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Agent-based Modelling

Project: An Agent-based Model of Civil Violence

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Abstract

An agent-based model (ABM) for civil violence was developed with an aim of capturing the core effects of incorporating a social media network on the model dynamics. The model comprises a local grid with citizens, who riot against a central authority, and cops who aim to curb the violent outbursts. As an addition citizens are connected to each other by means of a network, both the influences of different types of networks are considered and the effect of applying different legitimacy feedback mechanisms. Results of the one-factor-at-a-time and Sobol sensitivity analysis (SA) on the model are discussed in detail. It was found that the maximum jail term and cop vision parameter were more influential than the amount of links in the network. Besides this it was found that including a network in the ABM for civil increases the size of rebellious outburst and the distribution of times between outbursts. Connecting citizens with a network does not significantly affect the number of outbursts.

Key words: Civil Violence, Social Network, Legitimacy Feedback

1 Introduction

On January 6, 2021, on Capitol Hill a meeting was scheduled for the United States Congress to count results of the Electoral College vote and formalize the victory of Democratic candidate Joe Biden. Before this certification could take place, supporters of the Trump administration, fuelled by false claims of widespread voter fraud, marched to the Capitol. Police forces were outnumbered and not before long the protesting crowd turned into looting and rioting rebels. According to an article in the New York Times, plans for the riot were coordinated on social media platforms such as Parler, Telegram and Gab [1].

Over the course of history, riots and protests have emerged in times of hardship. However, since the rise of social media, a shift has appeared in the way citizens are organised and mobilised to act together in large numbers. A notable difference is that social media can act as a vehicle for spreading opinions as well as plans for certain events [10]. As a result large gatherings can emerge when enough people with the intention of participating are reachable through their social influence networks [15]. The occupation of Capitol Hill, the Gilets Jaunes movement in France [8], the Arab spring [14] and the UK riots in 2011 [3] are all examples of uprisings where social media played a role, be it of debatable size.

Epstein et al. [6] introduced a simple yet successful agent-based model (ABM) for simulating civil violence against a central government. This model has been proposed for the simulation of social conflict phenomena in different contexts. It thanks its popularity mostly to its clear formulation, simplicity and descriptive power. Solutions produced by the model display the hallmarks of complex systems: a punctuated equilibrium [6]. Epstein presented this model with the intention of offering a novel and reproducible approach to comprehending the complex dynamics of decentralized rebellion. As his work was published in 2002, one can wonder to what extend Epstein and his colleagues took into account the influence of social media networks, and whether incorporation of such a network will effect the core dynamics of the model. In 2014 Lemos et al [12] proposed an extension of the original civil violence model by including a time delay for imprisonment and formulating different types of legitimacy feedback, expressing legitimacy in terms of the proportion of citizens that do not support the government. The legitimacy feedback in the paper of Lemos et al. can be viewed as a way incorporating the 'news media' in the model as it allows agents to be aware of the state of agents elsewhere.

[1]Frenkel, Sheera (January 6, 2021). "The storming of Capitol Hill was organized on social media", `https://www.nytimes.com/2021/01/06/us/politics/protesters-storm-capitol-hill-building.html`, consulted on January 26, 2021

In this paper we propose an ABM for civil violence with the inclusion of legitimacy feedback based on Lemos et al [12] and a network influence representing the media and a social media network respectively. The purpose of the adapted model is to formulate an answer to the following questions:

- How does the network effect the characteristics of the solutions obtained by the model (equilibrium, peak sizes, inter-outburst times)?
- Is there a difference in effects between different types of networks: Albert-László Barabási Albert, Erdős–Rényi and Small-World?
- To what extend do different legitimacy feedback mechanisms influence the outcome of the model?

We expect the introduction of a social media network to increase both the frequency and sizes of rebellions in comparison to the original model, as the extended model will generally allow additional citizens to become active based on their neighbors in the network.

The remainder of this paper is organized as follows. Section 2 presents a description of the present model using the “Overview, Design Concepts, and Details” (ODD) protocol [9]. Section 3 contains the results and discussion of both local and global sensitivity analysis performed on some main parameters of the model. Additionally section 4 consists of the results of different experiments comparing the different types of network structures and types of legitimacy feedback. Section 5 establishes a discussion of the presented work and suggests future research to be performed on the topic.

2 Theory

2.1 ODD of the model

The formal description of the Agent-based model (ABM) used in this paper follows the guidelines of the ODD (Overview, Design concepts, and Details) protocol [9]. These are standardized directives, meant to make the building of the model clear and to make the experiments easy to be reproduced.

The model was constructed in Python with the use of the Apache2 licensed agent-based modeling framework Mesa [2]. All implementations in code are available on the following Github repository: https://github.com/DCCdelang/ABM.

[2] https://mesa.readthedocs.io/en/stable/

Purpose The model described in this paper is an extension of Epstein's civil violence model [6]. Similar to Lemos et al. [13] we broaden Epstein's Model I with *(i)* a delay in time before agents are imprisoned, representing the fighting time prior to an arrest; *(ii)* a feedback mechanism that allows the legitimacy to vary as a function of the number of arrests and violent episodes. The purpose of the present work is to introduce a network representing social media contacts in the extended version of the ABM of civil violence of Epstein. The effort of this research will be mainly focused on comparing the effect of different types of social graphs on the nature of the solutions of the model. Additionally the effects of different legitimacy feedback mechanisms on the model (with network) will be analysed.

Entities, state variables and scales The entities of the model are the scenario (grid), the agents and the networks. Table 1 shows the global parameters of the model and their standard values. The scenario consists of a homogeneous 2D torus space, which is a fitting space given the abstract ABM. The scenario can theoretically be thought of as a city.

The network is represented by an undirected Graph, modelled with the `networkx` package, which will be created according to the rules of any of the three models: Albert-László Barabási, Erdős–Rényi or the Small-world network. The network is supposed to incorporate dynamics similar to those of an online social network, where users interact and influence each other, some more actively than others. The network remains fixed during the whole simulation. All processes of the model will still occur on the grid, agents of the type citizen will be connected in the network regardless of their position in the grid.

The model includes two types of agents: citizens and cops. Both agent types have a movement rule M and one action rule. Table 2 and Table 3 show the attributes of the citizens and cops respectively. The movement rule M prescribes that the agent moves to a random empty cell within its vision radius. The action rule for citizens determines in which state their condition is. Whenever citizens are not in the Fighting or Jailed state, their state can change between Quiescent and Active.

The action first rule for the citizen is:

$$\text{Rule A1: If } G - N > T \text{ be Active; else be Quiet.} \tag{1}$$

Political grievance is assigned an important role in this action rule, the definition of grievance is simple and exists of two components called hardship and legitimacy. Hardship and the perceived legitimacy are connected to lead to grievance by the following simple equation:

$$G = H \cdot (1 - L)$$

Hardship, $\mathbf{H}$, is exogenous as it is perceived by the each citizen, each individual's value is drawn from $\sim U(0,1)$. Additionally $\mathbf{L} \in [0,1]$, the perceived legitimacy of the authority can be either fixed, globally or locally determined. In the latter two cases it is calculated with the legitimacy feedback loop as explained in Lemos et all [13]. The reasoning behind the formulation is rather intuitive and entails the idea that with high legitimacy, when citizens place trust in the authorities, hardship will not induce political grievance. The computation of legitimacy will be explained in greater detail in section 2.2.

