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On Agent-Based Modelling of Large Scale Conflict Against a Central Authority: from Mechanisms to Complex Behaviour

A Thesis presented in partial fulfillment of the Requirements for the Degree of *Doctor of Philosophy* in *Complexity Sciences*

By

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December, 2016

To my wife São and my daughters Mariana and Marta

Abstract

In this work, an Agent-Based model of large scale conflict against a central authority was developed. The model proposed herein is an extension of Epstein's Agent-Based model of civil violence, in which new mechanisms such as deprivation-dependent hardship, generalised vanishing of the risk perception ('massive fear loss') below a critical ratio between deterrence and 'group support', legitimacy feedback, network influences and 'mass enthusiasm' (contagion) were implemented. The model was explored a set of computer experiments and the results compared with statistical analyses of events in the "Arab Spring".

The main contributions of the present work for understanding how mechanisms of large scale conflict lead to complex behaviour were (*i*) a quantitative description of the impact of the "Arab Spring" in several countries focused on complexity issues such as peaceful vs violent, spontaneous vs organized, and patterns of size, duration and recurrence of conflict events; (*ii*) the explanation of the relationship between the estimated arrest probability and the size of rebellion peaks in Epstein's model; (*iii*) a new form of the estimated arrest probability with a mechanism of 'massive fear loss'; (*iv*) the derivation of a relationship between the legitimacy and action threshold for complex solutions to occur with both low and high values of the legitimacy; (*v*) a simple representation of political vs economic deprivation with a parameter which controls the 'sensitivity' to value; (*vi*) the effect of legitimacy feedback; and (*vii*) the effect of network influences on the stability of the solutions.

Keywords: Social Conflict, Complexity, Mechanisms, Agent-Based Model, Social Simulation, "Arab Spring"

Resumo

Neste trabalho, é apresentado um modelo baseado em agentes para o estudo do conflito massivo contra uma autoridade central. O modelo proposto é uma extensão do modelo baseado em agentes para o estudo da violência civil devido a Epstein, incluindo os mecanismos de relação entre a privação relativa e 'provação' (*hardship*), o desaparecimento generalizado da percepção de risco abaixo de uma relação crítica entre a capacidade de dissuasão e o 'apoio colectivo', a retroalimentação da legitimidade em função da contestação, as influências associadas as redes, e o mecanismo do 'entusiasmo colectivo' (contágio). O modelo foi explorado através de um conjunto de experiências de simulação, e os resultados comparados com uma análise estatística de eventos ocorridos durante a "Primavera Árabe".

Os principais contributos do presente trabalho foram (*i*) a descrição quantitativa do impacto da "Primavera Árabe" em diversos países, focada em aspectos de complexidade; (*ii*) a explicação da relação entre a função de estimativa de probabilidade de prisão e a magnitude dos picos de revolta social; (*iii*) uma nova forma para a função de estimativa de probabilidade de prisão, como mecanismo de 'perda generalizada do medo'; (*iv*) a dedução de uma relação entre a legitimidade e o limiar de acção para a ocorrência de soluções com comportamento complexo, tanto para valores elevados como baixos da legitimidade; (*v*) uma representação simples da privação política e da privação económica, com um parâmetro regulador da 'sensibilidade' ao valor; (*vi*) a introdução do mecanismo de retroalimentação da legitimidade; e (*vii*) o efeito das influências devidas a redes na estabilidade das soluções.

Palavras-chave: Conflito Social, Complexidade, Mecanismos, Modelo Baseado em Agentes, Simulação Social, "Primavera Árabe"

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Finally, I thank my wife São and my daughters Mariana and Marta for their continuous love, support, trust and enthusiasm, without which this work would have never been completed. They were, are and will always be my strongest source of energy and inspiration.

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List of Symbols and Abbreviations

α Shape parameter in the Pareto distribution

α_i Learning constant for the i-th agent in Rescorla-Wagner conditioning model (salience of conditioned stimulus)

β_i Learning constant for the i-th agent in Rescorla-Wagner conditioning model (salience of unconditioned stimulus)

δ Exponent in generalized Rescorla-Wagner conditioning model

$\mathcal{AG}_i$ The set of 'active' citizens in the `group` network, in the i^{th} 'citizen' in the ABM of social conflict

$\mathcal{AINFL}_i$ The set of 'active' citizens in the `infl` network, in the i^{th} 'citizen' in the ABM of social conflict

$\mathcal{N}(\mu, \sigma^2)$ Normal distribution with mean value μ and variance σ^2

$\mathcal{U}(a, b)$ Continuous uniform distribution with support $[a, b]$

$\mathscr{A}$ Generic agent

$\mathscr{M}$ 'Mass enthusiasm' term in the action rule for a 'citizen' agent in the ABM of social conflict

$\mathscr{P}$ Agent's percept

$\mathscr{R}$ Set of possible finite runs

$\mathscr{S}$ Sum of social influences in the action rule for a 'citizen' agent in the ABM of social conflict

$\mu(X)$ Mean (or expected) value of random variable X

ρ — C/A, the ratio between the number of 'cops' and the number of 'active' citizens in the ABM of social conflict

ρ_c — Critical 'cop'-to-'active' ratio below which risk perception vanishes; a parameter in the proposed form of the estimated arrest probability function (P_a) which models the mechanism of 'massive fear loss' in a population

ρ_f — Fixed point value of the 'cop'-to-'active' ratio in the analytical model described in § 5.2.1

ρ_v — $= (C_v/A_v)$

$\text{var}(X)$ — Variance of random variable X

$A(t)$ — Total number of 'active' citizens at time step t

A_v — Number of 'active' citizens within a citizen's vision radius in the ABM of social conflict

Ac — Set of actions available to an agent $\mathscr{A}$

C — Number of 'cops' in the analytical model described in § 5.2.1

C_v — Number of 'cops' within a citizen's vision radius in the ABM of social conflict

E — Set of possible environment states

G — Grievance

g_G — Probability density function of G

H — Hardship

I — Agent's internal state

J — Jail term for a citizen in the ABM of social conflict

$J(t)$ — Total number of 'jailed' citizens at time step t

J_{max} — Maximum jail term in the ABM of social conflict

k — Arrest constant in the expression of the estimated arrest probability function (P_a)

L — Legitimacy

L_0 — Initial legitimacy in the social conflict model with endogenous legitimacy feedback; also the value of the `government-legitimacy` input parameter

L_{cons} — "Acts of consent" (component of legitimacy)

L_{just} "Views of justification" (component of legitimacy)

L_{leg} "Views of legality" (component of legitimacy)

L_p Citizens' perceived legitimacy (in the case of endogenous legitimacy feedback)

N Net risk, $= R \cdot P_a$

n_{active} Total number of 'citizens' in the 'active' state, in the ABM of Social conflict

$N_{citizen}$ Total number of citizens in the social conflict model

n_{jailed} Total number of 'citizens' in the 'jailed' state, in the ABM of Social conflict

N_{MJC} Maximum jail capacity

n_N Probability density function of N

n_{quiet} Total number of 'citizens' in the 'quiet' state, in the ABM of Social conflict

P Deliberative component of disposition, in Epstein's *Agent_Zero* framework

R Risk aversion

S Social component of disposition, in Epstein's *Agent_Zero* framework

T Threshold in threshold rules of binary decision

T_i Threshold for agent $\mathscr{A}_i$

U_X Probability distribution of X

u_X Probability density function of X

V Affective component of disposition, in Epstein's *Agent_Zero* framework

v Citizens' vision radius in the ABM of social conflict

v' Cops' vision radius in the ABM of social conflict

X $= G - N$

x_m Scale parameter in Pareto distribution

γ Parameter in the proposed form of RD in the ABM of social conflict which expresses sensitivity to value (to differentiate political from economic RD)

$\mathcal{A}_v$ Set of 'active' citizens within an agent's vision radius in the ABM of social conflict

$\mathcal{E}_v$ Set of empty cells within an agent's vision radius in the ABM of social conflict

P_a	Estimated arrest probability
ABM	Agent-Based model(s)
AS	"Arab Spring"
CAST	Conflict Assessment System Tool
FFP	The Fund For Peace
FSI	Fragile States Index (indicator published by The Fund For Peace)
FWI	Freedom in the World Indicator
ICT	Information and Communication Technologies
ODD	"Overview, Design Concepts and Details" protocol for describing ABM
RD	Relative deprivation
SCAD	Social Conflict Analysis Database
SN	Social networks
SOA	State-of-the-art
UN	United Nations
WDI	World Development Indicators (published by the World Bank)

Chapter 1

Introduction

Social conflict and violence are two fundamental characteristics of human societies [86, 1]. Both are deeply rooted on biology and evolution, and depend on culture and situational factors [67]. As such, they are extremely heterogeneous and varied in terms of type, motif, scale, intensity and evolution pattern. They are distinct and related – not all forms of social conflict are violent and not all violence results from social conflict.

Understanding how the social context leads to latent social conflict, and how this can evolve to large protests, civil violence or unanticipated revolution, is a topic of central importance in history, political science, sociology, social psychology, and also in military and security studies. Rulers and governments fear the "power of the crowds" [12]. History provides striking examples of large street protests sparking revolutions and overthrowing regimes, as in the French Revolution in 1789, the October Revolution in Russia in 1917 and the Iran Revolution of 1979 [57]. Widespread access to Social Networks (SN) and Information and Communication Technologies (ICT) changed the dynamics of social conflict processes in dramatic ways, as they allow organizations or groups of activists to summon, coordinate and show protest events or violence to a worldwide audience in almost real time [85, 34, 18]. The protesters' motifs may range from challenging the authorities on specific issues (e.g. the 2013 protests in Turkey against the transformation of the Gezi Park and the 2014 protests in Brazil against the FIFA World Cup), general aspects of governance (e.g. anti-austerity protests in several European countries following the European Sovereign Debt Crisis, whose roots can be traced to 2007 [19]), or regime change, as in the "Arab Spring" (AS) uprising that began in December 2010 or the Hong-Kong protests of 2014.

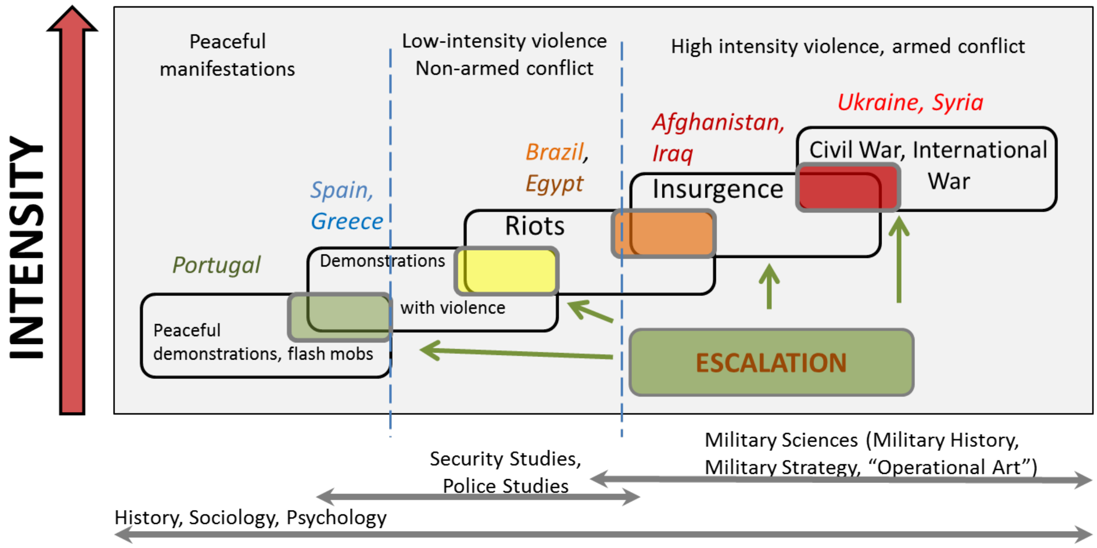


Figure 1.1: Classification of social conflict manifestations based on their intensity (level of violence), showing the disciplines in which they are studied. Transitions between different manifestations are represented by rounded rectangles. (Source: author)

Social conflict encompasses an extremely wide spectrum of processes and phenomena and is a multidisciplinary topic [2]. It can be latent or manifest, and manifest conflict can be non-violent (e.g. peaceful demonstrations, strikes, public petitions) or violent (demonstrations with violent confrontation, riots and civil violence). There is no single criterion for classifying social conflict processes and phenomena. Figure 1.1 shows a simplified classification of some typical manifestations of social conflict, using the intensity of violence as a criterion and showing the scientific disciplines in which they are studied. In this figure, conflict manifestations were divided into three broad categories: (*i*) peaceful manifestations, (*ii*) low-intensity violence (non-armed conflict) and (*iii*) high-intensity violence (armed conflict).[1] This division is consistent with general definitions of 'violence' [109], 'civil violence' [49] and 'armed conflict' [101]. There is also the possibility of escalation, represented by coloured rounded-corner rectangles in figure 1.1. Predicting the time evolution of social conflict and whether or not violence and escalation will occur, and if possible controlling these processes, is a problem of great practical importance in security studies and political science. However, these processes are very complex and path-dependent on social

[1]'Armed conflict' is defined as *"a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths."* in page 1 of the UCDP/PRIO Armed Conflict Dataset Codebook [101]. Specific forms of armed conflict are thoroughly studied in the realm of Military Sciences. Modern definitions of 'insurgence' and 'war' can be found in military doctrine publications, such as the AAP6 – NATO GLOSSARY OF TERMS AND DEFINITIONS [77].

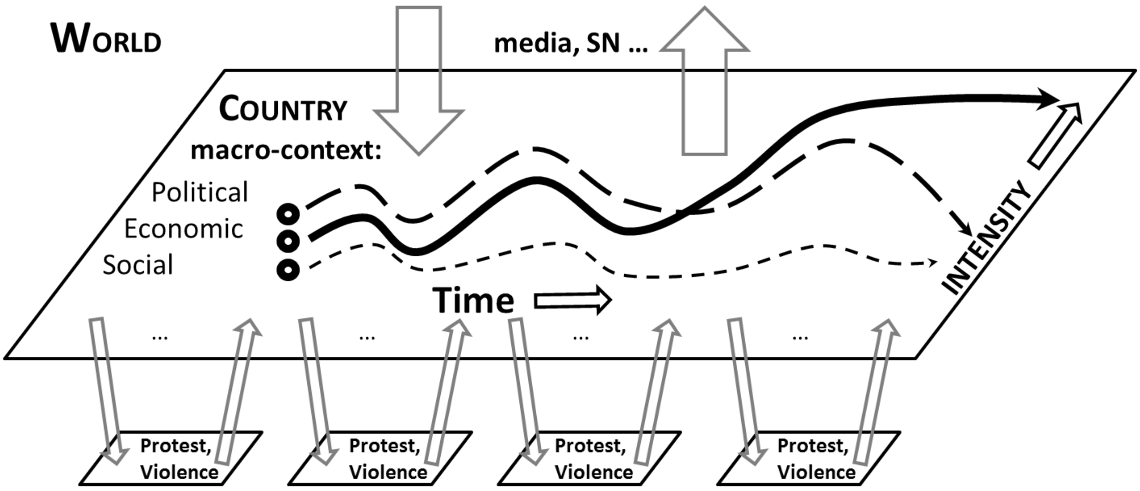


Figure 1.2: Evolution of social conflict viewed as complex and path-dependent process with micro-macro and feedback links. (Source: author)

factors, particular settings, types of interactions and scales (of time, space, and size or proportion of individuals involved). Such processes may be stable or unstable, as sketched in figure 1.2. Unstable processes may be gradual (build-up of tension or violent confrontations) and lead to sudden changes (e.g. revolution or outbreak of armed conflict) [57, 58].

Figure 1.2 shows a simplified model of the evolution of large scale social conflict and civil violence in which the details of events in the lower layer are described in a very crude way.

Real conflict processes are strongly dependent on the dynamics of particular events, such as motif, mobilization (organized or spontaneous), crowd size, emotional intensity, place, occurrence of violent confrontation, and police action. One critical aspect is the formal or informal media coverage of specific events, and whether or not the transmitted contents increase the population's grievance towards the government. Describing the dynamics of these events (e.g. street protests) and their intensity (likelihood and magnitude of violent confrontation) requires a much more complicated modelling of the physical and social environments and individual entities (actors) than the framework shown in figure 1.2.

The development of computers and software tools added simulation to the traditional methods of scientific research – observation, laboratory experimentation, mathematical deduction and empirical inference. Simulation has the advantages of providing a deep level of insight and understanding, and allows the consideration of many different scenarios which would be impossible to test in reality. Social simulation using Agent-Based models (ABM) has been successfully introduced to study many social phenomena such as segregation [90, 91], the formation of culture [5], opinion dynamics [110], or rumour spreading [42]. Several ABM were proposed to study conflict phenomena such as civil or ethnic violence [33, 31], urban crime [35], worker protest [56], riots [25], insurgence [28] and land combat [53], and also for modelling crowd dynamics with different degrees of sophistication. ABM are suitable for studying the dynamic of protests, escalation and civil violence, because these are large-scale, weakly organized peaceful or low-violence conflict manifestations, whereas armed conflict requires a high degree of leadership and organization [49]. Thus, the problem of modelling the dynamics of protests and violence is one of complexity and Agent-Based modelling is a promising approach for providing insight and understanding of their underlying mechanisms.[2]

In this work, an ABM for studying large scale conflict against a central authority was developed and explored in a set of computer experiments. The model proposed herein is an extension of Epstein's ABM of civil violence, in which new mechanisms such as deprivation-dependent hardship, vanishing of the risk perception ('massive fear loss') below a critical ratio between deterrence and 'group support', legitimacy feedback (drop of the central authority's legitimacy due to uprisings), network influences and 'mass enthusiasm' (contagion) were implemented.

1.1 Motivation

The motivation for studying the dynamics of protests and civil violence in terms of mechanisms using ABM is due to the following aspects:

- Protests, violence and other manifestations of social conflict in many countries became part of our daily experience. The AS was a startling example of a series of unanticipated very large scale uprisings that started in December 2010 and ravaged several Arab countries, with profound consequences. During the course of this work, anti-government protests against austerity measures due to the European Sovereign Debt Crisis were frequent in Portugal and other European countries;
- There is a need for improving our understanding on how social context factors lead to large scale protests and civil violence, and how these in turn affect the

[2] Although in the modern conceptions insurgence and war are also studied using methods from complexity sciences [53], in this work we will only consider protests and civil violence, as defined in §1.2 and §2.1.2, respectively.

social context factors (figure 1.2);

– Simulation using ABM and the methods of complex systems studies provides insight and explanatory power not attainable using the theories and methods of other disciplines (e.g. sociology and social psychology).

1.2 Purpose and Scope

The purpose of the present work is to study the mechanisms by which social context factors lead to large scale protests and civil violence and these in turn affect the social context, using ABM with the maximum simplicity possible, i.e. with a small number of agent types and parameters, and simple rules and submodels. More specifically, the focus will be on how the complex patterns of size, duration and recurrence of bursts of social unrest in large scale conflict processes (like the AS) can be explained in terms of underlying mechanisms and modelled via ABM.

The scope of the present work is framed by the peaceful and low intensity conflict phenomena shown in figure 1.1, which involve a significant proportion of a population, and for which self-organization is important. To make this scope more precise, it is convenient to introduce the following general definitions:

Definition 1. Social conflict – Confrontation or dynamic balance of social powers, which can be latent or manifest, direct or indirect, coercive or non-coercive. (Source: author, based on Coser [20], Rummel [86] and Allan [1])

Definition 2. Demonstration – Distinct, continuous, and largely peaceful action directed toward members of a distinct "other" group or government authorities. (Source: Salehyan and Hendrix [88])

Definition 3. Riot – Distinct, continuous and violent action directed toward members of a distinct "other" group or government authorities. The participants intend to cause physical injury and/or property damage. (Source: Salehyan and Hendrix [88])

Definition 4. Mechanism – An intelligible description and general explanation of the relationships between causes and effects in a system, in terms of the system's entities and their activities. (Source: author, adapted from Machamer et al. [68])[3]

[3]Machamer et al. [68] define "mechanisms" as follows: "Mechanisms are entities and activities organized such that they are productive of regular changes from start or set-up to finish or terminal conditions." and add "Descriptions of mechanisms show how the termination conditions are produced by the set-up conditions and intermediate changes. Activities are the producers of change.

In this work we are only interested in politically motivated large scale conflict against a government or authority. Other important forms of violence such as ethnic clashes, hooliganism, or riots mobilized by groups via Facebook, will not be treated. These forms of collective violence will be mentioned only in those aspects that are relevant for the present work.

Likewise, the study and modelling of revolution will not be explicitly considered. Although revolution is an extremely important topic in the study of large scale conflict (e.g. [57, 58, 69, 74]), the present work will be centred on the stability, instability and complexity of the patterns of confrontation of a grieved population demanding change from a government, and not on the process of overthrowing governments.

1.3 Objectives and Research Questions

The specific objectives of the present work are:

- Discuss Epstein's classic ABM of civil violence [33, 31], which includes two types of agents 'citizens' and 'cops' (which represent the population and law-enforcing capability of the central authority, respectively), each with two action rules. 'Citizen' agents decide between being 'quiet' or 'active' (rebellious), and 'cops' arrest 'active' citizens;
- Extend this model to include the mechanisms of deprivation-dependent hardship, 'massive fear loss', endogenous legitimacy feedback, network influences, and 'mass enthusiasm';
- Develop the extended ABM by combining four viewpoints: (*i*) theories of social conflict, to identify the key concepts and variables for model specification (scope, entities and interactions); (*ii*) analysis of datasets of social indicators and conflict events; (*iii*) consideration of the role and meaning of each input parameter and agent attribute; (*iv*) analysis of the mechanisms described by the theories and represented in the ABM;
- Investigate and discuss how social context factors and different mechanisms influence the nature of the solutions (equilibrium, intermittent peaks of unrest, alternating periods of calm and turmoil or permanent rebellion) and the distributions of size, duration and interval between successive rebellion bursts,

Entities are the things that engage in activities."

by means of simulation. In other words, investigate how mechanisms and combinations of input parameters and distributions of the agents' attributes generate complex time-dependent solutions;

– Validate the model using existing datasets of political, social and economic indicators, and non-armed conflict events.

The main research questions considered in this work are the following:

1. Which mechanisms and social context variables are the most relevant to describe the potential for social conflict and the likelihood and magnitude of large scale protest (peaceful or violent)?
2. How can the important mechanisms identified in theories be modelled by extending existing ABM of large scale social conflict (i.e. Epstein's model)?
3. Which combinations of input parameters, distributions of agents' attributes, and functional forms of the agents' action rules lead to complex solutions (i.e. with intermittent peaks of rebellion, complicated trajectories in a suitable phase space, tipping points and changes of qualitative behaviour, etc.), and how can the complexity of the solutions be associated with mechanisms?

1.4 Methodology of Development

The methodology of development used in this work consisted of the following steps:

1. Survey of conflict theories, to identify the main mechanisms and the most relevant variables that must be considered in ABM of large scale conflict against a central authority;
2. Survey of datasets of international indicators and conflict events, which can be used for model parametrization and validation, respectively;
3. Discussion of Epstein's classical ABM and its extensions proposed by other authors, to characterize their explanatory power and limitations;
4. Analysis of conflict events and international indicators for eight African countries affected by the AS – Algeria, Egypt, Libya, Mali, Mauritania, Morocco, Sudan and Tunisia – to:
   – Characterize the significance of demonstrations and riots in the AS, and

of complexity issues (e.g. spontaneous vs organized events, escalation, etc.) in this recent and important conflict process;

– Derive statistical descriptions of the patterns of size, duration and recurrence of conflict events;

– Obtain plausible estimates for important social context variables for those countries, such as legitimacy and the Gini index of inequality.

5. Extension of existing ABM based on Epstein's model to include new mechanisms;

6. Exploration of the extended ABM via a set of computer experiments, illustrative of its explanatory power.

The first three items above were done in the state-of-the-art (SOA) revision presented in chapters 2 and 3. The last three contain most of the innovations and contributions of the present work, and are presented in chapters 4 and 5. Figure 1.3 shows a representation of the relationships between the development steps. Each box (rectangle or rounded rectangle) corresponds to a different chapter, as described in the next section.

1.5 Structure of the Work

The remainder of the present work is structured in six chapters, as described below.

Chapter 2 contains a review of the theories and concepts relative to social conflict against a central authority, as well as a reference to the datasets of social indicators an conflict events that can be used for ABM parametrization and validation. The most salient aspects of this review are the analyses of Ted Gurr's frustration-aggression theory on the psychological factors of civil violence [49] (which clearly identifies the mechanisms and key variables that determine the likelihood and intensity of social unrest), Gene Sharp's theory on non-violent action [92] (which is important for the analysis and discussion of the AS in chapter 4) and the importance of legitimacy [43, 44]. This chapter also contains a brief survey of the datasets of international indicators and information on conflict events which provide elements of observation on patterns of conflict events and plausible values for social context variables.

Chapter 3 contains a review of the existing ABM for simulation of large scale social conflict. Consistent with the framework in figure 1.2, the review is restricted

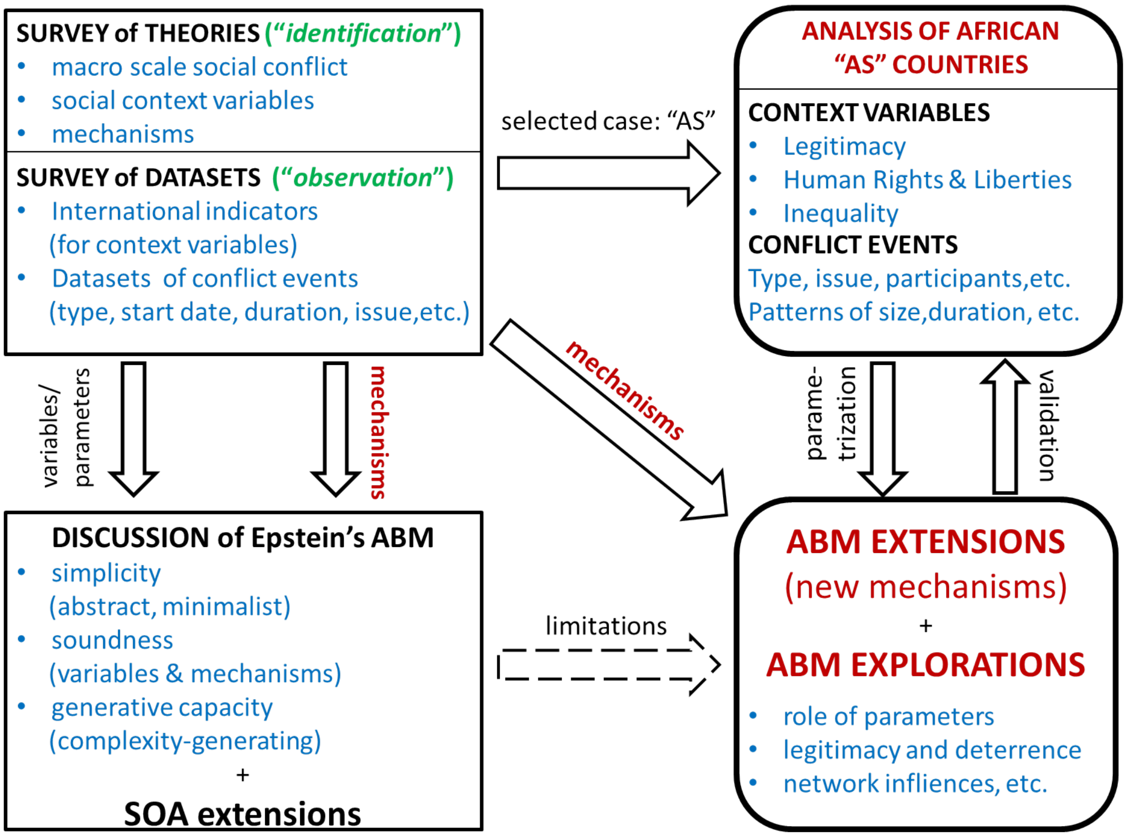


Figure 1.3: Schematic representation of the relationships between the steps of methodology of development. The steps within rectangles correspond to SOA review and those within rounded rectangles to contributions of the present work. (Source: author)

to ABM of 'abstract' type [41]. Epstein's landmark model of civil violence (Model I, [33, 31]) is described and discussed at length. In this model, the time evolution of conflict events is described using just two agent types ('citizens' and 'cops'), simple rules (all agents have random movement; 'citizens' make a binary decision 'rebel'/'not rebel', and 'cops' arrest rebellious citizens) and interactions (modelled as a variable risk perception for 'citizens'). Other ABM inspired in Epstein's ABM are also analysed. The limitations of existing models are discussed in terms of the mechanisms and key variables described by the theories.

Chapter 4 describes an analysis of conflict events and international indicators for eight African countries affected by the AS (Algeria,Egypt, Libya, Mali, Mauritania, Morocco, Sudan and Tunisia) based on the Social Conflict Analysis Database (SCAD) [97], the Fragile States Index (FSI) [96] indicators by the Fund For Peace, the Freedom in the World Indicator (FWI) by Freedom House [37], and the "All the Ginis" database of welfare inequality [13]. The results of this analysis provided justification for the theoretical framework in figure 1.1, as well as statistical descriptions of the duration, recurrence and size (in terms of the estimated % of the population) of conflict events, for comparison with ABM simulations. The analysis of the international indicators (FSI, FWI, "All the Ginis") led to representative values for social context variables, like legitimacy or the Gini index, for the African AS countries. The results of this chapter were used for the discussion of the simulation results presented in chapter 5.

Chapter 5 contains the description of the proposed 'abstract' ABM for simulation of large scale conflict against a central authority, followed by a set of model explorations. These latter started with an analytical study of the 'citizens' decision rule in Epstein's ABM to show why some forms of the estimated arrest probability function lead to solutions with large rebellion peaks whereas others do not, followed by a set of simulation experiments to show how the various input parameter and newly introduced mechanisms lead to plausible results (by comparison with those obtained in chapter 4) and influence the solutions' behaviour (permanent unrest, complex solutions with intermittent peaks of rebellion, or permanent calm).

Chapter 6 describes the innovations and the contributions of the present work to the SOA on ABM simulation of large scale conflict processes.

In terms of methodology of development, the main contributions of the present work were (*i*) the combination of theory, analysis of mechanisms, data from real processes, and ABM, in a coherent and integrated way, and (*ii*) the use of datasets of indicators and information on conflict events to guide both model development and exploration.

Another contribution was the analysis of the indicators of social and political context and of the SCAD database of conflict events for the eight African AS countries, which provided a quantitative description of the type, issue, estimated number of participants, spontaneous vs organized conflict events and escalation, as well as statistical distributions of size, duration and waiting time between successive events, for the case of demonstrations and riots. The analysis of the international indicators (FSI, FWI, "All the Ginis") led to representative values for social context variables, like legitimacy or the Gini index, for the African AS countries.

The innovations introduced in the proposed ABM were (*i*) the introduction of two subtypes of 'citizen' agents, called 'normal' and 'activist'; (*ii*) an improved form of the estimated arrest probability function; (*iii*) a simplified model to set the hardship as a function of relative deprivation, with a power law for describing the 'commitment to value' (or difference between types of deprivation); (*iv*) network influence effects due to two different networks ('group' and 'influentials'); (*v*) legitimacy feedback with variable 'memory effect'; and (*vi*) 'mass enthusiasm' (or dispositional contagion by 'active' citizens). The design concept for implementing these extensions was the generalization of the 'citizens' action rule to include social influences and 'mass enthusiasm', via the mechanism of 'dispositional contagion' proposed in [32]. The submodels for relative deprivation and legitimacy feedback were inspired in [49] and [44], respectively.

The most salient contributions for the understanding of the relationship between mechanisms and complexity in the ABM of social conflict were:

- The proposal of a form of the estimated arrest probability with a parameter for representing the effect of a mechanism of 'massive fear loss' (or vanishing of the risk perception for the whole population);
- The derivation of a 'rule of the thumb' condition between the legitimacy, estimated arrest probability and population threshold, for the solutions to have intermittent peaks of rebellion with both low and high values of the legitimacy;
- The identification of tipping points associated with the 'massive fear loss' and 'sensitivity to deprivation' parameters;
- The identification of the appearance of trajectories with complicated shapes in the appropriate phase spaces associated with the mechanisms of deprivation-dependent hardship and legitimacy feedback, once the level of deprivation surpasses a certain threshold;
- The destabilizing effects of legitimacy feedback and network influences.

Chapter 6 contains a more complete listing of the specific contributions relative to the general research questions enunciated in §1.3. Finally, chapter 7 contains a reference to possible future developments, which include improvements in model exploration and capabilities, as well as extension to ethnic and religious conflict.

Chapter 2

Theoretical Foundations

In this chapter a review of the SOA on theories of large scale social conflict against a central authority will be presented, followed by a discussion on published international indicators which may provide quantitative estimates for the social context variables identified in these theories as well as datasets with detailed information about conflict events. The chapter is divided in two parts. The first contains a presentation of theories of and civil violence (§2.1-2.3). The second contains a description of international indicators and databases with information about conflict events, which can the used for model parametrization and validation (§2.4-2.6).

Theories of social conflict are the basis for model development. The literature on this subject is extremely vast, so that only a summary account social conflict theories will be presented. The review will be centred on two theories: Ted Gurr's frustration-aggression theory on the psychological factors of civil violence [49], and Gene Sharp's theory of non-violent action [92].

The first theory was found to be particularly useful because it is very systematic and identifies the key variables (such as relative deprivation and legitimacy) and mechanisms of positive and negative drive for large scale protest and violence to be considered in ABM of social conflict. The second theory was found to be important because of its connection with the AS, which will be analysed in chapter 4. Other interesting aspects of Gene Sharp's theory are the emphasis on both organized and self-organized protest the postulated relationship between large and continuous protests and 'massive fear loss', which will be discussed in chapters 4 and 5. Thus, Ted Gurr's theory is mostly valuable for model development and parametrization, and Gene Sharp's for discussing emergent patterns of conflict events and ABM simulations.

The second part of this chapter contains a comparative review and discussion of the available datasets of political, economic and social indicators that are related to the potential for conflict, and to the variables that identified in the theories of social conflict. These are the 'elements of observation' for inferring the correctness of the theories and the model to be developed and explored (chapter 5).

The political, economic and social indicators were analysed under the perspective of their potential usefulness as predictors of the AS, which is a recent and important example of a large scale conflict process which involved several countries, and for setting plausible values of input parameters in ABM. Legitimacy is a key concept in political science and a key variable identified in theories and ABM of social conflict. Consequently, it will be treated with greater development than other context variables in a separate section (§2.6).

Datasets of conflict events contain information for understanding the sources of deprivation, the relative importance of the protests and riots (figure 1.1) as well as the patterns of size, duration and recurrence (waiting time between successive events) of episodes of social unrest.

2.1 Social Conflict and Violence

2.1.1 Social Conflict Theories

In general terms, conflict can be defined as a confrontation or dynamic balance of powers. Power can also be defined in very general terms as the capability of imposing will or produce a desired effect. Thus, social conflict is a confrontation of social powers (Definition 1, page 5).

Theories of social conflict played a central role in the development of sociology [1]. Karl Marx presented the first theory of social conflict based on the struggle between strata of the society (the "classes") over economic resources and the conditions that lead to such stratification. Max Weber considered the limitations of the Marxian concept of "class" (which he thought to be more complex than Marx assumed), stressed the importance of state and economy (inequality, status, party and power) for setting up conditions for social conflict, and introduced legitimacy, authority and legitimation of institutions as notions of fundamental importance for analysing social conflict.

Later theorists such as Georg Simmel, Lewis Coser and Ralph Dahrendorf combined elements from Marx and Weber and brought new perspectives to social conflict theory [1]. Simmel and Coser considered social conflict as an essential element in the evolution of society and the persistence of social order (whereas for previous theorists it was understood as a factor of instability and disintegration).

Coser [20] recognized conflict as an instinctual characteristic of human life (individual and social), and theorized about its sources, level of violence and functional consequences. For this author, uneven stratification of "class", status and power, causes a sense of deprivation that leads to arousal of "class consciousness". He stated that conflicts resulting from rational goals tend to be less violent (e.g. strikes and passive resistance movements) than those about "transcendent goals" (moral or group values) and emotional involvement can be violent.

Dahrendorf [22, 23] stated that the level of violence in social conflict depends on technical, political and social conditions of organization, as well as on effective regulation of conflict within the society. This author viewed power, not "class", as the main feature of social conflict, although he was in agreement with the ideas of dialectical change and bi-polarized society (from Marx), power and authority (from Max Weber). Dahrendorf considered that the level of violence in social conflict can be measured by the kinds of weapons used (peaceful demonstrations have a very low level of violence, whereas protests with exchange of stoning and tear gas are much more violent).

Modern theories replaced "absolute deprivation" by "relative deprivation" (RD), as the key concept for evaluating the potential for conflict. Gurr [50] defined RD as the tension due to the gap between value expectations and value capabilities and considered three patterns of RD, namely decremental, aspirational and progressive (figure 2.1).[4] Progressive RD generalizes the "J-curve hypothesis" of Davies [24] –*"revolutions are most likely to occur when a prolonged period of objective economic and social development is followed by a short period of sharp reversal"* –by including expectations. Frustration associated with the potential for revolt due to RD leads to revolt as RD increases above a tolerance threshold [11] (§2.1.2). Bischof [11] considers three types of RD: political (e.g. deprivation of political participation in authoritarian regimes), economic (e.g. periods of economic growth followed by economic and financial crises) and social (e.g. ethnic segregation or exclusion). This author states that although economic RD is the most commonly considered type, political and social deprivation may be more important. The evaluation of RD from

[4] Time and awareness of past own capabilities as well as of capabilities of other groups are essential elements of RD.

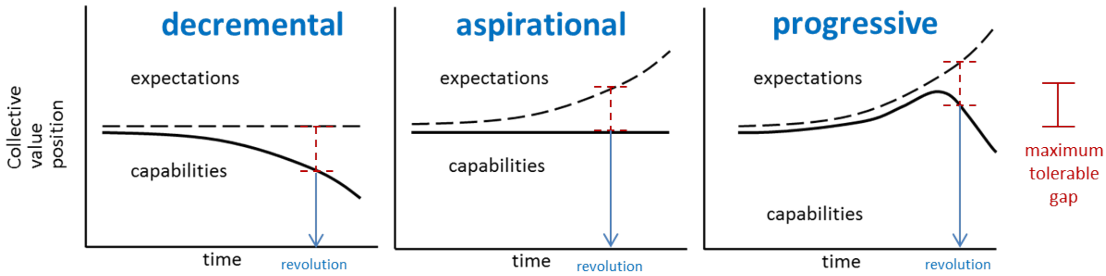


Figure 2.1: Patterns of RD: decremental (left), aspirational (middle) and progressive (right). (Source: author, adapted from Gurr [50])

datasets of social indicators and variables is a very important but difficult issue (§2.4).

The social conflict theories of Marx, Weber, Simmel, Coser and Dahrendorf are based on a macro-level perspective. Randall Collins [15] introduced a micro-level perspective in social conflict theory. He also considered power and unequal distribution of resources as key features of the problem, but stressed the fundamental role of symbolic goods, emotion and ritual. In this way, he approaches the evolutionary concepts of Lorenz [67] (on aggression in animal societies) and Coser [20]. Another important point of this theory is the role of the State as holder of the legitimate use of power (and force) and the consideration of legitimacy as a special kind of emotion. Collins also analysed conflicts in the context of history and geopolitics and concluded that:

– Unequal distribution of scarce resources (power, economic, cultural) causes potential conflict;

– Potential conflict turns to actual conflict depending on the degree of mobilization (emotional, moral, symbolic and derived collective rituals) of the opposing groups;

– Conflict generates subsequent conflict;

– Conflict intensity lowers as mobilization resources are used.

We conclude this brief survey of social conflict theories with a reference to the conceptual approach of Rummel [86]. This author considers the following elements of social conflict: (*i*) space; (*ii*) structure; (*iii*) situation and (*iv*) behaviour. The conflict space is the multidimensional biopsychological (needs, drives, instincts) and sociocultural (religion, ethics, law, etc.) space of resources that generate potential conflict. The structure of social conflict is the sociocultural distances between individuals and groups, which generate cleavages in the society. Awareness of these distances creates disposition towards action. The conflict situation is the activation of opposing attitudes, due to expectations, arousal of needs, conflicting interests, capabilities and will of the parties. The tension created by the conflict situation may lead to manifest action or peaceful resolution. Rummel highlights the importance of triggering events and states that much of social conflict is latent and not manifest.

The conceptual approach of Rummel can be viewed as a cycle of dynamic change of power unbalances and subsequent adjustments (figure 2.2).

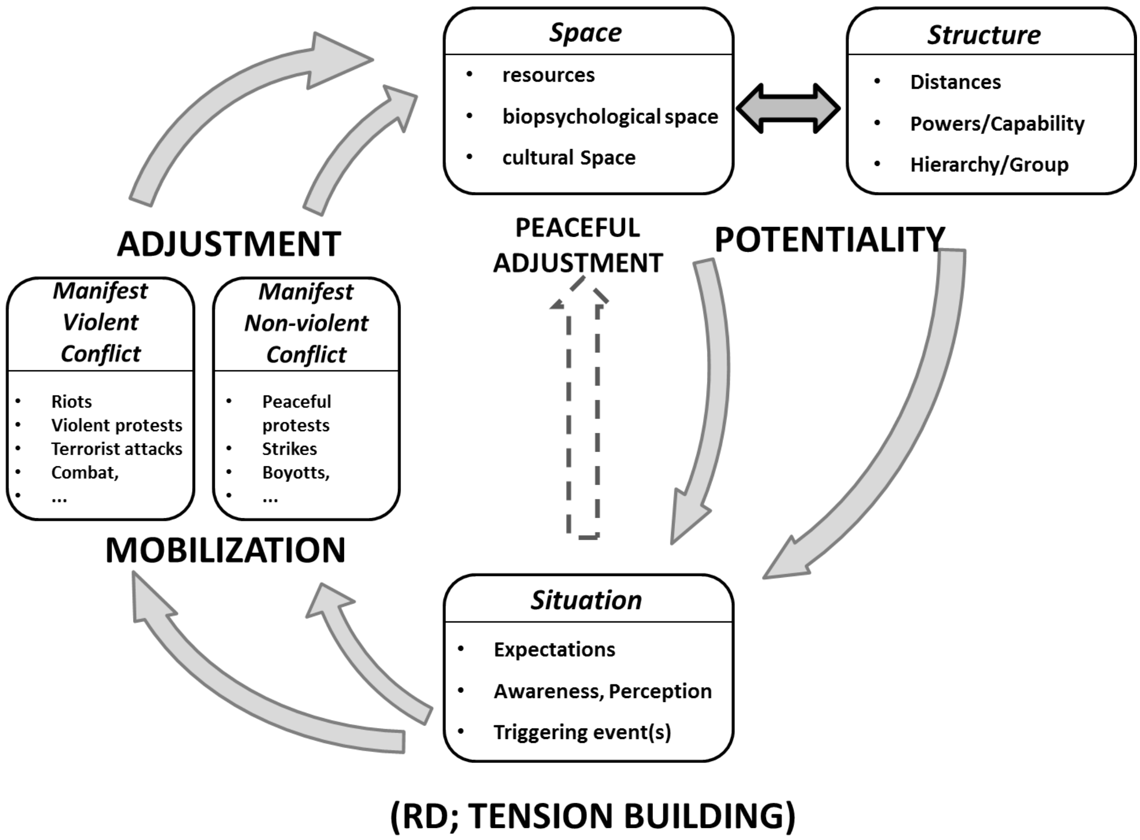


Figure 2.2: Social conflict cycle, derived from Rummel's conceptual approach [86]. (Source: author)

2.1.2 Violence

The study of violence is an extremely vast and difficult topic:

> *One reason why violence has largely been ignored as a public health issue is the lack of a clear definition of the problem. Violence is an extremely*

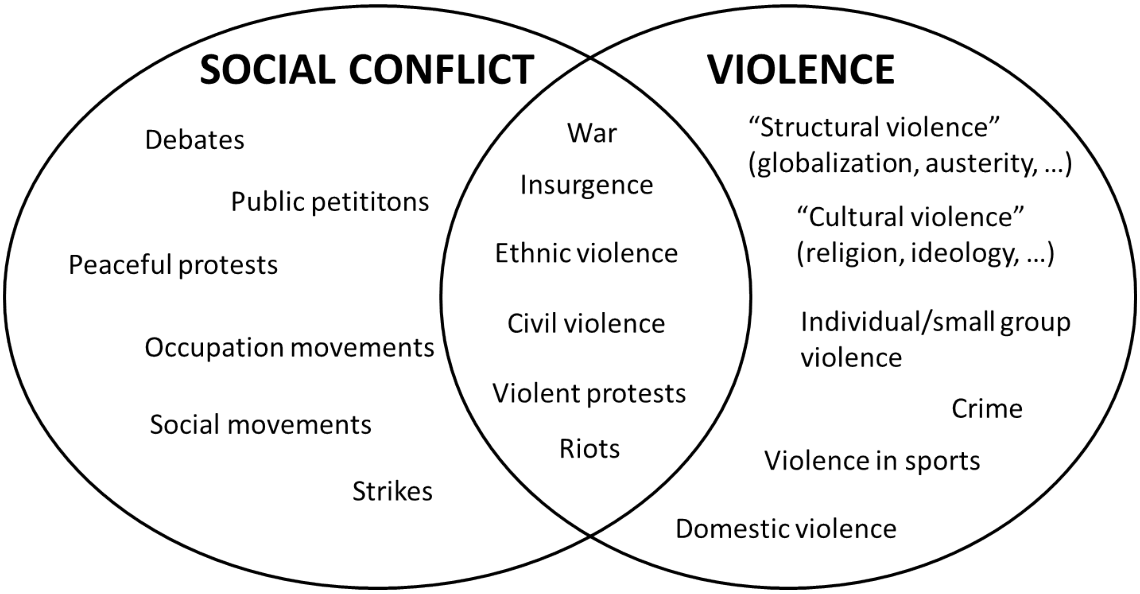


Figure 2.3: Social conflict vs violence manifestations. (Source: author)

> *diffuse and complex phenomenon. Defining it is not an exact science but a matter of judgement. Notions of what is acceptable and unacceptable in terms of behaviour, and what constitutes harm, are culturally influenced and constantly under review as values and social norms evolve.* - in World report on health and violence: summary [109], page 4

There are two conceptions of violence [83]: (*i*) minimalistic, based on coercive use of physical force, response and harm; and (*ii*) comprehensive, which includes avoidable factors that impede human realization and violate rights or integrity. The following definition is an example of the latter type, which further divides violence in three broad categories: self-directed, interpersonal and collective.

Definition 5. Violence – The intentional use of physical force or power, threatened or actual, against oneself, another person, or against a group or community, that either results in or has a high likelihood of resulting in injury, death, psychological harm, maldevelopment or deprivation. (Source: World Report on Violence and Health: Summary [109], page 4)

This definition includes a very wide range of acts, from self-inflicted violence (e.g. suicide) to armed conflict. In this work, we are only interested in the very general aspects of politically-motivated, spontaneous and large scale collective violence, such as occurs in demonstrations with escalation and riots (figure 1.1), which can be discussed in the framework of 'abstract' ABM (chapter 1). In this work, the following definition of civil violence was adopted:[5]

Definition 6. Civil violence – All collective, non-governmental attacks on persons or property, resulting in intentional damage to them, that occur within the boundaries of an autonomous or colonial political unit. (Ted Robert Gurr [49], page 247)

There is a strong relationship between social conflict and violence [83], so that many theorists of social conflict (e.g. Marx, Weber, Dahrendorf, Gurr, Collins, Žižek) also presented theories on violence. Theoretical explanations for the causes of violence have been proposed from the viewpoints of evolutionary biology [67], sociology [83], psychology [49, 9] and criminology [82]. These can be classified in two broad categories: macro-oriented and micro-oriented. Figure 2.4 shows some representative authors of theories of social conflict and violence in both categories.

Macro-oriented theories are focused on structural conditions leading to collective violence, from the standpoints of sociology, economy and historical analysis. One example is the Marxist theory of class struggle, according to which class division and conflict of interests of the different classes over economic resources is the main cause of conflict throughout History [83]. More modern theories are wider in scope and reflect important factors other than economical to explain violence due to social conflict. For instance, Galtung introduced the concepts of 'structural violence' [39] and 'cultural violence' [40]. The former is a designation for all forms by which social structures or institutions harm individuals by preventing their attainment of basic goals. The latter encompasses the aspects of a culture that can be used to legitimize direct or structural violence.[6] Žižek introduced the concepts of 'subjective' and 'objective' violence to distinguish between forms of violence that are 'seen' and acknowledged (e.g. through 'media' reports), like crime, terror, riots and war, and forms of violence of symbolic and systemic origin that are 'unseen', i.e. which are always present, but tend to pass unnoticed in the citizens' everyday life [111].[7]

Micro-oriented theories on the causes of violence are mainly based on evolutionary biology and psychology. Gurr [49] considers three types psychological theories of aggression, namely instinctual-only, learned-only and frustration-aggression.

[5]We will not consider insurgence and war, since these conflict manifestations involve the use of weapons, a higher degree of organization, and different mechanisms than those of the phenomena at the lower end of the violence intensity spectrum (figure 1.1).

[6]Nationalism, racism and sexism are typical examples of 'structural violence'. Religion and ideology are potential sources of 'cultural violence'.

[7]Žižek's 'objective' violence thus includes 'structural' and 'cultural' forms of violence. Unemployment, job insecurity and cuts in public institutions that provide social welfare fit into the categories of 'structural' and 'objective' violence.

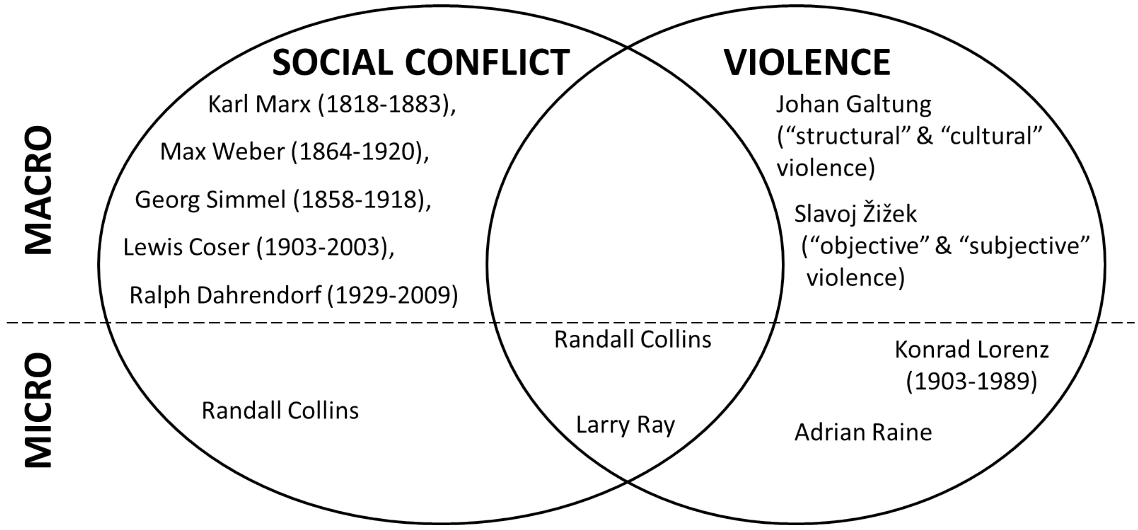


Figure 2.4: Social conflict vs violence perspectives. (Source: author)

Instinctual theories of Freud and Lorenz assume that aggression is a 'hard wired' trait of human behaviour. According to Lorenz [67] aggression has a fundamental evolutionary value for the preservation of species by ensuring the spreading over the available habitat, thus securing territory and resources. Aggressive behaviour results from a tension between conflicting drives, aggression (attack) and fear (escape). There is a stimulus threshold for eliciting attack which can be lowered by situational factors. Symbolic and ritual behaviour, and the formation of habits, are evolutionary mechanisms for redirecting aggression and avoiding excessive and harmful intra-specific aggression. Flocking is an evolutionary mechanism of collective behaviour for providing protection from predators. Lorenz also attempts to explain crowd behaviour in terms of the mechanism of "mass enthusiasm". According to Lorenz [67] the development of weapons associated with intra-specific violence in response to ecological crises and struggle for dominance prompted cultural restraints on the use of violence.

Learned-only theories were developed mainly by child and social psychologists [49]. According to these theories, aggressive behaviours are learned and used rationally in pursuing specific goals.

