# Chapter 8
# Extortion Rackets: An Event-Oriented Model of Interventions

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## 8.1 Introduction

This chapter documents the final NetLogo (Tisue & Wilensky, 2004) version of the Palermo case study simulation model.[1] Its predecessors were originally prepared as rapid prototypes to prepare and to instruct the Java-based model but soon developed into a flexible tool with a graphical user interface. The predecessors have been described in a number of publications (Troitzsch, 2015a, 2015b, 2016a, 2016b)—they were designed as period-oriented simulations, i.e. in every period agents made their decisions and performed their actions, usually several in a row, e.g. for an extorter the action of approaching a potential victim and taking its money, being denounced, prosecuted and finally put to custody and convicted. For the purpose of serving as a guide for the GLODERS-S simulator (Nardin et al., 2016) and for sensitivity analyses this was sufficient, but it turned out to be a matter of a few days of programming to turn the period-oriented NetLogo model into an event-oriented one with the help of the time extension (Sheppard & Railsback, 2014).

As GLODERS-S and the period-oriented NetLogo model, the event-oriented version consists of four types of agents: enterprises or shops, extorters, police and consumers. Unlike GLODERS-S, the extorters are independent and can form families; the police officers are independent, too, i.e. both extorters and police officers can make decisions according to the individual norms they learnt during the simulated history. Hence for all types of agents the salience of norms is computed before any action decision is taken.

[1] The model can be downloaded from http://ccl.northwestern.edu/netlogo/models/community/EONOERS.

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**Table 8.1** Agent type, norms and actions

| Agent type | Norms | Actions |
|---|---|---|
| Shops | Denounce-extortion | Denounce |
| | Do-not-denounce | |
| | Do-not-pay-extortion | Pay |
| | Pay-extortion-as-everybody-does | |
| Consumers | Do-not-shop-at-extortion-payer | Switch to Addiopizzo shop |
| | Buy-from-extortion-payer | |
| Police | Anxiety-is-justified | Prosecute |
| | Try-hard-to-imprison | |
| Extorters | Do-not-betray-colleagues | Become pentito |
| | Abjure-crime | |

## 8.2 The Repertoire of Norms and Actions

The actions and the behaviour of the four types of agents are controlled by a number of norms whose salience is continuously updated by observations of norm-related behaviour and particularly of norm invocations issued by other agents of the same or of a different type. The agent types, their norms and their actions are listed in Table 8.1. The salience of a norm is calculated according to a formula discussed in Sect. 7.3 which converts the counters of norm-related observations and invocations into a number between 0 and 1. The saliences of the two norms relevant for an action are in turn converted into a normative drive to perform this action and finally mixed with the individual drive calculated from the utility of the action, and this weighted sum of normative and individual drive is taken as the probability to perform the respective action in the current situation.

So far the period-oriented and the event-oriented versions are equal (and use the same code) but the event-oriented version needs much more sophistication for scheduling events in a reasonable order. The actions of agents which trigger events starting new actions of the same agent or an agent of another type are listed in Table 8.2 together with the delay between the triggering and the triggered actions (which is usually a random number of hours or years[2]).

Table 8.2 also gives a nearly complete overview of the actions which can be taken by the agents of the different types (some of these actions use additional procedures to describe what the agent will have to do in order to perform them). Besides

[2] The standard duration of a run is 2 years, which—for 100 shops, 50 extorters, 10 police and 800 customers, some 2000 extortion attempts and 37,000 exchanged invocation messages—takes a standard PC with eight processors about 2 min on an average in batch mode (a single run takes 20–30 min). Three times as many agents of each type with about 5000 extortion attempts and about 100,000 messages exchanged means about 30 min per run. The delays mentioned in Table 8.2 are not calibrated against any empirical data as even the Sicily and Calabria database (see Chap. 6) does not contain sufficient details for such a calibration. The simulated time units can only have a rough correspondence to real-time units.

