The calm after the storm? Looting in the context of disasters

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Abstract. We report the results of an agent-based model to study the strategies that policy makers can apply to prevent the escalation of deviant behaviour in the aftermath of a disaster. Three policies are tested, namely: a reinforcement of the police power; an increase of the information available to the affected population and a combination of both policies. We test the effect of time in the implementation of these policies. The model shows that the policy which minimises deviant behaviour is the mixed one applied early after the occurrence of a disaster. Therefore, the outcome of this policy depends ultimately of the timing of their application, which is consistent with what has been observed in some real episodes.
Keywords: Agent-based modelling, deviant behaviour, escalation, disasters

1 Introduction

Collective action tends to be adaptive after a disaster: most of the affected residents perform themselves many critical tasks, such as searching for and rescuing victims. Both social cohesiveness and informal mechanisms of social control increase during disasters, resulting actually in a lower incidence of deviant behaviour [1]. However, there are also documented cases where civil disturbances escalate in the aftermath of a disaster [2]. From a policy viewpoint it is of paramount importance to know why this escalation of violence might emerge in the aftermath of a disaster and what steps can be taken to prevent it.

In Section 2 we put forward our assumptions. Then, in Section 3 the model is presented. We evaluate the effect of the proposed policies in Section 4. The article finishes with some concluding remarks in Section 5.

2 Why can crime pay during disasters?

Assumption 1. *Disasters increase the perceived benefits and decrease the perceived costs individuals expect to obtain from their participation in looting.* As Becker's [3] work demonstrates, when the marginal benefit of deviant behaviour increases and the expected marginal cost falls, deviant behaviour escalates.

Firstly, disasters disrupt most of the facilities and communication systems. Public institutions are seriously damaged and this reduces their response capability and causes a decrease in the likelihood of being punished for deviant behaviour. According to Congleton [4, p. 18], this was the case in New Orleans in 2005, after the hurricane Katrina. Because much of the New Orleans' police force had left town during the emergency, "the probability of being punished for crimes such as looting fell to nearly zero." Secondly, disasters increase the benefit of participating in looting, because the available goods to satisfy basic needs are scarcer and, consequently, more valuable. In the case of hurricane Katrina, Congleton [4, p. 18] argued that "the marginal benefit of a bit of theft for honest folk who had been forced out of their homes clearly increased."

Assumption 2. *Disasters reduce the amount and quality of the information individuals perceive from their environment*. Firstly, a disaster is a situation that causes great distress, which can impair individuals' decision making [5,6]. Secondly, a disaster might cut off all the communication systems individuals use to be informed about their social environment (e.g., electronic broadcasting, Internet, telephone). It has been established that failures of these technologies increase the number of casualties and social costs [7]. This was observed after the earthquake that struck Central Chile in February 2010, where all communication systems were cut off for up to one week [8]. Something totally different was observed in April 2009 after the earthquake that struck the Italian city of L'Aquila: there, even mobile phones companies operated normally [9]. Looting was observed in Central Chile, but not in L'Aquila.

This framework poses some interesting research questions. In this article, we want to study the extent to which a delay in response from safety agencies can favour looting behaviour or make more difficult to thwart it. Empirical research has documented that delays in help from public safety agencies, or misinformed individuals, can trigger the escalation of looting [2]. The extensive looting reported after hurricane Katrina in 2005 and in Central Chile after the earthquake that struck this country in February 2010 can be explained, at least in part, by the late reaction of safety agencies [10]. After the earthquake that struck L'Aquila in 2009, safety agencies such as The Red Cross arrived to the affected area a few hours after the earthquake [11,12]. There was no reported looting in L'Aquila.

3 The simulation

We developed an agent-based model (ABM) to understand the escalation of deviant behaviour after a disaster strikes a population. Besides, we tested different policies in order to prevent or react to this escalation of crime. This model is an extension of the 'civil violence model' developed by Epstein [13] and it was built by considering the two assumptions we discussed in Section 2.

