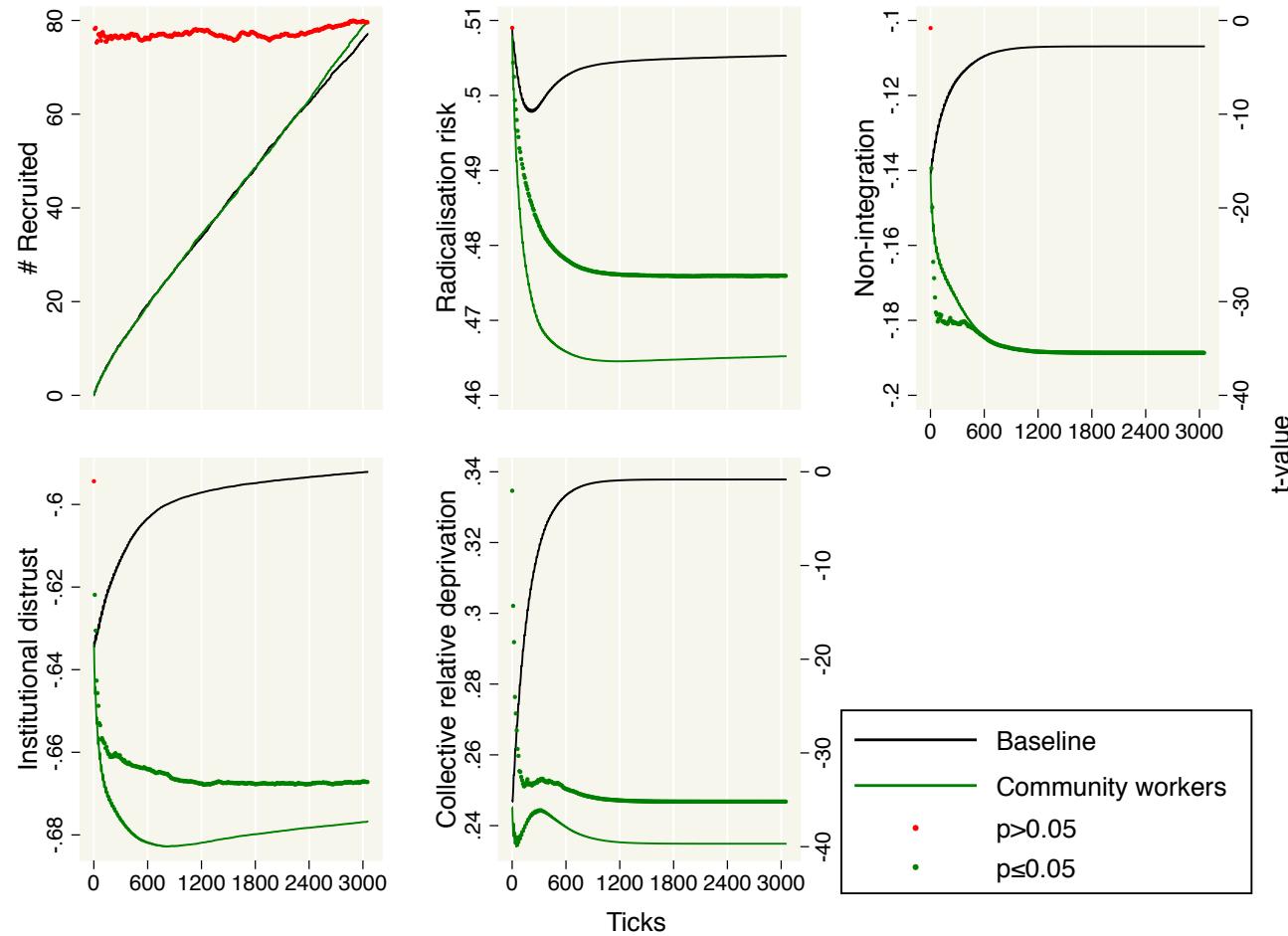


This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 699824.

Outcome	Treatments		Significance
	Baseline (n=40)	Community (n=40)	
Recruited agents	77.200 (8.422)	79.875 (8.234)	$t(78)=1.436^{\text{n.s.}}$
Average risk of citizens (radicalization)	0.504 (0.006)	0.467 (0.006)	$t(78)=-26.070^{***}$
Opinion: Non-integration	-0.109 (0.007)	-0.185 (0.012)	$t(78)=-35.045^{***}$
Opinion: Institutional distrust	-0.599 (0.008)	-0.679 (0.013)	$t(78)=-32.915^{***}$
Opinion: Subjective rel. deprivation	0.332 (0.009)	0.237 (0.015)	$t(78)=-34.985^{***}$

Standard deviations in parentheses, *** $p<0.0001$.

Figure 28. Comparison of outcome dynamics for Baseline and Employment



3.7.3 COMMUNITY POLICING

In the experimental model for community policing the average risk score (radicalization) was 0.50 ($SD=0.01$) and the average number of recruited citizens was 78.38. In comparing these results to the base model, there were no statistically significant differences across these two outcomes. However, the experiment did have statistically significant effects on improving trust/legitimacy, as predicted.

Table 35. Comparison of outcome averages for Baseline and Community policing

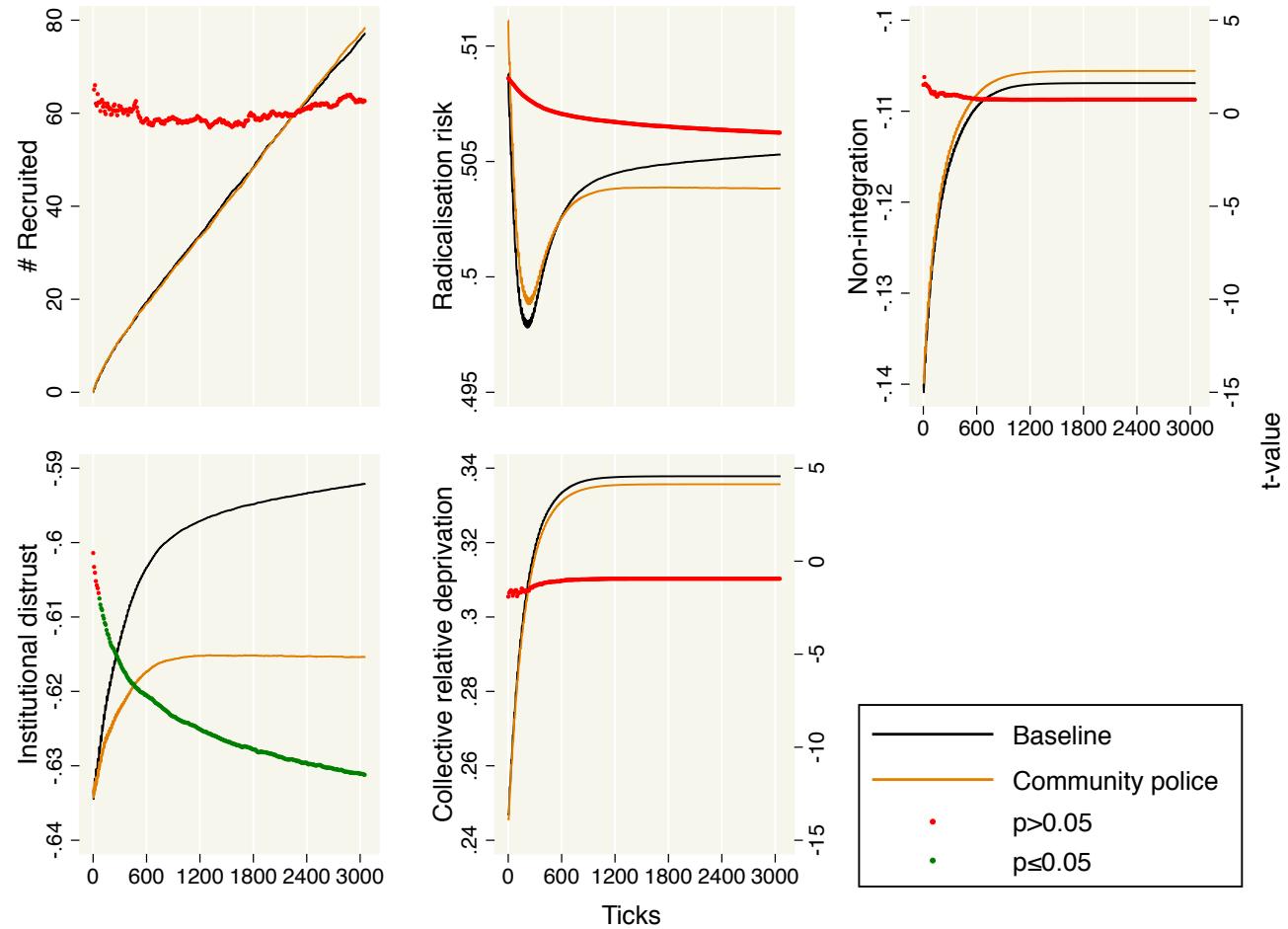
Outcome	Treatments		Significance
	Baseline (n=40)	Policing (n=40)	
Recruited agents	77.200 (8.422)	78.375 (7.358)	$t(78)=0.665^{n.s.}$
Average risk of citizens (radicalization)	0.504 (0.006)	0.503 (0.006)	$t(78)=-0.434^{n.s.}$
Opinion: Non-integration	-0.109 (0.007)	-0.108 (0.008)	$t(78)=0.775^{n.s.}$
Opinion: Institutional distrust	-0.599 (0.008)	-0.617 (0.009)	$t(78)=-9.293^{***}$
Opinion: Subjective rel. deprivation	0.332 (0.009)	0.330 (0.010)	$t(78)=-1.014^{n.s.}$

Standard deviations in parentheses, $^{n.s.}=\text{not significant}$ ($p>0.05$),
 $^{***}p<0.0001$.



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 699824.

Figure 29. Comparison of outcome dynamics for Baseline and Community policing



3.8 Discussion and conclusions

In this ABM, we simulated the processes of radicalization and recruitment to terrorism in an environment that replicates a prototypical borough of a major European city. Based on extensive empirical data and established theoretical frameworks, the model included a large population of heterogeneous agents who perform daily routine activities, including socialization. Based on these dynamics, and information and data on risk and protective factors derived from PROTON (WP2), changes in agents' risk for radicalization and recruitment was examined over a span of time representing 6 months. The base model demonstrated a high degree of both internal and external validity, with levels of radicalization remaining quite stable, and levels of recruitment growing in a relatively linear fashion over the period and falling within the predicted range.

In this ABM we examined three key policy interventions that aimed to reduce radicalization and recruitment by targeting key risk-protective factors and



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mechanisms; community workers, community policing, and employment initiatives. Each of these policies have been recommended as possible counter-radicalization initiatives or are already being implemented to some extent in most European countries (Vidino & Brandon, 2012b, 2012a). The theoretical framework that underpins these policies is that by improving scores on risk-protective factors, radicalization, risk of recruitment, and actual recruitment will be lowered.

In this study we found that only the employment initiative had a statistically significant effect on recruitment. However, the initiative had no significant effects on radicalization or on any of the opinion-related risk-protective factors. On the other hand, the community workers' initiative had a significant effect on the mean risk of the population (radicalization), as well as on improving overall integration. The community policing policy improved overall trust and legitimacy but had no significant effect on any of the other outcomes.