**Table 8.2** Scheduling of events

| Acting agent | Controlling action | Condition | Activated agent | Triggered action | Delay |
|---|---|---|---|---|---|
| Court | Convict | Sentenced | Extorter | Leave-jail | 3–8 years |
| Court | Convict | Acquitted | Extorter | Become-active | 24 h |
| Extorter | Become-active | Met nobody | Extorter | Become-active | 730 h |
| Extorter | Return-to | | Shop | Wait-for-extorter | 5–72 h |
| Extorter | Find-victims | Shops available | Shop | Wait-for-extorter | 72 h |
| Extorter | Find-victims | No shops available | Shop | Become-active | 150–200 h |
| Extorter | Give-up | Banished by a more successful extorter | Extorter | Become-active | 24–72 h |
| Extorter | Leave-jail | | Extorter | Become-active | 12–36 h |
| Police | Start-prosecute | Started | Police | Put-to-custody | 0–5000 h |
| Police | Put-to-custody | Escaped | Extorter | Become-active | 360–720 h |
| Police | Put-to-custody | Not escaped | Police | Convict | 720–5000 h |
| Shop | Wait-for-extorter | Denounced | Police | Start-prosecute | 12–84 h |
| Shop | Wait-for-extorter | Denounced | Extorter | Punish | 0–168 h |
| Shop | Wait-for-extorter | Denounced | Extorter | Become-active | 24–168 h |
| Shop | Wait-for-extorter | Paid | Extorter | Return | 600–700 h |
| Shop | Wait-for-extorter | Neither denounced nor paid | Extorter | Punish | 0–168 h |
| Shop | Wait-for-extorter | In criminal records | Police | Start-prosecute | 12–83 h |
| Shop | Wait-for-extorter | Not met | Extorter | Return | 600–700 h |
| Shop | Decide-to-pay-or-not | Nothing paid | Extorter | Become-active | 8–12 h |
| Shop | Decide-to-pay-or-not | Paid | Extorter | Become-active | 160–240 h |
| Shop | Decide-to-pay-or-not | Refused to pay | Extorter | Become-active | 8–12 h |

the actions listed in Table 8.2 there are norm invocations (which happen immediately, as in the period-oriented version) and periodic events which happen:

- Once a week
- Consumers go shopping or
- Once a month
- Shops pay salaries to consumers in the latter's role of employees
- The state (which is represented by the NetLogo observer, as is the court) compensates extortion victims from confiscated assets if there are any
- Extorters pay into a funds from which needy extorters of the same family are subsidised
- Statistics are collected

To describe how the model works in detail it will be best to list the actions which are taken in a sequence by the respective agents.

The initialisation puts agents of all four types to patches in a way that no patch is occupied by more than one agent. Agents stay on their patches throughout a simulation run; that is, they do not move for their actions (one could also say that they immediately return to their patches after they have performed an action which in reality necessitates a visit at a distant place, for instance—for an extorter—to take the extortion money home from a victim or—for a police officer—to arrest an extorter or—for a customer—to buy something from a shop or to work for a shop).

Immediately after the initialisation all consumers are scheduled to go shopping at 10:00 of the first day (and to repeat this action once a week at the same time) and to select a shop from whom they will buy—later they will have an opportunity to switch to another shop when their norm salience calculations recommend them to buy from a shop which does not pay extortion. At the same time the extorters are scheduled to become active after a delay of 3–5 days. Moreover the periodic events mentioned above are scheduled.

Once an extorter becomes active it starts to find possible victims in its vicinity (whose initial radius is given by a parameter valid for all extorters but which can be extended by a factor which is another input parameter whenever the search for victims turns out unsuccessful). If a victim was found it is approached after a small delay (the time between find-victims and wait-for-extorter in Table 8.2); if not, another attempt at finding victims is made with a delay between approximately 6 and 8 days (150 and 200 h).

If victim and extorter meet, the former makes a decision whether it denounces the latter or whether it pays the requested amount to the latter—the requested amount is a percentage of the current income from sales determined by an input parameter. If the shop decides not to pay or if it has not had any income during the current month it cannot pay, the extorter is scheduled to return within a week. In these cases two outcomes are possible:

If the shop refused to pay in the first meeting the extorter will only be successful if the shop reconsiders its decision neither to denounce nor to pay or in case the shop was unable to pay anything before the extorter might be successful if the shop in turn was meanwhile successful in selling anything to a paying customer; otherwise the shop will be bankrupt and perhaps be reopened when extortion and/or punishment was the reason of its bankruptcy and the state compensated it from confiscated extorter assets.

If the victim decides to denounce it asks a police officer nearby and schedules its start-prosecution procedure for some time within the next 2 weeks, and there is also a chance that the police officer has observed the extorter's approach (but only if the latter is already in the police's criminal records, i.e. was denounced earlier on by some other shop or who was found punishing another shop—an activity which is always observable and cannot be concealed, much like arson), and in this case the prosecution also starts within a week. After the extorter was denounced it is scheduled to become active again to find other victims during the following 2 weeks (but if it is meanwhile caught by the police the scheduled task will, of course, never be performed). As a further consequence of denunciation, the denounced extorter will also plan to punish the shop, and this is scheduled for some time within the next 2 weeks, provided that this extorter has not been brought to custody before this date.

If the same victim is approached by several extorters before the former makes the decision between denouncing and paying discussed above, it has to choose among the competing extorters. The successful extorter subordinates its competitors, thus forming a growing hierarchy of families which is documented in one of the NetLogo windows (but not analysed in depth so far). The unsuccessful extorters will become active again and try to find victims during the next few days. At the end of each month the extorters' incomes are redistributed within each family (isolated extorters do not participate in this redistribution process).

When a police officer starts to prosecute an extorter (either after denunciation or after police observation) it will take up to 200 days until the extorter is either brought to custody or escaped. In the latter case the extorter will become active again; otherwise it stays in custody until the court (represented by NetLogo's observer) passes a sentence, which will take between 1 and about 7 months. If the extorter is acquitted it becomes active the next day, and if it is sentenced his or her period of being inactive in jail will be an integer number of years (between three and eight). When the prisoner is released it will again become active and try to find victims within the next few days.