2.2 Ted Gurr's Frustration-Aggression Theory on the Psychological Factors of Civil Violence

Ted Gurr's frustration-aggression theory of civil violence [49] is more systematic and complete and has stronger empirical support than the ones mentioned above. It is based on the frustration-aggression hypothesis of Dollard et al. [27] according to which aggression is caused by frustration due to interference with goal-directed behaviour and expectations [9, 49]. Also, threat of punishment may cause aggression to be displaced to a substitute target or to a change of form.[8]

Gurr formulated a theory on the psychological factors that determine the likelihood and magnitude of civil violence, based on the assumption that frustration is a function of (illegitimate) RD. The core of this theory consists of: (*i*) the identification of the variables that determine the magnitude of civil violence; (*ii*) a set of propositions concerning their effect on the potential for civil violence and collective response; and (*iii*) a scheme for describing the possible outcomes in terms of (*i*) and (*ii*).

Table 2.1 lists the propositions of the theory, which are divided in three groups [49]. The propositions in the first group (I) describe the potential for civil violence in terms of RD, commitment to a goal, and legitimacy. The second group (M) includes propositions relating the collective response to fear/deterrence (retribution), group protection/support, persistence of anger and memory effects, and institutionalized forms of protest (e.g. authoritarian vs democratic regimes). The last group (F) includes additional propositions on the type and scale of civil violence. Figure 2.5 shows the effect of the variables considered in this theory on the potential for civil violence (DISCONTENT-ANGER-RAGE), reinforcement/inhibition of collective action (COLLECTIVE RESPONSE ALTERNATIVES) and type/scale of civil violence (when it exists).

This theory is important in the context of the present work, because it (*i*) links psychological and individual factors to structural social context factors considered in social conflict theories; (*ii*) identifies important variables and mechanisms that determine the likelihood, magnitude and type of civil violence (i.e. the macroscopic emergents of conflict processes); and (*iii*) is very systematic and based on a set of propositions which can be translated into ABM. Inspection of table 2.1 and figure 2.5 shows that, according to this theory:

[8] This is in agreement with the aggression theory of Lorenz [67], which explains the role of redirection in terms of its evolutionary value.

Table 2.1: Ted Gurr's propositions on the influence of psychological factors in the likelihood and magnitude of civil violence. (Source: Ted Gurr, [49])

I.1	The occurrence of civil violence presupposes the likelihood of relative deprivation among substantial numbers of individuals in a society; concomitantly, the more severe is relative deprivation, the greater the likelihood and intensity of civil violence.
I.2	The strength of anger tends to vary directly with the intensity of commitment to the goal or condition with regard to which deprivation is suffered or anticipated.
I.2a	The strength of anger tends to vary directly with the degree of effort previously invested in the attainment or maintenance of the goal or condition.
I.2b	The intensity of commitment to a goal or condition tends to vary inversely with its perceived closeness.
I.3	The strength of anger tends to vary inversely with the extent to which deprivation is held to be legitimate.
I.4	The strength of anger tends to vary as a power function of the perceived distance between the value position sought and the attainable or residual value position.
I.5	The strength of anger tends to vary directly with the proportion of all available opportunities for value attainment with which interference is experienced or anticipated.
M.1	The likelihood and magnitude of civil violence tend to vary curvilinearly with the amount of physical or social retribution anticipated as a consequence of participation in it, with likelihood and magnitude greatest at medium levels of retribution.
M.1a	Any decrease in the perceived likelihood of retribution tends to increase the likelihood and magnitude of civil violence.
M.2	Inhibition of civil violence by fear of external retribution tends in the short run to increase the strength of anger but in the long run to reduce it.
M.2a	The duration of increased anger under conditions of inhibition tends to vary with the intensity of commitment to the value with respect to which deprivation is suffered.
M.3	The likelihood and magnitude of civil violence tend to vary inversely with the availability of institutional mechanisms that permit the expression of nonviolent hostility.
M.4	The likelihood and magnitude of civil violence tend to vary directly with the availability of common experiences and beliefs that sanction violent responses to anger.
M.4a	Given the availability of alternative experiences and beliefs, the likelihood that the more aggressive of them will prevail tends to vary with the strength of anger.
M.5	The likelihood and magnitude of civil violence tend to vary directly with the extent to which the deprived occupy organizational and/or ecological settings that provide (1) normative support through high levels of interaction, (2) apparent protection from retribution, and (3) congruent models for violent behaviour.
F.1	The characteristic form of civil violence tends to vary with the differential incidence of relative deprivation among elite aspirants and masses: (1) mass deprivation alone tends to be manifested in large-scale civil violence with minimal organization and low intensity; (2) elite-aspirant deprivation tends to be manifested in highly organized civil violence of high intensity.
F.1a	Whether organized and intense civil violence is large-scale or small scale is a joint function of the extent of mass deprivation and strategic access of deprived elite aspirants to the incumbent potential elite.

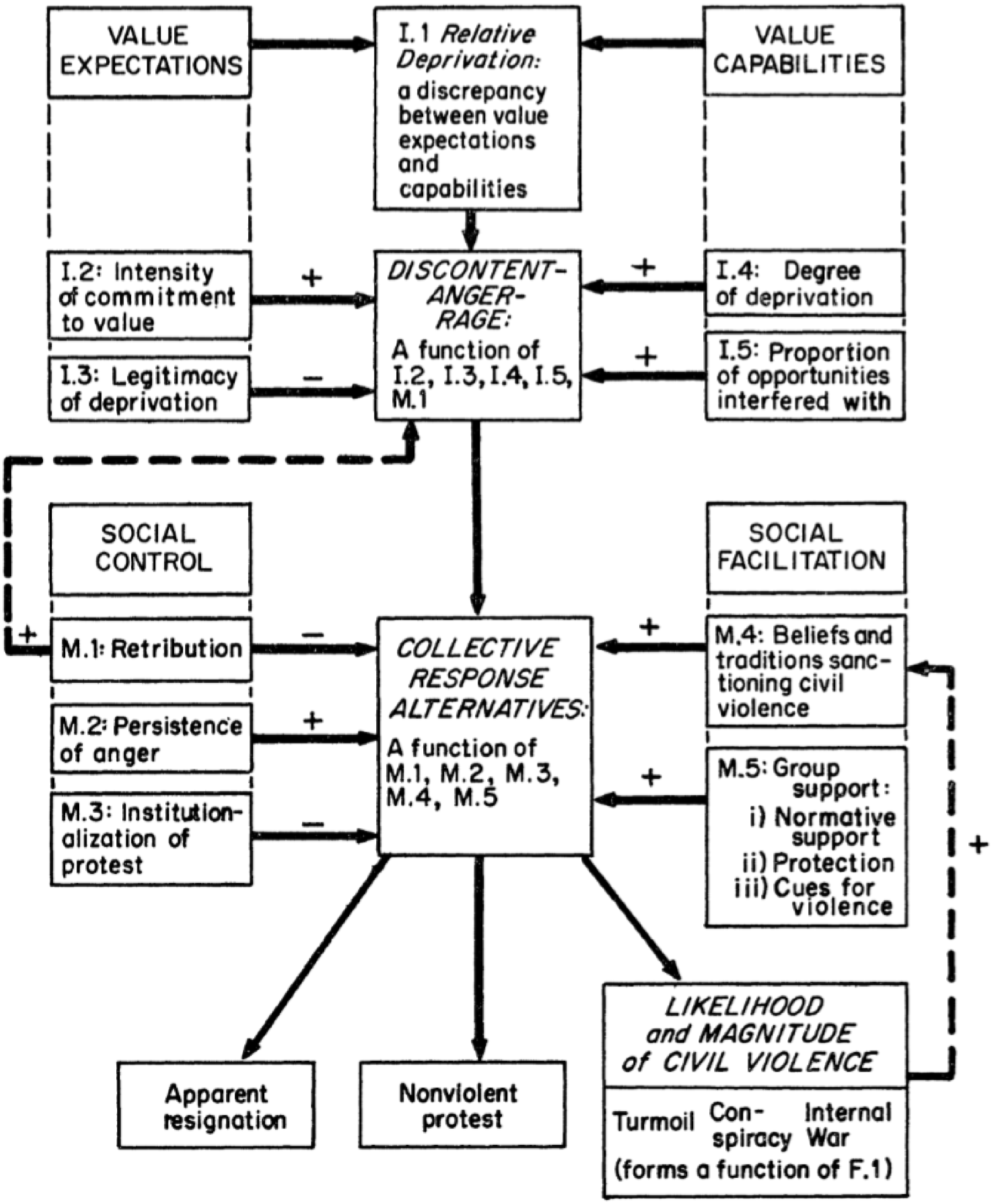


Figure 2.5: Variables determining the likelihood and magnitude of civil violence. (Source: Ted Gurr [49], page 252)

– The three sets of propositions in table 2.1 and the upper, middle and bottom blocks in figure 2.5 bear a correspondence with the potential/mobilization/outcome sequence of the cycle sketched in figure 2.2;

– RD, commitment and legitimacy are important factors of aggression potential;

– Deterrence (perceived likelihood of retribution) and institutional mechanisms for expression of non-violent confrontation inhibit collective violence;

– Group protection and "energizing" enhance collective violence;

– Massive RD within a population tends to result in large-scale, "minimal organization" and low intensity violence, whereas deprivation among "elite aspirants" tends to result in organized, high-intensity violence.

This last proposition conveys some theoretical support for the classification of conflict phenomena sketched in figure 1.1. It is also consistent with the idea that the methods of complex systems studies are suitable for studying conflict phenomena at the low end of the violence spectrum, in the sense that it identifies a set of basic mechanisms – illegitimate RD and commitment to value leading to grievance, group support/protection as an amplifier, and retribution/deterrence as an inhibitor of collective response – that expressed in terms of simple rules lead to large scale (almost) self-organized peaceful or violent protests involving a large proportion of a society. Furthermore, this theory states a key precondition for the likelihood of insurgence and war instead of large scale, self-organized, low violence uprisings: the existence of deprived aspiring elites.

2.3 Gene Sharp's Theory of Non-violent Action

Although not as formal as Gurr's frustration-aggression theory, Gene Sharp's theory of non-violent action is also relevant for the present work, for it has been considered as strongly influential in large scale conflict processes against authoritarian regimes and has been closely associated with the AS [75, 80], which will be considered in chapter 4.

In his extremely influential book "From Dictatorship to Democracy, A Conceptual Framework for Liberation" [92], Gene Sharp considered the problem of overthrowing authoritarian regimes without allowing new dictatorships to emerge and developed his well-known theory of non-violent action. This author argues that violence is a bad way of fighting a dictatorship, for this only triggers brutal repression and the government usually has much superior military and police forces than liberation movements. Likewise, guerilla warfare (insurgence) is usually prolonged, causes many victims, and rarely leads to democracy, either because of external influences or because insurgents later turning into new dictators. A *coup d'etat* lead by military forces is not usually a solution, since it tends to prolong the asymmetry of power distribution within the society and leads to new dictatorships. Sharp also considers that external intervention, even under the auspices of the United Nations (UN), has doubtful outcome, because international powers act according to their interests and for that reason may even support authoritarian regimes.

After considering the drawbacks of violence, Sharp considers two other forms of conflict resolution, negotiations and resistance via non-violent action.

Negotiations may be effective in labour questions (e.g. involving Unions, strikes, etc.) but not in situations involving fundamental issues such as human rights, or individual political or religious liberties, because these latter do not admit compromise. Furthermore, it is vital for negotiators to avoid confusing the goals with the negotiation process and falling into the trap of conferring legitimacy to dictators. For this author also, legitimacy is a key variable.

In Gene Sharp's theory, resistance via non-cooperation and non-violent action is the only effective way of fighting dictatorships, and the force of the movement must come from within the society. This theory has many points of interest for the present work. First, non-violent action is a complex process, involving a diversity of methods (in Annex 1 of [92], Sharp lists 198 different methods of non-violent action, particularly demonstrations, strikes, and boycotts). Second, large and continued protests tend to generate a collective sense of fear control in the population, which can be interpreted as a hypothetical mechanism of 'massive fear loss' once protests become sufficiently large and frequent. On the other hand, large and continued protests weaken the government's strength, but may lead to brutal repression and further loss of legitimacy. Third, the existence of strong, independent social groups and institutions, and careful strategic planning are vital for the success of non-violent fight against dictatorships. Thus, Sharp's theory of the fight for democracy in authoritarian regimes blends considerations of complexity with hierarchical and strategic thinking.

The interest of Gene Sharp's theory for the present work lies in trying to confirm some of its premises via the analysis of datasets of conflict events and international indicators for countries affected by the AS. More specifically, it would be interesting to try to confirm that both organized and spontaneous events were important in the conflict processes in these countries, and whether or not the time patterns of large events (particularly demonstrations and riots) suggest that a mechanism of 'massive fear loss' was at work.

2.4 Social Context. Macro-Scale Variables and Indicators

Theories of social conflict and violence introduce variables such as RD, legitimacy, commitment and expectations. In the exact sciences, particularly in physics, all quantities are either pure numbers or expressed in terms of fundamental or derived units. In the social sciences the situation is very different because:

- Obtaining estimates for all variables needed to determine the potential for conflict requires using several different datasets or collecting original (context-specific) data;
- Variables such as RD, legitimacy and expectations are often "latent concepts" and must be expressed in terms of other variables available in datasets [44];[9]
- The variables that must be aggregated in ranking formulas or model parameters typically have different nature and meaning, so that the resulting empirical formulae, parametrisations or rankings do not have the kind of dimensional consistency of the formulae in exact sciences;[10]
- Results from questionnaires and opinion polls often measure other factors related to the variables but not the variables themselves [26].

These points highlight fundamental differences between exact and social sciences and the difficulties and limitations of making predictions in the latter. Nevertheless, it is necessary obtain objective (quantitative) indicators for the macro-sociological variables related to the potential of conflict and violence.

There are two types of data sources useful for studying and modelling conflict processes: (i) datasets of indices of political, economic and social factors (related to

[9] A "latent concept" is a variable of that cannot be measured directly and must be expressed in terms of other variables [66, 44].

[10] For instance, variables like economic indices are objective and can be obtained from reliable datasets, but other variables such as "economic expectations" and "legitimacy perception" are subjective and cannot be evaluated in the same way.

causes/potential), and (*ii*) datasets with information on conflict events (related to effects/manifestations). Table 2.2 shows a summary of data sources of both types.

Table 2.2: Representative datasets of potential conflict indicators (indices of political, economic and social factors) and information on conflict events. (Source: author)

Name	Organization	Variables	Description
Fragile States Index (FSI)	The Fund for Peace (FFP)	cause	Twelve social, economic, political & military subindicators for 178 countries (in 2015)
World Development Indicators (WDI)	The World Bank	cause	Extensive database of economic indicators for all countries
The Economist Intelligence Unit (EIU)		cause	Economic, political and socio-demographic indicators for about 200 contries
Freedom in the World	Freedom House	cause	Political rights & civil liberties indicators, classification of 195 countries as "free", "partially free" and "not free"
World Database of Happiness	Erasmus University of Rotterdam, Happiness Economics Research	cause	Database on subjective enjoyment of life
Uppsala Conflict Data Program (UCDP)	Uppsala University	effect	Tabular information on state & non-state armed conflicts (location, opponents, year, intensity, start/end dates, etc.)
Social Conflict Analysis Database (SCAD)	University of North Texas & University of Denver	effect	Tabular information of conflict manifestations (demonstrations, strikes, riots,anti-government violence, etc.) - Africa, Mexico, Central America, Caribbean

The Fragile States Index The Fragile States Index (FSI), issued by The Fund for Peace (FFP) since 2005, is an annual index for measuring vulnerability to conflict that includes 178 countries.[11] The FSI is computed from a large number (about 11.000) of public sources using the Conflict Assessment System Tool (CAST) software [6], based on 12 political, social and economic indicators (see table 2.3) which in turn are based on more than 100 sub-indicators. There is also a CAST Manual for simplified hand-calculation of the FSI [38].

The FSI score was developed as an indicator of state vulnerability to conflict, and has the advantage of providing aggregate quantitative indicators of variables like economic decline, human rights and rule of law, group grievance and state legitimacy, which are of primary importance for the present work. However, it also has significant limitations. For instance, it is only available since 2006, which is a limited period for

[11]Each indicator is computed in a 0-10 scale. The lower the score, the more stable the country. For 2015, the FSI ranges from 17.8 (for Finland) to 114.5 (for South Sudan), with Portugal ranking 15^{th} in stability with a score of 29.7.

Table 2.3: Social, Economic, and Political & Military sub-indicators of the FSI. (Source: The Fragile States Index (FSI) [38])

Social Indicators	**Economic Indicators**	**Political and Military Indicators**
Demographic Pressures	Uneven Economic Development	State Legitimacy
Refugees and Internally Displaced Persons	Economic Decline	Public Services
Group Grievance		Human Rights and Rule of Law
Human Flight and Brain Drain		Security Apparatus
		Factionalized Elites
		External Intervention

deriving trends. Also, the final score is the arithmetic average of the indicator scores, whereas in reality some indicators are more important the others.[12] Also, none of the indicators is directly related to levels of expectation, frustration or symbolic values, or to thresholds of violence.

The World Development Indicators The World Development Indicators (WDI) published by the World Bank provide statistics for a large number of indicators related to global development for 214 countries (188 World Bank member countries and all economies with populations of more than 30,000) [54]. Many indicators are economic, but some are related to other important factors such as access to the Internet and the use of mobile phones, which are useful for model parametrization.

Freedom in the World The Freedom in the World is a annual report on political rights, civil liberties and status published by the Freedom House. The 2015 edition covers 195 countries [54]. The country scores for Political Rights and Civil Liberties are given as two numerical ratings from 1 to 7, and the status can be “Free”, “Partially Free” and “Not Free”. Scores can also be computed manually by analysts based on descriptors. This database is useful for obtaining estimates of political RD.

World Database of Happiness The World Database of Happiness is an archive of indicators on subjective enjoyment of life. Another database of this type is the

[12]This may be one of the reasons why the FSI ranking leads to some unrealistic results, e.g. in 2015 Portugal scores ahead of Belgium, the United Kingdom, France, the United States and Japan.

World Happiness Report [52], issued by the United Nations Sustainable Development Solutions Network. This latter is more general and contains international scores of subjective well-being in a scale 0-10, but is relatively recent.[13] Trends in happiness scores were found to convey important clues for explaining the AS uprising ([78], page 37).

Social Conflict Analysis Database The Social Conflict Analysis Database (SCAD) [89][14] is an extensive database of tabular information on conflict manifestations in the years 1990-2013. It includes very important information for the purposes of the present work, such as the type of event (organized/spontaneous demonstrations, limited/general strikes, organized/spontaneous violent riots), the motif (issue), occurrence of repression or escalation, start and end dates, estimate of the number of people involved, and number of deaths (if any). These items of information are useful for comparing model results of test cases with sequences of real events. For instance, it is possible to relate protests and riots to political, social or economic issues, and to determine the proportion of events that escalated up the violence ladder (figure 1.1, page 2). However, the SCAD database also has limitations: it only includes countries in Africa and Latin America, and so does not contain information about protests in European countries, which would be very valuable, and only the order of magnitude of number of participants in each conflict event is given.

2.5 Indices of Economic Deprivation

Economic RD is related to poverty and inequality, since the concept of RD implies comparison of value and frustrated expectations.[15] Measuring poverty and inequality is an important problem in global economics and politics and also in studies of vulnerability of countries to conflict. A very thorough survey on measures of poverty, inequality and indices for expressing them can be found in Haughton and Khander [51]. In the present work, inequality indices other than the FSI Inequality indicator are important for synthesising simplified distributions of value in the artificial populations generated in the ABM.

The Lorenz curve is often used to characterize the inequality of income of wealth

[13] The first edition of this report was published in 2012.
[14] The SCAD was previously known as the *Social Conflict in Africa Database*.
[15] Poverty and inequality can also be factors of exclusion or social RD.

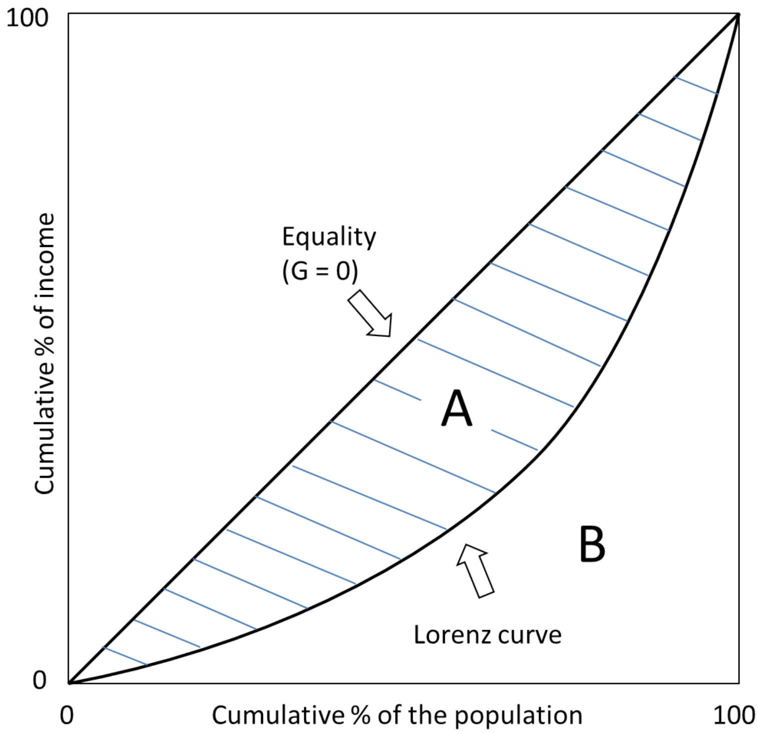


Figure 2.6: Lorenz curve for representing inequality of income. (Source: author)

distributions. This curve describes the cumulative proportion or % of the income as a function of the proportion or % the population sorted from minimum to maximum income. If $x(F)$ is the inverse of the cumulative distribution function of the income, the Lorenz curve is given by the expression

$$L(F) = \frac{\int_0^F x(F')dF'}{\int_0^1 x(F')dF'} \tag{2.1}$$

where F is the cumulative proportion of the population. In the case of perfect equality of income or wealth, the Lorenz curve would be a straight line (figure 2.6). In real cases, the Lorenz curve is concave upwards.

The Gini index or Gini coefficient is an indicator used to reduce the information in the Lorenz curve to a single number. The Gini index is defined as the area between the Lorenz curve and the straight line that would correspond to perfect equality, divided by the area under this latter curve (which is equal to 1/2). Denoting by A the area between the curve of perfect equality and the Lorenz curve, and by B the area under the Lorenz curve (figure 2.6), the Gini coefficient G is equal to either $2A$ or $1 - 2B$. Perfect equality corresponds to $Gini = 0$ and $Gini = 1$ to the extreme situation of the richest citizen having all the income.[16] A Gini coefficient below 0.3 is considered low inequality and above 0.6 high inequality.

The "All the Ginis" dataset [13] provides information about "standardized" Gini coefficients, based on 4132 Gini observations for 166 countries in the period 1950-2012, from nine different sources [71]. This dataset is provided as a `.dta` file which can be imported into R [81]. The overall coverage is about 21 %, relative to the maximum theoretical value of $166 \times 63 = 10,458$ country $\times$ year measurements. The standardized coefficients are expressed as percentages, based on three different concepts of welfare, income, consumption/expenditures, and gross or net value, for households and individuals. The methodology for aggregating information from different sources is described in [71]. As mentioned by Milanovic, the dataset has many limitations on accuracy, namely its limited coverage or the aggregation of data from different sources using more than one concept of welfare. Nevertheless, in the context of the present work, the information in the "All the Ginis" dataset is useful for comparisons with the FSI indicators of Uneven Economic Development and Poverty & Economic Decline, and for modelling RD in ABM (§5.2.5).

2.6 Legitimacy

Legitimacy is the value which confers recognition and acceptance of the exercise of power by an authority or institution. It plays a key role in the theories on social conflict and civil violence, for governments perceived as illegitimate by a population are unstable and usually overthrown. Although the concept of legitimacy is a central one in political science, it is an example of a latent concept because it cannot be measured directly. Thus, it has to be expressed in terms of other (lower-order) variables and indicators, or via opinion polls. The first approach is difficult because the concept of legitimacy is multi-dimensional and multi-layered [7], and there is no generally accepted formula for evaluating the legitimacy of states. The second approach also meets with difficulty, because opinion polls often measure other factors related to legitimacy but not legitimacy itself [26].

According to Maurice Duverger, the concept of power is at the root of political science. The ruling authorities always strive to obtain acceptance of their exercise of power, based on a system of beliefs [30]. The belief held by a large proportion of a society that power must be conferred and exerted based on certain origins,

[16] The Gini coefficient usually denoted by G. In this work, it will be denoted by $Gini$ to avoid confusion with the 'grievance' variable in ABM mentioned in chapters 3 and 5.

principles and forms leads to the concept of legitimacy. In this way, legitimacy is not only a key concept in political science, but also a sociological perception, which is therefore relative and contingent. Thus, to Duverger there is no *single* legitimacy, but *legitimacies* that depend on epoch, country, social group, etc.

Beetham [7] considers that legitimacy can be expressed in terms of three main components: legality, normative justifiability and expressed consent. Following this three-component conception, Gilley [43] devised a formula for computing an aggregate legitimacy score for 72 countries in terms of sub-indicators related to three subtypes of legitimacy: *views of legality* (related to formality and law), *views of justification* (related to moral beliefs) and *acts of consent* (related to behaviour).

Table 2.4 summarizes the indicators, data sources, type of variable and relationship with attitude and behaviour considered by Gilley [44] for evaluating the legitimacy scores. Constitutive variables conceptually define the higher-order concept (legitimacy) and substantive variables are selected based on how they correlate with the latent concept [44]. Attitude indicators relate to beliefs of citizens whereas behavioural indicators relate to actions.

The computation of a legitimacy score from raw scores of sub-indicators with different meanings based on datasets of various origins illustrates the difficulties mentioned in §2.4. Gilley computed the score for each legitimacy subtype by first converting the raw values of the variables related to the subtypes' definition and then taking the arithmetic average. This implies accepting the hypothesis that the factors that contribute to each legitimacy subtype are equally important. Aggregating across subtypes raises questions of even greater theoretical importance: are all subtypes equally important? Should legitimacy be evaluated using a weighted average or using a formula (e.g. of the geometric mean type) that requires all three subtypes to be non-zero for non-zero legitimacy? Gilley argues that justification has been the most underestimated legitimacy subtype and proposes a weighted average legitimacy score with 50% weight for *views of justification* and 25% for *views of legality* and *acts of consent* [44].

Although much less formal than the theoretical developments mentioned above, it is worthwhile mentioning the "State Legitimacy" indicator of the FSI. Table 2.5 shows the simplified descriptors for the legitimacy scores in the 0-10 scale, used for manual estimation [38]. It can be observed that corruption is taken as a major issue related to illegitimacy, as eight descriptors contain the word, the other factor being criminal action by the government (in the four top scores). One important drawback of this procedure is the neglect of important factors such as the government's

Table 2.4: Legitimacy indicators related to legality, justification and consent. (Source: Gilley [44]).

Legitimacy sub-type	**Indicator**	**Source**	**Constitutive or Substantive**	**Attitude or Behaviour**
Views of legality	Evaluation of state respect for human rights	World Values Survey 1999-2002 Question 173	Constitutive	Attitude
	Confidence in police	World Values Survey 1999-2002 Question 152	Substantive	Attitude
	Confidence in civil service	World Values Survey 1999-2002 Question 156	Substantive	Attitude
Views of justification	Satisfaction with democratic development	World Values Survey 1999-2002 Question 168	Constitutive	Attitude
	Evaluation of the current political system	World Values Survey 1999-2002 Question 163A	Constitutive	Attitude
	Satisfaction with operation of democracy	Global Barometer Regional Surveys, 2001-2002 Euro Barometer 2001 Euro Candidate 2002	Constitutive	Attitude
	Use of violence in civil protest	World Handbook of Political and Social Indicators IV 1996-2000	Substitutive	Behaviour
Acts of consent	Voter turnout	International Institute for Democracy and Electoral Assistance, 1996-2002	Constitutive	Behaviour
	Quasi-voluntary taxes	International Monetary Fund, Government Finance Yearbook 1996-2002	Substitutive	Behaviour

Table 2.5: Qualitative descriptors for the "State Legitimacy" indicator of the FSI. (Source: CAST Conflict Assessment Framework Manual [38], page 11.)

10	The government on all levels is considered completely illegitimate, and violent opposition exists. Corruption is endemic.
9	High-level government is considered completely illegitimate and criminal, and violent national opposition exists.
8	Government is considered highly illegitimate and criminal, and violent regional opposition exists.
7	Government is considered illegitimate and criminal, and opposition exists on some level but is not violent.
6	Corruption is a major issue but not endemic. Some levels of government may be working on addressing it.
5	Corruption is a major issue but strong policies and programs have been put into place and are having some success.
4	Corruption in government is sporadic and there are some questions regarding legitimacy of some actors within government.
3	Corruption in government is sporadic and oversight mechanisms should be made stronger.
2	Corruption in government is rare but oversight mechanisms should be made stronger.
1	Corruption in government is rare and proper oversight mechanisms exist.
0	There is no corruption in government, there are strong oversight mechanisms and the legitimacy of the government is never questioned.

competence and trust in the police and military apparatus, which are considered in other indicators. Another important drawback is that the weight of state legitimacy is the same as for other indicators, which represents a clear underestimation.

2.7 Concluding Remarks

The main conclusions of the above review of theoretical foundations of social conflict against a central authority can be summarized as follows:

- The two key concepts that determine the potential for conflict are RD and legitimacy. RD is the primary source of conflict potential, and can be political, social or economic. Legitimacy is variable that confers acceptance of the exercise of power to an authority. As such, it plays a central role, because

RD must be perceived as illegitimate to be a source of conflict. Large scale conflict or revolution occurs once the frustration arising from the gap between legitimate expectations and actual capabilities rises above a tolerable gap;

- Two theories were reviewed, Ted Gurr's RD-based frustration-aggression theory on the psychological factors of civil violence, and Gene Sharp's theory of non-violent action. The first is very systematic in its identification of the important variables and mechanisms. Therefore, it is useful because it is based on variables and propositions which can be implemented in ABM of large scale conflict. The second has been considered as an inspiration for large scale conflict processes such as the AS, and contains premises on the role of self-organization and a mechanism of 'massive fear loss' due to large and continued protests which can be discussed using datasets of conflict events (chapter 4);

- Gilley's theoretical framework on the meaning and measure of legitimacy expresses this latent concept as a weighted average of three components: namely views of legality, views of justification and acts of consent. This approach is also suitable as a starting point for tentative implementation of legitimacy feedback in ABM;

- The two types of data sources useful for ABM parametrization and validation are international indicators related to political, social and economic factors, and datasets with summary information on conflict events. Some of these sources were briefly described, together with their advantages, limitations and potential use for model parametrization and validation.

Chapter 3

Review of Agent-Based Models of Social Conflict and Civil Violence

In this chapter we present a review of the SOA on ABM for simulation of large scale social conflict and violence. Existing ABM are focused on specific scales and types of conflict phenomena, and according to Gilbert [41] can be classified as 'abstract', 'middle-range' and 'facsimile' models. 'Abstract' ABM describe emergent properties of conflict phenomena (such as intermittent bursts of protest or rebellion) in terms of a small number of agent types, simple rules and interactions. The main issues of 'abstract' models are explanatory power, clear representation of mechanisms, and simplicity of formulation. Models of this type have been proposed for describing civil and ethnic violence [33, 31], revolution [70] and insurgence [28, 8], as well as workers' protest [56] and urban crime [35]. 'Middle-range' ABM are used to describe phenomena with definite space and time scales, such as the model of the London riots by Davies et al. [25]. The purpose of 'facsimile' ABM is the description of the system's dynamics with as much realism as possible. Models of this type have been proposed for the simulation of riotous crowds [29, 100, 65] and land combat [53].

The review will be centred on 'abstract' ABM, which are of primary interest given the scope and purpose of the present work, which is to study the mechanisms by which context factors lead to large scale conflict events with the maximum simplicity possible (§A.1). Models of other types will be mentioned occasionally, if they contain aspects relevant for the issues considered in 'abstract' ABM. The various ABM are presented and discussed using a simplified ODD framework [48].

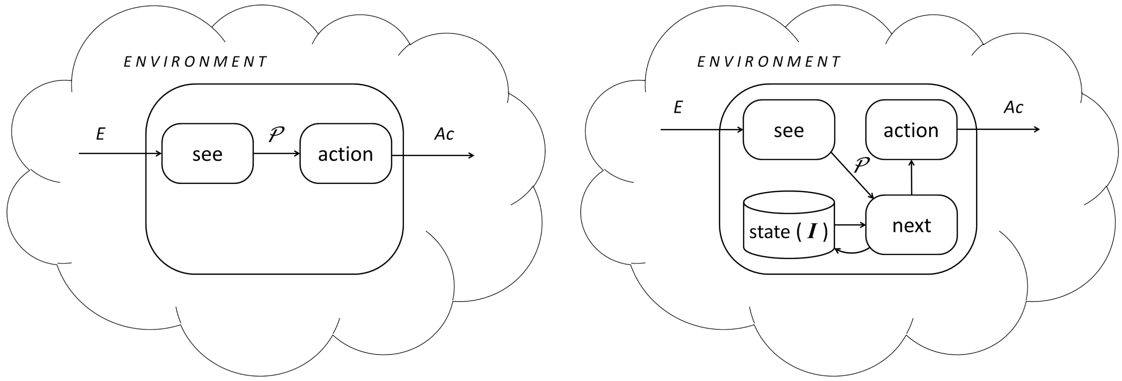
The present chapter is organized in four parts. The first (§3.1) contains a short summary of general definitions and concepts, such as agent architectures and rule-based models of binary decision (e.g. rebel or not; adopt an innovation or not; attack or remain passive; etc.) used in ABM of 'abstract' type. The second (§3.2) contains the presentation and discussion of Epstein's ABM, which is a landmark model of civil and ethnic violence due to its simplicity, soundness and explanatory power. The presentation of Epstein's ABM is complemented by a qualitative discussion of its scope (peaceful vs violent uprisings), mechanisms and scales/contexts (individual, local and global), and role and meaning of the input parameters (§3.3.1-3.3.3). The third part contains a review of extensions of Epstein's ABM proposed by several authors (§3.4), presented by chronological order. These models were aimed at studying conflict phenomena other than civil violence, such as worker protest, revolution and urban crime, and/or including new mechanisms not considered in Epstein's ABM, such as RD-dependent hardship, legitimacy feedback and network influence effects. The chapter ends with a fourth part containing concluding remarks on the limitations of existing ABM, suitable agent architectures and representations of internal processes, and guidelines for the model described in chapter 5 (§3.5).

3.1 Agent Definitions, Architectures and Rule-Based Models of Binary Decision

In this work, the following definitions of "Agent" and "Agent architecture" were adopted:

Definition 7. Agent – An *agent* $\mathscr{A}$ is a computer system that is situated in some environment and is capable of perceiving, deciding and performing actions in an autonomous way. In more abstract terms, if $E = \{e, e', \ldots\}$ is the set of possible environment states; $Ac = \{\alpha, \alpha', \ldots\}$ is the set of actions available to $\mathscr{A}$; $r = (e_0, \alpha_0, e_1, \alpha_1, \ldots)$ is a *run* (sequence of environment states alternating with actions by $\mathscr{A}$); $\mathscr{R}$ is the set of possible finite runs; $\mathscr{R}^{Ac}$ is the subset of $\mathscr{R}$ ending with an action and $\mathscr{R}^E$ is the subset of $\mathscr{R}$ ending with an environment state; then an *agent* is a function that maps runs ending in environment states to actions [108]: $\mathscr{A} : \mathscr{R}^E \to Ac$. (Source: Wooldridge [108])

Definition 8. Agent architecture – An *agent architecture* is a scheme that illustrates the internal arrangement and inter-relations of the data structures, functions,



(a) (b)

Figure 3.1: Agent architectures for a reactive agent (a) and for an agent with internal state (b). In these figures, $\mathscr{P}$ is the agent's percept. (Source: author, adapted from Wooldridge [108])

operations and control flow of an agent. (Source: author, adapted from Wooldridge [108])

3.1.1 Reactive Agents and Agents with Internal State

Agents are called reactive if their agent function is of stimulus-response type and they have no memory or internal representation of the environment, and deliberative if they have reasoning capabilities (deliberation and planning) and internal representation of the the environment [14]. Russel and Norvig [87] consider four agent types: (*i*) simple reflex (reactive), which respond immediately to percepts; (*ii*) agents with internal state, which respond based on percepts and on tracking of their internal state; (*iii*) goal-based agents, which try to achieve goals (by means of searching and planning); and (*iv*) utility-based agents, which try to maximize an utility function. In 'abstract' ABM only the first two types have been used, since the agents only perform very simple actions and do not need to be endowed with sophisticated reasoning capability (for planning and deciding).

Reactive agents are functions that map the current state of the environment into an action, i.e. $\mathscr{A} : E \to Ac$. In the ABM of 'abstract' type discussed below, the agent forms a percept $\mathscr{P}$ through a `see` function and then $Ac \leftarrow$ `action`($\mathscr{P}$), where `action` is another function. Agents with internal state decide by combining their percept $\mathscr{P}$ with their internal state I, which is updated via a `next` function [108]. Figure 3.1 shows the agent architectures for these two agent types.

Table 3.1: Threshold rules used in ABM of complex systems. (Source: author)

Author	Rule(s)	Phenomenon	Comments
Schelling (1971)	$N_{other}/N > T_i$	Segregation	N_{other}: number of agents of "other" type in neighbourhood
Granovetter (1978)	$N_{active} > T_i$	Rioting	N_{active}: number of agents that joined the riot
Epstein (2001)	$G_i > T + R_i \cdot P_{ai}$	Civil Violence	G_i: grievance R_i: risk aversion P_{ai}: estimated arrest probability
Miller & Page (2007)	$Q + e_i > T$ $N_{active}/N > X$	Standing ovations	Q: quality of show (exogenous) e_i: "error" (individual variability in quality perception) N_{active}: number of standing visible agents N: number of visible agents X: threshold proportion of standing visible agents

3.1.2 Rule-Based Models of Binary Decision

Threshold rules have been widely used to model problems of binary decision ($Ac \in \{0, 1\}$, where 0 means "not act" and 1 "act") involving a cost-benefit balance that depends on individual factors and external influences. These rules have been used in 'abstract' ABM of complex systems based on reactive agents to simulate social phenomena such as sorting in segregation [90], behavioural contagion in rioting [47], peer pressure (or majority influence towards conformity, [3, 36]) in standing ovations (SOV) [72], and opposing drives, deterrence and fear extinction in civil violence [33]. Table 3.1 shows examples of classic models of this type. In this table, T is a constant threshold (typically an input parameter) and T_i a threshold for a generic agent i in models for which the threshold is an heterogeneous variable (agent attribute).[17] Combinations of threshold rules are also used for programming agents with more complicated architectures (e.g. in Ilachinsky's ABM of land combat [53]).

Epstein proposed an agent model (*Agent_Zero*) of binary action based on a threshold rule with memory effects, which is an additive combination of three components, affective (V), deliberative (P) and social (S) [32]. The i-th agent *solo disposition* D_i^{solo}, *total disposition* D_i^{total} and action rule are given by the following equations [32]:

$$D_i^{solo}(t) = V_i(t) + P_i(t) \tag{3.1}$$

$$D_i^{total}(t) = D_i^{solo}(t) + \sum_{j \neq i} \omega_{j,i} D_j^{solo}(t) \tag{3.2}$$

$$\text{Action Rule: Act iff } D_i^{tot} > T_i \tag{3.3}$$

[17] The SOV model of Miller & Page involves two rules, with thresholds T and X. The details of the SOV model can be found in [72].

where T_i is the threshold of the i-th agent and the weights $\omega_{j,i}$ represent a dispositional influence network [32]. These equations model the mechanism of *dispositional contagion* instead of *behavioural imitation*, since the behavioural state of other agents does not appear as a variable in equations (3.1)-(3.3). The affective component of the i-th agent is modelled according to a generalized Rescorla-Wagner theory of conditioning [84]:

$$\frac{dV_i}{dt} = \alpha_i \beta_i V_i^{\delta}(\lambda - V_i) \tag{3.4}$$

where V_i is the associative value of the conditioned stimulus CS (e.g. attack–anger) for agent i, $\alpha_i \in [0,1]$ and $\beta_i \in [0,1]$ are learning constants, $\delta \in [0,1]$ is an exponent which determines the form of the "learning trajectory",[18] λ is the maximum associative value of the CS and t is time. Equation (3.4) describes both acquisition and extinction of emotional disposition, by setting λ different or equal to zero, respectively. Epstein's *Agent_Zero* model successfully represents the phenomenon of an agent that initiates action without imitating any other agent, because of susceptibility to dispositional contagion.

3.1.3 Framework for Presentation and Discussion of ABM

ABM can be described using different schemes. One of the most popular is the "Overview, Design Concepts and Details" (ODD) method [48]. However, it would be impractical to describe all the ABM considered in this chapter using the full ODD specification. Thus, the review and discussion of the models will be done according to the simplified framework described in Table 3.2.

3.2 Epstein's ABM of Civil Violence

The ABM by Epstein et al. [33], herein referred as Epstein's model [31], is a successful and popular model for simulation of civil violence. Epstein's ABM is an 'abstract' model, since it describes the mechanisms of large-scale rebellion in terms of a small number of agent types, rules and parameters.

[18] $\delta = 0$ implies an exponential variation, $\delta = 1$ a logistic (S-curve), and $\delta \in (0,1)$ other S-curves which are not analytically solvable (see [32], page 67).

Table 3.2: Framework for the review and discussion of existing ABM of social conflict and civil violence. (Source: author)

Items	**Description**
Purpose	Scope of the model; type of phenomena to be simulated
Entities	Agent types and specification; model environment
Process overview and scheduling	Main cycle and agents' behaviour
Submodels	Submodels that represent processes in 'Process overview and scheduling'
Main results	Phenomena explained by model; scales of the emergent properties
Limitations	Reference to gaps between model results and real processes or events

Purpose The purpose of the model is the description of the dynamics of large-scale decentralized uprisings. The model has two variants of civil violence: rebellion against a central authority (Model I) and ethnic violence between two rival groups mediated by a central authority (Model II).

Model Entities The model includes two types of agents, 'citizens' and 'cops'. The environment is a 2D homogeneous torus space. Tables 3.3 and 3.4 show the global parameters and agent attributes, respectively.

Table 3.3: Global model parameters in Epstein's ABM and their values/ranges taken from Appendix A to Epstein et al. [33]. (Source: Epstein et al. [33])

Parameter	**Value**
Grid dimensions	40×40
Initial population density	0.7
Initial cop density	0.04
Legitimacy, L	0.8 - 0.9
Arrest probability constant, k	2.3
Population threshold, T	0.1
Max. Jail term, J_{max}	15 - ∞
Max. Age (Model II)	200
Cloning probability (Model II)	0.05

Process Overview and Scheduling In this model, 'citizens' remain 'quiet' or become 'active' (rebellious) depending on their grievance towards the central authority (in Model I) or the rival group (in Model II), and on their risk perception. 'Cops'

Table 3.4: Agent attributes in Epstein's ABM and their values/ranges taken from Appendix A to Epstein et al. [33]. (Source: Epstein et al. [33])

Agent type	**Parameter name**	**Variable name**	**Value/ Range**
'citizen'	Vision radius	v	1.7 - 7
	Hardship	H	$\sim \mathcal{U}(0,1)$
	Risk aversion	R	$\sim \mathcal{U}(0,1)$
	Grievance	G	$= H \times (1 - L)$
	Group (Model II)	$group$	"Blue" or "Green"
	Death age (Model II)	$death\_age$	$\sim \mathcal{U}(0, max\_age)$
	Cloning probability (Model II)	p	0.05
'cop'	Vision radius	v'	1.7 - 7

represent the central authority and try to keep order by arresting 'active' citizens. 'Citizen' and 'cop' agents have one movement and one action rule. The move rule is the same for 'citizens' and 'cops':

Rule M: move to a random empty cell within the agent's vision radius.

The (threshold) action rule for 'citizen' agents describes the cost-benefit balance of turning rebellious:

Rule A:	if $G - N > T$	be 'active'; otherwise be 'quiet' (Model I)
	if $G - N > T$	kill one agent of the rival group within the vision radius; otherwise be 'quiet' (Model II)

where $G = H \cdot (1 - L)$ is the grievance, $H \sim \mathcal{U}(0, 1)$ is the perceived hardship, L is the perceived legitimacy[19] assumed equal for all agents, $N = R \cdot P_a$ is the net risk perception, where $R \sim \mathcal{U}(0, 1)$ is the risk aversion, P_a is the estimated arrest probability, and T is a threshold (assumed constant for all 'agents'). The form of the arrest probability presented in [33] and [31] is

$$P_a = 1 - \exp(-k \cdot (C/A)_v) \tag{3.5}$$

where C_v and A_v are the number of 'cops' and 'active' agents within the agent's vision radius v and $k = 2.3$ is the arrest constant [33, 31]. Wilensky [107] proposed to replace equation (3.5) by the alternative form

$$P_a = 1 - \exp(-k \cdot \lfloor (C/A)_v \rfloor) \tag{3.6}$$

[19] In Model I L is the legitimacy of the central authority; in Model II L is the group's assessment of the legitimacy of the rival group to exist, assumed equal for both groups [33, 31].

which leads to a drop of P_a from 0.9 to zero for $C_v < A_v$ and produces complex solutions with large intermittent bursts of rebellion [107, 62]. Other forms for the estimated arrest probability with properties similar to those of equation (3.6) have been proposed by other authors [35, 25]. The action rule for 'cops' is

Rule C: Inspect all sites within v' and arrest a random 'active' citizen

Arrested citizens are removed from the simulation space ('jailed') for $J \sim \mathcal{U}(0, J_{max})$ cycles (jail term). The jailing of citizens introduces a memory effect in the system, with a time scale proportional to J_{max}. All agents are activated one per cycle in random order. Since Model II involves killing of 'citizen' agents, a simple form of population dynamics is implemented in this case: 'citizens' clone offspring with probability p upon activation, and die after *death_age* cycles (Table 3.4).

Main Results Epstein's ABM successfully describes many characteristics of large scale civil violence: large intermittent peaks of rebellion (punctuated equilibrium), and the effects of sudden or gradual drops of legitimacy (controlled increase of the number of jailed 'citizens' in the first case and a sudden large burst of rebellion in the second case), or progressive 'cop' reductions (a sudden burst of rebellion due to the central authority neglecting its deterring capability below a critical point). The strength of Epstein's model lies in its explanatory power, which derives from the simplicity of the formulation and the relevance of the variables chosen for representing the social context and individual factors (§2.1.1 and §2.6).

Submodels The submodels in Epstein's ABM are (i) the expression of grievance as the product of hardship by the perceived illegitimacy, (ii) the expression of the net risk as the product of risk aversion by the estimated arrest probability, and (iii) equation 3.5 for the estimated arrest probability.

Limitations Epstein's ABM is consistent with important aspects of social conflict theories: the potential for conflict is expressed by G, legitimacy is a key variable (Table 2.1, item I.3) and the effects of "retribution" (Table 2.1, item M.1a) and "protection" (Table 2.1, item M.5) on the likelihood and magnitude of violence bursts are represented by equation 3.5. However the model also has limitations towards a more refined representation of real civil violence processes. First, it does not use context data for parametrization. Second, several important mechanisms identified in social conflict theories are not considered, namely:

– The hardship is not defined in terms of RD (Table 2.1, item I.1);

– The effect of collective behaviour on the grievance (i.e. the mechanism that Le Bon [12] calls "madness of the crowds" and Lorenz [67] "mass enthusiasm");

– There is no representation of goal/commitment, leadership, memory and cultural effects (Table 2.1, items I.2, F and M.4);

– Feedback effects, particularly legitimacy variations due to the system's state are not taken into account;

– Network influences (e.g. due to activists using SN) are not considered.

3.3 Discussion of Epstein's ABM

Given the importance of Epstein's ABM of civil violence, it is appropriate to discuss it in greater detail with respect to three aspects: scope, mechanisms and scales. More specifically, the key questions for such discussion are:

– Is the model applicable to civil violence only, or to both peaceful and violent conflict phenomena (demonstrations and riots, in figure 1.1)?

– Which quantities should be used to compare the duration, interval and size of conflict events in real processes and model simulations?

– Which parameters or combinations of parameters are related to scales (of time, space or artificial population), and how do they influence the behaviour of the solutions?

3.3.1 Scope

The scope of the model, i.e. its applicability to peaceful or violent conflict manifestations, is related to the micro-scale mechanisms of individual decision and interaction, and to the macro (system level) memory induced by jailing. The threshold decision rule of 'citizens' expresses a conflict between opposing drives, the impulse to rebel (similar to what Kuran [57] calls the "private preference") associated with G and the fear of retribution expressed by N.

The impulse to manifest opposition to the central authority exists in both peaceful demonstrations and riots. If peacefully showing opposition to the government entails a perceived risk, and law-enforcing agents effectively harm or arrest citizens that peacefully challenge the government (which is the case in dictatorships), then the model can be used to study both peaceful and violent forms of self-organized large scale conflict (mainly peaceful demonstrations and riots), although the values of the parameters G, R and T and the arrest probability P_a may be different in each case.[20]

Ted Gurr's frustration-aggression theory on the psychological factors of civil violence (figure 2.5) is fully consistent with this argument: the mechanisms that relate discontent to collective response are determined by the same mechanisms and factors, but the manifest response may be either peaceful or violent. This hypothesis on the scope of Epstein's ABM can be validated by examining records of conflict events of both types, including escalation in peaceful protests.

3.3.2 Measures of Size, Duration, and Interval (Waiting Time) of Outbursts

In Epstein's ABM the time scale is indefinite. In abstract terms, one model cycle can be thought of as the time interval for all 'citizen' agents in the artificial society to move and decide their next state, and for 'cops' to react. In real societies this depends on how fast the information about the state of other citizens reaches and influences a particular (randomly chosen) citizen and agents of authority respond. In today's highly connected world a time scale of one day is a sensible choice for large conflict events that recur intermittently over longer periods.[21]

One possible way of defining a correspondence between one model cycle and the characteristic time scale of duration and interval between conflict events is to compare dimensionless quantities, such as the proportion of total time with calm and activity or the ratio between duration and interval between successive events, in real processes and simulations.

The absolute size (number of participants) in large demonstrations or riots is perhaps the most important element in terms of news impact. However, in long-term

[20] This situation is similar to e.g. the use of the diffusion equation for modelling both heat and mass transfer in Physics. The mechanism of diffusion at the molecular scale is the same, so that it can be represented by an equation of identical form, with different parameters in the constitutive equation that relates the heat or mass flow to the gradient of temperature or concentration, respectively.

[21] Also, one day is the time unit for the duration and interval between events (start date) in databases of conflict events [88]. In ABM of meso-scale and micro-scale processes like those by Davies et al. [25] for the 2011 London riots, by Jager et al. [55] for fighting between two-party crowds, or by Lemos et al. [63, 65] for street protests, smaller time scales must be used.

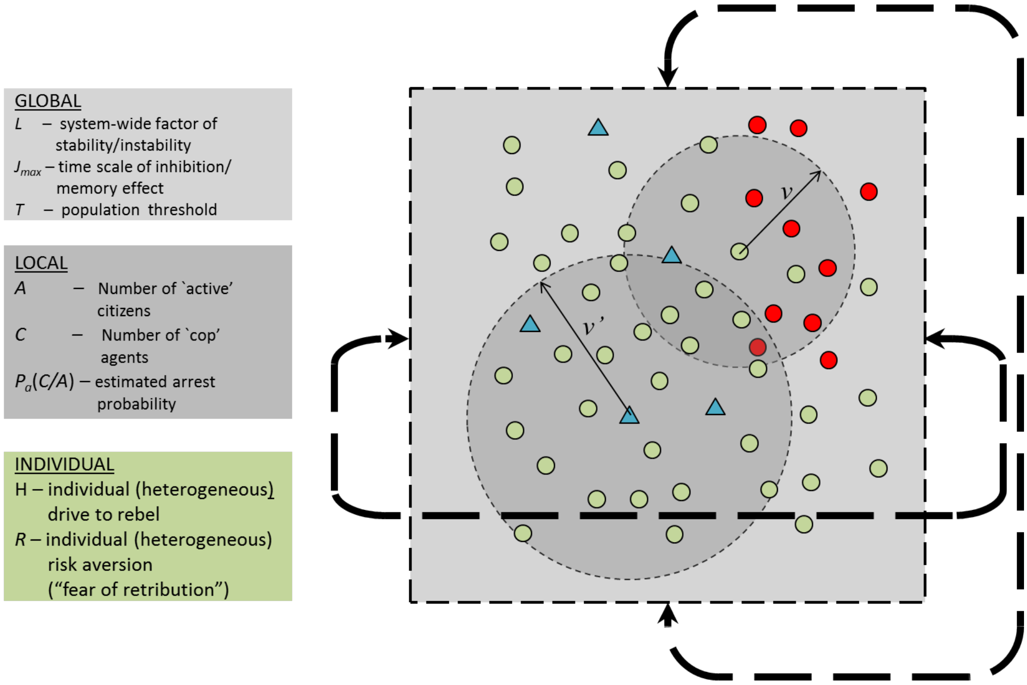


Figure 3.2: Contexts and input parameters in Epstein's ABM of civil violence. The dashed lines represent the boundary wrapping of the 2D torus model space. (Source: author)

nationwide conflict processes, the proportion or % of the population involved in those events is more significant as a measure of the society's mobilization, and more appropriate to compare related processes in different countries. In ABM simulations, the ratios $A(t)/N_{citizen}$ and $J(t)/N_{citizen}$, where $N_{citizen}$ is the total number of 'citizens' and $A(t)$ and $J(t)$ are the numbers of 'active' and 'jailed' citizens at time t, are appropriate measures of simulated uprisings, because they are independent of the number of agents used. It is interesting to try to determine whether or not the % of participants in large scale conflict events depends on a country's population, and how the properties of ABM solutions vary with $N_{citizen}$.