It is important to assess these findings both independently and jointly. A wide literature on de-radicalization and disengagement from terrorism indicates that for most terrorism offenders who desist from terrorism, their beliefs are still often quite radical. Many researchers now agree that rather than focussing on de-radicalization, or counter-radicalization, the focus should be on preventing radicalized individuals from moving to recruitment, and action (e.g. Altier et al., 2017; Horgan & Braddock, 2010). While policies that seek to improve specific beliefs may be successful in improving those beliefs, this does not necessarily translate into a reduction in the risk of radicalization and recruitment at the population level. If we accept the notion that only about 1% of radicalized individuals will ever be recruited (McCauley & Moskalenko, 2017), small changes in the proportion of the population that is radicalized will have only nominal impacts on the number of individuals recruited.

This in no way means that programs that focus on improving beliefs, opinions and values should be abandoned. Indeed, they could very well have positive impacts. It could also be the case that these types of changes require much more time in order to demonstrate an appreciable effect on radicalization and recruitment outcomes. Indeed, researchers and policy makers acknowledge that such policies should be implemented as part of a long-term strategy in which multiple initiatives are being implemented simultaneously (Heydemann, 2014; Vidino, 2010; Vidino, Seamus, & Katerina, 2017).

Indeed, our community workers' initiative had the intended effects on all opinion-related factors, which did spill-over into having an effect on radicalization. Similarly, our community policing initiative did have an effect on trust and legitimacy, supporting evidence produced in the literature and in PROTON's WP2. Nevertheless, changes in these beliefs should not be relied upon as being the vehicle by which recruitment will most likely be reduced; At least not in the short-term. The differences in the findings between community



workers and community police may reflect the different dynamics that govern the way in which they interact with citizens. As discussed above, whilst citizens voluntarily decide whether or not to interact with community workers, community police may insist that the citizen listens. As in the real world, these differences reflect the differences in the nature of community-oriented approaches delivered by different agencies.

On the other hand, our initiative to give employment to high-risk individuals was found to have an almost immediate and significant impact on recruitment. Traditionally, the underlying rationale behind employment programs is that they may have an indirect effect on radicalization by increasing integration and reduce feelings of deprivation (Vidino & Brandon, 2012b, 2012a). However, given that the experiment had no effect on radicalization or opinion-related risk-protective factors, these findings therefore indicate that it was the changes in routine activities that affected this outcome. Changes in routine activities affect the opportunities, and the time available for opportunities, for socialization with agents that promote and encourage recruitment. These findings are in line with the overlaps between routine activities and social control theory which state that by engaging in conventional activities—such as employment—an individual simply has less time with which to engage with deviant elements and deviant behaviours (Apel & Horney, 2017).

This issue of available time also may explain why lower levels of opinion-based risk factors were found to have no effect on recruitment. Recruiters also have routine activities that condition and limit the amount of time they can spend each day in recruiting activities. As such, there is also a limit as to how many individuals can be recruited based on the availability and opportunity of recruiters. Availability and opportunity for socialization is a key issue when it comes to differential associations and social learning. Availability is a key determinant of the frequency and duration of differential associations (Akers, 1998). Our findings are also supportive of the results of PROTON's T2.1, namely that while employment has a relatively small effect on radicalization of beliefs, it has a moderate effect on radicalization of actions (recruitment) that is only marginally smaller than having contacts with another radicalized/recruited individual. Additionally, T2.1 found that employment had a stronger effect in European samples compared to non-European samples.

3.8.1 CONCLUSIONS

The literature has consistently highlighted the lack of policy and intervention evaluation work as being a key gap in the work on radicalization and terrorism more broadly. The lack of this type of study can be understandable however. It is quite difficult to assess outcomes such as radicalization and recruitment, let alone identify the causes of changes to them. Additionally, operating experiments in the real-world carry a host of challenges, from financial to ethical. It is based on these considerations that ABM provides an ideal



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platform for simulating the effects of interventions that seek to reduce radicalization and recruitment to terrorism using both broadly applied and more focussed and targeted treatments.

Our simulations demonstrated a high level of consistency with the theoretical frameworks and mechanisms that informed them, and they operated in a plausible and realistic manner. Community based interventions, namely the addition of community workers and community-police officers, had direct effects on the specific factors that they should theoretically affect. In one case, community workers, this led to a spill over effect on radicalization, although not on recruitment. It is therefore possible that we need to reconsider the theoretical premises that there is a type of linear relationship between risk factors, radicalization, and recruitment, and that by targeting individual risk factors to reduce radicalization, this will necessarily have an impact on recruitment. Nevertheless, even these policies show potential promise in the long-run, and even if they turn out to not have direct effects on radicalization outcomes, improving feelings of integration, trust, and depravation remain desirable for any society. Future analyses may seek to examine the effects of multiple policies operating at different levels of implementation simultaneously. However, similar to the need to run similar models for durations that simulate longer periods of time of up to a few years, computational complexity, and the demanding resources for such an endeavour must be taken into consideration.

In terms of achieving more immediate and appreciable results, mechanisms may be more important. While mechanisms can also be risk factors, they alter lifestyle, routine activities, and thereby the opportunities for recruitment. Employment has long been known to have an inverse relationship with deviant behaviours and our simulations show that employing previously unemployed individuals who are radicalized, reduces the likelihood of recruitment. One issue with employment initiatives is that in practice, in addition to the need to identify the population of high-risk individuals, the simple offering of employment may not be inducement enough. Policy makers will need to develop strategies in order to ensure that individuals targeted by such initiatives take up employment offers and opportunities.



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5 Appendix: OCN Model

5.1 OCN model calibration

5.1.1 CALCULATION OF THE HOUSEHOLD ALGORITHM

There are two levels of iteration within the model concerning the setting up of households: the first level is aimed at generating a household and the second level at generating a household of a particular size. To do this, the simulation identifies the household type before selecting the actual agent that will be the "head" of the household. If the household is a couple, the male will be chosen first and then the female (according to their age), as the male is identified as the head of the household. If the household is single parent, it is assumed that the parent is female and proceed accordingly. This leaves out single-father households, that however will be allocated to the set of households that cannot be allocated because they do not fit the household categories in the model and are defined as "complex households" (e.g. single-father households).

5.1.2 OVERCOMING THE "DARK FIGURE" OF CRIME ISSUE

An important step in the creation of the criminal activity component of the model is to overcome the problem of underestimation of crimes that arises from only using the reported number of offences. Many crime categories suffer from the so-called "dark number" problem. The dark number maps the proportion of offences that are not reported to law enforcement. This number varies based on the crime type and the geographical context. Official estimates of the dark number for several crime categories can be retrieved from Istat victimization surveys. The most recent accessible data are related to years 2008 and 2009. Our aim is to derive an estimated real number of crimes based on the following steps:

- Download of the Istat number of reported offences per crime category for the years 2012-2016 in the province of Palermo.
- Compare the overall number of categories with the categories for which a dark number figure exists.
- Derive the dark number of categories for which we can assume that the dark number is close to 0 (e.g.: murders, meaning that we assume that all murders are actually reported) and apply the Istat dark number to crime categories that are very similar to ones for which the official figure exist.
- For all the categories for which the dark number is not available, cannot be derived nor assumed, we have imputed a value computed via a weighted average of dark number and number of crimes for each



category, using Palermo province data for the year 2016 as reference. Specifically, the imputed dark number for the remaining categories has been calculated as follows:

- where represents the total number of crimes reported for category k and represents the dark number for the same crime category. Applying this method, we have obtained and imputed a weighted average value of 0.68.
- Correcting the absolute reported number of offences for each year, via the simple following transformation and computation of the rate calculated per 10,000 inhabitants using the Palermo population for the year of reference retrieved by Istat.
- Synthesis of the results in order to calculate the average corrected absolute values () and rates for the 2012-2016 period. We have provided both the figures per crime category and an aggregate number regardless of crime type. synthetizes the information on the employed data and steps.
- After correcting the number of crimes using figures on each crime category¹¹ “dark” number, we calculated yearly rates (per 10,000 inhabitants) for each gender and age class. The rates have been calculated using official statistics of the Sicilian population for each year of reference (2012-2016).

Table A1. Information for estimating the real number of crimes in Sicily

Item	Procedure summary
Dark number	The dark number for each crime category in the dataset is reported. Most of the data have been retrieved from the Italian National Victimization Survey of 2008-2009 with data disaggregated at the macro-regional level (in the case of Palermo, we used data of the “Islands” Italian macro-region). For certain offences we applied to that specific crime a dark number of another very similar crime, assuming figures do not vary. For other crimes, we applied a dark number equal to 0, assuming that all crimes are reported (reported crimes = real number of crimes, e.g.: infanticides). For all the other crimes

¹¹ The crime categories retrieved from Istat website and slightly modified in order to control non-exclusive subcategories are: other offences, mafia-type association, criminal association, terror attack, sexual offence against juveniles, smuggling, counterfeiting of brands and industrial products, corruption of juvenile, damages, arson-derived damages, cybercrimes, extorsions, theft (residual), petty theft, breaking and entering, theft of heavy goods vehicle, grand theft auto, motorcycle theft, theft of cultural heritage, house burglary, theft of parked cars, shoplifting, arson (residual), forest arson, infanticides, insults, assaults, threats, drug-related crimes, unintentional homicides, manslaughters, intentional homicides, robbery homicides, terror homicides, mafia homicide, beating, child pornography, robberies (residual), house robberies, bank robberies, shop robberies, postal office robberies, fencing, money laundering, kidnapping, stalking, prostitution, mass murders, attempted homicides, computer-mediated frauds, violation of intellectual property, sexual violence.



	(where the value of dark number is equal to 0.68) we have calculated the average dark number weighted by the summation of each crime category absolute values (0.68), using 2016 as the year of reference.
2012-2016 absolute and raw data	We gathered data from 2012 to 2016 on absolute reported number of suspects (offenders) for each year of reference in the Sicilian region divided per sex and age class.
2012-2016 corrected data	A further step in the data processing involved the correction of reported offenders for each year of reference in the Sicilian region divided per sex and age class.
2012-2016 corrected rates	We calculate rates per 10,000 inhabitants from 2012 to 2016 distinguishing by sex using corrected data.
Average rates	The final step is the calculation of the average rate per 10,000 inhabitants using data from the 2012-2016 individual years corrected rates, maintaining the distinction between gender and age class.

5.1.3 CO-OFFENDING FIGURES IN THE LITERATURE

Table A2. Co-offending figures in the literature

Author	Period	Country	Num. offenders (%)							
			1	2	3	4	5	6+	2+ subtotal	
(Carrington, 2002)	1990-99	Canada	88.1	8.8	2.0	0.6	0.3	0.1	11.8	
(Hodgson, 2007)	1998-03	UK	88.1	9.5	1.7	0.4	0.1	0.2	11.9	
(van Mastrigt & Farrington, 2009)	2002-05	UK	89.6	NA	NA	NA	NA	NA	10.4	
(Carrington et al., 2013)	2011	Canada	89.0	8.0	3.0				11.0	
(Carrington & van Mastrigt, 2013)	2006-09	Canada	85.5	10.7	2.5	0.8	0.3	0.2	14.5	
(Carrington & van Mastrigt, 2013)	2002-05	England	89.4	8.1	1.7	0.5	0.2	0.1	10.6	
(Carrington & van Mastrigt, 2013)	2010	USA	86.1	11.1	2.0	0.4	0.1	0.1	13.9	
(Hodgson & Costello, 2006)	1995-01	UK	86.3	10.9	2.4	0.4			13.7	



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6 Appendix: PROTON Stakeholders

Below we include lists of stakeholders, limited to those who are policy makers, who attended the following PROTON project meetings.