## 8.3 Input Parameters and Output Metrics

Model runs are initialised with a number of input parameters, not all of which will turn out relevant in the end (and, indeed, sensitivity analysis of earlier versions of the NetLogo model showed that many are not), but all of them were kept for the event-oriented version to find out whether they might become relevant under the new circumstances. The parameter space is spanned by uniform distributions of the global variables listed in Table 8.3. The simulation model was run 1280 times

**Table 8.3** List of input parameters for the sensitivity analysis

| Name | Function | Minimum value | Maximum value |
|---|---|---|---|
| Background (bg) | Fills the memories of all agents with observations and invocation referring to their respective norms | −5 | 5 |
| NDW (ndw) | Weight of the normative drive; the weight if the individual drive is 1–NDW | 0.3 | 0.7 |
| Discount (disc) | Multiplier applied to each counter whenever new norm invocations arrive | 0.8 | 1.0 |
| Local (loc) | Distance within which norm-relevant observations can be made and norm invocations can be received | 2 | 10 |
| Benefit-for-victims (bfv) | Value of the protection offered by an extorter for the extortion money requested as a percentage of the requested sum | 75 | 150 |
| Conviction-probability (cvp) | Probability that the court will sentence an arrested extorter for a longer period in jail | 0.1 | 0.8 |
| Extortion-level-low[a] | Lower bound of the percentage of the current turnover from sales of a shop requested by an extorter, the upper bound being fixed as 10 | 5 | 10 |
| Punishment-severity-low | Lower bound of the percentage of the current wealth of a shop requested robbed by an extorter after refusal to pay, the upper bound being fixed as 10 | 10 | 10 |
| Escape-chance (ec) | Probability that an extorter is not caught by the prosecuting police | 0.1 | 0.8 |
| Extortion-radius-extension | Multiplier of the initial distance within which an extorter can find victims, applied after each unsuccessful search | 1.0 | 1.2 |
| Vision-range (vr) | Distance within which a shop can find a police officer to whom it can report an extortion attempt | 5 | 85 |
| Hide-denounce-propensity | Probability that a shop publishes its readiness not to denounce an extortion attempt | 0 | 0.125 |

The abbreviations in the first column of the table are used in Table 8.5. Input parameters without such an abbreviation do not have any significant influence in the linear regressions reported in Table 8.5.

[a]Extorters can individually differ in their extortion level and punishment severity instance variables; hence in principle four types of extorters are possible: those with both levels low, those with both levels high and those with low (high) extortion level and high (low) punishment severity. This typology stems from earlier versions and did never turn out important, and with the values reported in Table 8.3 only two types occur as the severity level is constant

**Table 8.4** Output metrics of the simulation

<table>
<tr><td>Percentage of undetected cases</td><td rowspan="5">All of these measured as moving averages over the recent two simulated months, percentages are based on all attempts which happened within the respective 2 months, including those which only became known to extorter and victim, i.e. there is no “dark figure”</td></tr>
<tr><td>Percentage of undenounced extortions</td></tr>
<tr><td>Percentage of completed extortions</td></tr>
<tr><td>Percentage of cases with arrest</td></tr>
<tr><td>Percentage of cases with punishment</td></tr>
<tr><td>Percentage of critical consumers</td><td>Measured as the moving average of the means of the individual propensity to buy only from non-denouncing shops</td></tr>
<tr><td>Denunciation rate</td><td rowspan="5">All of these measured as moving averages over the recent two simulated months, percentages are based on all attempts which happened within the respective 2 months, not including those which only became known to extorter and victim, i.e. these rates are better comparable to empirical data</td></tr>
<tr><td>Prosecution rate</td></tr>
<tr><td>Success rate</td></tr>
<tr><td>Arrest rate</td></tr>
<tr><td>Conviction rate</td></tr>
</table>

with 100 shop agents, 50 extorter agents, 10 police agents and 800 consumer agents; each run lasted two simulated years.[3]

The list of output metrics which can be used for statistical analyses is even longer. It can be found in Table 8.3.

Besides this list, the graphical user interface offers a variety of plots, both showing the history of some of the metrics listed in Table 8.4 and some histograms of norm saliences and action propensities changing over time. The history of some of the output metrics is stored in separate files for each run, and the distribution of norm saliences at the end of the run is also available for statistical analysis.

## 8.4 Results of 1280 Simulation Runs

The results of the event-oriented version of the model are fairly similar to the results of the period-oriented version, as Fig. 8.1 shows. Not surprisingly there is a high correlation of the 2 % of undenounced and of completed extortions, as extortions are either successful from the point of view of the extorter or denounced—except the case when the victim is unable to pay at all but does not want to denounce. The correlations between these two output metrics and the input parameters of the model are smaller than in the period-oriented case, presumably due to the higher

[3] Runs with different numbers of agents per type—e.g. three times as many as mentioned in footnote 16—generate results which are very similar to the ones reported here, but consume disproportionate computing time.

