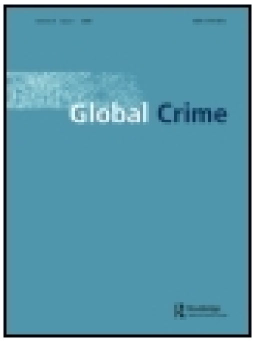

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# Small-world networks and synchronisation in an agent-based model of civil violence

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**ABSTRACT**

The rapid evolution and current ubiquity of social media as a form of communication calls for a revision of many models of collective behaviour. In this paper, we modify a classic agent-based model of civil violence by Epstein (2002) consisting of citizen and law-enforcement agents by integrating a Watts-Strogatz small-world network (SWN). The SWN simulates non-local connections between citizens, enabling influence by both local and distant neighbours and providing an analogue to social media. The objective was to examine the influence of non-local connections on civil violence dynamics for varied law-enforcement concentration and network density. For lower law-enforcement concentrations, the SWN influence leads to more frequent large-scale violent outbursts, while for higher law-enforcement concentrations, outcomes depended most strongly on the number of local neighbours. The long-range coupling across the lattice due to the SWN provides a new mechanism for non-trivial dynamics and leads to a synchronisation effect.

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**KEYWORDS**
Agent-based model; civil violence; social media; small-world networks

## 1. Introduction

17 November 2018 marked the sudden beginning of a new movement in France that would lead to several protests in the following months. While France is a nation built on popular revolts, most experts agree that the Gilets Jaunes movement is unique for at least two reasons. First, unlike other protests in France's history, which were often led by unions or other well-defined groups, the Gilets Jaunes movement appears to have been a leaderless, decentralised revolt.[1] Second, the movement emerged from rural areas of France with small distinct groups organised locally occasionally joining forces to engage in civil disobedience and violence in larger urban centres. These events brought hundreds of thousands of citizens together, most notably, for the violent protests that erupted in Paris in December 2018.[2]

How can a geographically diffused movement lacking any centralised leadership organise so quickly and mobilise citizens from all corners of France to act together in such large numbers? Only a few years ago, such a phenomenon would have been difficult to sustain or explain. Today, however, geographically distant groups can coordinate protests and tactics without any formal leadership structure. The use of social

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media has modified the way protests are organised and carried out and the Gilet Jaunes movement is only but one recent example of this new trend.

Violent protests fuelled by discontent with governments are not new phenomena, but with the advent of the Internet and social media, they receive far more real-time coverage than any other time in history. While some have argued that the influence of social media on the emergence of protests is limited,[3] there are several recent studies that have demonstrated the role social media platforms play in amplifying civil protests and spreading information about them.[4] The debate surrounding the influence of social media on actual involvement in protests, particularly violent protests, lies in part in the disconnect between the low cost of expressing support for a cause on Twitter or Facebook and the high risk involved with joining the action. Early work on involvement in high-risk activism suggests that it is far more likely to be fostered through strong personal ties to a movement, rather than through acquaintances.[5] However, recent research on the 2015 Baltimore protests showed that social media can provide an important source of information where perceptions of moral convergence – the perceived level of agreement on moral attitudes – are formed.[6] Furthermore, the work of Gould[7] suggests that relationships emerging during periods of upheaval between different local, informal groups can combine the benefits of cohesiveness of small pre-existing organisations with the strength of a more coordinated, formal organisation. As Oliver and Marwell[8] have pointed out, the success of a movement is not necessarily based on whether *all* members of a social group mobilise but rather, that 'there [are] enough people who *are* willing to participate and who are also reachable through social influence networks'. Evidence from Central America,[9] the Middle East[10] and the United States[11] suggest s that social media platforms may act as a mechanism to bring together otherwise isolated groups of local participants in social movements.

In this paper, we consider how acts of civil disobedience and the social dynamics behind spontaneous outbursts of civil violence are influenced by the increasing social connectivity brought about by social media. For the purpose of this paper, we define civil disobedience and violence broadly as any action committed by citizens to express their disagreement with the State which can range from minor acts of civil disobedience (e.g. vandalism, peaceful protests) to more serious acts such as riots and physical violence directed towards representatives of the State (e.g. government officials, police officers). We bring together under a single model two important contributions to the study of social dynamics: 1) an agent-based model of the dynamics of civil violence by Epstein,[12] and 2) a model of the small-world organisation of social networks by Watts and Strogatz.[13] The introduction of a small-world network to an agent-based model thus enables non-local influence between agents and provides a mechanism to study the effect of social media connectivity in civil violence dynamics. We find that the presence of a small-world network in our model makes large-scale violent outbursts more likely, and leads to an apparent synchronisation between levels of violence and the response of authorities.

The paper is organised as follows. We first review the Epstein model of civil violence. Second, we review the literature on the influence of social media on social movements, introduce the Watts and Strogatz small-world model, and discuss research on the spread of behaviour on these types of networks. Third, we introduce the components of the agent-based model. Fourth, we present the results of the model obtained for two different cases: one with a high rate of violence and one with a rate of violence more representative of observed real-world rates. Finally, we discuss our conclusions.

## 2. Epstein's model of civil violence

Epstein[14] developed an agent-based model of civil violence where citizens rebel against a central authority. Citizen agents in the model decide to become actively engaged in civil violence dependent on factors such as their level of grievance–a combination of perceived hardship and perceived legitimacy of their government–and their evaluation of the net risk of getting involved in rebellious activity. The last factor–the net risk of becoming active–is a function of an exogenous risk aversion parameter and an evaluation of the probability of arrest which is based on the ratio of active citizens to police officers in a citizen's visible surroundings on a lattice. Police officers in the model patrol the lattice randomly, and arrest active citizens, making them inactive for a period randomly varying between 0 and a set value for the maximum time of incapacitation. We will return to a more detailed specification of the model in a later section as our model replicates much of Epstein's model.

Epstein's model produced a number of interesting stylized facts. First, it led to the emergence of deceptive behaviour by individual citizens. This occurred when actors with a high level of grievance appeared to be quiescent when police officers approached, only to become immediately active again once the police left their surroundings. Criminologists may recognise in this emergent result from Epstein's model the well establish finding that the standard model of policing (i.e. reactive, random patrol across the community) as well as community policing without a problem-oriented component have little influence on crime rates.[15] Such approaches have been shown to have little influence on general deterrence,[16] which has led to the emergence of problem-oriented policing,[17] and place-based strategies.[18] Despite these advances in policing, it is unclear to what extent these evidence-based strategies have displaced the standard model of policing,[19] and some research has shown that officers still believe in the effectiveness of random patrolling strategies.[20]

A second emergent finding from Epstein's model relates to the dynamics of 'tipping points' that generate violent outbursts. For example, Epstein describes how incremental decreases in legitimacy in the model never lead to violent outbursts because of what the author calls 'salami tactics.' As legitimacy decreases, individuals most aggrieved become active but their numbers are easily contained by law enforcement before they can influence others to join in the action. However, if legitimacy drops quickly and drastically, a large enough number of individuals become active at once to generate diffusion to less aggrieved individuals, which in turn leads to violent outbursts. While Epstein's model is designed to represent political upheavals and revolutions, this particular finding may be helpful to explain large protests following what are perceived to be particularly egregious abuses of power by the state, such as homicides of unarmed black men at the hands of the police. There are unfortunately many high profile events that have sparked such protests: the Los Angeles riots in 1992, following the acquittal of officers who violently beat Rodney King, an African American cab driver, and more recently, violent protests of 2014 following the killing of unarmed Michael Brown by a police officer in Ferguson, MO, and 2015 in Baltimore, MD, following the death of Freddie Gray as a result of excessive use of force during his arrest.

## 3. Social media, protests, and small worlds

In Epstein's model, actors only consider local conditions in their evaluation of the risk of getting caught. Since the publication of Epstein's paper in 2002, there have been unprecedented changes in the ways people communicate. The social media platform Facebook was founded in 2004 and opened up to the broader public in 2006, with Twitter being launched that same year. Apple ushered in the modern era of the smartphone with its release of the iPhone in 2007. The emergence of social media platforms as an information sharing tool, combined with the increased mobility of devices to access this information has been shown to contribute to and facilitate social movements and protests.[21]

In recent years, researchers have examined how information shared on social media sites contributed to individual decisions to join in offline protest activities. Tufekci and Wilson[22] interviewed participants in Egypt's Tahrir Square protests during the 'Arab Spring' of 2011. The authors found that an important predictor of participating on the first day of the protests–deemed by the authors to be a particularly risky endeavour compared to joining the action once the protest had begun–was the use of Twitter and Facebook to access information and communicate with others about the protests.[23] Similarly, Harlow[24] conducted a content analysis of communications and interviews with members of Facebook groups calling for the resignation of Guatemalan president Alvaro Colom following allegations that he approved the assassination of a lawyer. The author showed that interactions between organisers, highly active and more infrequent users alike, motivated many to join the offline protests, and the documentation of protest activities led more to subsequently join. The use of social media was particularly effective in motivating individuals who had never protested before. Similar studies have found that social media was an important driver in recent social movements leading to offline protests in Turkey and Ukraine,[25] in the United States,[26] and in Canada,[27] among others.

Empirically studying the dynamics of civil violence and social movements can be challenging, leading researchers to develop different agent-based and game theoretic models to gain insight into these phenomena. Many game theoretic models have been designed to resolve what Tullock[28] called 'paradox of revolution' (p.455). This paradox becomes evident when considering individual rational decisions to join a revolution. For a revolution to succeed, a vast majority of citizens must rebel against the oppressive regime and such a rebellion would be beneficial to all oppressed citizens, even for those who do not join in the action. Therefore, from the point of view of the oppressed group, it may seem rational to start a revolution. However, individuals who do not join the revolution will benefit from a successful revolution, while at the same time avoiding the substantial risks associated with engaging in the rebellion. Assuming individuals seek to maximise utility when making decisions, it appears that the rational decision for all individuals would be to not engage in the revolution, particularly when considering the fact that the decision of a single individual to join the action is unlikely to sway the outcome of a revolt one way or another. As Tullock,[29] Kavka[30], and Vanderschraf[31] point out, a key aspect in resolving the paradox of revolution is that the benefits of joining a revolution may not be solely tied to public goods. For example, those who join revolutions may receive honours, government positions, and other privileges if successful. While this may be true for a small number of citizens, particularly leaders and early joiners, it does not apply for the average citizens whose participation is necessary to a successful revolution. Kavka[32] argued that utility-maximising behaviour of average citizens may change over time as more people join the revolution, which both increases the perception that the efforts will be successful, and reduces the risks associated with participation.