3.3.3 Input Parameters, Scales and Mechanisms

The input parameters in Epstein's ABM are related to three contexts (or scales): individual (agent), local (cells within the agent's vision radius) and global (system). They also influence the mechanisms of emergence and recurrence of large intermittent peaks of rebellion, and consequently the size, duration and interval between these simulated bursts of activity. It is worthwhile discussing how the values (or combinations of values) of these parameters influence the qualitative and quantitative properties of the solutions.

Hardship and risk aversion

The hardship H and risk aversion R are individual attributes specified using probability distributions. The size of rebellion peaks depends on the difference $\mu(H) - \mu(R)$ and on $\mathtt{var}(H)$ and $\mathtt{var}(R)$. It can be expected that the proportion of 'citizen' agents that can potentially turn 'active' increases with diversity (i.e variance) of the individual attributes. As mentioned before, one drawback of Epstein's original formulation is that the hardship is held constant for all agents instead of being expressed in terms of RD. Modelling RD requires some sort of comparison between individual and local or global attributes, and introduces more variability in the grievance term.

Legitimacy, estimated arrest probability and threshold

The decision rule also involves L and P_a, which are global and local, respectively. Legitimacy directly affects the grievance (driving term, impulse to rebel) of the whole population. The estimated arrest probability expresses the effect ot the local context on the risk perception (fear of retribution). To describe the mechanisms that lead to large cascades of rebellion it is necessary to study the decision rule in terms of the distribution of $G - N$ (not just the mean and variance of G and N) and threshold T.

The threshold T can be interpreted as a 'barrier' of perceived risk that cannot be lowered by collective behaviour. In real conflict processes, it is a function of the level of repression and collective experiences and beliefs about violent response by the government (in the spirit of proposition M.4 of Ted Gurr's frustration-aggression theory of civil violence, in table 2.1, page 22).

Vision radii (v and v')

The grid size and 'citizen' and 'cop' densities determine the number of agents of each 'population', $N_{citizen}$ and N_{cop}, as well as their mobility (% of empty cells within the move range). The vision and movement radii v and v' can be interpreted as the size of mobility and influence spaces surrounding an agent. The 'citizens' estimated arrest probability and the 'cops' detection capability depend on v and v', respectively. In previous works such as Epstein et al. [33], Epstein [31]) and Fonoberova et al. [35] the approximation $v = v'$ has been used. Since the two parameters have different effects at the micro level, it is important to discuss the expected behaviour of the solutions for different values of each one and relationships between these values.

For 'citizen' agents, the variance of the ratio $(C/A)_v$ of agents in equations (3.5) and (3.6) decreases for increasing vision radius v. Thus, it can be expected that small v increments the probability of occurrence of localized bursts of rebellion, triggered by agents in the population with larger $G - N$. For increasing v, $\texttt{var}((C/A)_v)$ decreases, and rebellion bursts are hindered. Also, a larger v leads to greater mobility of 'citizen' agents. For 'cop' agents, both the detection capability and the mobility increase with v'. For small v', 'cops' are 'myopic' and rover the space in shorter hops, which limits their efficiency.

The difference between v and v' can be interpreted as a difference between the sphere of influence of 'citizens' in their random contacts, and the information space of the law-enforcing agents. Therefore, *ceteris paribus*, v is associated with the triggering (emergence) and size of the rebellion peaks, and v' (together with the number or density of 'cops') with their suppression (duration of rebellion peaks). Thus, it can be expected that the difference between v and v' has a significant impact on the solutions' behaviour. Although these considerations shed some light on the behaviour of Epstein's model, the mechanisms by which different combinations of input parameters may lead to stable or complex solutions must be studied via computer experiments.

<u>Deterrence</u>

Deterrence, or the capability of the central authority to prevent and suppress rebellion, is an essential element in the dynamics of conflict. In Epstein's ABM deterrence is a function of 'citizen' agents' local conditions via $P_a(C/A)$. The parameters that influence deterrence are the threshold (considered above), the density of number of 'cop' agents, v' and J_{max}. The influence of progressively reducing the number of 'cops' was studied in Epstein et al. [33], and Epstein [31], but the effect of the other two parameters on the solutions' behaviour was not investigated in a systematic way.

The probability of detecting an 'active' citizen in a randomly chosen cell depends on the density (or number) of 'cops' and on v'. If the union of the 'cops' individual information spaces does not cover the whole simulation space (due to an insufficient number of 'cops', small v', or both), then rebellion bursts can start and grow undetected. This explains the sudden rebellion burst as the number of 'cops' is progressively reduced found by Epstein [33, 31], and also suggests that the model has tipping points associated with v', in a way similar to percolation or the formation/break up of the giant component in random networks.

3.4 Abstract ABM Based on Epstein's Model

Epstein's model has been extended by various authors to implement more mechanisms and study conflict phenomena other than civil and ethnic violence [59]. Since the structure of these models is similar to that of Epstein's ABM, only the salient aspects of the formulations and the main results will be mentioned.

3.4.1 The EMAS Civil Violence Model of Goh and Collaborators

Goh et al. [45] proposed an improvement of Epstein's Model II for civil violence between rival groups. In this model, the tendency to revolt is expressed in terms of two attributes, grievance G and greed Gr plus a time factor T_f weighting these attributes. Also agents' movement is performed according to specific strategies which are improved by evolutionary learning. Furthermore, arrest is not automatic – instead, 'cops' and 'actives' play an Iterated Prisoners Dilemma (IPD) game and an arrest is made when the 'cop' wins. The main results obtained with this model can be summarized as follows: (*i*) the model produced solutions with punctuated equilibrium as with Epstein's model; (*ii*) grievance is more important than greed for the onset of rebellion; and (*iii*) the introduction of purposeful movement resulted in patterns of group clustering.

The EMAS model introduces interesting formulations such as non-automatic arrest and purposeful movement with evolutionary learning, which may provide better representation of the some psychological factors of civil violence such as M.4 and M.5 in Table 2.1. On the downside, the authors do not present empirical evidence and it is not clear that in practice the more sophisticated formulation is any better than Epstein's. For instance, there is no link between RD and grievance, and it is questionable whether greed is a very relevant factor of group grievance and social deprivation.

3.4.2 An ABM of Worker Protest by Kim and Hanneman

Kim and Hanneman [56] proposed and ABM of worker protest with 'citizens' replaced by 'workers' in which the grievance is expressed as a function of RD resulting from wage inequality, and state changes (between 'quiet' and 'active') depend on group identity effects. This approach is well founded since RD and group grievance are positively correlated with the potential for conflict [94, 50]. The model has one global variable, the 'wage dispersal' WD, and 'worker' agents have three more attributes with respect to Epstein's model: wage $w \sim \mathcal{N}(WD/2, (WD/6)^2)$, "tag" $t \simeq \mathcal{U}(0, 1)$ and "tolerance" $T \sim \mathcal{N}(1/2, 1/6^2)$. In this model RD is computed as the difference between the ego's wage and the average wage of visible 'workers', and the grievance is expressed in terms of RD as (figure 1 of [56]):

$$G = \left| \frac{2}{1 + e^{min(0,RD)}} - 1 \right| \tag{3.7}$$

which gives zero grievance for ego's wage above average and rapid increase of G for small negative values of RD. For agent i, an agent j within vision radius is labelled as "us" if $|t_i - t_j| < T_i$ and "them" otherwise. If group identity is not taken into account, 'workers' change state according to Rule A (§3.2, page 43). If group effects are taken into account, the number of visible "us" must be greater then the number of visible "them" for 'workers' to turn 'active', in addition to Rule A. Solutions obtained with this model showed punctuated behaviour as in Epstein's Model I, and protest frequency was more influenced by wage inequality than by group tag effects. This model introduces important ideas, such as RD and group effects. However, the authors did neither present a clear theoretical justification for the chosen form of $G = f(RD)$ (e.g. in relation to Ted Gurr's frustration-aggression theory of civil violence), nor attempt any empirical validation of their results.

3.4.3 A Study of Urban Crime by Fonoberova and Collaborators

Fonoberova et al. [35] used Epstein's model to study the dynamics of crime and violence in urban settings. The purpose of this study was to determine the dimension of a police force necessary to keep crime and violence in a city below a certain threshold level. These authors considered: (i) different forms of the arrest probability function with monotonic and non-monotonic variation; (ii) the effect of 'citizens' that never change state; (ii) different grid sizes (to simulate the conditions in small and large cities), population densities and number of "law enforcement officers" per 1,000 inhabitants. The model simulations were compared with datasets on crime and violence in 5,560 U.S. cities. The main findings of these authors are:

– The proportion of Â´'law enforcement officers" required to maintain a steady low level of criminal activity increases with the size of the population of the city;

– The number of criminal/violent events per 1,000 inhabitants in a city shows non-monotonic behaviour with the population size;

– For all population sizes considered, the model showed tipping points, for reducing the number of "law enforcement agents" below a critical level rapidly increases the incidence of crime and violence;

– The solutions are sensitive to the form of the arrest probability function. Forms of P_a with non-monotonic variation with $(C/A)_v$ (which the authors consider to encode "partially irrational behaviour" associated with risk perception) lead to better agreement with data;

– Violence in small cities is characterized by global outbursts whereas in large cities these peaks are decentralized.

The work by Fonoberova and collaborators [35] has important and distinctive aspects, such as highlighting the importance of the form of P_a, the use of large numbers of agents and real data for model validation, and systematic exploration of the 3D parameter space of 'citizen' density, number of "law enforcement agents" and population size. However, it also has significant drawbacks. For instance, the grievance is expressed in terms of legitimacy, which is very questionable in a model of urban crime. The authors did not explain why non-monotonic forms of P_a significantly change the solutions' behaviour. Also, the values $L = 0.8$ and $T = 0.1$ are similar to those used in Epstein's Run 2.[22] In the exploration of the parameter space, the vision radius of 'citizens' was set to $v = \sqrt{N_c/(\pi * \texttt{citizens density})}$, where $N_c = 2124$ is the number of nearest neighbours of a citizen, and $v = v'$, but the authors did not investigate the solutions' behaviour as a function of these parameters.

3.4.4 Extensions of Epstein's Model I by Lemos, Lopes and Coelho

Lemos, Lopes and Coelho proposed extensions of Epstein's Model I, including imprisonment delay (a time cost for 'cops' to arrest 'citizens') [61], endogenous

[22]In §3.3 it was show by a qualitative analysis that legitimacy and the vision radii v and v' strongly influence the solutions' behaviour. In §5.2.1, it will be shown that there exists a relationship between L, T and P_a which determines the proportion of 'citizens' that can potentially turn active.

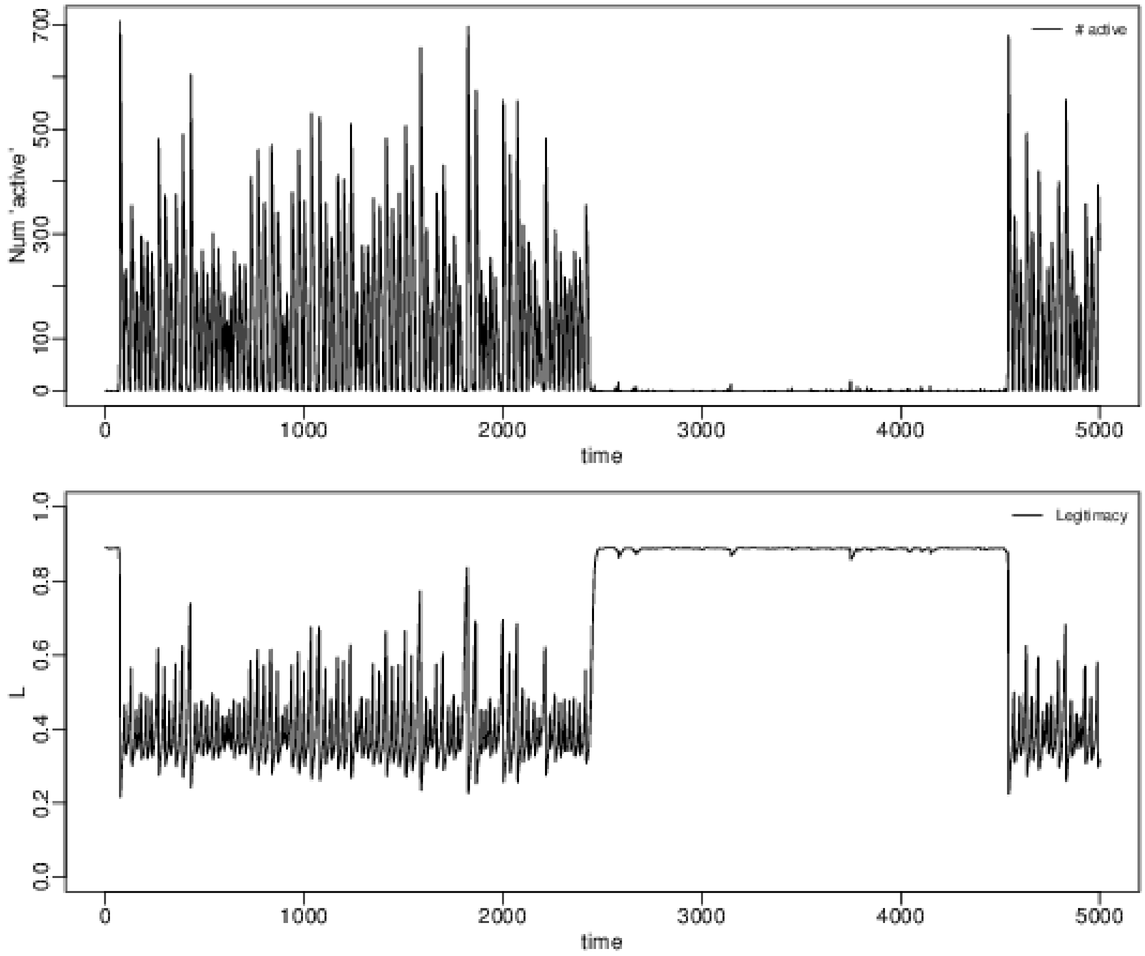


Figure 3.3: Time history of the number of 'active' citizens (for a population of 1120 'citizens') and legitimacy for a simulation of the R21G case reported in [64], showing long alternating periods of calm and unrest. (Source: Lemos et al. [64])

legitimacy feedback [61, 64] and network influence effects [62]. Two of these models included a new type of agent called 'media', endowed with a primitive form of purposeful movement, which were not arrested by 'cops' and provided non local information to 'citizens'. These extensions lead to more complicated dynamics than the original model.

Imprisonment delay effectively introduces a second time scale (in addition to J_{max}). If the ratio between the imprisonment delay interval and the jail term is sufficiently small, the solutions show intermittent bursts of rebellion which show a fine structure (due to individual arrests taking place at different time steps) and take longer to be suppressed by 'cops' than with Epstein's ABM. As this ratio is increased, the solutions' long term behaviour changes to permanent rebellion [61].

Epstein et al. [33] suggested a mechanism for introducing endogenous legitimacy feedback in Model II (ethnic violence), but this approach was neither implemented nor further explored for the case of civil violence (Model I). In [61] and [64], the authors implemented various formulations of legitimacy in Epstein's Model I, based on Gilley's approach described in §2.6. Two types of legitimacy feedback were considered, homogeneous and heterogeneous. The authors found that legitimacy feedback leads to very interesting effects, such as intermittent alternations of regime (very long periods of calm followed by very long periods of unrest, with unpredictable transitions between them, as shown in figure 3.3) or apparently stable authoritarian regimes facing an unexpected massive uprising and struggling afterwards with intermittent rebellion because they never recover their initial legitimacy [64]. Also, heterogeneous legitimacy feedback leads to more unstable solutions than homogeneous legitimacy feedback, showing that non linear effects are important.

In [60], the same authors presented and extension of the ABM described in [61] and [64], with network influence effects due to two different networks, 'family' and 'news'. These two networks represent the information spaces for two important influence modes in a society, one associated with small and highly cohesive communities (strong ties, two way influence) [46] and another associated with influential agents that shape global perceptions (weak ties, one way influence) [103]. In this model, the 'family' network consists of the union of cliques of citizens connected by undirected links, and the 'news' network of the union of directed star networks with 'media' agents as hubs.

The influence due to the 'family' network was implemented by replacing the action rule for citizens by a two step rule (somewhat similar to the two step rule in the Standing Ovation model of Miller and Page [72]):

Rule A_1: if $G - N > T$ be 'active'; otherwise be 'quiet'
Rule A_2: if more than 50 % of 'family members' are 'active', be 'active'

where G, N and T are the grievance, net risk and threshold, respectively. Hence, the 'family' influence is expressed via the mechanism of majority influence [36] (or conformity-driven *behavioural imitation* [32]). The 'news' influence is modelled in a different way, via legitimacy feedback. The expression for the (endogenous, variable) legitimacy [60]:

$$L = L_0 \cdot \left(\frac{1}{4} \cdot (L_{leg} + L_{cons}) + \frac{1}{2} L_{just} \right) \tag{3.8}$$

with

$$L_{leg} = \frac{n_{quiet}}{N} \tag{3.9}$$

$$\begin{aligned} L_{just} =& \frac{1}{2} \cdot \left(1 - \frac{n_{active} + n_{fighting}}{N}\right) + \\ &+ \frac{1}{2} \cdot \left(1 - \exp\left[-\frac{\ln(2)}{2} \cdot \left\lfloor \frac{N}{n_{active} + n_{fighting} + n_{jailed} + 1} \right\rfloor\right]\right) \end{aligned} \tag{3.10}$$

$$L_{cons} = L_{leg} \tag{3.11}$$

where L_0 is the initial legitimacy[23] N is the population size and n_{quiet}, n_{active}, $n_{fighting}$ and n_{jailed} are the total number of 'citizens' in each state. The influence of the 'news' network is computed by replacing n_{quiet}, n_{active}, $n_{fighting}$ and n_{jailed} by aggregate values:

$$n^*_{active} = \alpha \cdot A_v + \alpha_f \cdot \overline{A_f} + \alpha_m \cdot \overline{A_m} \tag{3.12}$$

and analogous expressions for n^*_{quiet}, $n^*_{fighting}$ and n^*_{jailed}. In equation (3.12), A_v, A_f and A_m denote the numbers of 'active' citizens that are 'visible', 'visible by family members' and 'visible in news', respectively; α_f and α_m are the influence weights for the 'family' and 'news' networks; and $\alpha = 1 - \alpha_f - \alpha_m$.

The model was run for different combinations of network sizes and influence factors, legitimacy feedback modes (homogeneous and heterogeneous) and values of the initial legitimacy. In was found that network influences did not change either the system's long term behaviour or the periodicity of the violence bursts but increased their size. Legitimacy feedback had a more profound influence, since it changed the system's long term behaviour from punctuated equilibrium to permanent unrest with no calm periods, or produced solutions with intermittent regime (unpredictable alternations between long periods of calm and turmoil).

Although the model described in [60] produced interesting results, it also has several drawbacks. The influences of the 'family' and 'news' networks are represented in very different ways. The 'family' network directly influences the 'citizen's state and, in the case of heterogeneous legitimacy feedback, the perceived legitimacy. The 'news' network only influences the legitimacy perception, whereas in reality network influences have other effects. Also, variations of the artificial society's size were not considered, and no validation or parametrization using real data or social indicators

[23] In the ABM presented in this work, L_0 is the value of the `government-legitimacy` input parameter (table A.4, page 194).

was performed.

3.4.5 The ABM of Violent Political Revolutions by Alessandro Moro

Recently, Alessandro Moro proposed an ABM for the dynamics of violent political revolutions with three types of agents: citizens, armed revolutionaries, and agents of a central authority [74]. Citizens may be quiet or rebellious, armed revolutionaries try to kill agents of the central authority, and agents of the central authority try to maintain order by arresting rebellious citizens and killing armed revolutionaries. The purpose of the model was to describe the patterns of the time evolution of revolutions, including (*i*) pre-revolutionary spontaneous riots, (*ii*) rebellion, and (*iii*) its different outcomes (revolution, or overthrowing of the regime, failed rebellion or anarchy/destabilization), for different initial scenarios.

Although armed uprisings are not within the scope of the present work, the model by Moro is inspired in Epstein's Model I and has many interesting features. It is assumed that citizens turn rebellious motivated by poor economic conditions, according to the following rule [74]

Rule C': if $G(y_i) - N(y_i) > f$ be 'active'; otherwise be 'quiet'

where $G(y_i)$ and $N(y_i)$ are the grievance and net risk, which depend on the agent's income y_i. The income is a random variable modelled using a log-normal distribution $d(y_i) = 1/(by_i\sqrt{2\pi})exp(-(\ln(y_i) - a)/(2b^2)),\ y_i > 0$. The expressions for $G(y_i)$ and $N(y_i)$ are

$$G(y_i) =(1 - L)H(y_i) \tag{3.13}$$

$$N(y_i) =A_i J(y_i) \tag{3.14}$$

where L is the legitimacy, $H(y_i) = \exp[E(y_i)-y_i]/(1+\exp[E(y_i)-y_i])$ is the hardship index, $A_i = 1 - \exp(-w_1 P_v/(1 + C_v + R_v))$ is the estimated arrest probability, and $J(y_i) = 2\exp(w_2 y_i jmax)/(1 + \exp(w_2 y_i jmax)) - 1$ is the risk aversion, where P_v, C_v and R_v are the number of visible agents of the central authority, 'active' citizens and revolutionaries, respectively, and w_1, w_2 and $jmax$ are constants. In this formulation, the hardship index models economic RD using a logistic function, the risk aversion is a function of the fear of loosing income whilst at jail, and the estimated arrest probability is a straightforward extension of the expression used in Epstein's model.

The modelling of the armed revolutionaries and agents of the central authority is very simple and straightforward. Armed revolutionaries can be 'active' or 'hidden' and their action rule is

Rule R: if $\dfrac{R+C}{P} > n$, be 'active' and kill a randomly selected policeman inside vision radius v with a probability equal to r; otherwise, remain 'hidden'.

where R, C and P are the total numbers of revolutionaries, 'active' citizen agents and agents of the central authority, respectively.[24] The action rule for the agents of the central authority is

Rule P: randomly select an agent from the 'active citizens' and ' active revolutionaries' within vision radius v.
If the randomly selected agent is a citizen, arrest him;
if he is a revolutionary, kill him with a probability equal to p.

The results presented show examples of three different outcomes (successful revolution, failed revolution and anarchy) in terms of the time evolution of the number of 'active' and 'jailed' citizens, the proportion of policemen killed as a function of p and r, the distribution of the time of occurrence of a revolution, and the probability of killing a policeman as a function of the revolutionaries' threshold [74]. The focus was not on the study of the patterns of intermittent bursts of rebellion.

Although the ABM presented by Moro has important features such as the representation of grievance as a function of economic RD, it also has some limitations. For instance, there is no attempt to model political RD, which was the key factor of conflict potential in many cases (e.g. the AS [11]), or to use data or indicators from real processes for parametrization or validation. Also, the values of the grid size, initial citizen and policeman density, vision radius v and maximum jail term $jmax$ used in the simulations are the same as in Epstein et al. Run 2 [33]. The legitimacy was set $L = 0.85$ in all simulations, which is hardly representative of governments that face revolutions, regardless of the measure or concept of legitimacy adopted.

[24] In this model, revolutionaries have perfect information whereas citizens do not, because it is assumed that the revolutionary organization is spread across the country (model space) and can obtain an estimate of the total number of 'active' citizens [74].

3.5 Concluding Remarks

The review of existing ABM of 'abstract' type for simulation of large scale social conflict and violence in this chapter can be summarized as follows:

- Epstein's ABM of civil violence played a central role in generative social simulation of conflict due to its simplicity, soundness of the formulation, and explanatory power;
- Legitimacy L is a key variable in Epstein's ABM, for it affects the grievance of the whole artificial society. The estimated arrest probability P_a and the threshold T also determine (for given distributions of hardship H and risk aversion R) whether or not large rebellion peaks will occur;
- Epstein's ABM can be applied to civil violence and peaceful manifest conflict, provided the relevant mechanisms are the same in both cases;
- Epstein's ABM has the drawbacks of not representing RD or commitment to value (to distinguish political from economic deprivation), and the mechanisms of legitimacy feedback, network influences, or 'mass enthusiasm' (dispositional contagion of grievance);
- There are theoretical and empirical arguments for considering that the mechanism of legitimacy feedback is important. Thinking in terms of Gilley's theoretical framework [43, 44], the recurrence of large uprisings and the subsequent imprisonment of citizens implies that 'justification' and 'consent' are affected by such events.[25] Also, the qualitative and quantitative properties of the solutions are different for homogeneous and heterogeneous legitimacy perceptions, showing that non-linear effects are significant [64]. This suggests that legitimacy feedback is an important mechanism to explore;
- The implementation of network influences in [60] uses different approaches for each of the networks considered. This formulation can be simplified and made more consistent;
- Other authors improved Epstein's model, for example by introducing economic RD [74], but did not implement other mechanisms such as legitimacy feedback, network influences or 'mass enthusiasm'. Also, existing studies did not explain why some forms of P_a lead to large peaks of rebellion whereas others do not,

[25] This basic idea was used in the formulation of the legitimacy feedback mechanism in the present ABM.

and (except for the work of Fonoberova et al. [35]) did not use context data for model parametrization or validation.

This suggests the following ways for improving the existing ABM:

– Investigate the foundations of the decision rule and estimated arrest probability function in Epstein's ABM, and analyse and discuss alternative forms of the estimated arrest probability function;

– Determine the relationship between the combinations of legitimacy, estimated arrest probability and threshold which lead to stable, complex and unstable solutions (i.e. with permanent calm, intermittent bursts of rebellion and permanent turmoil, respectively);

– Include mechanisms such as legitimacy feedback, network influences and 'mass enthusiasm' using simple extensions of the 'citizens' action rule in Epstein's model, to analyse their importance and impact on the system's long term behaviour(permanent instability, complex solutions with intermittent peaks of rebellion, or stable solutions with permanent calm);

– Explore which input parameters (and related mechanisms) are associated with tipping points, and explain how such tipping points are consistent with the theories and explain patterns of conflict events inferred from datasets;

– Investigate possible forms for modelling hardship in terms of RD and compare the simulated results with real cases (e.g. time evolution of protests and riots during the AS);

– Discuss the possibility and prospects for more elaborated architectures for 'citizen' agents, such as memory effects and simple aggregation of rational and emotional dispositions, within the generative minimalism principle of 'abstract' ABM [32].

These extensions would narrow the gap between 'abstract' ABM of civil violence and the propositions of Gurr's frustration-aggression and Gene Sharp's non-violent action theories, using data and indicators about real processes to assess the validity of theory and models.

Chapter 4

Analysis of Conflict Datasets and Indicators. The Case of the "Arab Spring"

The ABM of 'abstract' type for simulation of large scale social conflict reviewed in the previous chapter require input parameters like legitimacy and threshold, and the specification of distributions of other variables (e.g. hardship and risk aversion) in the artificial 'citizens' population. Depending on the combination of these input parameters and the distributions of heterogeneous agents' attributes, the solutions may be stable (permanent calm), complex (with intermittent bursts of rebellion) or unstable (permanent rebellion of a large proportion of the population).

Before introducing the ABM developed in this work and the strategy for its exploration, it is important to analyse published international indicators related to the input parameters (e.g. legitimacy) and datasets of conflict such as those described in §2.4. This will provide elements of observation for parametrization and for analysing the plausibility of the solutions obtained, and hence the model's explanatory power.

In this chapter, an analysis of conflict events and international indicators for eight African countries affected by the AS – Algeria, Egypt, Libya, Mali, Mauritania, Morocco, Sudan and Tunisia – will be presented. The AS was a recent and very important large scale conflict against the central governments of several Arab countries in Africa and the Middle-East, whose main issue was the struggle for human rights and political liberties. The African countries mentioned above were selected because were the ones for which both international indicators and records of conflict events were available. The purposes of the analysis were to:

– characterize the significance of the complexity issues of large scale conflict processes represented in figure 1.1, such as the importance of demonstrations and riots (in terms of number of events and estimated number of participants), of spontaneous vs organized events, and of escalation in demonstrations and riots;

– determine whether or not values of international indicators have any value as "prognostic" tools for anticipating large scale uprisings, or as sources of plausible values for the input parameters in ABM of social conflict;

– obtain plausible estimates for emergent patterns of conflict events, such as distributions of event size, duration and time between successive events, which could be useful for model validation and exploration;

– investigate whether or not mechanisms and propositions in conflict theories, like those by Gurr and Gene Sharp, can be confirmed via international indicators or records of conflict events in the case of the AS.

These aspects will be treated by first analysing the SCAD database [97], to answer specific questions about demonstrations and riots concerning issues, organization, escalation, and patterns of duration, recurrence and size. Then, the FSI [96] and FWI [37] indicators related to the potential for conflict will be analysed, as well as the Gini index of inequality for some of the African AS countries [13]. Both the statistics of conflict events and the indicators will be used for setting parameter values in the computer experiments reported in chapter 5.

4.1 Analysis of the SCAD database for the African "Arab Spring" Countries

The SCAD database [97] contains 42 items of information (fields) about 16730 social conflict events (protests, strikes, anti- and pro-governmental violence, etc.) for 61 countries in Africa, Central America and the Caribbean region from 1990 to 2013 based on an extensive compilation of news from Associated Press and *Agence France Presse*, via the Lexis-Nexis news service. The database is provided as two CSV files and one Codebook which describes the information item, type (date, numeric, categorical, Boolean, etc.) and coding for each field of the database [88]. Table 4.1 shows a summary of the information items that were used in the present work.

Table 4.1: Summary of the information items (fields) in the SCAD database. (Source: Salehyan and Hendrix [97])

Field	Type	Description
countryname	text	Country name
startdate	date	Start date
duration	numeric	Duration (days)
etype	categorical (nominal)	Type of event
escalation	categorical (nominal)	0 for no escalation; 1-10 otherwise (according to type of the subsequent event)
cgovtarget	Boolean	*true* (1) if Central Government was targeted, *false* (0) otherwise
npart	categorical (ordinal)	Estimated number of participants
ndeath	numeric	Number of death (if any)
repress	categorical (ordinal)	no repression, non-lethal repression or lethal repression used
locnum	categorical (nominal)	Coding of event location
issue1	categorical (nominal)	Main issue that caused event
issuenote	text	Brief description of event

The information in SCAD allows the retrieval of the time evolution of conflict events by type and estimated number of participants, as well as its relation with actor(s), target(s), issue(s), escalation, geographic location (urban, rural, multiple or single, regional or nationwide, etc.) and use of repression by the government. This can be done efficiently for one country or a group of countries in a given period using R [81]. Table 4.2 shows the set of functions coded in R by the author to perform frequent database operations (queries, validation, saving, etc.).

The R functions were used to analyse the conflict events that occurred before and after the AS in Algeria, Egypt, Libya, Mali, Mauritania, Morocco, Sudan and Tunisia.[26] These countries are important in the context of large scale social conflict against a central authority, due to the magnitude of the publicized events, the impact of the conflict process on the respective societies (violence, regime changes, and even war), and the quick propagation of the uprisings from country to country. The general questions for exploration are:

1. How important were demonstrations and riots, in terms of number of events and mobilization (estimated number of participants)?
2. Which were the most significant issues (grievance factors) that triggered conflict events?
3. Which were the issues, organization and escalation in large demonstrations and riots?
4. What were the patterns of recurrence, duration and size of demonstrations and

[26]The current version of SCAD does not include information about conflict other countries affected by the AS such as Bahrain, Jordan, Kuwait, Oman and Syria, or about European countries involved in the European Sovereign Debt Crisis (which would be worthwhile studying and comparing with those in the AS).

Table 4.2: R functions coded by the author for exploration of the SCAD database. (Source: author)

R function	Usage
`get.events.in.database()`	Construct a data frame from CSV files
`get.country.list(scad.data.frame)`	Get list of countries in a SCAD data frame
`get.country.events(scad.data.frame,country.names)`	Retrieve events for one or more countries
`get.dates.range(scad.data.frame)`	Get time limits of events in a SCAD data frame
`get.events.between.dates(scad.data.frame,from.date,to.date)`	Get SCAD data frame with events between from.date and to.date in an input data frame
`get.events.by.category(scad.data.frame,key,values)`	Get a subset of a SCAD data frame
`get.categories(scad.data.frame)`	Get a list of user-defined categories (used for filtering)
`get.categories.map(scad.data.frame)`	Get a list of user-defined category mappings (used for merging/redefining factor levels)
`validate.scad.data.frame(scad.data.frame)`	Auxiliary function (input validation)
`save.scad.data.frame(scad.data.frame)`	Auxiliary function (save data frame)

riots?

and for each of these questions:

5. How did these characteristics of the social conflict process change after the beginning of the AS?

4.1.1 A Note on Geographic Information, Accuracy of the Information, and Exceptional Events

The SCAD database provides geographic information on event locations. Each record (row) corresponds to a particular location, so that events that took place in more than one location are listed separately, but for the purpose of the present work and the analysis of the questions above they should not be treated as separate events. If the user is not interested in detailed geographic information the database must be filtered to avoid over-counting the same event, as described in [88]. The R function `get.events.in.database()` implements this procedure.

It is also important to notice that events resulting from escalation are not coded in separate records. For instance, if a demonstration escalated into a riot, the latter will not appear as a new record. Consequently, if the user wants to determine the total number riots that occurred in a country, place, or time interval, it is necessary to query the `escalation` field of all events of other type, and add the number of these that escalated to (organized or spontaneous) riots to the number of riots explicitly coded in the database. However, detailed information about escalated events (e.g. the estimated number of participants) is not be available in SCAD. In the analysis below, only primary events will be taken into account.

As stated in the SCAD codebook, it is often difficult to obtain information about conflict events from published news accounts [88]. For instance, the estimated number of participants is given in terms of its order of magnitude and coded as a categorical variable (`npart`). For a substantial number of events, even the order of magnitude is unknown. This poses significant limitations for comparing the size of conflict activity peaks in ABM simulations with the corresponding values in real events. If the variable of interest is the proportion of a country's population involved in conflict events instead of the estimated number of participants, the analysis is further complicated by the differences of population size and demographic growth among the countries analysed.

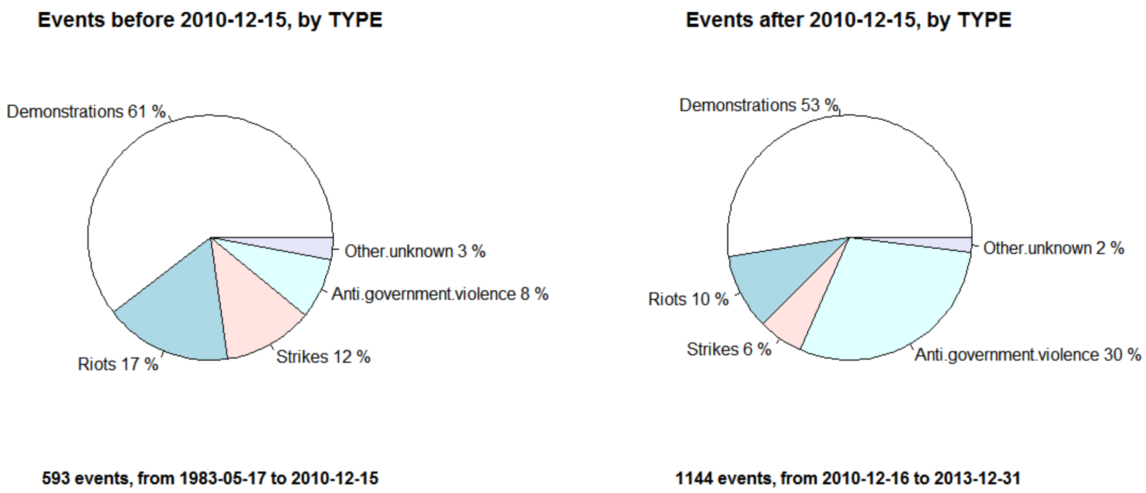
In some cases, the start and end dates couldn't be determined precisely [88]. For some events, the coded value of `duration` is several hundred days. Analysis of the summary description in the `issuenote` field shows that these event records correspond in fact to an aggregate of many shorter but related events. Thus, in the statistical analyses of duration and recurrence time, it is necessary to inspect these exceptional events more carefully, and to use measures of centrality and dispersion that are less sensitive to outliers.

For events with very large number of participants or any other exceptional characteristic (e.g. very long duration) it is also important to analyse the contents of `issuenote` and other fields (e.g. `etype`, `duration`, `escalation`, `actor1`, `location`) in order to interpret their significance and relationship with other events.

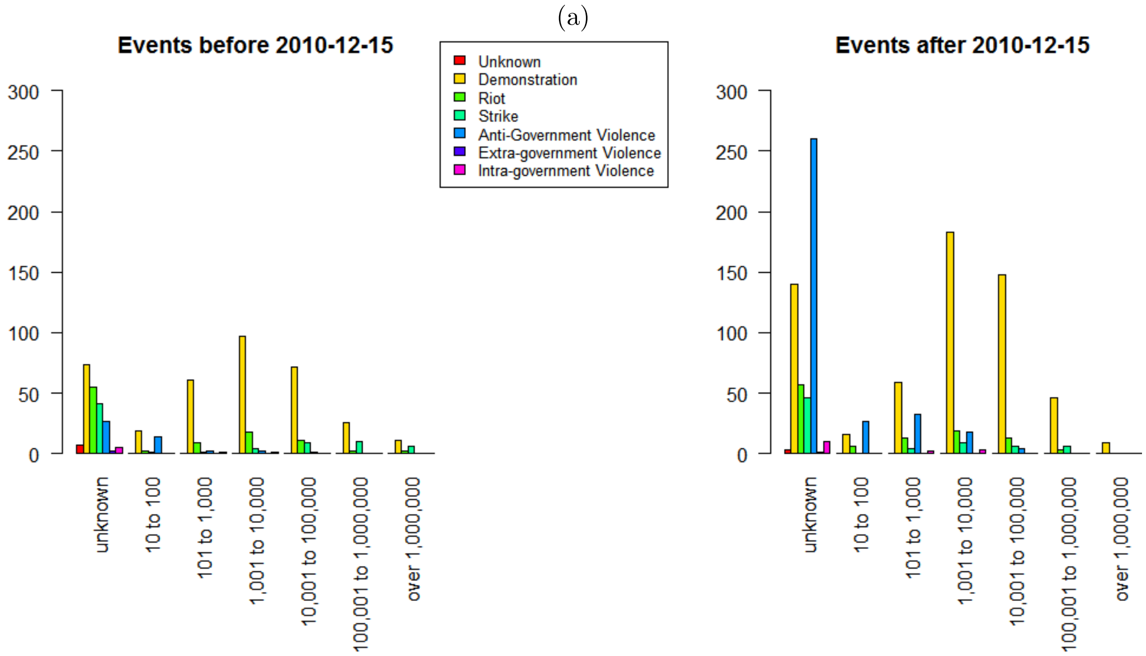
4.1.2 Question 1: How important were demonstrations and riots, in terms of number of events and mobilization (estimated number of participants)?

Demonstrations and riots are the two event types of primary interest in the present work (figure 1.1), so it is important to compare their number and mobilization potential with other types of events (peaceful or violent). The analysis started by selecting all events for the countries of interest that were targeted against the central governments (`cgovtarget == 1`). The date December 15^{th}, 2010 – mid-December, two days before Bouazizi's self-immolation and three days before the first subsequent protests – was adopted in this work as conventional date from splitting the periods before and after the AS.

Figure 4.1 shows the proportion of conflict events by type and by estimated



(a)



(b)

Figure 4.1: Type of social conflict events against central governments in African countries (Algeria, Egypt, Libya, Mauritania, Morocco, Sudan and Tunisia) in the SCAD database, before and after the beginning of the "Arab Spring": % of events of each type (a) and event type by estimated number of participants (b). (Source: author, based on [97])

number of participants, before and after the beginning of the AS. First, it can be observed that the frequency increased notably after the beginning of the AS, from an average of 0.41 to 7.21 events per week (more than one event per day, considering all event types and sizes in the eight countries taken together). The proportions of event type changed after the beginning of the AS, with an increase of anti-governmental violence.[27] This is further confirmed by running a Pearson χ^2 test with factors `before/after` vs `etype`, which gives $\chi^2 = 125, df = 4,$ p-value $< 2.2 \times 10^{-16}$ for a χ^2 distribution with four degrees of freedom. Thus, the proportions of event type are not statistically independent of the period (before/after the AS).

Demonstrations were clearly the most common form of conflict event, both before and after the beginning of the AS, and also the most important in terms of mobilization (estimated number of participants). After the beginning of the AS, most events with more than 100,000 estimated participants were demonstrations (figure 4.1(b)). It is interesting to note that very large demonstrations and strikes (with more than 100,000 and more that 1,000,000 estimated participants) occurred before December 15^{th}, 2010 (figure 4.1(b)). This shows that strong signs of social conflict were already manifest in the countries analysed, several years before the beginning of the AS.

Riots were of secondary importance when compared with demonstrations, representing the second most frequent type of conflict event before the beginning of the AS and the third most frequent thereafter. It is evident that peaceful conflict manifestations, either organized (demonstrations and strikes) or spontaneous (demonstrations), were much more frequent and mobilizing than events involving violence. This predominance of non-violent forms of protest is consistent with Gene Sharp's theory of non-violent action.

Strikes and anti-governmental violence had a significant expression in the conflict processes in African AS countries. These are organized forms of protest, which are not of primary concern in the present work. Anti-governmental violence became more significant after the beginning of the AS, but was less mobilizing (in terms of estimated number os participants) than riots (figure 4.1b).

Figure 4.1(b)also shows that the order of magnitude of the estimated number

[27] In SCAD, anti-governmental violence is defined as "Distinct violent event waged primarily by a non-state group against government authorities or symbols of government authorities (e.g., transportation or other infrastructures). As distinguished from riots, the anti-government actor must have a semi-permanent or permanent militant wing or organization" [89]. Anti-governmental violence is considered to be outside the scope of the present work.

of participants is not known for a substantial proportion of events.[28] This poses significant limitations on subsequent analysis (as mentioned in §4.1.1). Nevertheless, it is reasonable to assume that events with unknown number of participants were not salient, otherwise estimates would be given. Therefore, events with unknown estimated number of participants were excluded from all the analyses below.

4.1.3 Question 2: Which were the most significant issues (grievance factors) that triggered conflict events?

Figure 4.2 shows the number of events associated with each issue, considering the type (figure 4.2(a)) and estimated number of participants (figure 4.2(b)). Human rights and democracy were very clearly the major grievance factor, before and after the beginning of the AS.

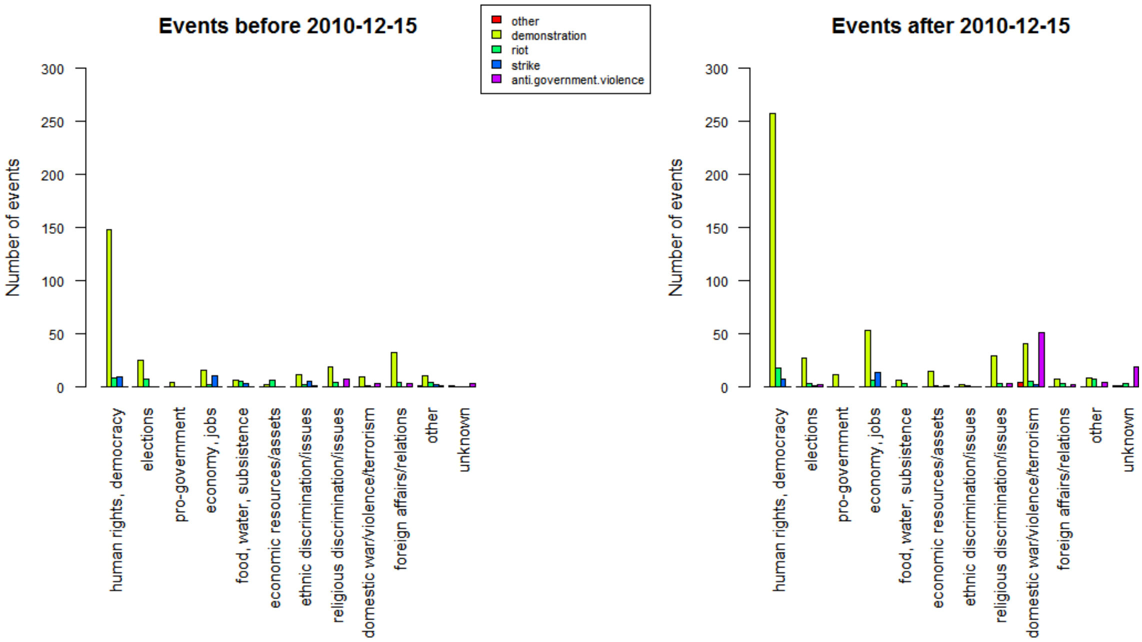
Figure 4.2(a) shows that demonstrations were the most frequent type of conflict event associated with the issues `human rights, democracy` and `elections` (political RD), `economy, jobs` (economic/social RD), and `ethnic discrimination/issues` and `religious discrimination/issues` (inclusion-exclusion and social RD). Riots were not a significant form of collective struggle and expression of grievances, either before or after the beginning of the AS. This conclusion is consistent with Gene Sharp's theory of non-violent action and will be confirmed in the analyses of Questions 3 and 4.

4.1.4 Question 3: Which were the issues, organization and escalation in large demonstrations and riots?

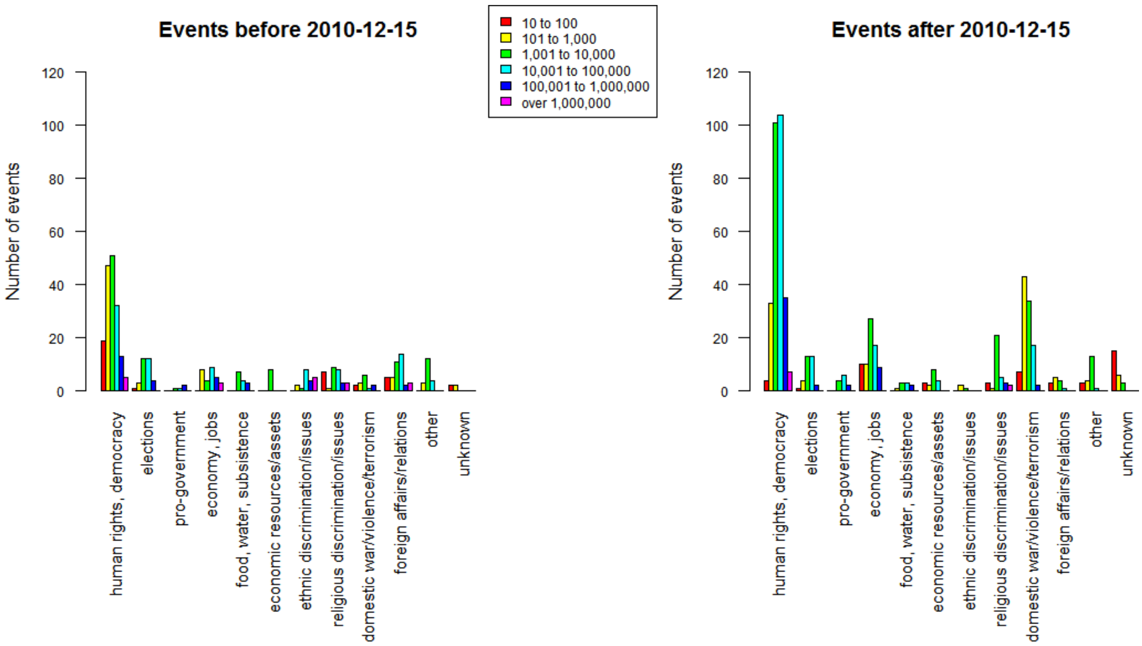
Large events involving a significant proportion of a country's population are of primary interest for the present work, and the issues that triggered these events are particularly important. The proportion of spontaneous large events provides indirect evidence on the relevance and correctness of the conceptual framework shown in figure 1.1 (page 2), while escalation characterizes the real importance of the transitions also shown in that figure.

Before proceeding, it is necessary to define the lower limit of estimated number of participants for a "large" event. Thinking in terms of the proportion of the

[28] More specifically, this is the case for 728 events, representing 42% of all events in the database from May 17^{th}, 1983 to December 31^{th}, 2013.



(a)



(b)

Figure 4.2: Issues in conflict events against central governments in African "Arab Spring" countries (Algeria, Egypt, Libya, Mauritania, Morocco, Sudan and Tunisia) - event type (a) and estimated number of participants (b). (Source: author, based on [97])

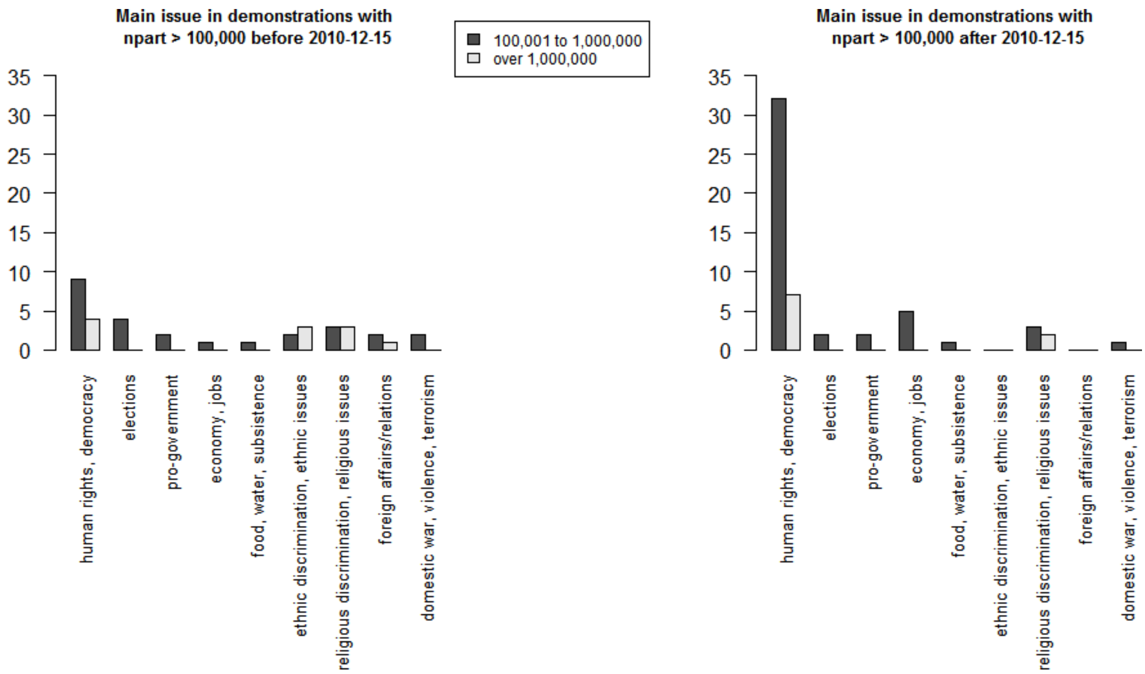


Figure 4.3: Issues in very large and huge demonstrations in African "Arab Spring" countries, before and after the beginning of the AS. (Source: author, based on [97])

population, it is plausible to consider that limit to be 1%. Taking 10,000,000 as the order of magnitude of a country's the population (figure 4.6, page 75), the events of interest for this question are those with 100,001 to 1,000,000 and with more than 1,000,000 estimated participants, which from here on will be called "very large" and "huge" events, respectively. Table 4.3 shows that for the time period of recorded events (before and after the AS) and for the eight countries analysed, there were 92 demonstrations and only seven riots that were very large or huge. Since very large or huge riots were rare events, no definite conclusions can be formulated about their relative frequency before and after the AS.