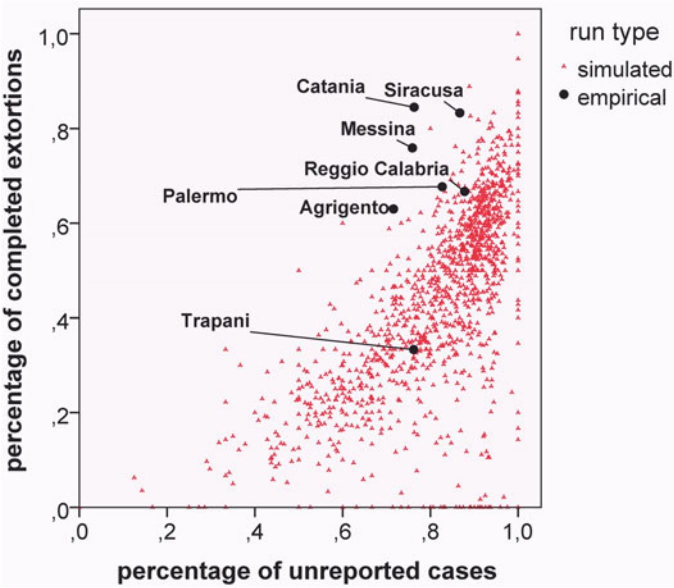


**Fig. 8.1** Scattergram of the two main output metrics: percentage of undenounced cases vs. percentage of completed extortions

**Table 8.5** Regression coefficients and reduction of the variance of the main output metrics by input parameters

| Per cent of all cases | $R^2$ | Standardised regression coefficients | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Bg | Loc | disc | ndw | bfv | cvp | vr | Ec |
| Undetected | .312 | −.545 | −.055 | .102 | n.s. | .064 | n.s. | n.s. | n.s. |
| Unreported | .424 | −.623 | n.s. | n.s. | −.123 | .077 | −.076 | n.s. | .062 |
| Completed | .308 | −.460 | n.s. | n.s. | .267 | .095 | n.s. | .124 | n.s. |
| Arrest | .118 | .091 | n.s. | −.072 | .124 | −.061 | .109 | .139 | −.241 |
| Conviction | .325 | .522 | n.s. | −.046 | −.217 | −.091 | n.s. | n.s. | n.s. |
| *Per cent of detected cases* | *$R^2$* | *bg* | *Loc* | *disc* | *ndw* | *bfv* | *cvp* | *vr* | *Ec* |
| Denounced | .357 | .585 | n.s. | n.s. | n.s. | −.096 | .053 | −.073 | n.s. |
| Successful | .290 | −.378 | n.s. | n.s. | .341 | .104 | −.067 | .136 | n.s. |
| Prosecuted | .368 | −.100 | .074 | −.085 | .474 | n.s. | −.062 | .335 | .067 |
| Arrested | .119 | −.055 | .054 | n.s. | .144 | n.s. | .109 | .146 | −.249 |
| Convicted | .028 | n.s. | n.s. | n.s. | n.s. | n.s. | .140 | n.s. | −.062 |

randomness which comes into the model as a consequence of the random delays between triggering action and triggered action which leads to path dependence: if one runs the model with identical input parameters but different seeds of the random number generator, then for the first about 150 days the difference between runs is small, but from then the random events cumulate and increase the variance between

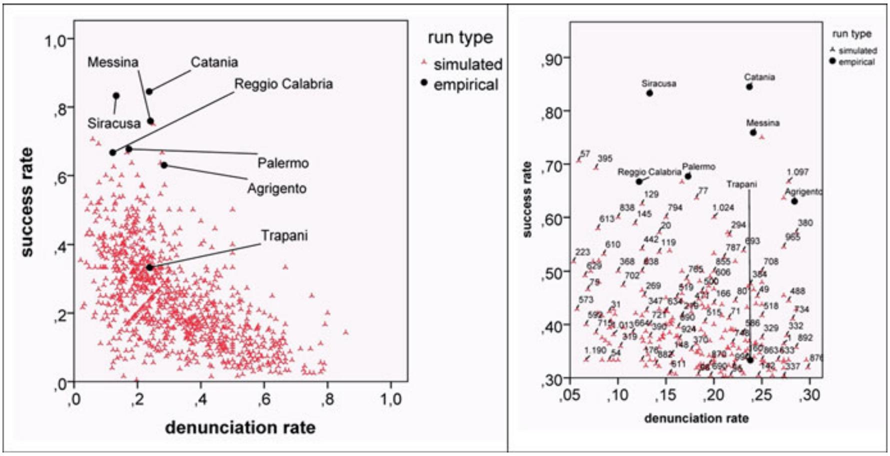


**Fig. 8.2** Comparison between provinces in Southern Italy and simulation runs: cases which came into the open

runs considerably. There are significant influences of a number of input parameters (see Table 8.5), but the overall reduction of variance is only about 30 %, and although the contributions of the third and fourth less important input parameters are often smaller than 1 %, they are still significant on a 5 % level, which is only due to the large number of simulation runs, another hint at the fact that the effect is more meaningful than the level of statistical significance (cf. Ziliak & McCloskey, 2007).