Besides hardship, the decision to rebel is highly dependent on the citizen's inclination to take risks. Accordingly $N = R \cdot P$ is the net risk perception. Here $\mathbf{R}$, the level of each citizen's risk aversion, is exogenous and drawn from $U(0,1)$. Each citizen determines an arrest probability based on the number of cops and active citizens within its vision radius, C_v and A_v respectively. The arrest probability is computed using the following formula:

$$P = 1 - \exp(-k \cdot \lfloor C_v / A_v \rfloor).$$

Here the arrest constant k is 2.3. T is a constant exogenous variable and represents a threshold in the agent's decision to start fighting, T is fixed at 0.1. The decision to fix the arrest constant and threshold T at the aforementioned numbers was made based on the parameter settings as applied by Lemos et al. [13] and Epstein et al. [6]. In addition if the agent remains quiet after applying rule $A1$, the citizen will act based on the influence of its network. More specifically a citizen will be affected by the states of its direct neighbours.

$$\text{Rule A2: If} > 50\% \text{ of the network neighbors are active, then be active.} \quad (2)$$

This rule is based on the conjecture that first an individual will act based on its surroundings, but even in a hazardous situation the same agent can become Active if encouraged by its network. The same holds when an citizen is not located amidst a rebellion but sees many rebelling citizens in its network. This rule is based on the method applied by Lemos et al. to model family networks [11].

Opposed to the citizen agents, there are the cop agents. Cop agents can be in one of the two states, Fighting or Non-fighting. The cop agents have the same movement rule M as the citizen agents however the action rule is focused on arresting Active agents. If cops are Non-fighting they will find Active agents and start fighting with them for a predetermined number of cycles.

Scheduling The time in the model is discrete, each time step corresponds to one day. Every day, both citizens and cops move or stay still, depending on their condi-

Symbol	Description	Type	Values
d_{cops}	Cop density	float	0.04
d_{citizens}	Citizen density	float	0.7
$I_{\max}$	Max number of steps in simulation	int	400
m_{BA}	Number of edges in BA graph	int	7
P_{Reyni}	Connection probability	float	$\ln(n)/n + 0.001$
$P_{\text{small world}}$	Rewiring probability	float	0.5
$m_{\text{small world}}$	Number of edges in Small-world graph	int	7
L_0	Initial government legitimacy	float	0.82
L	Government legitimacy	float	[0,1]
$J_{\max}$	Maximum jail term	int	30
$F_{\max}$	Maximum fighting time	int	1
k	Arrest constant	float	2.3
L_{type}	Legitimacy type	string	Global, Local

Table 1: Global parameters.

Symbol	Description	Type	Values
V	Vision radius	int	7
H	Hardship	float	$U(0,1)$
R	Risk aversion	float	$U(0,1)$
L_{p}	Perceived legitimacy	float	$[0,1]$
G	Grievance	float	$H(1-L)$
T	Threshold	float	0.1
J	Jail term	int	$U(0,30)$
F	Fight duration	int	1
ID	Unique Identity Number	int	
(x,y)	Agent position on grid	tuple	$([0,39],[0,39])$
G ID	Place in the network	int	-
Agent state	Quiescent, Active, Jailed, Fighting	string	Q,A,J,F

Table 2: Attributes of citizen agents.

Symbol	Description	Type	Values
V	Vision radius	int	7
F	Fight duration	int	1
ID	Unique Identity Number	int	-
(x,y)	Agent position on grid	tuple	$([0, 39], [0, 39])$
Agent state	Fighting, Non-fighting	string	F, NF

Table 3: Attributes of cop agents.

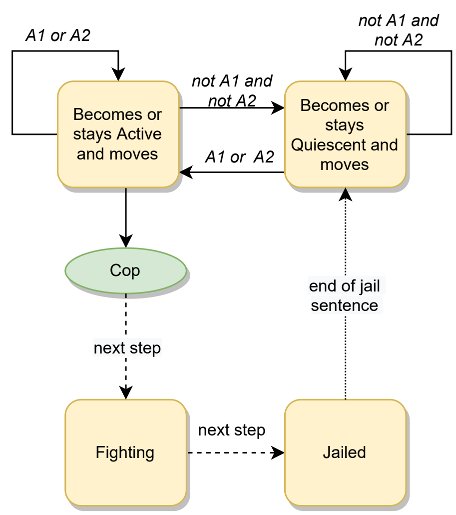


Figure 1: Flow chart for the Citizen's step.

tions. Each time step all agents will be selected in a random order to execute their processes.

Quiet and Active citizens change their status according to rule $A1$ and $A2$, as stated previously. After their status condition is updated, citizens move to an empty cell in their own field of vision. Cops randomly choose one active citizen, not sentenced yet, within their own visual field and move to the same cell; if there is no citizen with the required attributes, the cop moves to an empty cell. The citizen is sentenced to a random amount of days in jail and the two agents start fighting for one time step; while fighting, agents always stay still. After that, the citizen changes his or her condition to Jailed and stays still until the end of the jail sentence; once free, the citizen's status is set to Quiescent. The scheduling for citizens is explained more clearly by the flowchart in Figure 1.

Design concepts *1)Basic principles* The basic principle of this paper is to consider the influence of different kind of networks on civil violence. In this way, the citizens *physical* vision is extended on a *virtual* level, meant to represent the social media aspect of modern reality.

2) Emergence The model should show oscillations in the number of Active, Quiescent, Fighting and Jailed agents, which would result in a punctuated equilibrium. We expect that by adding the network structure, the model will have more frequent peaks of Actives, with a bigger amount of agents per peak. This is because agents become Active, not only by following the standard rule ($G - N > T$), but also when more than half of their connections is Active.

3) Objectives Citizens decide whether to become Active by taking into consideration various factors: the perceived legitimacy of the government, the hardship of the actual situation and the risk of being arrested, which is given by the personal risk aversion and the probability of being arrested. Citizens are influenced by what happens in their vision radius, as the probability of being arrested depends on the amount of cops and Active citizens in the surroundings.

4) Sensing Agents can sense other agents in the surroundings, according to the extent of their vision field, which is a parameter set by the modeller. Cops sense all the conditions of the citizens in the proximity. Citizens sense the presence of cops and the amount of Active agents surrounding them; they do not distinguish between Quiescent, Jailed or Fighting. Moreover, citizens perceive the amount of Actives among their connections in the network.

5) Interactions Cops and citizens interact directly only when they are in the same grid cell, that is to say when a cop sentences a citizen and the two of them start a fight. Citizens interact indirectly with other citizens, changing their status accordingly to the amount of Active perceived among the neighbors and the connections in the network.

6) Stochasticity There are several stochastic processes in the model. Cops choose one Active citizen randomly between the Actives in the grid cells around; if there is no Active agent, the cop would move to a random empty cell. When citizens move, they select randomly an empty place in the surroundings. The length of the time spent in jail is drawn every time from a uniform distribution with boundaries [0, `max jail term`], where `max jail term` is a parameter set by the modeller, as is shown in table 2. The citizen and cop density are given initial parameters, these parameters determine the chance of positioning a citizen or cop on a cell of the grid.

7) Collectives A rebellion is defined as the time period when the amount of Active citizens exceeds 50 and this is referred to as *peak* in the paper; the rebellion lasts the amount of time steps where there are more than 50 Actives consecutive.

Rebellions do not have practical consequences in the model, but are used as reference point in the analysis.

8) Observation For each time step, the total number of Active, Quiescent, Fighting and Jailed citizens is saved together with the legitimacy value, which changes along the single run in the case it is set as "Global" or "Local", if it is "Fixed" it will remain the same value during the run. A second dataset is created, where for every agent in the model, for every time step, the following information is saved: time step, agent ID, coordinates in the grid, type of agent (citizen or cop), number of days to spend in jail, status, perceived arrest probability and legitimacy value. The first dataset saves every agents condition globally per step and it is used to visualize the course of the model, to analyse the number of rebellions (peaks) that occurred during a single run. The second one saves every agents condition for every step and it is interesting when analysing the behaviour of the average legitimacy or the average arrest probability.

Initialization The initial values of the model are selected based on Run 2 of the model of Epstein [6] and are depicted in Table 1. These values are chosen based on their potential to generate the punctuated equilibrium which is characteristic of the civil violence model. Adhering to the simplification that there are neither deaths nor births, the number of all agents, both cops and citizens remains the same during the whole simulation.

The parameters that are initialized are for the larger part the same for each simulation. However Risk aversion and Hardship are set stochastically for each citizen at the initialization of each simulation, similarly the position on the grid is set stochastically for each agents. Lastly the network can vary for different simulations, be it marginally because it will belong to a predetermined structure with fixed parameters.

