Supplementary Materials

1 Formalization of the ABM

1.1 Agent's Probability of Committing a Crime ($C_{i,t}$)

We model the probability of committing a crime $C_{i,t}$ for an individual i at time t as:

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

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 from j to m 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 t and for each subset of the population (g, a) of given gender and age class, the following equation shall hold:

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

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 1 of the main text, 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:

$$F_C \left[C(g,a)_{t_1}, \dots, C(g,a)_{t_k} \right] = F_C \left[C(g,a)_{t_{1+\tau}}, \dots, C(g,a)_{t_{k+\tau}} \right] \text{ for } \forall\, \tau, t_1, \dots, t_k \tag{3}$$

Overall the ABM is designed to generate a realistic number of crimes. In particular, the crime-commission process ensures that the total number of annual crimes in the simulation corresponds to the observe number offenses, corrected for the dark figure, observed in Sicily in the 2012-2016 period. $C_{i,t}$ has been computed to provide realistic figures on committed offenses within the model, in the form of rates by 100,000 inhabitants, using official statistics for different years (2012-2016, specifically).

1.2 Organized Crime Embeddedness ($R_{i,t}$)

In mathematical notation, a multiplex network $\mathcal{G} = \left\{G^1, ..., G^l, ..., G^M\right\}$ similar to our simulated society is a set of M single-layer networks updated at each time unit t. Each single-layer network is denoted as $G^l = (V, E)$, where V is the set of vertices and E is the set of edges connecting them. G^l takes the form of a $V \times V$ matrix. Given this notation, for each G^l, we define an h-hop neighborhood graph for each vertex i. The vertex set of the h-hop neighborhood graph is defined as the set $V_i^h = \left\{j | k \in V_i^{h-1}, j \in V, (k,j) \in E\right\} \cup V_i^{h-1}$ with $h \geq 1$. The set of edges is then formalized as $E_i^h = \left\{(j,k) | j \in V_i^{h-1}, k \in V_i^h, (j,k) \in E)\right\}$. The local neighborhood of agent i in the single layer network $G^l = (V, E)$ becomes then a vector $\mathbf{w}_i^{G^l} = \left[\mathrm{w}_{i,l}^{G^l} \cdots \mathrm{w}_{i,j}^{G^l}\right]$ where each element represents the weight of the edges included in the h-hop local neighborhood of the agent. Each value of the vector follows the relation $\mathrm{w} \propto h^{-1}$, meaning that the weights are inversely proportional to the distance between the agent i and any agent j included in the h-hop network. To compute the embeddedness R_i of a agent i in his local community, we sum over the vectors derived from each G^l:

$$\mathbf{w}^{\mathcal{G}} = \left[\mathrm{w}_{i,l}^{G^1} \cdots \mathrm{w}_{i,j}^{G^1}\right] + \cdots + \left[\mathrm{w}_{i,l}^{G^l} \cdots \mathrm{w}_{i,j}^{G^l}\right] = \left[\mathrm{w}_{i,l}^{\mathcal{G}} \cdots \mathrm{w}_{i,j}^{\mathcal{G}}\right] \tag{4}$$

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 $\Theta_i^{\mathcal{G}} = \left[\theta_{i,l}^{\mathcal{G}} \cdots \theta_{i,j}^{\mathcal{G}}\right]$, 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:

$$R_i = \frac{\sum_{i=1}^{N_{OC}^h} \theta_{i,j}^{\mathcal{G}}}{\sum_{i=1}^{N^h} \mathrm{w}_{i,j}^{\mathcal{G}}} \in [0,1] \tag{5}$$

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 that all agents in agent i h-hop networks are organized crime members and 0 that no organized criminals are present in the local community of the agent. The proposed method implicitly weights the organized crime embeddedness such that the importance of organized crime ties (i.) is inversely proportional to the distance and (ii.) the importance of ties in general is proportional to the number of different relations shared between any two individuals.

2 Data

This section provides additional detail regarding the data used to calibrate and validate the ABM.