Key to this solution to the paradox of revolution is the adoption of threshold models of participation.[33] Such models assume that people choose to engage in a given behaviour based both on the proportion of their neighbours already engaged in the behaviour and on some individually defined threshold. Kavka[34] argued that in such a model revolutions are likely to occur if many people have a low threshold for joining the action or if 'the thresholds are evenly distributed and relatively "connected" so that the crossing of one subgroup's threshold adds enough participants to breach the threshold of the next group.' In other words, increasing the connections between individuals may help diffuse the adoption of a behaviour across subgroups with different thresholds. Kiss et al.[35] considered how social media influences citizen decisions to join a revolution. They suggest that social media provide a channel through which individuals can evaluate the history and evolution of a movement in more detail than through mass media by accessing information about other citizens' prior decisions to engage or not in the revolt. This allows individuals to better evaluate the likelihood of a revolution being successful by knowing how many other citizens are currently willing to engage, therefore influencing their own decision to join in.

These studies make a convincing case that non-local influences may play a role in citizens' likelihood to engage in rebellious activities and join protests. To account for the role non-local actors may play in decisions to engage in civil violence, we consider how the small-world nature of social networks might influence how individuals decide to join in acts of civil violence.

Watts and Strogatz[36] argued that the topology of many real-world networks falls somewhere in between completely regular and completely random networks. A completely regular network is one in which each node is connected to its $k$ nearest neighbour nodes, and a completely random network is one in which each node is connected to $k$ randomly chosen nodes. Watts and Strogatz called a network between these two extremes a small-world network. By describing a network by a characteristic path length $L$, defined as the average number of edges in the shortest path between each pair of nodes, and a clustering coefficient $C$, related to the tendency for local nodes to connect to each other versus to distant nodes, small-world networks can be qualitatively defined as having relatively small values of $L$ (i.e. on average, any two nodes can be traversed between by following a relatively small number of edges) and large values of $C$ (i.e. a large fraction of edges from any given node connect to nearby nodes). This places them in a distinct region between regular networks, which have large values of $L$ and $C$, and random networks, which have small values of $L$ and $C$. Small-world network behaviour has been described in many real-world networks, including social networks.[37]

The insight provided by small-world networks is that the addition of only a few ties between actors that are not immediately adjacent can dramatically alter the flow of information or the spread of epidemics within the entire system.[38] These non-local ties act as bridges or short-cuts to more distant parts of the network and such ties in social networks have been described as 'weak ties'.[39] Although weak ties can be described qualitatively in terms of the type of relationship between individuals (e.g. weak ties tend to describe relationships between acquaintances rather than close friends or family members), they also have important structural properties in networks. Weak ties tend to connect social groups that otherwise would not be connected, providing important conduits of information between different subgroups in a network. Weak ties are critical in bringing novel information to localised clusters of social networks because more distant actors may have access to different sources of information compared to local actors.[40] Such ties may also reproduce the connections between subgroups of individuals with different thresholds for behavioural adoption described by Kavka.[41] Weak ties present in small-world networks have been shown to influence the dynamics of diffusion of several types of behaviours such as in the spread of political movements,[42] the critical acclaim of Broadway musicals,[43] and the adoption of healthy behaviours.[44] An important feature of small-world networks is their influence on the dynamics of synchronisation of collective behaviour.[45] In the context of epidemics, the shortening of the average path length of the network caused by bridges between otherwise distant networks leads individuals' phases in the epidemic cycle (susceptible, infected, refractory) to become synchronised over time.[46]

## 4. Current study

### *4.1. Model*

We consider an agent-based model of civil violence to describe the effects of a small-world network. The agent-based model described in Epstein[47] was used as a starting point in developing the model described below. The abstract societal features represented are the dissatisfaction level of the citizens in a society with their government or other authority, their tendency to engage civil violence, and the capabilities and behaviour of law enforcement agents. The model consists of two types of agents: citizens and law enforcement officers (LEOs). Citizens are civilian members of the population who bear no responsibility for controlling crime. Each citizen agent on the lattice represents nine individuals. Active citizens are engaged in rebellious activity, whereas quiescent citizens are not. Active citizens may become quiescent and vice versa, depending on a number of factors that describe each agent. These include the agent's grievance level, representing a measure of the agent's dissatisfaction and perception of the government's legitimacy, and the agent's perceived net risk, related to the likelihood of that agent engaging in rebellious activity based on the behaviour of its neighbours and the presence of LEOs. LEOs are forces of authority whose function is to detect criminal activity and to attempt to curtail it by intimidating individuals committing crimes, where intimidation is an abstraction of any mechanism by which an active citizen ceases engaging in criminal activity for some period of time (e.g. incarceration, fear of increased risk of arrest, etc.). LEOs always seek out and intimidate active citizens, whereupon the intimidated citizen is removed from the lattice for a variable time period. All events transpire on a two-dimensional lattice with periodic boundaries. All citizens move once per day, and LEOs move multiple times per day. Figure 1 gives a schematic representation of the lattice.

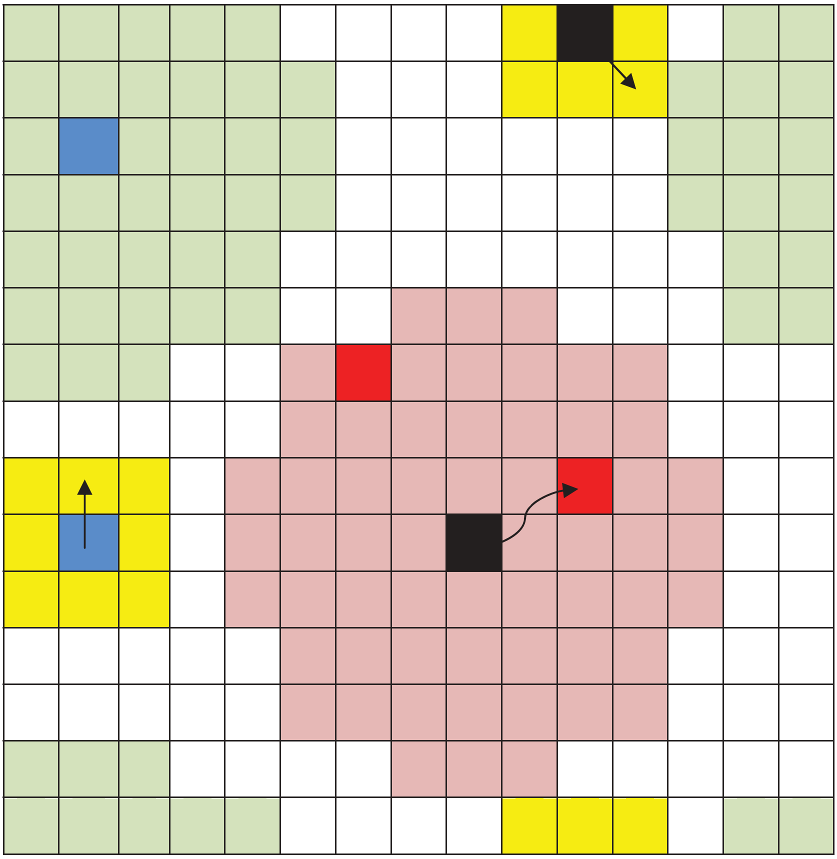

**Figure 1.** Sketch of the model. Currently quiescent (active) citizens are represented by blue (red) cells, LEOs are represented by black cells. Yellow cells show the Moore neighbourhood of an agent. During a move, an agent picks a random cell in its neighbourhood and if the selected cell is unoccupied, it moves that cell, otherwise the agent remains in its original cell. Pink cells show a vision of radius 4 for the LEO (black cell). The LEO intimidates the nearest active citizen in its field of vision. Green cells show vision of radius 4 for the citizen (blue cell).

## *4.2. Agents*

### *4.2.1. Citizens*

Citizens are civilian members of the population who bear no responsibility for controlling crime and can be either active or inactive. Active citizens engage in rebellious law-breaking activities while inactive citizens are law-abiding. The likelihood that a citizen becomes active depends on three factors: perceived hardship ($H$), legitimacy ($L$) and grievance ($E$). Hardship refers to the physical and economic hardship perceived by the actors. It is an exogenous factor in the current model and each actor is assigned a value from the uniform distribution between 0 and 1. Legitimacy ($L$) refers to citizens' willingness to accept the government's use of authority 'to determine what their behaviour will be within a given set of situations'.[48] In the current model, $L$ is equal across citizens and can vary between 0 and 1. The value of $L$ is exogenous to the model and can be inferred by the fraction of actors who will never engage in law-breaking activity and the f r action of actors who are always active using the following function:

$$L = 1 - \frac{2R}{G(1-G)}. \quad (4.1)$$

where $R$ is the proportion of actors who are always active, and $G$ is the proportion of actors who are never active. In the models described in this paper, $R$ and $G$ are set at 0.025 and 0.5, respectively.

Together, H and L determine the level of grievance ($E$) of each actor where $E = H(1-L)$. Each actor is assigned a value of risk aversion ($K$) from the uniform distribution between 0 and 1. $K$ contributes in changing states of actors between quiescent and active when combined with an assessment of the risk of getting caught engaging in disorderly conduct. The probability of arrest ($P$), or the citizen's perceived risk, is defined as:

$$P(C/A) = 1 - exp(-k'(C/A)) \sum_{i=0}^{15} \frac{(k'(C/A))^i}{i!}, \quad (4.2)$$

where $A$ is the number of active citizens (including the citizen itself) within the citizen's vision ($v$, the radius of a circle on the lattice a citizen is able to inspect), $C$ is the number of LEOs within a citizen's vision, and the constant $k' = 62.6716$ is found from the condition that $P(1/4) = 0.5$ (see Figure 2). The perceived risk is in fact zero up to a threshold value, after which it increases monotonically, thus giving it a sigmoidal shape. The sigmoidal shape leads to citizens' perceived risk to be less than the actual risk of arrest by LEOs, which is expected to increase greater than linearly for increasing ratio of LEOs to active citizens.

The citizen's perceived net risk N is defined as the product of the perceived probability of arrest ($P$) and the risk aversion parameter ($K$). If for a law-abiding citizen the difference $E - N$ exceeds $T$, where $T$ is some threshold, then the citizen becomes criminally active. If, for an active citizen, the difference $E - N$ exceeds $T$, then the citizen stays active. Otherwise, it becomes law-abiding. In summary, the citizen's rule for being

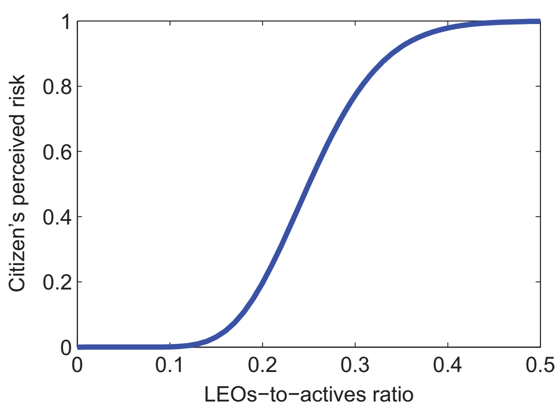


**Figure 2.** Citizen's perceived risk function.

active or quiescent is the following: If $E - N > T$ be active; otherwise, be quiescent. Similar to $L$, $T$ can be inferred from the proportions $R$ and $G$ of the population:

$$T = \frac{2R}{1 - G}. \tag{4.3}$$

#### 4.2.2. LEOs

LEOs seek to deter crime and incapacitate citizens involved in rebellious activities (through arrest and incarceration). LEOs intimidate the nearest active citizen on the lattice within the LEO's vision radius ($w$). Once intimidated, a citizen stops having an influence on the lattice for specific amount of time randomly assigned from the uniform distribution between 0 and $J_{max}$, where $J_{max}$ is the maximum amount of intimidation. For this study, we fix this maximum to be 120 days. Once this time expires, the citizen is released to the lattice in the quiescent state.