Input data The model does not use input data to represent time-varying processes.

2.2 Legitimacy Feedback

An important addition implemented in our civil violence model is the legitimacy feedback mechanism. This mechanism was first described in a research from Lemos et al. [12]. In this first implementation the feedback was implemented as a surrogate for the influence of media and news on the perceived legitimacy, this implementation was further expanded by Lemos et al. to a mechanism using a more complex concept of legitimacy [13] [11]. Based on concepts used in political science a three-component concept was implemented, dividing legitimacy in three subtypes: views of legality, views of justification and acts of consent. For each subtype an equation was formulated using the number of citizens in certain states.

The equations of the legitimacy feedback are presented in equations 3-6. Where n_{a}, n_{q}, n_{j} and n_{f} stands for the number of Active, Quiescent, Jailed and Fighting citizens. Furthermore, L_{leg}, L_{just} and L_{consent} represent the subtype equations. The legitimacy is then calculated using the weighted average sum function L_{wa}. While Lemos et al. provided more functions in order to calculate the legitimacy, the weighted average function caused the most interesting behaviour and was therefore implemented [13].

$$L_{\mathrm{leg}} = \frac{n_{\mathrm{q}}}{N} \tag{3}$$

$$L_{\mathrm{consent}} = L_{\mathrm{leg}} \tag{4}$$

$$L_{\mathrm{just}} = \frac{1}{2}\Big(1 - \frac{n_{\mathrm{a}} + n_{\mathrm{f}}}{N}\Big) + \frac{1}{2}\Big(1 - \exp(-\ln(2)/2 \left\lfloor \frac{N}{n_{\mathrm{a}} + n_{\mathrm{f}} + n_{\mathrm{j}} + 1} \right\rfloor\Big) \tag{5}$$

$$L_{\mathrm{wa}} = L_0 \cdot \Big(\frac{1}{4}\Big(L_{\mathrm{leg}} + L_{\mathrm{consent}}\Big) + \frac{1}{2} L_{\mathrm{just}}\Big) \tag{6}$$

With the legitimacy feedback mechanism implemented, it became possible to choose between three different legitimacy configurations: Fixed, Global and Local. Here the Fixed legitimacy resembles a constant value as initialized in Epstein's original model [6]. For the Global feedback mechanism the legitimacy is updated every step based on the whole population, all citizens still perceive the same updated legitimacy, making it homogeneous. The Local feedback mechanism uses the same equations as the Global method but uses only the agents within a citizens vision. Therefore, every citizen perceives its own legitimacy, making it heterogeneous.

2.3 Networks

In the analysis, besides the configuration without network, the influence of three different kinds of networks on the civil violence model were investigated. The benchmark network used in the analysis is the Albert-László Barabási model [1]. This model generates a random scale-free network, where there are few nodes which are highly connected and lots of nodes with few connections.

The second network is the Erdős–Rényi model [7]. This model generates a random graph. The last network that is used in the analysis is the small-world model[18]. Most nodes in the small-world model have a small amount of neighbours were these neighbours of a node are likely neighbours as well. Furthermore most nodes can be reached from any other node through a small number of hops or moves.

Both the Albert-László Barabási and the Small-world network are often used to represent the world wide web and social networks [2, 5], due to their feature of creating cliques and clusters; specifically for this reason they were chosen for this analysis. Even if the Erdős–Rényi graph model can be argued to describe the reality well, we thought that still it would be interesting to compare the previous-described graphs with a totally random representation of society.

A representation of the networks can be found in Appendix C.

3 Sensitivity analysis

Even though the described ABM of Civil violence might be useful, it is a simplified representation of reality and therefore essentially wrong, like all models if we are to believe Box and Draper [4]. With complex models such as the ABM presented in this paper performing a sensitivity analysis (SA) can be helpful to understand how the output of a model can be traced back to the parameter settings. Using methods presented in work of Saltelli et al. and Sobol et al. an SA will be performed in order to get some understanding on the prioritization of the parameters [16] [17]. It is important to mention that the SA was only conducted on the civil violence model with the Albert-László Barabási network since this is the benchmark model.

3.1 Global SA

For this research we executed both local and global sensitivity analysis. For the global analysis the `saltelli.sample` function from the SALib package [3] was used in order to create a parameter sample set. This parameter set was based on a problem consisting of four global parameters ($D = 4$) with corresponding bounds: Maximum jail term [1,50], Cop density [1,10], Citizen density [1,10] and number of edges in the network (links) [1,7]. Due to time and computational restrictions we choose to take 100 distinct samples ($N = 100$), while we ignored the second and higher order sensitivity, the total sample size was $N * (D + 2) = 600$. Each parameter setting was used to run a simulation of 400 steps and was replicated five times in order to compensate for stochasticity. As output we defined multiple measures that were also used by Lemos et al. [13], examples are the mean or standard deviation of peak intervals, the number of peaks and the percentage of time in rebellion ($N_{\text{Active}} > 50$) or calmness ($N_{\text{Active}} = 0$).

[3] https://salib.readthedocs.io/en/latest/

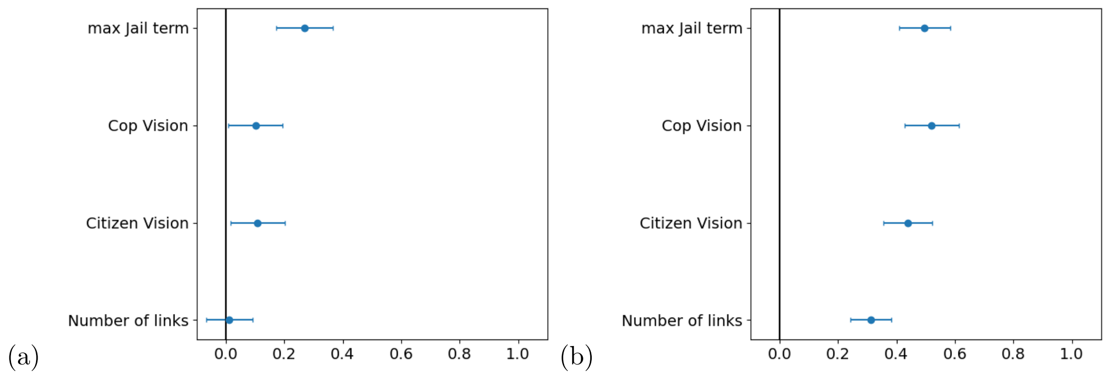


Figure 2: First (2a) and total (2b) sensitivity analysis on all four parameters with the number of peaks as output.

In order to analyze the collected data, the `sobol.analyze` extension of the SALib package was used. Using this method the first and total order sensitivity with corresponding confidence intervals are returned for all four parameters. This was done for multiple output measures. In Figure 2 the first and total order SA are displayed with the mean number of peaks as output measure. The first order SA displays the expected reduction in variance that would be achieved if that parameter would be fixed. The total order SA also includes all interactions between parameters and displays the expected variance that would be left if all factors but that parameter were fixed. As displayed in Figure 2 for the first order SA only the max jail term seems to have a reasonable influence on the variance of the output. For the total order however, the cop vision parameter seems to have the most influence.

For the number of links parameter, needed in the Albert-László Barabási network model, both the first and total SA show less influence on the output variance. This can be explained by the $A2$ rule (2), since the number of links in a citizen network does not strictly change the probability of becoming active, the influence on the output variance will also be limited. In appendix A additional results of the global SA are presented for different output measures.

To get more insight in the importance of the tested parameters an additional local SA was executed. This is mostly focused on the cop vision parameter in order to understand the difference between the first and total order SA, see next section. Furthermore, in order to explore the network interaction in the model, number of links was chosen as a second parameter for the OFAT analysis.