Table 36. First PROTON Consortium meeting, October 16th-17th 2017, Jerusalem

Stakeholders	Participants
DPPS - Italian Ministry of the Interior, Department of Public Security (IT)	Roberto Di Tullio
WODC - Dutch Ministry of Security and Justice, Research and Documentation Centre (NL)	Viktor van der Geest
UNODC - United Nations Office on Drugs and Crime (International)	Joaquin Zuckerberg
EUCPN - European Crime Prevention Network (EU)	Cindy Verleysen
EUROPOL - European Police Office (EU)	Eleonora Forte
	Paula Switon
BRÅ (SE)	Daniel Vesterhav
	Per Ottosson

Table 37. PROTON meeting with practitioners to discuss factors driving terrorism recruitment processes, 5th September 2018, Amsterdam

Stakeholders	Participants
Dutch Ministry of Security and Justice (NL)	Casper van Nassau
	Marnix Croes
	Jan Kees Hordijk
NCTV - Dutch Ministry of Security and Justice, National Coordinator for Security and Counterterrorism (NL)	Joost van Rossum
	Michelle van Duin
DJI - Dutch Judicial Institution Agency (NL)	Arie van den Hurk
Flemish Government (NL)	Sike Verspecht
Dutch Public Prosecution Service (NL)	Femke Becht
Munich Higher Regional Court, 7 th Criminal Division (Terrorism) (DE)	Manfred Dauster
UNODC - United Nations Office on Drugs and Crime (International)	Joaquin Zuckerberg



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Table 38. PROTON meeting with practitioners to discuss factors driving Italian Organised Crime recruitment processes, 20th September 2018, Milan

Stakeholders	Participants
EUROPOL - European Police Office (EU)	Eleonora Forte
DPPS - Italian Ministry of the Interior, Department of the Public Security (IT)	Domenico Martinelli
ROS - Italian Carabinieri, Special Operation Group (IT)	Rino Coppola, <i>Lieutenant Colonel</i>
Italian Juvenile Court, Reggio Calabria (IT)	Sebastiano Finocchiaro, <i>Judge</i>
SCO - Italian Police, Central Operational Service (IT)	Alessandro Giuliano
Italian Public Prosecution Service (IT)	Giovanni Melillo (Naples) Michele Prestipino (Rome)

Table 39. PROTON meeting with practitioners to discuss factors driving Dutch Organised Crime recruitment processes, 21st September 2018, Amsterdam

Stakeholders	Participants
EUROPOL - European Police Office (EU)	Jelmer Brouwer
EUCPN - European Crime Prevention Network (EU)	Chadia Dehbi
Dutch Ministry of Security and Justice (NL)	Bart Naaijkens
Dutch Public Prosecution Service (NL)	Peter Klerks
Dutch Police (NL)	Dennis Maier

Table 40. Second PROTON consortium meeting, October 15th-16th 2018, Milan

Stakeholders	Participants
EUROPOL - European Police Office (EU)	Jelmer Brouwer
	Eleonora Forte
MUNIPA - Municipality of Palermo (IT)	Germana Console
	Enza Patrizia Savarino
EUCPN - European Crime Prevention Network (EU)	Chadia Dehbi
DPPS - Italian Ministry of the Interior, Department of the Public Security (IT)	Domenico Martinelli
BRÅ (SE)	Daniel Vesterhav



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Table 41. Third PROTON consortium meeting, June 17th-18th 2019, Palermo

Stakeholders	Participants
MUNIPA - Municipality of Palermo (IT)	Leoluca Orlando, <i>Mayor of Palermo</i>
	Osvaldo Busi
	Germana Console
	Tommasa Sucameli
EUCPN - European Crime Prevention Network (EU)	Katrijn Hoedemakers
	Febe Liagre
UNODC - United Nations Office on Drugs and Crime (International)	Joaquin Zuckerberg
DPPS - Italian Ministry of the Interior, Department of the Public Security (IT)	Domenico Martinelli
WODC - Dutch Ministry of Security and Justice, Research and Documentation Centre (NL)	Edwin Krulsbergen
BRÅ (SE)	Erik Nillson



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7 Appendix: PROTON- S data for the PROTON Wizard

In addition to the simulations presented above, we have also conducted a larger set of simulations in order to explore the parameter space and provide data to populate the PROTON Wizard.

For the Organized Crime Recruitment Model, we have explored variations on five parameters, extended on three different values each (high/base/low). These explorations have been performed for all the five policy interventions and the two scenarios (Northern European Context and Southern European Context) and they have been repeated three times for each combination, thus bringing the total number of simulations provided to the PROTON Wizard to 7290 runs, needing about 20 hours each (with a wide variation depending on parameters and computational quirks), with a total computing time of approximately 14K hours (60 days on 100 threads). Computational time was provided by CNR (64 threads), UCSC (100 threads) and from a sponsorship from EGI (<https://www.egi.eu/>).

For the Terrorist Recruitment Model, we have explored variations on a subset of parameters, selected on the basis of their significance. This amounted to a total of 320 simulation runs, each of which required about 8 days for a total of 2560 hours. Computational time was provided by CNR (32 threads) and HUJI (reserved access to the HUJI supercomputer with a peak usage of 500+ threads).



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8 Appendix: Prototype of and Technical Guide to PROTON-S



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Appendix: Prototype of and Technical Guide to PROTON-S Organised Crime Model

This section of D5.1 is a technical guide to allow researchers, policy makers, and stakeholders, with the support of computer programmers, to model how multiple social relations may influence individuals' involvement into organised crime: family, friendship, school, professional, and criminal relations. The goal is to set up (a) the *model parameters* in order to run simulations representing different realities, such as different types of intervention to reduce recruitment into OC (b) the *configuration files* that allow to define the social and economic system in which the agents are located, for example the family structure, and the working, professional and criminal relationships.

Section **Network structure and simulation flow** describes the structure of social networks included in the PROTON OC model and the steps of the simulation. Section **How to run the simulation** describes how to launch the simulations without the graphic interface. Section **Using the interface section** presents the use of the graphic interface. Finally, section **Netlogo definitions** describes the part of the source code that contains values that can be edited.

All the code mentioned in this guide is publicly accessible on GitHub (<https://github.com/LABSS/PROTON-OC/releases>).



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1 How to Modify Parameters (Introduction)

The PROTON-S OC setup allow us to load the parameters in three different ways:

- (1) by the **experiment.xml** file (see section [MODIFY PARAMETERS BY EXPERIMENT.XML](#)) or by the interface (see section [USING THE INTERFACE](#))
- (2) by the **choose-intervention-setting** procedure. This procedure, called "to setup", uses the slider INTERVENTION to set the intervention to test (baseline, preventive, disruptive, students etc.) (see section [MODIFY PARAMETERS BY CHOOSE-INTERVENTION-SETTING](#)), or USE_CURRENT_VALUES to modify the values using the sliders into the graphical interface (see section [USING THE INTERFACE](#))
- (3) by the **setup** procedure¹. This procedure sets the parameters getting the values from the configuration files in the directory structure (see section [MODIFY PARAMETERS BY SETUP PROCEDURE](#)).

¹ The code, parameters, and setup data are located in different folders and files. To indicate the name of the folder we use the \convention (i.e.\datainput means that the files are in the \datainputs folder). The names of the files are in **bold**.



Experiment Data

2 How to Modify Parameters by Experiment.xml

PROTON OC allows to set the parameters using the *experiment.xml file*, a file that contains the couples name-value for the parameters or using the *interface* (see the section [Using the interface](#)).

The *experiment.xml file* is used when the user launches the simulation in batch mode, both in windows and in unix environment. (without using the interface, see the section [How Can I Run Proton-OC?](#)).

The XML file starts by describing how many ticks the simulation runs, which are the names of the two procedures that respectively start the simulation (loading the parameters) and start the calculations, in the following example SETUP and RUN.

.\experiments-xml\run-at-1000\example.xml

```
<?xml version="1.0" encoding="UTF-8"?>
<!DOCTYPE experiments SYSTEM "behaviorspace.dtd">
<experiments>
  <experiment name="exp" repetitions="1" runMetricsEveryStep="true">
    <setup>setup</setup> procedure for SETUP
    <go>go</go> procedure to RUN simulation
    <!-- assuming 40 years -->
    <timeLimit steps="480"/> DURATION
    <variable="ticks-per-year">
      <value value="12"/>
```

Parameters list

Below is the list of parameters that can be modified in the experiment.xml file. It includes the name of the variable and a description of its use, along with some example values. The experiment.xml file is an XML file and can be modified with any text editor. To obtain the complete definition of the parameters, you can click



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on the name of variable and go to the NETLOGO definition (see the NETLOGO definition at the end of this document)

<!-- 1. NUMBER OF OC MEMBERS -->

```
< variable="num-oc-persons">
  <value value="20"/>
  <value value="25"/>
  <value value="30"/>
```

<!-- 2. PALERMO SETUP -->

< Criminal rate -->

```
< variable="criminal-rate">
  <value value="0.5"/>
  <value value="1.0"/>
  <value value="2.0"/>
```

< Employment rate -->

```
< variable="employment-rate">
  <value value="1"/>
```

< Education rate. The value for education rate -->

```
< variable="education-rate">
  <value value="1"/>
```

< Law enforcement intervention rate -->

```
< variable="law-enforcement-rate">
  <value value="0.5"/>
  <value value="1.0"/>
  <value value="1.5"/>
```

< Punishment length -->

```
< variable="punishment-length">
  <value value="0.5"/>
  <value value="1.0"/>
  <value value="1.5"/>
```

<!-- 3. FIXED PARAMETERS >

Number of OC families

```
< variable="num-oc-families">
  <value value="8"/>
```

Number of persons that act into the simulation

```
< variable="num-persons">
  <value value="1000"/>
```



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Flag that indicate if there is some kind of welfare support

```
< variable="welfare-support">
<value value=""none""/>
```

When the intervention against OC starts

```
< variable="intervention-start">
<value value="13"/>
```

When the intervention against OC ends

```
< variable="intervention-end">
<value value="36"/>
```

Flag that indicates if there is some kind of social support

```
< variable="social-support">
<value value=""none""/>
```

The radius which permits to compute the OC-EMBEDENESS

```
< variable="oc-embeddedness-radius">
<value value="2"/>
```

< variable="nat-propensity-sigma">

```
<value value="0.25"/>
```

< variable="nat-propensity-m">

```
<value value="1"/>
```

< variable="targets-addressed-percent">

```
<value value="10"/>
```

< variable="family-intervention">

```
<value value=""none""/>
```

< variable="OC-members-scrutinize?">

```
<value value="false"/>
```

< variable="probability-of-getting-caught">

```
<value value="0.05"/>
```

< variable="max-accomplice-radius">

```
<value value="2"/>
```

< variable="OC-boss-repression?">

```
<value value="false"/>
```

< variable="retirement-age">

```
<value value="65"/>
```



3 How to Modify Parameters by choose-intervention-setting

This procedure loads (and overrides at setup) a set of fixed parameters that constitute sets 8 parameters that allow to modify the interventions. The intervention is set by a "chooser" in the interface. It could also be set to "use current values". In this case, there is no override and the value for the parameters derives from the slider (see the [interface description](#)).