As in the case of the period-oriented version, most of the empirical cases—calculated from the Sicily and Calabria database for seven provinces (Frazzica et al., 2015)—are situated in the margin of the frequency distribution of the simulation runs, except for the provinces of Trapani[4] and Reggio Calabria. The main reason for this weak validation of the model is that the empirical data are blurred with all those cases which never became known to the police, the prosecutors or the media and thus remained in the dark—which cannot happen in a simulation where all attempts at extorting are documented in the simulation output. As the simulation model also reports the extortions which were only known to extorter and victim these can be used as an estimate for "dark cases", and denounced and completed extortions can be calculated as percentages of all the simulated cases which came into the open (denounced or observed by the police without the help of the victim). If one uses these percentages instead of the raw percentages as in Fig. 8.2, the validation is more successful, and simulation runs matching the empirical data of some of the provinces can be identified.

Still, most of the provinces can be found at the margin of the joint distribution of the two output metrics comparable to empirical data, but a few simulation runs can be identified whose results are similar to the provinces of Trapani (#990 and many

[4] That the province of Trapani is different from the other provinces was already clear from the findings in Chap. 9.

others), Agrigento (#1097 and #521), Messina (#342 and #355) and Palermo (#181); the representative point of province of Reggio Calabria lies between #129 and #395; and only the other two (Siracusa and Catania) have no simulation runs with a similar combination of these two output metrics whereas the large majority of runs resemble much more regions outside Southern Italy where a high prevalence of denunciations and a small proportion of successful extortions can be expected—unfortunately for these empirical data are not available as in these regions no statistics are produced (see Sects. 9.3 and 12.1) because extortion attempts are very rare there.

## 8.5 Interventions

As in the period-oriented version, interventions are possible (Troitzsch, 2016a, 2016b). At a certain point of time, e.g. at the end of the first year, all memories of all agents of one or several or all types are emptied and refilled with a number of invocations of "liberal" norms (the norms listed in the first row of each pair of rows in Table 8.1). In single runs the effect of such an intervention can immediately be observed via the GUI; in batch runs a CSV file is written which can be analysed afterwards.

Figure 8.3 shows the two main output metrics over two simulated years with all 16 possible interventions applied at the end of the first simulated year (the combinations of interventions are partly suppressed in these two diagrams showing only dashed curves to enable readers to follow the histories of the four runs in which the agent of only one agent type was subject to intervention). During the first simulated year all runs have an identical history as all of them were started with the same seed of the pseudorandom number generator. Immediately after the intervention injecting a high number of liberal or civic norm invocations the histories run apart: when the intervention is only applied to the shop agents, very soon all extortion attempts are denounced, and none is successful. Applying the interventions to the agents of any of the other types has only a moderate effect, which is, however, still better than no intervention at all. To find out whether combinations of interventions to the agents of more than one type have special effects, the diagram in Fig. 8.4 shows the values of the two main output metrics about six simulated weeks after the intervention at the end of the first year (to be precise: on day 400) for 10 groups of runs (different pseudorandom number generator seeds between groups, different intervention targets within each group). One sees that

The distribution of the outcomes of interventions only to shops does not differ from the distribution of the outcomes of intervention applied to the agents of all four types or the distribution of the outcomes of intervention applied to shops and any other agent type.

The distribution of the outcomes of intervention to all but the shops (mean 0.6591) does not significantly differ from the distributions produced when no intervention was applied at all.