The artificial society is made of a square grid where agents are given the ability to move on. The grid is made of 33×33 patches which can be of three kinds:: resources, houses and streets. Resources resembles real-world places where there are storage goods (e.g., shops, warehouses, silos). In our artificial society, each patch-resource stores unlimited goods; in case of a disaster, such amount of goods becomes limited, arbitrarily set at 30 units. Houses are locations where a single civilian agent is created and where she drops stolen goods. All the other patches are streets, where all the agents are free to move. Houses, resources and streets are randomly located over the grid according to an arbitrary density (resource density = 5%, house density = 15%).

There are two types of agents: civilians (G) and police (D). Civilians have four states: law-abiding (LA), agents that can move randomly on streets; hawks (H), agents that are willing to steal goods, so if within their proximity there is a resource, they move on to it and pick up a single good; stealers (B), agents that hold a stolen good and head to their house; and caught (Z), agents that are arrested by the police and sent into their house for an arbitrary amount of time (10 simulation ticks). Police are agents in charge of arresting stealers (only agents who are actually holding a stolen good can be arrested). Finally, agents have a limited visibility radius expressed in terms of patches. v and v^* are the visibility radius for civilians and police respectively. Both are initially set equal to 10 patches

The rule that governs the transition state of a civilian agent i is shown in equation 1. This is a refinement of the one proposed by Epstein in his 'civil violence model' [13].

$$[E(U_i) - N_i] > T_i \qquad T_i \in [0,1] \tag{1}$$

where,

$$E(U_i) = (1 - p_i) \cdot M_i - p_i \cdot C_i \tag{2}$$

and

$$N_i = \begin{cases} R_i \cdot p_i & R \cdot p \neq 0 \\ -[1 - E(U)] \cdot \left(\dfrac{H}{TOT} \right)^2_v & R \cdot p = 0 \end{cases} \tag{3}$$

Equation 1 compares the difference between the agent i's expected utility of looting and her net risk propensity with a non-negative threshold between 0 and 1, with that threshold randomly set across the civilians. Therefore, we can state the simple local rule that governs the civilians' state transition as: if for a 'law-abiding' agent the difference $E(U_i) - N_i$ exceeds T_i, then that law-abiding agent becomes a Hawk and she starts to search for goods to steal; otherwise, she remains as a law-abiding. On the other hand, if for an agent in state 'hawk', the difference exceeds T_i, then that agent stays as hawk; otherwise, she becomes law-abiding.

The agent's expected utility of looting, equation 2, is the difference between the agent i's private benefit of looting M_i and the agent's private cost of being caught C_i, both arbitrarily initialised equal to 0.2.

$$p_i = 1 - \exp\left[-k \cdot \left(\frac{D}{H}\right)_v\right] \tag{4}$$

Equation 4 describes the agent's estimated arrest probability p_i, being set in the same way as presented by Epstein [13]. This probability allows civilians to be aware of other agents in their proximity, ultimately affecting their states in the next step of the simulation. D and H are the number of police and hawks within the agent's visibility radius respectively. However, this equation produces a problem in our model. The limitation of computing p_i as shown in equation 4 is when $D = 0$. In that case $p_i = 0$, whereby the civilians would lose their awareness of both the presence and the state of other civilians in their proximity, behaving as atomistic agents. We overcame this weakness by equation 3. R_i is the agent i's risk aversion; in case that $R_i \cdot p_i = 0$ the net risk propensity N_i is a function of the proportion of hawks (H) within the agent's visibility radius and the total number of civilians within the visibility radius (TOT).

Equation 5 shows that, when S is equal to 1, a disaster has occurred, therefore, the private benefit of looting M_i increases as the total amount of resources Q decreases; J_t is the actual amount of resources available at time t. For simplicity we assume a linear relationship between M_i and Q, and that all the civilians are aware of the amount of resources left.