2.1 Demographic Data

The population of the model is initialized by implementing different household types. It is important that household structure is based on data as this will influence the demography in our simulated society. 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 initialize their agent ABM population. See the Appendix of Andrighetto et al (2019) 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 (Istat, 2011) and from data made specially available by the Municipality of Palermo. One part of this, the population distribution in Palermo, is shown in Figure 1.

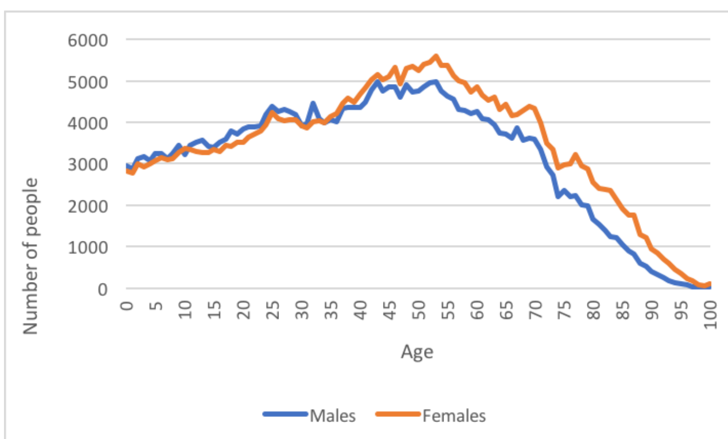

Figure 1: Population distribution by gender in Palermo

2.2 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 2).

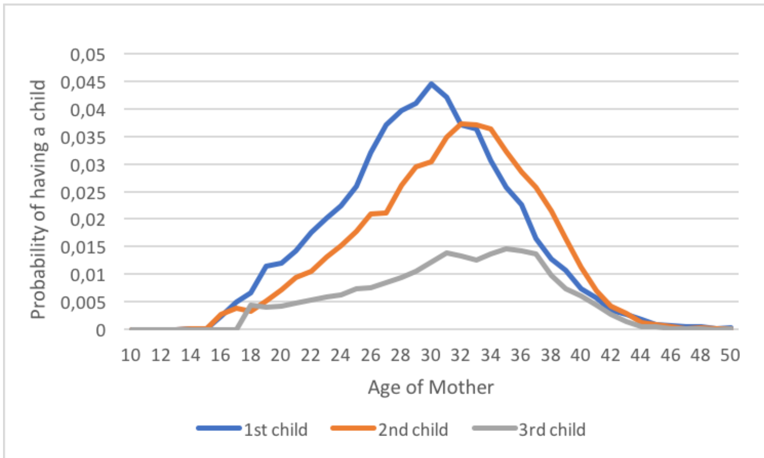

Figure 2: Fertility Rate in Palermo

To calibrate agents' deaths, we use data on people's probabilities of living depending on their age and gender in Palermo (Istat, 2016b) (Figure 3). The age range for this is 0-119 years.

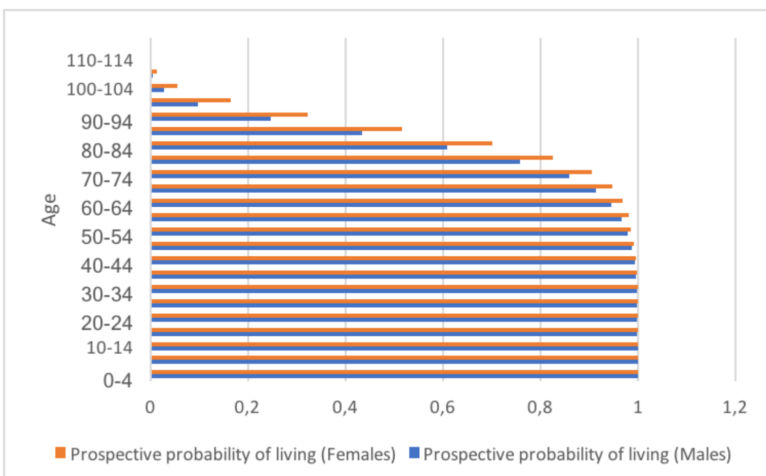

Figure 3: Probability of living by sex and age class, Palermo

2.3 Employers' Number, Size, and Distribution

Employers 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 this is the legal age for employment under Italian law. 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.