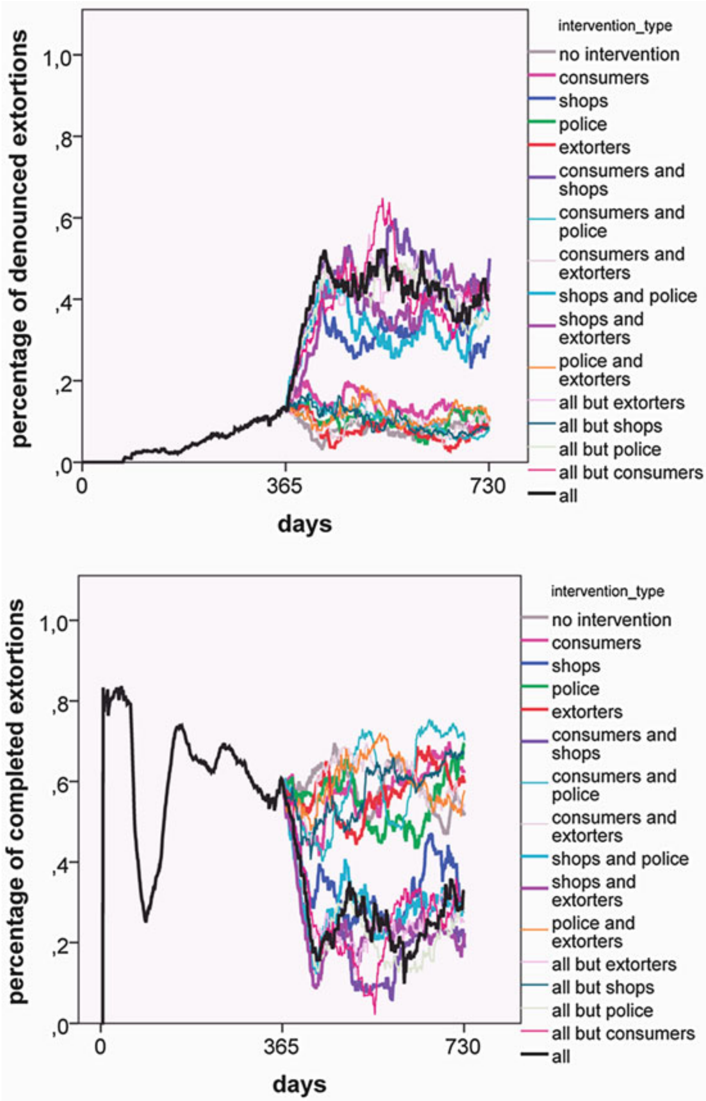


**Fig. 8.3** Effects of interventions on the percentage of denounced and completed extortions, respectively

For more details of these results see Table 8.6 which shows that for nearly all output metrics it is only the interventions including shops that differ significantly—and with absolute t-values beyond 8—from the no-intervention cases. Only the output metrics referring to arrest and conviction differ from these overall diagnosis. Figure 8.4 shows the state of these 10 groups of 16 runs each with the 16 possible intervention combinations 12 simulated months after the interventions; again the 2

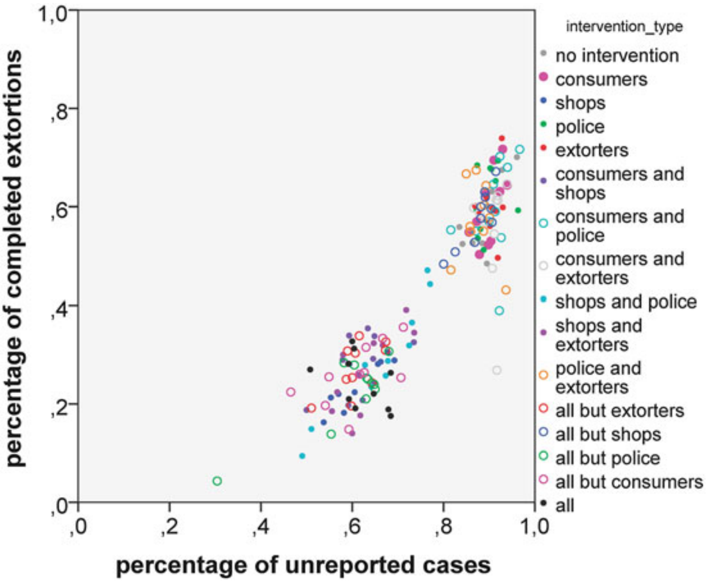


**Fig. 8.4** Effects of interventions on the success of extortion attempts

variables spanning the coordinate system of these scattergrams are averages over the past 2 simulated months. The diagram shows that the ten runs without any intervention (grey-filled circles) are strictly separated both from the ten runs in which only shops (blue-filled circles) or all agents (black-filled circles) were subject to intervention whereas the region occupied by the runs without any interventions is also filled with the representative points of runs where only police (green-filled circles) or extorters (red-filled circles) or all but shops (blue open circles) had their memories refilled. This becomes even clearer from Table 8.6 which shows the difference between the means of the moving averages for each intervention type and the mean of the no-intervention runs as well as the effect sizes (measured as Dunnett's $t$ and $\eta^2$), all of which are highly significant for the interventions including the shops ($\alpha < 0.0005$) except for the percentage of cases with arrest. And for all extortion-related output metrics it is the interventions in which shops are involved which differ most from the no-intervention runs. Interventions directed to agents of the other three types (and only to these) have a very small effect, and interventions directed to two or three agent types leaving out the shops have only an intermediate effect which is not statistically significant. It seems that the chance of getting hold of criminals does not depend on any interventions—there are some differences, but they are not significant.