3.2 Local SA (OFAT)

One-factor-at-a-time (OFAT) analysis is a local sensitivity analysis method that allows observation of relationships between parameters and model outputs. OFAT operates by varying one parameter and fixing the rest. Local sensitivity of our model was examined in terms of two parameters, namely cop vision radius and number of edges created when adding a new node in the Albert-László Barabási network model. Model outputs chosen for OFAT were Mean peak size, Mean peak interval, Fraction time calm and the Total number of peaks. Fixed parameters were set according to the values in Tables 1, 2 and 3 and 10 simulations were ran for each analysis.

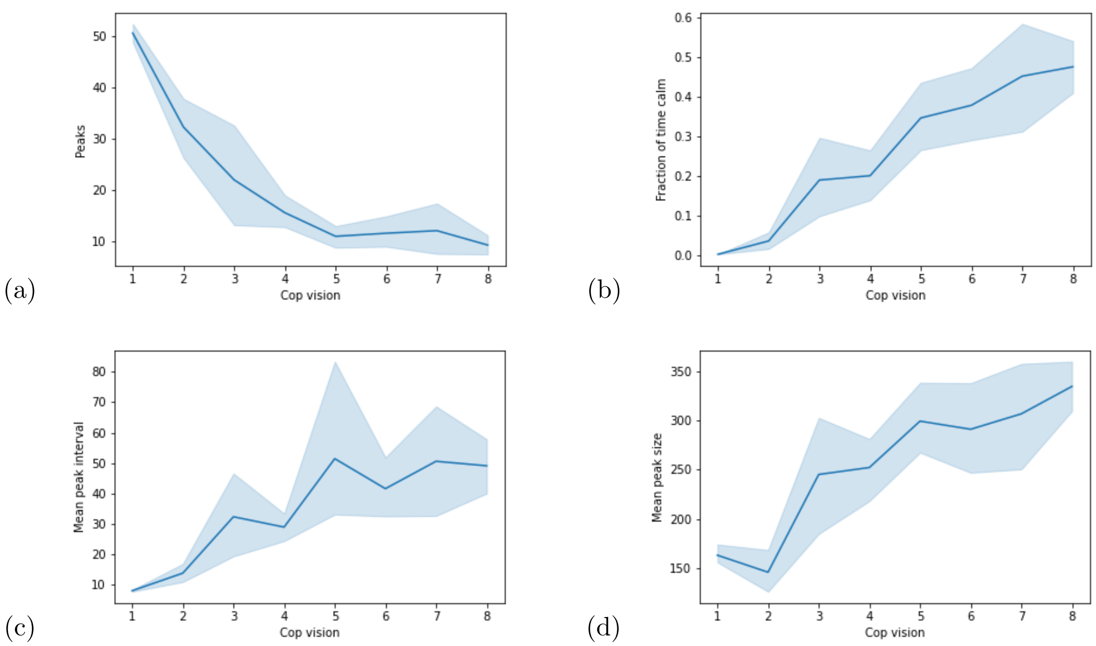


Figure 3: OFAT for cop vision radius of (a) total number of peaks (b) fraction of time calm, (c) mean peak interval and (d) mean peak size.

Cop vision radius Results of the mean values with corresponding 95% confidence intervals of the 10 runs of OFAT analysis for cop vision radius can be observed in Figure 3. From 3a we can observe that higher cop vision radius values result in smaller number of peaks in the simulation with values stagnating after cop vision radius above 5. This behaviour is logical as a broader vision of the cop increases its chances of catching an active citizen in its vision. Furthermore, the time system spends in a calm state and the interval between peaks increases with cop vision radius (see 3b and 3c). Interestingly, the size of the peaks increase with the cop vision radius (see 3d), meaning that even though there are less rebellions in the simulation, the outburst are bigger and further apart in time from each other.

Links in the network The same OFAT analysis was also carried out for the number of links in the Albert-László Barabási network model. For the selected parameter settings the analysis did not produce any statistically significant results. The results can be found in Appendix B.

4 Experiments

4.1 Quantitative experiments

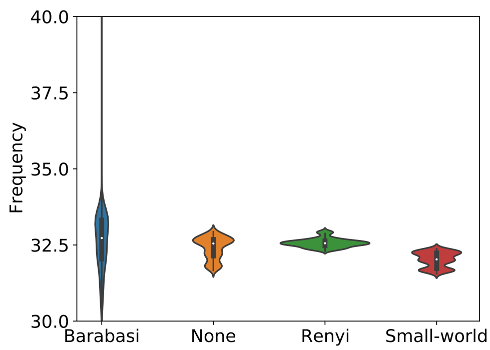
The performed experiments discussed in this section were conducted over 400 simulations of 150 steps. In the first part, a comparison between networks was made, followed by the second part where experiments on the influence of different legitimacy mechanisms were conducted. The following features were in both experiments extracted and analyzed: the average interval between peaks, the average peak size, the total number of peaks and the total number of actives.

4.1.1 Difference between networks

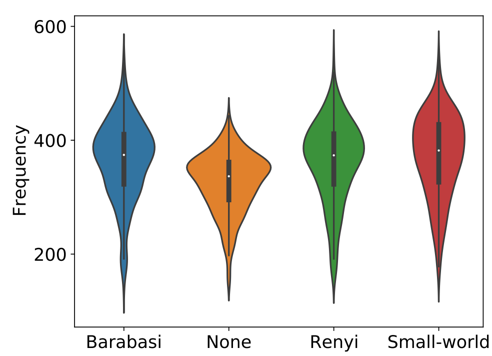
Experiments with the four different network instances were conducted in order to investigate how different networks influence the behavior of the model. The above mentioned features were computed on the following network configurations: Albert-László Barabási, Erdős–Rényi, Small-world and no network (1). Furthermore, a global legitimacy feedback is used throughout the experiments, as mentioned in section 2.2. The results are reported in the form of violinplots in Figure 4. A t-test was performed between each model, for all the above-mentioned measures; the p-value can be found in Table 4. These outcomes show a significant increase in the total amount of peaks between no network and a Small-world network. The addition of the Albert-László Barabási or the Erdős–Rényi network does not have a significant influence on the total amount of peaks of the model. It further shows that the addition of any network has a highly significant influence on the mean peak size as well as interval between the peaks and the total amount of actives. There appears to be a significant difference between the networks on the total amount of active citizens, where the Albert-László Barabási and Erdős–Rényi network have a significantly lower amount of total Actives than the model with a small-world network. It also revealed that the mean-peak interval between the networks is significantly different.

		Small world	Renyi	Barabási
Total peaks	None	0.002	0.097	0.167
	Small world	-	0.22	0.12
	Renyi	-	-	0.75
Mean peak size	None	$p < 0.001$	$p < 0.001$	$p < 0.001$
	Small world	-	0.059	0.098
	Renyi	-	-	0.84
Mean peak interval	None	$p < 0.001$	$p < 0.001$	$p < 0.001$
	Small world	-	$p < 0.001$	$p < 0.001$
	Renyi	-	-	$p < 0.001$
Total actives	None	$p < 0.001$	$p < 0.001$	$p < 0.001$
	Small world	-	$p < 0.001$	0.04
	Renyi	-	-	0.166

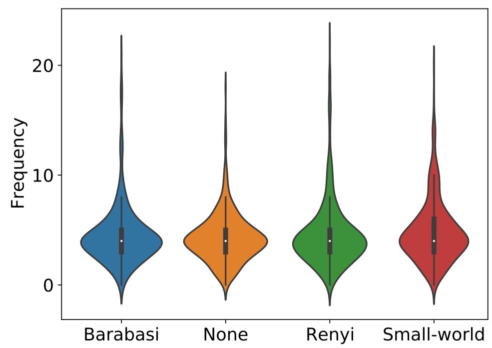
Table 4: P-value of the t-test between the four network configurations, for the four measures of interest.