Figure 4.3 shows the number of very large and huge demonstrations for each issue category (complementing the information in figure 4.2(a)). `human rights, democracy` was the main issue, particularly after the beginning of the AS. The four major riots before the AS, two were related to `human rights, democracy` and two to `foreign affairs/relations`, and the three major riots after the beginning of the AS were due to `human rights, democracy`, `food, water and subsistence`, and `domestic war, violence, terrorism`. It is very clear that the main drive of the AS was the strive of the populations for more democracy and human rights (individual liberties and political participation), and large peaceful demonstrations were the tool for pressing central governments.[29] The driving issues of riots were

[29]This result is consistent with Gene Sharp's theory, in that resistance and non-cooperation

Table 4.3: Number of very large and huge demonstrations and riots for African "Arab Spring" countries, before and after December 15^{th}, 2010. (Source: author, based on [97])

Country	Before/ After	Demonstrations 100,001 to 1,000,000 estimated participants	Demonstrations over 1,000,000 estimated participants	Riots 100,001 to 1,000,000 estimated participants	Riots over 1,000,000 estimated participants
Algeria	before	15	8	1	0
	after	4	0	1	0
Egypt	before	5	2	0	1
	after	31	9	2	0
Libya	before	0	0	0	0
	after	1	0	0	0
Mali	before	2	0	1	0
	after	0	0	0	0
Mauritania	before	2	0	0	0
	after	0	0	0	0
Morocco	before	1	1	0	1
	after	7	0	0	0
Sudan	before	1	0	0	0
	after	0	0	0	0
Tunisia	before	0	0	0	0
	after	3	0	0	0
TOTAL	before	26	11	2	2
	after	46	9	3	0

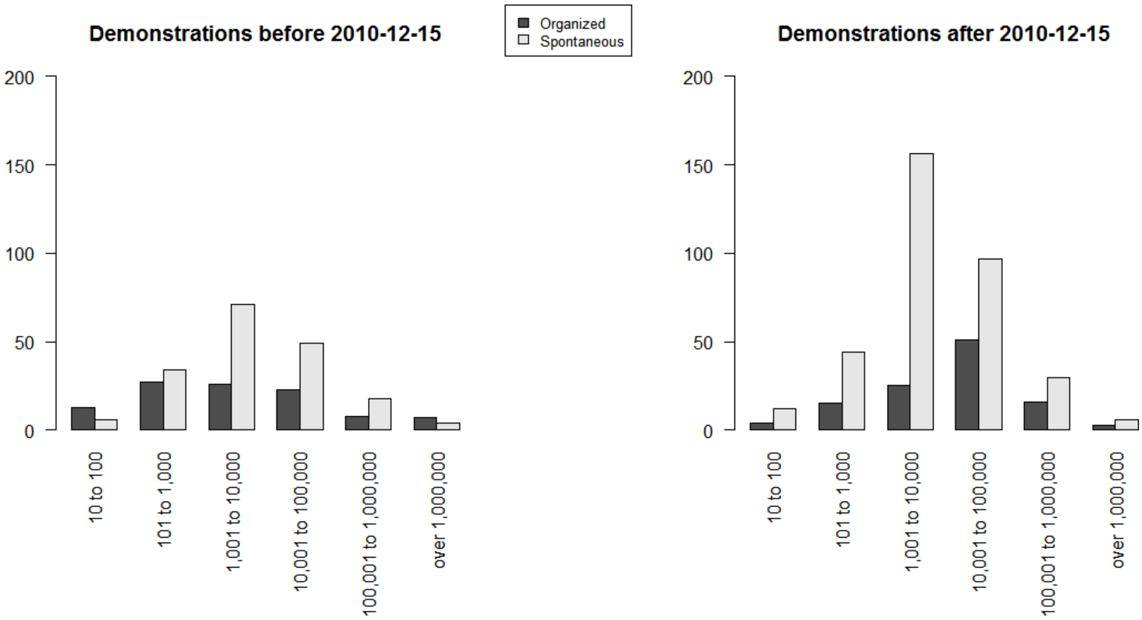
(arguably) more heterogeneous.

Figure 4.4 shows the number of organized and spontaneous very large and huge demonstrations and riots, before and after the beginning of the AS. For demonstrations (figure 4.4(a)), it can be observed that before the beginning of the AS spontaneous events were more numerous than organized ones, but organizations also played an important role (organized demonstrations accounted for a significant proportion of very large and huge events). After the beginning of the AS, the proportion of spontaneous demonstrations increased. A Pearson χ^2 test with factors `before/after` vs `organized/spontaneous`, gives $\chi^2 = 10.56, df = 1,$ p-value $<$ 0.001156 for a χ^2 distribution with one degree of freedom, shows that the proportions of organized/spontaneous events are not statistically independent of the period (before/after the AS). The increase of importance of spontaneous demonstrations is very likely related to the key role of activists using SN in the AS [18].

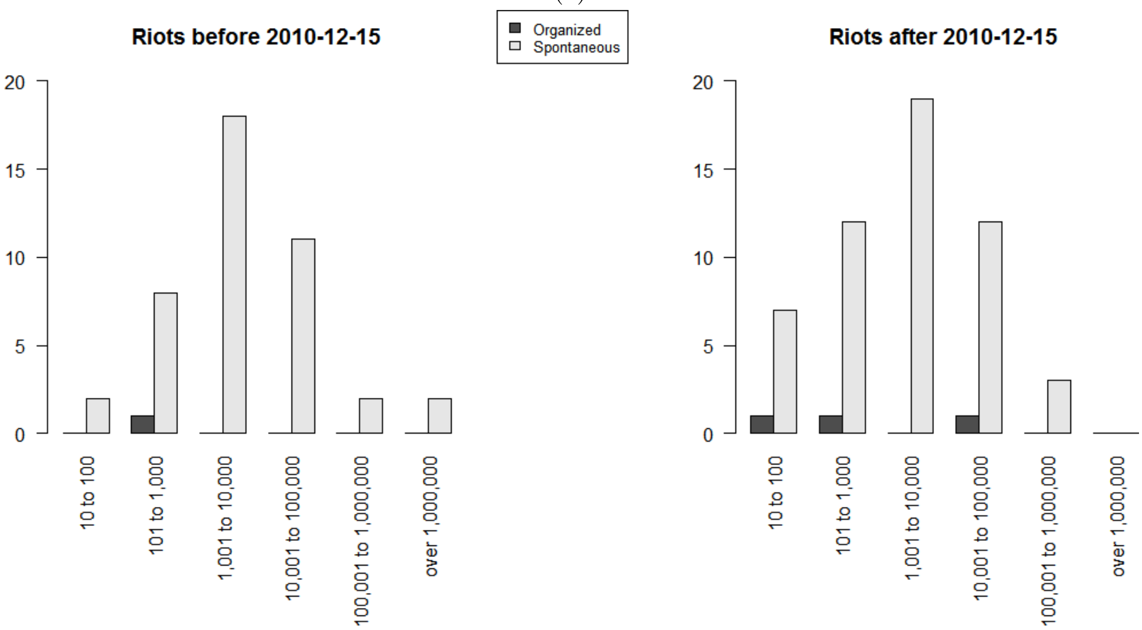
The observed proportion of spontaneous very large and huge events, even if convoked or publicized by activists, is a strong argument supporting the study of large scale conflict against a central authority from the viewpoint of complexity.

Figure 4.4(b) confirms that massive riots were much less frequent than massive demonstrations. They were very markedly spontaneous – only four of the 98 very

is the only strategy for fighting autocratic regimes when fundamental issues are at stake, and large non-violent forms of protest are the most effective for carrying non-violent action. It is also consistent with the hypothesis that political RD is a more significant source of large scale conflict potential that economic RD [11].



(a)



(b)

Figure 4.4: Organized vs spontaneous demonstrations (a) and riots (b), before and after the beginning of the AS. (Source: author, based on [97])

large and huge riots in the database were recorded as organized.[30] Although it is not possible to test for statistical independence of organization with respect to the period (before/after the beginning of the AS) due to the very small number of organized events, it is clear that organization was not significant for triggering

[30]Possible explanations for this are that organizations whose goal is to overtly organize large riots would be strongly repressed by governments, or lead to events classified as `Anti-governmental violence`, which were shown to be much less mobilizing.

massive riots in the countries analysed. Also, all huge riots (more than 1,000,000 estimated participants) occurred before the beginning of the AS.

It is also important to analyse escalation, in order to understand the transitions from peaceful to violent collective behaviour in very large and huge demonstrations and riots, and its influence on the evolution of conflict intensity. Figure 4.5 shows the distribution of escalation in very large and huge demonstrations before and after the AS. Escalation from peaceful demonstrations to spontaneous riots was very significant, in particular for huge demonstrations. After the beginning of the AS, the number of huge demonstrations that escalated to spontaneous violent riots was larger than the number of huge demonstrations that remained peaceful. In general, the proportion of participants that rioted in each case is not indicated, but some `issuenote` descriptions mention how many people were injured or killed.[31] It is interesting to argue whether or not escalation in very large and huge demonstrations changed after the beginning of the AS, but the number of events in some escalation categories is too small for applying statistical tests.

Although the number of very large and huge riots was too small for drawing conclusions, none of the four events that occurred before the AS escalated. After the beginning of the AS, two events did not escalate and one escalated to `Spontaneous demonstration`.[32] This suggests that escalation to violence tends to occur in large peaceful demonstrations but not in large riots, and also that riots do not degenerate into more intense acts of violence, such as insurgence or civil war, unless other factors

[31] Analysing the `issuenote` field for all events in the eight countries would be extremely time consuming, but is feasible for very large and huge events and sometimes yields useful details. For instance, the `issuenote` description for the very large demonstration in Algiers, Algeria, on January 22^{th}, 2011, whose main issue was `food, water, subsistence` reads: "Arab Spring. Rock and chair throwing protesters defy a ban on public gatherings and clash with police, they also demand radical change to the regime. 20,000 police stop the protests, leaving 5 dead and 800 hurt". This shows that although the coded `issue1` was related to economic RD, the event was in fact associated with the AS movement and its main issues (struggle for individual liberties and regime change), and was repressed by a massive and violent police force. The description of the huge demonstration in several cities in Egypt on January 25^{th}, 2013, whose main issue was `human rights, democracy` reads: "An estimated 500,000 people marched across Egypt against the Morsi government and against the Muslim Brotherhood and the protests turned violent, with 11 people killed and several hundred wounded". This also illustrates the uncertainty of the estimates of participation (the `npart` field is coded "over 1,000,000", which contradicts the estimate in the `issuenote`). For the very large, nationwide demonstration in Morocco on February 2^{nd}, 2011, whose main issue was `economy, jobs`, the description reads: "Arab Spring. Protests erupt in favor of constitutional reform, social justice, and economic reform. 37,000 people take to the streets. Marches escalate to violence in Hoceima, where several people die after setting a bank on fire". Once again, the number of participants mentioned in the `issuenote` does not match the `npart` value.

[32] In SCAD, "escalation" has a different meaning than usual; it refers to events of one type that degenerated into another type, regardless of violence intensity, organization, etc. It does not mean that the degenerated event was more violent than the original one.

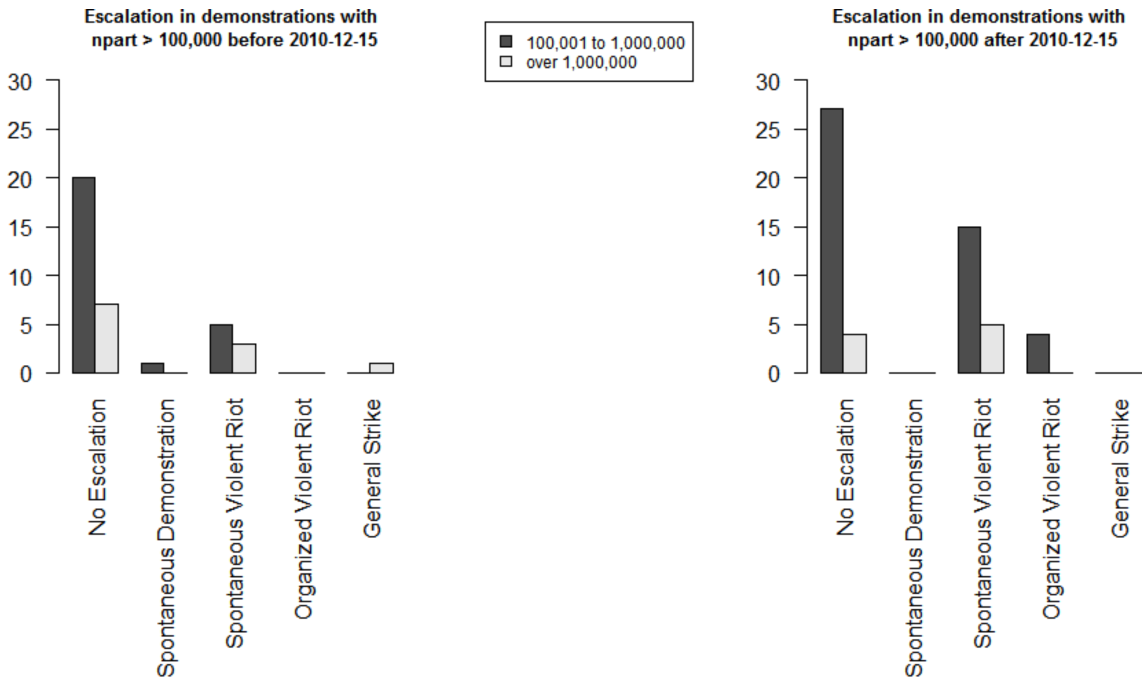


Figure 4.5: Escalation in very large and huge demonstrations in African "Arab Spring" countries, before and after the beginning of the AS. (Source: author, based on [97])

come into play.[33]

4.1.5 Question 4: What were the patterns of recurrence, duration and size of demonstrations and riots?

The previous questions were centred on the overall importance of demonstrations and riots, the possible escalation of violence, and the suitability and soundness of the study of large scale conflict from the viewpoint of complexity (figure 1.1). In the analysis of the current question, the purpose was to obtain more specific information for model parametrization and for interpretation of the solutions' behaviour, by examining the distributions of event size, duration and recurrence (time between successive events) for each country separately.

Before proceeding, it is necessary to define the lowest size of demonstrations and riots considered relevant for the analysis of this question. This is determined by three factors: the order of magnitude of the population size for the countries considered, the distributions of estimated number of participants (`npart`), and the

[33]The two notable examples of escalation to civil war in AS countries are Syria and Libya. In both cases, external intervention and important geopolitical or economic interests were present, as well as organized armed factions.

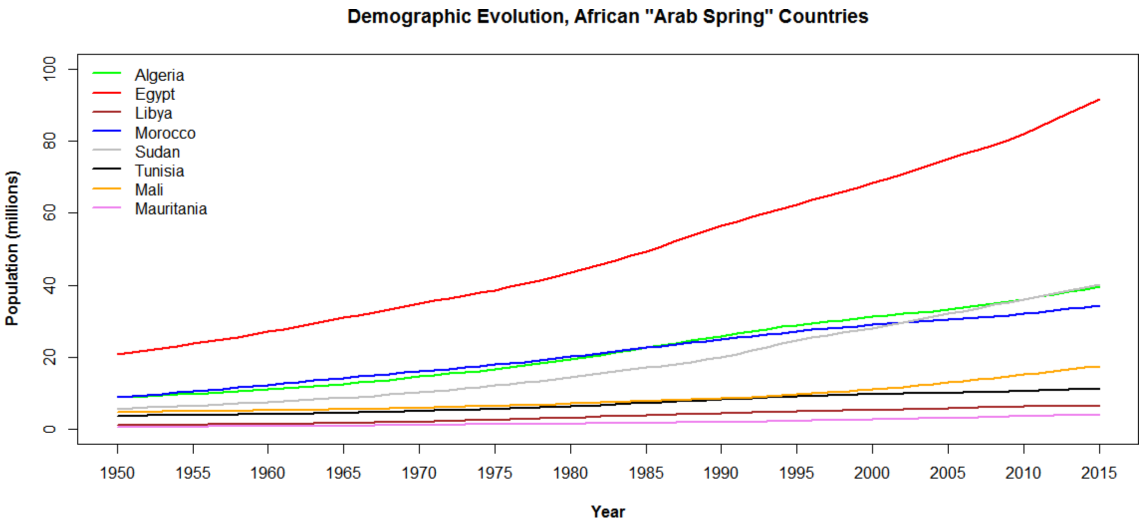


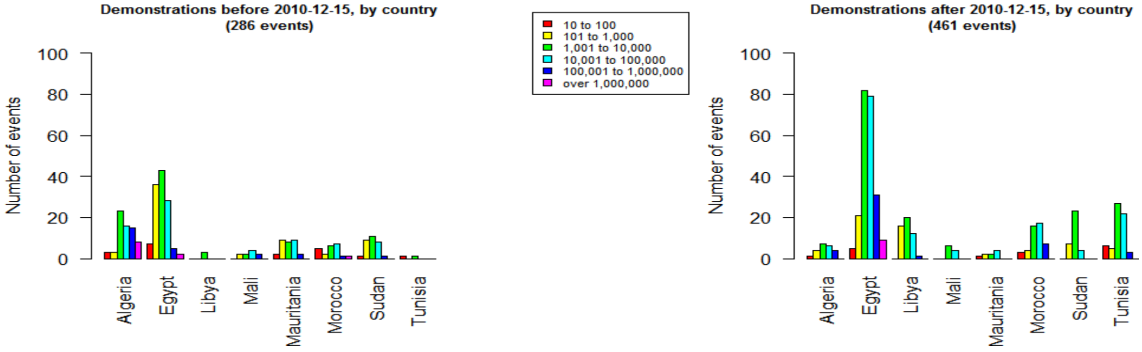
Figure 4.6: Demographic evolution of African "Arab Spring" countries, from 1950 to 2015. (Source: author, based on [102])

manageable number of agents that can be included in ABM. From figure 4.6, it can be concluded that ten million inhabitants is a suitable order of magnitude of the population size.

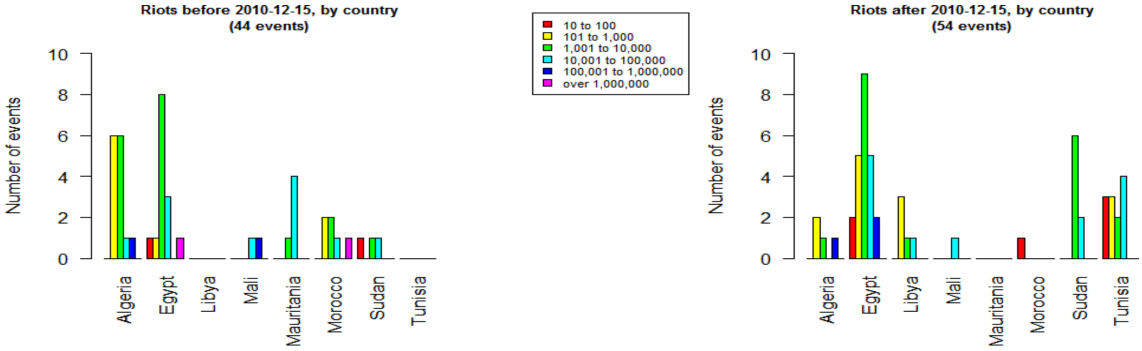
Figure 4.7(a) shows that the mode of the country distributions of the `npart` categorical variable is `1,001 to 10,000` for five countries before the beginning of the AS and for six thereafter. This corresponds to 0.01% of the order of magnitude of the population size and to just one 'active' in an ABM with 10,000 agents. Thus, it is reasonable to take 1,000 estimated participants as the lowest size of demonstrations relevant for the analysis of this question. In the case of riots the mode of the country distributions of `npart` is more variable than for demonstrations (figure 4.7(b)), but choosing 1,000 participants as the lowest size is also expected to include the events relevant to the conflict process.

* * *

Figure 4.8 shows box-and-whisker diagrams for the duration of demonstrations and riots with more than 1,000 estimated participants for the African AS countries. Before the beginning of the AS the median of duration is two days for Egypt and Tunisia and one day for the other countries. The third quartile of duration is 7.75 for Egypt, 10 for Mali and 13.5 for Morocco, and less than or equal to two for the other countries. Thus, except for Egypt, Mali and Morocco, about 75% of the demonstrations with more than 1,000 estimated participants were short events. Egypt is notable for the large number of outliers in figure 4.8(a) and the exceptionally long duration of some events. Analysis of the `issuenote` field shows that these



(a)



(b)

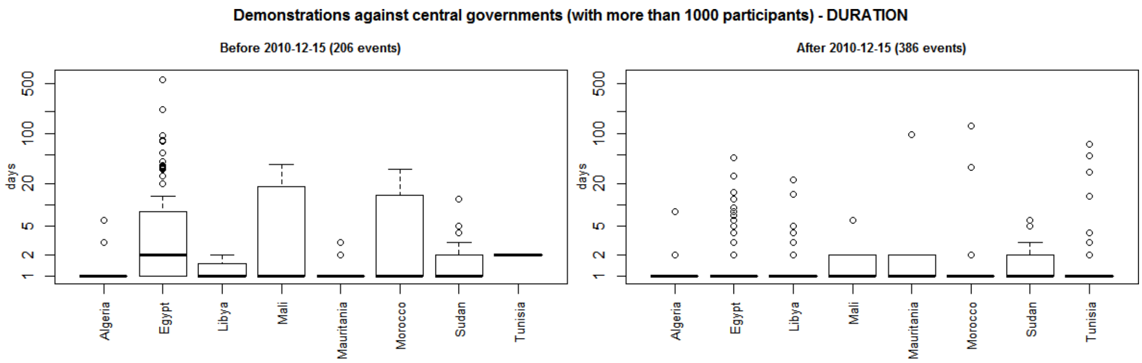
Figure 4.7: Distribution of estimated number of participants in demonstrations (a) and riots (b) in African "Arab Spring" countries (Algeria, Egypt, Libya, Mauritania, Morocco, Sudan and Tunisia). (Source: author, based on [97])

exceptionally long demonstrations were in fact long successions of shorter events related to particular conflict situations, coded as a single record for convenience or lack of more precise information.[34] After the beginning of the AS the median of duration is one for all countries; the third quartile is one for Algeria, Egypt, Libya, Morocco and Tunisia, two for Sudan and 1.75 for Mali and Mauritania.

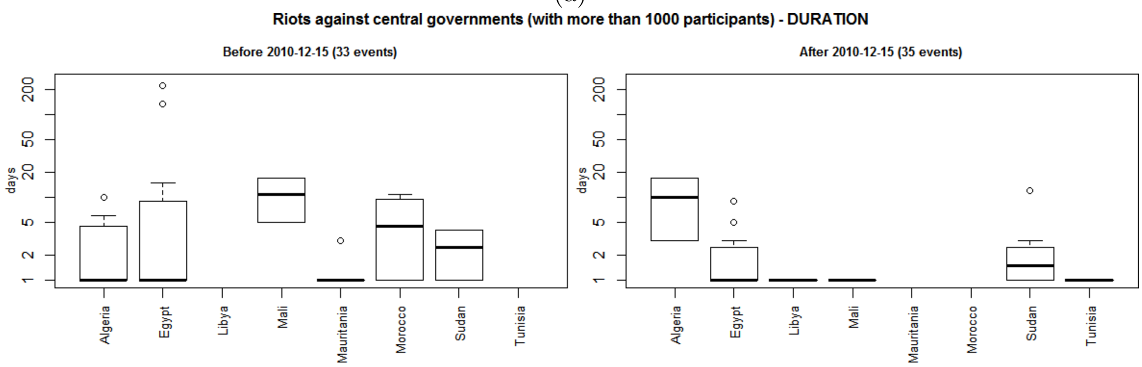
Although demonstrations tended to be shorter after the beginning of the AS, figure 4.8a also shows that more countries had demonstrations with exceptionally long duration than before the AS.[35]

[34]The longest demonstration in Egypt before the beginning of the AS started on October 7^{th}, 1995, had `duration` = 560 days and `npart` = `'1,001 to 10,000'`, and its `issuenote` reads: "Palestinians expelled from Libya by Col. Gadhafi lay in the main road between Libya and Egypt for 16 hours, closing the border to traffic and brawling with Egyptians trying to cross" with complementing `notes` field "End date is an estimate". The second longest demonstration in the same period started on February 24^{th}, 2005, had `duration` = 216 days and `npart` = `'100,001 to 1,000,000'` (a much larger event than the previous one), and its `issuenote` reads: "Tens of thousands of supporters of The Egyptian Movement for Change organize numerous protests across Egypt for several months calling for democratic reforms and an end to President Hosni Mubarak's reign".

[35]The longest demonstration after the beginning of the AS started in Morocco on January 1^{st}, 2012, with `duration` = 126 days, `npart` = '10,001 to 100,000' its `issuenote` is as follows:



(a)



(b)

Figure 4.8: Box-and-whisker diagrams for the distribution of duration of demonstrations with more than 1,000 (a) and riots with more than 1,000 participants (b) in African "Arab Spring" countries (Algeria, Egypt, Libya, Mauritania, Morocco, Sudan and Tunisia). (Source: author, based on [97])

Riots with more than 1,000 participants were in much smaller number than demonstrations. Also, not all countries analysed had riots that large before and after the beginning of the AS (figure 4.8(b)). The estimates of the median of duration are more variable than for demonstrations. Riots tended to be shorter after the beginning of the AS for Egypt, Mali and Sudan, but the reverse is true for Algeria.

* * *

Figure 4.9 shows box-and-whisker diagrams for the time interval between suc-

"Thousand of Berbers participated in protests throughout various regions of Morocco to demand the government for more democratic reform and more government services for Berbers". In Mauritania, the demonstration that started on May 2^{nd}, 2012, with `duration` = 95 days, `npart` = '10,001 to 100,000' has the `issuenote`: "The Coordination of a Democratic Opposition, a coalition of opposition parties, held a lengthy series of weekly protests in Nouakchott demanding the resignation of President Mohamed Ould Abdel Aziz. Police arrested, beat, and tear gassed protesters on several occasions. Some youth demonstrators resorted to throwing rocks and burning tires. Attendance ranged between hundreds and thousands". In Tunisia, the demonstration that started on September 17^{th}, 2012, with `duration` = 71 days, `npart` = '1,001 to 10,000' has the `issuenote`: "Prisoners protested against the Justice Ministry". In Egypt, the longest demonstration after the beginning of the AS had `duration` = 46 days.

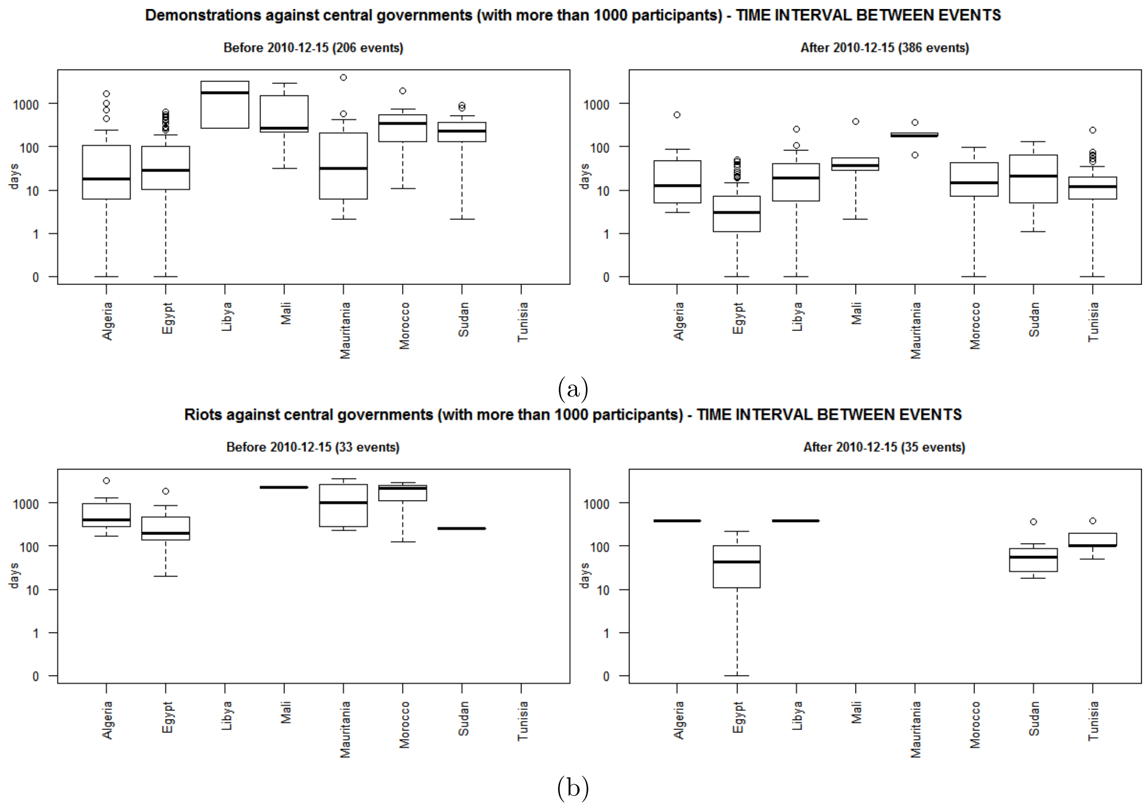
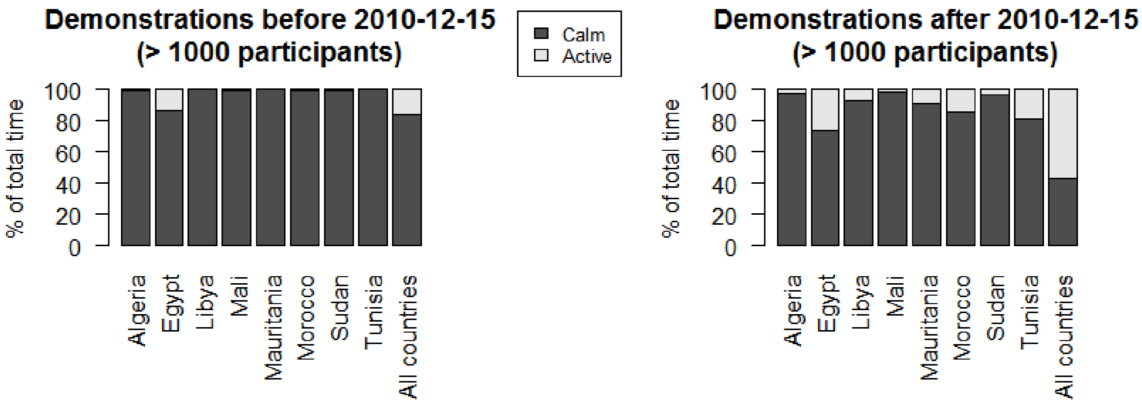


Figure 4.9: Box-and-whisker diagrams for the distribution of time interval between demonstrations with more than 1,000 (a) and riots with more than 100 participants (b) in African "Arab Spring" countries (Algeria, Egypt, Libya, Mauritania, Morocco, Sudan and Tunisia). (Source: author, based on [97])

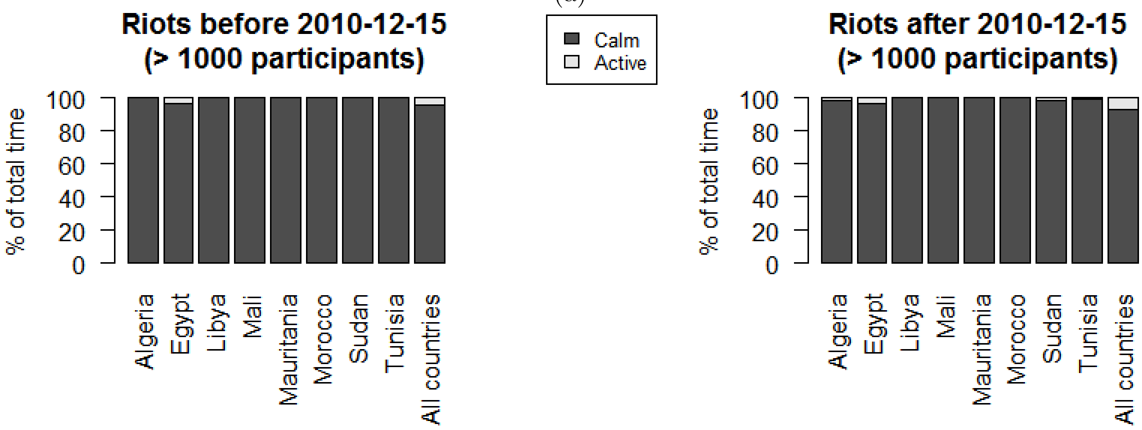
cessive demonstrations and riots with more than 1,000 estimated participants for the African AS countries. It can be observed that the distributions of time interval between successive events are very heterogeneous among the eight countries (figure 4.9(a)).

Before the beginning of the AS demonstrations were relatively frequent in Algeria, Egypt and Mauritania (the median of the time interval is 18, 29 and 32 days respectively, with 75% of time intervals smaller than half a year for Algeria and Egypt). Mali, Morocco and Sudan had longer recurrence times, and in Libya and Tunisia demonstrations were rare (in the period considered, the median of time intervals is 1,802 days for Libya, and in Tunisia there was only one demonstration with more than 1,000 estimated participants).

After the beginning of the AS demonstrations became more frequent than in the previous period for all countries except Mauritania, which is consistent with the notable increase of the number of conflict events shown in figure 4.1(a). This is



(a)



(b)

Figure 4.10: Proportions of time with calm and activity in demonstrations (a) and riots (b) with more than 1,000 estimated participants for African AS countries, before and after the beginning of the AS.(Source: author, based on [97])

particularly striking for Egypt, Libya, Mali, Morocco, Sudan and Tunisia.[36]

Riots were rarer than demonstrations and consequently the time intervals between successive events was larger than for demonstrations. However, it is apparent that the distributions are also heterogeneous among the countries analysed (figure 4.9(b)). In Egypt, riots became more frequent after the beginning of the AS. In Sudan there were two riots with more than 1,000 participants before the beginning of the AS and eight thereafter. In Tunisia no major riots were recorded before the beginning of the AS, but between December 15^{th}, 2010 and December 31^{th}, 2013 there were six riots with more than 1,000 estimated participants.

Another variable of interest for comparing records of conflict event with ABM

[36]The median of the interval between successive events changed from 29 to three days for Egypt; 1,802 to 18.5 days for Libya; 266 to 36 days for Mali; 346.5 to 26.3 days for Morocco; 226 to 35.4 for Sudan; and in Tunisia the median of the time between successive demonstrations was 21.5 days after the beginning of the AS.

simulations is the proportion (or %) of the time in which a country or set of countries had calm (no conflict events) or activity (at least one conflict event taking place).[37] Figure 4.10 shows the percentages of the time with calm and active events for demonstrations (figure 4.10(a)) and riots (figure 4.10(b)) with more than 1,000 estimated participants, considering each country individually, and all eight countries taken together.[38]

Before the beginning of the AS, Egypt was the only country with a significant percentage of the time (13.79%) with demonstrations occurring. In the other countries, the percentage of the time with demonstrations occurring was very small, so that the corresponding percentage for all countries together (16.27%) is hardly distinguishable from that for Egypt in figure 4.10.[39] After the beginning of the AS, the situation changed dramatically. The percentage of time with demonstrations for all countries jumped to 56.6%.[40] The proportion for Egypt was 26.33 %, and countries which previously had only residual % of total time with active demonstrations had much higher %'s after the beginning of the AS: Tunisia 18.69% (previously 0.02%), Morocco 14.47%, Mauritania 9.07 %, Libya 6.65%, and values below 5% for Algeria, Mali and Sudan.

Riots were rarer events than demonstrations, and consequently the % of time with active riots was smaller than for demonstrations. The value for all countries taken together was 4.39% before and 7.46% after the beginning of the AS. Egypt was the only country with significant % of time with active riots (3.87% before and 3.14% after the beginning of the AS).

* * *

To conclude the exploration of SCAD with respect to question 4 above, it remains to analyse the time history of event size for demonstrations and riots with more than 1,000 estimated participants. The two variables of interest are the event size (estimated number of participants), and the proportion of the population

[37]This proportion or % is independent of the time unit and thus of the time step in an ABM, which for models of 'abstract' type like Epstein's is usually indefinite.

[38]The % shown in figure 4.10 are only approximate, since the time unit considered in the SCAD is one day. In 'abstract' ABM, the time scale is also discrete and usually indeterminate.

[39]The second and third countries were Morocco with 1.09% and Mali with 0.72% of the time with active demonstrations. The difference between the sum of the countries' individual % of time with active demonstrations (16.96%) and aggregated value (16.27%), is a measure of the percentage of the total time with demonstrations occurring simultaneously in more than one country.

[40]This is a surprising result, especially because only major demonstrations against the central governments were considered, which in itself gives an objective measure of the intensity of social conflict manifest in the AS. Also, the sum of proportion of the total time with active events for all countries was 63.97%, showing that more events occurred simultaneously in more than on country then before the beginning of the AS.

involved in conflict events. The former is of primary importance in terms of news impact and international visibility. The latter is more relevant as a measure of a country's mobilization and also more useful for comparing simulation results, for it is independent of the population size or the number of agents used in an ABM.

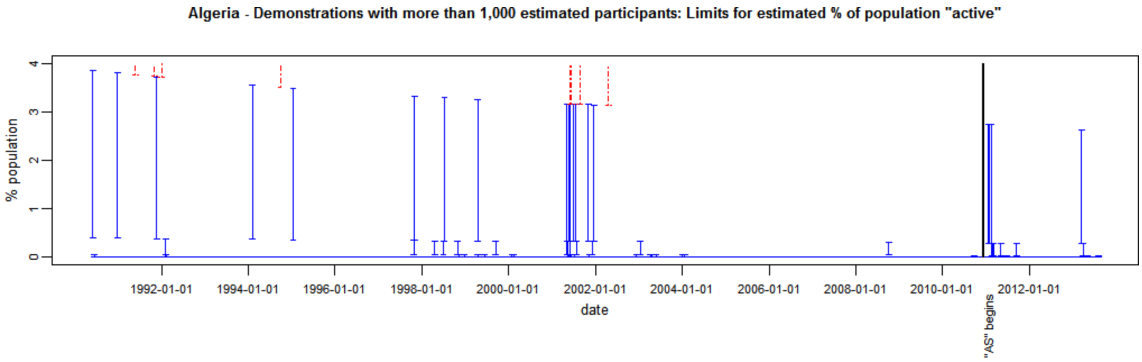
As mentioned before, only the order of magnitude of the estimated number of participants is provided as a categorical variable in the SCAD database. There is no general theoretical or empirical procedure for obtaining an expected value for the number of participants within each category. Therefore, it is only possible to construct time histories for the range of event size. To obtain the ranges for the proportion of the population involved in conflict events, it is necessary to divide the size limits for each category by the country's population. In the analysis below, this was done by dividing the size limits by the value of the country's population at the start date of each event, computed via a spline interpolation of the UN World Population Data [102]. For huge events with `npart` = `'more than 1,000,000'`, the lower limit (1,000,000) was divided by the interpolated estimate of the country's population, and the upper limit was left undetermined.

Using this approach, graphical representations of the time history of the range of % of population participating in conflict events were obtained for demonstrations and riots with more than 1,000 estimated participants, for the eight countries. Only the cases of demonstrations in Algeria, Egypt, Morocco and Tunisia will be presented and discussed below, since they are the most representative and interesting, for a number of reasons: demonstrations were the most important type of conflict event; Algeria, Egypt and Morocco are very populous countries (figure 4.6) with a history of conflict events before December 2010; and Tunisia is generally acknowledged as the origin of the AS.

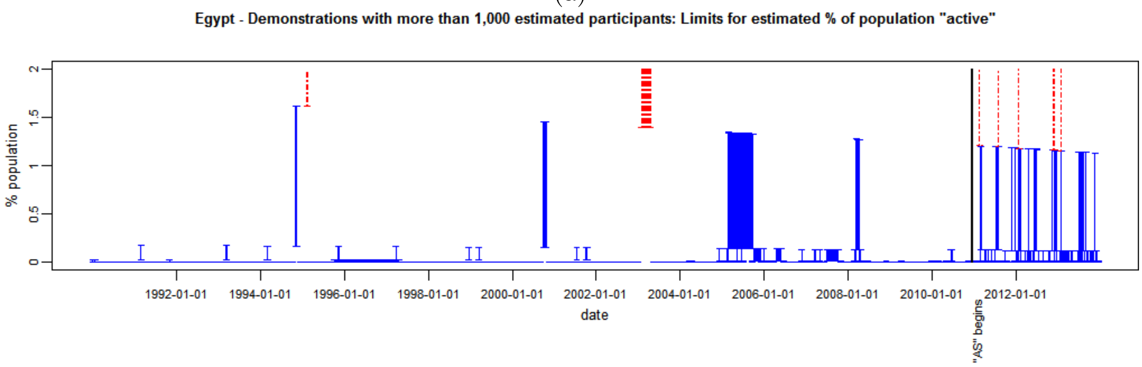
Figures 4.11 and 4.12 show the time history of the % of population involved in demonstrations for Algeria and Egypt, and for Morocco and Tunisia, respectively. In these figures, the range of estimated % of the population is represented by blue error bars drawn in solid line, except for demonstrations with more the 1,000,000 estimated participants, which are represented by dashed red lines with indefinite upper limit. The conventional date December 15^{th}, 2010 is marked by a thick black line in each graph.

From figure 4.11, it can be concluded that the estimated % of the population involved in demonstrations was small in Algeria and Egypt, because these countries are very populous.[41] Plausible ranges of the % of the population for very large

[41] The monotonic decrease of the width of the error bars, particularly for very large demonstrations



(a)



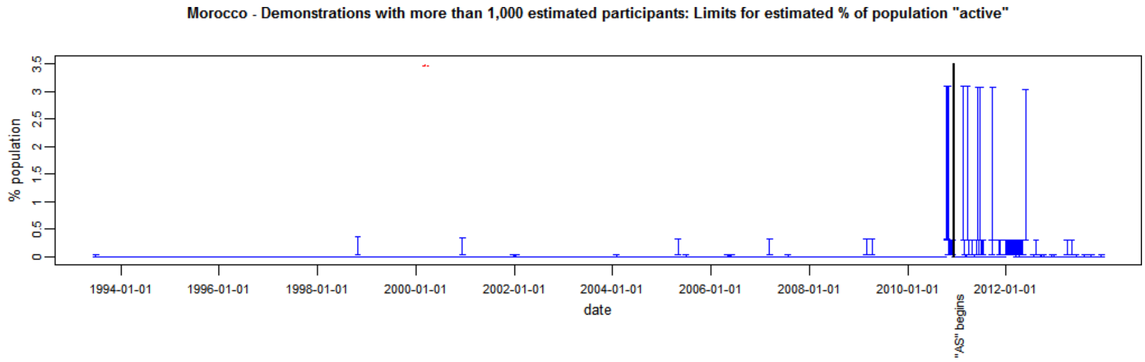
(b)

Figure 4.11: Time history of the range of estimated % of the population participating in demonstrations with more than 1,000 estimated participants, for Algeria (a) and Egypt (b). Events with more than 1,000,000 estimated participants are represented by dashed red lines with indefinite upper limit. All other events are represented by blue error bars. (Source: author, based on [97] and [102])

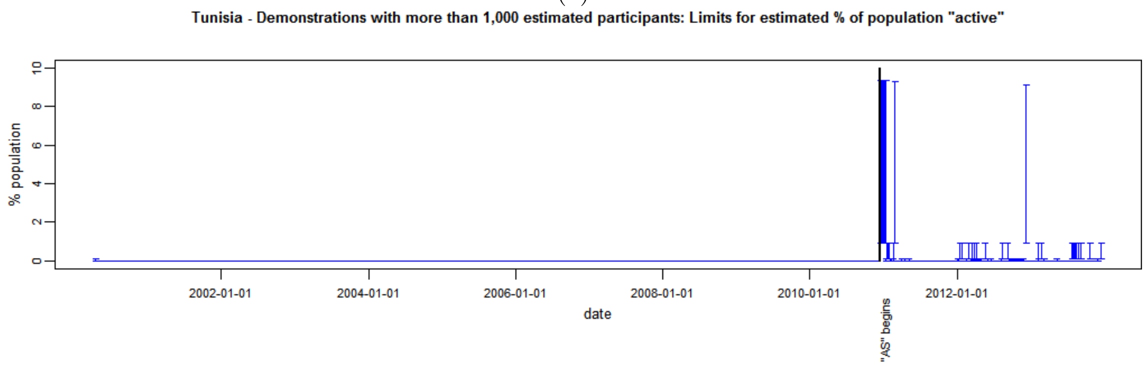
demonstrations are [0.5,4.0] for Algeria and [0.2,1.6] for Egypt. These proportions were exceeded in the few huge demonstrations shown in this figure. The effect of the AS on the time history of demonstrations was different in these two countries: in Algeria, the frequency of conflict events was not significantly altered by the AS, whereas in Egypt demonstrations (both very large and huge) became more frequent after the beginning of the AS (confirming the results in figures 4.8(a), 4.9(a) and 4.10(a)). The thick blue bars in the plot for Egypt correspond to demonstrations with exceptional duration (also shown in figure 4.8(a)).

The situation was different for Morocco and Tunisia (figure 4.12). Except for one isolated huge demonstration (shown as a small red trace in figure 4.12(a)), there were no massive demonstrations in Morocco before the beginning of the AS, although there were some demonstrations which involved at most an estimated 5% of the population. In Tunisia, there were no major demonstrations before the beginning

(`npart = '100,000 to 1,000,000'`) is due to the population growth (figure 4.6), and consequently is more pronounced for Egypt.



(a)



(b)

Figure 4.12: Time history of the range of estimated % of the population participating in demonstrations with more than 1,000 estimated participants, for Morocco (a) and Tunisia (b). Events with more than 1,000,000 estimated participants are represented by dashed red lines with indefinite upper limit. All other events are represented by blue error bars. (Source: author, based on [97] and [102])

of the AS. Just before December 15^{th}, 2010, there were two demonstrations (one of them very large) in Morocco, as shown in figure 4.12(a).[42] In Tunisia, there were very large demonstrations after that date, but they were less frequent then for Egypt in the same period. Plausible ranges of the % of the population for very large

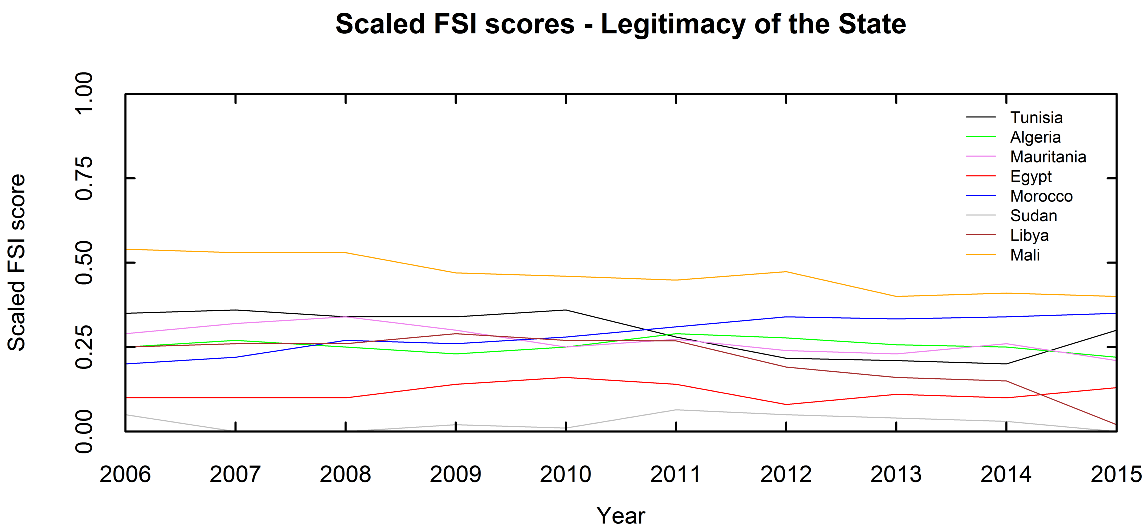
[42]Figure 4.12(a) induces the impression that the AS started in Morocco, which was not the case. The first of these two events was a spontaneous demonstration by Western Saharans, with issue `'economy, jobs'` and an estimated number of participants between 100,001 and 1,000,000, which started on October 18^{th}, 2010 and ended on November 10^{th}, 2010. The `issuenote` for this demonstration reads: "Western Saharans set up a camp to protest, demanding a better standard of living and more jobs". The second event was a spontaneous demonstration by Textile Workers, with issue `'economy, jobs'`, with an estimated number of participants between 10,001 and 100,001, which started on October 29^{th}, 2010 and ended on November 27^{th}, 2011. The `issuenote` is: "Textile workers stage a sit-in, protesting the decision to close four textile plants". The two following demonstrations in Morocco started on Februry 10th and 20th, 2011, and were related to the AS. The `issuenote` field for these events reads: "Arab Spring. A Moroccan dies after self-immolating to protest his situation after being dismissed from the army" and "Arab Spring. Protests erupt in favor of constitutional reform, social justice, and economic reform. 37,000 people take to the streets. Marches escalate to violence in Hoceima, where several people die after setting a bank on fire". The `issue1` field for these two events is coded as `economy, jobs`. These remarks show the importance of paying attention to the details of each situation when exploring the SCAD database.

demonstrations are [0.4,3.0] for Morocco and [1.1,8.5] for Tunisia.

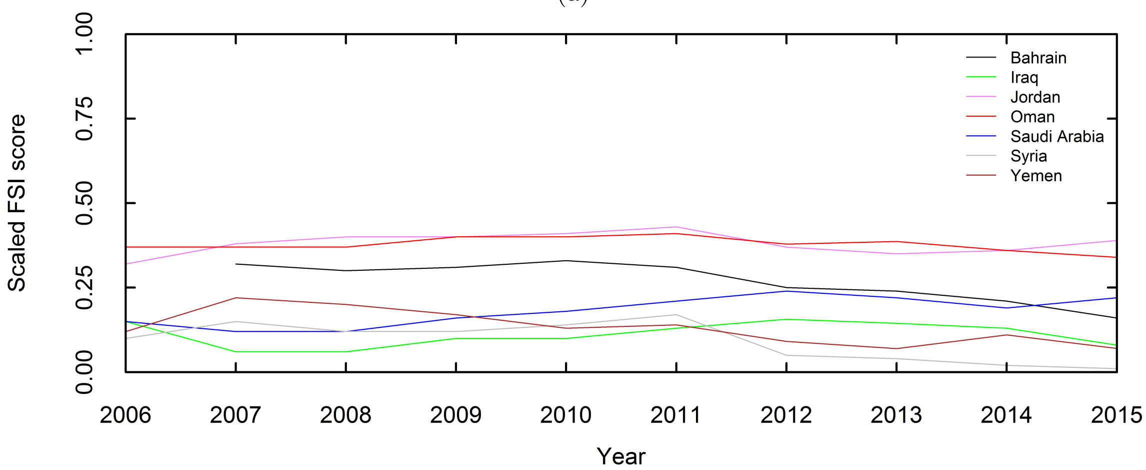
4.2 Analysis of the FSI Indicators for the African "Arab Spring" Countries

The SCAD database is a useful "diagnostic" tool for analysing the evolution of conflict processes in a country or group of countries, but provides little information about key variables (such as RD, identity-related grievance, legitimacy, influence of access to ICT, or level of deterrence) and typical patterns of RD (figure 2.1). Thus, it is natural to ask whether or not international indicators related to the political, economic and social context can be used to explain the outburst of processes like the AS. For instance, Cuniedioğlu et al. [21] attempted to explain how the AS evolved by comparing social and economic indicators from different sources for Egypt, Syria, Tunisia and Turkey, and found that economic and freedom indicators couldn't explain the differences between the outcomes of the AS in these countries. Youth unemployment and the "Life Satisfaction Index" were the only indicators that could explain such differences, but the author's didn't reach definitive conclusions.