2.4 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 Bank of Italy's survey about Sicilian families' income and expenditures (Banca d'Italia, 2018).

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 university. 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 1).

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

Table 1: Number of schools per education level and age

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 manager. We derived the distribution from the Bank of Italy survey (Table 2) and subsequently adjusted the categories, e.g. by splitting Other Unemployed between inactive and unemployed, based on the distribution reported by Eurostat (2019).

After exiting the education system, active agents look for a job which level is determined by their education score. If they cannot find 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.

Work Status	**N**
Blue Collar Workers	132 (0.168)
White Collar Workers	126 (0.160)
Management	18 (0.023)
Entrepreneur/Private Practitioner	29 (0.037)
Other Self-Employed	39 (0.050)
Other Unemployed	443 (0.563)
Total	787 (1.000)

Table 2: Distribution of work status categories

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 Co-Offending

Criminal links are established between two agents through co-offending. A criminal link 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 subsequently 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).

2.6 Crimes committed by organized crime members

To calculate the number of crimes committed on average by organized crime members in Italy specifically, we resorted to the Proton Mafia Members dataset, which contains information on the entire criminal career of individuals with at least one final conviction for mafia offenses from 1982 to 2017 (Campedelli et al, 2019; Savona et al, 2020). We extracted only individuals who were born in the province of Palermo since 1960 (n=428). We calculated that organized crime members commit on average 4.5 times more crimes than the general population. We transformed this figure into a probability and included it into the C-function to distinguish the crime commission process based on the status of each given individual.

3 Model Assumptions

ABMs are based on a number of assumptions, which may impact the outcomes and the results of the simulations (Groff et al, 2019). In addition to the theoretical framework and to the empirical calibration, our ABM relies on several assumptions which we summarize in Table 3 .

Assumption	**Detail**
Social relations influence the recruitment into organized crime	Six types of social relations are important for the recruitment into organized crime: household, kinship, school, work, friends, and co-offending These relations can be modeled as a multiplex network with six layers
Recruitment into organized crime	Recruitment occurs when a non-organized-crime agent co-offends with at least one organized-crime agent and the latter is the initiator of the crime. Social embeddedness in relations with organized crime members favors recruitment, all other things equal
Agent probability of committing a crime ($C_{i,t}$)	The following factors determine $C_{i,t}$: Age. gender, unemployment, education, natural propensity, criminal history, criminal family, criminal friends and co-workers, and organized crime membership Crime commission is modeled as a probabilistic approach based on agents' individual probabilities
Co-offending	Co-offender selection is driven by social proximity and the potential co-offenders' probability to commit crimes
Modelling organized crime embeddedness $R_{i,t}$)	The importance of social ties with organized crime members is inversely proportional to the distance in the networks. The influence of the ties is proportional to the number of different relations between any two agents across the six layers of the multiplex network
Targeting OC Leaders	It is possible to identify, capture and imprison organized crime leaders. Organized crime leaders are identified by their centrality in the multiplex network
Targeting Facilitators	Facilitators important in the criminal activities of organized crime groups. Facilitators can be identified, captured and imprisoned
Primary Socialization	It is possible to identify children living in organized crime families. It is possible to limit the influence of fathers and relatives who are members of organized crime.
Secondary Socialization	Support to targeted schoolchildren leads to higher educational attainment and larger, more diverse, network connections than without the support.

Table 3: Selected Assumptions of the Models

4 Sensitivity Analysis

Sensitivity analysis is a collection of tools and methods for investigating a target model, and to show what happens to results when small[1] changes in the parameters are allowed (Chattoe et al, 2000). When presenting usable results, for example about policy, it must also be shown how those results vary against parameter variation. Ideally, a region of linear response should be specified.