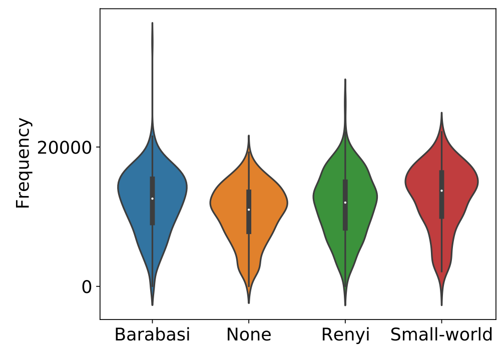
(a)



(b)



(c)



(d)

Figure 4: Violinplots for different network of (a) mean peak interval (the spread of the Albert-László Barabási network is 25.81-49.06), (b) mean peak size, (c) total number of peaks and (d) total number of actives.

		Local	Global
Total peaks	Fixed	0.094	0.34
	Local	-	0.44
Mean peak size	Fixed	0.43	0.96
	Local	-	0.42
Mean peak interval	Fixed	$p < 0.001$	0.007
	Local	-	$p < 0.001$
Total actives	Fixed	0.48	0.89
	Local	-	0.40

Table 5: P-value of the t-test between the three legitimacy kinds (Fixed, Local and Global), for the four measures of interest.

4.1.2 Legitimacy experiments

In addition to exploring the effect of various types of networks on the model, experiments are conducted to look at the influence of different kind of legitimacy mechanisms on the model. For these experiments the model with the Albert-László Barabási network is used. A t-test was performed between each legitimacy kind, for all the above-mentioned measures; the resulting p-value can be found at Table 5. There is significant difference only while considering the mean peak interval, for the three combinations of legitimacy; there is no significance for the other measures.

This can also be seen from the violin plots in Figure 5: the three distributions are similar and overlap for: mean peak size, total number of peaks and total number of actives.

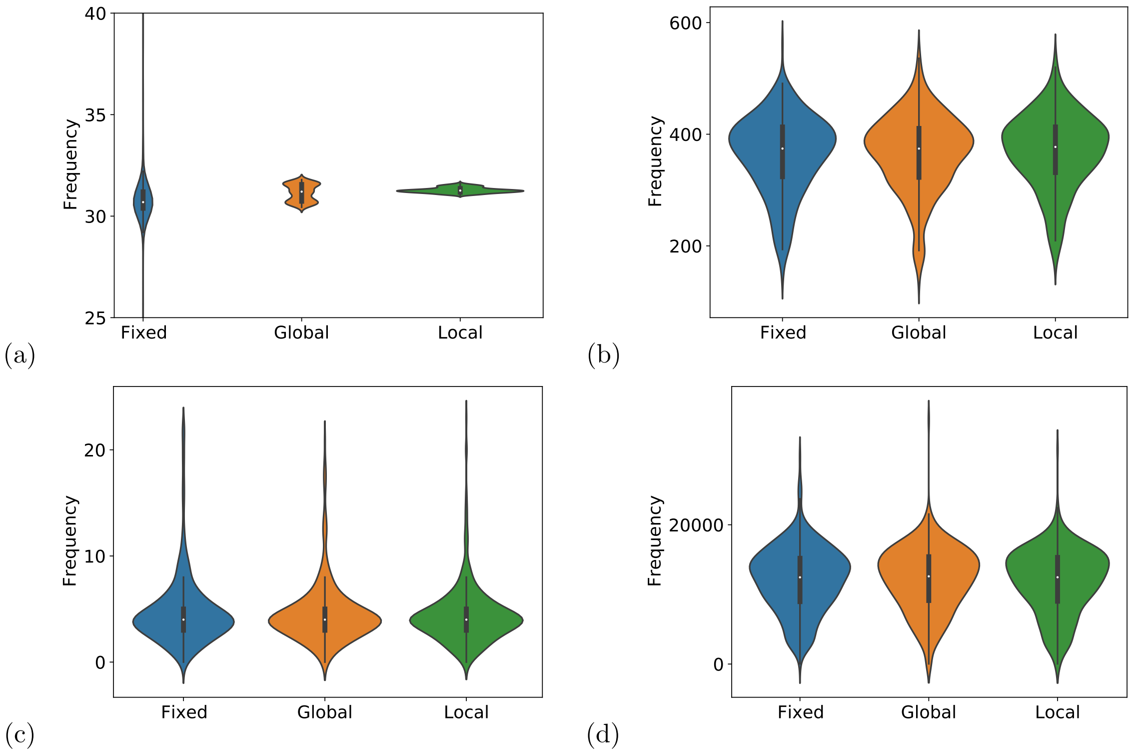


Figure 5: Violinplots for different legitimacy kinds of (a) mean peak interval (the spread of the Fixed legitimacy is 24.25-56.56), (b) mean peak size, (c) total number of peaks and (d) total number of actives.

4.2 Qualitative experiments

Experiments are performed in order to see how the model with a global legitimacy feedback loop behaves over a long time span. First an exploratory analysis is conducted on a time span of 2000 steps (see Figure 6). This Figure shows the states of the citizens over a time span of 2000 iterations for the four different models. What can be observed is that the amount of active citizens in each model seems to decrease over the course of time. The experiments have been repeated for 5 times because of the stochastic nature of the model, the results of these repetitions show that the model repeatedly express this behaviour for all the different runs (see Appendix B Figure 13).

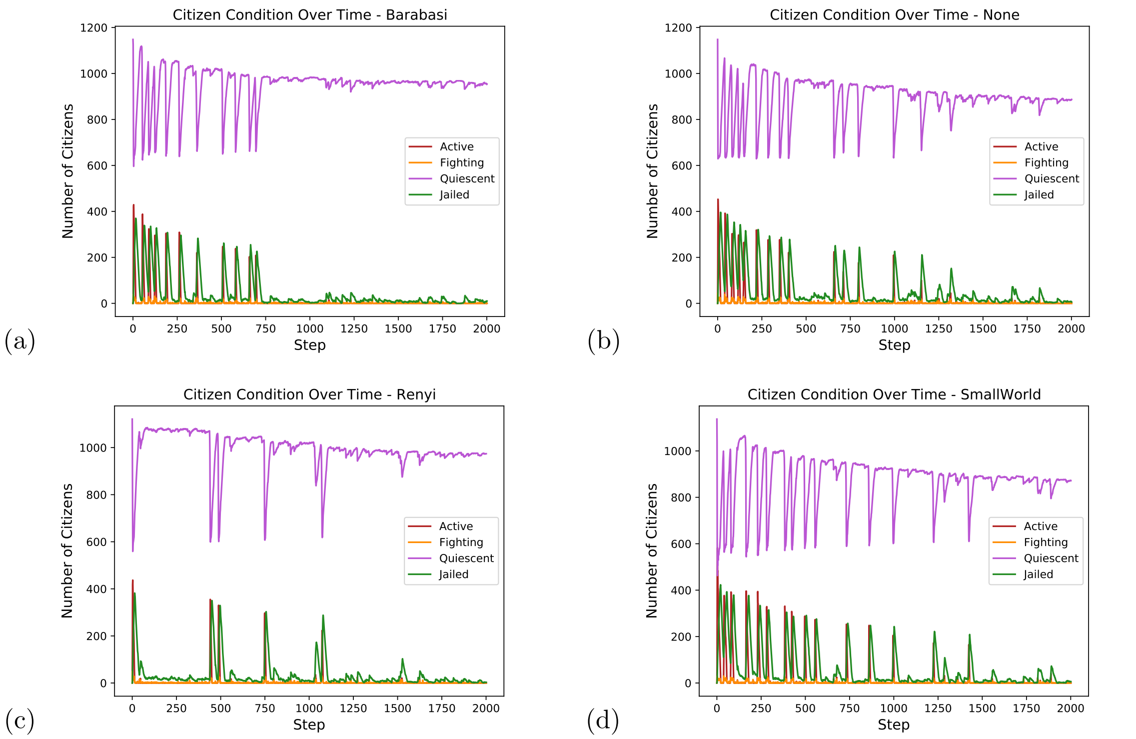
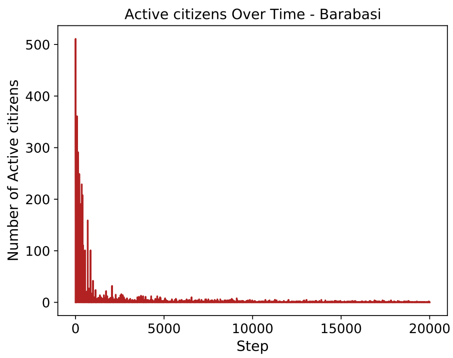
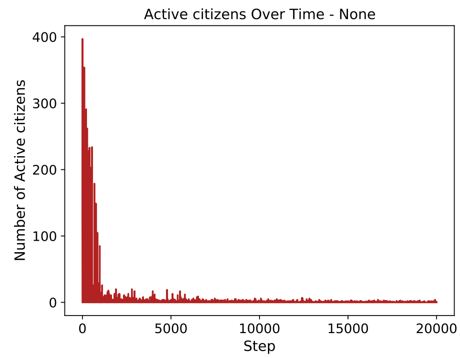