In this section, the FSI scores for "Legitimacy of the State", "Human Rights and Rule of Law" (related to political deprivation), "Uneven Economic Development" and "Economic Decline" (related to economic deprivation)" and "Group Grievance" and "Factionalized Elites" (related to social/identity-related deprivation and the potential for civil war) are compared for the set of African "Arab Spring" countries considered in §4.1. Since the FSI is available for all countries, the comparison includes a set of Middle-East countries affected by the "Arab Spring" (Bahrain, Iraq, Jordan, Oman, Saudi Arabia, Syria and Yemen) and four countries affected by the European Sovereign Debt Crisis (Portugal, Ireland, Spain and Greece), to analyse differences between countries in different regions and affected by different types of crisis. The values of the FSI indicators and the final scores are evaluated in a 0-10 scale from "best" to "worst". To compare the FSI values with ABM parameters (e.g. legitimacy) it is convenient to express them in a 0-1 scale from "worst" to "best" via a simple linear mapping.



(a)



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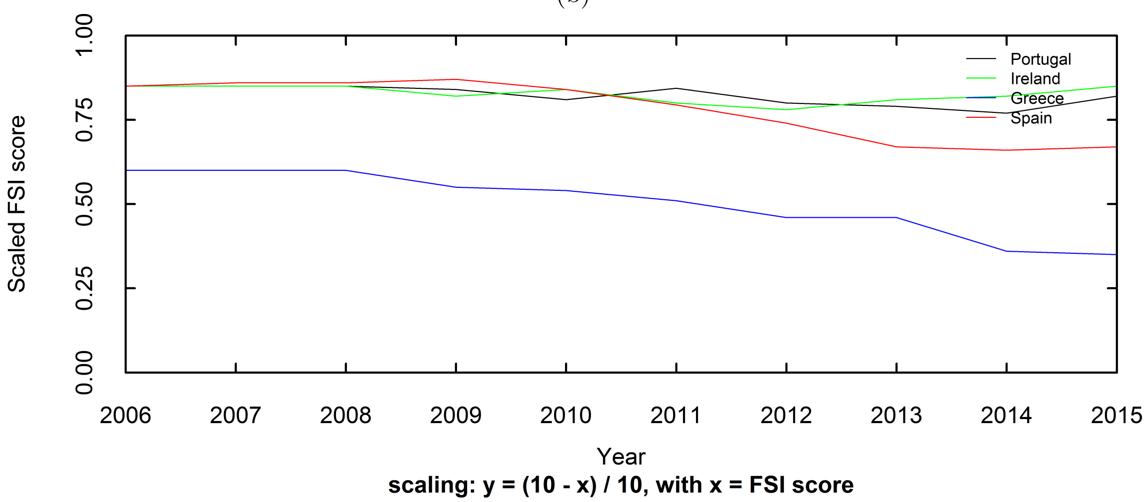


(c)

Figure 4.13: Scaled FSI "Legitimacy of the State" scores for "Arab Spring" countries in Africa (a) and Middle-East (b), and countries affected by the European Sovereign Debt Crisis (c). (Source: author, based on [96])

"Legitimacy of the State"

Figure 4.13(a) shows that before the AS the variations of the legitimacy scores were relatively small for all the African countries considered. After 2010 the scores dropped for Tunisia, Egypt, Libya and Mali. Figure 4.13(b) shows that before 2010 the variations were also small for the Middle East countries. Iraq, Syria, Yemen and Saudi Arabia had lower scores than Tunisia, were the AS started. For Syria, the score only dropped after 2011 (due to Bashar al-Assad's repressive response to the AS, and to other external factors, which lead to escalation into a civil war) while for Saudi Arabia (where the uprising was successfully crushed by the authorities) the score improved slightly. Figure 4.13(c) shows that, with the possible exception of Greece, the crises in the European countries have little relation with the legitimacy.

It can be concluded that the FSI "Legitimacy of the State" indicator has no significant predictive value for anticipating phenomena like the AS, because the variations prior to the beginning of the uprisings were small, and judging from the scores alone the movement should have started in Egypt, Yemen, Syria or Sudan[43] instead of Tunisia. This lack of predictive value can be explained by several factors:

- The scores are based on time-delayed data, some of which is provided by governments;
- Legitimacy is a latent concept that is difficult to measure;
- The FSI legitimacy score does not take into account important aspects like the components of legitimacy (as in Gilley [43, 44]), or the difference between the legitimacy of the government and the legitimacy of the regime;[44]
- The outburst of large scale processes of this type depend on many factors not accounted by a single indicator, such as triggering events, the level of repression, or existing group grievances or other sources of cleavage.

It is also interesting to question whether or not legitimacy feedback effects were significant. The information in figure 4.13 does not lead to conclusive answers, although in the cases of Tunisia, Egypt, Libya, and Syria there were legitimacy drops after the beginning of the AS.[45] It's also interesting to note that a similar effect occurred with Greece after 2013, albeit in a different context (the European

[43]Iraq also had a very low legitimacy score, but was in a state of war when the AS began.

[44]Bischof [11] argues that monarchies are more stable than republics in authoritarian regimes.

[45]The relative legitimacy drops were 22% for Tunisia, 43% for Egypt, 35% for Yemen and 26% for Sudan.

Sovereign Debt Crisis).

"Human Rights and Rule of Law"

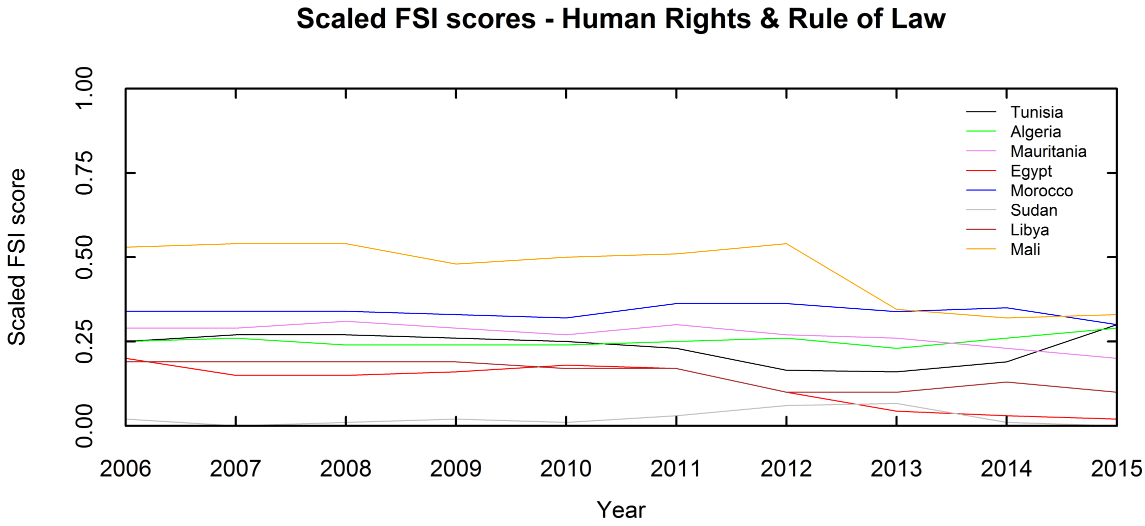
Figures 4.14(a)-(c) show the scaled FSI "Human Rights and Rule of Law" scores for the same sets of countries of figure 4.13. For the African and Middle East AS countries, the conclusions are same as for the legitimacy: (*i*) the indicators show no significant variation before the uprisings and thus have small "prognostic" value; and (*ii*) the values are inconsistent with the sequence and the intensity of conflict events in each country. It can also be observed that, with the notable exception of Tunisia, the scores show a generalized negative trend after the AS, indicating a (paradoxical) potential increase of political deprivation.

"Uneven Economic Development" and "Poverty and Economic Decline"

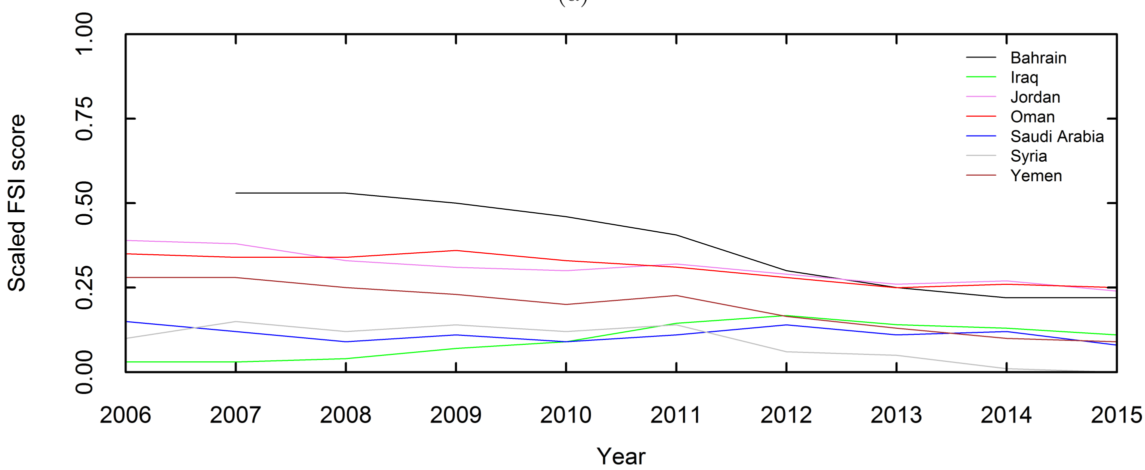
After considering political indicators, two economic indicators will be analysed: "Uneven Economic Development" (related unequal wealth distribution and the Gini coefficient) and "Poverty and Economic Decline" (related to the RD patterns due to economic and financial crises).

Figures 4.15(a)-(c) show the scaled FSI scores of "Uneven Economic Development" for the same sets of countries as before. Except for Sudan, the scores of the African countries are fairly consistent and show a small but clear positive trend. Middle-East countries show a wider variation, from Oman at the level of the European countries (but with a clear negative trend) to Syria, Iraq and Yemen with low scores.

Figures 4.16(a)-(c) show the scaled FSI scores of "Poverty and Economic Decline" for the same three sets of countries. With the exception of Morocco (which shows a clear positive trend), the scores for the other countries show negative trends typical of "decremental RD" (figure 2.1, page 16), particularly after the AS. In the Middle-East, the scores for Oman, Jordan, Iraq, Syria and Yemen suggest these countries were likely (negatively) affected by the AS, particularly in the cases of Syria (which is currently in a state of civil war) and Yemen. The scores for the European countries show a decremental RD pattern consistent with the economic and financial crisis.



(a)



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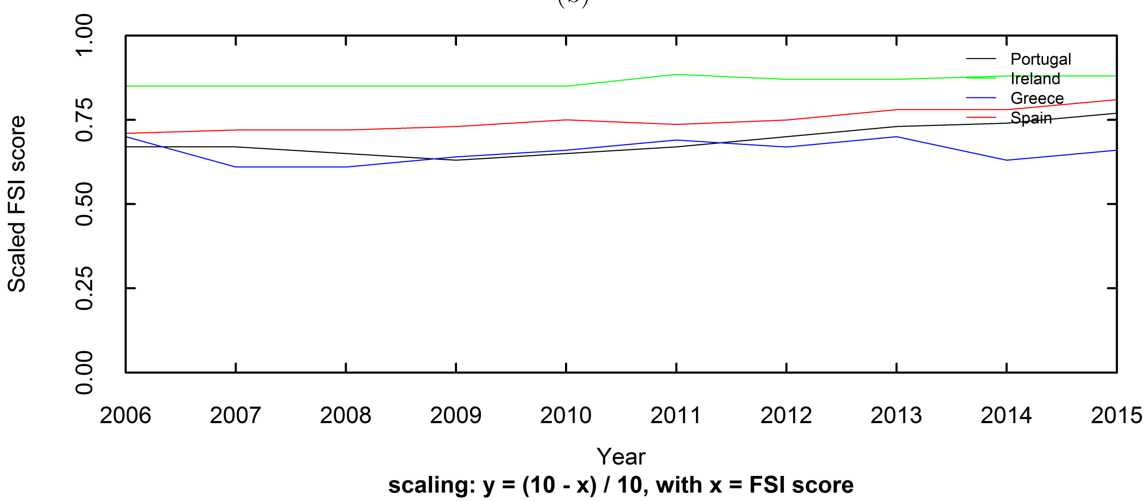


(c)

Figure 4.14: Scaled FSI "Human Rights and Rule of Law" scores for "Arab Spring" countries in Africa (a) and Middle-East (b), and countries affected by the European Sovereign Debt Crisis (c). (Source: author, based on [96])

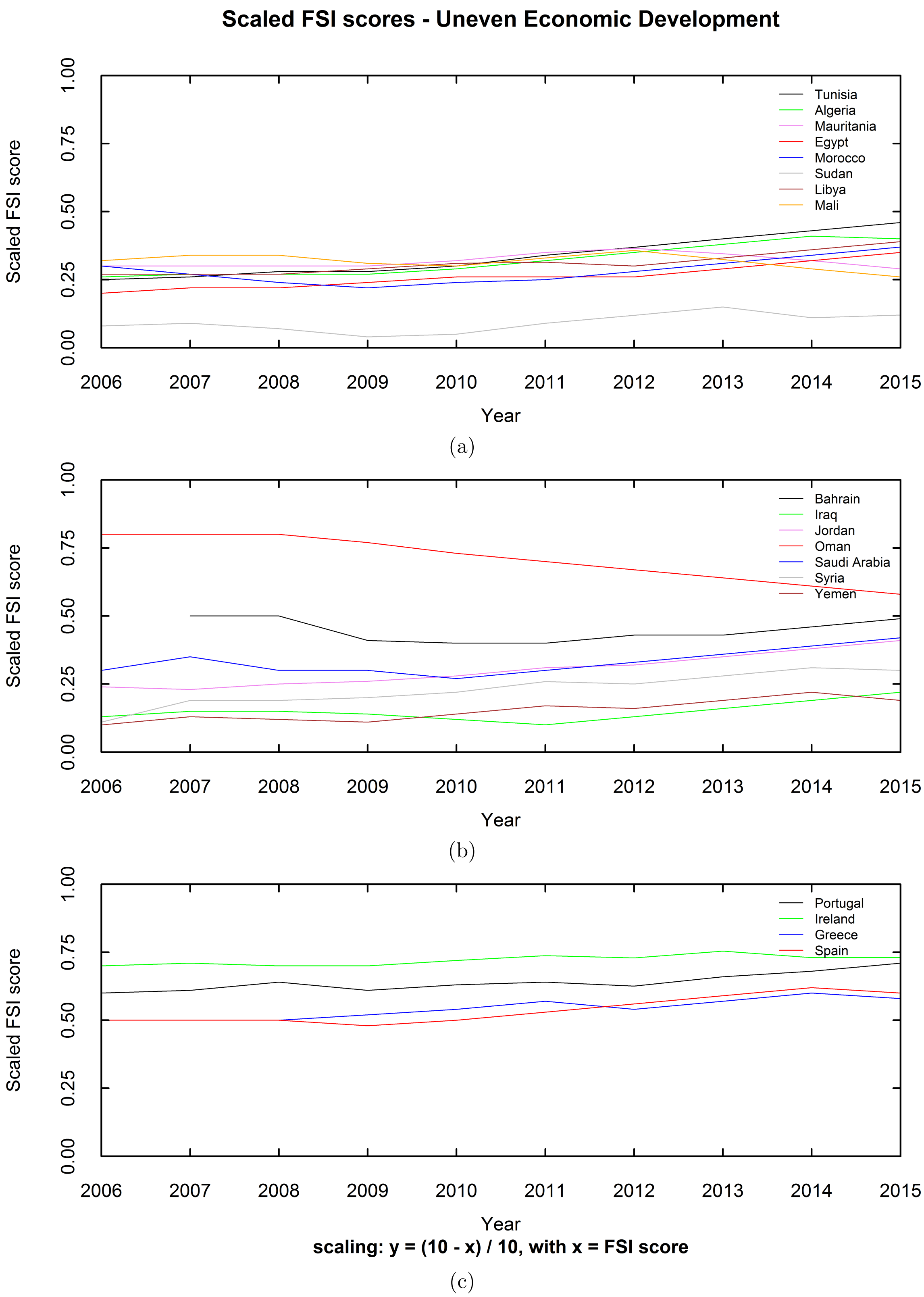


Figure 4.15: Scaled FSI "Uneven Economic Development" scores for "Arab Spring" countries in Africa (a) and Middle-East (b), and countries affected by the European Sovereign Debt Crisis (c). (Source: author, based on [96])

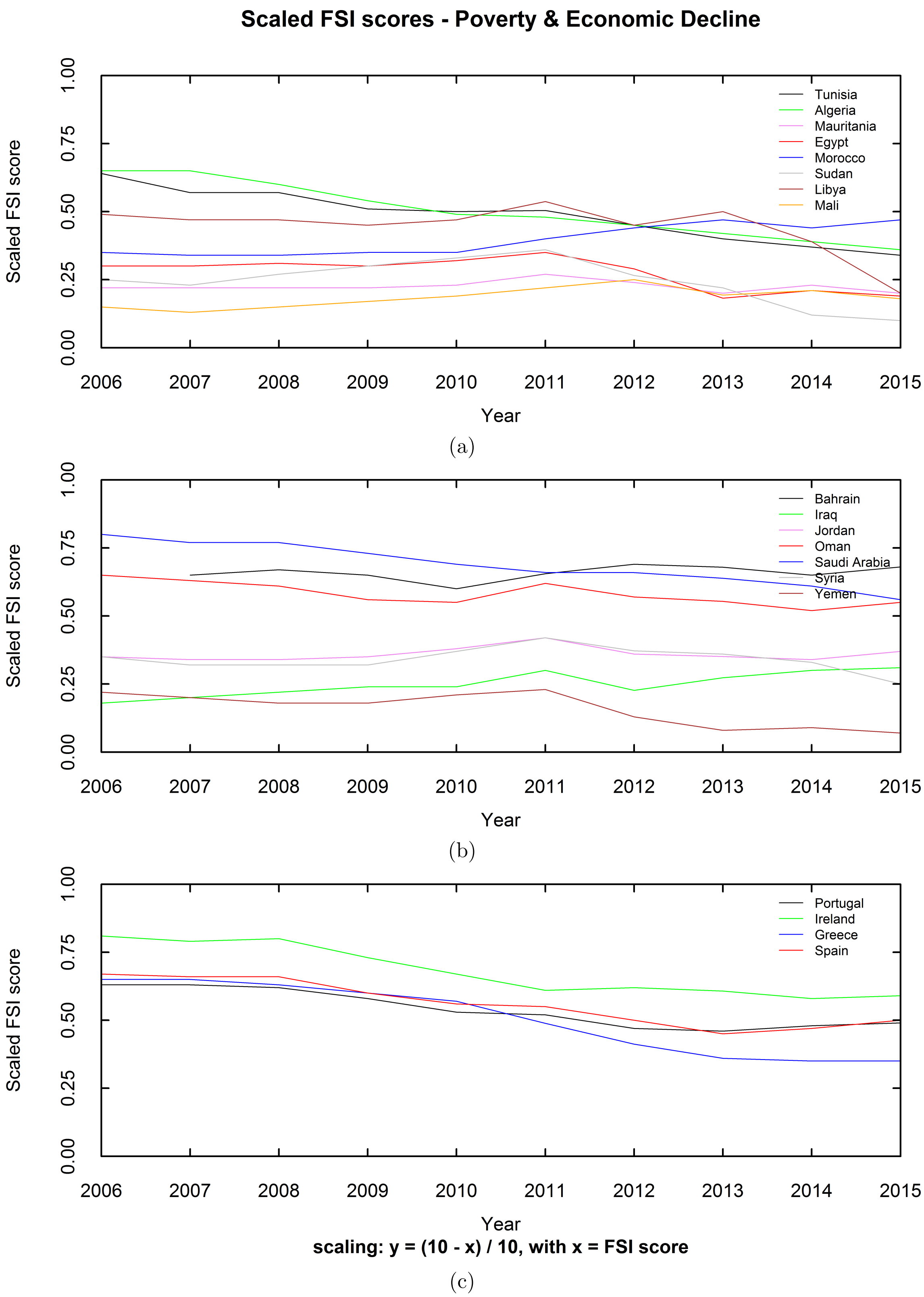
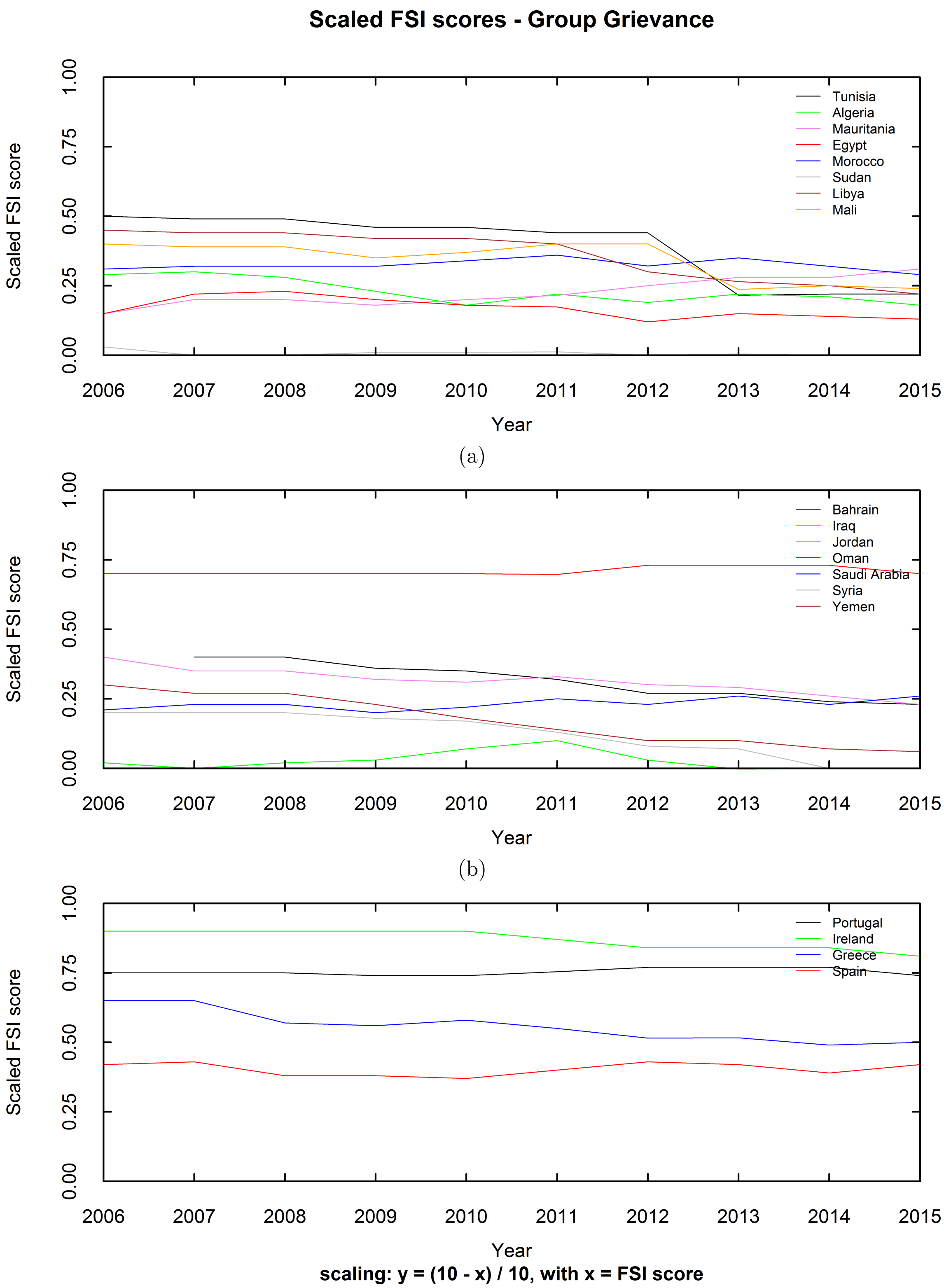


Figure 4.16: Scaled FSI "Poverty and Economic Decline" scores for "Arab Spring" countries in Africa (a) and Middle-East (b), and countries affected by the European Sovereign Debt Crisis (c). (Source: author, based on [96])



(a)

(b)

(c)

Figure 4.17: Scaled FSI "Group Grievance" scores for "Arab Spring" countries in Africa (a) and Middle-East (b), and countries affected by the European Sovereign Debt Crisis (c). (Source: author, based on [96])

"Group Grievance"

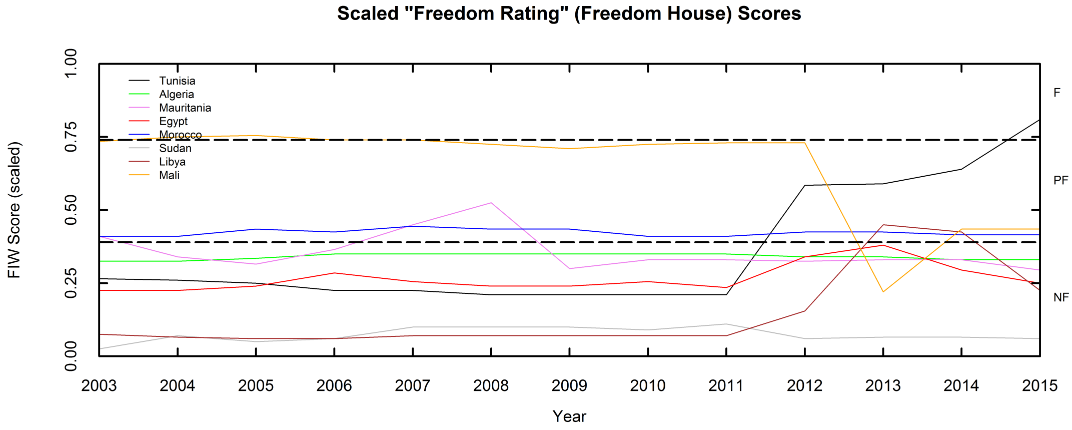
Figures 4.17(a)-(c) show the scaled FSI "Group Grievance" scores for the same sets of countries as in the previous figures. According to these scores, group grievances were smallest in Tunisia than in the other African countries before the onset of the AS. Based on the values and trends in figure 4.17(a), an AS starting in Egypt would be more plausible. Also, in Tunisia, Libya and Mali group grievance worsened after the uprisings. In the case of European countries the scores have small trends but larger differences than the previous scores. The low values for Spain can be attributed to regionalism and well-known separatist movements, and the negative trend for Greece to the prolonged effects of the economic and financial crisis.

Concluding Remarks about the FSI The FSI scores have some "diagnostic" value, for countries with notoriously low scores in several indicators are in a state of civil war (Syria and Iraq), near collapse (Libya), or already divided (Sudan). However, the scores of "Legitimacy of the State" and "Human Rights and Rule of Law" neither show significant variations before the "Arab Spring" nor help explaining the sequence and intensity of events (demonstrations and riots), and thus have no clear predictive ("prognostic") value. Paradoxically, the scores of many countries deteriorated after the AS. The FSI scores for the "Legitimacy of the State" are lower than the typical values of L reported in ABM simulations of civil violence (e.g. [33, 31]), and the scores for "Human Rights and Rule of Law" suggest higher mean values of "hardship" than used to parametrize those models. It is therefore interesting to study the behaviour of such models for parameter ranges consistent with the FSI scores, and the eventual existence of tipping points.[46]

4.3 Analysis of the Freedom in the World Indicator for the African "Arab Spring" Countries

Since the main issues in the AS were political (demand for democracy and human rights), it is interesting to compare the FSI "Human Rights" score with the "Freedom in the World" score, available from the Freedom House datasets.

[46]Tipping points are important for they may explain the occurrence of sudden transitions after small but persistent negative trends.



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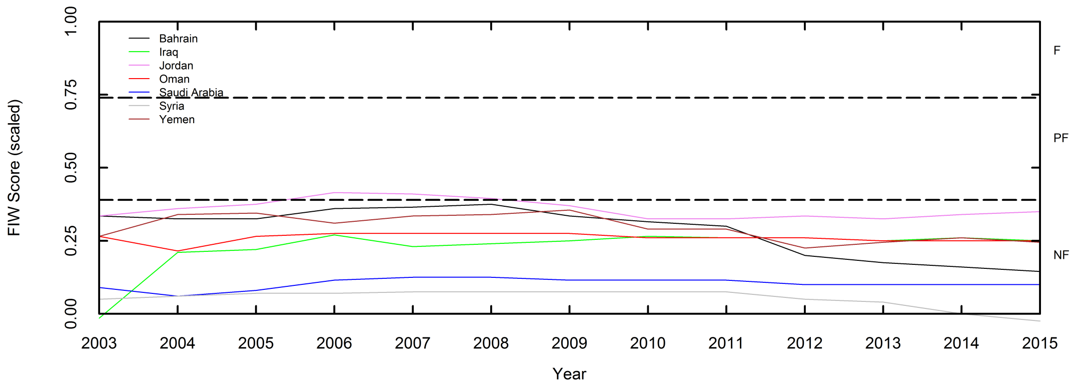

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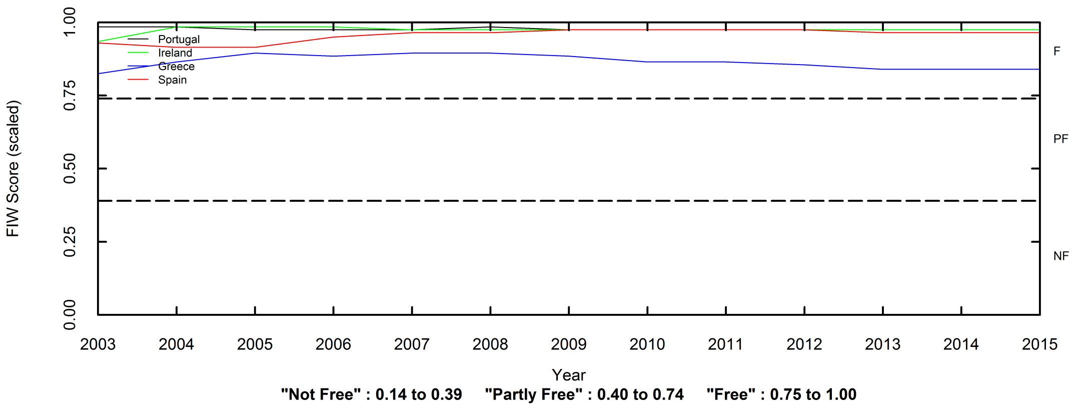


(c)

Figure 4.18: "Freedom in the World" scores for "Arab Spring" countries in Africa (a) and Middle-East (b) and countries affected by the European Sovereign Debt Crisis (c). (Source: author, based on [37])

Figure 4.18 shows the scaled "Freedom Rating" scores for the two sets of countries considered in figure 4.18. In the case of the African "Arab Spring" countries, it can be observed that between 2006 and 2010 the "Freedom Rating" scores are relatively stable and the ordering of the countries is not very different from that of the FSI-"Human Rights" indicator (Mali, Morocco and Mauritania have highest scores and Egypt, Libya and Sudan the lowest). After the "Arab Spring", the results of the two indicators are somewhat different: (*i*) Tunisia occupies the first place and is considered "Free"; (*ii*) Mali and Morocco come second and third and are "Partly Free" (with Mali worsening after 2012 from "Free" to "Partly Free"); (*iii*) Libya and Egypt improved from 2011 to 2013, but worsened again since 2014. In both indicators, Sudan's score is the worst. The European countries (figure 4.18(c)) have consistently high scores.

In summary, the "Freedom Rating" by the Freedom House shows higher variability and response to the particular situation of each country than the FSI, but it is not clear if it can be used as a "prognostic" tool for assessing the plausibility of occurrence of large uprisings.

4.4 Analysis of the "All the Ginis" Dataset for the African "Arab Spring" Countries

Although the main issues in the AS were not due to economic RD, it is useful to consider indicators other than FSI's Uneven Economic Development and Poverty & Economic Decline to characterize the potential relevance of this type of deprivation in the African AS countries. For this purpose, it is worthwhile analysing the values of this index available in the "All the Ginis" dataset [13], mentioned in §2.5.

Figure 4.19 shows the aggregated Gini index and table 4.4 provides a summary of the information available in [13] for the countries of interest. The information is scarce and the number of values too small for drawing conclusions about the evolution of inequality and economic RD in these countries.

The time coverage is very uneven in different countries and ends before the beginning of the AS for all countries. In this way, trends in inequality and their potential effect of the AS cannot be inferred from the "All the Ginis" dataset. Nevertheless, it is plausible to assume that welfare inequality was moderate (closer to 30% than to 60%) and relatively uniform among the countries considered. In this sense, the information on the Gini index conveys a more favourable picture than the

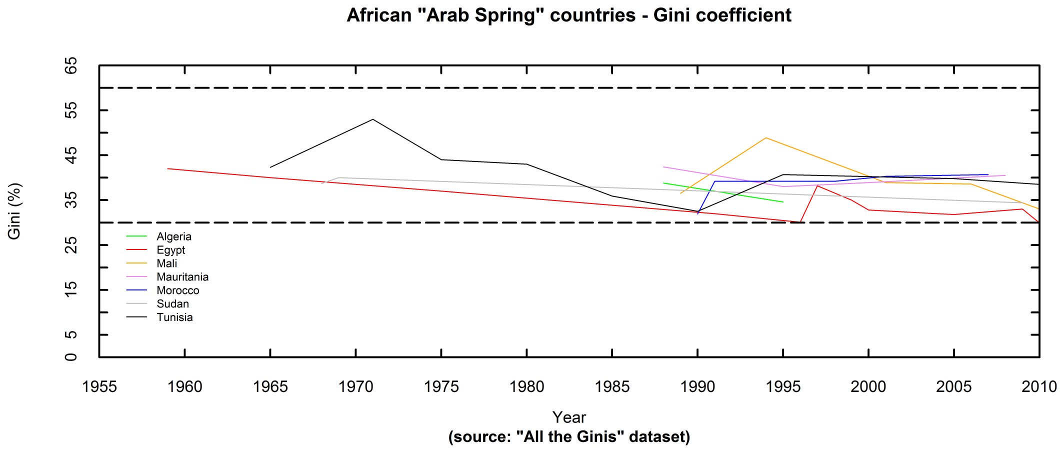


Figure 4.19: "All the Ginis" scores of the Gini index for "Arab Spring" countries in Africa. The generally assumed bounds for "small" and "large" inequality (30% and 60%, respectively) are represented by horizontal dashed lines. (Source: author, based on [13])

Table 4.4: Summary of the information on the aggregated Gini index (field Giniall in [13]) for the African "Arab Spring" countries. (Source: Milanovic [13])

Country	**First year**	**Last year**	**Number of values in the dataset**	**Mean value of "Giniall" (%)**
Algeria	1988	1995	2	36,7
Egypt	1959	2010	12	34,5
Libya	–	–	0	–
Morocco	1990	2007	5	38,3
Mali	1989	2010	5	39,2
Mauritania	1988	2008	4	40,0
Sudan	1968	2009	3	37,7
Tunisia	1965	2010	9	41,1

relatively low scores of the FSI indicators related to economic RD.

One advantage of the Gini index is that it can be used for synthesizing approximate distributions of welfare in ABM in a more direct way than other indicators (§2.5). For this purpose, the information in table 4.4 suggests that 0.4 (or 40%) is a representative value of the Gini index for the African AS countries.

4.5 Concluding Remarks

The analysis of the SCAD database and the FSI, FWI and "All the Ginis" indicators for eight African countries affected by the AS (a notable example of a large scale conflict process against centgral governments of several countries) was performed to determine qualitative and quantitative elements for ABM validation and parametrization.

The SCAD database contains information about conflict events which is useful to compare with ABM solutions, and its exploration was guided by five specific questions which can be answered as follows:

Question 1: How important were demonstrations and riots, in terms of number of events and mobilization (estimated number of participants)?

Demonstrations were the most important form of conflict event, both in number of events and mobilization (estimated number of participants). Riots were rarer and less significant. Egypt was the country with greatest number of conflict events, before and after the AS.

Question 2: Which were the most significant issues (grievance factors) that triggered conflict events?

The main triggering issue for demonstrations the AS countries analysed was the struggle for more political participation and civil liberties (`human rights, democracy`). The triggering issues for riots were more heterogeneous than for demonstrations.

Question 3: Which were the issues, organization and escalation in large demonstrations and riots?

The main issue in massive demonstrations (more than 100,000 estimated participants) was `human rights, democracy`. Massive riots had more heterogeneous causes (`human rights, democracy`, `foreign affairs/relations`, `food, water and subsistence`, and `domestic war, violence, terrorism`). Spontaneous demonstrations and riots were more numerous than organized events, which suggests that the methods of complex systems studies are useful for studying large scale conflict processes. Escalation of large demonstrations to riots was significant, but riots did not escalate to more intense forms of violence. This is consistent with Ted Gurr's frustration-aggression theory and with the 'dividing lines' sketched in figure 1.1.

Question 4: What were the patterns of recurrence, duration and size of demonstrations and riots?

Demonstrations and riots occurred intermittently. The analysis provided estimates for the % of total time with calm and rebellion (for each country and for all eight countries taken together), and for the distributions of duration and interval between successive events. In general, demonstrations were short events with median 1 day and 75% of the cases with duration less than ten days. The interval between successive events was heterogeneous among the eight countries, and was much shorter after the beginning of the AS (characteristic value of 15-20 days). The % of the population participating in demonstrations was smaller for more populous countries (e.g. Egypt and Argelia) than for less populous countries. Typical ranges of these % are [0.5,4.0] and [1,10], respectively, meaning that activity peaks involving 10% or more of the population are very unlikely.

Question 5: How did these characteristics of the social conflict process change after the beginning of the AS?

There were very large demonstrations and riots in Algeria, Morocco and Egypt several years before December 2010, but after the beginning of the AS the frequency of events increased notably. Taking all eight countries together, the % of total time with demonstrations increased from 16% to 57%. For riots, the corresponding figures are 4% and 7%, showing that demonstrations were indeed the main form of protest after the beginning of the AS. The most common issue in massive demonstrations was `human rights, democracy` before and after the beginning of the AS. Demonstrations tended to have shorter duration (median 1 day) and the interval between successive events (15-20 days) after the beginning of the AS.

The analysis of the FSI, FWI and "All the Ginis" lead to the following general conclusions:

- None of these indicators had "prognostic" value for anticipating the onset of the AS or the order by which the movement propagated from country to country;

– The scaled FSI score for "Legitimacy of the State" were below 0.4 (in a scale 0-1) for all countries analysed except Mali, with very low values for Sudan and Egypt;

– In some countries, the scaled "Legitimacy of the State" and "Human Rights and Rule of Law" scores deteriorated after the beginning of the AS. This supports the conjecture that legitimacy feedback is significant, with characteristic variations in the range [20%,40%];

– A plausible value of the Gini index for the countries analysed is 0.4 (or 40%), which is above "low inequality" (30%) but below "strong inequality" (60%). This characteristic value can be used to model economic RD for the countries considered.

Chapter 5

Agent-Based Model of Social Conflict Against a Central Authority. Description and Computer Experiments

In this chapter, a new 'abstract' ABM of large-scale civil violence is described and explored in a series of computer experiments. This model is an extension of Epstein's Model I that includes: (*i*) a more general form of the estimated arrest probability; (*ii*) a (simplified) description of grievance as a function of RD; (*iii*) endogenous legitimacy feedback (homogeneous or heterogeneous); (*iv*) network influence effects, considering two types of networks ('group' and 'influentials'); and (*v*) a representation of the mechanism of 'mass enthusiasm'. The model is explored in a series of computer experiments and its explanatory power is discussed by comparing the results obtained with patterns of conflict events in African countries affected by the AS obtained in the previous chapter.

The methodology consisted of the following steps:

1. Formulation of model representations of the new processes and mechanisms, and their stepwise implementation as extensions to Epstein's Model I;
2. Exploration of the model via a series of computer experiments, to evaluate how different parameter values and newly introduced processes and mechanisms influence the nature and behaviour of the solutions. One aspect of particular interest was the tentative identification of the parameters with associated

tipping points;

3. Discussion of the model's explanatory power by comparing the solutions obtained in the computer experiments with the results of the qualitative and quantitative analysis of the conflict events and indicators.

The computer experiments were idealized in the spirit of a sensitivity analysis. Hence, the purpose of each experiment was to highlight the influence of one particular parameter, effect or mechanism on the solutions' behaviour, as independently as possible from other parameters, effects and mechanisms.

The model exploration started with an analysis of the decision rule in Epstein's model, to show how the legitimacy and the form of the estimated arrest probability determine the occurrence and amplitude of intermittent bursts of rebellion. The results of this analysis provided important clues for setting up the subsequent computer experiments.

The first set of experiments was performed to determine the influence of the critical 'cop'-to-'active' ratio in the estimated arrest probability on the size, duration, and recurrence of rebellion bursts is investigated. The second set of experiments was set to investigate the influence of the maximum jail term and its relationship with the interval between successive rebellion bursts in solutions in punctuated equilibrium. The third set of experiments was performed to study the stability of the solutions in a scenario of low government legitimacy (values in the typical range of the FSI indicators analysed in Chapter 4) for varying deterrence capability. The next computer experiments were devised to explore the impact of mechanisms and processes included in the present ABM: grievance expressed as a function of RD, legitimacy feedback, and network influence effects.

This chapter is organized in three sections. In the first section, a summary description of the ABM of large-scale civil violence is presented. This is complemented by a more complete description in Appendix A, based on the ODD protocol [48]. The second section contains a description of the computer experiments mentioned above. The descriptions of each computer experiment end with a discussion of the results and their plausibility and explanatory power for analysing large-scale conflict processes (e.g. the AS).

5.1 Abstract ABM of Civil Violence. Summary Description

The present model extends Epstein's ABM by considering new entities, mechanisms and submodels relevant to large scale social conflict processes, such as:

– Different forms of the estimated arrest probability function P_a, with a discussion of their theoretical foundations and plausibility;

– Representation of hardship as a function of RD, with a parameter for controlling the sensitivity to deprivation (to simulate economic and political RD);

– Legitimacy feedback effects, by which the citizens' perceived legitimacy is a dependent variable of the system state;

– Network influence effects, by considering two networks, one associated with highly cohesive small scale communities connected by strong undirected links (two-way influence) [46], and another for representing the 'news impact' through which influential agents (such activists or formal media) shape global perceptions [46, 103]. This provides an abstract representation of two important influence modes in societies;

– Representation of the 'mass enthusiasm' effect [67].

5.1.1 Synopsis

The model was implemented in NetLogo [106], using the "Rebellion" NetLogo Library Model [107] as starting point. Table 5.1 shows a summary of the model characteristics, using a subset of the "Overview, Design Concepts and Details" (ODD) protocol [48]. A more complete description based on the ODD protocol is presented in Appendix A.

5.1.2 Model Entities

The model entities are the agents, the scenario (model space) and the networks.

Table 5.1: Simplified ODD description of the ABM of civil violence. (Source: author)

ODD item	Description
Purpose	Extend Epstein's ABM of civil violence to include new mechanisms: hardship as a function of RD, network influence(s), legitimacy feedback and 'mass enthusiasm'
Entities, state variables and scales	Agents: – Two types of agents, 'citizen' and 'cop', with one 'move' and one 'behave' rule; – 'Citizen' agents can be of two subtypes: 'normal' and 'activist'. Networks: – Two networks, `group` and `infl` (for 'influentials') • The `group` network is a union of undirected cliques of size defined by the input parameter `group-size` • The `infl` network is a union of star networks, with 'activist' citizens as central hubs, each of which is connected by directed links to a % of 'citizens' defined by the input parameter `infl-size`
Scenario	Homogeneous 2D torus space.
Scales	– Whole artificial society, undefined time step and patch size. – Spatial scales in units of patch size: vision radius. – Time scales in units of time step size: maximum jail term (J_{max}).
Process overview and scheduling	– All agents activated once per cycle in random order.
Submodels	– Arrest probability function (with a parameter for controlling the 'massive fear loss' mechanism); – Hardship as a function of RD (economic or political); – Legitimacy feedback (homogeneous or heterogeneous); – Aggregation of network influences; – Representation of the 'mass enthusiasm' mechanism.

Agents

There are three types of agent, the 'observer' (model user), 'citizen' and 'cop'. 'Citizen' agents can be of two subtypes, 'normal' and 'activist'. 'Activist' agents only exist if the `infl` network is introduced, as explained below. Figure A.1 (page 186) shows the class diagram for all model entities in the NetLogo implementation. As in Epstein's Model I, 'citizen' and 'cop' agents have one move and one action rule.

The move rule for 'citizen' agents of the 'normal' subtype is:

$$\begin{array}{lll} \text{Rule M}_1 : & \textbf{if} & \texttt{jail-term} = 0 \wedge \mathcal{E}_v \neq \emptyset \textbf{ then} \text{ move to a random cell } c_r \in \mathcal{E}_v \\ & \textbf{else} & \text{stand still} \end{array}$$

where $\mathcal{E}_v$ is the set of empty cells[47] within the agent's vision radius. 'Activist' citizen agents have a slightly different move rule, by which they approach visible concentrations of 'active' citizens:

$$\begin{array}{lll} \text{Rule M}_2 : & \textbf{if} & \texttt{jail-term} = 0 \wedge \mathcal{E}_v \neq \emptyset \textbf{ then} \\ & & \quad \textbf{if } \mathcal{A}_v \neq \emptyset \textbf{ then} \text{ move to one } c_r \in \mathcal{E}_v \text{ with } \texttt{min}(d(\hat{x}_g, \hat{y}_g)) \\ & & \quad \textbf{else} \text{ move to a random cell } c_r \in \mathcal{E}_v \\ & \textbf{else} & \text{stand still} \end{array}$$

[47] A cell is considered empty if it contains no agent or 'jailed' citizens only.

where $\mathcal{A}_v$ is the set of visible 'citizens' that are 'active' and $d(\hat{x}_g, \hat{y}_g)$ is the distance to the centroid $(\hat{x}_g, \hat{y}_g)$ of $\mathcal{A}_v$. This departure from a random move rule is a simple representation of the 'agenda setting bias' of 'activists' and traditional media towards showing protests and violence [10]. 'Citizen' agents can be in one of three ststes, 'quiet', 'active' or 'jailed'. Their action rule consists of the binary decision of assuming the 'quiet' or 'active' state:

$$\begin{array}{lll} \text{Rule A:} & \textbf{if} & G - N + \mathscr{S} + \mathscr{M} > T \textbf{ then} \text{ be 'active'} \\ & \textbf{else} & \text{be 'quiet'} \end{array}$$

where

$$\begin{array}{ll} G & = H \cdot (1 - L_p) \text{ is the level of grievance;} \\ N & = R \cdot P_a(\rho_v) \text{ is the net risk perception;} \\ \mathscr{S} & = \texttt{w-group} \cdot \sum\limits_{\mathscr{A}_k \in \mathcal{AG}_i} (G_{\mathscr{A}_k} - N_{\mathscr{A}_k}) + \texttt{w-infl} \cdot \sum\limits_{\mathscr{A}_l \in \mathcal{AINFL}_i} (G_{\mathscr{A}_l} - N_{\mathscr{A}_l}) \\ & \quad \text{is the sum of network influences;} \\ \mathscr{M} & = \texttt{w-crowd} \cdot \sum\limits_{\mathscr{A}_j \in \mathcal{A}_v} (G_{\mathscr{A}_j} - N_{\mathscr{A}_j}) \text{ is the 'mass enthusiasm' term.} \end{array}$$

in which

$$\begin{array}{rl} P_a(\rho_v) & \text{is the estimated arrest probability;} \\ \rho_v & = (C_v / A_v); \\ C_v & \text{is the number of visible 'cops' and} \\ A_v & \text{is the number of 'active' citizens visible to a generic} \\ & \text{'citizen' } \mathscr{A}_i; \\ \mathcal{A}_v,\ \mathcal{AG}_i,\ \mathcal{AINFL}_i & \text{are the sets of visible 'active' citizens,} \\ & \text{'active' citizens in the } \texttt{group} \text{ network} \\ & \text{and 'active' citizens in the } \texttt{infl} \text{ network} \\ & \text{for citizen } \mathscr{A}_i, \text{ respectively;} \end{array}$$

and the remaining variables and parameters are described in tables A.1 (page 187) and A.4 (page 194). The terms $\mathscr{S}$ and $\mathscr{M}$ are zero if network influences and 'mass enthusiasm' are turned off, respectively.

The move rule for 'cop' agents is:

$$\begin{array}{lll} \text{Rule M}_3\ : & \textbf{if} & \mathcal{E}_{v'} \neq \emptyset \textbf{ then} \text{ move to a random cell } c_r \in \mathcal{E}_{v'} \\ & \textbf{else} & \text{stand still} \end{array}$$

and their action rule is:

Rule C : **if** $\mathcal{A}_{v'} \neq \emptyset$ **then**
select one random $\mathscr{A}_i \in \mathcal{A}_{v'}$
set 'active?'$_{\mathscr{A}_i} = \textit{false}$
set `jail-term`$_{\mathscr{A}_i} = \sim \mathcal{U}(0, J_{max})$
move to $(x_{\mathscr{A}_i}, y_{\mathscr{A}_i})$
endif

where $\mathcal{A}_{v'}$ is the set of visible 'active' citizens and $\mathscr{A}_i$ is a random 'citizen' in this set.

Scenario

The scenario is a 2D homogeneous torus space, which is typical of 'abstract' ABM.

Networks

The `group` network is set up by forming cliques of undirected links of type `group-member` between 'citizens'. The clique (group) size is defined via the `group-size` input parameter (table A.4, page 194).

The `infl` network is set by connecting each 'activist' (randomly chosen 'citizen') to a proportion of the population defined by the `infl-size` input parameter, via directed links of `infl-follower` type. The `infl` network is a union of `num-infl` directed star networks, each with one 'activist' as central hub. One 'citizen' can be connected to more than one 'activist' agent.

5.1.3 Process Overview and Scheduling

The model is implemented in two main procedures, `setup` and `go`. The `setup` procedure clears all variables from the previous run, resets the simulation clock, creates the agents and sets their attributes, builds the networks (if appropriate) and displays the simulation space and NetLogo interface monitors. The `go` procedure implements the model cycle, which consists of (i) activating all agents except 'jailed' citizens by random order and executing their move and action rules; (ii) decrementing the `jail-term` of 'jailed' citizens and releasing them if `jail-term` $= 0$; (iii) updating the global legitimacy (if appropriate); and (iv) advancing the simulation clock and updating the displays.

5.1.4 Submodels

The three submodels required to implement the 'citizens' action rule are the estimated arrest probability (associated with the mechanism of collective fear loss), the expression of RD (associated with the generation of conflict potential) and the formulation of legitimacy feedback.

The estimated arrest probability is computed as follows:

$$P_a(\rho) = \begin{cases} 0 & \rho < \rho_c \\ 1 - \exp(-k\,\rho) & \rho \geq \rho_c \\ 1 & \rho = +\infty \quad (A_v = 0) \end{cases} \tag{5.1}$$

where $k = 2.3$, $\rho = C_v/A_v$, and C_v and A_v are the numbers of 'cops' and 'active' citizens within the agent's vision radius, respectively. This equation is a generalization of the expression (5.11) (page 118) proposed by Fonoberova et al. [35], which contains equation (3.5) as a special case and is an approximation of equation (3.6) for $\rho_c = 1$. The parameter ρ_c in equation (5.1) was introduced to model the mechanisms of 'massive fear loss'. The meaning and theoretical justification of equation (5.1) will be analysed in §5.2.1 in connection with the occurrence of solutions with cascades and large peaks of rebellion.

The submodel for expressing the hardship of 'citizens' as a function of RD consists of (i) defining a `value` attribute; (ii) computing the difference between the agent's `value` and the median of the `value` of the 'citizens' within the vision radius; and (iii) computing the final RD using a power law for representing the sensitivity to deprivation [49], to distinguish between political and economic deprivation. The expression for the RD model is:

$$\mathtt{RD} = \{\max(\mathrm{median}(\mathtt{value})_v - \mathtt{value}, 0)\}^\gamma \tag{5.2}$$

where $\mathrm{median}(\mathtt{value})_v$ is the 'expectation' and $\gamma > 0$ is an input parameter which determines the sensitivity to deprivation. $\gamma = 1$ corresponds to a 'neutral' response to the gap between expectation and deprivation (economic RD) whereas for $0 < \gamma < 1$ the 'citizens' become more sensitive (less tolerant) to deprivation (as occurs with political issues). The `value` attribute is set using a Pareto Type I distribution, as explained in §A.4, page 196.