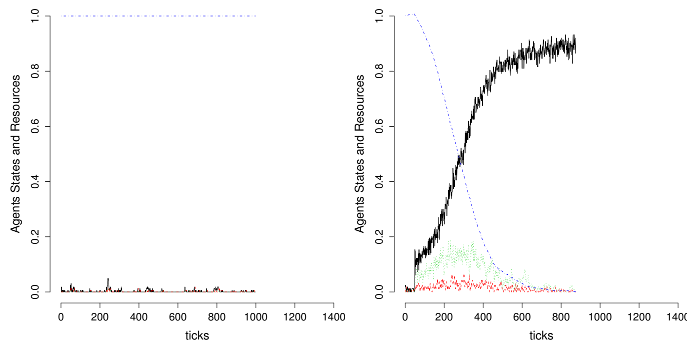
$$M_i = \begin{cases} M_i & S = 0 \\ M_i(t) = 1 - \left[\dfrac{(1 - M_i)}{Q} \cdot J_t\right] & S = 1 \end{cases} \tag{5}$$

Finally, equation 6 expresses the effect of the magnitude of a disaster MD (which it ranges between 0 and 10 in our simulation) on both civilians' and police' visibility. Thus,

$$v^{(*)} = \begin{cases} 10 & S = 0 \\ 10 - MD & S = 1 \end{cases} \tag{6}$$

Police agents are much simpler than prospective looters and stealers. Police move randomly on the grid; if within its visibility radius v^* there is one or more civilians in state stealer (B), the police captures one stealer, returns the good to a resource chosen at random and the civilian is sent into her house where she stays for 10 simulation ticks.

Figure 1 shows the results of implementing the previous specifications in our artificial society. Figure 1a shows the artificial society in ordinary conditions, with no disaster, where there are few hawks and occasional stealers and resources are constant. These situations change dramatically when a disaster strikes the population. Figure 1b shows that, when a disaster strikes, we observe a sharp increase in the proportion of hawks and stealers, being just few of the latter caught (the effectiveness of police is low given the dramatic drop in their visibility v^* caused by the disaster). The increase in the proportion of hawks is mainly driven by the sudden decrease of available resources.



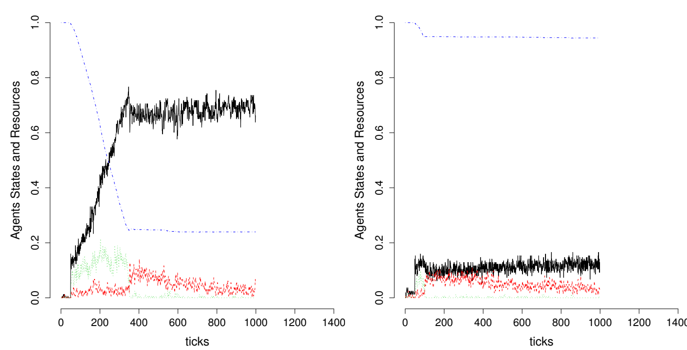
(a) No Earthquake (b) Earthquake

black = Hawks; red = Caught; green = Stealers; blue = Resources.

Fig. 1: Earthquake effects

4 Testing policies: results and analysis

By following our research topic presented in Section 2, we test three different policies, namely: a reinforcement of the police power (*Police Intervention*); an increase of the information available to the affected population (*Social Policy*) and, finally, a combination of both policies (*Joint Policy*). We used the artificial society presented above to study the effect of these policies.



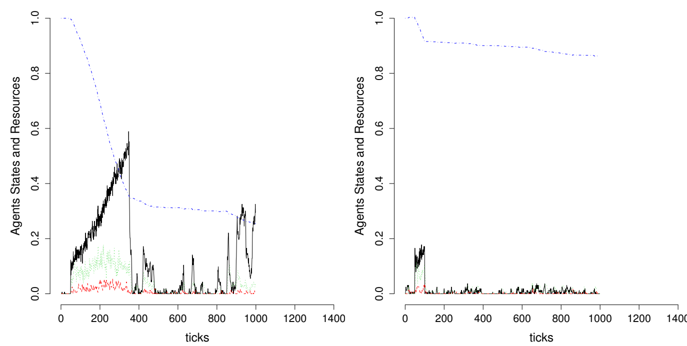
(a) Late Intervention (b) Early Intervention

black = Hawks; red = Caught; green = Stealers; blue = Resources.