### 4.3. Small-world network

We introduce a small-world network (SWN) to extend the vision of the citizens in the agent-based model. While other types of network topologies could be used, we chose to use the SWN model because it allows us to move between a completely regular network (where all ties are local) to a completely random network. In effect, a perfectly regular network would mimic situations where actors only know their neighbours, whereas a completely random network would simulate a situation where physical distance has no bearing on social connections. The introduction of randomness to regular networks produces a system where local clusters remain but information from other distant clusters is accessible. Both clustering and short-path distances are critical for the spread of information and behaviour adoption in social networks, and the SWN model has been used in many studies to explore the spread of rumours,[49] epidemics,[50] the diffusion of innovations[51] and the evolution of collaborative behaviour strategies.[52]

The effect of the SWN is that about 90% of neighbours of a citizen remain in its local vision, while 10% of neighbours (distant neighbours) are visible remotely through the SWN. This SWN can be envisioned as representing social media connections between citizen agents. The SWN is constructed as an undirected graph with $V$ nodes and $V * S/2$ edges, where the number of nodes $V$ is the population size and the mean degree $S$ is the number of distant neighbours for every citizen. The choice of an undirected graph is justified by the assumption of bidirectional information exchange between people, which is consistent with social media connections. We follow the Watts-Strogatz model of SWN.[53] First, a regular ring lattice is constructed, which is a graph with $V$ nodes each connected to $S$ neighbours, with $S/2$ on each side. Then, for every node $v_i = v_0, \ldots, v_{V-1}$ we take every edge $(v_i, v_j)$ with $i < j$, and rewire it with a given probability $\beta$ (where $0 \leq \beta \leq 1$). Rewiring is done by replacing $(v_i, v_j)$ with $(v_i, v_l)$ where $l$ is chosen with uniform probability from all possible values that avoid loops ($l \neq i$) and link duplication (i.e. there is no edge $(v_i, v_{l'})$ with $l' = l$ at this point in the algorithm).

### 4.4. Movements, run procedure, and outcomes

Citizens and LEOs move on the lattice by using the following movement rule: Pick a random neighbouring location on the lattice (from the agent's Moore neighbourhood), and if that location is unoccupied–move there, or if the location is occupied–stay in the original position. We have included the pseudo-code describing the simulation procedure in Appendix 1.

The procedure of a run is the following. A citizen or a LEO is selected at random. The probability of selecting a LEO is higher according to the number of moves a LEO can make per day. If the selected agent is a non-intimidated citizen, then it moves according to the movement rule; if the citizen is intimidated, the assigned intimidation term is checked and if it is over the citizen is released in the 'non-active' state to the same spot where it was intimidated or, if that spot is occupied, to the spot closest to the spot where the citizen was intimidated. After that, the state of the citizen is calculated depending on the current lattice situation. If the selected agent is a LEO, then it inspects all sites within its vision radius, intimidates the nearest active citizen (if any) and jumps to the location of that intimidated citizen. The intimidated citizens are placed outside the lattice. Then, the LEO moves according to its movement rule. The model iterates this procedure until the simulation time is reached.

We now describe the output variables of our model; their explicit functional definition is given in Table 1. The total number of citizens active at the end of the day is denoted by *Act*; *AJ* denotes the total number of citizens active at the end of the day or intimidated during the day; *pop* is the population size; and *tp* is the length of a specific time period. Following Epstein,[54] we introduce a threshold (e.g. 5% of population) and say there is a large-scale violent outburst (or revolution) if the number of active citizens per day in per cent ($NA_{tp}$) exceeds the threshold. *NR* is the total number of large-scale violent outbursts (or revolutions) per 1,000 days. The rate of violence, denoted by $RV_{tp}$, is the number of citizens active at the end of the day or intimidated during the day per 1,000 citizens for a specific time period. Let *AMNA* be the maximum number of active citizens during the large-scale violent

**Table 1..** Model Outputs.

| No. | Output Name | Output Definition |
|---|---|---|
| 1 | Number of active citizens per day in percent | $NA_{tp} = \frac{\frac{1}{tp}\sum_{tp} Act}{pop} * 100$, where *Act* is the total number of citizens active at the end of the day, *tp* is the length of a specific time period, *pop* is the population size |
| 2 | Number of large-scale violent outbursts (revolutions) per 1,000 days | *NR* |
| 3 | Peak number of active citizens | $PNA = \frac{AMNA}{pop} * 100$, where *AMNA* is the maximum number of active citizens during the large-scale violent outburst averaged over all large-scale outbursts, *pop* is the population size |
| 4 | Number of violent outbursts per year | $NV_Y = \frac{365}{AWT}$, where *AWT* is the waiting time between two large-scale violent outbursts averaged over all outbursts |
| 5 | Rate of violence | $RV_{tp} = \frac{\frac{1}{tp}\sum_{tp} AJ}{pop} * 1000$, where *AJ* denotes the total number of citizens active at the end of the day or intimidated during the day, *tp* is the length of a specific time period, *pop* is the population size |
| 6 | Number of intimidated citizens just before an outburst begins in percent | $NIC = \frac{MNIC}{pop} * 100$, where *MNIC* be the minimum number of intimidated citizens in the 20 day period before the peak of the outburst, *pop* is the population size |

outburst averaged over all large-scale outbursts. We denote the peak number of active citizens in percentage by *PNA*. The variable *AWT* denotes the waiting time between two large-scale violent outbursts averaged over all outbursts. The number of violent outbursts per year, denoted by $NV_Y$, is inversely proportional to *AWT*. Let *MNIC* be the minimum number of intimidated citizens in the 20-day period before the peak of the outburst. We denote the number of intimidated citizens just before an outburst begins in percentage by *NIC*. Each realisation of the simulation differed by the random number seed used. All output variables were averaged over all realisations. These outputs are calculated and plotted, depending on the situation, for specific time intervals.

### 4.5. Selection of parameters

The parameters we use for the model are based both on Epstein's original model, and the analysis conducted in previous papers to validate the parameters against real-world data.[55] In Fonoberova et al.[56] an agent-based model was used to explain surprising trends in crime and law enforcement data. Analysis of FBI data on violent crimes in 5,660 U.S. cities over the period of 2005–2009 shows that the proportion of law enforcement officers (LEOs) grows nonlinearly (super-linearly) with population size, as also observed in Bettencourt et al.[57] For example, using FBI data with the fixed average number of crimes per 1,000 citizens equal to 6, it was found that cities with 10,000 people generally have 2.4 LEOs per 1,000 citizens, whereas cities of 1 million people have 3.7 LEOs per 1,000 citizens. These ratios of LEOs to citizens are in agreement with those recommended ones by police organisations. The implication is that a non-linear scaling of LEOs with population size is necessary to maintain crime levels below some common target. Intuition would hold that the number of LEOs needed to keep the criminal and violent activity below a certain level would grow proportionally to the size of the population in a city, provided the population density is kept constant. However, by using the agent-based model it was found that an increase in the proportion of LEOs was necessary to keep the crime rate below a target value for larger cities. It was shown that the per capita rate of criminal/violent events in a city shows non-monotonic behaviour with size of the population. The agent-based model allowed for system-level, mechanistic understanding of these trends. There was found to be a strong dependence on the size of the population, where the nature of violence changes from global outbursts of criminal/violent activity in small cities to spatio-temporally distributed, decentralised outbursts of activity in large cities, indicating that in order to maintain peace, larger cities need larger ratios of law enforcement officers than smaller cities. This leads to the existence of tipping points for communities of all sizes in the model: reducing the number of law enforcement officers below a critical level was found to rapidly increase the incidence of criminal/violent activity. These trends observed from the agent-based model were found to be in agreement with FBI data on violent crime rates.

## 5. Results

### 5.1. Test case with high rate of violence

In this section, we consider the case when the number of LEOs per 1,000 citizens is selected in such a way that large-scale outbursts occur so that we can clearly show the effects of introducing a SWN to the original Epstein model. All model parameters have the fixed values listed in Appendix 2 (for sensitivity analysis of this class of models see Fonoberova et al.[58]).

One thousand days were computed for each simulation. We consider lattices of three different sizes (100x100 cells, 200 × 200 cells, and 300 × 300 cells), and three different SWN cases: without a SWN, a SWN with $\beta = 0.2$, and a SWN with $\beta = 0.8$. Each experiment was repeated at least 10 times and the results averaged over all simulations.

We require that LEOs and citizens see an approximately equal number of cells, given a LEO vision radius of 10.5. This requires that the citizen vision radius be less than the LEO vision radius because citizens see cells in both their vision radius and in their SWN (each distant neighbour occupies one cell). To determine the number of distant neighbours, we first consider the same vision radius value of 10.5 for both citizens and LEOs. We calculate that the initial number of neighbours for a citizen is 244.3, which is the total number of cells within its vision radius multiplied by the population density. This is believed to be a realistic number, based on a finding from a 2014 Pew survey[59] that the median number of Facebook friends for users of all age groups was 200. We require that the number of distant neighbours be about 10% of the total number of neighbours, which gives a number of 22 distant neighbours. To satisfy the criterion of LEOs and citizens seeing equal numbers of cells, we use as a final value for the citizen vision radius 10.01, which gives 221.9 local neighbours within the vision radius.

Figures 3 and 4 show positions of citizens and LEOs just before an outburst begins and during an outburst for the 200 × 200 cell lattice and the cases without the SWN and with the SWN with $\beta = 0.2$.

Both cases are qualitatively similar, with a cluster of active citizens forming an initial nucleus of unrest that then spreads across the lattice, though it is suppressed at its initial origin location. The cases with and without a SWN do differ in several respects however. Before the outburst begins, the case without a SWN has a number of active citizens spread across the lattice in addition to the largest cluster, and the violent outburst takes 8 days to reach its height. This differs from the case with a SWN, in which there are almost no active citizens outside of the main cluster before the outburst begins, and the outburst reaches its peak in only 6 days. This demonstrates the contribution of the SWN to the formation and growth of violent outbursts.