Figure 6: One simulation for 2000 time steps with different network structure: (a) Barabasi, (b) None, (c) Renyi and (d) SmallWorld

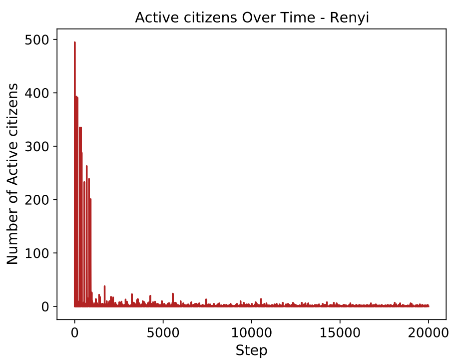
The outcome of the exploratory analysis has resulted in a follow-up experiment where the models all run for a total amount of 20000 steps. The outcome of this experiment can be observed in Figure 7 and Figure 8. Figure 7 shows the amount of Active citizens over a time span of 20000 steps. In these graphs the same results can be found as in the exploratory experiment, but more clearly. All the models start with a fluctuating amount of active citizens with high peaks and configure to a state where almost all citizens are Quiescent. Figure 8 shows that not only the state of the citizens configures but also the perceived legitimacy of the citizens, which configures around 0.68.



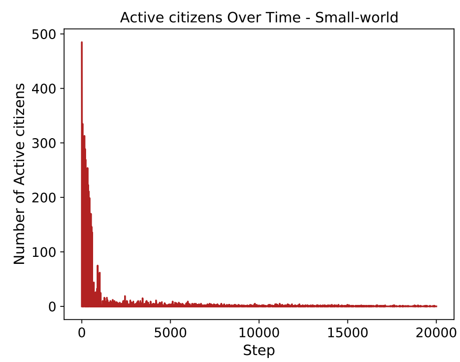
(a)



(b)

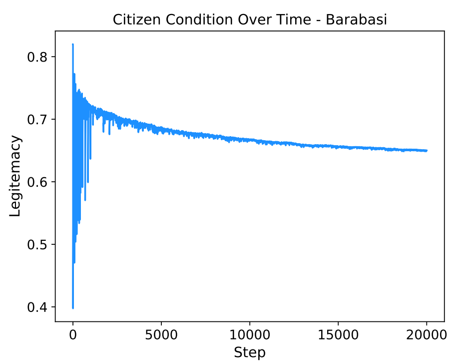


(c)

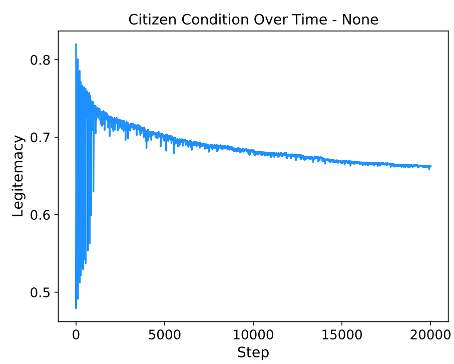


(d)

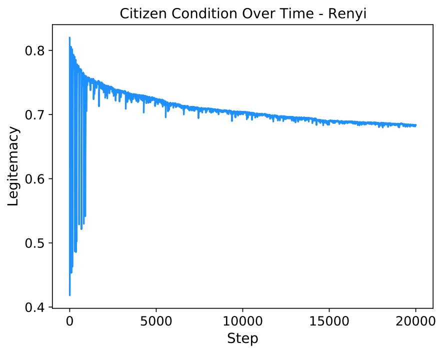
Figure 7: Active citizens for different networks over a time period of 20000 steps.



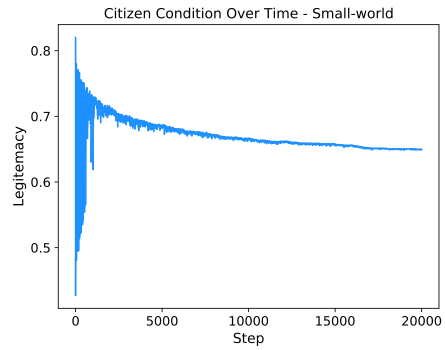
(a)



(b)



(c)



(d)

Figure 8: Legitimacy of citizens for different networks over a time period of 20000 steps.

4.3 Political crowd data

The Crowd Counting Consortium (CCC) [4] collects data on political crowds in the United States, including marches, protests, rallies, demonstrations, strikes and similar actions. The CCC is co-directed by faculty at Harvard University and the University of Connecticut.

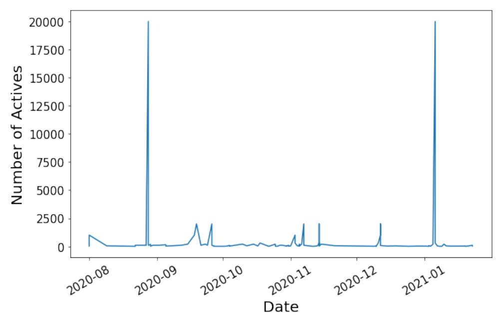
The CCC collects data in the public interest and to further scholarly research, gathering the crowd info is accomplished amongst others by a webcrawler that captures events data from local newspaper and television sites on a daily basis.

The database of the CCC contains multiple fields of information about political crowds, such as the date, state, city and the lowest and highest reported participant count, the type of event and amount of arrests. Figure 9 displays an overview of an estimate of the lowest reported participation count for political crowds for the time period August 2020 until January 2021. The first large peak (10000 participants) from Figure 9a refers to the "Commitment March: Get Your Knee Off Our Neck" protest against racism and police brutality on August 28, 2020, at the Lincoln Memorial in Washington and the second large peak originates from the Capitol takeover on January 6, 2021, that was described previously in the introduction of this paper. Other smaller peaks of about 2000 participants, as visible in Figure 9b, stem from Black lives matter protests, pro-Trump protests and other political gatherings. It should be noted that counting crowds is a difficult task and the numbers depicted in Figure 9 are often (not always) the number cited by police and public officials and comprise a low estimate of the crowd.

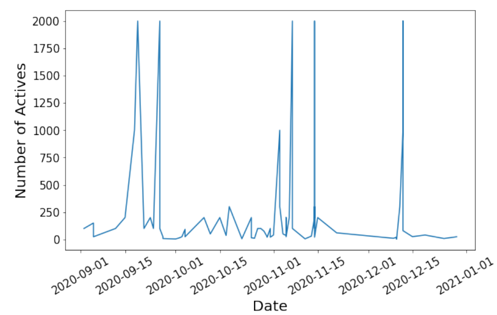
The appearance of the plot of the political crowds resembles that of the simulation of 2000 time steps shown in Figure 6. Although not comparable in terms of time-

[4] https://sites.google.com/view/crowdcountingconsortium/about

frame, location and population size, both the plot of the real data and the plot of the simulation display recurring higher peaks enclosed by lower frequent peaks and moments of calm where there are no political crowds (riots).



(a)



(b)

Figure 9: Lowest reported size of political crows in the city Washington DC, with Figure (a) from August 2020 until January 2021 and Figure (b) from September 2020 until December 2020.