In the present work, we attempted to calibrate all parameters to the relevant empirical values, when obtainable; this allowed us to navigate the issue of exploring parameter space. However, any calibration includes necessarily errors - in the best case, a measuring error, but in most cases, especially in the social science, one should assume that error could have been influenced by systematic factors.

Hence, we have explored the variation of our model response - the total number of organized crime members - around the calibration we have performed for five parameters presented in Table 4. We have added here a substantial amount of variation, increasing and decreasing each one of the selected parameters in the measure of $\pm 50\%$.

	low	base	high
num-oc-persons	15.0	30.0	45.0
number-crimes-yearly-per10k	1000.0	2000.0	3000.0
unemployment-multiplier	0.5	1.0	1.5
number-arrests-per-year	15.0	30.0	45.0
punishment-length	0.5	1.0	1.5

Table 4: Parameters for sensitivity analysis. Runs are performed for all interventions, varying one parameter at a time.

The variations shown above are explored one by one and then compared to the base points for a total of 3^5 points. This is performed for the baseline and the four policy scenarios, thus with a multiplier of 5, for a total of 1215 cases, each repeated ten times.

The numeric result of this exploration is presented in Table 5, where we show, for all combinations of factors, the average result and the standard error. There is no evidence here of large differences.

[1]"Small" should be defined on the grounds of error or potential change on a per parameter base.

	baseline	facilitators	students	preventive	disruptive
num-oc-persons:15	07.23±01.23	08.00±01.42	07.00±01.72	08.00±01.24	07.00±01.63
num-oc-persons:30	07.87±00.63	07.23±01.05	08.16±00.65	06.46±01.20	07.23±01.04
num-oc-persons:45	10.77±01.23	10.38±01.53	09.77±01.33	10.85±00.81	11.15±01.18
number-crimes-yearly-per10k:1000	04.92±00.59	05.54±01.15	08.00±01.52	07.46±01.21	06.08±01.03
number-crimes-yearly-per10k:2000	07.87±00.63	07.23±01.05	08.16±00.65	06.46±01.20	07.23±01.04
number-crimes-yearly-per10k:3000	09.46±01.47	10.92±01.70	09.15±01.16	09.15±00.95	10.15±01.14
unemployment-multiplier:0.5	06.15±01.11	10.00±01.36	06.46±00.85	06.85±00.84	06.92±00.88
unemployment-multiplier:1.0	07.87±00.63	07.23±01.05	08.16±00.65	06.46±01.20	07.23±01.04
unemployment-multiplier:1.5	08.23±01.19	08.00±01.56	11.62±01.77	08.62±01.11	10.08±01.65
number-arrests-per-year:15	08.00±01.38	09.31±01.48	06.62±00.78	08.31±01.28	08.00±01.63
number-arrests-per-year:30	07.87±00.63	07.23±01.05	08.16±00.65	06.46±01.20	07.23±01.04
number-arrests-per-year:45	06.08±00.89	07.62±01.07	09.62±01.48	09.15±01.25	07.85±00.90
punishment-length:0.5	06.08±00.80	09.38±01.16	07.85±01.04	09.46±01.75	07.69±01.00
punishment-length:1.0	07.87±00.63	07.23±01.05	08.16±00.65	06.46±01.20	07.23±01.04
punishment-length:1.5	08.00±01.38	07.00±01.20	09.00±01.18	08.54±01.23	09.23±01.13

Table 5: Number of organized crime members at step 360, with standard error. Ten runs for each point, for all the parameter variations considered in the sensitivity analysis.

To produce a visual summary of the variations revealed, we show in Figure 4 the value of the distance between the average values for baseline and policy scenario, divided by the sum of their standard errors. [2] If this ratio is lower than one, the two measures overlap; the simulation result does not distinguish between these starting parameters. We present results for the last simulation step (step 360).