#editzone

| | |
|---------------------|--|
| family-intervention | <p>This parameter defines the conditions under which the relation that OC members have with their families and children temporarily decreases:</p> <pre><code>"remove-if-caught" ["remove-if-OC-member" ["remove-if-caught-and-OC-member" [let kids-to-protect persons with [age < 18 and age >= 12 and any?] if any? kids-to-protect [....]</code></pre> |
| social-support | <p>This parameter defines the socio and cultural aspects that can provide social support:</p> <pre><code>ifelse social-support = "educational" [<u>soc-add-educational targets</u>][ifelse social-support = "psychological" [<u>soc-add-psychological targets</u>][if social-support = "more friends" [<u>soc-add-more-friends targets</u>]]]</code></pre> |



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DEVELOPMENT OF AGENT BASED SIMULATIONS OF OCTN

| | |
|----------------------------|---|
| | |
| welfare-support | <p>This parameter defines the different economic actions that can provide a better welfare:</p> <pre> ifelse welfare-support = "job-mother" [set targets all-persons with [not male? and any? partner-link-neighbors with [oc-member?] and my-job = nobody]] if welfare-support = "job-child" [set targets all-persons with [age > 16 and age < 24 and not any? my-school-links and any? in-offspring-link-neighbors with [male? and oc-member?] and my-job = nobody]] </pre> |
| OC-boss-repression? | <p>This parameter defines the behavior of the "arrest-probability-with-intervention":</p> <pre> if-else (intervention-on? and OC-boss- repression? and any? group with [oc- member?]) [report OC-repression-prob group * law- enforcement-rate] [report probability-of-getting-caught * law- enforcement-rate] </pre> |
| targets-addressed-percent | <p>This parameter defines the number of potential targets of the intervention:</p> <pre> set targets n-of ceiling (targets-addressed- percent / 100 * count targets) targets </pre> |
| ticks-between-intervention | <p>This parameter defines how much time passes between an intervention and another.</p> <pre> to-report intervention-on? </pre> |



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| | |
|--------------------|--|
| | $ \begin{aligned} & \text{report ticks mod ticks-between-intervention} \\ & = 0 \text{ and} \\ & \quad \text{ticks} \geq \text{intervention-start} \text{ and} \\ & \quad \text{ticks} < \text{intervention-end} \\ & \text{end} \end{aligned} $ |
| intervention-start | <p>This parameter defines when the intervention starts.</p> $ \begin{aligned} & \text{to-report intervention-on?} \\ & \quad \text{report ticks mod ticks-between-intervention} \\ & \quad = 0 \text{ and} \\ & \quad \quad \text{ticks} \geq \text{intervention-start} \text{ and} \\ & \quad \quad \text{ticks} < \text{intervention-end} \\ & \quad \text{end} \end{aligned} $ |
| intervention-end | <p>This parameter defines when the intervention ends.</p> $ \begin{aligned} & \text{to-report intervention-on?} \\ & \quad \text{report ticks mod ticks-between-intervention} \\ & \quad = 0 \text{ and} \\ & \quad \quad \text{ticks} \geq \text{intervention-start} \text{ and} \\ & \quad \quad \text{ticks} < \text{intervention-end} \\ & \quad \text{end} \end{aligned} $ |

#editzone

The interface includes a chooser, "choose-intervention-setting", that allows to define a pre-cooked set of values for the parameters that characterizes the specific type of intervention to be tested, e.g., baseline, preventive, disruptive. A self-explanatory code snipped follows:

```

to choose-intervention-setting
  if intervention = "baseline" [
    set family-intervention "none"
    set social-support "none"
    set welfare-support "none"
    set OC-boss-repression? false
    set facilitator-repression? false
    set targets-addressed-percent 10
  ]

```



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DEVELOPMENT OF AGENT BASED SIMULATIONS OF OCTN

```
set ticks-between-intervention 1
set intervention-start 13
set intervention-end 9999
]
if intervention = "preventive" [
    set family-intervention "remove-if-OC-member"
    set social-support "none"
    set welfare-support "none"
    set OC-boss-repression? false
    set facilitator-repression? false
    set targets-addressed-percent 10
    set ticks-between-intervention 1
    set intervention-start 13
    set intervention-end 9999
]
if intervention = "disruptive" [
    set family-intervention "none"
    set social-support "none"
    set welfare-support "none"
    set OC-boss-repression? true
    set facilitator-repression? false
    set targets-addressed-percent 10 ; not applicable
    set ticks-between-intervention 1
    set intervention-start 13
    set intervention-end 9999
]
if intervention = "facilitators" [
    set family-intervention "none"
    set social-support "none"
    set welfare-support "none"
    set OC-boss-repression? false
    set facilitator-repression? true
    set facilitator-repression-multiplier 2
    set targets-addressed-percent 10 ; not applicable
    set ticks-between-intervention 1
    set intervention-start 13
    set intervention-end 9999
]
```



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4 How to Modify Parameters by setup procedure

Below is the code, indicating with #editzone the points where it is possible to modify the parameters.

```

to setup in proton-oc
choose-intervention-setting
load-stats-tables
setup-education-levels
init-breed-colors
setup-persons-and-friendship
generate-households
setup-siblings
setup-schools
init-students
setup-employers-jobs
ask persons with
[ my-school = nobody and age >= 18 and age < retirement-age and job-level > 1 ] [ find-job ]
init-professional-links
calculate-criminal-tendency
setup-oc-groups
setup-facilitators
reset-oc-embeddedness

#editzone

set this-is-a-big-crime      3
set good-guy-threshold      0.6
set big-crime-from-small-fish 0 ; to add in behavior space reporters
ask persons [set hobby random 5] ; hobby is used only in wedding procedure to compute
wedding sim.
set removed-fatherships []

```

The setup runs a list of procedures, each of which has a different effect on the parameters' setting. We list these procedures in the order they are called.

TO LOAD-STATS-TABLES IN SETUP

Load ...

```

"inputs/general/data/num_co_offenders_dist"
"initial_fertility_rates"
"initial_mortality_rates"

```



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```

"edu"
"edu_by_wealth_lvl"

"work_status_by_edu_lvl
"wealth_quintile_by_work_status"

"criminal_propensity_by_wealth_quintile"
"work_status"
"wealth_quintile"
"criminal_propensity"

"imprisonment-length.csv"
"jobs_by_company_size"

"crime_rate_by_gender_and_age_range"
"crime_rate_by_gender_and_age"

#editzone

set number-weddings-mean 18
set number-weddings-sd 3
end

```

Data Folder Structure

The statistical information to feed the simulation is organized into two different structures: the **raw** data, i.e. the data coming from the socio/economic sources and the **data** data, i.e. the csv file with the info ready to be used in the simulation.

The root is

./inputs folder

The structure is

./inputs/eindhoven
./inputs/general
./inputs/palermo

In **general** and in **Palermo** there are R script to convert *raw* data into *data* data. The **Eindhoven** folder contains only *raw* data. The folder structure is set into a TEXT-FORM into Netlogo-Proton_OC_Interface (data-folder).

#editzone

./inputs/general



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num_co_offenders_dist.csv

Probability to have # of co-offenders

n,p

1,0.87

2,0.09

3,0.02

4,0.005

5,0.001

6,0.001



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The blue files are currently used

#editzone

./inputs/palermo

edu_by_wealth_lvl.csv

Used for test

criminal_propensity_by_wealth_quintile.csv

wealth,gender,criminal_propensity,rate

1,TRUE,1,0.48888

Used for test

criminal_propensity.csv

gender,criminal_propensity,rate

TRUE,1,0.2454

Used for test

jobs_by_company_size.csv

size,level,rate

1,2,341

1,3,540

Used in setup-employers-jobs. To set the level of the own job as a function of the size of the firm

employer_sizes.csv

Used in setup-employers-jobs

initial_mortality_rates.csv

initial_fertility_rates.csv

age,male?,p

[0,...,119],TRUE/FALSE, Prob.

TRUE means male. You can set the prop to born or die as a function of the age

imprisonment-length.csv

1,0.125,0.0731

3,0.1903,0.1317

6,0.2711,0.2494

The probability of a duration of imprisonment

household_type_dist_by_age.csv

age,type,prob

18,couple,0.0344

Used in generate-household



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household_size_dist.csv*size,p*

1,0.28208

Used in [generate-household](#)**head_age_dist_by_household_size.csv***size,age,p*

1,18,0.004

Used in [generate-household](#)**partner_age_dist.csv***age_of_head,age_of_partner,p*

18,19,0.0833333333333333

Used in [generate-household](#)**children_age_dist.csv***child_number,age_of_mother,age_of_child,p*Used in [generate-household](#)**proportion_of_male_singles_by_age.csv**Used in [generate-household](#)**proportion_single_fathers.csv**Used in [generate-household](#)**edu.csv***gender,edu_level,rate*

TRUE,1,0.037

The probability to have an education level, group by gender (TRUE means male)

crime_rate_by_gender_and_age_range.csv*male?,age_from,age_to,p*The probability to commit crime as a function of gender and age. Used in [commit-crime](#)**crime_rate_by_gender_and_age.csv**Used in [calculate-criminal-tendency](#)**work_status_by_edu_lvl.csv**Used in [init-person](#)**work_status.csv**Used in [init-person](#)**wealth_quintile_by_work_status.csv**

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work_status,gender,wealth,rate

Used in init-person

TO SETUP-EDUCATION-LEVELS IN SETUP

enter-age,escape-age,enter-prob,n-school,pop
 6,10,1.0,202,668405
 11,13,1.0,105,668405
 14,18,1.0,95,668405
 19,25,0.1,1,50000000

To set the education-levels from the file **schools.csv**

TO SETUP-PERSONS-AND-FRIENDSHIP IN SETUP

```
let age-gender-dist from FILE "initial_age_gender_dist.csv"
; Using Watts-Strogatz is a bit arbitrary, but it should at least give
us
; some clustering to start with. The network structure should evolve
as the
; model runs anyway. Still, if we could find some data on the
properties of
; real world friendship networks, we could use something like
; http://jasss.soc.surrey.ac.uk/13/1/11.html instead.]
```

nw:generate-watts-strogatz persons **friendship-links** num-persons 2 0.1
 [init-person age-gender-dist]. In this procedure we set the gender and
 the age of persons, using the distributions in /datafolder

TO GENERATE-HOUSEHOLDS IN SETUP

household_size_dist.csv

size,p
 1,0.28208

head_age_dist_by_household_size.csv

size,age,p
 1,18,0.004

partner_age_dist.csv

age_of_head,age_of_partner,p
 18,19,0.0833333333333333

children_age_dist.csv

age_of_head,age_of_partner,p

child_number,age_of_mother,age_of_child,p

1,21,5,0.0652173913043478

proportion_of_male_singles_by_age.csv

age,p_male



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27,0.6258515283842795

proportion_single_fathers.csv

0.1536

To define the structure of the household.

TO SETUP-SIBLINGS IN SETUP

```
ask persons with [ any? out-offspring-link-neighbors ]  
let num-siblings random-poisson 0.5 ;
```

To compute the number of siblings using a Poisson distribution, with parameter 0.5

TO SETUP-SCHOOLS IN SETUP