The submodel for the legitimacy feedback is computed using a simplification of

Table 5.2: R functions for post-processing of model output files. (Source: author)

R function	usage
`duration.stats(a,peak.threshold)`	Compute statistics of event duration for a time series of proportion of 'active' citizens
`event.start.end(a,peak.threshold)`	Find start and end of rebellion bursts for a time series of proportion of 'active' citizens
`find.peaks(a,peak.threshold,diff.threshold)`	Find position of rebellion peaks for a time series of proportion of 'active' citizens
`peak.interval.stats(a,peak.threshold,diff.threshold)`	Compute statistics of event duration for a time series of proportion of 'active' citizens
`peak.size.stats(a,peak.threshold,diff.threshold)`	Compute statistics of rebellion peak size for a time series of proportion of 'active' citizens

the 'weighted average' formula proposed by Gilley [43, 44]:

$$L = L_0 \cdot \left(\frac{1}{4} + \frac{3}{4} \cdot \frac{n_{quiet}}{N_{citizen}} \right) \tag{5.3}$$

where L_0 is the value of the `government-legitimacy` input parameter, $N_{citizen}$ is the population size and n_{quiet} is the total number of 'citizens' in the 'quiet' state. The foundations and details of the procedure can be found in §A.4 and in [64].

5.1.5 Model Output. R Scripts for Pre- and Post-Processing

The model output consists of the display of the model space (where the agents move) and plots of legitimacy and the proportions of 'citizen' agents in each state in the NetLogo interface. Also, records of the time evolution of the global variables that characterize the system's state (e.g. deprivation and legitimacy) can be obtained for post-processing.

The model can be run interactively from the NetLogo GUI for quick visualization of tentative simulations, or off-line for conducting systematic experiments involving parameter sweeping. The pre- and post-processing of sets of simulations with systematic variation of one or more input parameters was done using R scripts and the RNetLogo package [99, 98]. This approach has several advantages over using NetLogo's `BehaviorSpace` tool, such as faster execution (by avoiding display updates), efficient storage of parameter sets and output records in R objects (lists, dataframes, vectors or arrays) for post-processing, and combining script and interactive processing, all within the R environment.

Two R-scripts were written, one for setting up and running a set of simulations with varying parameters and storing the results in a `.RData` file, and another for post-processing the results (i.e. computing statistics related to the long-term behaviour of the solutions, and simulated rebellion events if present). The pre-processing script does the following operations:

– Start an instance of NetLogo and load the model with default values of the input parameters (Table A.4, page 194);

– Read the names of the input parameter(s) to be changed from a vector, and the values for each parameter from a list of numeric vectors (one vector of values for each parameter);

– Initialize a global list for storing the parameters and output for each run;

– Sweep over all parameter values using nested loops (one per parameter), and:

  - Set and store a new random seed;[48]

  - Set the parameter values for the new run;

  - Run the model in an inner loop for a user-specified number of cycles;

  - Store a global list with (*i*) the random seed and full set of parameter values, and (*ii*) an output data frame with the time history of the proportion of 'quiet', 'active' and 'jailed citizens', plus the (median) of the legitimacy, expectation and deprivation, for each simulation.

– Save the run information (global list) in a `.RData` file for post-processing;

– Close the NetLogo instance.

The post-processing script does the following operations:

– Read a `.RData` file;

– Loop over all elements of the global list and:

  - Retrieve the variable parameters and the output data frame;

  - Compute the statistics of rebellion events and peaks.

– Store the input parameters and computed statistics in an EXCEL file for analysis and production of tables to include in documents.

[48]This allows the exact reproducibility of the simulations, if required at a later time.

Table 5.2 shows the auxiliary functions used by the post-processing script. In this table, `a` is a vector of the proportion of ‘active’ citizens, `peak.threshold` is the minimum proportion for a significant rebellion event with default value 10^{-3}, and `diff.threshold` is a second threshold for peak detection (variation in the neighbourhood of a local maximum or minimum) with default value 5×10^{-4}. It is also possible to do further processing of the results (plotting time series, computation of further statistics, etc.) from within the R environment.

5.2 Model Explorations and Computer Experiments

5.2.1 Analysis of the Decision Rule in Epstein’s ABM

In this section, the dependence of the long-term behaviour of the solutions of Epstein’s ABM on the legitimacy L,[49] threshold T and arrest probability function P_a will be analysed. It will be shown that solutions with large intermittent peaks of rebellion only occur if the form of P_a leads to a drop of the risk perception for the whole population (herein called “massive fear loss”) when the ratio between the number of ‘cops’ and ‘active’ citizens’ falls below a critical value. The analytical results obtained clarify the relationship between the solutions’ behaviour and the particular combination of L, P_a and T for given distributions of H and R. These findings were confirmed via a series of computer experiments (described below) in which L, P_a, T, and the level of deterrence (number of ‘cops’ and J_{max}) were varied in systematic ways, to discuss whether or not this “massive fear loss” mechanism can be identified in real processes (such as the AS).

If network influence effects and ‘mass enthusiasm’ are not considered, the decision Rule A (page 103) can be written in the form

$$G > T + R \cdot P_a \tag{5.4}$$

and expresses a balance between conflicting drives: motivation for rebelling on the left hand side, and inhibition (fear of being arrested) on the right hand side. The right hand side of (5.4) can be interpreted as a “variable fear threshold” which

[49]In the analytical study presented in this section, it will be assumed that the legitimacy is a dependent variable for the sake of generality, but $L = L_0$ in the sense that it does not depend on the system’s state.

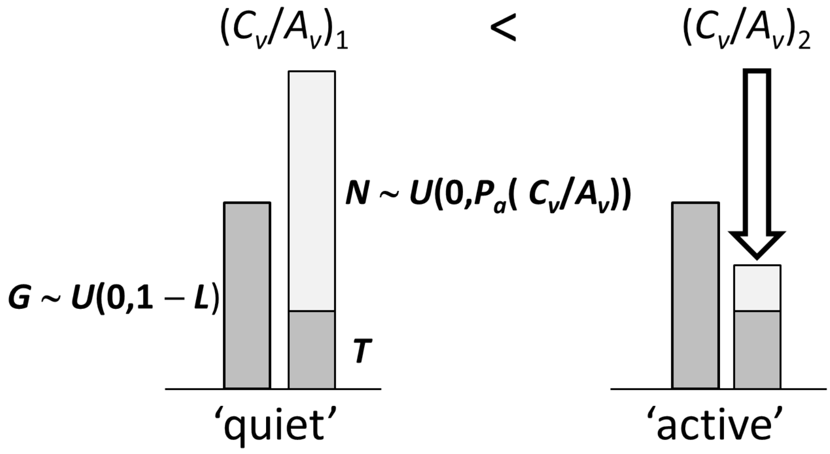


Figure 5.1: Illustration of the "fear threshold lowering" mechanism for switching between 'quiet' and 'active' states in Epstein's ABM, for H and G uniformly distributed in the $[0,1]$ interval ([33, 31]). A 'citizen' agent remains 'quiet' if the inhibiting term $N+T$ exceeds the drive to rebel G (left). If $N+T$ drops below G due to collective behaviour the 'citizen' turns 'active' (right). In this figure, $N = R \cdot P_a$. (Source: Lemos et al. [62])

depends on individual factors (R) and collective behaviour (P_a). Action is elicited once this variable threshold drops below the drive for rebelling (represented by the grievance G). Since P_a decreases with $(C/A)_v$, transitions from 'quiet' to 'active' result from lowering of the "variable fear threshold" due to other 'citizen' agents turning rebellious. Figure 5.1 shows a graphical illustration of this mechanism. Notice that the term $N = R \cdot P_a$ is a very compact analytical representation of propositions M.4 (positive feedback due to group support) and M.1 (fear of retribution) of Ted Gurr's frustration-aggression theory (Figure 2.5, page 23).

In Epstein's ABM intermittent peaks of rebellion result from 'citizen' agents turning 'active' faster than 'cops' can arrest them (by a cascade effect), 'cops' jailing rebellions 'citizens', and progressive release of the latter into the model space. The method for analysing the possibility of occurrence of large cascades consists in considering the probability density function (pdf) of $G - N$ for different forms of P_a and given distributions of H and R.[50]

The analysis below will be based on the parameter values of the 'Run 2' simulation reported in [33] and [31], which has often be used as a reference case in which Epstein's ABM produces solutions with intermittent peaks of rebellion, for P_a given by the

[50] This can be imagined as a "$\frac{1}{2}$Epstein ABM" without 'cops' and arrests, to describe the 'production' stage only. This method of analysis was introduced by Granovetter in his threshold model of collective behaviour [47].

Table 5.3: Reference values for the analysis of cascades in Epstein's ABM. (Source: Epstein et al. [33])

Parameter	**Value**	**Description**
$N_{citizen}$	1120	Number of 'citizens'
C	64	Number of 'cops'
L	0.82	Legitimacy of Government
k	{ 1, 2.3, 5 }	Arrest constant

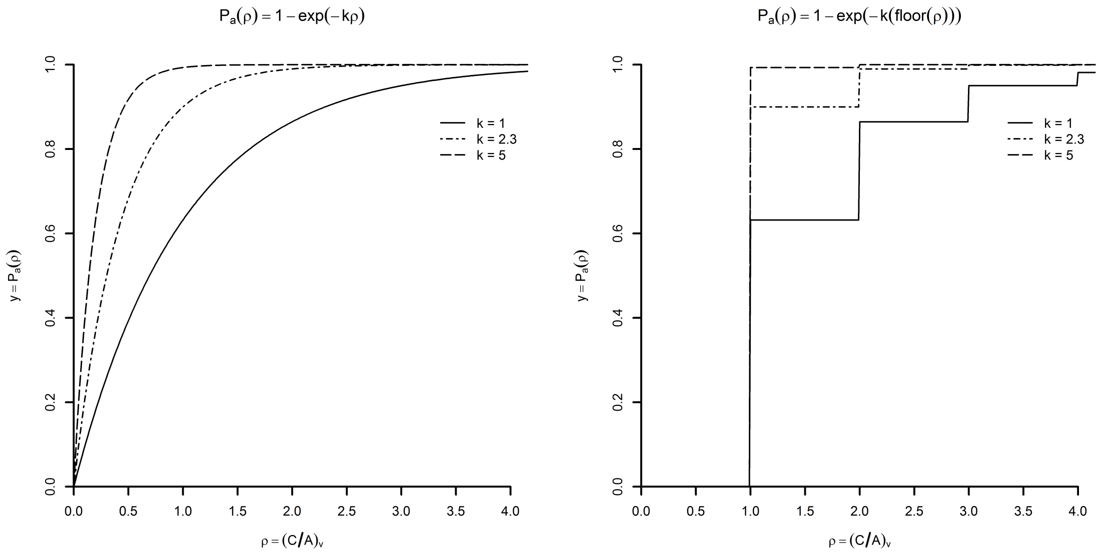
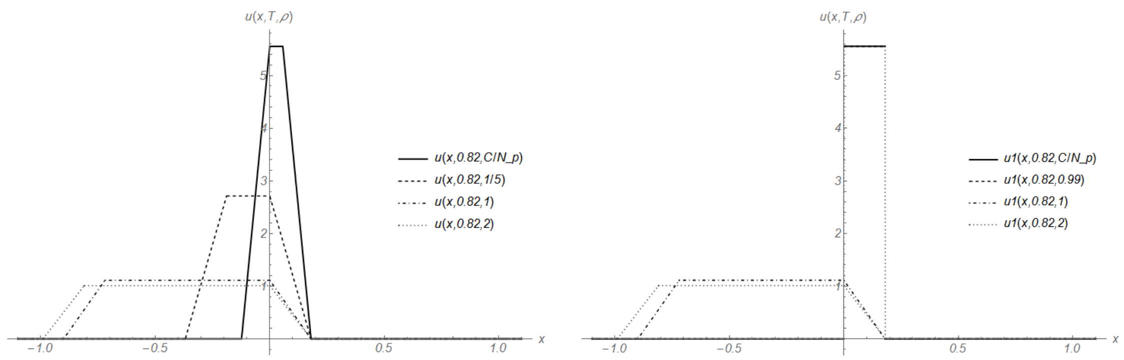


Figure 5.2: Variation of P_a as a function of $(C/A)_v$ for three values of the arrest constant k, for equations (3.5) (left) and (3.6) (right). (Source: author)

forms proposed by Epstein and Wilensky (equations (3.5) and (3.6) respectively). Before proceeding, it is convenient to introduce the variable $\rho = C/A$. This simplifies the notation and the interpretation of the graphical representations.

Equation (3.5) implies a monotonic decrease of the estimated arrest probability as the number of visible rebellious 'citizens' A_v increases for all values of the arrest constant k, whereas equation (3.6) leads to P_a dropping to zero for $C_v < A_v$ for all values of the arrest constant k. Figure 5.2 illustrates the variation of the functions defined by equations (3.5) and (3.6) for three different values of the arrest constant, including the reference value $k = 2.3$. The form given by equation (3.6) effectively introduces a second threshold in the decision rule associated with the perceived level of deterrence, which is a function of ρ. It remains to determine the proportion of rebellious 'citizen' agents that results from each of these formulae for the estimated arrest probability.

The pdf for the grievance and risk perception in Epstein's original model ([33,



(a) (b)

Figure 5.3: Probability density functions $u_X(x, L, \rho)$ for $L = 0.82$ and estimated arrest probability functions given by equations (3.5) (left) and (3.6) (right), with $G(L) \sim \mathcal{U}(0, 1 - L)$ and $N(\rho) \sim \mathcal{U}(0, P_a(\rho))$. (Source: author)

31]) are $G(L) \sim \mathcal{U}(0, 1 - L)$ and $N(\rho) \sim \mathcal{U}(0, P_a(\rho))$, respectively. The pdf and distribution of the random variable $X = G - N$ are [73]:

$$u_X(x, L, \rho) = \int_{-\infty}^{+\infty} g_G(z, L) \cdot n_N(z - x, P_a(\rho))\, dz \tag{5.5}$$

and

$$U_X(x, L, \rho) = \int_{-\infty}^{x} u_X(x', L, \rho)\, dx' \tag{5.6}$$

respectively, where g_G and n_N are the pdf of G and N. The number of 'active' citizens is

$$A(L, \rho, T) = N_{citizen} \cdot (1 - U_X(L, \rho, T)) \tag{5.7}$$

and the corresponding proportion is $A(L, \rho, T)/N_{citizen}$.

Figure 5.3 shows graphs of $u_X(x, L, \rho)$ for $L = 0.82$ and four different values of ρ. When $P_a(\rho)$ is given by equation (3.5) the four functions have the same trapezoidal variation (figure 5.3(a)). The pdf is flatter and the probability density is mainly concentrated on negative values of x for high levels of deterrence, and becomes progressively taller and concentrated on positive values of x for decreasing level of deterrence. When $P_a(\rho)$ is given by equation (3.6) the pdf have a trapezoidal variation similar to that of the previous case when the level of deterrence is high, but below the critical value $\rho = 1$ the probability density functions change into a pulse function in $[0, 1 - L]$ (the graphs for $\rho = 0.99$ and $\rho = C/N_{citizen} = 64/1120 = 2/35$ in figure 5.3(b) are coincident).

Figure 5.4 shows the variation of the proportion of 'active' citizens with ρ for $T = 0.05$ and $T = 0.1$, when the arrest probability function is given by equations

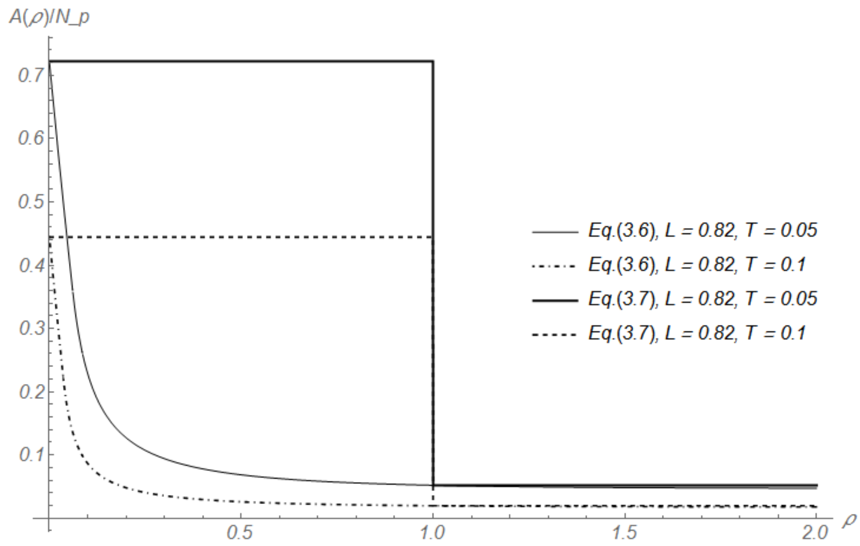
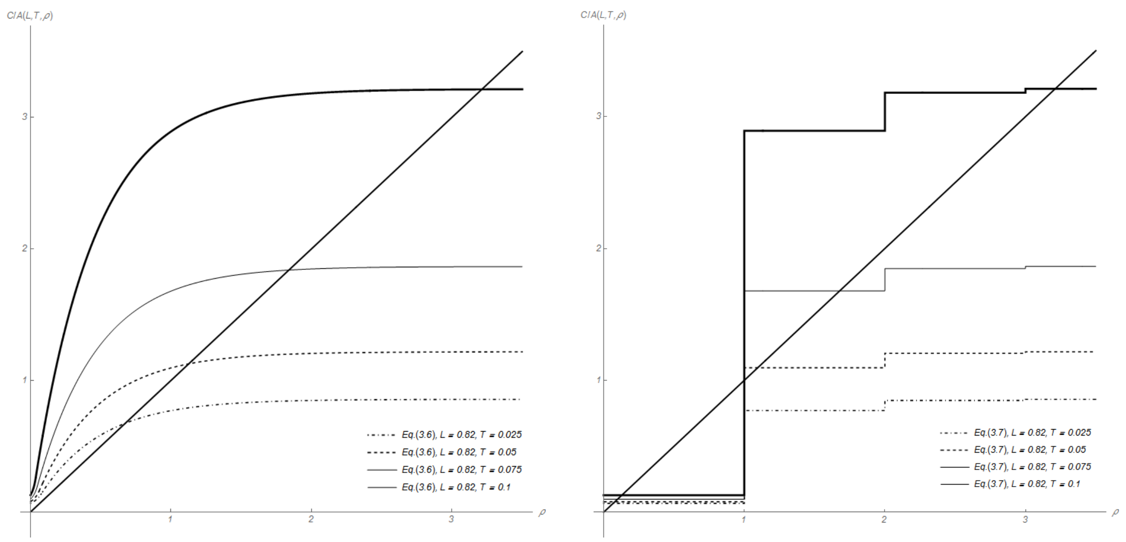


Figure 5.4: Proportion of 'active' citizens as a function of ρ for $L = 0.82$ and two values of the threshold ($T = 0.05$ and $T = 0.1$), with $G(L) \sim \mathcal{U}(0, 1-L)$ and $N(\rho) \sim \mathcal{U}(0, P_a(\rho))$. (Source: author)

(3.5) and (3.6). When $\rho \geq 1$ the proportions are small and nearly equal for both forms of the arrest probability function, but when $P_a(\rho)$ is given by equation (3.6) the proportion suddenly increases to the maximum possible value (which depends on the value of T) for $\rho < 1$. This latter form of $P_a(\rho)$ provides a mathematical representation of a mechanism of 'massive fear loss' by which the risk perception (or 'fear of retribution') disappears for the whole population when the level of deterrence falls below a critical value.

This (hypothetical) mechanism leads to large cascades of 'citizen' agents rebelling. Thus, unless the level of deterrence is very low (for $\rho \ll 1$), the decision rule in Epstein's ABM leads to 'bandwagon' effects and large peaks of rebellion for $P_a(\rho)$ given by equation (3.6) but not for equation (3.5). This can also be confirmed by means of the fixed point iteration $A_{n+1} = N_{citizen} \cdot (1 - U_X(L, C/A_n, T))$, which can be written in terms of ρ as $\rho_{n+1} = C/A_n$. When $P_a(\rho)$ is given by equation (3.5) there exists a stable fixed point ρ_f which corresponds to a relatively high value of C/A and low proportion of 'active' citizens (figure 5.5, left). For $P_a(\rho)$ given by equation (3.6) one or two fixed points may exist, but there is always one stable fixed point for $\rho \ll 1$ which corresponds to a high proportion of 'active' citizens (figure 5.5, right).

These analytical results can be further confirmed by computer experimentation using a simplified ABM implemented in NetLogo [106], with only 'citizen' agents equipped with the same attributes and Rules M and A as in Epstein's ABM. 'Cops'



(a) (b)

Figure 5.5: Graphical representations of $C/A(L,T,\rho)$ vs ρ for $L = 0.82$ and $T = 0.025$, 0.05, 0.075, and 0.1, and estimated arrest probability functions given by equations (3.5) (left) and (3.6) (right), with $G(L) \sim \mathcal{U}(0, 1-L)$ and $N(\rho) \sim \mathcal{U}(0, P_a(\rho))$. (Source: author)

are not modelled explicitly, but C_v is set equal to the average number of visible cops in the reference simulation (Epstein et al. [33], Run 2) for all agents. Starting from an initial condition with all 'citizen' agents 'quiet' this simplified ABM is run until the number/proportion of 'active' agents remains constant.

Figure 5.6 shows the simulated histogram of $G - N$ and time variation of the proportion of 'active' citizens for two simulations with estimated arrest probability given by equations (3.5) (left) and (3.6) (right). In both cases, the simulated histograms are consistent with the theoretical pdf shown in figure 5.3. Denoting by ρ_f the value of ρ at a fixed point, it is observed that in the first case the simulated steady state value of the proportion of 'active' citizens was 0.018 for a theoretical value of 0.019 ($\rho_f = 3.2$ in figure 5.5), and in the second case the simulated steady state value was 0.44 for a theoretical value of 0.43 ($\rho_f = 0.13$ in figure 5.5). Thus, when the estimated arrest probability was given by equation (3.6), there was a cascade with a large proportion of agents turning 'active' in a few cycles.[51]

The analysis above shows that the legitimacy and the estimated arrest probability are critical variables in the decision Rule A in Epstein's ABM. For uniform distributions of H and R, the legitimacy determines the support of G, and the estimated arrest probability the support of N. For other distributions, they become

[51]In the Epstein ABM, these 'active' agents would be jailed by 'cops' and progressively released in the simulation space until a new cascade occurs, generating intermittent peaks of rebellion.

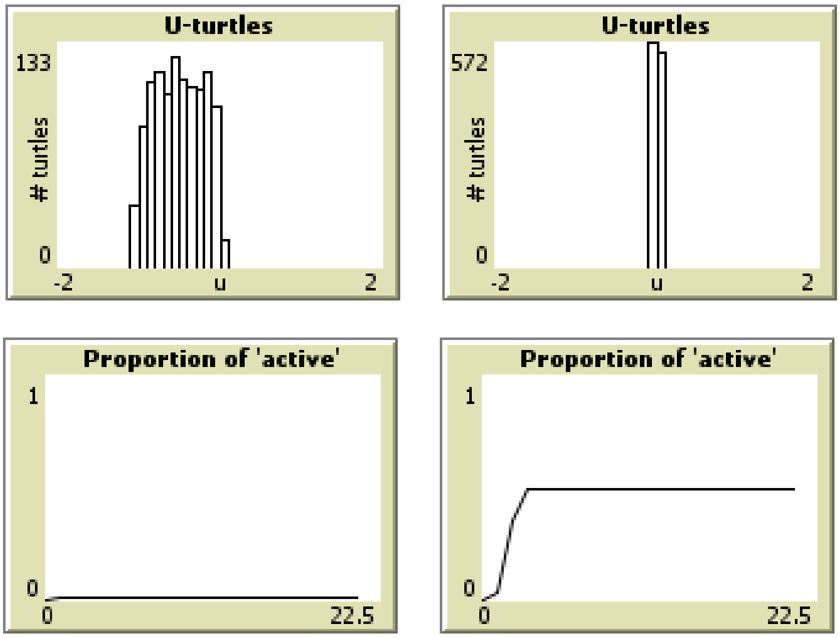


Figure 5.6: Simulated histogram of $G-N$ (top) and time variation of the proportion of 'active' citizens (bottom), for estimated arrest probability given by equations (3.5) (left) and (3.6) (right). (Source: Lemos et al. [62])

scale factors for the moments of g_G and n_N respectively, and therefore determine the interval over which the pdf of $G-N$ is significant.

This later statement can be illustrated by repeating the analysis above using normal distributions for G and N in Rule A, with the same mean values and variances as the uniform distributions. In this case $G(L) \sim \mathcal{N}((1-L)/2, (1-L)/\sqrt{12})$ and $N(\rho) \sim \mathcal{N}(P_a(\rho)/2, P_a(\rho)/\sqrt{12})$ respectively,[52] and $G-N$ is normally distributed with $\mu(G-N) = (1-L-P_a(\rho))/2$ and $\mathrm{var}(G-N) = ((1-L)^2 + P_a^2(\rho))/12$ [73]. The pdf of $G-N$ is

$$u_X(x, L, \rho) = \sqrt{\frac{6}{\pi}} \cdot \frac{\exp\left(-\frac{6\left(x+\frac{1}{2}\left(L-e^{-k\rho}\right)\right)^2}{(1-L)^2+\left(1-e^{-k\rho}\right)^2}\right)}{\sqrt{(1-L)^2+(1-e^{-k\rho})^2}} \tag{5.8}$$

[52]This implies that the supports of g_G and n_N will be $]-\infty, +\infty[$, so that the hardship H and risk aversion R may take values outside the interval $[0, 1]$, which violates the premises on the range of these variables for the case of uniform distributions. However, the probability of H or R falling outside $[0, 1]$ is small.

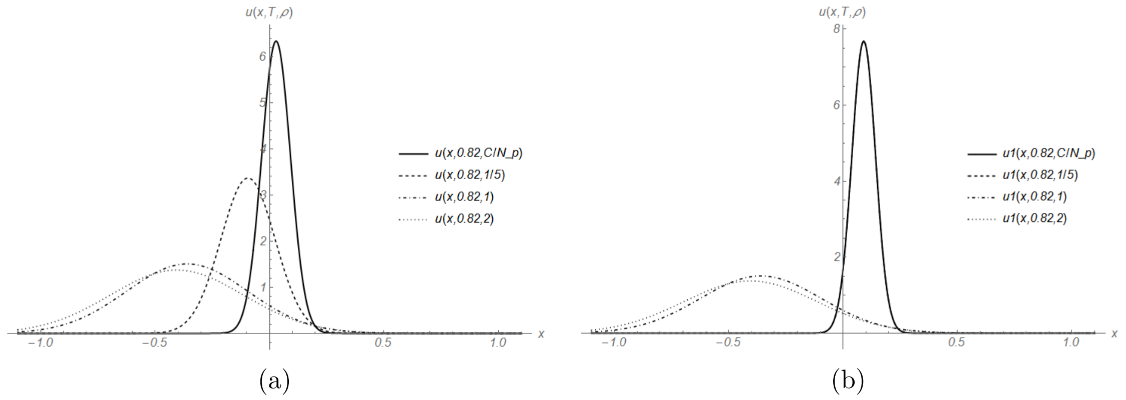


Figure 5.7: Probability density functions $u_X(x, L, \rho)$ given by equations (5.8) (left) and (5.9) (right), for $L = 0.82$. (Source: author)

for $P_a(\rho)$ given by equation (3.5) and

$$u_X(x, L, \rho) = \sqrt{\frac{6}{\pi}} \cdot \frac{\exp\left(-\frac{6\left(x+\frac{1}{2}\left(L-e^{-k\lfloor\rho\rfloor}\right)\right)^2}{(1-L)^2+\left(1-e^{-k\lfloor\rho\rfloor}\right)^2}\right)}{\sqrt{(1-L)^2+\left(1-e^{-k\lfloor\rho\rfloor}\right)^2}} \tag{5.9}$$

for $P_a(\rho)$ given by equation (3.6).

Figures 5.7 to 5.9 show the pdf $u_X(x, L, \rho)$, proportion of 'active' citizens as a function of ρ for $L = 0.82$ and $T = 0.05$ and 0.1, and graphical representations of $C/A(L, \rho, T)$ for $L = 0.82$ and $T = 0.025$, 0.05, 0.075 and 0.1, when $u_X(x, L, \rho)$ is given by equations (5.8) and (5.9). The qualitative behaviour of the expected solutions is similar to the previous case, in the sense that equation (3.6) leads to sudden vanishing of the risk perception for the whole population when $C/A < 1$ and to solutions with larger peaks of rebellion than would occur using equation (3.5). However, by comparing figures 5.8 and 5.9 with figures 5.4 and 5.5 it is clear that these peaks are much smaller when G and N are normally distributed than when they follow uniform distributions, for the same values of L, T, $\mu(G)$ and $\mu(N)$.

The analysis of the pdf of $G - N$ in the decision rule of Epstein's model clarifies the importance of L and P_a and why some forms of the latter lead to solutions with large rebellion peaks and other forms do not (this was noted but not explained by Wilensky [107] and Fonoberova et al. [35]). It also suggests the following qualitative condition ('rule of thumb') between L, $P_a(\rho)$ and T for a significant proportion 'citizens' turning 'active':

$$T \leq \frac{1}{2}\left(1 - L - P_a(\rho)\right) + \sqrt{\frac{(1-L)^2 + P_a^2(\rho)}{12}} \tag{5.10}$$

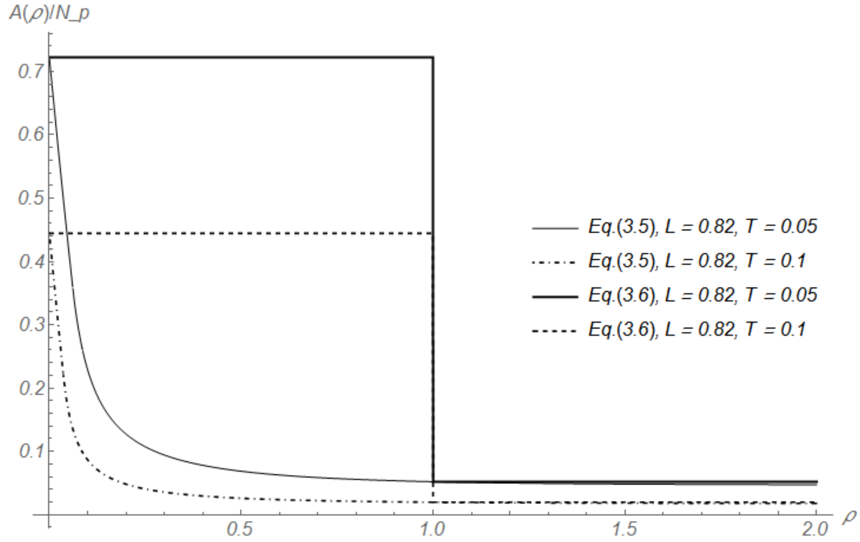
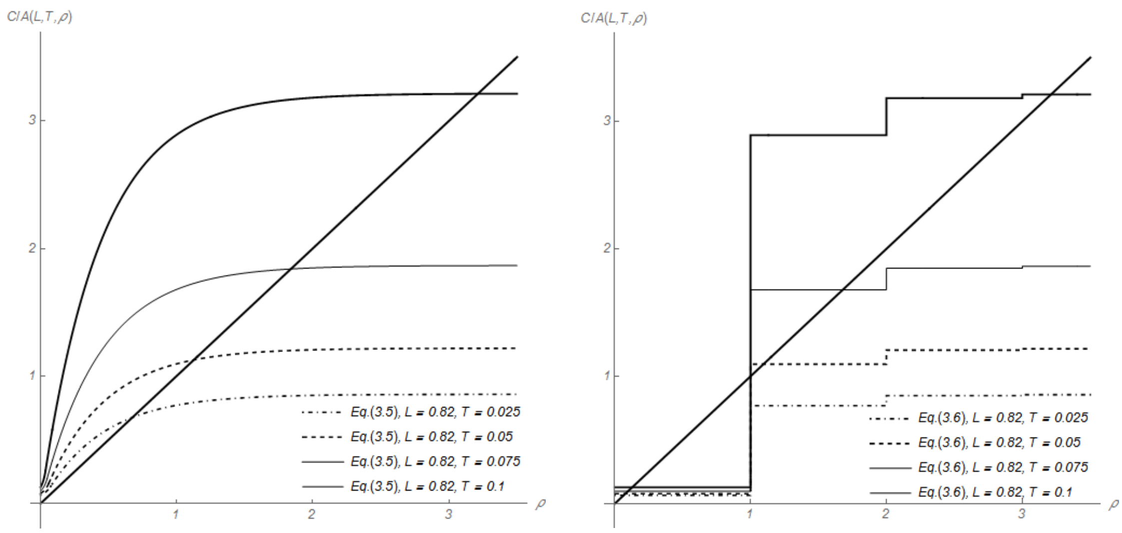


Figure 5.8: Proportion of 'active' citizens as a function of ρ for $L = 0.82$ and two values of the threshold ($T = 0.05$ and $T = 0.1$), with $g_G \sim \mathcal{N}((1-L)/2, (1-L)/\sqrt{12})$ and $n_N \sim \mathcal{N}(P_a(\rho)/2, P_a(\rho)/\sqrt{12})$. (Source: author)



(a) (b)

Figure 5.9: Graphical representations of $C/A(L,T,\rho)$ vs ρ for $L = 0.82$ and $T = 0.025$, 0.05, 0.075, and 0.1, with $u_X(x, L, \rho)$ given by equations (5.8) (left) and (5.9) (right). (Source: author)

* * *

It is important to consider the theoretical justifications for the use of a threshold decision rule with an 'aggression' and a 'risk inhibition' drive and for selecting the form of the estimated arrest probability function.

Ethology provides a very general and low-level conceptual foundation for using a threshold rule like Epstein's Rule A. According to Lorenz [67], aggression (harmful action towards members of one's own species) has a fundamental evolutionary value, and behavioural patterns in animals result from a tension between conflicting drives, namely aggression (attack) and fear (escape). The threshold for initiating an attack is lowered by situational factors. This tension-threshold model, combined with the mechanism of redirection of aggression to avoid excessive intra-specific damage, explains cyclic patterns of animal fights and confrontation rituals. The tension-threshold model is also consistent with the key elements of micro-situational theories of violence (e.g. [16, 17, 105]).

As far as the form of P_a is concerned, two important questions arise:

1. What is the theoretical foundation for the use of an exponential variation like the one in equation (3.5)?
2. Are discontinuous functions for which the risk perception (or estimated arrest probability) drops to zero below a critical value of ρ more adequate than continuous monotonic functions for modelling real conflict processes?[53]

Exponential laws like that described by equation (3.5) are widely used for modelling interaction terms in systems whose dynamics involves random encounters between entities of different types, where the outcome of such encounters depends on the number (or density) of the interactions [62]. For instance, the interaction terms in predator-prey systems in population dynamics can be related to the modelling of P_a in Epstein's ABM, for both prey mortality due to predators and the jailing of 'active' citizens by 'cops' are assumed to result from random encounters proportional to the size of both 'populations'(predator/prey and 'active'/'cop'), and prey mortality is limited by some factor (competition among predators in population dynamics, or 'cop'-to-'active' ratio in the civil violence model).[54] Also, in detection theory, the probability of a platform (ship or aircraft) detecting a target in a random patrol is described by an exponential law similar to equation (3.5), with the sweep width of

[53] In other words: is the mechanism of 'massive fear loss' real, or just a mathematical artefact in some ABM of civil violence?

[54] There are important differences between the two systems, because in Model I arrested citizens are only temporarily removed and not eliminated, and 'cops' do not die.

the platform's sensor, the distance travelled in a random path and the patrol area replacing k, C_v and A_v, respectively [79, 62].

There are also theoretical arguments in favour of modelling P_a with functions for which the perceived risk drops to zero below a critical value of ρ. The occurrence of large protests and uprisings in real processes also supports the conjecture that forms of P_a with properties similar to that in equation (3.6) are more correct than an exponential variation.[55] These forms involve two parameters, one determining the slower or faster rate of change, and another the threshold of zero risk perception. From now on, this latter threshold will be denoted by ρ_c (which stands for 'critical ρ'). One way of determining which forms of P_a are more plausible and suitable values for its two parameters is to compare simulated distributions of the size of rebellion peaks (proportions of 'active' citizens) with estimates from real processes (such as those considered in §4.1).

Fonoberova and collaborators proposed estimated arrest probability functions with properties similar to that in equation (3.6) in a study of urban crime using Epstein's model [35]:

$$P_a(\rho) = \begin{cases} 0 & \rho < 1/4 \\ 1 - \exp(-k\,\rho) & \rho \geq 1/4 \end{cases} \tag{5.11}$$

$$P_a(\rho) = 1 - \exp(-k'\,\rho) \cdot \sum_{i=0}^{15} \frac{(k'\,\rho)^i}{i!} \tag{5.12}$$

where $k = 9.2104$ and $k' = 62.6716$, which they called "step" and "sigmoidal" respectively (figure 5.10). In this model k was chosen so that $P_a(1/4) = 0.9$ in equation (5.11) and k' was chosen so that $P_a(1/4) = 1/2$ in equation (5.12). Notice that, in the notation used in this work, equation 5.11 leads to the perceived risk dropping to zero for $\rho_c = 1/4$.

Equation (5.11) can be generalized to include a variable critical ratio ρ_c for "massive fear loss", as was done in equation (5.1). This includes the exponential variation of P_a as a special case ($\rho_c = 0$) and allows studying the influence of ρ_c on the solutions' behaviour. The consideration of ρ_c as a parameter in a generalized form of P_a, the study of its influence on the size of the rebellion peaks, and the

[55] At the micro-level, there are situations where discontinuous or "irrational" risk estimation seems to exist: in street protests 'cops' need a local numeric superiority to arrest violent protesters, and in the Standing Ovation Model the rule for imitation due to peer effects is equivalent to the action threshold dropping to zero. However, it cannot be concluded that these situations have a correspondence in "abstract" ABM of civil violence.

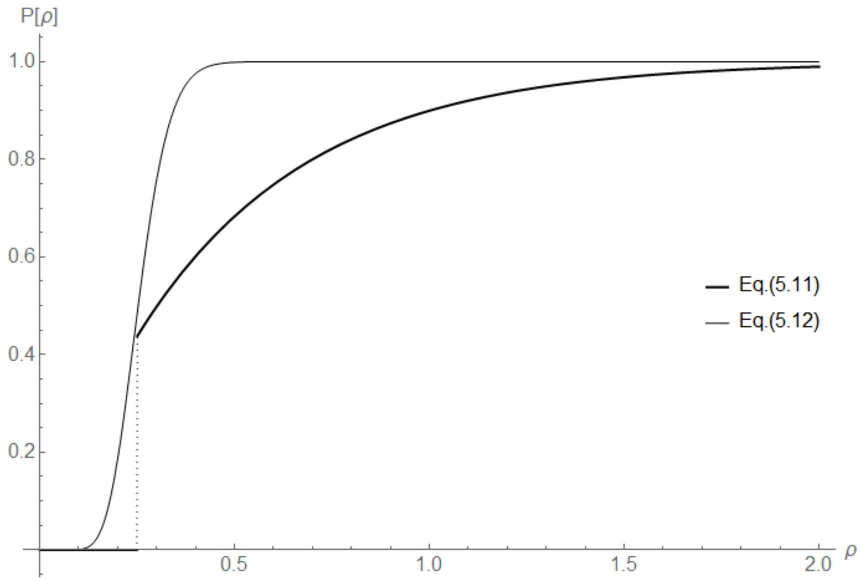


Figure 5.10: Forms of P_a in the ABM of urban crime of Fonoberova et al. [35]. (Source: author, based on [35])

discussion of plausible values for this parameter using empirical data (§5.2.2), are important contributions of the present work.

Although the choice of the form of P_a is a key aspect for determining the stability of the solutions obtained using Epstein's ABM, there are important factors and mechanisms not represented by the decision rule. First, constant legitimacy L and the distributions of H and R cannot be correct in real processes, since the political, social and economic contexts are variable. Also, H should be related to some modelled form of RD. Finally, there is no mathematical representation of mechanisms of collective influence (imitation or dispositional contagion) in the grievance term, which Lorenz calls "mass enthusiasm": "Here the laws of mass enthusiasm are strictly analogous to those of flock formation ... the excitation grows in proportion, perhaps even in geometric proportion, with the increasing number of individuals" [67].

5.2.2 Risk Perception and the Estimated Arrest Probability

This set of computer simulations was performed to investigate the influence of the parameter ρ_c in equation (5.1) in the qualitative and quantitative behaviour of the solutions, and to discuss plausible values for this parameter by comparing the simulated results with the patterns of conflict events discussed in §4.1. In this set of experiments all extensions to Epstein's model (legitimacy feedback, RD, network

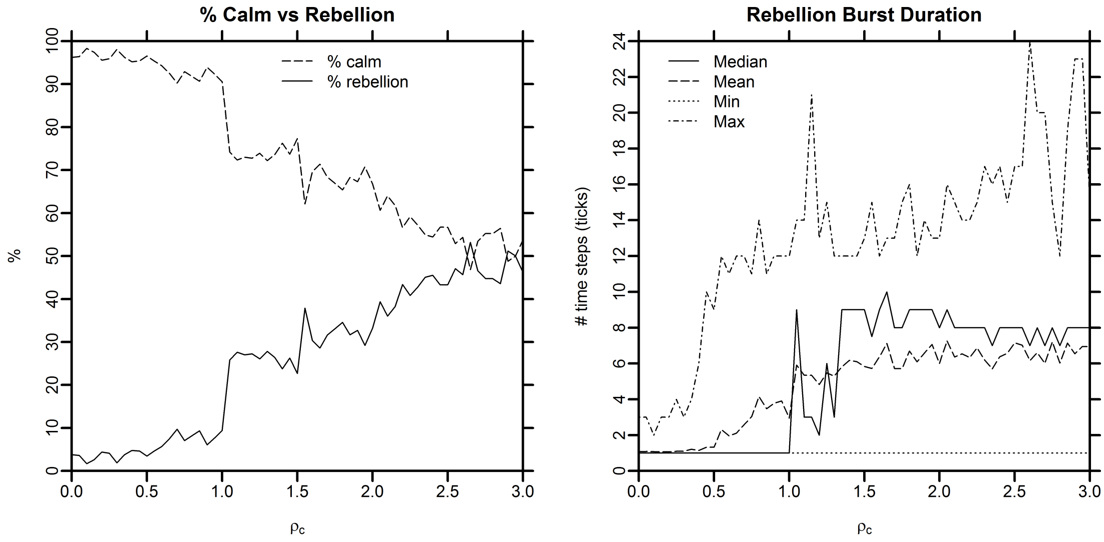


Figure 5.11: ρ_c variation experiment. Percentage of time with calm and rebellion (left) and statistics of rebellion burst duration (right) for the ρ_c variation experiment. (Source: author)

influences) were turned off.

The parameter ρ_c in the estimated arrest probability function controls the magnitude of the (hypothetical) 'massive fear loss' mechanism discussed in the previous section. For $\rho_c = 0$ the model reduces to Epstein's ABM. The value $\rho_c = 0.25$ was adopted by Fonoberova et al. [35], and $\rho_c = 1.0$ approximately corresponds to the formula of P_a proposed by Wilensky [107].

A total of 60 runs were performed, for values of ρ_c between 0 and 3, in steps of $\Delta\rho_c = 0.05$. Each simulation was run for 10,000 cycles, to obtain a number of simulated activity peaks allowing the calculation of meaningful statistics of size, waiting time and duration of rebellion events. The remaining input parameters were set to their default values in Table A.4 (page 194), which are representative of the Run2 simulation reported in [33]. This default setup corresponds to a small artificial society (1120 'citizens' and 64 'cops') with total density 74%, relatively high `government-legitimacy` (0.82) and low `threshold` (0.1). The variables `peak.threshold` and `diff.threshold` were set to their default values (0.1% and 0.05% respectively) in the post-processing stage for detecting the peak size, interval and duration of rebellion bursts.

Figure 5.11 shows the proportion of total time with calm and rebellion as a function of ρ_c (left) and duration of rebellion bursts in time steps (right). The variation of the % of rebellion time (social unrest) is below 5% for $\rho_c \leq 0.5$, increases to values near 10% for $0.5 \leq \rho_c \leq 1.0$ and jumps suddenly to $\sim 26\%$ at $\rho_c = 1.05$. The % of rebellion time remains nearly constant for $1.05 \leq \rho_c \leq 1.5$, then jumps again at $\rho_c = 1.55$ to $\sim 38\%$, and shows a positive trend for $\rho_c > 1.55$. This suggests the existence of a tipping point associated with ρ_c near the value 1.0, and of two other possible tipping points near 0.5 and 1.5. This is also apparent in the variation of rebellion burst duration (figure 5.11, right). At $\rho_c = 0.5$ the maximum and mean value of burst duration rise, but the median remains with value one. At $\rho_c = 1.0$ the median rises and then oscillates as ρ_c is increased. This shows a change of qualitative behaviour of the system, which also corresponds to larger rebellion peaks (as shown below). At $\rho_c = 1.35$ another qualitative change occurs: the mean and median of burst duration show small trends, with the median larger than the mean. It is clear that ρ_c strongly influences the qualitative and quantitative properties of the solutions.

Recalling figure 4.10, it can be observed that for demonstrations before the AS the typical and maximum % of time with such events in the countries analysed are $\sim 1\%$ and $\sim 14\%$ respectively, and that after the beginning of the AS these figures increased to $\sim 26\%$ and $\sim 5\%$ respectively. Thus, $\rho_c \leq 0.5$ and $0.9 \leq \rho_c \leq 1.1$ are plausible ranges of values for representing the % of time with social unrest in stable and unstable situations, respectively, like those before and after the beginning of the AS.[56] This supports the conjecture that the mechanism of 'massive fear loss' has a real meaning and its magnitude changes as a function of the system's state and time history, as stated in Gene Sharp's theory of non-violent action [92].

Figure 5.12 shows variation of the statistics of the size of rebellion peaks normalized by the size of the population (left) and the waiting time between rebellion peaks (right) as a function of ρ_c. The statistics of peak size of % of population in the 'active' state again shows that ρ_c strongly influences the behaviour of the solutions, with sharp transitions that may correspond to tipping points associated with this parameter, namely:

- At $\rho_c \sim 0.25$, the maximum increases from 2% to 5%;
- At $\rho_c \sim 0.5$, the mean increases from 0.7% to 3% and the maximum peak size reaches 16%;
- At $\rho_c \sim 1.0$ the median increases from 0.2% to 15% and the maximum peak size exceeds 30%;

[56] The burst duration is a weaker variable for estimating plausible values of ρ_c, because of the difficulty of setting a correspondence between the time unit of one day in the analysis of section §4.1 and one time step in the ABM.

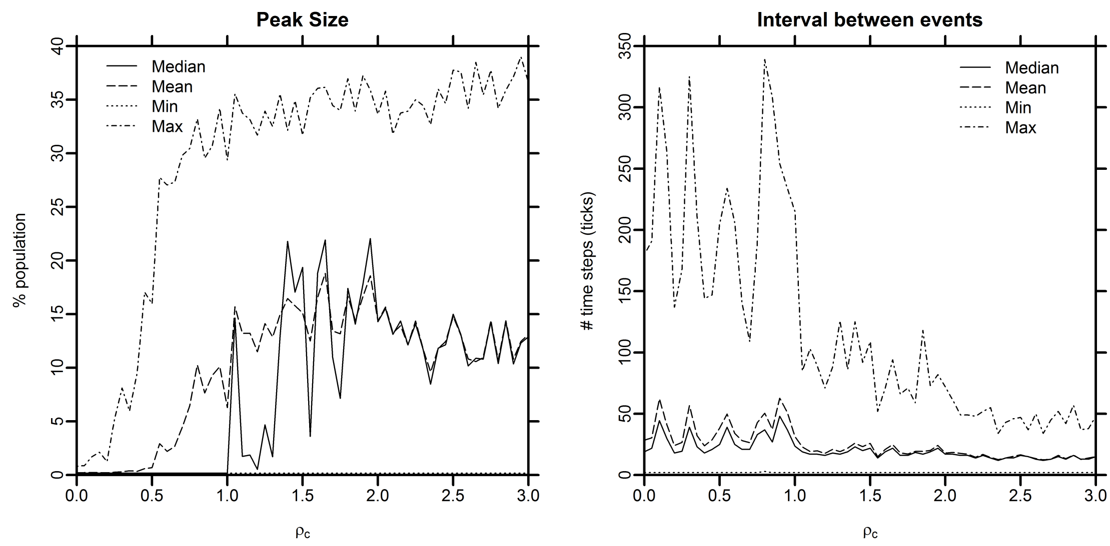


Figure 5.12: Statistics of rebellion peak size (% 'active' citizen agents) and interval (waiting time between peaks, in time steps) as a function of ρ_c. (Source: author)

– For $\rho_c \geq 1.4$ the median oscillates, reaching values as high as 22% with maximum peak size reaching 39%.

From the analysis in section §4.1, it is not possible to obtain upper bounds for the maximum estimated % of the population involved in huge demonstrations and riots, for comparison with the values obtained in the simulations. Nevertheless, it seems reasonable to assume that peaks as large as 30% are unrealistic. This suggests that the condition $\rho_c < 1.0$ is required for meaningful correspondence between simulated and real events in large scale conflict processes. The variation of the statistics of waiting time between successive events has some relation with variation of the % of calm and rebellion, because at $\rho_c \geq 0.9$ the interval between successive events suddenly decreases. It is clear that the waiting time between successive peaks is related to J_{max}. For $\rho_c \geq 1.1$, the mean and median approach the value $\mu(J) = 15$.

Another way of showing how ρ_c influences the behaviour of the solutions is to analyse the simulated time series of % of 'active' citizens for different values of this parameter. Figure 5.13 shows the first two thousand cycles for four important cases considering the full range $[0, 3]$. The first (top) corresponds to Epstein's expression for the estimated arrest probability. The record consists of many small intermittent peaks (maximum 0.8%), consistent with the analysis in §5.2.1. The next three cases (from top to bottom) show the first two thousand cycles of simulated time series of % of 'active' citizens for three values of ρ_c near tipping points suggested by the previous

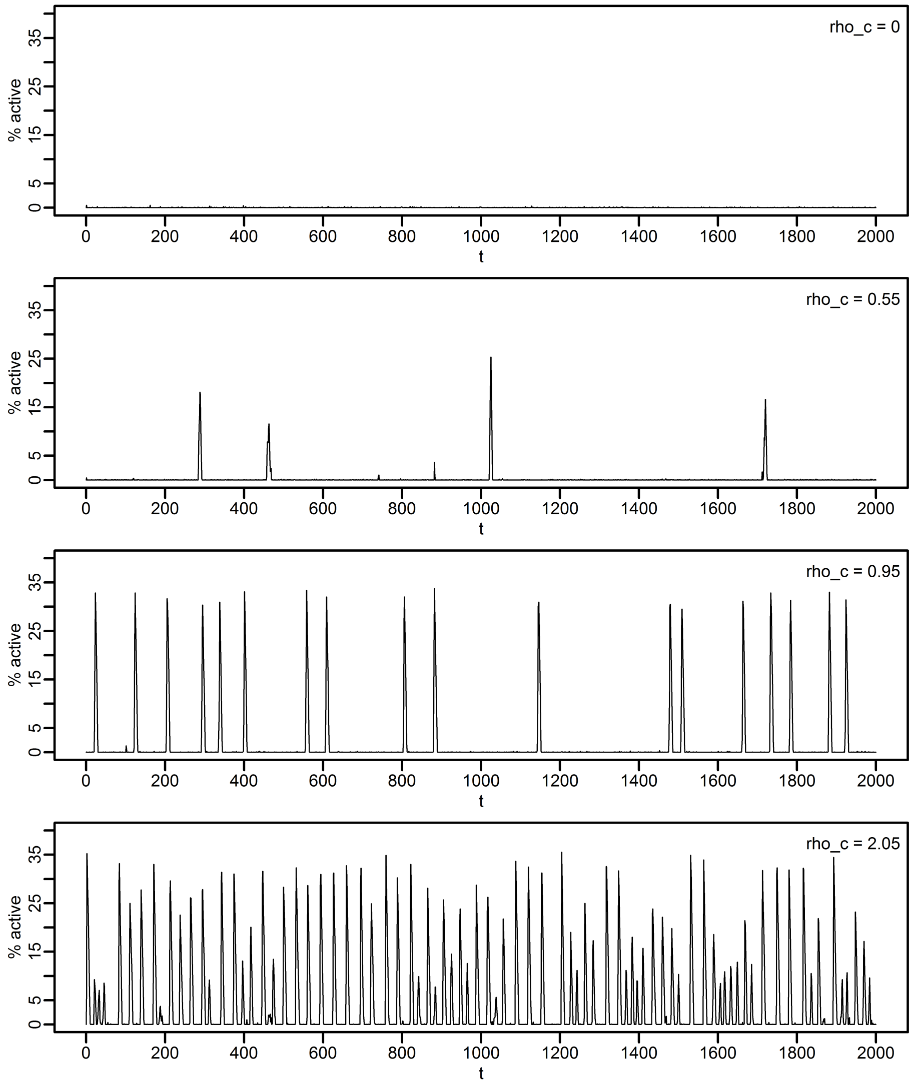


Figure 5.13: Simulated time series of the proportion of 'active' citizens for the first two thousand cycles, for $\rho_c = 0.0$, 0.55, 0.95 and 2.05. (Source: author)

graphs. It can be observed that this parameter has indeed a strong influence on the behaviour of the solutions, both qualitatively and quantitatively. Although the size and interval between rebellion peaks depend on many other factors (values of L_0 and T, distributions of H and R, vision radii, relative deprivation, network influences, etc.) this figure shows that $\rho_c > 1.0$ leads to unrealistic results.