Fig. 2: Police intervention

The experimental set consists of six simulations. Disasters always strike after 50 simulation ticks and policies are implemented either at 100 ticks (*early inter-*

vention) or at 350 ticks (*late intervention*). When the disaster strikes, resources become limited, so there will be no goods supply thereafter. Furthermore, both civilians' and police's visibility drop from 10 to 2 patches. Police intervention was implemented in the model by increasing the police agents' visibility v^* to 10 patches; the Social Policy by increasing the civilians' v to 10 patches; the Joint Policy is a combination of the previous two policies. Results are shown by plots which illustrates the proportion of hawks, stealers, caught agents and resources available over time.



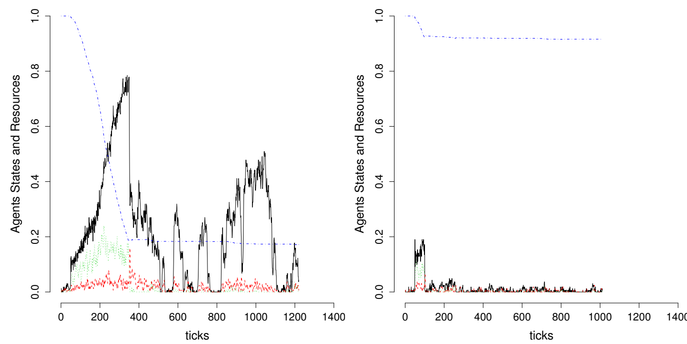
(a) Late Social Policy (b) Early Social Policy

black = Hawks; red = Caught; green = Stealers; blue = Resources.

Fig. 3: Social Policy

Figure 2a illustrates the effect of a late Police Intervention. This intervention seems to protect the resources efficiently as well as dropping the proportion of stealers dramatically. However, this intervention does not decrease the proportion of hawks. An early Police Intervention, as shown in Figure 2b, would bring about the same effect except that, since it is applied earlier, will impede a sharp decrease of resources and consequently solely few hawks are observed. A late social policy, as shown in Figure 3a, causes a sudden drop of hawks but it can not maintain the artificial society stable and fluctuations in the proportion of hawks are observed over time. Moreover, it affects the decrease of resources sensibly, but does not maintain them constant. Just an early social policy, Figure 3b, will both maintain the society stable and bring about a moderate decrease of resources.

The joint effect of the two policies tested in this article results the best policy to apply after a disaster. A late social and joint intervention will preserve the current amount of resources as well as drop the proportion of stealers, however it generates wide fluctuation of the proportion of hawks over time. Figure 4b shows the best intervention policy observed in our experimental set. An early



(a) Late Joint Policy (b) Early Joint Policy

black = Hawks; red = Caught; green = Stealers; blue = Resources.

Fig. 4: Social Policy and Police Intervention

joint intervention seems to protect the current amount of resources efficiently as well as to maintain ordinary behavior in society.

5 Concluding remarks

In this paper we have reported the results of an ABM to study the emergence of looting behaviour after the occurrence of a disaster. The model suggests that, in absence of any external policy, a disaster triggers a deviant behaviour escalation in the system.

We analysed also the impact of three different policies that can be implemented by government agencies: an increase of the police power, an increase of the information available to the affected population and, finally, a combination of both policies. Additionally, we test the effect of time in the implementation of these policies. The results indicate that an early joint intervention successfully contains the escalation of deviant behavior. Late interventions are not able to restore the artificial society to its initial ordinary state. Moreover, the intervention policies taken into account seem to affect two different aspects of the artificial society. Whilst applying a social policy would bring about an overall decrease of hawks, a police intervention would efficiently protect the resources available. Therefore, the outcome of those policies depends ultimately upon the timing of their application. Thus, a mixed policy of reinforcement of police forces and a recovery of the communication systems that allows people to be informed of their environment early after a disaster strikes a population might prevent or thwart the escalation of looting behaviour.

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