Figure 5 shows time series of the number of active and intimidated citizens for the 200 × 200 cell lattice, for the cases without the SWN and with the SWN for $\beta = 0.2$ and $\beta = 0.8$. The overall structure is the same in all three cases, that is, the number of active citizens shows regular spikes and the number of intimidated citizens shows a sawtooth pattern of jumps and decays (the decay rate is related to the length of the intimidation time periods). The cases with a SWN show an increased number of active citizens in each outburst spike, consistent with the SWN's effect of increasing the growth rate of the number of active citizens. Close analysis of the SWN cases' time series shows greater periodicity of each time series (i.e. more equal spacing between the active citizen spikes and for each period of the sawtooth pattern) and a consistent phase between the two time series over the entire time period of the model run. This is a synchronisation effect, which leads to the consistent height of the active citizens' spikes and the extremes in the magnitude of the intimidated citizens' sawtooth pattern. Synchronisation effects in complex networks such as these have attracted much attention (e.g. SWNs of Rössler

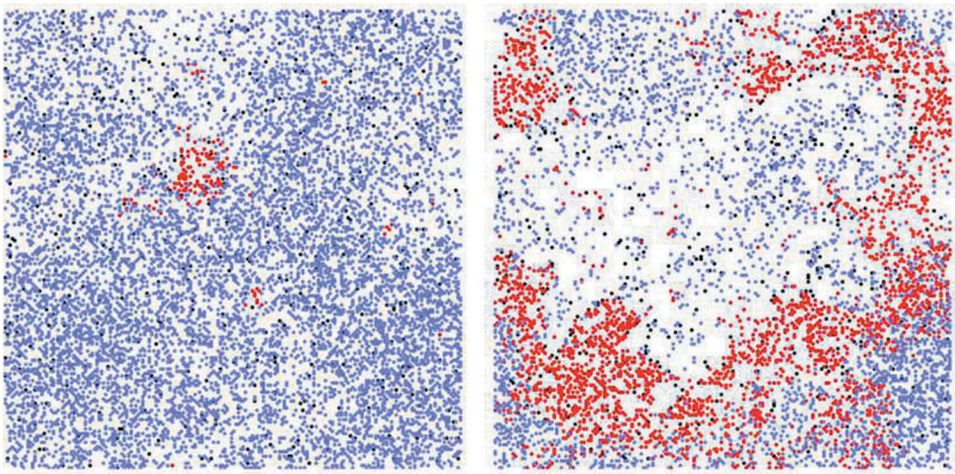

**Figure 3.** (High crime case) Lattice situation at day 981 and day 989 for the 200 × 200 cell lattice in the case without the SWN. Citizens are coloured blue if quiescent and red if active. LEOs are coloured black, and never-active citizens and unoccupied sites are white.

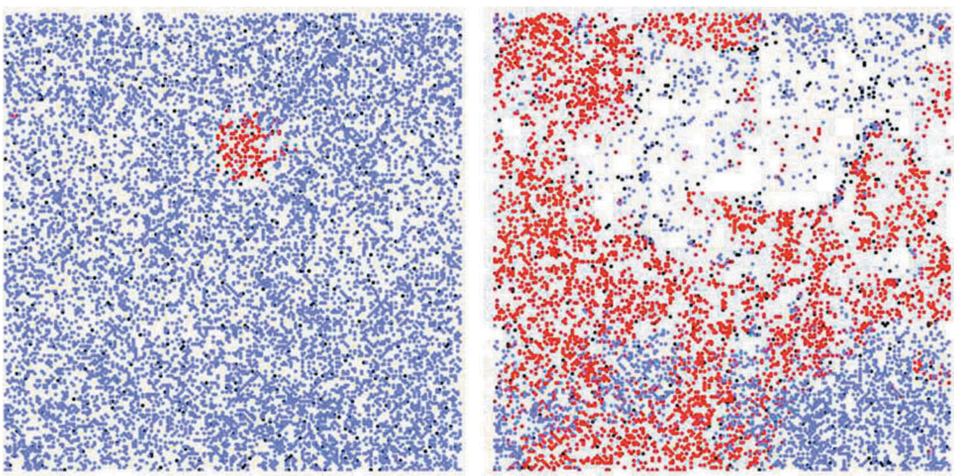

**Figure 4.** (High crime case) Lattice situation at day 214 and day 220 for the 200 × 200 cell lattice in the case with the SWN. Citizens are coloured blue if quiescent and red if active. LEOs are coloured black, and never-active citizens and unoccupied sites are white.

oscillators studied in Wu et al.[60]). This synchronisation is explained by the SWN providing a coupling mechanism between different lattice regions, which makes some fraction of the lattice behave in a coordinated manner as a single large region, instead of as multiple smaller regions with independent dynamics. The greater amplitudes of both the spikes of active citizens and the sawtooth pattern of intimidated citizens in the beta = 0.8 case demonstrates the effect of increasing the coupling across the lattice by decreasing the distance between nodes in the network.

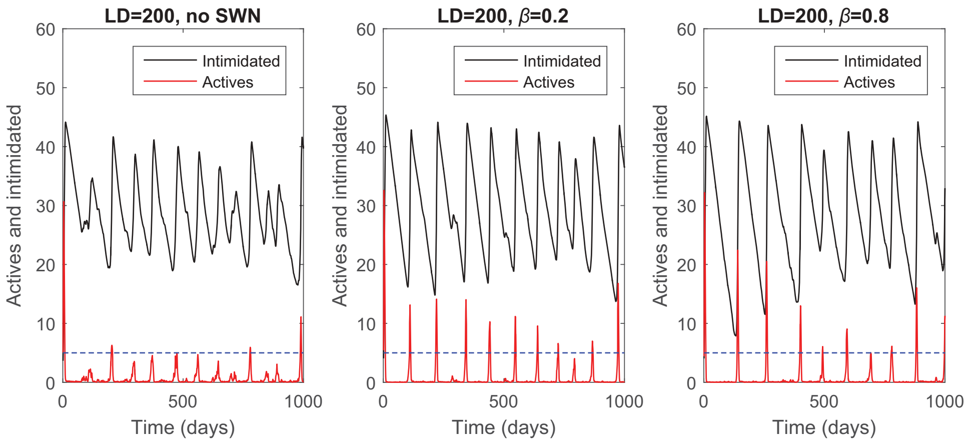


**Figure 5.** (High crime case) Number of active and intimidated citizens in per cent for the 200 × 200 cell lattice in the cases without the SWN (left) and with the SWN with $\beta = 0.2$ (middle) and $\beta = 0.8$ (right). The dotted blue line at 5% is the threshold level for defining a large-scale violent outburst to be occurring.

The output variables for lattices of sizes 100 × 100 cells, 200 × 200 cells, and 300 × 300 cells for the case without a SWN and the case with SWNs with $\beta = 0.2$ and $\beta = 0.8$ are plotted in Figure 6–11. The standard deviations of the observables from Table 1 were small, so considering the uncertainty $U$ in the mean of a given observable $A$ to be $U(A) = \sigma(A)/\sqrt{N}$, where $N = 10$, the number of realisations we used gave uncertainties of around $5\%$ or less in almost all cases. Figure 6–11 include error bars based on these calculated uncertainties. The two cases with a SWN are seen to produce very similar results, because the SWN is built on the already randomised positions of citizens.

As we can see from Figures 6 and 7 the number of active citizens per day and rate of violence are comparable for the cases with and without a SWN for all three lattice sizes. This can be explained by the fact that in this high violence case, the proportion of LEOs is small and the total number of actives per day is saturated, with the saturation level set by the length of the intimidation time period and the total number of active citizens that LEOs can intimidate per day. The introduction of a SWN does not produce a significant change because, for the predominant situation in which there is not a violent outburst occurring, the activity levels of a given citizen's local and distant neighbours are the same on average. This equivalence does not hold during a violent outburst and leads to the differences between the cases with and without a SWN described below.

Figure 8 shows that the peak number of active citizens increases substantially after introducing a SWN. This can be understood by the non-local effect of the SWN, which enhances the growth of violent outbursts by enabling them to spread across the lattice much faster than would be possible with only the influence of local neighbours. The faster growth of such outbursts leads to more citizens becoming active before the LEOs can intimidate a sufficient number of citizens and end the outburst.

Figure 9 shows that the number of intimidated citizens before an outburst is just about to begin is significantly larger in the case without a SWN. This suggests that another contributor to the differences in the peak number of active citizens from Figure

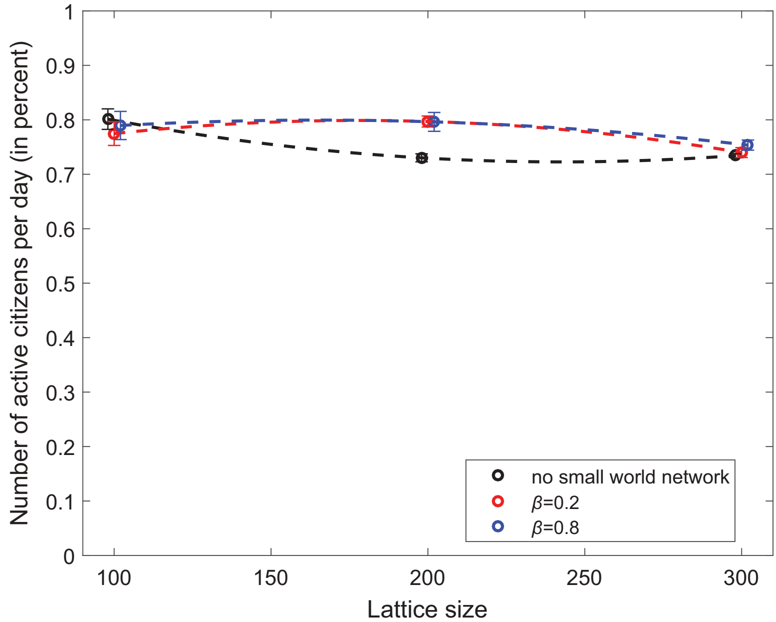


**Figure 6.** (High crime case) Number of active citizens per day in per cent.

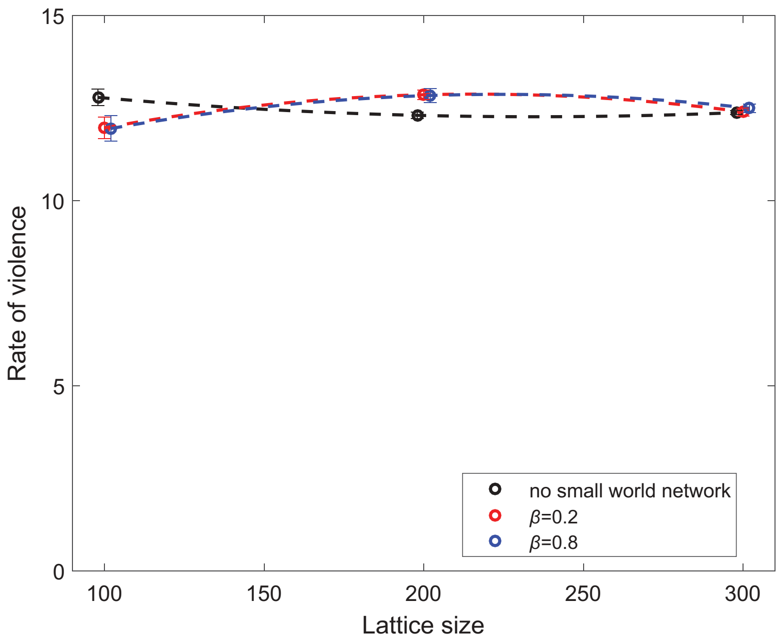


**Figure 7.** (High crime case) Rate of violence.

8 is the availability of non-intimidated citizens to become active, because the more distributed nature of the active citizens in the SWN case results in LEOs being slower to intimidate active citizens.