```
enter-age,escape-age,enter-prob,n-school,pop  
6,10,1.0,202,668405  
11,13,1.0,105,668405  
14,18,1.0,95,668405  
19,25,0.1,1,50000000
```

To setup the structure of the schools from the file **schools.csv**

TO INIT-SCHOOLS IN SETUP

To setup the links between student and school.

TO SETUP-EMPLOYERS-JOBS IN SETUP

To setup the links between people and jobs.

TO FIND-JOBS IN SETUP (ONLY ADULTS)

To setup people looking for jobs.

TO INIT-PROFESSIONAL-LINKS IN SETUP

To create professional links.



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TO CALCULATE-CRIMINAL-TENDENCY IN SETUP

To calculate the criminal tendency based on age and gender.

TO SETUP-OC-GROUPS IN SETUP

To create OC groups.

TO SETUP-FACILITATORS IN SETUP

To create facilitators. facilitators are agents who engage in criminal activities that use many accomplices.

TO RESET-OC-EMBEDDEDNESS IN SETUP

To reset the status of OC

5 Network Structure and Simulation

Flow

Here follows a list of the PROTON OC networks.

Family relationships networks

```
undirected-link-breed [household-links household-link] ; person <--> person
undirected-link-breed [partner-links partner-link] ; person <--> person
undirected-link-breed [sibling-links sibling-link] ; person <--> person
directed-link-breed [offspring-links offspring-link] ; person <--> person
```

Friendship relationships network

```
undirected-link-breed [friendship-links friendship-link] ; person <--> person
```

Criminal, professional and educational relationships networks

```
undirected-link-breed [criminal-links criminal-link] ; person <--> person
undirected-link-breed [professional-links professional-link] ; person <--> person
undirected-link-breed [school-links school-link] ; person <--> person
```

Below the flow of the simulation, the sequence of steps taken during the execution, is described.



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to go

; intervention clock

if intervention-on? [In this step, we decide if some kind of intervention go on.

```

if family-intervention != "none" [ family-intervene ]
if social-support != "none" [ socialization-intervene ]
if welfare-support != "none" [ welfare-intervene ]
]
if ((ticks mod ticks-per-year) = 0) [ (for 'year time' only)
calculate-criminal-tendency ;           to compute the criminal tendency
graduate (enroll to schools, change school if there are conditions);

```

find-job (*only the adults*) to change job status

let-migrants-in Migrant dynamic

| | |
|-------------------------------|-------------------------------|
| wedding. | Wedding phase |
| reset-oc-embeddedness. | Computation of OC-embededness |
| commit-crimes. | Agents committing crimes |
| retire-persons. | Agents retiring from work |

retire-persons Agents retiring from work
make-baby New agents into the simulation
remove-excess-friends

| | |
|------------------------------|---------------------------------|
| remove-excess-friends | to reduce the number of friends |
| make-friends | to create friendship |

ask prisoners [(end of the prisoner status)]

1

make-people-die to remove agents who died
end

6 How To Run PROTON-OC In Batch Mode

The simulation is aimed to produce repeated runs and parameter space explorations in batch mode, with large numbers of agents on parallel threads. To launch a simulation in batch mode, instructions for linux machines are normally provided with the release. An example of those scenarios is provided below:

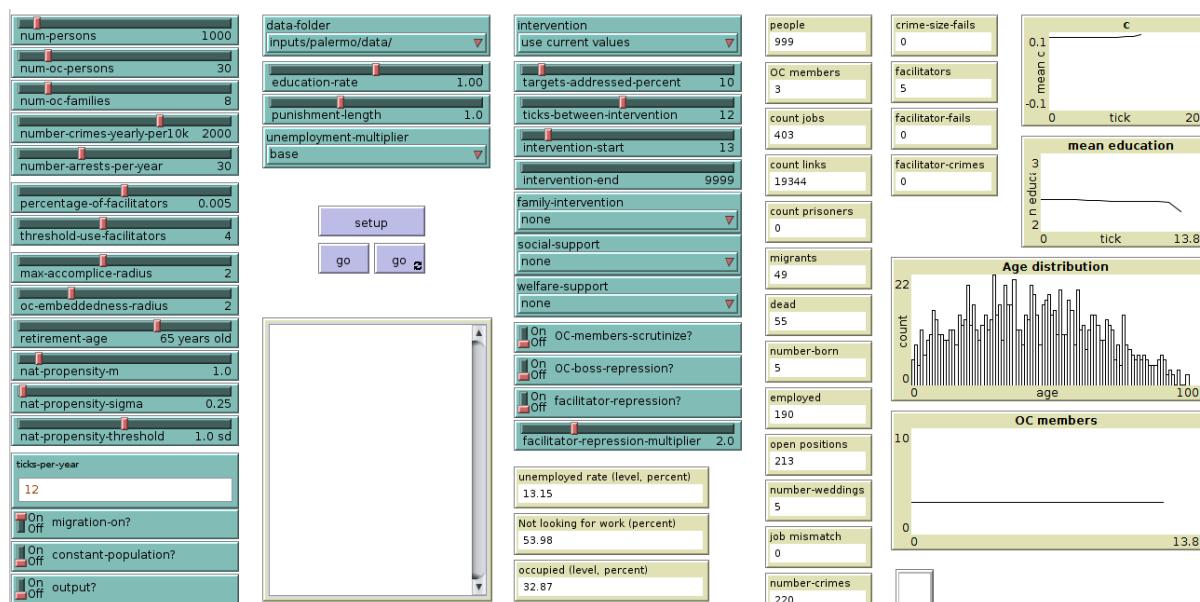


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```
nohup time ~/Documents/NetLogo\ 6.0.4/netlogo-headless.sh --model
~/Documents/PROTON-OC/PROTON-OC.nlogo --setup-file
~/Documents/PROTON-OC/experiments-xml/rp0.6emorearr.xml --table
OC5.rp0.6emorearr.xml.5d01500.csv >
OC5.rp0.6emorearr.xml.5d01500.log 2>&1 &
```

7 How to Use The Interface

This section describes how to set the parameters using the PROTON OC interface. An overview follows below. The interface is divided in four main areas, three columns for setup and operation and a composite area for outputs.



The left column provides general configuration items, the most important of which are the topmost five. These set the number of agents in the simulation, the OC size together with the number of families involved at startup (the number is for the reference setting of 10K agents), the number of crimes and the number of police interventions (also for 10K agents, yearly). The detail is shown in the next page.



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| | |
|---|--------------|
| <input type="checkbox"/> num-persons | 1000 |
| <input type="checkbox"/> num-oc-persons | 30 |
| <input type="checkbox"/> num-oc-families | 8 |
| <input type="checkbox"/> number-crimes-yearly-per10k | 2000 |
| <input type="checkbox"/> number-arrests-per-year | 30 |
| <input type="checkbox"/> percentage-of-facilitators | 0.005 |
| <input type="checkbox"/> threshold-use-facilitators | 4 |
| <input type="checkbox"/> max-accomplice-radius | 2 |
| <input type="checkbox"/> oc-embeddedness-radius | 2 |
| <input type="checkbox"/> retirement-age | 65 years old |
| <input type="checkbox"/> nat-propensity-m | 1.0 |
| <input type="checkbox"/> nat-propensity-sigma | 0.25 |
| <input type="checkbox"/> nat-propensity-threshold | 1.0 sd |
| ticks-per-year | |
| <input type="text" value="12"/> | |
| <input checked="" type="checkbox"/> On migration-on? | |
| <input checked="" type="checkbox"/> On constant-population? | |
| <input checked="" type="checkbox"/> On output? | |

num-persons: the number of agents

num-oc-persons: how many persons in the OC network (for 10K persons, so the 30 shown here would produce 3 persons)

num-oc-families: families where the OC members are distributed.

number-crimes-yearly-per10k: number of crimes.

number-arrest-per-year: police interventions.

Percentage-of-facilitators: how many facilitators exist in the environment

threshold-of-facilitator: the threshold (measured in number of accomplices) that needs the presence of a facilitator

max-accomplice-radius: how far agents can look into their social relationships and networks to find potential accomplices

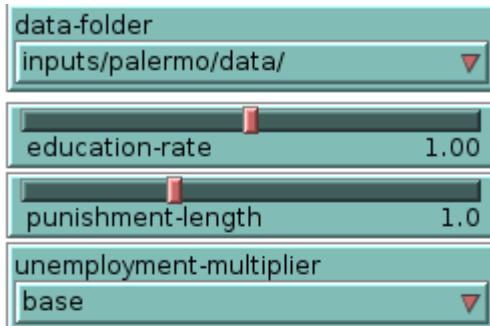
oc-embeddedness-radius: distance at which OC-embeddedness is calculated

retirement-age: age of retirement

nat-propensity(m,sigma,threshold): parameters that define the constant part of the crime propensity.

This last set of choices allows to run the simulation in special cases: stretching time (ticks-per-year), deactivating migration, or forcing the population to stay constant. The output variable activates the window in the next column where the state of the networks is reported.





This column defines the scenario we are addressing with the simulation. Here, the “palermo” setup would load data from southern Europe, while the “eindhoven” setup would load a set of data from northern Europe. The other sliders modify the loaded data increasing or decreasing the education rate, the duration of jail time, and the level of unemployment.



These are the standard buttons that activate a NetLogo simulation.



This output window will show, when activated, internal count data describing the size of different networks in the model.



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| | |
|-----------------------------------|----------------------------------|
| intervention | |
| use current values | <input type="button" value="▼"/> |
| targets-addressed-percent | 10 |
| ticks-between-intervention | 12 |
| intervention-start | 13 |
| intervention-end | 9999 |
| family-intervention | |
| none | <input type="button" value="▼"/> |
| social-support | |
| none | <input type="button" value="▼"/> |
| welfare-support | |
| none | <input type="button" value="▼"/> |
| On
Off OC-members-scrutinize? | |
| On
Off OC-boss-repression? | |
| On
Off facilitator-repression? | |
| facilitator-repression-multiplier | 2.0 |
| unemployed rate (level, percent) | |
| 13.15 | |
| Not looking for work (percent) | |
| 53.98 | |
| occupied (level, percent) | |
| 32.87 | |

This column contains all the controls needed to select the interventions we may want to activate. The first chooser, if set to anything else but “use current values”, will load at setup a set of pre-cooked values for specific interventions of interest. The other sliders allow for fine tuning of the above, starting with quantity (targets-addressed-percent) and timing (start and end) of interventions.

These three sliders detail the level of interventions for family, social and welfare support, components of the preventive intervention.

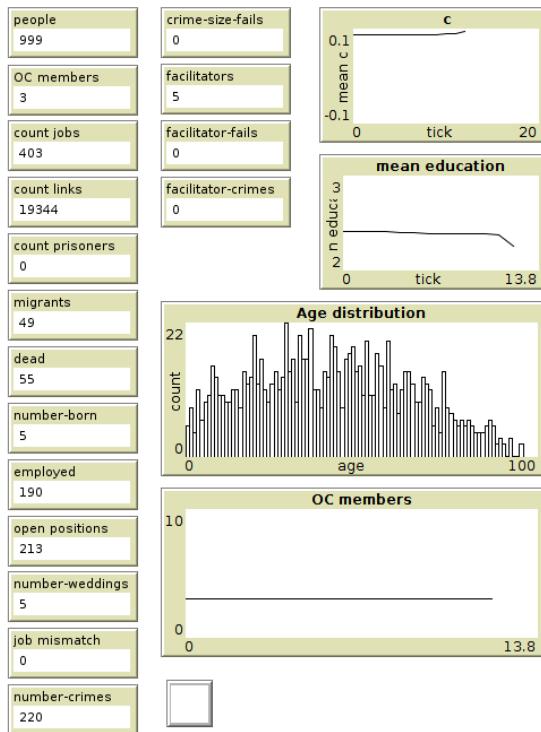
The *scrutinize* slider makes OC members act more cautiously, while the *repression* slider activates the disruptive intervention.