The output metric "percentage of critical consumers" follows another pattern. Its $\eta^2$ is fairly high (and significant) with 0.398, but the effect in mean differences is only modest: without intervention the value of this output metric is 21.7 %; with interventions applied to consumers it increases to 29.8 %; if other groups are also

**Table 8.6** Effects of interventions: Moving averages over two simulated months of output metrics one simulated year after the intervention

| Comparisons between intervention with… addressed and no intervention | Standard error | $\eta^2$ | | Con-sumers | Shops | Police | Extorters | Consumers and shops | Consumers and police | Consumers and extorters | Shops and police | Shops and extorters | Police and extorters | All but extorters | All but shops | All but police | All but consumers | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Percentage of undetected cases | 0.0611 | 0.631 | MD | −0.027 | −0.288 | 0.046 | −0.013 | −0.346 | −0.118 | −0.006 | −0.364 | −0.329 | −0.006 | −0.338 | −0.053 | −0.313 | −0.388 | −0.433 |
| | | | **Dt** | −0.437 | **−4.718** | 0.748 | −0.213 | **−5.657** | −1.932 | −0.097 | **−5.957** | **−5.383** | −0.105 | **−5.525** | −0.860 | **−5.126** | **−6.345** | **−7.085** |
| Percentage of unreported cases | 0.0593 | 0.731 | MD | −0.054 | −0.399 | −0.047 | −0.015 | −0.498 | −0.030 | −0.040 | −0.429 | −0.471 | −0.052 | −0.463 | −0.069 | −0.448 | −0.350 | −0.512 |
| | | | **Dt** | −0.919 | **−6.736** | −0.801 | −0.260 | **−8.401** | −0.513 | −0.682 | **−7.237** | **−7.941** | −0.876 | **−7.811** | **−1.166** | **−7.554** | **−5.898** | **−8.643** |
| Percentage of denounced extortions | 0.0593 | 0.731 | MD | 0.054 | 0.399 | 0.047 | 0.015 | 0.498 | 0.030 | 0.040 | 0.429 | 0.471 | 0.052 | 0.463 | 0.069 | 0.448 | 0.350 | 0.512 |
| | | | **Dt** | 0.919 | **6.736** | 0.801 | 0.260 | **8.401** | 0.513 | 0.682 | **7.237** | **7.941** | 0.876 | **7.811** | 1.166 | **7.554** | **5.898** | **8.643** |
| Percentage of completed extortions | 0.0675 | 0.682 | MD | −0.017 | −0.377 | 0.127 | 0.079 | −0.407 | −0.053 | 0.040 | −0.331 | −0.348 | 0.000 | −0.360 | 0.044 | −0.391 | −0.417 | −0.428 |
| | | | **Dt** | −0.248 | **−5.586** | 1.880 | 1.176 | **−6.023** | −0.786 | 0.599 | **−4.904** | **−5.148** | 0.002 | **−5.335** | 0.645 | **−5.783** | **−6.180** | −6.340 |
| Percentage of cases with arrest | 0.0342 | 0.151 | MD | 0.022 | 0.029 | 0.087 | 0.034 | 0.023 | 0.058 | 0.033 | 0.103 | 0.067 | 0.076 | 0.036 | 0.024 | 0.057 | −0.005 | 0.084 |
| | | | **Dt** | 0.656 | 0.858 | 2.548 | 0.998 | 0.676 | 1.680 | 0.957 | 3.018 | 1.957 | 2.222 | 1.049 | 0.687 | 1.651 | −0.138 | 2.453 |
| Percentage of cases with punishment | 0.0652 | 0.606 | MD | 0.030 | 0.261 | −0.074 | −0.038 | 0.349 | 0.072 | −0.003 | 0.293 | 0.311 | −0.026 | 0.307 | −0.002 | 0.328 | 0.400 | 0.373 |
| | | | **Dt** | 0.460 | **3.999** | −1.138 | −0.589 | **5.355** | 1.108 | −0.040 | **4.489** | **4.761** | −0.394 | **4.711** | −0.032 | **5.026** | **6.135** | **5.714** |
| Denunciation rate | 0.0757 | 0.663 | MD | 0.083 | 0.485 | 0.128 | −0.010 | 0.553 | −0.001 | 0.056 | 0.446 | 0.535 | 0.047 | 0.516 | 0.098 | 0.511 | 0.342 | 0.507 |
| | | | **Dt** | 1.099 | **6.409** | 1.692 | −0.129 | **7.295** | −0.015 | 0.743 | **5.890** | **7.059** | 0.615 | **6.818** | 1.290 | **6.744** | **4.516** | **6.694** |
| Prosecution rate | 0.0840 | 0.305 | MD | 0.067 | −0.076 | 0.260 | 0.187 | −0.145 | 0.029 | 0.063 | −0.005 | −0.124 | 0.151 | 0.057 | 0.129 | −0.183 | 0.019 | −0.038 |
| | | | **Dt** | 0.792 | −0.909 | 3.098 | 2.222 | −1.732 | 0.350 | 0.750 | −0.063 | −1.475 | 1.795 | 0.684 | 1.540 | −2.176 | 0.225 | −0.450 |
| Success rate | 0.0736 | 0.460 | MD | −0.124 | −0.289 | 0.050 | 0.091 | −0.306 | −0.042 | −0.010 | −0.258 | −0.299 | −0.197 | −0.286 | −0.021 | −0.312 | −0.288 | −0.298 |
| | | | **Dt** | −1.683 | **−3.928** | 0.680 | 1.235 | **−4.156** | −0.574 | −0.136 | **−3.504** | **−4.065** | **−2.674** | **−3.889** | −0.282 | **−4.236** | **−3.921** | **−4.052** |
| Arrest rate | 0.0791 | 0.204 | MD | 0.039 | 0.009 | 0.253 | 0.072 | 0.009 | 0.108 | 0.066 | 0.094 | 0.062 | 0.293 | 0.012 | 0.037 | 0.062 | −0.039 | 0.061 |
| | | | **Dt** | 0.492 | 0.108 | **3.202** | 0.908 | 0.116 | 1.361 | 0.836 | 1.194 | 0.781 | **3.708** | 0.157 | 0.465 | 0.778 | −0.495 | 0.777 |
| Conviction rate | 0.0070 | 0.076 | MD | −0.011 | −0.011 | −0.011 | −0.011 | −0.011 | −0.003 | −0.002 | −0.001 | −0.011 | −0.011 | −0.006 | −0.011 | −0.011 | −0.011 | −0.005 |
| | | | **Dt** | −1.591 | −1.591 | −1.591 | −1.591 | −1.591 | −0.398 | −0.289 | −0.098 | −1.591 | −1.591 | −0.795 | −1.591 | −1.591 | −1.591 | −0.749 |