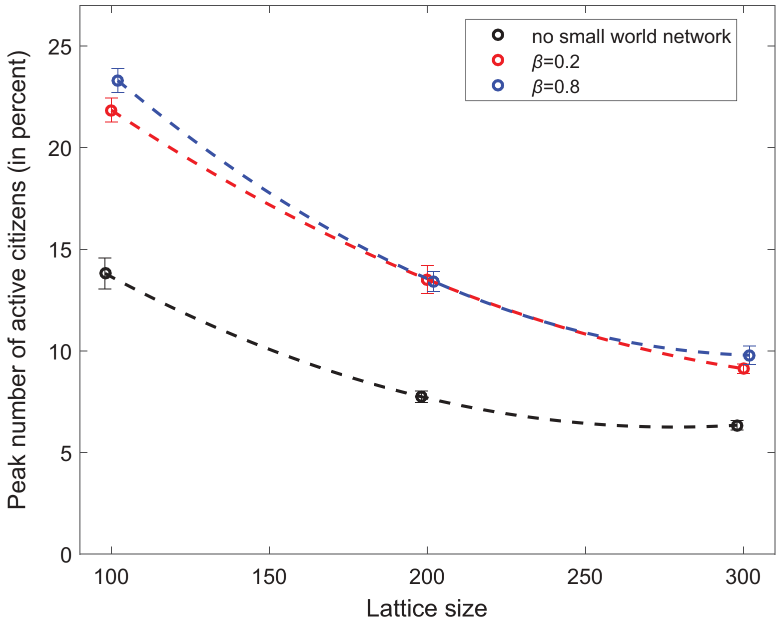


**Figure 8.** (High crime case) Peak number of active citizens in per cent.

Figures 10 and 11 show that the number of violent outbursts and large-scale violent outbursts (revolutions) per year increase substantially after introducing a SWN for the two larger lattice sizes and remains approximately constant for the smallest lattice size. The observed increase in the number of both outbursts and revolutions is consistent with the previously described role of the SWN in enhancing the growth rate of the number of active citizens due to the reduced effectiveness of the LEOs, which increases the likelihood of fluctuations in the number of active citizens growing into a violent outburst and thus increases the number of observed outbursts and revolutions. The ratio of the number of revolutions and outbursts does not significantly or systematically change with the introduction of a SWN, suggesting that once an outburst reaches a sufficient size, it is wide spread enough that the non-local influence through the SWN no longer contributes significantly to the growth dynamics and the activity of the LEOs thus eventually limits the outburst growth. It is worth noting the difference in the dependence on the lattice size for the cases with and without a SWN.

For the smallest lattice size, the introduction of a SWN produces a small but significant decrease in the number of violent outbursts, while for the larger lattice sizes the SWN cases show a significant increase in the number of violent outbursts, though the size of the increase over the no SWN case decreases with increasing lattice size. Without a SWN, the number of violent outbursts decreases with increasing lattice size. This effect is explained by the observation that for increasing lattice size, the average height (i.e. maximum number of active citizens) of the spike in the number of active citizens decreases. Figure 8 shows an aspect of this, as the peak number of active citizens decreases with increasing lattice size, both with and without a SWN. As we follow Epstein's definition of a large-scale violent outburst as when more than 5% of the total number of citizens is active, and because the

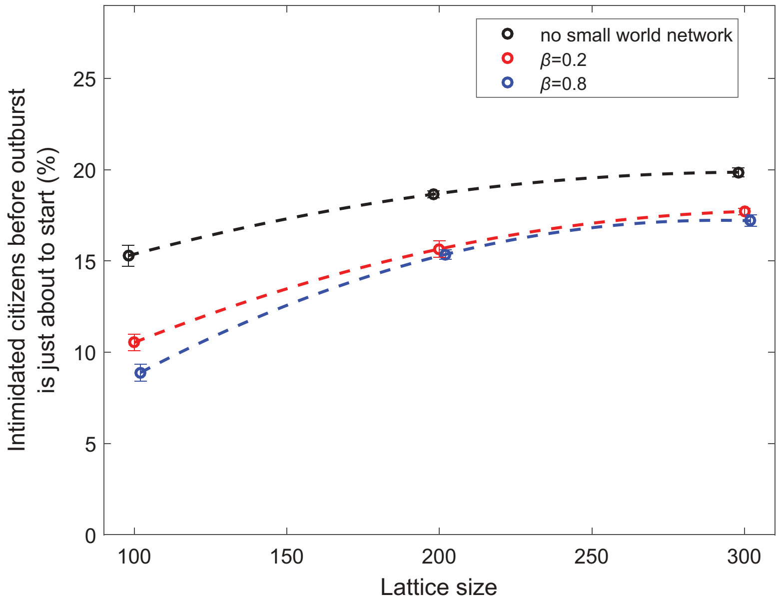


**Figure 9.** (High crime case) Number of intimidated citizens before outburst is just about to start, in per cent.

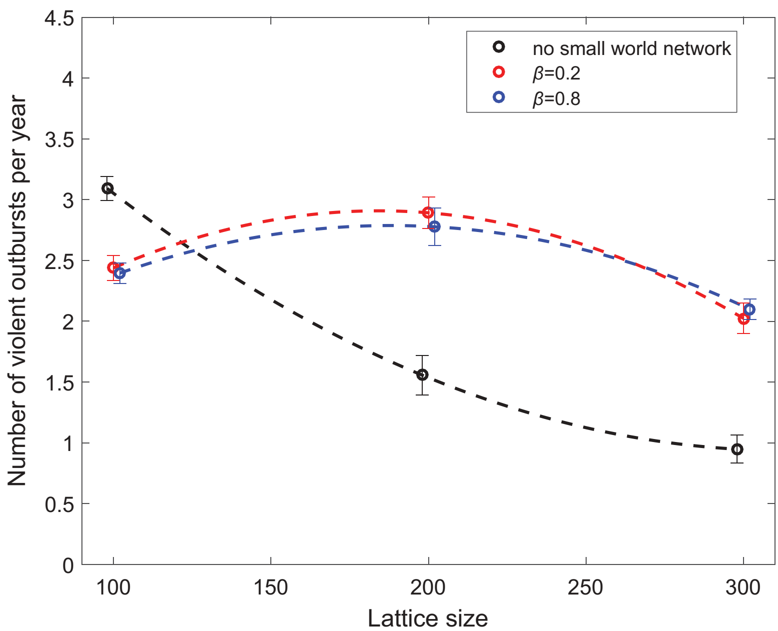


**Figure 10.** (High crime case) Number of violent outbursts per year.

maximum number of active agents in each spike decreases with increasing lattice size, there will be a corresponding decrease in the number of spikes that reach the threshold to be categorised as large-scale outbursts. We can therefore conclude that the effect of adding a SWN to the simulation depends on lattice size. For the $100 \times 100$ lattice size, where outbursts

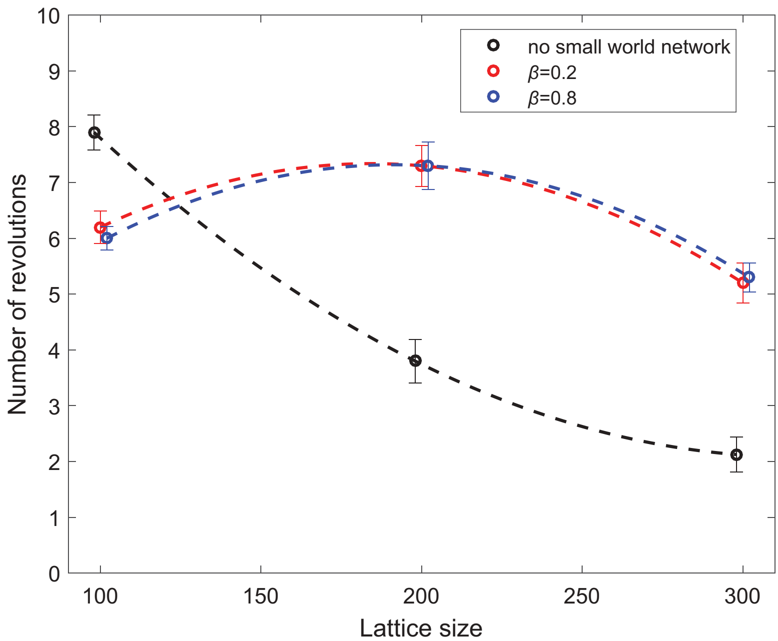


**Figure 11.** (High crime case) Number of large-scale violent outbursts (revolutions).

tend to spread from a starting point and cover a large fraction of the lattice, the small decrease in the number of violent outbursts can be explained by the SWN serving to expose non-active citizens with active neighbours to as-yet non-active distant neighbours and thereby slow the increase in the number of active citizens and give the LEOs more time to suppress the outburst. For increasing lattice size, the SWN increases the number of outbursts by speeding the spread of citizens becoming active from an initial starting point, whereby the citizens with distant neighbours in an active region need fewer local neighbours to be active in order to become active themselves.

### 5.2. *Case with the realistic number of LEOs per 1,000 citizens*

In the following, we consider a lower-crime case in which the number of active citizens per day is 0.2%, which is comparable with observed crime statistics[61] and is thus considered more realistic. All parameter values are again listed in Appendix 2.

We consider two situations with different citizen vision radius values. In one case, we use the same vision radius value of 14 for both citizens and LEOs. In this case, citizens can see more cells than LEOs, because citizens see the cells within their vision radius in addition to their distant neighbours whereas LEOs only see the cells within their vision radius. This vision radius value gives the average number of local neighbours for a citizen of 429.1. We require that the number of distant neighbours is about 10% of the total number of neighbours, so each citizen has approximately 42 distant neighbours. The other case is the same as in Section 5.1, where the criterion is for citizens and LEOs to see an equal number of cells, given a LEO vision radius of 14 and citizens having 42 distant neighbours. This requires that the citizen vision radius be smaller than that of

LEOs, because citizens also see the cells occupied by their distant neighbours. To satisfy this criterion, the citizen vision radius must be 13.16, which gives 387.1 neighbours within the vision radius.

Fifty thousand days were computed for each simulation. We consider lattices of three different sizes (100x100 cells, 200 $\times$ 200 cells, and 300 $\times$ 300 cells), and cases without a SWN and with SWN with $\beta = 0.8$. The cases with different $\beta$ were found to produce similar results, so we only present the case of $\beta = 0.8$. Each experiment was repeated at least 28 times and the results averaged over all simulations.