This last couple of controls activate the facilitator interventions and set its intensity.

A first set of monitors ends this column, reporting on occupation rates.



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This last area of the simulator contains all the (self-explanatory) numerical reports that constitute the visual output of the simulator. The main observables are the number of OC members, also in the plot, and the evolution of the mean criminal activity (c) and the mean education. Visualizing age distribution is important to understand the evolution of the population in the long time scale of the simulation.



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8 NETLOGO DEFINITIONS

Below the source code that contains values that can be edited is described. Modifying the source code requires an advanced Netlogo competence.

TO-REPORT FACTORS-C. PROBABILITY TO COMMIT A CRIME

#editzone

TO REPORT FACTORS-C

This procedures describes the calculation of the agents' tendency to commit criminal acts. This tendency is based on a set of **FACTORS**

if-else-value it is the method to evaluate the alternative.

the syntax is:

the first [] contains the value for the **factor** is the test give a TRUE results, the second [] contains the value for the **factor** is the test give a FALSE results, example

(list "employment" [-> ifelse-value (my-job = nobody) [1.30] [1.0]])

Employment is a factor, if agent has NOBODY job, the **factor** is 1.30, if the agent has a job, the **factor** is 1.0.

Turtle-set means a 'set that contains some agents'. With the instruction **neighbors** we indicate the neighbors into some network (a neighbor is an agent that I can reach with a single move on the network)

```
report (list
  ; var-name normalized-reporter
  (list "employment" [ -> ifelse-value (my-job = nobody) [ 1.30 ]
  [ 1.0 ] ])
  (list "education" [ -> ifelse-value (education-level >= 2) [ 0.94 ]
  [ 1.0 ] ])
  (list "propensity" [ -> ifelse-value (propensity >
```

$$\text{Propensity} = e^{(m-\sigma^2/2)} + th \cdot \sqrt{e^{\sigma^2} - 1} \cdot e^{(m+\sigma^2/2)}) \\ [1.97] [1.0]]$$



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```

(list "crim-hist" [ -> ifelse-value (num-crimes-committed >= 0) [ 1.62 ] [
1.0 ] ])

(list "crim-fam" [ -> ifelse-value
(any? family-link-neighbors and count family-link-neighbors
with [ num-crimes-committed > 0 ] /
count family-link-neighbors > 0.5) [ 1.45 ] [ 1.0 ] ])

(list "crim-neigh" [ -> ifelse-value
( (any? friendship-link-neighbors or any? professional-link-neighbors) and
(count (turtle-set friendship-link-neighbors with [ num-crimes-committed >
0 ] professional-link-neighbors with [ num-crimes-committed > 0 ])) /
(count (turtle-set friendship-link-neighbors professional-link-neighbors)) >
0.5) [ 1.81 ] [ 1.0 ] )

(list "oc-member" [ -> ifelse-value
(oc-member? and not (intervention-on? and OC-members-scrutinize?)) [ 4.50 ] [ 1.0 ] ])

)
End

```

#editzone

TO WELFARE-INTERVENE

This procedure identifies the agents (targets) who receive the welfare intervention. The method used to select them influences their number. In **bold**, we indicate the variables. No-turtles means 'no agents'

```

let the-employer nobody
let targets no-turtles
ifelse welfare-support = "job-mother" [
  set targets all-persons with [not male? and any? partner-link-neighbors with [
  oc-member? ] and my-job = nobody ]
][
  if welfare-support = "job-child" [
    set targets all-persons with [ age > 16 and age < 24
      and not any? my-school-links
      and any? in-offspring-link-neighbors with [ male? and oc-member? ]
      and my-job = nobody ]
    ]
  ]
if any? targets [

```



```

set targets n-of ceiling (targets-addressed-percent / 100 * count targets)
targets
  welfare-createjobs targets
]
end

```

TO SETUP-OC-GROUPS

This procedure creates the OC-groups.

Weighted means 'using some kind of probabilistic selection method', for example

```

ask rnd:weighted-n-of num-oc-families persons [
  criminal-tendency + criminal-tendency-addme-for-weighted-extraction
] [set oc-member? true]

```

means ... select persons using the criminal-tendency as a factor that increases the probability of being selected

```

ask rnd:weighted-n-of num-oc-families persons [
  criminal-tendency + criminal-tendency-addme-for-weighted-extraction
] [set oc-member? true ]

```

```

let suitable-candidates-in-families persons
with
[age > 18 and not oc-member? and any? household-link-neighbors with [ oc-
member? ]]
ask rnd:weighted-n-of min
(list count suitable-candidates-in-families (num-oc-persons - num-oc-families))
suitable-candidates-in-families [
  criminal-tendency + criminal-tendency-addme-for-weighted-extraction
] [
  set oc-member? true
]

```



TO INIT PERSON [AGE-GENDER-DIST]; PERSON COMMAND

This procedure describes the creation of a person, setting age,gender,job and education

```

let row rnd:weighted-one-of-list age-gender-dist last ;
select a row from our age-gender distribution
set birth-tick 0 - (item 0 row) * ticks-per-year
; ...and set age...
init-person-empty
set male? (item 1 row)
; ...and gender according to values in that row.
set retired? age >= retirement-age
; persons older than retirement-age retire

; education level is chosen, job and wealth follow in a conditioned sequence

set max-education-level tune-edu pick-from-pair-list table:get edu male?
set education-level max-education-level
limit-education-by-age
ifelse age > 16 [
  set job-level from work_status_by_edu_lvl list education-level ]
[
  set job-level 1
  set wealth-level 1 ; this will be updated by family membership
]
end

```

TO SETUP-EMPLOYERS-JOBS

This procedure describes

```

output "Setting up employers"
let job-counts reduce sentence read-csv "employer_sizes"
let jobs-target manipulate-employment-rate (count persons with [ job-level != 1 ])
while [ count jobs < jobs-target ] [
  let n manipulate-employment-rate (one-of job-counts)
  create-employers 1 [
    set my-jobs nobody
    hatch-jobs n [
      set my-employer myself
      ask my-employer [ set my-jobs (turtle-set my-jobs myself) ]
      set job-level random-level-by-size n
    ]
  ]
]

```



```

set my-worker nobody
set label self
]
set label self
]
]
```

TO-REPORT ARREST-PROBABILITY-WITH-INTERVENTION [GROUP]

This procedure describes

```

if-else (intervention-on? and OC-boss-repression? and any? group with [ oc-
member? ])
[ report OC-repression-prob group * law-enforcement-rate ]
[ report probability-of-getting-caught * law-enforcement-rate ]
end
```

TO REPORT OC-REPRESSION-PROB [A-GROUP]

This procedure describes

```

let representative one-of a-group with [ OC-member? ]
let n [ count person-link-neighbors with [ OC-member? ] ] of representative
report (n / (n + 1)) ^ 2 * degree-correction-for-bosses
end
```

TO RETIRE-PERSONS

This procedure describes

```

ask persons with [ age >= retirement-age and not retired? ] [
  set retired? true
  if my-job != nobody [ ask my-job [ set my-worker nobody ] ]
  set my-job nobody
  ask my-professional-links [ die ]
```

TO-REPORT FIND-ACCOMPLICES [N]; PERSON REPORTER

This procedure describes

Accomplices are identified on the basis of a radius that can vary.

```
let d 1 ; start with a network distance of 1
```



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```
let accomplices []
nw:with-context persons person-links [
  while [ length accomplices < n and d < max-accomplice-radius ] [
    let candidates sort-on [
      candidate-weight
    ] (nw:turtles-in-radius d) with [ nw:distance-to myself = d ]
    while [ length accomplices < n and not empty? candidates ] [
      let candidate first candidates
      set candidates but-first candidates
      if random-float 1 < [ criminal-tendency ] of candidate [
        set accomplices lput candidate accomplices
      ]
    ]
    set d d + 1
  ]
]
if length accomplices < n [ set crime-size-fails crime-size-fails + 1 ]
report accomplices
end
```



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TO GET CAUGHT [CO-OFFENDERS]

This procedure describes

```
set number-law-interventions-this-tick number-law-interventions-this-tick + 1
ask co-offenders [
  set breed prisoners
  set shape "face sad"
  ifelse male?
    [ set sentence-countdown item 0 rnd:weighted-one-of-list male-punishment-
length-list [ [ p ] -> last p ] ]
    [ set sentence-countdown item 0 rnd:weighted-one-of-list female-
punishment-length-list [ [ p ] -> last p ] ]
    set sentence-countdown sentence-countdown * punishment-length
    if my-job != nobody [
      ask my-job [ set my-worker nobody ]
      set my-job nobody
    ]
    if my-school != nobody [ leave-school ]
    ask my-professional-links [ die ]
    ask my-school-links [ die ]
    ; we keep the friendship links and the family links
  ]
end
```



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TO CALCULATE-CRIMINAL-TENDENCY

The **epsilon_c** c is how many we change the criminal-tendency for any person, based on some individual feature, like age or gender.. It derive from the table **c-by-age-and-sex**

```

set epsilon_c table:from-list map [ x -> list x 0 ] table:keys c-by-age-and-sex
foreach table:keys c-range-by-age-and-sex [ genderage ->
    let subpop all-persons with [ age = item 1 genderage and male? = item 0
    genderage ]
    if any? subpop [
        let c item 1 item 0 table:get c-range-by-age-and-sex genderage
        ; put only the individual part into personal values
        ask subpop [
            set criminal-tendency 0
            foreach factors-c [ x ->
                set criminal-tendency criminal-tendency * (runresult item 1 x)
            ]
        ]
        ; then derive the correction from the average of
        let epsilon mean [ criminal-tendency ] of subpop
        ask subpop [
            set criminal-tendency criminal-tendency + c - epsilon
        ]
        assert [ -> mean [ criminal-tendency ] of subpop - c < 0.01 * c ]
    ]
]
calc-criminal-tendency-addme-for-weighted-extraction
calc-criminal-tendency-subtractfromme-for-inverse-weighted-extraction
calc-degree-correction-for-bosses
end

```



TO-REPORT SOCIAL-PROXIMITY-WITH[TARGET]; PERSON REPORTER

We use the measure of 'social proximity' when it is necessary to decide whether a relationship between two undivided persons will or will not end well, typically in the procedure that manages marriage. These are the procedures that perform the calculation

to-report factors-social-proximity ; person reporter.

```

let ego myself
let alter self
report (list
  ; var-name weight normalized-reporter
  (list "age" 1.0 [ -> ifelse-value (abs (age - [ age ] of ego) > 18) [ 0
] [ 1 - abs (age - [ age ] of ego) / 18 ] ])
  (list "gender" 1.0 [ -> ifelse-value (male? = [ male? ] of ego) [ 1 ][ 0
] ])
  (list "wealth" 1.0 [ -> ifelse-value (wealth-level = [ wealth-level ] of
ego) [ 1 ][ 0 ] ])
  (list "education" 1.0 [ -> ifelse-value (education-level = [ education-level
] of ego) [ 1 ][ 0 ] ])
  (list "closure" 1.0 [ -> ifelse-value (any? (other [ friendship-link-
neighbors ] of alter) with
[ friendship-link-neighbor? ego ]) [ 1 ][ 0 ] ])
)
end
```