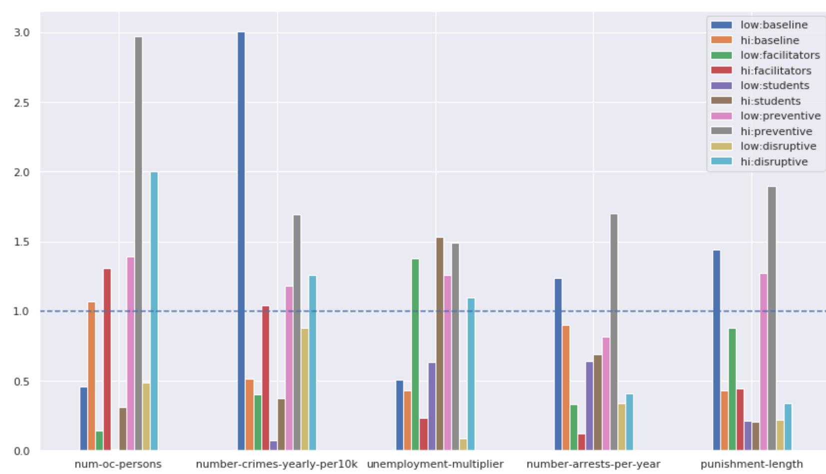

Figure 4: Ratios between absolute distance intervention-baseline to their sum of standard errors. Values larger than hint to the parameter having an effect. For example, in the unemployment-multiplier intervention (center), the baseline simulation is indifferent to the change in unemployment. For a different example, setting the number of crimes to low doesn't affect the disruptive strategy, while setting it to high does.

[2]Note that this measure shows the strength, but not the direction of the effect.

As the figure shows, 30 over 50 of our variations are undistinguishibale from the baseline. Those that are measure up to a factor of 3 - meaning that, for that particular combination, a change of 50% in the parameter space brings about a change in result about 3 times the standard error. Overall, the system shows a stable behavior around the parameter we have used for our study.

5 Analytical strategy: Model Selection

To test and assess the effect of the four different policies on our simulated societies, we have relied on Generalized Estimating Equation (GEE) models. This approach is designed to handle longitudinal data that are either clustered or correlated, thus representing a perfect fit for our data. GEE requires to specify a working correlation matrix for the data under analysis. However, GEE - conversely to the GLM method - is not based on the maximum likelihood theory for independent observations. Contrarily, it works without making any assumption about the underlying data distribution, thus being based on quasi-likelihood theory. For this reason, the classic Akaike's Information Criterion (AIC) cannot be applied to compare and select the correct working correlation structure for a GEE mode. In light of this, Pan (2001) proposed a method called *Quasi Information Criterion*, which appropriately modifies the AIC method to accommodate the quasilikelihood nature of GEE.

The equation for the Quasi Information Criterion reads as:

$$\mathrm{QIC} = -2Q(\hat{\mu}; I) + 2\mathrm{tr}(\hat{\Omega}^{-1}\hat{V}_R) \tag{6}$$

where I represents the independent covariance structure used to calculate the quasi-likelihood, $\hat{\mu} = g^{-1}(x\hat{\beta})$ (with $g^{-1}()$ being the inverse link function). When comparing QIC across different correlation structures, the smallest value has to be chosen. The results are reported in Tables 6 and 7.

	Autoregressive (1)	**Exchangeable**	**Independence**
QIC	20785.2007	20786.2334	20785.1974
Quasi Likelihood	1266390.111	1273834.03	1290016.584
Trace	8.6178	8.3581	8.6161

Table 6: QIC results for model selection - Newly recruited members

	Autoregressive (1)	**Exchangeable**	**Independence**
QIC	-2528182.091	-2500762.05	-25777213.741
Quasi Likelihood	1266390.111	1273834.03	1290016.584
Trace	2229.066	23453.01	1409.713

Table 7: QIC results for model selection - Total organized crime members

Both Tables show that for both models, an Independence correlation structure is preferred as the QIC is minimized. This result is certainly stronger in the first model, with the difference across specifications being lower in the case of models focusing on newly recruited individuals.

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