5 Discussion

This research investigates the influence of media and social media networks on the core dynamics of the civil violence model of Epstein. This paper focused on finding the most influential parameter of the model, the influence of different types of networks on the model dynamics and the different mechanisms of legitimacy perception. It is important to firstly add the disclaimer that research described in this paper was written within a very limited amount of time. In order to give more in-depth conclusions on the influence of (social) network incorporation's within the civil violence model, more time and computational power is needed.

Mostly because of these limitations the sensitivity analysis and the experiments were conducted on rather short simulations. While this is done consistently, it can be argued that it gives a skewed image of the real equilibrium behaviour. While earlier research by Epstein et al.[6] and Lemos et al.[12] show clear punctuated equilibria, our model was not able to reproduce this behaviour within the executed simulations (see Figure 7).

For the global sensitivity analysis the max jailed term parameter showed to be the most predominant parameter when considering only first order interactions. Furthermore, the follow-up OFAT analysis solidified our beliefs about the influence of the cop vision parameter on the dynamics of our model. Within the chosen parameters, the links parameter showed to be the least influential in the global SA.

Although it is a challenging task to draw conclusions about the exact mechanism in which social media is able to fuel civil violence, it is not disputed that including a network leads to different dynamics in the civil violence model. Our model has shown that incorporating a network can increase the sizes of rebellious outbursts. However, no significant differences were found for the number of peaks. The model showed that with a Small-world network the total amount of active citizens reaches a higher amount than with the Erdős–Rényi or Albert-László Barabási network (section 4.1.1). This can be summarized as follows, the addition of a social network of citizens causes the rebellious outbursts to be fiercer. This can be explained through the added action rule 2. Namely, through the addition of this rule a citizen can become active without having to meet active citizens physically.

Furthermore, with the Albert-László Barabási network model, the feedback legitimacy type (fixed, local or global) resulted in significant different distribution for the mean peak intervals. For the mean peak size and total amount of peaks and actives the distributions were not significantly different (section 4.1.2). An explanation for this result can again be the added rule for a citizen to become active (Equation 2). With this rule the influence of the legitimacy parameter on an agent's action is reduced as some citizens can become active without having to consult this parameter.

As mentioned this research was conducted within a limited time frame. Therefore future research would be desirable to both confirm and extend the results of our research. One idea worth further deliberation would be changing how citizens are connected in the network. Currently this is done randomly without looking at the "identity" of a citizen. In order to resemble reality more closely it would be very interesting to connect citizens that "look" like each other. For instance through some sort of euclidean distance based on their hardship or perceived legitimacy. This method could give interesting results on the role of social media, which in reality also mostly connects like-minded people.

Additionally interested researchers could attempt to extend the explanatory power of the model by exploring different types of rules for incorporating the network in the model. Would it make a difference, for instance, if the rule implies that opinions of neighbours in the graph impact the legitimacy perception of the citizens instead of directly affecting the decision to become active?

Lastly it is of interest for future research to attempt to confirm or dismiss the argument that incorporating a network in the ABM of civil violence is essential. In doing so, researchers could try to gather more data on civil violence and compare the dynamics in periods before and after the rise of social technologies. Is there truly a notable difference in the way violent outbursts erupt due to the increasing influence of social media? Or does the original model of Epstein not need an addition to capture the dynamics of civil violence in the digital age?

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A Global SA

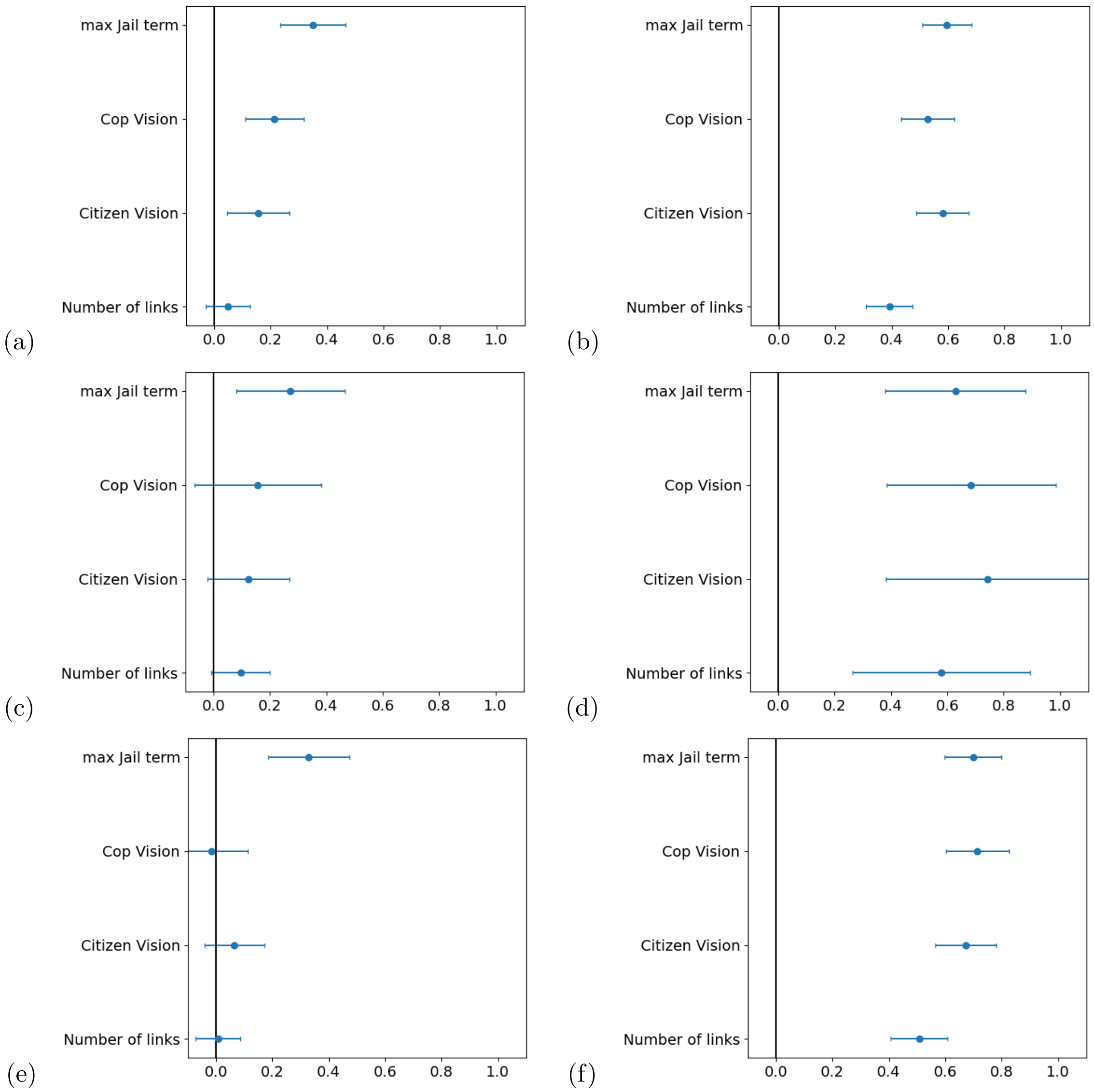

Figure 10: The above figures show results on the global SA for multiple output measures. Figure 10a and 10b represent the first and total order for the percentage of calmness as output. Figure 10c and 10d represent the first and total order for the peak interval as output. Lastly, Figure 10e and 10f show the first and total order for the mean peak size as output.