TO-REPORT OC-EMBEDDEDNESS; PERSON REPORTER

This procedure computes the oc-embeddedness

```
if cached-oc-embeddedness = nobody [
    ; only calculate oc-embeddedness if we don't have a stored value
    nw:with-context all-persons person-links [
        set cached-oc-embeddedness 0 ; start with an hypothesis of 0
        if any? oc-members [
            ....
            ;      sum [ 1 / nw:weighted-distance-to myself dist ] of other
oc-members /
            ;      sum [ 1 / nw:weighted-distance-to myself dist ] of other
agents
            ;      )
            ]
            ]
            ]
            ]
            ]
report cached-oc-embeddedness
end

; we do no track time of crime so for now the requirement of
; "at least one crime in the last 2 years." is not feasible.
; for now we use just "at least one crime."
```



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Appendix: Prototype of and Technical Guide to PROTON-S Terrorism Recruitment Model

This section of D5.1 is a technical guide to allow researchers and stakeholders, with the support of computer programmers, to i) adapt the Proton Terrorism Model to other contexts and scenarios and ii) expand the Proton Terrorism Model to be able to test additional policies or including additional social dynamics. More specifically, in this section we explain i) how to assign parameters for running the simulation experiments, ii) which files need to be modified, iii) which settings are assigned by default, iv) what is the expected calculation time and finally v) how to retrieve and analyze the results.

All the code mentioned in this guide is publicly accessible on GitHub at
<https://github.com/LABSS/PROTON-T/releases>



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1 How to Modify Parameters

The PROTON T setup allows us to load the parameters in two different ways:

- (1) by the **setup** procedure¹. This procedure sets the parameters getting the values from the configuration files in the directory structure (see section [MODIFY PARAMETERS BY SETUP PROCEDURE](#)).
- (2) by the **experiment.xml** file (see section [MODIFY PARAMETERS BY EXPERIMENT.XML](#)) or by the interface (see section [USING THE INTERFACE](#))

2 How to Modify Parameters by Set Up Procedure

The procedure in the code which loads the parameters is called setup. Inside the setup procedure, parameters are loaded from files through another procedure called load-totals. These parameters define the demographic and socio-economic features of the synthetic population.

At the beginning of the code, a file defining i) the behavioural parameters, ii) which actions are allowed and iii) how much they affect the radicalization process is loaded: this file is called [SCENARIO.NLS](#).

Parameters from load-totals

to *load-totals*

```
set local group-by-first-item read-csv "neighborhoods"  
set population group-by-first-item read-csv "neukolln-totals"  
read-csv      ."neukolln-by-citizenship-migrantbackground-gender-  
religion-age"
```

¹ The code, parameters, and setup data are located in different folders and files. To indicate the name of the folder we use the \convention (i.e.\datainput means that the files are in the \datainput folder). The names of the files are in **bold**.



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load-totals sets some tables. **local** is the table with the main parameters. It is located in the file .\PROTON-T\inputs\neukolln\data\ **neighborhoods.csv**. This file contains all the general parameters for the simulation and it is possible to edit it with a text editor. The file contains the same parameters for four (4) different areas. Here, we show data only for the first area.

The data about the four neighborhoods of Neukolln are stored into the **neighborhoods.csv** file

factor,area,value

Population size,1,155950. Number of agents

Population density,1,13e3. The population density

Demography

percent of males,1,51.2

num of immigrant Muslims,1,31316

num of immigrants,1,51691

percent non-citizens,1,0.34

percent 0-17,1,0.16

percent18-64,1,0.74

percent65 on,1,0.1

Economy

Unemployment males,1,0.12

Pverty rates,1,0.3

Low education (Male immigrants),1,0.47

Religion, culture

num of mosques,1,14

numof radical mosques,1,3

num of community centers,1,6

num of parks,1,10

numof coffees,1,50



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The data about the geography are stored into the ***neukolln-totals.csv*** file.

area_code,area_name,sum(value)

1,Neukölln,142621.3333333334
2,Britz/Buckow,61477.3333333336
3,Gropiusstadt,31491.3333333332
4,Buckow Nord/Rudow,45918

The data about individual characteristics are deduced by the ***neukolln-by-citizenship-migrantbackground-gender-religion-age.csv*** file.

area_code,migrant?,male?,muslim?,age,value

1,false,false,false,16,18
1,false,false,false,17,18
1,false,false,false,18,140.42857142857142
1,false,false,false,19,140.42857142857142
1,false,false,false,20,140.42857142857142
1,false,false,false,21,140.42857142857142

Finally, individual opinions are loaded, on the base of the characteristics above, from the ***combination_data*** file that offers a set of individual characteristics for that combination, from which one is extracted to populate an individual's opinion set.

immigrant?,male?,muslim?,age,integration,trust,deprivation,fundamentalism

0.0,0,0.0,1.0,"[1.272727272727273, 0.72727272727271, -
0.5454545454545454, ...],"[1.375, 1.125,
0.625,...],"[0.7922248995983936, 0.6894136546184741,
0.8767871485943775, ...]"



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Parameters from SCENARIO.NLS

In PROTON-T, the parameters that define the behavior of the agents are stored into the **SCENARIO.NLS** file. It is possible to edit SCENARIO.NLS with a text editor.

Propensity-factors

Below the factors that can lead to radicalization are described. The syntax is based on the ifelse-value instruction, which works as follows: if the condition is true, then the propensity of the agent is assigned to have the corresponding value. Propensity is defined between 0 and 1.

to-report propensity-factors;

```
[ -> ifelse-value (get "male?") [ 0.113 ] [ 0 ] ]
[ -> ifelse-value (employed?) [ 0 ] [ 0.208 ] ]
[ -> ifelse-value (get "criminal-history?") [ 0.678 ] [ 0 ] ]
[ -> ifelse-value (get "immigrant?") [ 0.081 ] [ 0 ] ]
[ -> ifelse-value (get "authoritarian?") [ 0.9 ] [ 0 ] ]
[ -> ifelse-value (age <= 25) [ 0.1 ] [ 0 ] ]
```

Make-attribute-set

Below is indicated the relationship between age and radicalization. The relationship is defined in the file **neukolln-by-citizenship-migrantbackground-gender-religion-age.csv**

to-report make-attributes-set [the-area];

```
(list "male?" item 1 my-group)
(list "muslim?" item 2 my-group)
(list "immigrant?" item 0 my-group)
(list "authoritarian?" one-of [true false])
(list "criminal-history?" one-of [true false])
```

List of locations

Below is the list of places available to the agents.

to-report location-names;

```
report (list "propaganda place" "community center" "public space" "workplace" "coffee")
```

Mandatory activities

Below is the list of activities which have to be necessarily accomplished by the agents, once that given conditions are verified. In the present release of PROTON-T there is only one mandatory activity that is "sleeping when at home between 0 and 8 am".

to-report mandatory-activity-definition-list;

```
report (list
;      start-time duration location-type task criteria
(list          0        8 "residence"  [ -> sleep ] [ -> true ] )
```



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Job definition

Below is the list of the non-mandatory activities which can be accomplished once some conditions are verified.

to-report job-definition-list;

```
;      num-jobs start-time duration location-type task priority
;  initialization
(list      number-workers-per-community-center
          8           12 "community center" [ -> preach ]    0)
(list      1           12     "propaganda place" [ -> preach ]    0)
(list      round (population-employed-% * total-citizens / 100 / 20)
          8           8 "workplace"        [ -> work ]    2)
```

Free-time definition

Below is the list of activities related to leisure time.

to-report free-time-activity-definition-list;

```
;      location-type      task
(list "residence"      [ -> socialize ]      )
(list "residence"      [ -> socialize-online ] )
(list "coffee"          [ -> socialize ]      )
(list "public space"   [ -> socialize ]      )
(list "propaganda place" [ -> socialize ]      )
(list "community center" [ -> socialize ]      )
```

Topic definitions

The table below describes the topics for the agents' opinion dynamics. For example, if agent i interacts with agent j , and the opinion of the former on the Non-integration topic has a positive value (that is, agent j considers himself/herself as non-integrated), the former will increase his/her own opinion on the same topic (that is, agent i ends up feeling more non-integrated).

to-report topic-definitions;

| type | risk-weight | protective-weight |
|-----------------------------------|-------------|-------------------|
| "Non integration" | 0.188 | 0.178) |
| "Institutional distrust" | 0.277 | 0.153) |
| "Collective relative deprivation" | 0.116 | 0 |



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3 How to Modify Parameters by EXPERIMENT.XML

EXPERIMENT.XML is a configuration file containing the same parameters which can be set in the simulation interface (see [using the interface](#)). This file can be edited from a text editor.

```
<experiment name="sensitivity_01" repetitions="10"
runMetricsEveryStep="true">
  <setup>setup</setup> procedure to assign parameters
  <go>go</go> procedure which starts the simulation
  <!-- assuming 6 months -->
  <timeLimit steps="3060"> length of the simulation

    list of results
    <!-- Metrics for the wizard -->
    <!-- t1 recruited citizens -->
    <metric>t1</metric>
    <!-- t2 citizen at risk (over threshold) -->
    <metric>t2</metric>
    <!-- t3 risk of citizens -->
    <metric>t3 "mean" 0</metric>
    <metric>t3 "median" 0</metric>
    ...
    list of results
    <!-- variable parameters (and population) -->
    <enumeratedValueSet variable="total-citizens">
      <value value="40000"/>
    </enumeratedValueSet>
    <enumeratedValueSet variable="police-density">
      <value value="0.05"/>
    </enumeratedValueSet>
    <enumeratedValueSet variable="alpha">
      <value value="0.0"/>
      <value value="1.0"/>
    </enumeratedValueSet>
```



4 Simulation Flow

Below the flow of the simulation is described. In this model, agents follow a simulated *routine activity*; each agent is endowed with links to activities that can be compulsory (sleep), jobs, or leisure activities. Thus, initially the program assigns new activities to all free agents, that is, agents that have completed their activity, and then starts that activity, resetting a counter for that activity duration. The simulation flow happens all here, with the only exception of the police agents that move with a different routine.

```
ask citizens [
  assert [ -> countdown >= 0 ]
  if countdown = 0 [ ; end of activity or activity without duration
    set current-task nobody
    set current-activity nobody
    ; first: try mandatory, then jobs..
    let new-activity one-of activity-link-neighbors with [
      [ start-time = current-time and is-mandatory? ] of my-activity-type
    ]
    if new-activity = nobody [
      set new-activity one-of activity-link-neighbors with [
        [ workday? ] of myself and [ start-time = current-time and is-job? ] of my-activity-type
      ]
      ; ...then try leisure activities, including socializing at home
      if new-activity = nobody [
        let candidate-activities activity-link-neighbors with [
          [ not is-mandatory? and not is-job? ] of my-activity-type and not is-full?
        ]
        set new-activity rnd:weighted-one-of candidate-activities [
          (([ value ] of link-with myself + 2) / 4) + (1 / (1 + distance myself)) ; this weights
          value the same as inverse distance.
        ]
        ; everything hopeless. In this case, it would sleep, if at least that link still exists.
        if new-activity = nobody [
          set fail-activity-counter fail-activity-counter + 1
          ; at least the sleep activity will always be there. We're also protecting the home
          activities now.
          set new-activity one-of activity-link-neighbors with [ [ location-type ] of my-activity-
          type = "residence" ]
        ]
      ]
    ]
    start-activity new-activity
  ]
]
```

Activities that still running are performed, and their countdown is decreased. The procedure run current-task allows agents to decide which activity to accomplish on the basis of i) his/her own characteristics, ii) the week day and iii) the precise hour of the day. Depending on the activity, different interactions take place.

```
if current-task != nobody [
  run current-task
```



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```
    set countdown countdown - 1  
]
```

And finally, police agents (both normal police and CPOs) make their move:

```
move-police
```

What is left in the main routine is only a further randomization of the recruiter activity, the export of opinions if requested, output update and the printing of a pulse in the batch runs. The tick command ends the main routine.