Figure 5.14 shows the first two thousand cycles for four important cases with $\rho_c \in [0, 1]$, in which the simulation with $\rho_c = 0$ (top) is repeated for reference. It can be observed that the simulation for $\rho_c = 0.25$ (value adopted by Fonoberova et al. [35] for studying urban crime) has qualitative properties similar to those found in e.g. demonstrations in Morocco and Tunisia before the beginning of the AS, in terms of the amplitude of peak size. The simulation for $\rho_c = 0.5$ shows more frequent

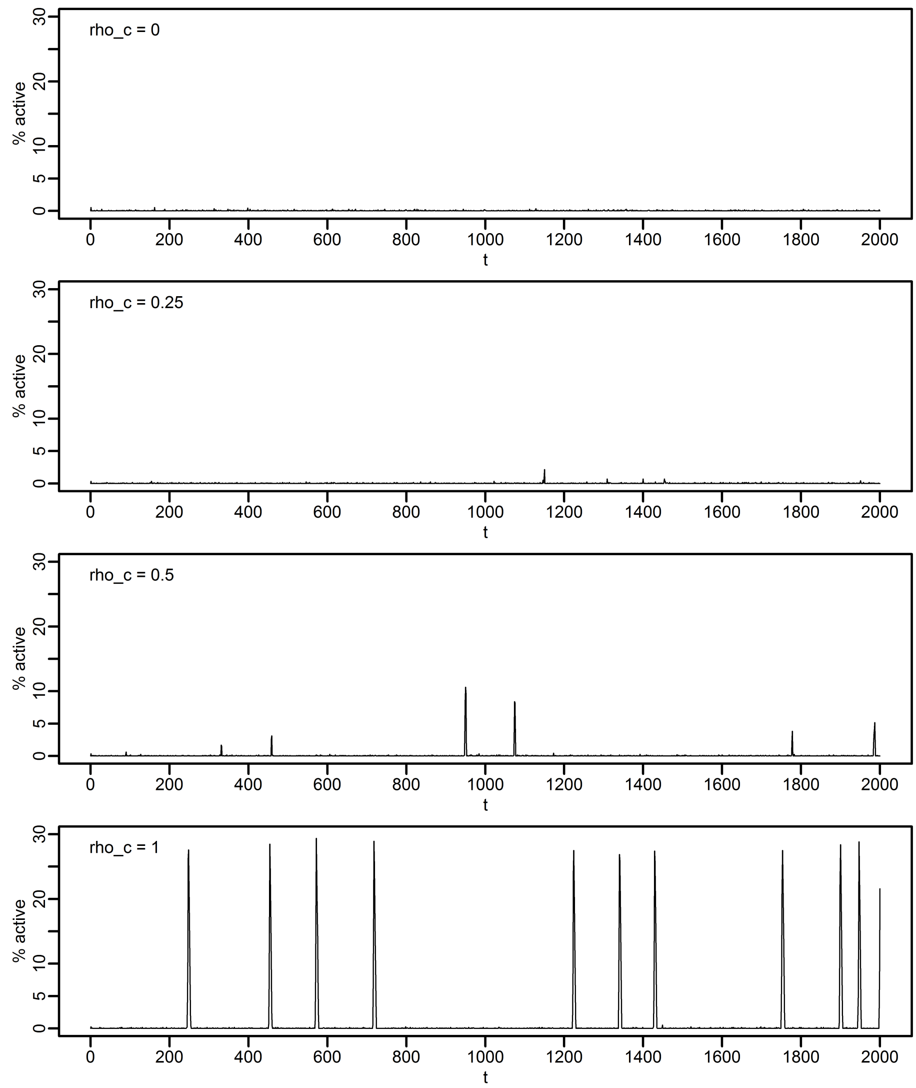


Figure 5.14: Simulated time series of the proportion of 'active' citizens for the first two thousand cycles, for $\rho_c = 0.0$, 0.25, 0.50 and 1.0. (Source: author)

intermittent bursts of rebellion, as well as larger peaks and a wider range of peak sizes. This corresponds to a greater instability of the society, closer to the situation after the beginning of the AS. The simulation with $\rho_c = 1.0$ is qualitatively similar to the case of $\rho_c = 0.95$ in figure 5.13, with peaks larger than 25% which are probably unrealistic.

Figures 5.15-5.17 show box plots of the distributions of peak size, event duration, and interval between successive events for the four cases considered above. The information in these figures is consistent with the previous conclusions. It is interesting to note that the interval between rebellion bursts is relatively insensitive to the value of ρ_c (although it is strongly dependent on the value of J_{max}, as will be shown below).

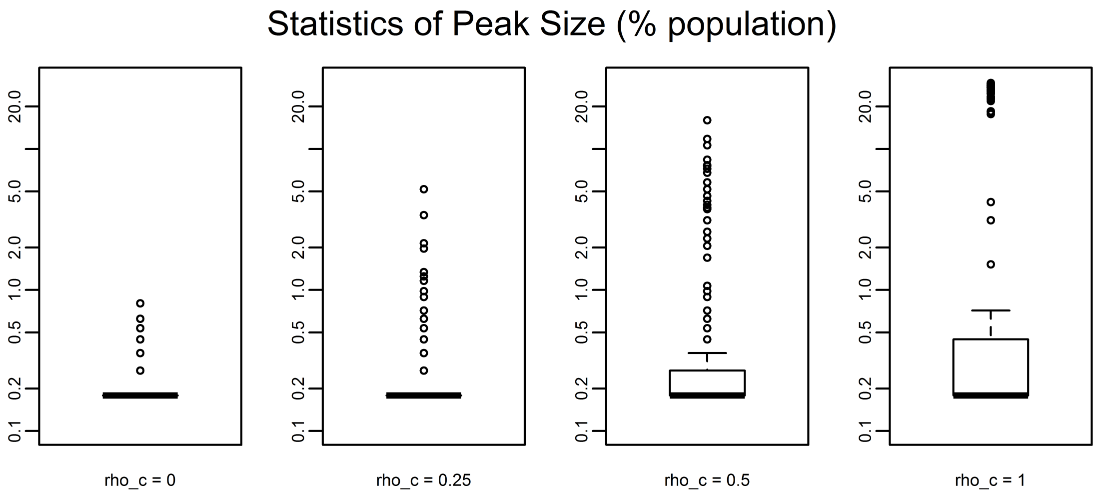


Figure 5.15: Box plot summary representation of the distributions of rebellion peak size (% of 'active' citizens) for $\rho_c = 0$, 0.25, 0.5 and 1. (Source: author)

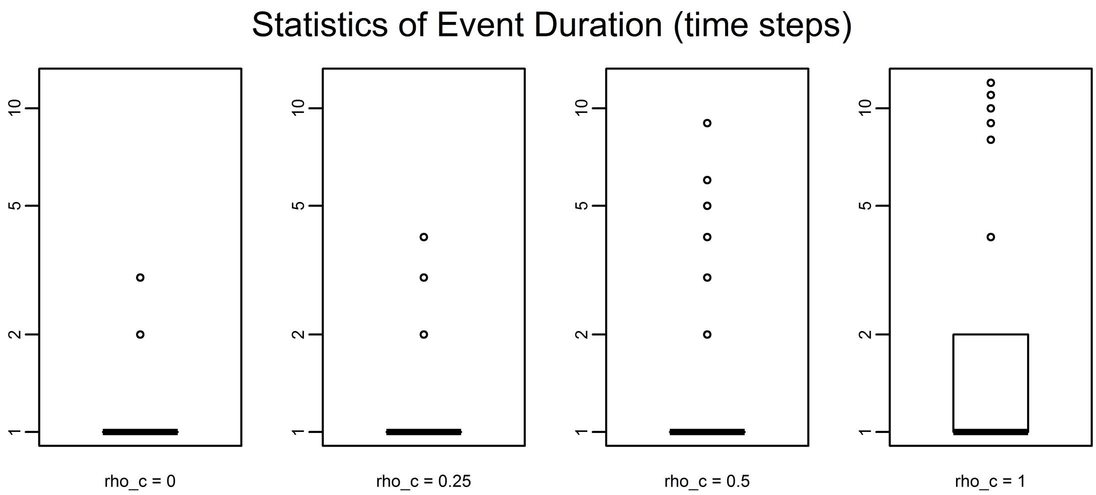


Figure 5.16: Box plot summary representation of the distributions of rebellion burst duration (in time steps) for $\rho_c = 0$, 0.25, 0.5 and 1. (Source: author)

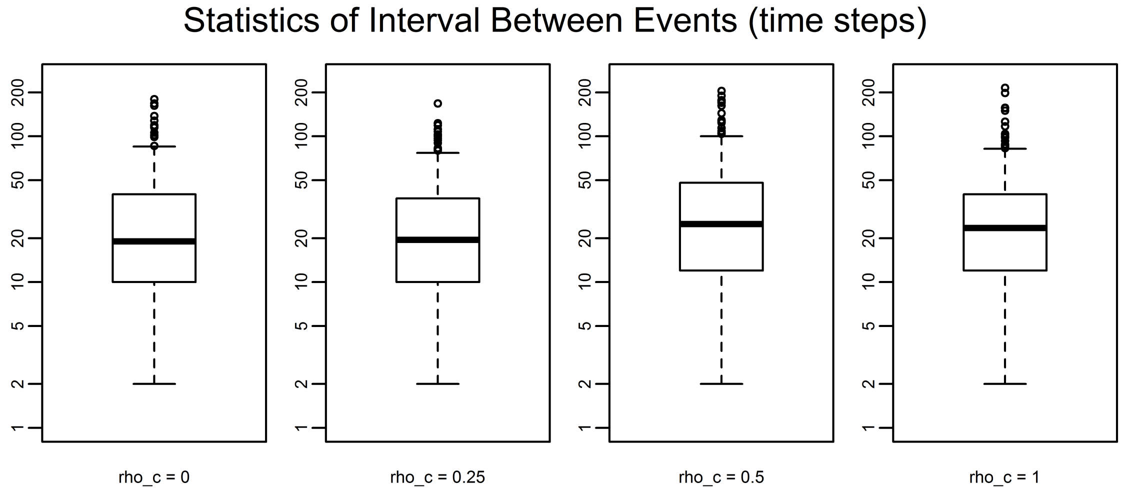


Figure 5.17: Box plot summary representation of the distributions of interval (waiting time, in time steps) between successive bursts for $\rho_c = 0$, 0.25, 0.5 and 1. (Source: author)

The results of this computer experiment lead to the following conclusions:

- The parameter ρ_c in equation (5.1) has a strong impact on the behaviour of the solutions;
- The computer experiments showed that, for the combination of parameters in a reference simulation (Run 2 in [33] and [31]), there are tipping points associated with ρ_c;
- For this reference case, the plausible values for ρ_c which lead to meaningful correspondence between peak sizes in simulations in real events lie in the interval [0,1];
- The values 0.25 and 0.5 are useful for setting ρ_c in further explorations, for they lead to solutions with meaningful qualitative correspondence with conflict events in societies with moderate or strong conflict intensity (e.g. the conditions before and after the beginning of the AS), respectively. The choice $\rho_c = 1.0$ leads to peaks of unrealistic magnitude.

5.2.3 The Influence of the Jail Term

In the previous experiment, it was shown that ρ_c has a strong impact on the size of rebellion peaks, but a smaller influence on the interval between successive events.

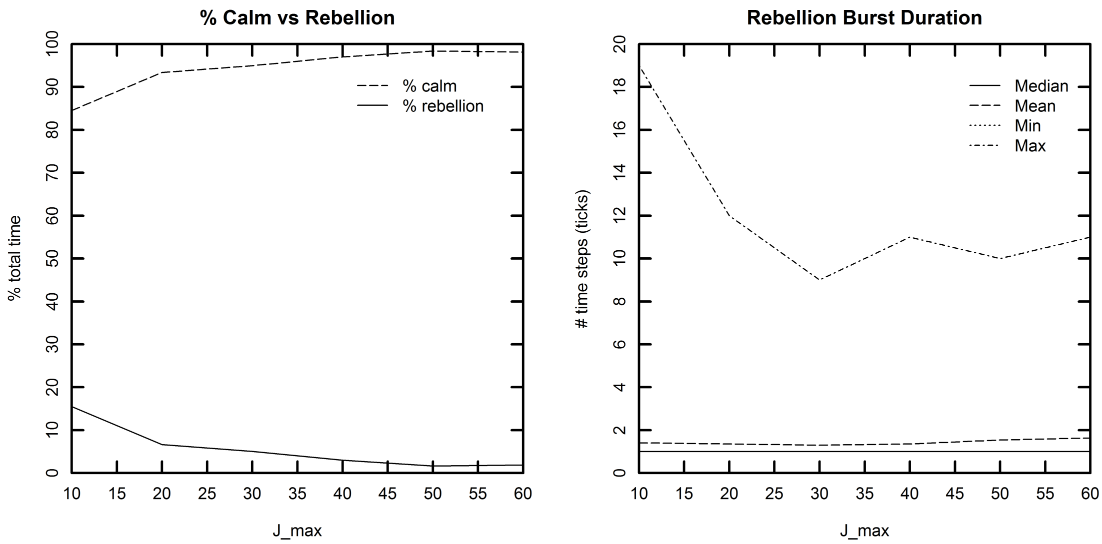


Figure 5.18: J_{max} variation experiment, for the case $\rho_c = 0.5$. Percentage of time with calm and rebellion (left) and statistics of rebellion burst duration (right). (Source: author)

The purpose of this set of experiments was to evaluate the influence of J_{max} on the behaviour of the solutions, for $\rho_c = 0.25$ and 0.5. Twelve runs were performed, six for each value of ρ_c for J_{max} between 10 and 60, in steps of $\Delta J_{max} = 10$. Each simulation was run for 10,000 cycles. The remaining input parameters were set to their default values, which correspond to the same general setup of the previous experiment (small artificial society, high `government-legitimacy` and low `threshold`). The variables `peak.threshold` and `diff.threshold` were set to their default values (0.1% and 0.05% respectively) in post-processing.

Figure 5.18 shows the % of total time with calm and rebellion (left) and burst duration statistics (right) as a function of J_{max} for the case $\rho_c = 0.5$. Comparing this with figure 5.11 it can be concluded that, for the conditions of this experiment (based on the reference case in Epstein et al. [33]), J_{max} has a much smaller influence on these two properties than ρ_c . In contrast with ρ_c, there are no tipping points associated with J_{max}.

The mean and median of burst duration are almost insensitive to variations of J_{max}. This was expected, since burst duration depends on how many 'citizens' can turn 'active' and how fast 'cops' can suppress rebellion bursts, and neither of these processes is directly influenced by J_{max}. Because burst duration is almost constant, the % of total time with rebellion bursts decreases slowly with increasing J_{max}, because jailed agents are released sooner for smaller J_{max}.

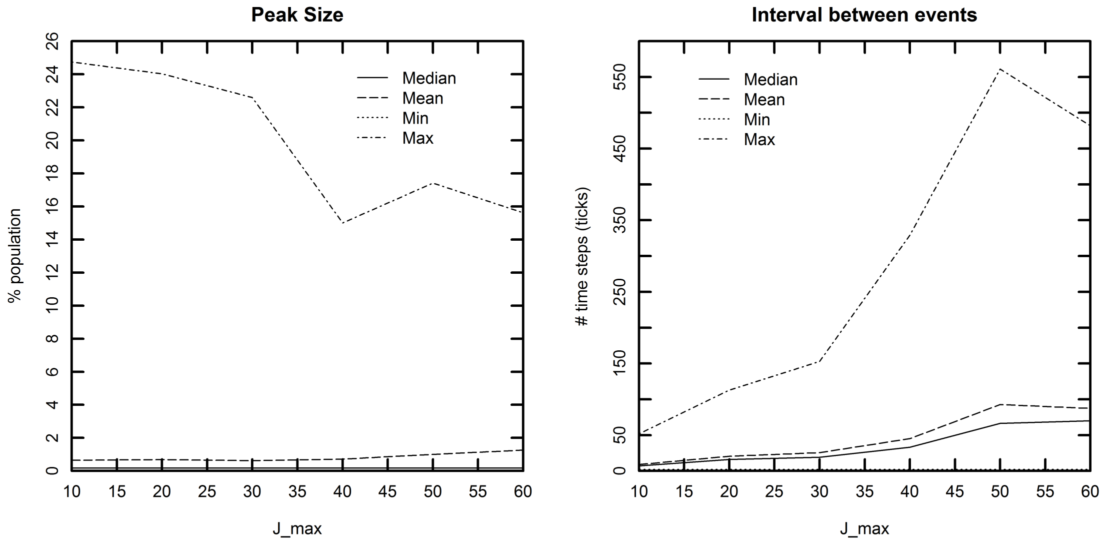


Figure 5.19: J_{max} variation experiment, for the case $\rho_c = 0.5$. Statistics of rebellion peak size (% 'active' citizen agents) and interval (waiting time between peaks, in time steps). (Source: author)

Figure 5.20 shows the statistics of peak size and interval between successive events as a function of J_{max} for the case $\rho_c = 0.5$. The mean and median of peak size are relatively insensitive to J_{max}. The interval between successive events increases almost linearly for $10 \leq J_{max} \leq 40$, but apparently with variable trend for $40 \leq J_{max} \leq 50$ and $50 \leq J_{max} \leq 60$. Thus, the interval between successive events is strongly dependent on J_{max} and almost proportional to the value of this parameter. This is further confirmed by examining figure 5.20.

Like in the case of the previous experiment, it is important to analyse the simulated time series of % of 'active' citizens for different values of J_{max}. Figure 5.21 shows the first five thousand cycles of the simulations for $J_{max} = 20$, 40 and 60 and $\rho_c = 0.5$. In all cases, the maximum peak size is consistent with the values found in the previous experiment, for the same value of ρ_c. A qualitative comparison between maximum peak sizes (dashed lines in figure 5.21) obtained in this experiment and the analysis of large demonstrations in §4.1 suggests that the values $J_{max} = 10$ and 20 may lead to unrealistic peak sizes.

The simulations in this experiment with $\rho_c = 0.25$ (not shown) lead to the same general conclusions as those with $\rho_c = 0.5$ discussed above, but with smaller rebellion peaks and a larger proportion of small events (figure 5.22).

The results of this experiment showed that for constant densities of 'citizens' and 'cops', global variables (e.g. legitimacy) and individual attributes (e.g. H, R, v, v')

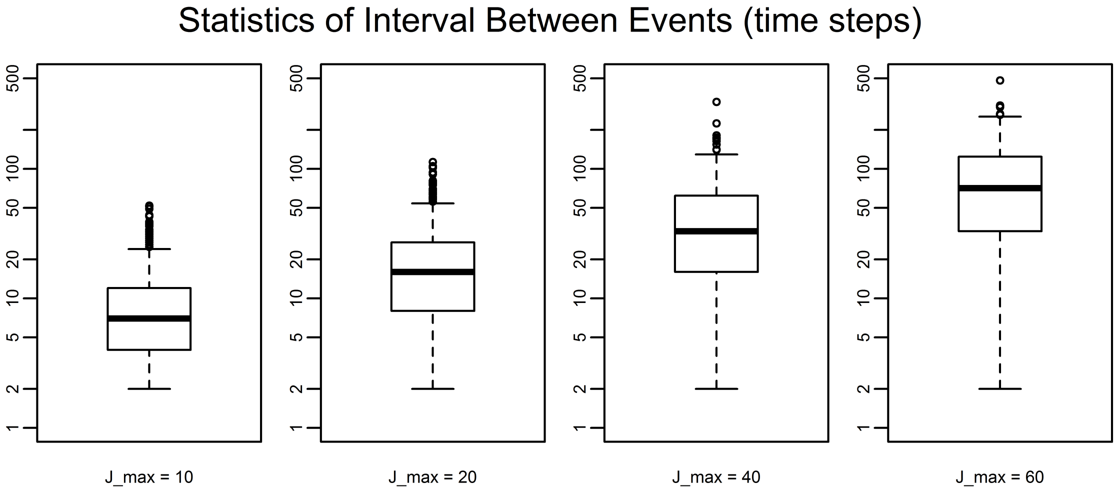


Figure 5.20: Box plot summary representation of the distributions of the interval (waiting time, in time steps) between successive bursts for four cases of the J_{max} variation experiments, with $\rho_c = 0.5$. (Source: author)

the jail term strongly influences the interval between successive bursts. The results also suggest that if the ratio between the maximum jail term and the duration of the rebellion bursts is sufficiently large ('active' citizens are not released too fast), this parameter has small influence on the magnitude of the peak sizes.

Before proceeding to further explorations of the model, it is important to consider how to set J_{max} for the simulations to have meaningful correspondence with conflict events in real processes, such as those analysed in §4.1.5 for the case of the African AS countries. This is difficult for a number of reasons. For instance, the statistics of event interval are different among the countries, for the type of event (e.g. demonstration or riots) and for the period considered (before and after the beginning of the AS). Also, it is not possible to define a precise correspondence between the time scale of one day real events as described in SCAD, and one time step in the ABM. However, it is possible to determine at least a plausible range for J_{max}, as follows.

Table 5.4 shows summary statistics of event interval for demonstrations in African AS countries after 2010-12-15[57] and the simulations of the J_{max} variation experiment. The median of duration of demonstrations after 2010-12-15 was one for all countries (figure 4.8(a)). Except for the cases of Egypt and Mauritania, the range for the ratio between event interval and duration is [10,40]. For the conditions of this experiment (size of artificial society, distributions of individual attributes, legitimacy, threshold,

[57]The period after the beginning of the AS was selected, because it is representative of manifest large scale conflict and the variability among the countries is smaller.

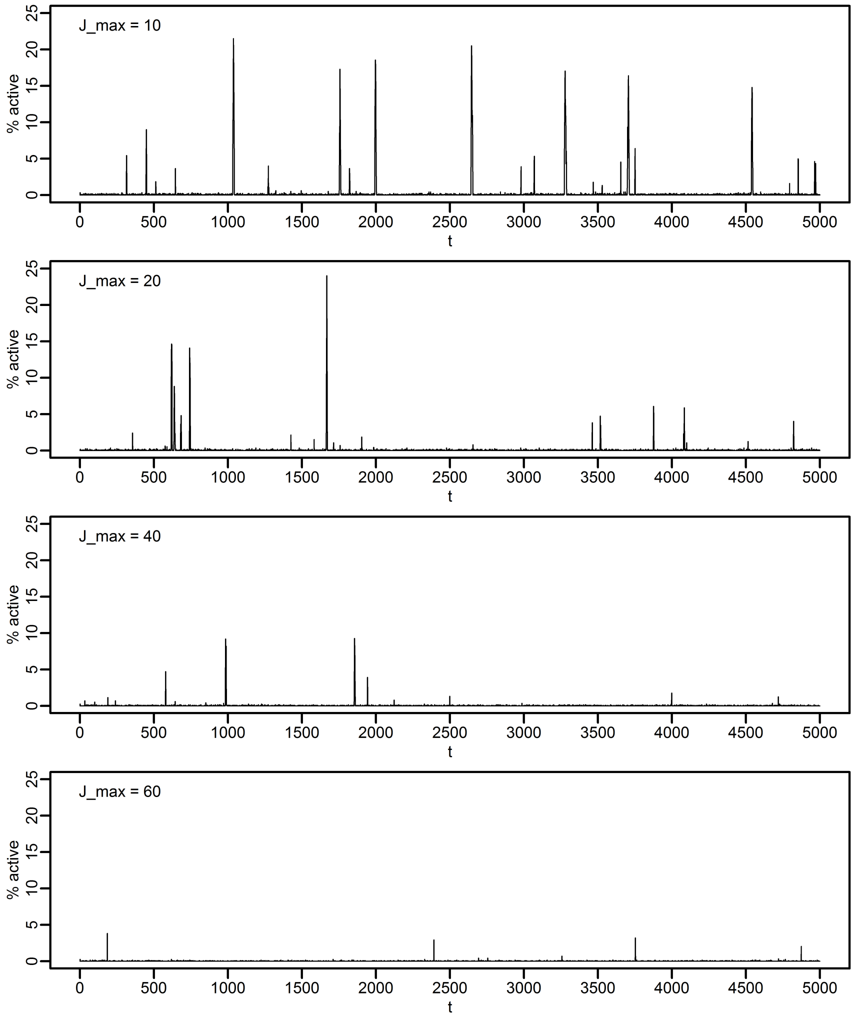


Figure 5.21: Simulated time series of the proportion of 'active' citizens for the first five thousand cycles, for $J_{max} = 10$, 20, 40 and 60, and $\rho_c = 0.5$. (Source: author)

etc.) a plausible range for J_{max} is [20,50], which includes the default value $J_{max} = 30$ in the reference simulation (Epstein et al. [33], Run 2).

5.2.4 Variable Deterrence in a Scenario of Low Legitimacy

The experiments in §5.2.2-5.2.3 were based on Run 2 in references [33, 31], in which the legitimacy is high ($L = 0.82$) and the threshold is low ($T = 0.1$). This combination of legitimacy and threshold, which is often used in studies based on Epstein's model (e.g. [35, 74]), is typical of democratic regimes.

The purpose of this experiment was to investigate the model's capability to produce solutions with intermittent peaks of rebellion in a scenario of low legitimacy,

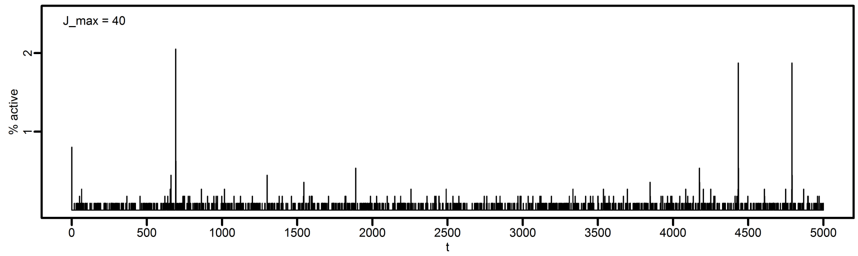


Figure 5.22: Simulated time series of the proportion of 'active' citizens for the first five thousand cycles, for $J_{max} = 40$ and $\rho_c = 0.25$. (Source: author)

for varying deterrence capability of the central authority. Thus, the legitimacy was set $L = 0.20$, which is a typical value of the FSI "Legitimacy of the State" indicator for the countries studied in Chapter 4[58] and, making use of inequality (5.10), the threshold was set to $T = 0.60$. The level of deterrence was varied considering two sweeping variables, the `initial-cop-density` and `vision-c` ('cop' vision radius).

Since the population size is expected to be an important parameter, the experiment was performed for two different grid sizes, one representing a 'small society' and another a 'large society'. The thresholds for the minimum 'significant' % of the population for a rebellion event used in the post-processing stage were set to 10^{-3} (0.1%) and 10^{-4} (0.01%) for the 'small' and 'large' society settings, respectively.

Table 5.6 shows the input parameters for this experiment which are different from the default values (Table A.4, page 194). One simulation with 10,000 cycles duration was performed for each combination of the sweeping parameters (`initial-cop-density` and `vision-c`).

Figure 5.23 shows colour level plots of the % of time with rebellion for the 25 simulations in this experiment. It can be observed that there are three distinct regimes (or long term behaviours of the solutions): permanent rebellion for low density and 'myopic' cops, complex solutions with intermittent bursts of unrest and stationary solutions with permanent calm (stability). This confirms that inequality (5.10) correctly relates the values of L and T for intermittent peaks to occur, and that the three regimes are possible with both low and high L. The solutions' behaviour is sensitive to both the initial 'cop' density and the 'cops' vision radius, but more

[58]This does not imply that we consider the value of the FSI "Legitimacy of the State" indicator to be representative of the 'true' legitimacy of the central authorities of these countries. However, it is clear that only governments with low legitimacy are prone to face large scale uprisings.

Table 5.4: Summary of statistics of waiting time between successive demonstrations in African "Arab Spring" countries, and rebellion bursts in simulations of the J_{max} variation experiment. (Source: author, based on model simulations and [97])

Large Demonstrations	**Min.**	**Median**	**(after 2010-12-15) Mean**	**Max.**	N_{events}
Algeria	3.0	12.5	57.8	546	16
Egypt	0.0	3.0	5.2	49.0	200
Libya	0.0	18.5	32.2	259	32
Mali	2.0	36.0	74.2	377	9
Mauritania	65.0	180	199	367	5
Morocco	0.0	15.0	26.3	98.0	39
Sudan	1.0	21.0	35.4	131	26
Tunisia	0.0	12.0	21.4	243	51
Simulations J_{max}	**Min.**	**Median**	($\rho_c = 0.5$) **Mean**	**Max.**	N_{events}
10	2.0	7.0	9.1	52.0	1096
20	2.0	16.0	20.5	113	488
30	2.0	19.0	25.7	153	388
40	2.0	33.0	45.1	329	222
50	2.0	66.5	92.7	561	107
60	2.0	70.0	87.4	482	115

sensitive to the former.[59]

The size of the artificial society has a significant impact on the behaviour of the solutions. The transitions of regime in the parameter space are more gradual and the % of time with unrest for low deterrence capability is higher in the 'large society' case, with permanent rebellion for low deterrence capability (`initial-cop-density` $= 2$ and `vision-c` $\in \{7, 9\}$). The values of % of time with unrest shown in figure 5.23 include most of the typical % of time for which African AS countries experienced large demonstrations after the beginning ot the AS (figure 4.10(a), page 79), although the 'large society' contains solutions with permanent unrest.

Figure 5.24(b) shows colour level plots of the minimum, median and maximum peak size of the rebellion bursts (in % of the population), for the 'small' and 'large' society cases. It can be observed from the median and maximum peak sizes that the solutions are more sensitive to the `initial-cop-density` than to `vision-c`. This can be explained by the fact that the number of 'cops' influences both the detection

[59]The onset of rebellion peaks as the 'cop' density drops below critical value was already found in [33], but the role and influence of the vision radius was not considered.

Table 5.5: Values of the input parameters and number of 'citizen' and 'cop' agents for the experiments with low legitimacy and variable deterrence capability, for the cases of 'small society' and 'large society'. (Source: author)

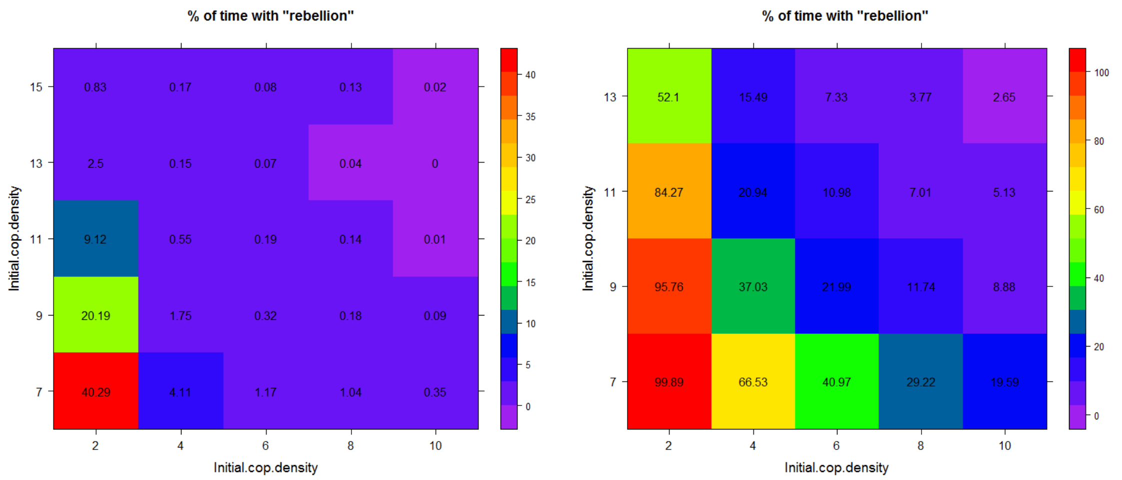
Variable name	'Small society' Value(s)	'Large Society' Value(s)
`world-width`	40	120
`world-height`	40	120
`initial-cop-density`	{2%,4%,6%,8%,10%}	{2%,4%,6%,8%,10%}
`initial-citizen-density`	70%	70%
Number of 'citizen' agents	1120	10080
Number of 'cop' agents	{32,64,96,128,160}	{288,576,864,1152,1440}
`threshold`	0.60	0.60
`government-legitimacy`	0.20	0.20
`max-jail-term`	40	40
`vision-c`	{7,9,11,13,15}	{7,9,11,13,15}

probability and the rate at which arrests can be done, whereas their vision radius only influences the former.

In summary, the results of this experiment confirm that the present ABM can produce solutions with distinct qualitative behaviour, even for low values of the legitimacy, which is the case of authoritarian governments that maintain stability via a high level of repression. The variation of the solutions' long term behaviour as a function of the sweeping parameters is also consistent with the discussion in §3.3.3, in that large peaks of rebellion can occur if the number of 'cops' is too small to quickly arrest 'active' citizens, or the union of the cells within their vision radii is insufficient to cover the model space (so that bursts of rebellion can start and grow before being detected). Also, the size of the artificial society has a large impact on the behaviour of the solutions, for the same values of `initial-cop-density` and `vision-c`.

5.2.5 Dependence of Hardship on Relative Deprivation

The purpose of the present experiment was to set values of legitimacy and welfare inequality consistent with the indicators for the AS countries studied in Chapter 4, specify the distribution of hardship as a function of RD using equation (5.2), and investigate how varying levels of deterrence and sensitivity to deprivation lead to complex behaviour. This experiment is also relevant to confirm the validity of inequality (5.10) as a stability condition for both low and high values of legitimacy,



(a) (b)

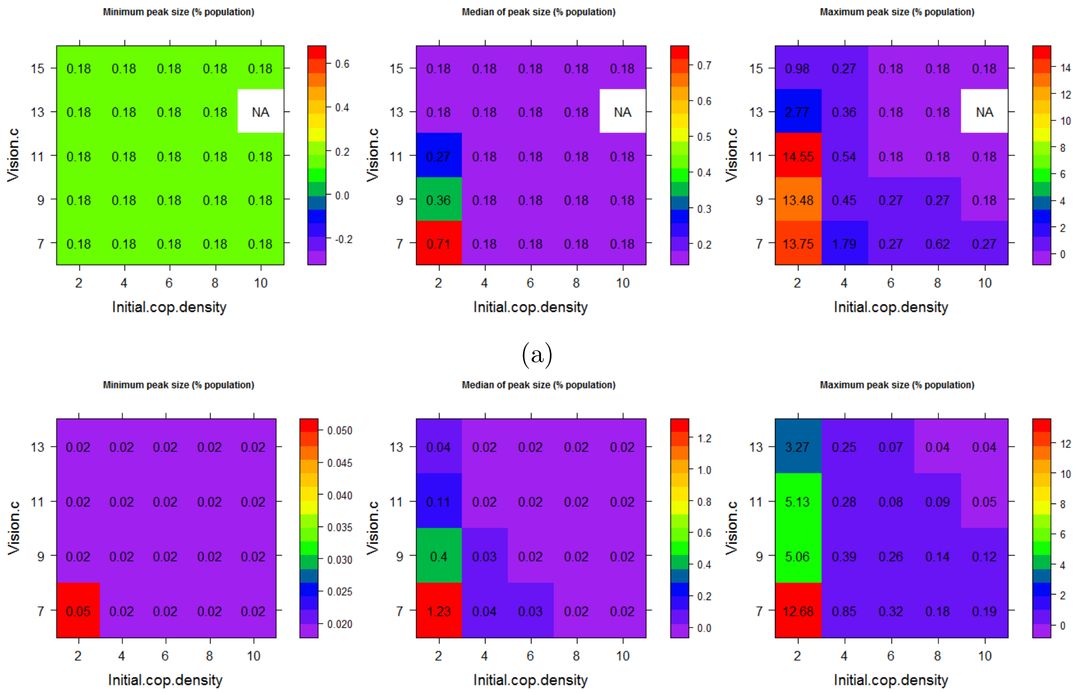
Figure 5.23: % of time with rebellion for the low legitimacy and variable deterrence capability experiment, for the 'small society' (a) and 'large society' (b) cases. (Source: author)

and an assessment of the present model's capability for representing different forms of RD (political vs economic).

Like in the previous experiment, the simulations were performed for two different grid sizes, one representing a 'small society' and another a 'large society'. The thresholds for the minimum 'significant' % of the population for a rebellion event used in the post-processing stage were 10^3 and 10^4 for the 'small' and 'large' society settings, respectively.

Table 5.6 shows the input parameters for this experiment which are different from the default values (Table A.4, page 194). The legitimacy was set to 0.20 and the Gini index to its default value 0.40. Of course, if the default value of the threshold ($T = 0.1$) was used in combination with a low value of legitimacy, the solutions would show permanent rebellion with a large proportion of 'active' citizens'. For complex solutions with intermittent bursts of rebellion, the threshold must have a higher value. Inequality (5.10) gives an estimate $T \sim 0.6$, which was the value used in the simulations (the same as in the previous experiment). The maximum jail term was set to 40, which was found in the previous section to be a plausible value.

The sweeping parameters were the `initial-cop-density`, which is related to the deterrence capability of the central authority (e.g. [33]), and the γ exponent in equation (5.2), which is related to the sensitivity to deprivation (commitment, or emotional factor). The values of γ chosen for this experiment were all smaller than 1, corresponding to varying degrees of 'political deprivation'. One simulation



(a)

(b)

Figure 5.24: Minimum, median and maximum peak size (% of the population) of rebellion bursts for the low legitimacy and variable deterrence experiment, for the 'small society' (a) and 'large society' (b) cases. (Source: author)

with a duration of 10,000 cycles was performed for each combination of the input parameters `initial-cop-density` and `gamma` (γ), and for the 'small society' and 'large society' cases.

Figure 5.25 shows colour level plots of the % of time with rebellion for the 50 simulations in this experiment. Depending on the combination of the two sweeping parameters, there are three distinct regimes: permanent rebellion (for small `initial-cop-density` and `gamma`), complex solutions with intermittent peaks of rebellion (with small or large amplitude), and stationary solutions with permanent calm.

It can be observed that γ is a critically important parameter. The solutions' behaviour is more sensitive to γ than to the 'cop' density. The results suggest that there is a tipping point associated with γ, between 0.10 and 0.15. There is permanent calm for $\gamma > 0.15$ for 'small society' and $\gamma > 0.20$ for 'large society'. It is also clear that the 'large society' requires a higher 'cop' density (or number of 'cop' agents per citizen) to remain stable, for the same value of γ.

It is interesting to consider the values of γ and `initial-cop-density` for which

Table 5.6: Values of the input parameters and number of 'citizen' and 'cop' agents for the RD experiment, for the cases of 'small society' and 'large society'. (Source: author)

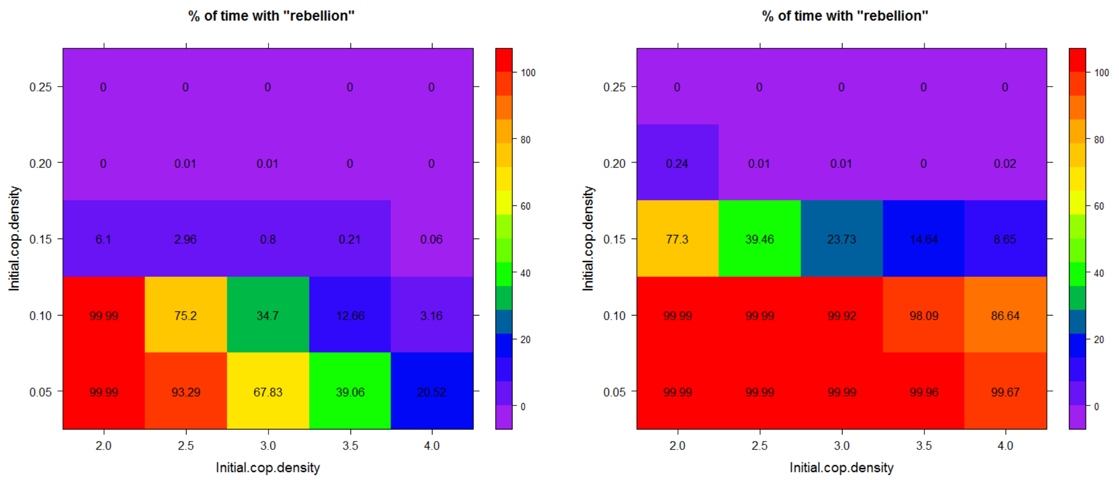
Variable name	**'Small society' Value(s)**	**'Large society' Value(s)**
`world-width`	40	120
`world-height`	40	120
`initial-cop-density`	{2.0%,2.5%,3.0%,3.5%,4.0%}	{2.0%,2.5%,3.0%,3.5%,4.0%}
`initial-citizen-density`	70%	70%
Number of 'citizen' agents	1120	10080
Number of 'cop' agents	{32,40,48,56,64}	{288,360,432,504,576}
`threshold`	0.60	0.60
`government-legitimacy`	0.20	0.20
`max-jail-term`	40	40
`RD?`	*true*	*true*
`gamma`	{0.05,0.10,0.15,0.20,0.25}	{0.05,0.10,0.15,0.20,0.25}

the percentage ot time with activity bursts, the size of rebellion peaks (in % of the population) and the duration of events are consistent with those found in real large scale conflict processes, e.g. for the case of demonstrations in African AS countries (figures 4.10(a), 4.8(a) and 4.11).

The percentages of total time with rebellion bursts are consistent with the typical values for demonstrations in the African countries analysed in Chapter 4 after the beginning of the AS for `initial-cop-density` $= 3.0$ and $0.05 \leq \gamma \leq 0.10$ in the case of 'small society', and for $2.0 \leq$ `initial-cop-density` ≤ 3.0 and $\gamma = 0.15$ in the case of 'large society'. In both cases, increasing the level of 'political RD' (e.g. to simulate conditions comparable to those before and after the beginning of the AS) can be modelled by decreasing γ.

Figure 5.26 shows colour level plots of the minimum, median and maximum peak size (% of the population) of the rebellion bursts. This figure shows the variations of the qualitative properties of the solutions in a more striking way than the previous figure. The `NA` values correspond to solutions with absolute calm or with a proportion of 'active' citizens below the threshold. The analysis of the maximum % of the population involved in large demonstrations in the AS (§4.1.5) shows that $\gamma \sim 0.15$ is a plausible estimate for simulating large scale conflict processes with low legitimacy and strong political RD.

Figure 5.27 shows colour level plots of the minimum, median and maximum event duration (in time steps) for this experiment. It is observed that $\gamma \sim 0.15$ also leads to event durations consistent with those in large demonstrations (or riots) studied in



(a) (b)

Figure 5.25: % of time with rebellion for the RD experiment, for the 'small society' (a) and 'large society' (b) cases. (Source: author)

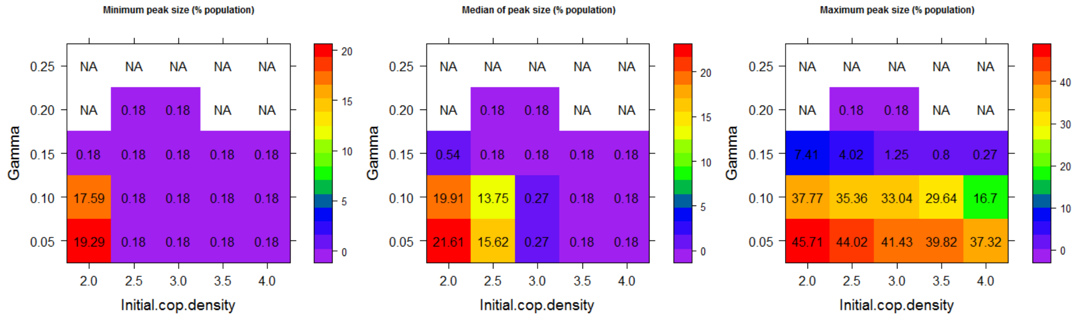
§4.1.5.

Expressing the hardship in terms of RD, and sweeping over the two parameters related to sensitivity to RD and level of deterrence, introduces complexity by changing the long term behaviour of the solutions. However, it is interesting to explore other ways of showing how the mechanism that associates illegitimate RD to grievance leads to complexity. One way of doing this is to consider a suitable phase space for representing the system's state and plotting the trajectories corresponding to the different runs. Figures 5.28 and 5.29 show the trajectories in the phase space with coordinates x_1 = % of 'active', x_2 = % of 'jailed' and x_3 = median of deprivation, for six selected runs, for the 'small' and 'large' society cases,respectively.

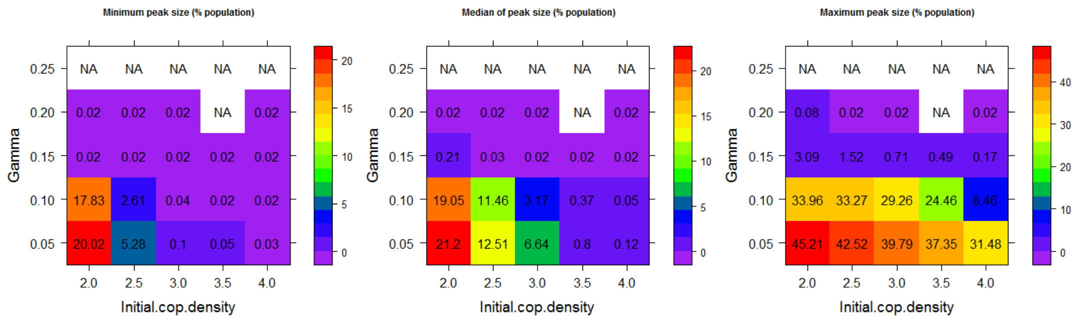
It can be observed that for $\gamma = 0.15$ the median of deprivation oscillates between 0 and approximately 0.6 but the society remains stable, with zero or very small proportions of 'active' and 'jailed' citizens, for both 'small' and 'large' societies. However, for $\gamma = 0.10$ the artificial society becomes unstable. When the median of deprivation surpasses ~ 0.6, the trajectories in the phase space describe more complicated shapes, whose form is different for the 'small' and 'large' society cases.

5.2.6 Legitimacy Feedback

As stated in §3.5, legitimacy feedback (i.e. how does the state of the system, described by the proportion of rebellious and/or jailed citizens, affects the legitimacy) is an important mechanism to explore.



(a)



(b)

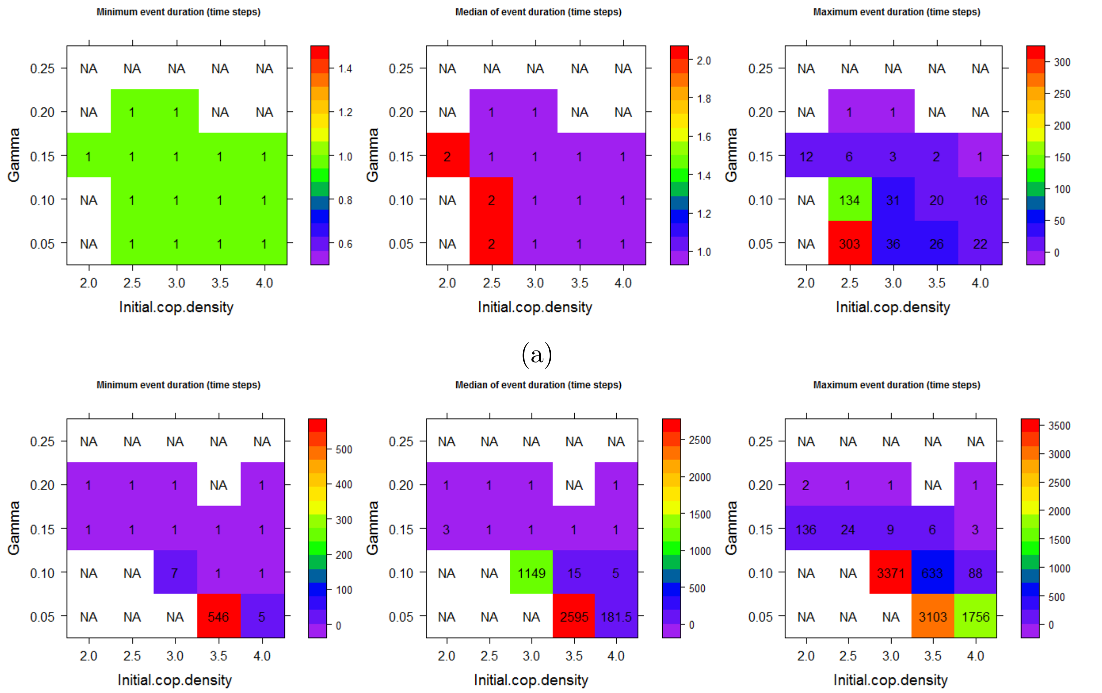
Figure 5.26: Minimum, median and maximum peak size (% of the population) of rebellion bursts for the RD experiment, for the 'small society' (a) and 'large society' (b) cases. (Source: author)

In this section, two different simulation experiments were performed, one on the combination of RD with legitimacy feedback, and another to study the differences between homogeneous and heterogeneous legitimacy feedback combined with variations of the `L-memory` input parameter.

The purpose of the first experiment in this section was to evaluate how the introduction of the legitimacy feedback mechanism changes the results of the grievance & RD simulations described in §5.2.5 above. More specifically, the goal was to simulate the effect of varying levels of deterrence and sensitivity to deprivation in small and large societies with low legitimacy of the central authority, under the *combined* effects of RD and legitimacy feedback.

The input parameters are the same described in the previous experiment (table 5.6), except that `LF?` was set to *true*. The simulations were run considering homogeneous legitimacy perception (`LF-agents?` = *false*) and the interval for time moving average is was set to its default value (`L-memory` = 5 cycles).

Figure 5.30 shows a colour level plot of the % of the time with rebellion for the 50 simulations of this experiment. The solutions show the same three regimes found



(a) (b)

Figure 5.27: Event duration (in time steps) for the RD experiment, for the 'small society' (a) and 'large society' (b) cases. (Source: author)

in the previous experiment (permanent rebellion, intermittent bursts of rebellion and stability/permanent calm). Once again, the solutions' behaviour is more sensitive to variations of γ than to variations of the 'cop' density. Comparing figures 5.25 and 5.30, it can be concluded that the sensitivity to value in the RD model is dominant with respect to γ and the 'cop' density. However, legitimacy feedback induces instability (larger values of % of time with rebellion), as was expected.

Figure 5.31 shows colour level plots of the minimum, median and maximum peak size (% of the population) of the rebellion bursts for the 50 simulations in this experiment. The `NA` values correspond to solutions with absolute calm or with a proportion of 'active' citizens below the threshold. These plots are consistent with those in figure 5.30 in showing that the solutions' behaviour is more sensitive to γ than to the 'cop' density. Also, $\gamma \sim 0.15$ is a plausible estimate for simulating large scale conflict processes with low legitimacy and strong political RD.

To better understand the changes of the solutions' behaviour with the variations of γ, the two simulations of the 'large society' case with `inital-cop-density` $= 4\%$ and $\gamma = 0.10$ and $\gamma = 0.15$ will be considered in greater detail. According to figures 5.30(b) and 5.31(b), there is a change of qualitative behaviour between these two simulations. This will now be analysed in terms of the time variation of the median

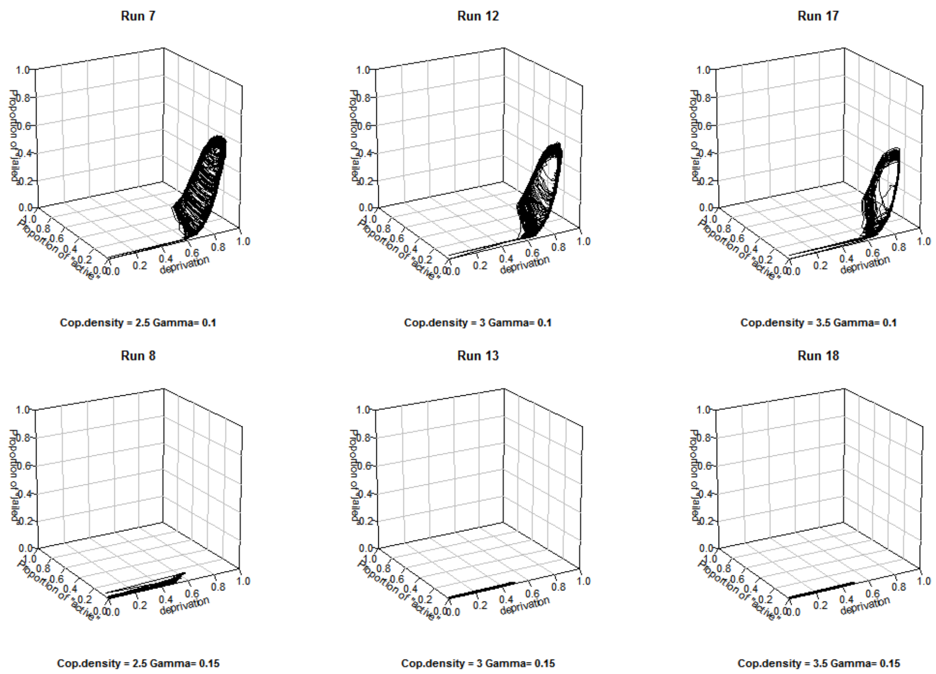


Figure 5.28: Trajectories in the phase space of % of 'active', % of 'jailed' and median of deprivation, for six selected runs of the RD experiment for the 'small society' case. (Source: author)

of the legitimacy (over all 'citizens' and the 'memory' length `L-memory`), the time variation of the medians of expectation and deprivation (over all agents), and the relationship between the medians of deprivation and legitimacy.