Figure 12 shows positions of citizens and LEOs during an outburst of activity for the 200 $\times$ 200 cell lattice in the cases without a SWN and with a SWN, for citizen vision radius values of 13.16 and 14. It is seen that the inclusion of a SWN increases the fraction of active agents during a violent outburst. This increase in active agents is a specific feature of violent outbursts; however, as in this realistic violence level case, the average rate of violence was found to be more dependent on the citizen vision radius than on the SWN.

Figure 13 shows time series of the number of active and intimidated citizens for the 200 $\times$ 200 cell lattice in the cases with and without a SWN for citizen vision radius values of 13.16 and 14. The dynamics of the number of active and intimidated citizens are seen

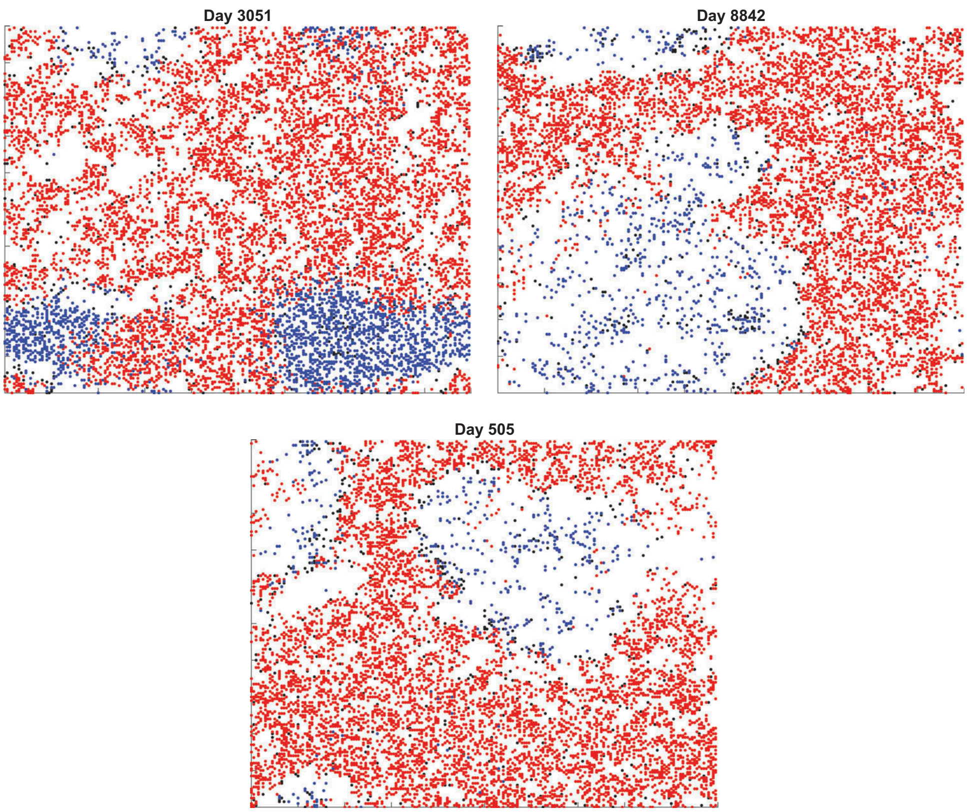


**Figure 12.** (Low crime case) Left: No SWN, Middle: SWN and citizen vision of 13.16, Right: SWN and citizen vision of 14. Lattice situation for the 200 $\times$ 200 cell lattice during an outburst of violent activity. Citizens, who can become active, are coloured blue if quiescent and red if active. LEOs are coloured black, never active citizens and unoccupied sites are white.

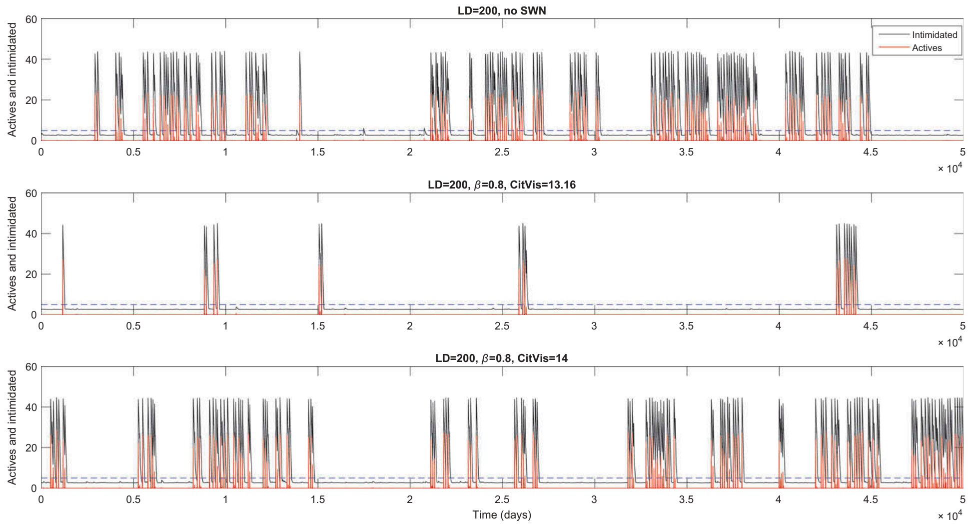


**Figure 13.** (Low crime case) Number of active and intimidated citizens in per cent for the 200 × 200 cell lattice in the realistic cases without a SWN and with citizen vision radius of 14 (left) and two cases each with a SWN with $\beta = 0.8$ and differing citizen vision radius values of 13.16 (middle) and 14 (right). The dotted blue line at 5% is the threshold level for defining a large-scale violent outburst to be occurring.

to be qualitatively different from the high crime rate case previously discussed. In this case, outbursts are seen to be less frequent (note that this simulation was run for 50 times longer than the high crime rate case, so the scales of the time axes are different), the outbursts are not periodic, and there is no apparent synchronisation effect. It is also seen that local vision plays a more important role than the SWN in the dynamics leading to violent outbursts, since the cases with the larger citizen vision radius have more frequent violent outbursts.

The results for lattices of sizes 100 × 100 cells, 200 × 200 cells, and 300 × 300 cells for the case without a SWN and the case with a SWN and citizen vision radius values of 13.16 and 14 are plotted in Figure 14–19. As in the test case with high rate of violence, Figure 14–19 include error bars based on the calculated uncertainties.

Figures 14 and 15 show that the number of active citizens per day and the rate of violence are much lower for the case with the smaller citizen vision radius value than the two cases with the larger citizen vision radius value. These values are higher for the larger citizen vision radius cases because each citizen has more neighbours, so active citizens can influence more neighbours. In this lower crime rate case, the local neighbours are seen to be more important than distant neighbours, based on the limited impact of the SWN. The proportional number of active citizens and the rate of violence increases with lattice size because the same saturation effect observed in the high crime case does not occur, so in the larger lattices, the variations in the LEO density over the lattice provide more LEO-free regions for citizens to become active.

From Figure 16 we can see that the peak number of active citizens is the lowest for the case without a SWN and then increases slightly with the introduction of a

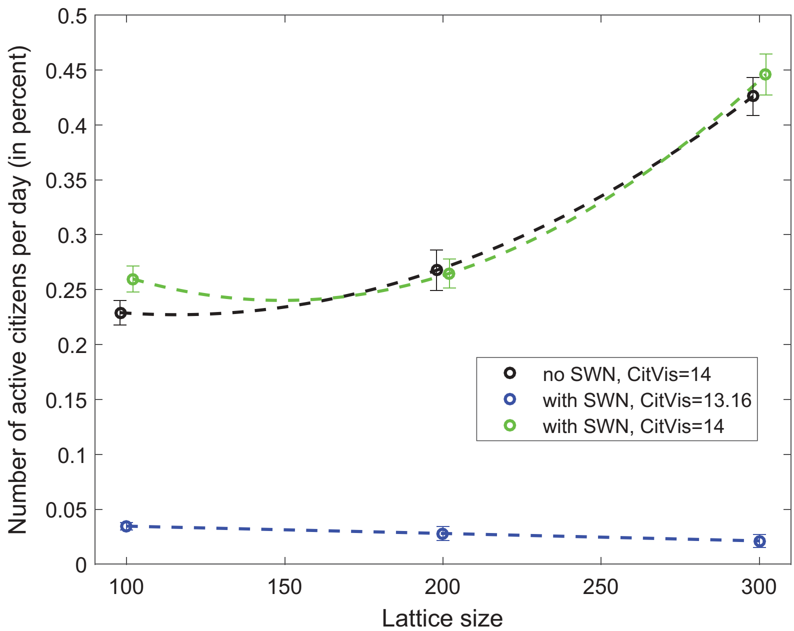


**Figure 14.** (Low crime case) Number of active citizens per day in per cent.

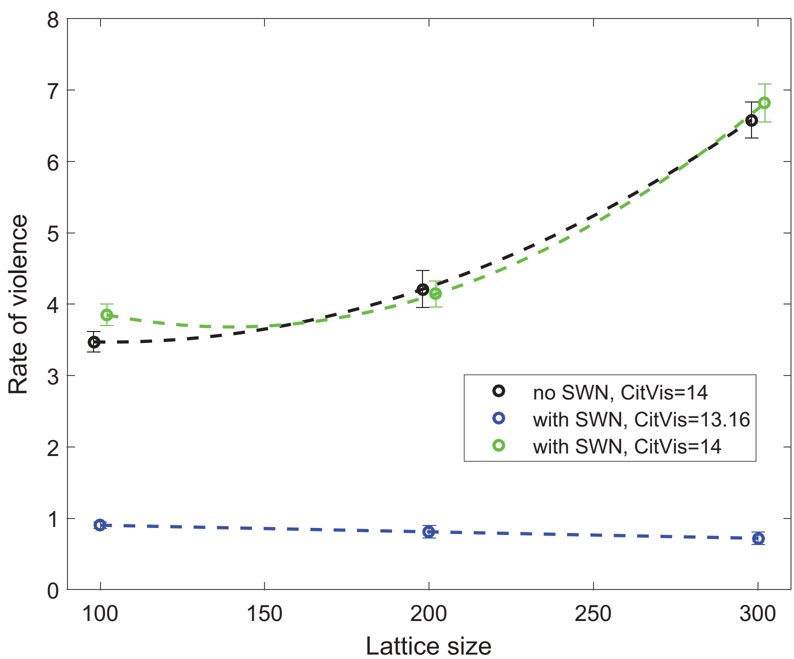


**Figure 15.** (Low crime case) Rate of violence.

SWN, although the peak number of active citizens is slightly higher for the case with smaller citizen vision. The downward trend with lattice size is due to the larger

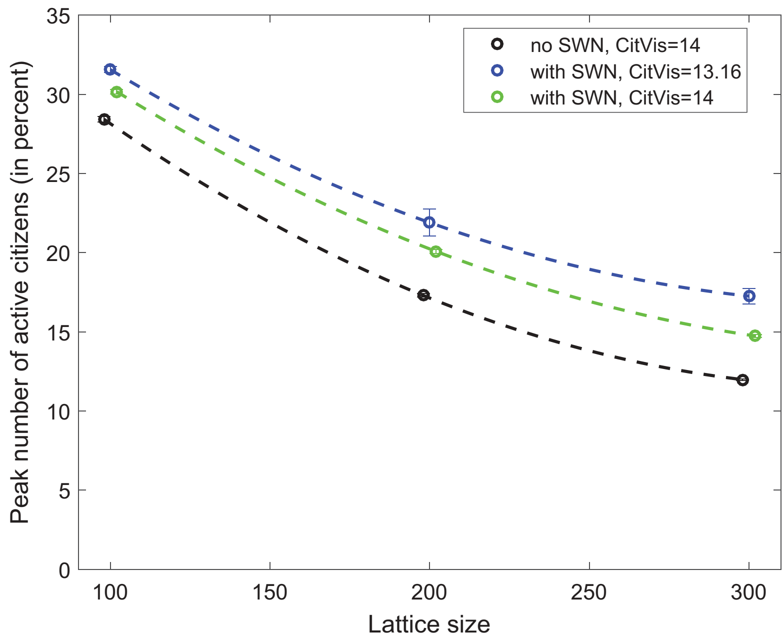


**Figure 16.** (Low crime case) Peak number of active citizens in per cent.

number of LEOs able to intimidate active citizens in a growing outburst, thus limiting the size of the outburst.