```
if ticks mod ticks-per-day = 0 [  
  ask activity-types with [ location-type = test-location-type and is-mandatory? and is-job? ] [  
    randomize-recruit-times  
  ]  
  if opinion-dumps-every < 99999 and ticks mod opinion-dumps-every = 0 [  
    export-risk  
    export-opinions  
  ]  
  if activity-debug? [ update-output ]  
  if behaviorspace-experiment-name != "" [  
    show (word behaviorspace-run-number "." ticks " t:" timer )  
  ]  
  tick
```



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5 How To Run PROTON-OC In Batch Mode

To perform multiple runs of the simulation, we employ the behaviorspace mode of NetLogo, using external xml configuration files. Those are stored in the experiments-xml subdirectory. Examples of run instructions can be found in the project releases, as the one in:

<https://github.com/LABSS/PROTON-OC/releases/tag/v0.9b>

An example of batch launch is with the instruction:

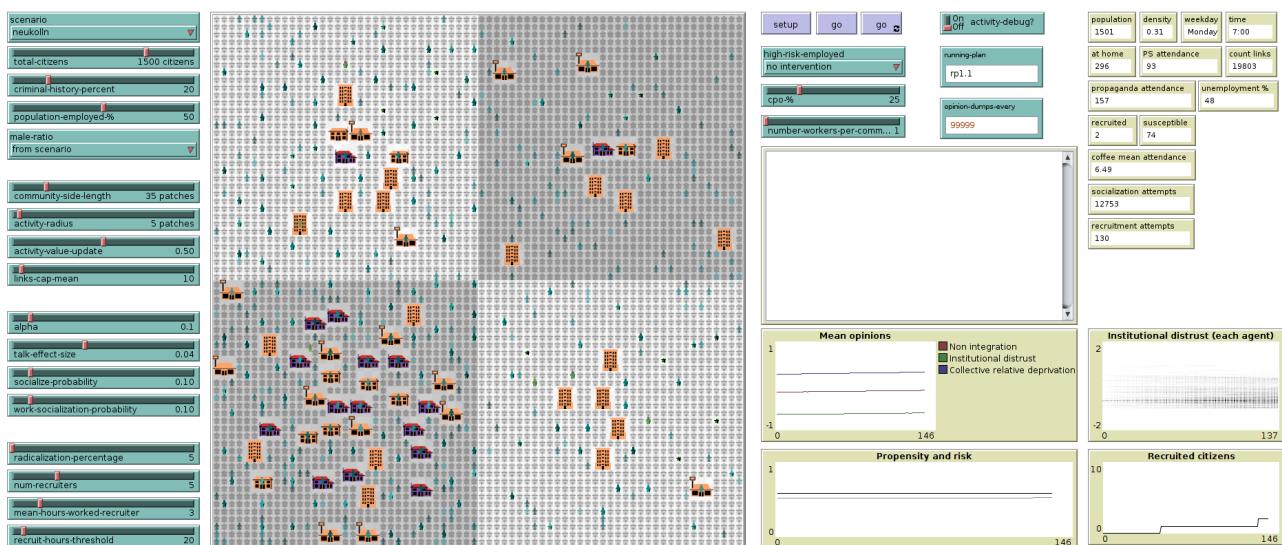
```
time nohup /home/paolucci/NetLogo\ 6.0.4/netlogo-headless-2.sh --model PROTON-OC.nlogo --setup-file experiments-xml/rp0.2/rp0.2-OC-speedtest.xml --table rp0.2-st.csv > rp0.2-st.out 2>&1 &
```



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6 How to Use The Interface

This section describes how to set the parameters using the PROTON T interface, presented below. The interface is divided in four columns. At the center, there is the view-only abstract implementation of simulated space, complete with the locations where activities happen. Details of the other areas are presented below.



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| | |
|--------------------------|---------------|
| scenario | neukolln |
| total-citizens | 1500 citizens |
| criminal-history-percent | 20 |
| population-employed-% | 50 |
| male-ratio | from scenario |

scenario: the set of parameters to be loaded from configuration file. Currently we only provide data from the neighborhood of Neukolln. The other sliders define size (*total-citizens*) and characteristic of the population (criminals, employed, and the male-female ratio that can be loaded from the Neukolln data or forced to a specific value).

| | |
|-----------------------|------------|
| community-side-length | 35 patches |
| activity-radius | 5 patches |
| activity-value-update | 0.50 |
| links-cap-mean | 10 |

This block of sliders define the space where agents move and activities happen. *community-side-length* gives the side length of the communities; this controls in turn the density of activities and citizens in the simulated space. The *radius* controls how far the agents see. *activity-value-update* weights how much a successful interaction will increase the weight of one activity (or the opposite), while *links-cap* limits the number of places the agents can remember.

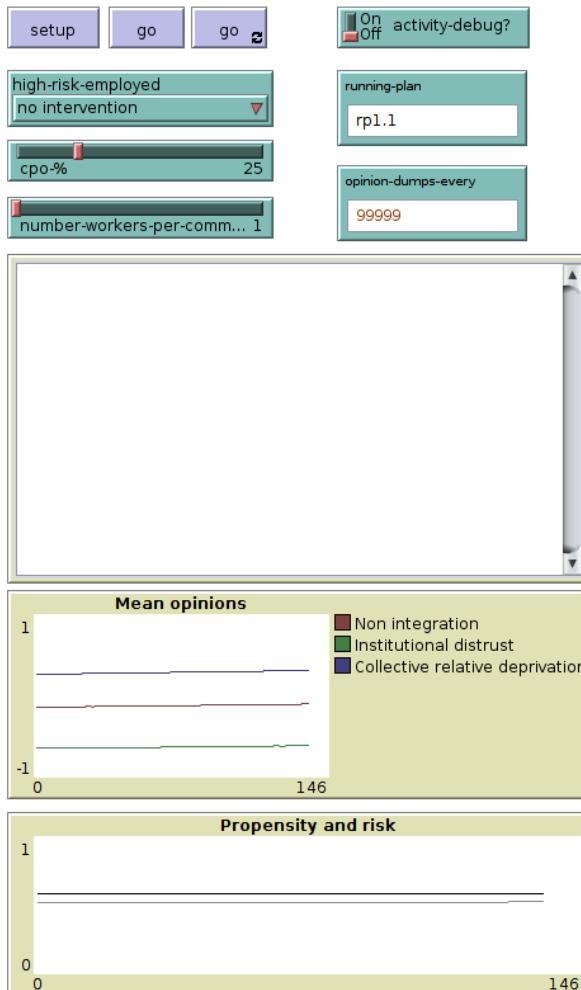
| | |
|--------------------------------|------|
| alpha | 0.1 |
| talk-effect-size | 0.04 |
| socialize-probability | 0.10 |
| work-socialization-probability | 0.10 |

This set of sliders controls the opinion dynamic subsyste. *Alpha* is the tolerance parameter, *talk.effect-size* controls how much will opinions change as a result of successful interaction, and the two *socialize-probability* sliders control the probability of interaction at work and in leisure activities.

| | |
|-----------------------------|----|
| radicalization-percentage | 5 |
| num-recruiters | 5 |
| mean-hours-worked-recruiter | 3 |
| recruit-hours-threshold | 20 |

Here, the recruitment process is controlled, starting by fixing the initial ratio of susceptible agents (*radicalization-percentage*) and then specifying how many recruiters we will have and how many hours they will be active, on average. The *recruit-hours-threshold* fixes, on average, the number of interactions with the recruiter that are needed before the recruitment attempt.





This area controls simulation executions and interventions. The setup, go, and repeated go buttons are customary in NetLogo. The control below give the percentage of high-risk agents that get employed, the percentage of CPO agents over the total police force, and the number of community workers for each community center.

The large space below can be filled with debug information if the *activity-debug* flag is activated. It will show step-by-step activities from the recruiters agents, and some other. The running-plan and opinion-dumps-every boxes are meant to activate a routine that saves to disk individual opinions and to give it a significant name.

The next plots show the position of individual opinions in the opinion space, and the mean value of propensity and risk.

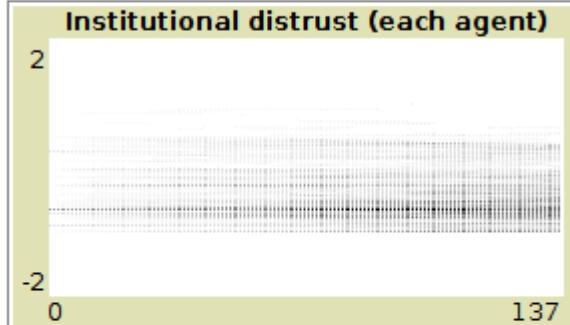


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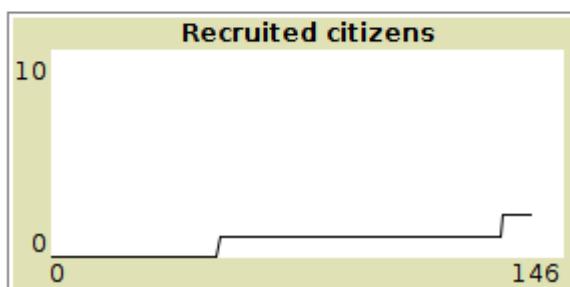
| | | | |
|---------------------------------|----------------------|-------------------|----------------------|
| population
1501 | density
0.31 | weekday
Monday | time
7:00 |
| at home
296 | PS attendance
93 | | count links
19803 |
| propaganda attendance
157 | unemployment %
48 | | |
| recruited
2 | susceptible
74 | | |
| coffee mean attendance
6.49 | | | |
| socialization attempts
12753 | | | |
| recruitment attempts
130 | | | |

The next column of the interface contains a set of reporters on the state of the simulation, mostly self-explanatory.

The main result appears here, in the number of recruited agents. The number of susceptible agents gives a reference on the potential recruitment pool. Coffees are the place where recruitment happens, so the mean attendance to coffee places is reported here. Finally, the number of recruitment attempts (including contacts that happen below the necessary time threshold) together with the total number of socialization attempts, is shown.



This plot gives a visual idea of the distribution of agents in the opinion space in time, for just one of the topics.



The number of recruited citizens is the last item in the interface



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