Values relate to groups of 10 runs of each intervention types, all runs of a group are started with the same pseudorandom number generator, “standard error” is the standard error of the distribution of the variables for the no-intervention runs, “MD” is the mean deviation between the no-intervention runs and the respective intervention runs, “Dt” is Dunnett’s two-sided t; t-values >2 and <−2 are in *bold* involved the mean over all ten runs increases to 29.9 %—the high $\eta^2$ is mainly due to the fact that the variance within the groups of size ten is very small, and the t-value is not even significant with 1.01.

This is certainly in line with the experience of high police officers in Sicily, one of which recently—after a success in getting hold of a number of high-ranked Mafiosi as a consequence of a series of denunciations made by entrepreneurs—was cited by a Sicilian newspaper with the remark that denunciation is worth the risk and useful (La Stampa, 03/11/2015), and it is also in line with the strategy of the Addiopizzo Movement (Vaccaro & Palazzo, 2015) although it is also argued that the revolution was on the side of the consumers, as the title of a recent book (Di Trapani & Vaccaro, 2014, 2016) announced that it was the attempt at leveraging consumers' responsible purchase that fought the mafia, but the authors also admit that the movement began with a list of "pizzo-free" entrepreneurs (and the Italian blurb says that the book is "a homage to all those who took the personal risk to affirm the values of legality and liberty"), and hence even they will accept that convincing entrepreneurs that denunciations are worth the risk was the main cause of Addiopizzo's success.

## 8.6 Summary

When one compares the event-oriented NetLogo version of the GLODERS model to its own period-oriented predecessors (with or without the agents' norm orientation) they have one feature in common: The joint distribution of the two main output metrics is more or less the same in all three versions, and all three versions predict the empirical cases of Southern Italy only at the margin of this distribution as most Monte Carlo runs show a behaviour which one would expect from regions where extortion is rare, rarely successful and often denounced. Hence neither the introduction of norm-oriented agent behaviour nor the introduction of an event-oriented action scheduling changed the overall behaviour of the model. GLODERS-S was purposefully calibrated to match the provinces in Southern Italy and was successful at least with respect to the province of Palermo and the scenarios between 1980 and 2015 (see Fig. 7 in Nardin et al. (2016)).

On the other hand there are a number of differences between the three NetLogo versions. The step from a simple stochastic model where agents made their action decisions only based on constant action probabilities to the period-oriented model with agents influencing each other and making their decision based on calculations of norm saliences introduced an additional complexity which led to more complicated trajectories of the output metrics which showed traces of path dependencies, among others, with the result that final outcomes depended much more on early events and that the proportion of the variance of output metrics explained by input parameters was reduced. The event orientation with its stochastically defined delays between triggering action and triggered action allowed for even more path dependence and less variance reduction which could best be seen in the variance of the 20 runs per intervention type in Fig. 8.4 where all of these runs were determined by the exactly equal set of input parameters and differed only in the seed of the pseudorandom number generator.

Further research and an even deeper comparison between the extortion racket simulation models will show whether it was worthwhile to deviate from the KISS ("keep it simple, stupid!") principle which was followed in the simple stochastic version (Troitzsch, 2015a, 2015b) and to expand the models according to the more descriptive KIDS (Edmonds & Moss, 2005) version where the actions are taken by the agents in a more sophisticated way and where the periods between actions taken by the agents of different kinds are explicitly modelled (albeit without much empirical background).

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