Figure 17 shows that in the case with smaller citizen vision radius there are fewer intimidated citizens before the outburst is about to begin and there are more citizens on the lattice capable of becoming active during the outburst, hence the slightly larger peak number of active citizens in Figure 16.

Figures 19 and 18 show that the number of large-scale violent outbursts (revolutions) and the number of violent outbursts per year are much lower for the smaller citizen vision radius case. The larger number of violent outbursts for the larger citizen vision radius case shows the importance of the larger number of neighbours in increasing the growth of the number of active citizens and thus the number of outbursts and revolutions. The upward trend with lattice size is due to the increasing fraction of active citizens and thus the increasing likelihood for fluctuations in the number of active citizens to grow to outburst size.

## 6. Discussion

When Epstein published in the early 2000s the agent-based model of civil violence upon which our own is based, he probably could not have foreseen the rise of social media, smartphones, and their ubiquity in our lives today. These new tools have significantly altered how people communicate and coordinate, making the world an increasingly smaller place where social networks are less constrained by geography. That said, while there are many examples showing the role social media played in sparking and

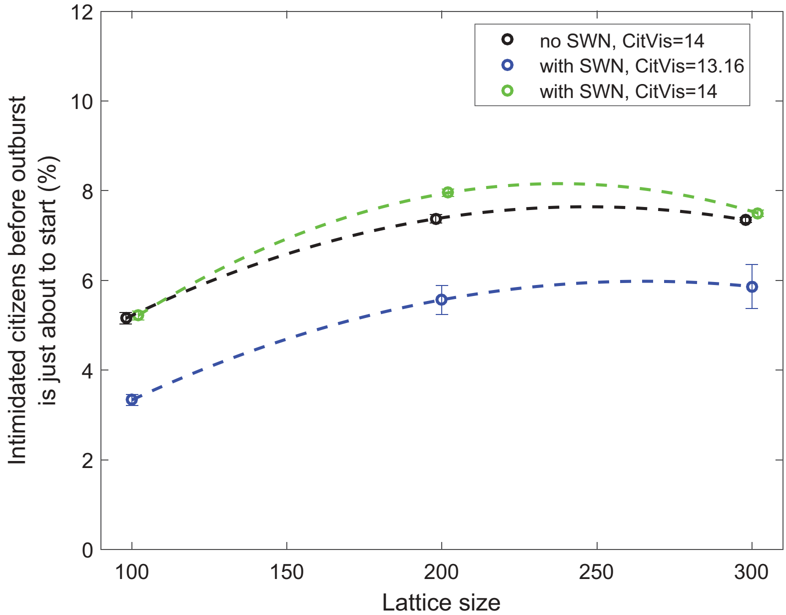


**Figure 17.** (Low crime case) Number of intimidated citizens before outburst is just about to start in per cent.

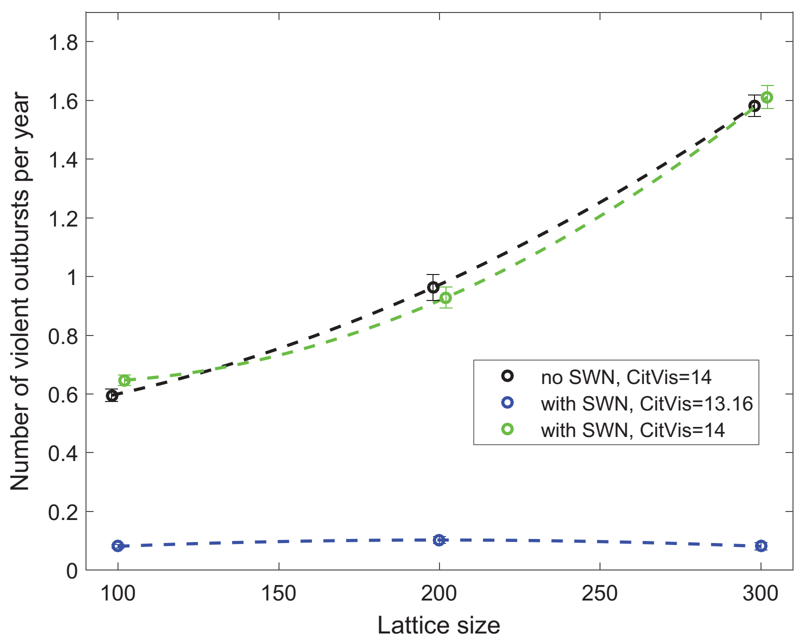


**Figure 18.** (Low crime case) Number of violent outbursts per year.

organising civil upheavals and protests,[62] many have been sceptical of these claims, often calling them overblown.[63]

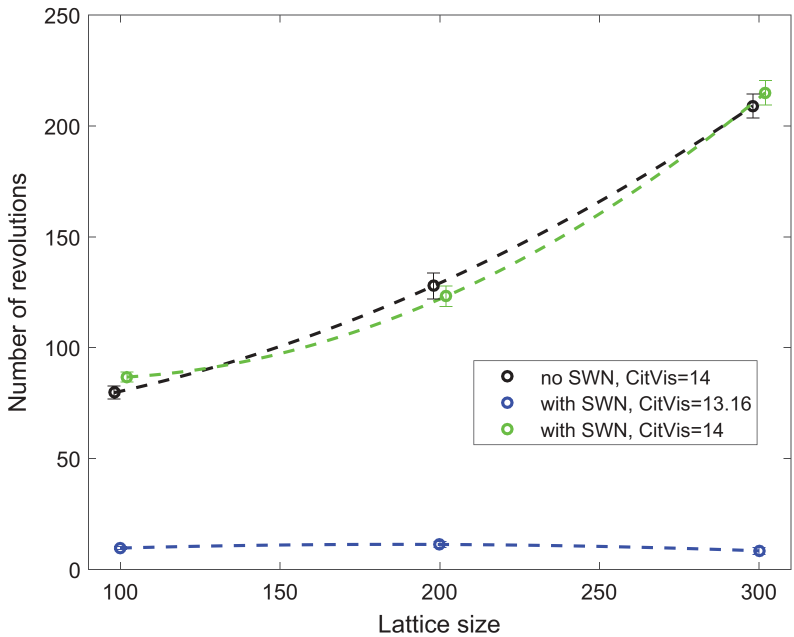


**Figure 19.** (Low crime case) Number of large-scale violent outbursts (revolutions).

In this paper, we introduced a SWN to Epstein's model in order to mimic the role social media may play in sparking violent outbursts during periods of civil unrest, similar to the current situation playing out in France with the Gilets Jaunes movement. Our goal was to determine how the dynamics of civil violence are modified when actors benefit from a more global view the system through weak ties to spatially distant actors in evaluating the risk and social acceptability of engaging in civil violence, rather than being limited to their local social environment (as in Epstein's model). The influence of a SWN was found to depend significantly on both the overall level of violence in the population and the lattice size.

In the case with the higher rate of violence, the number of active citizens and the rate of violence (the combination of active and intimidated citizens) was not influenced by the presence of a SWN. However, the SWN did have the effect of increasing the number of active citizens before a large-scale violent outburst (revolution) occurred and increasing the number of outbursts and revolutions. This can be understood by the non-locality of the SWN, which serves to homogenise the distribution of active citizens across the lattice. The influence of the LEOs thus reaches a limit related to their local vision radius, as more and more citizens become active outside of their ability to intimidate them. Large-scale violent outbursts can thus develop due to growth from multiple groups of active citizens. These observed effects of the SWNs did not depend significantly on $\beta$, thus suggesting that relatively few distant neighbours are needed for non-local influence to play a significant dynamical role.

For the case with a lower rate of violence, the SWNs played a less important role than in the higher crime case. Instead, the citizen vision radius was found to be the primary determiner of both the rate of violence and the number of violent outbursts. This suggests that when relatively few citizens are active, the number of local neighbours plays a greater role in controlling rates of violence than distant neighbours.

The relative importance of the local and non-local neighbours (controlled by the citizen vision radius and the SWN, respectively) thus depends at least in part on the overall number of active citizens. In the higher crime rate case (when the LEO vision radius is smaller), more citizens are active and the SWN does not affect the number of active citizens so much because a citizen's local neighbours are relatively more likely to be active. The SWN does contribute to somewhat homogenising the distribution of active agents across the lattice and thus leads to large-scale violent outbursts occurring with relatively fewer active agents. In the lower crime rate case (with larger LEO vision radius), a small increase in vision radius introduces more active citizens to a given citizen than the additional visible neighbours due to the SWN.

### 6.1. Synchronisation effect and the efficiency of social movements

A particularly interesting outcome of the introduction of the SWN to the model is the emergence of a synchronisation effect between the proportion of active citizens and intimidated citizens. The evidence of this synchronisation effect is shown in Figure 5 for the SWN cases, where the spacing between peaks in active and intimidated citizens is much more regular than in the non-SWN case. Furthermore, the periods between spikes of active citizens exhibit less noise than in the non-SWN case. This phenomenon occurs because the SWN allows citizens to base their decisions as to whether or not to join the action on what occurs in more distant parts of the system. While individual actors are still sensitive to what occurs locally, their ability to consider what occurs globally leads to what appears as a coordinated effort system-wide. This finding may suggest that even in the absence of centralised leadership, social media can lead to the consolidation of acts of civil violence over time. In other words, rather than seeing many smaller sporadic acts of civil violence in localised parts of the system (as is the case in the non-SWN model), social media may lead to a concentration of these efforts at specific points in time.

This finding may help clarify the mechanism through which social media can help sustain social protests. Our models show that the introduction of the SWN does not have an impact on the average proportion of active citizens per day or the overall rate of violence over the course of our simulations, indicating that social media (or a more global vision) is not necessary to maintain a certain level of participation. However, the introduction of the SWN leads to a more efficient temporal distribution of outbursts; peaks in the number of active citizens are higher, leading the overall civil violence being committed to be concentrated during singular events of violent outbursts rather than being more evenly spread out as smaller incidents over time and space. A more efficient distribution of acts of civil violence may be critical to the visibility of a movement and therefore to its longevity and legitimacy as larger protests and violent outbursts are more likely to bring media attention to the movement than several smaller isolated incidents.