B OFAT - Number of links in the network

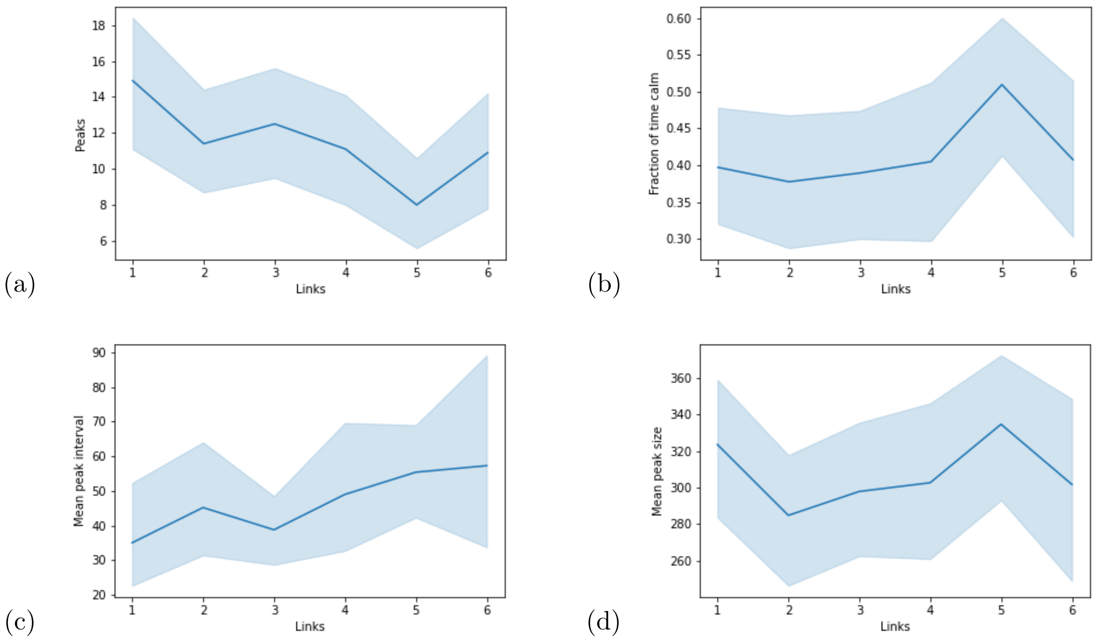

Figure 11: OFAT for links in the network of (a) total number of peaks (b) fraction of time calm, (c) mean peak interval and (d) mean peak size.

C Network setting

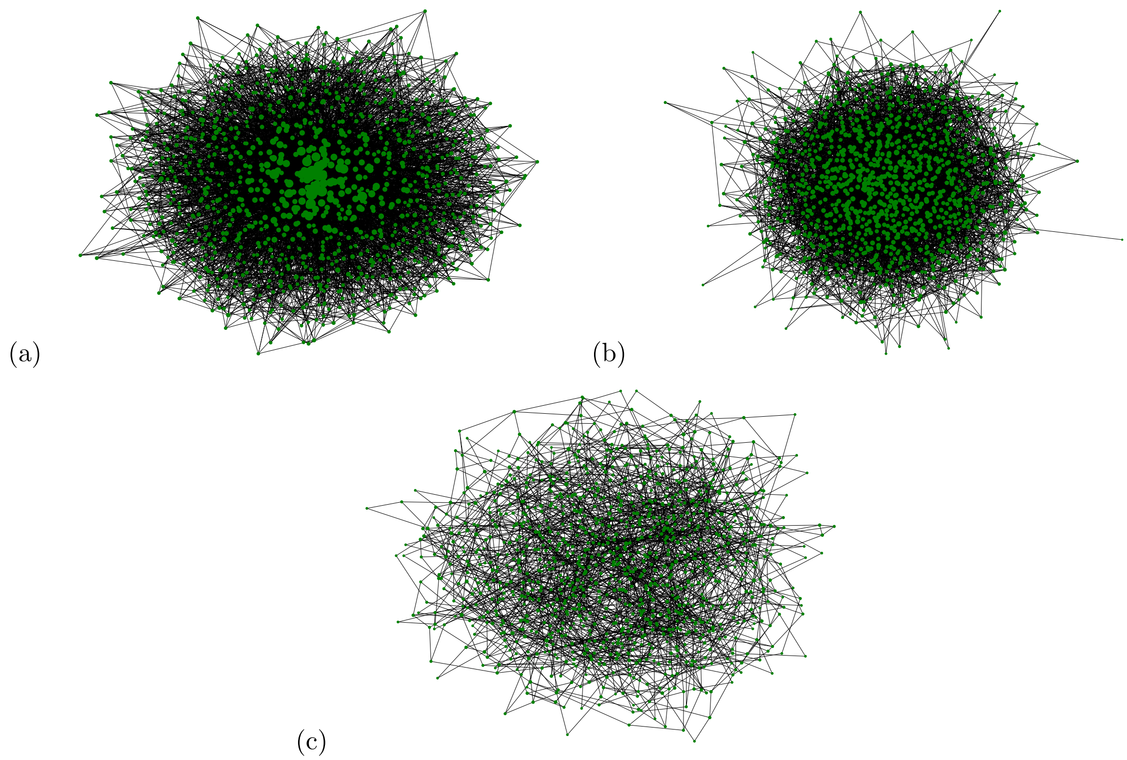

Figure 12: An example of the configuration of the (a) Albert-László Barabási, (b) the Erdős–Rényi and (c) the Small-world network.

D Qualitative experiments

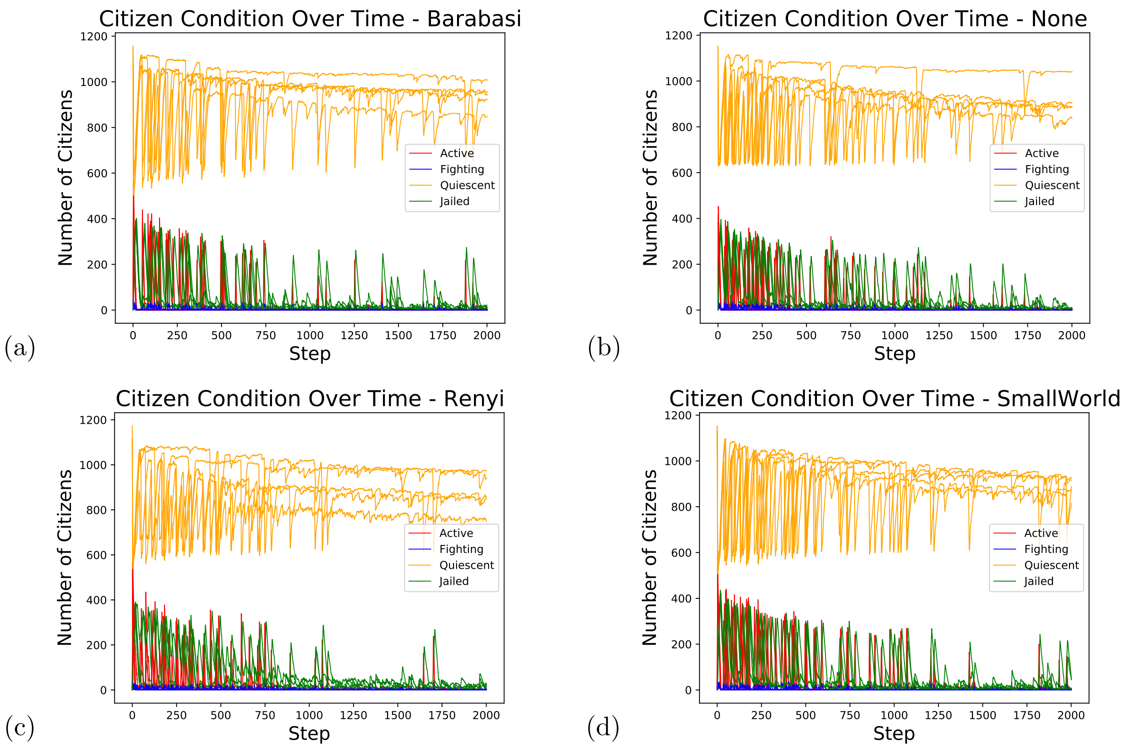

Figure 13: Five simulation for 2000 time steps with different network structure: (a) Barabasi, (b) None, (c) Renyi and (d) SmallWorld.