For instance, before large-scale protests erupted in Paris and other cities, the Gilets Jaunes movement began as a series of small acts of civil disobediences (i.e. roadblocks, protests) across different regions – particularly rural regions – of France, coordinated via Facebook to occur on 17 November 2018. As Bornstein[64] notes, the movement began several months earlier as individuals began circulating petitions against certain policy decisions of the Macron government, and eventually creating local Facebook groups around these issues. However, over the summer of 2018, these online groups grew in numbers and slowly began to attract the attention of local media, which led Facebook groups to grow beyond the immediate personal social networks of those who initiated them. Also according to Bornstein,[65] 10 of the currently largest Facebook groups linked to the Gilets Jaunes movement were all created within a single week in October. Boyer[66] analysed over 1,500 Facebook groups with 100 members or more created between October and December 2018, and found that 54% of these groups were associated with a single city or region of France.

Perhaps the most important role social media played for the Gilets Jaunes movement was to allow geographically dispersed groups to coalesce around a single date to launch protests. This fact alone likely explains the sudden and continued popularity of the movement. It is doubtful that locally isolated, sporadic protests would have generated the same momentum for the movement. However, social media also allowed individual participants to connect with others both locally and nationally, which likely played a role in decisions to join the action offline. Discussions in Facebook groups and links shared across groups allowed participants to evaluate the scope of the movement, question the legitimacy of the government's action, and evaluate the risk and social acceptability of joining the action offline. This has been a common finding in many other investigations of the role of social media in recent social movements.[67]

It is important to note that this synchronisation effect only occurs in a model with a large number of active citizens (high crime case). Although the parameters of the high crime case were chosen specifically to create a situation where many violent outbursts would occur, it may still be representative of regions and times where a large segment of the population is unhappy with the government. In contexts where many citizens are primed to engage in demonstrations against the government, such as during the Arab Spring, the Gilets Jaunes movement, or even the protests in Baltimore, MD, social media may provide just enough additional connections and weak ties to turn a diffused state of discontent into a cohesive social movement. However, the addition of the SWN had a limited influence in a model with a more realistic number of active citizens, which may reinforce claims that social media may not play as critical a role as it has been assumed.[68]

### *6.2. Implications for policing civil unrest*

Social media can provide an alternative source of information to traditional mainstream media during protests and social movements. Historically, researchers have found that mainstream media tend to delegitimize and marginalise protesters and side with the state and status quo.[69] As the enforcement arm of the state, police departments have an incentive to frame the public perception of protests and social movements in a way that discourages further citizen involvement in acts of civil violence, and traditionally this task was facilitated by the superiority of the organisational capacity of police departments to communicate directly with mainstream media organisation.[70] While police departments increasingly use social media platforms such as Twitter and Facebook to disseminate information about crime to the public,[71] the ubiquity of social media has somewhat equalised the playing field in terms of messaging and framing of the issues.

The importance of social media in today's world has at least two important implications for the policing of civil violence. First, police departments may be better prepared to respond with appropriate means if they can monitor conversations regarding potential protests. Our models show that under some circumstances, social media can facilitate the spread of acts of civil violence across geographic areas. For instance, police officers during protests in Ferguson, MO, tracked the geolocation of social media posts related to disorder occurring around the city to guide the deployment of units.[72] Second, the use of social media by protesters means that overly aggressive acts and overwhelming show of force against protesters can be shared instantly and reach a large audience in a short amount of time. This is likely to lead to even more individuals joining the protests, and perhaps, the emergence of other protests or acts of civil violence in other locations.

### 6.3. Limitations and future directions

The main objective of this paper was to examine how the addition of non-local influences would impact the model described by Epstein. Our model is the first to our knowledge to modify Epstein's original model in such a way and could be used to study additional social dynamics in the future through the modification of certain parameters. An important limitation of the model is that we do not assume that actors will seek specific distant connections. In our model, the connections to distant neighbours are randomly assigned. It is likely that citizens with a proclivity for engaging in civil violence will have connections to individuals with similar propensities. Future attempts at modelling the effect of social media on civil violence should consider how homophily (i.e. connections to similar others) or propinquity (i.e. connections to spatially close others) might influence emergent findings from the current model. Another opportunity related to the network could be to test whether other network topologies would lead to different results. For instance, many social networks exhibit a scale-free network topology where most actors in a network have few connections and very few have an inordinately large number of connections.[73] It is possible that using such a network topology would lead to interesting results, particularly when those actors with a large number of connections become active. Future work will investigate the influence of network topology on the dynamics of civil violence participation.

Another important limitation pertains to the choice of certain parameters such as the concentration of law enforcement officers and the percentage of active citizens. Given our objective to examine how findings from Epstein would be modified by the addition of a SWN, we used similar parameters for our model. Epstein[74] does not provide much rationale to guide his parameter choices. That said, we have anchored our decisions for the choice of these parameters on prior sensitivity analyses using violent crime statistics and concentration of law enforcement officers in US cities.[75] These analyses allowed us to identify a model where violent outbursts were likely to emerge and a model that we believe is closer to real-world conditions in US cities. Whether these conditions are generalisable in other countries where civil violence is likely to arise is unclear.

### 6.4. Conclusions

Although it is difficult to clearly specify the mechanism by which social media may facilitate civil violence and revolutions, recent research suggests that it clearly plays an important role in effectively diffusing information that can be used to form individual decisions to engage. In this paper, we have used an agent-based model to examine the role of non-local connections in the emergence of large-scale violent outbursts of civil violence. Our model proposes that social media may influence social movements by concentrating the energy of potential participants into fewer, but larger outbursts of civil violence. Weak ties in the SWN appear to be responsible for a synchronisation between the number of active and intimidated citizens.

## Notes

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5. McAdam, "Recruitment to high-risk activism"; and Snow, Zurcher Jr, and Ekland-Olson, "Social Networks and Social Movements."
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7. Gould, "Multiple Networks and Mobilization in the Paris Commune."
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12. Epstein, "Modeling Civil Violence."
13. Watts and Strogatz, "Collective Dynamics of 'Small-World' Networks."
14. See note 12 above.
15. Weisburd and Eck, "What can Police do to Reduce Crime, Disorder, and Fear?"
16. E.g. Eck and Maguire, "Have Changes in Policing Reduced Violent Crime?"
17. Weisburd et al., "Is Problem-Oriented Policing Effective in Reducing Crime and Disorder?"
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20. Lum et al., "Receptivity to Research in Policing."
21. Bonilla and Rosa, "# Ferguson"; Harlow, "Social Media and Social Movements"; Kidd and McIntosh, "Social Media and Social Movements"; Lotan et al., "The Arab Spring| the Revolutions Were Tweeted"; and Tufekci and Wilson, "Social Media and the Decision to Participate in Political Protest."
22. Tufekci and Wilson, "Social Media and the Decision to Participate in Political Protest."
23. See also Lotan et al., "The Arab Spring| the Revolutions Were Tweeted."
24. See note 9 above.
25. Jost et al., "How Social Media Facilitates Political Protest."
26. Vasi and Suh, "Online Activities, Spatial Proximity, and the Diffusion of the Occupy Wall Street Movement in the United States."
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48. Tyler, "Enhancing police legitimacy."
49. Zanette, "Dynamics of Rumor Propagation on Small-World Networks."
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54. See note 12 above.
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56. Fonoberova et al., "Nonlinear Dynamics of Crime and Violence in Urban Settings."
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62. Harlow, "Social Media and Social Movements"; Hussain and Howard, "What Best Explains Successful Protest Cascades?"; Lotan et al., "The Arab Spring| the Revolutions Were

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63. Gladwell, "Small Change: Why the Revolution will not be Tweeted," e.g.
64. Bornstein, "En immersion numérique avec les «gilets jaunes»."
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68. See note 63 above.
69. Cohen, *Folk Devils and Moral Panics*, e.g. McLeod and Detenber, "Framing Effects of Television News Coverage of Social Protest"; and Feigenbaum and McCurdy, "Activist Reflexivity and Mediated Violence."
70. Chermak and Weiss, "Maintaining Legitimacy using External Communication Strategies," e.g.
71. Hu, Rodgers, and Lovrich, "?We Are More Than Crime Fighters?"
72. Gillham and Marx, "Changes in the Policing of Civil Disorders Since the Kerner Report."
73. Barabási and Albert, "Emergence of Scaling in Random Networks"; and Barabási, "Scale-Free Networks."
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## Data availability

All datasets generated by our model are housed in a Zenodo public repository and can be found at https://doi.org/10.5281/zenodo.1493513. The datasets possess their own DOI number and can be cited as.[76]

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## Appendix 1. Model Simulation Pseudo-code

```
place agents on the lattice
set up characteristics for all citizens
place 'always active' citizens in the jail
create small world network and array of distant neighbours for the citizens
for each time step
  for each agent (note that a LEO can move several times per day and is accessed several times)
    an agent (citizen or LEO) is selected
    if the agent is a citizen
      if the citizen is not in the jail
        the citizen moves
    else
        the remained jail term is calculated and if the jail term is over the citizen is released
        and put on a spot where the citizen was arrested or the closest location to that one
      the state of the non-jailed citizen is calculated
    if the agent is a LEO
      the LEO arrests a nearest active citizen (if any) within the vision and jumps to the
      location of the arrested by him citizen
      the LEO moves
  the number of active and jailed citizens is calculated.
```

## Appendix 2. Model Parameters

The model input parameters for the case with the higher rate of violence are as follows:

The model input parameters for the case with the lower, more realistic rate of violence are as follows:

Threshold T and legitimacy L can be calculated by using formulas (4.3) and (4.1). All 'always active' citizens are initially intimidated.

| Parameter Name | Parameter Value |
|---|---|
| citizen density | 0.7 (i.e. citizens occupy 70% of the lattice) |
| number of LEOs per 1,000 citizens | 1.59 |
| LEO speed | 4 (i.e. LEOs move 4 times per day) |
| maximum intimidation term | 120 days |
| fraction of 'always active' citizens R | 0.025 |
| fraction of 'never active' citizens G | 0.5 |
| fraction of 'conditionally active' citizens | 0.475 |

| Parameter Name | Parameter Value |
|---|---|
| citizen density | 0.7 (i.e. citizens occupy 70% of the lattice) |
| number of LEOs per 1,000 citizens | 1.51 (100x100 cell lattice)<br>1.77 (200x200 cell lattice)<br>1.87 (300x300 cell lattice) |
| LEO speed | 4 (i.e. LEOs move 4 times per day) |
| maximum intimidation term | 120 days |
| fraction of 'always active' citizens R | 0.025 |
| fraction of 'never active' citizens G | 0.5 |
| fraction of 'conditionally active' citizens | 0.475 |