Figure 5.32 shows the time variation of the median of legitimacy during the first two thousand cycles for the two simulations considered. For $\gamma = 0.15$ the society is in a situation of stable calm and the legitimacy remains almost constant, with only small drops. However, for $\gamma = 0.10$ (larger sensitivity to value) the society is unstable and the legitimacy oscillates due to bursts of rebellion which result in a large proportion of 'citizens' turning 'active' and being jailed by the 'cops', leading to the legitimacy drops observed.

When compared with the variations of the legitimacy indicators in e.g. figure 4.13(a) it can be concluded that the legitimacy drops are larger in the ABM solution (maximum of 41%). The oscillations of the simulated legitimacy perception are not present in the FSI indicators for the eight countries considered, but these have very slow variation (one value per year) and so cannot be put in realistic correspondence with the model. Whether or not the legitimacy oscillations predicted by the model are realistic remains an open question. It can also be observed that in the case with $\gamma = 0.10$ there is a tendency for intermittent regime with long periods with calm,

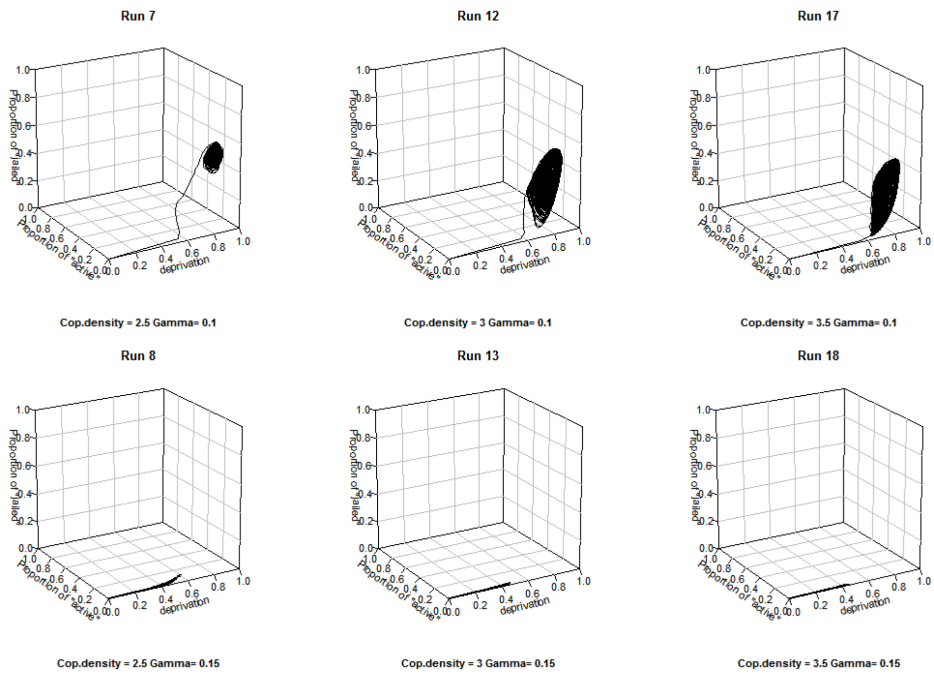
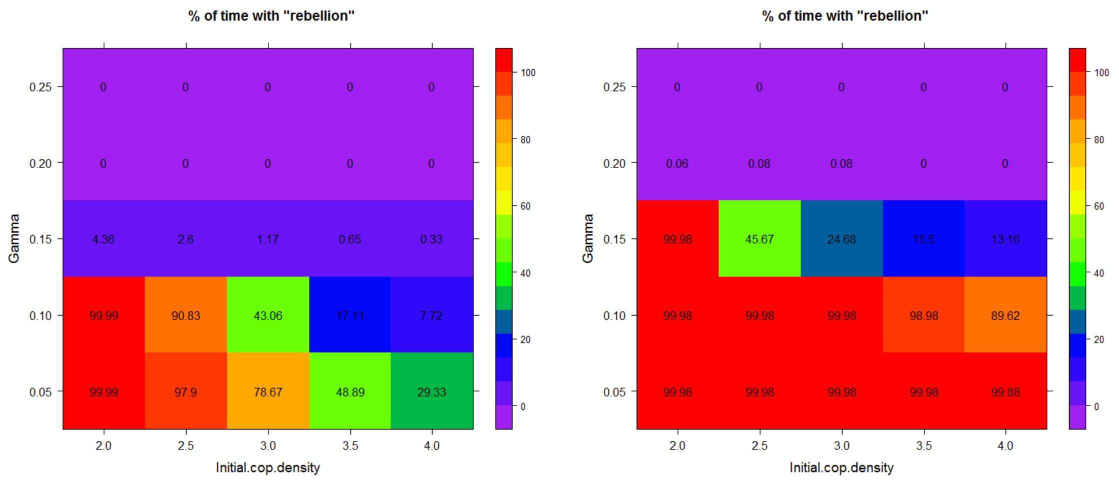


Figure 5.29: Trajectories in the phase space of % of 'active', % of 'jailed' and median of deprivation, for six selected runs of the RD experiment for the 'large society' case. (Source: author)

alternating with periods of turmoil, a behaviour that is somewhat similar to that shown in figure 3.3.

The change of qualitative behaviour between the two solutions can also be analysed by considering the time history of the medians of expectation and deprivation (over all 'citizens'). Figure 5.33 shows the first two thousand cycles of these dependent variables for the two simulations considered. It can be observed that for $\gamma = 0.15$ the median of expectation exceeds that of deprivation, whereas for $\gamma = 0.10$ the reverse is true. Thus, in the latter case, there is a generalized feeling of RD, with the consequent instability. The variations of the expectation and deprivation are also qualitatively different for the two simulations. In the $\gamma = 0.15$ case, the median of the expectation remains almost constant and the median of deprivation oscillates very rapidly, never surpassing 0.5. In the $\gamma = 0.10$ case, there are periods in which both medians oscillate, alternating with periods with almost constant expectation and small fluctuations of the deprivation.

Another way of analysing the difference of the qualitative properties of the two solutions is to consider the relationship between deprivation and legitimacy. Figure 5.34 shows the plot of the two solutions in the 2-D phase plane with coordinates x_1 = deprivation and x_2 = legitimacy. For $\gamma = 0.15$ the orbit is almost a horizontal



(a) (b)

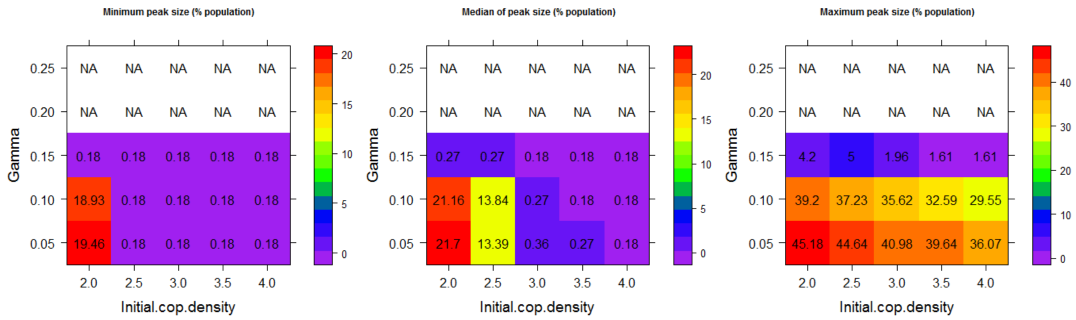
Figure 5.30: % of time with rebellion for the RD with legitimacy feedback experiment, for the 'small society' (a) and 'large society' (b) cases. (Source: author)

line segment – deprivation oscillates, but the legitimacy remains almost constant. However, for $\gamma = 0.10$ the orbit describes a more complicated shape once the deprivation surpasses ~ 0.6.

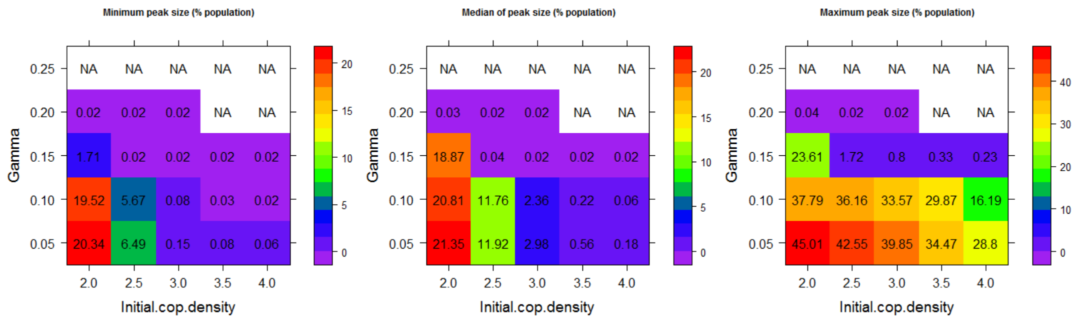
The system's behaviour for the two values of γ can also be studied by considering 3-D phase spaces, as was done in the previous section. Figures 5.35 and 5.36 show the trajectories in the phase space with coordinates x_1 = % of 'active', x_2 = % of 'jailed' and x_3 = median of deprivation for six selected runs, for the 'small' and 'large' society cases, respectively.

Comparing figure 5.28 with figure 5.35, and figure 5.29 with figure 5.36, it can be observed that for all cases displayed the trajectories are qualitatively similar for both the 'small' and 'large' society cases. Thus, for the parameter ranges considered, the model of RD-dependent hardship with the sensitivity parameter γ dominates the dynamics and the non-linear superposition of the legitimacy feedback mechanism does not change the qualitative features of the trajectories.

It is also possible to represent the solutions as trajectories in the phase space with coordinates x_1 = median of deprivation, x_2 = % of 'active' and x_3 = median of legitimacy. Figures 5.37 and 5.38 show these representations for six selected runs of the 'small' and 'large' society cases, respectively. It can be observed that for $\gamma = 0.10$ the trajectories show the same qualitative characteristics as before, i.e. beyond a critical value of deprivation the system becomes unstable and the trajectories describe a more complicated shape, different from the one in the % 'active' - % 'jailed' - median of deprivation phase space.



(a)



(b)

Figure 5.31: Minimum, median and maximum peak size (% of the population) of rebellion bursts for the RD with legitimacy feedback experiment, for the 'small society' (a) and 'large society' (b) cases. (Source: author)

* * *

In the second experiment in this section, the influences of homogeneous vs heterogeneous legitimacy and of time averaging interval were studied, keeping the 'cop' density and the parameter γ fixed. More specifically, the purpose of this set of simulations was to study how the variability (homogeneous vs heterogeneous) and time averaging of the legitimacy perception influence the qualitative properties of the solutions, keeping deterrence and sensitivity to RD fixed.

The simulations were run for the cases of 'small' and 'large' society, with a total of 10,000 cycles for each simulation. Table 5.7 summarizes the input parameters for this experiment.

Tables 5.8 and 5.9 show the results for the peak size (% of the population) and interval between successive bursts of unrest for the 'small' and 'large' societies, respectively. In both cases all simulations led to stable solutions with residual peaks of unrest.

For the 'small society' case (table 5.8), the peak size showed no significant variation with respect to either the time averaging interval or the type of legitimacy

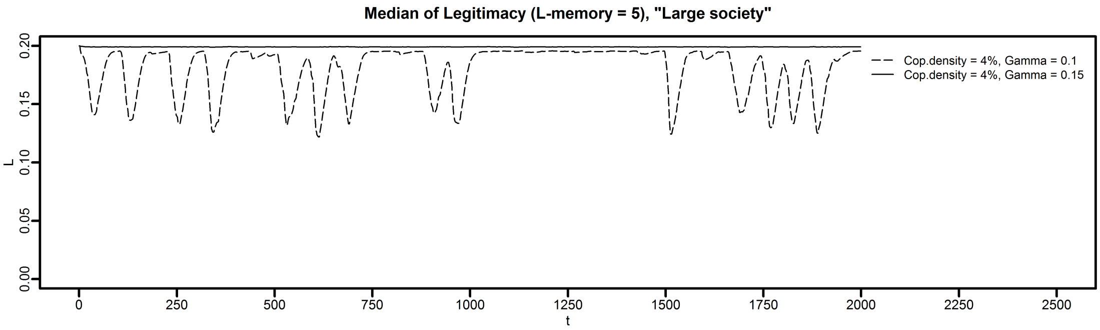


Figure 5.32: Time history of the first two thousand cycles of the median of legitimacy (over all agents and `L-memory` = 5 time steps) for the simulations of the 'large society' case with `initial-cop-density` = 4%, for the two values $\gamma = 0.10$ and $\gamma = 0.15$. (Source: author)

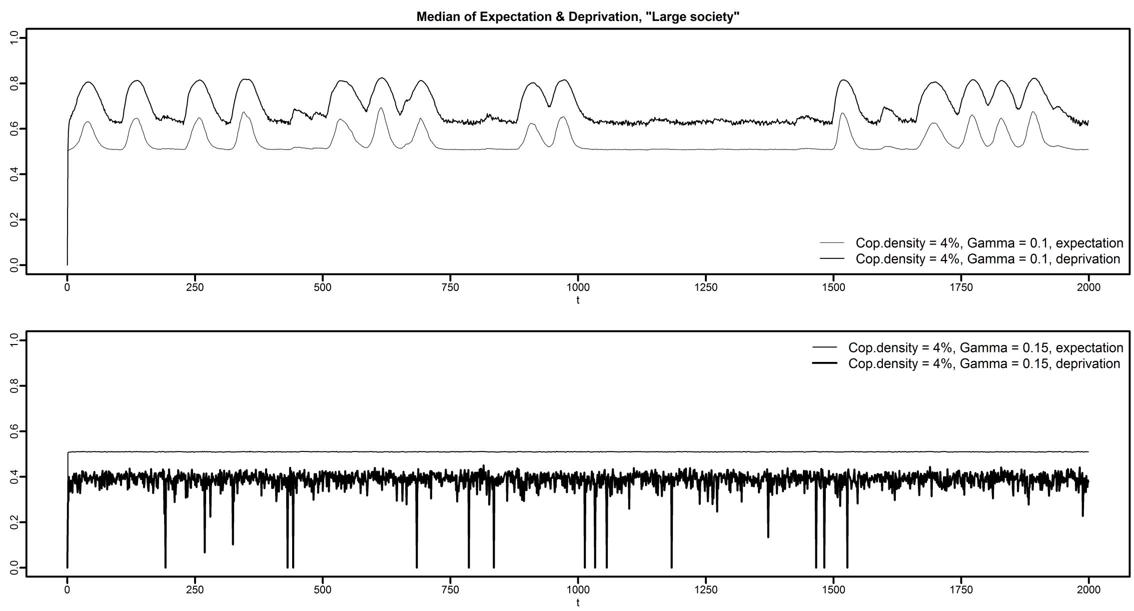


Figure 5.33: Time history of the first two thousand cycles of the medians of expectation and deprivation (over all 'citizens') for the simulations of the 'large society' case with `initial-cop-density` = 4%, for the two values $\gamma = 0.10$ and $\gamma = 0.15$. (Source: author)

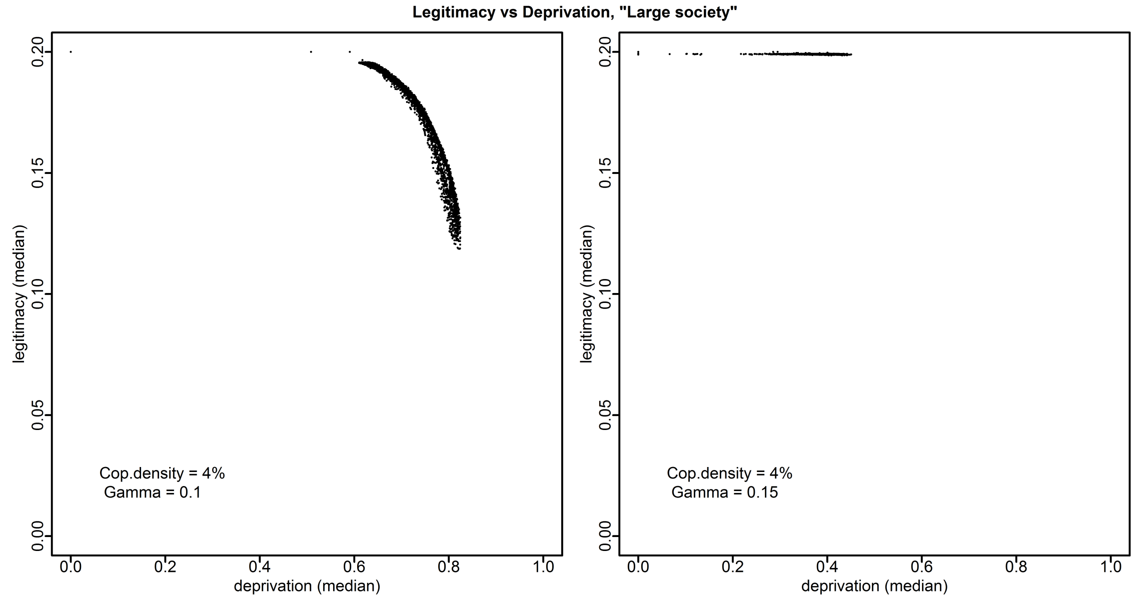


Figure 5.34: Plot of the median of legitimacy vs median of deprivation (both over all 'citizens') for the simulations of the 'large society' case with `initial-cop-density` = 4%, for the two values $\gamma = 0.10$ and $\gamma = 0.15$. (Source: author)

perception. The interval between successive events was sensitive to both the time averaging interval and the type of legitimacy perception, but from the results of table 5.8 no clear conclusion can be drawn on the relative importance of these parameters.

For the 'large society' case (table 5.9), the numbers of events and peaks of unrest were much larger than for the 'small society' case, because the threshold for event detection was one order of magnitude smaller. Consequently, the minimum and median of the peak size were also one order of magnitude smaller. For most (but not all) combinations of values of the sweeping parameters the peak sizes were smaller than in the 'small society' case. The intervals between successive events were much smaller for the 'large society' case, due to the large number of small size events (with just a few 'citizens' turning 'active') that were detected.

These results illustrate the influence of the size of the artificial society on the results of the simulations, but no definite conclusions could be obtained from this experiment regarding the relative importance of the time averaging interval and type of legitimacy feedback. In particular, the influence of the time averaging interval on the stability of the solutions needs to be investigated in further studies.

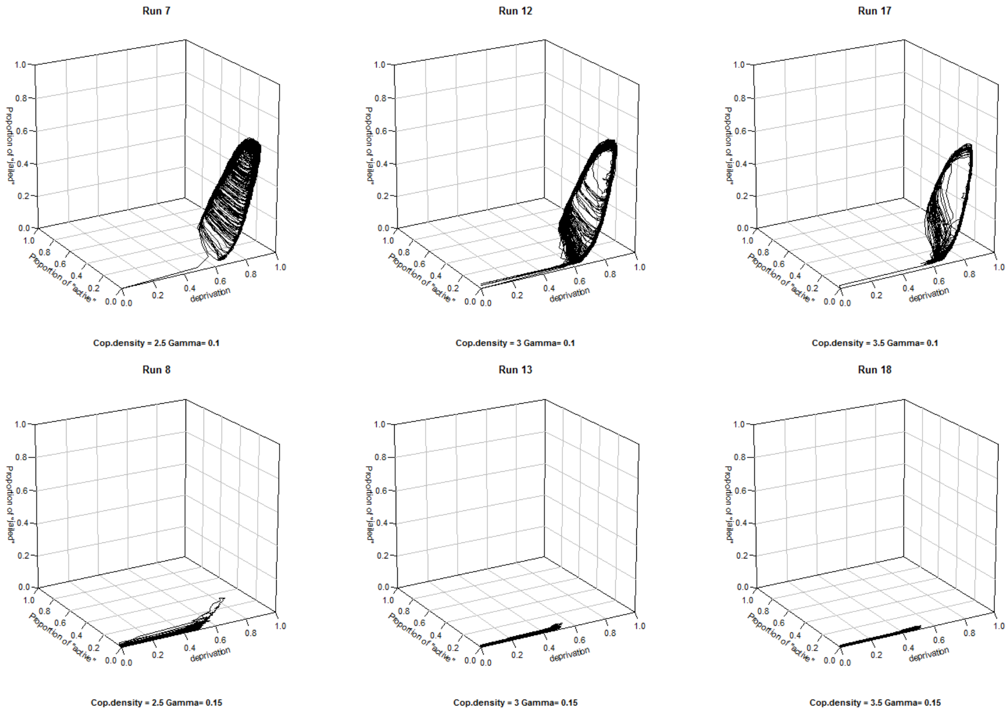


Figure 5.35: Trajectories in the phase space of % of 'active', % of 'jailed' and median of deprivation, for six selected runs of the RD with legitimacy feedback experiment for the 'small society' case. (Source: author)

5.2.7 Network Influences

Network influences are essential for describing social conflict phenomena. The widespread use of social media such as blogs and Facebook played a central role in the propagation of protests in recent conflict processes, particularly in the AS. Faris [34] and Comninos [18] discussed the use of SN in the AS and concluded that these are not the cause of social conflict and revolution but can trigger informational cascades that change the dynamics of the events. A similar conclusion was also obtained via simulation using the ABM described in [60].

In the 'abstract' ABM proposed herein, networks can be interpreted as simplified representations of fixed but non-local information and influence structures (involving fixed sets of link neighbours of an agent) whereas the vision radius can be thought of as a local-context 'crowd' or 'flock' influence space, because other agents come in and go out of the visibility space at random. Also, network influence effects depend on the type (directed or undirected) and structure of each specific network.

The submodel of network influences proposed herein differs from Lemos et al. [60] in several ways, to make it simpler and more consistent. For instance, the names of the networks were changed from 'family' and 'news' to 'group' and 'infl',

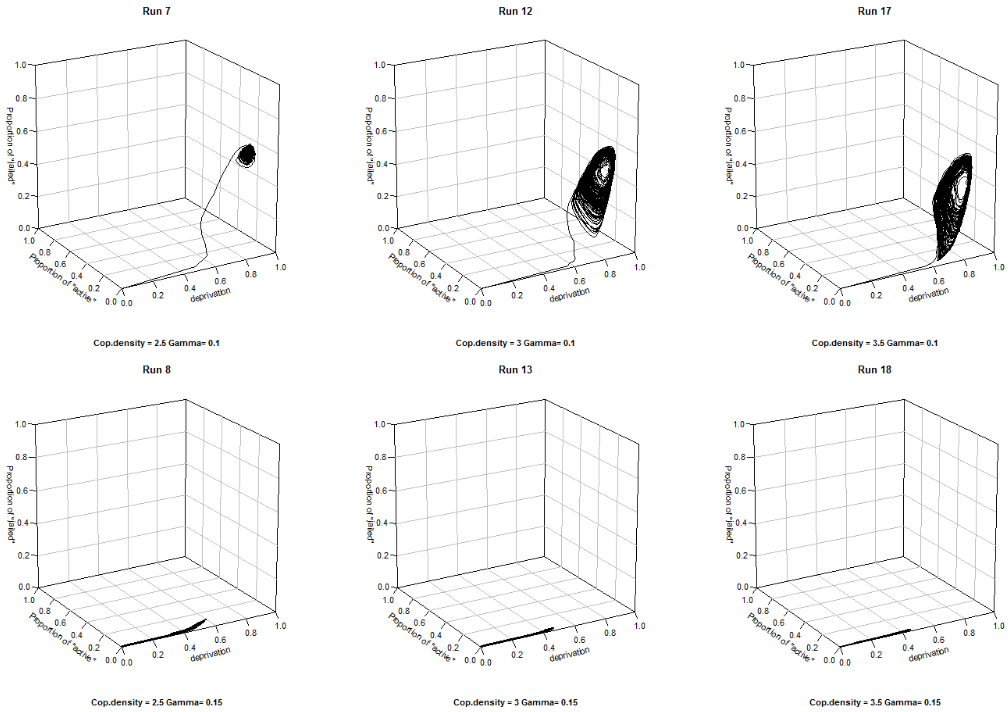


Figure 5.36: Trajectories in the phase space of % of ‘active’, % of ‘jailed’ and median of deprivation, for six selected runs of the RD with legitimacy feedback experiment for the ‘large society’ case. (Source: author)

respectively.[60] In the present model the influences due to these networks work differently, but the mechanism of influence is the same – dispositional contagion, as in [32]. The present formulation also dispenses the definition of a third agent type, called ‘media’ in [60], which was replaced by a subtype of the ‘citizen’ agent (‘activist’).

However, the present formulation also has drawbacks. One drawback is the linear superposition of influences, which has the advantage of simplicity [32] but is debatable. Also, the weights `w-group` and `w-infl` may be very different, because the number of ‘activists’ is small compared with the group size. Another potential drawback is that for two-way influences in clique networks there is cyclic reinforcement, whereas the ‘audience’ does not influence the disposition of influentials (‘activists’).

The purpose of the computer experiments reported in this section was to evaluate how network influences change the qualitative behaviour and the quantitative properties of the solutions (statistics of size, duration and waiting time), for a context of low government legitimacy, with RD-dependent hardship and legitimacy feed-

[60]The idea behind this choice is that some groups can have the same or higher influence than a family, and posts in blogs or Facebook accounts held by ‘influentials’ can have an influence comparable to traditional media.

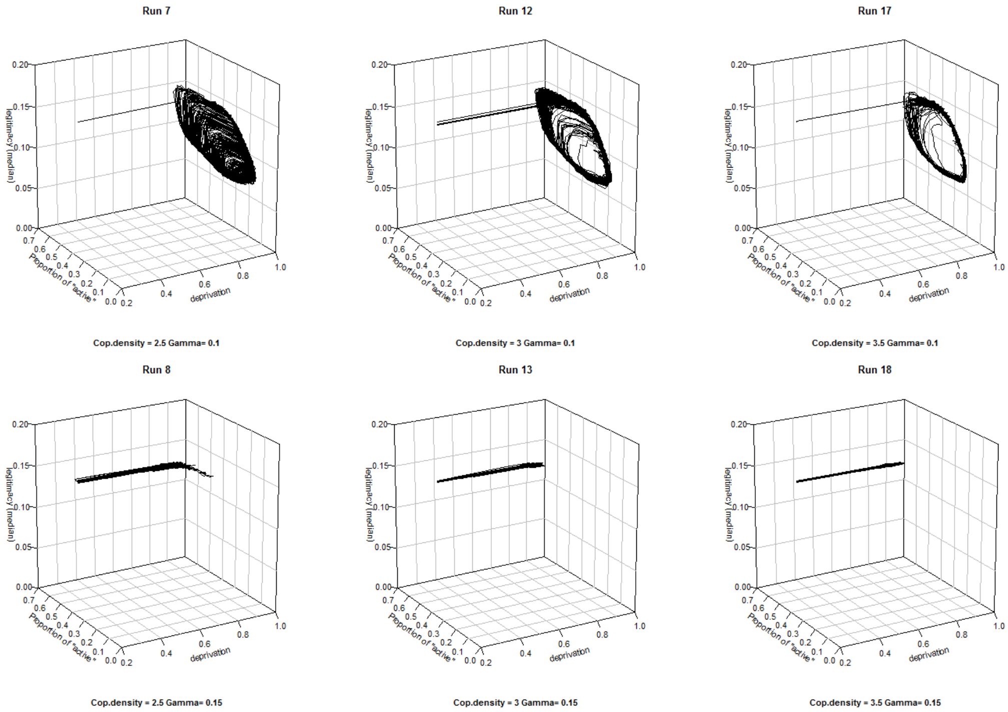


Figure 5.37: Trajectories in the phase space of median of deprivation, % of 'active', and median of legitimacy, for six selected runs of the RD with legitimacy feedback experiment for the 'small society' case. (Source: author)

back. The `initial-cop-density` was fixed in all simulations of the experiment. To study the model's sensitivity to network influence effects, two sets of experiments were performed, one with 'group' and another with 'infl' networks. The number of 'activist' citizens in the 'infl' simulations was arbitrarily set to `num-infl` = 4. The sweeping variables were the `group-size` and `w-group`, and the `infl-size` and `w-infl`, respectively.

Table 5.10 shows the values of the input parameters for the simulations of this experiment. Each simulation was run for 10,000 cycles. The model space was the default 40 × 40 2D torus in both 'group' and 'infl' experiments, which corresponds to the 'small society' setting.[61]

The idea behind the previous experiments was the study of how newly added mechanisms may change the system's behaviour. Therefore, when considering network influences, it is natural to ask the following questions:

1. What is the effect of network influences, relative to the corresponding case with the same legitimacy, deterrence level (threshold, 'cop' density and `vision-c`),

[61]Due to time constraints, it was not possible to perform the 'group' and 'infl' experiments for the 'large society' setting, with a 120 × 120 2D torus and 10080 'citizen' agents for a density of 70 %.

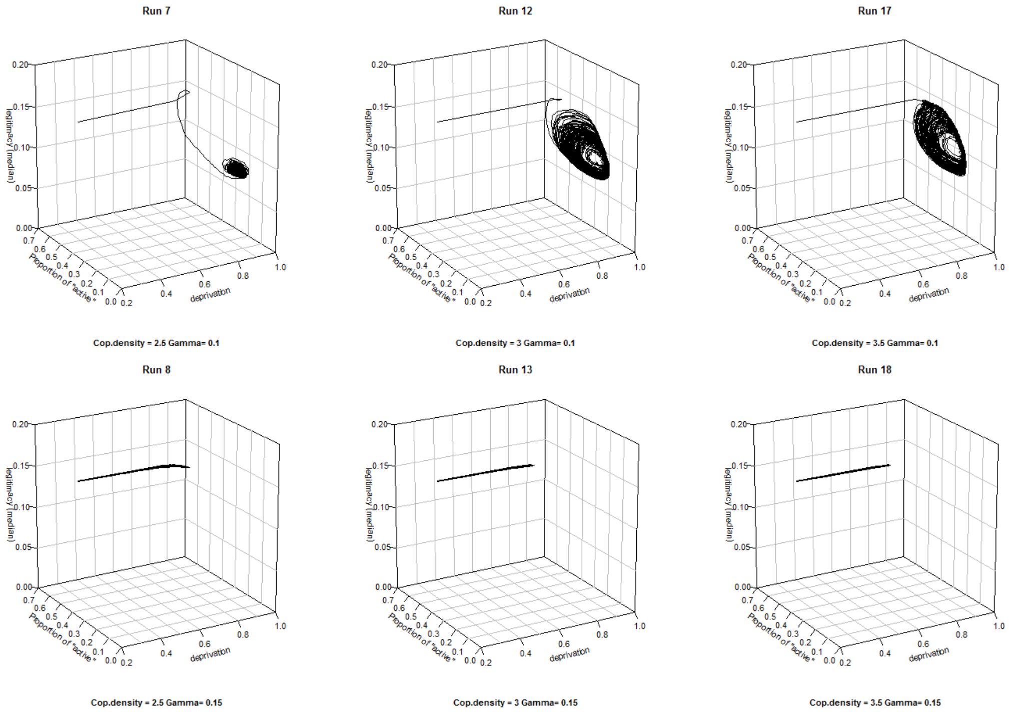


Figure 5.38: Trajectories in the phase space of median of deprivation, % of 'active', and median of legitimacy, for six selected runs of the RD with legitimacy feedback experiment for the 'large society' case. (Source: author)

and mechanisms of RD-dependent hardship and legitimacy feedback activated?

2. Which of the network influences, 'group' or 'infl', has greater impact on the solutions' behaviour?

To answer the first question, it is important to notice that the case of the previous experiment with $\gamma = 0.15$, `initial-cop-density` $= 3\%$ and homogeneous legitimacy feedback, presented in the previous section, is representative of calm stability, for the % of time with rebellion is 1.87% and the median of the peak size is 0.18% of the population (~ 2 'citizens' in 1120), as shown in figures 5.30(a) and 5.31(a). Also, the minimum, median and maximum of the event duration (not shown in §5.2.6) were one, one and five time steps respectively, which is also representative of stable solutions (without significant turmoil events). Therefore, it was chosen as reference case for the experiments in this section, to investigate whether or not network influences drive the system away from stability.

Figures 5.39-5.41 show the % of the total time with rebellion, the peak size (% of the population) and the duration of rebellion bursts for the simulations with the 'group' and 'infl' networks, respectively.

For the 'group' network the % of time with rebellion increased significantly for

Table 5.7: Input parameters for the simulations with RD and legitimacy feedback, with homogeneous and heterogeneous legitimacy perception and different time averaging intervals L-memory. (Source: author)

Variable name	'Small society' Value(s)	'Large society' Value(s)
world-width	40	120
world-height	40	120
initial-cop-density	4.0	4.0
initial-citizen-density	70%	70%
Number of 'citizen' agents	1120	10080
Number of 'cop' agents	64	576
threshold	0.60	0.60
government-legitimacy	0.20	0.20
max-jail-term	40	40
RD?	*true*	*true*
gamma	0.15	0.15
LF?	*true*	*true*
LF-agents?	{*false*,*true*}	{*false*,*true*}
L-memory	{5,6,7,8,9,10}	{5,6,7,8,9,10}

many combinations of the sweeping parameters, but there is no clear pattern showing transitions of regime in figure 5.39(a), as was the case in the experiments described in §§5.2.5 and 5.2.6. It is apparent that the tendency for instability increases with both the group size and the influence weight, but the variations are not monotonic with respect to both sweeping variables.

Figures 5.40(a) and 5.41(a) show that although the minumum and median of the peak size and event duration are identical to those obtained in the reference case (except for the three values of the median of peak size of 0.27 % shown in figure 5.40(a)), the maximum peak size and event duration are much larger when 'group' influence effects are added. Thus, in this model 'group' network influences lead to instability by amplifying the size and duration of some events, while the solutions remain stable for most of the time.

The results of the simulations with the 'infl' network were qualitatively similar to those for the 'group' network, but the % of time with rebellion and the medians and maxima of peak size of the extreme cases (e.g. 70% 'audience' and influence weight 0.9 in figure 5.39(b) and 80% audience and 0.8 influence weight in figure 5.40(b)) were even larger than those for the experiment with the 'group' network influences.

Table 5.8: Peak size (% of the population) and waiting time for bursts of social unrest (in time steps) with grievance expressed as a function of RD, for homogeneous and heterogeneous legitimacy perception and different time averaging windows (in time steps), in the 'small society' case. (Source: author)

Input	parameters	Peak	size	(% population)				Event	interval	(time steps)			
L-memory	**LF-agents?**	**Min**	**Median**	**Mean**	**Max**	σ	N_{peaks}	**Min**	**Median**	**Mean**	**Max**	σ	N_{events}
5	*false*	0.18	0.18	0.21	0.45	0.09	10	170	956	857.67	1894	604.23	10
6	*false*	0.18	0.18	0.18	0.18	0	14	79	489.5	662.17	1863	614.84	13
7	*false*	0.18	0.18	0.26	0.98	0.21	23	21	289	445.55	2073	466.51	23
8	*false*	0.18	0.18	0.18	0.18	0	13	37	606	800.36	3120	874.99	12
9	*false*	0.18	0.18	0.2	0.36	0.05	15	48	434.5	570.5	2886	710.67	15
10	*false*	0.18	0.18	0.2	0.36	0.05	17	4	424	581.69	1346	483.53	17
5	*true*	0.18	0.18	0.23	0.62	0.11	20	41	308	495.05	1664	467.07	20
6	*true*	0.18	0.18	0.18	0.18	0	8	118	1021	1018	2495	921.21	8
7	*true*	0.18	0.18	0.19	0.27	0.03	11	44	821.5	822.2	1590	499.11	11
8	*true*	0.18	0.18	0.21	0.62	0.09	29	21	229.5	328.46	939	275.32	29
9	*true*	0.18	0.18	0.21	0.62	0.1	45	17	171	218.8	861	194.07	45
10	*true*	0.18	0.18	0.21	1.07	0.13	57	6	133.5	162.48	630	137.52	57

Table 5.9: Peak size (% of the population) and waiting time for bursts of social unrest (in time steps) with grievance expressed as a function of RD, for homogeneous and heterogeneous legitimacy perception and different time averaging windows (in time steps), in the 'large society' case. (Source: author)

Input	parameters	Peak	size	(% population)				Event	interval	(time steps)			
L-memory	**LF-agents?**	**Min**	**Median**	**Mean**	**Max**	σ	N_{peaks}	**Min**	**Median**	**Mean**	**Max**	σ	N_{events}
5	*false*	0.02	0.02	0.02	0.24	0.01	886	2	8	11.29	81	9.76	884
6	*false*	0.02	0.02	0.02	0.27	0.02	1049	2	7	9.54	68	8.40	1047
7	*false*	0.02	0.02	0.03	0.36	0.02	912	2	8	10.96	62	9.45	912
8	*false*	0.02	0.02	0.02	0.14	0.01	531	2	14	18.78	103	16.87	530
9	*false*	0.02	0.02	0.02	0.21	0.01	982	2	8	10.19	55	8.21	982
10	*false*	0.02	0.02	0.02	0.32	0.01	952	2	8	10.54	58	8.91	949
5	*true*	0.02	0.02	0.02	0.23	0.01	880	2	8	11.36	62	9.29	879
6	*false*	0.02	0.02	0.02	0.11	0.01	884	2	9	11.32	66	9.41	884
7	*false*	0.02	0.02	0.02	0.23	0.01	917	2	8	10.91	82	9.59	917
8	*false*	0.02	0.02	0.02	0.15	0.01	1052	2	7	9.54	50	7.65	1048
9	*false*	0.02	0.02	0.02	0.22	0.01	1057	2	7	9.47	53	7.41	1056
10	*false*	0.02	0.02	0.02	0.31	0.02	964	2	8	10.38	58	8.53	963

The answers to the questions referred to above can be summarized as follows:

– Both the 'group' and 'infl' network influences induce instability for the parameter ranges tested, with large values of % of time with rebellion and maximum peak size;

– Instability increases with both group size/audience and influence weights, but the variations are not monotonic with respect to the sweeping parameters. In contrast with the results described in §§5.2.5 and 5.2.6, no transitions of regime were identified;

– It is difficult to compare the relative importance of the two networks for inducing instability, because the numbers of 'citizens' in a typical 'group' and in the 'audience' of an 'influential' are very different, and therefore the influence weights in the model must also be very different. However, if the same influence weight is used for both network influences, it is expected that the 'group'

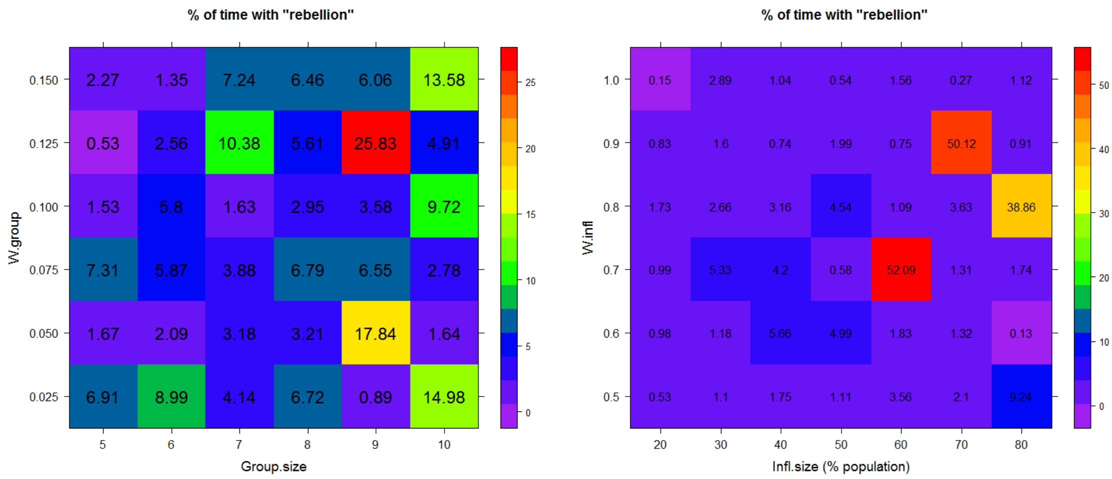
Table 5.10: Input parameters for the simulations with the 'group' and 'infl' networks. (Source: author)

	Group	**'Social Network'**
Variable name	**Value(s)**	**Value(s)**
`world-width`	40	40
`world-height`	40	40
`initial-cop-density`	3.0%	3.0%
`initial-citizen-density`	70%	70%
Number of 'citizen' agents	1120	1120
Number of 'cop' agents	64	64
`threshold`	0.60	0.60
`government-legitimacy`	0.20	0.20
`max-jail-term`	40	40
`RD?`	*true*	*true*
`gamma`	0.15	0.15
`LF?`	*true*	*true*
`GROUP?`	*true*	*false*
`group-size`	{5,6,7,8,9,10}	-
`w-group`	{0.025,0.05,0.0725,0.1,0.125,0.15}	-
`INFL?`	*false*	*true*
`infl-size`	-	{20%,30%,40%,50%,60%,70%,80%}
`num-infl`	-	4
`w-infl`	-	{0.5,0.6,0.7,0.8,0.9,1.0}

network would have a stronger impact on the stability of the solutions.

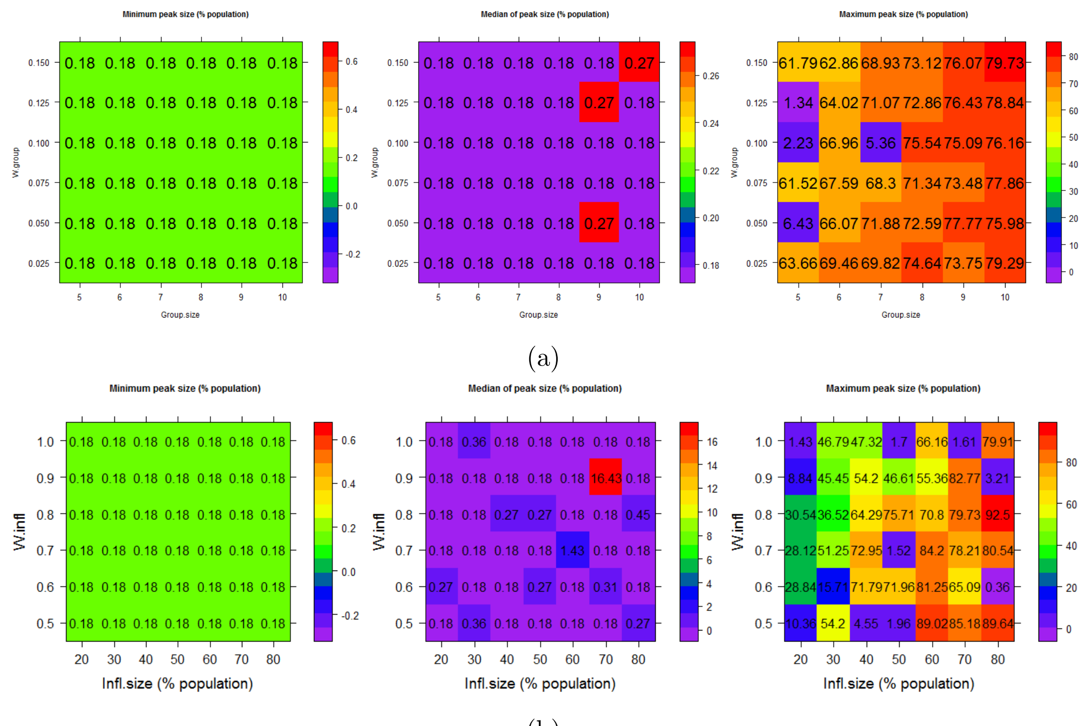
In future works, it would be important to run multiple experiments for each combination of the sweeping parameters, to determine whether or not the cases with most unstable solutions occur for the same or for different pairs of values. Also, it would be interesting to perform these experiments for the 'large society' setting (10080 'citizen' agents).

In summary, it can be concluded that the present model of network influences requires further exploration. Network influences are more complicated than modelled in the present ABM and usually involve variation of weights over time. Also, the relationship between the networks' sizes (e.g. a typical family size, and the number of influentials and their audiences) is difficult to reproduce in models (e.g. following arguments similar to those presented in §4.1.5). It is also difficult to determine plausible weights for the network influences by comparing the results of simulations with data from conflict events (e.g. in the SCAD database) because the impact of 'activists' on the size of those events, though extremely important [34, 18], is difficult to quantify afterwards.



(a) (b)

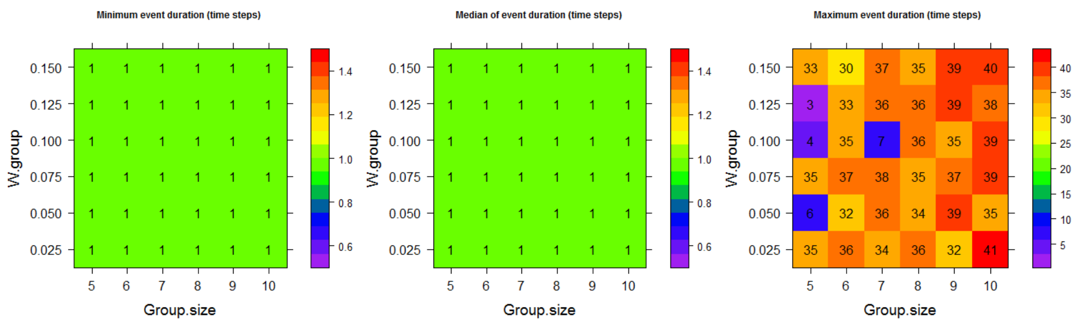
Figure 5.39: % of time with rebellion for the ‘group’ (a) and ‘infl’ (b) simulations of the network influence effects experiment. (Source: author)



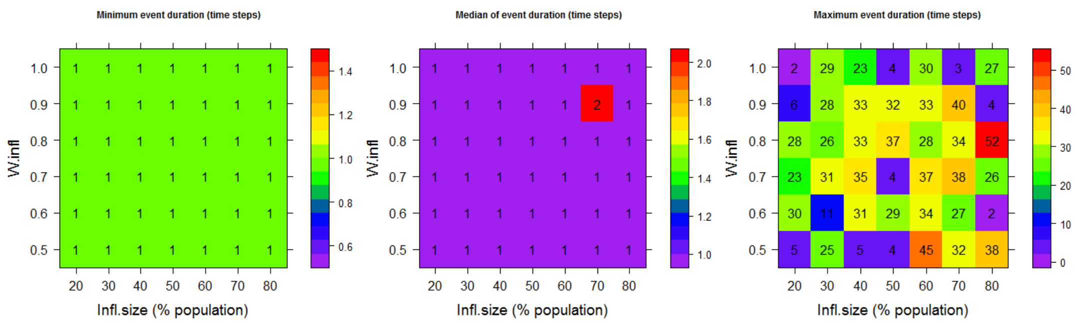
(a)

(b)

Figure 5.40: Minimum, median and maximum peak size (% of the population) of rebellion bursts for the ‘group’ (a) and ‘infl’ (b) simulations of the network influence effects experiment. (Source: author)



(a)



(b)

Figure 5.41: Minimum, median and maximum event duration (in time steps) of rebellion bursts for the 'group' (a) and 'infl' (b) simulations of the network influence effects experiment. (Source: author)

Chapter 6

Conclusions

6.1 Synopsis

In the present work the dynamics of politically motivated large scale conflict against a central authority was studied using an ABM of 'abstract' type. The purpose of the study was to improve knowledge on how social context factors lead to (mostly) self-organized large uprisings, such as demonstrations and riots, and how these events change the social context.

The leitmotiv of the work was the analysis and extension of Epstein's classical ABM of civil violence by combining four viewpoints: (*i*) theories of social conflict; (*ii*) analysis of datasets of social indicators and conflict events; (*iii*) the role and meaning of the model parameters; and (*iv*) analysis of the mechanisms described in theories and represented in the model. This conceptual approach differs from previous works by the coherent integration of datasets of indicators and conflict events (from eight African countries affected by the AS), with ABM development and exploration, and with a strong focus on the relationship between mechanisms and model parameters.

The work was organized in seven chapters, as described below.

Chapter 1

In the Introduction, the scope of the work was stated by means of a qualitative classification of social conflict manifestations and a set of definitions to delimit the key concepts, theories, events and processes to be investigated. Since the goal was to study large, mainly self-organized and low intensity conflict against a central authority due to some form of RD, the conflict manifestations of interest were large demonstrations and riots. Insurgence, war, and other forms of violence that involve militias or military forces were not further considered. Also, ethnic or religious conflicts which involve both identity and mediation by a central authority were not studied.

Chapter 2

Chapter 2 contains a review of the theoretical framework on social conflict. This includes the analysis of key concepts, main theories, and available datasets of conflict events and political, social and economic indicators related to conflict.

The two key concepts that determine the potential for conflict are RD and legitimacy. RD is related to the origin (frustration due to the gap between value expectation and value capability), forms (political, social, economic) and patterns of evolution of the conflict potential. Legitimacy (acceptance of the exercise of power by an authority) plays a central role, because RD must be perceived as illegitimate to be a source of conflict.

Two theories were reviewed, Ted Gurr's RD-based frustration-aggression theory on the psychological factors of civil violence [49], and Gene Sharp's theory of non-violent action [92]. The first of these is very systematic and identifies important variables (RD, legitimacy, intensity of commitment to value) and mechanisms (RD leading to anger, group protection vs fear of retribution) which can be implemented in ABM. The second is considered influential in large scale conflict processes against authoritarian regimes, particularly in the case of the AS.

The analysis of these theories was followed by a reference to datasets of events and international indicators related to large scale social conflict with relevance for ABM parametrization and exploration, and by a summary of Gilley's approach to the meaning and measurement of legitimacy [44].

Chapter 3

In Chapter 3 the ABM for simulation of large scale conflict against a central authority were reviewed, with emphasis on Epstein's Model I of civil violence [33, 31], which was discussed with respect to scope, role and meaning of variables and input parameters, and mechanisms.

After analysing Epstein's model, other 'abstract' ABM of conflict phenomena were reviewed, and their limitations for describing the mechanisms of large scale conflict were discussed. It was found that existing ABM fail to explain how the combination of legitimacy, estimated arrest probability and threshold lead to solutions with small or large rebellion peaks. Also, these models do not consider how different forms of RD (e.g. political, social or economic) influence the grievance, and do not include important mechanisms such as legitimacy feedback, network influences, or 'mass enthusiasm' [67]. Another drawback of existing models is that except for the work of Fonoberova et al. [35], the other authors did not attempt to use real data or indicators of conflict potential for model parametrization and validation.

Chapter 4

Chapter 4 contains an analysis of the (*i*) SCAD dataset of conflict events [97]; (*ii*) FSI indicators of grievance factors [96]; (*iii*) FWI indicators of political liberties [37]; and (*iv*) Gini index data [13] on welfare inequality, for eight African countries affected by the AS - Algeria, Egypt, Libya, Mali, Mauritania, Morocco, Sudan and Tunisia. These countries were chosen because the AS is a very important example of a large scale conflict process against central governments, and data on both events and international indicators related to model parameters (e.g. legitimacy) were available for them.

The analysis of the SCAD dataset was oriented by four questions regarding the importance of demonstrations and riots, issues (grievance factors), organization and escalation in large demonstrations and riots and the patterns of size, recurrence and duration of demonstrations and riots, and one overarching question: how did these change after the beginning of the AS? The analysis confirmed the well known fact that the main issue in the AS was the fight for human rights and democracy.

The exploration of SCAD is consistent with some aspects of Gene Sharp's theory of non-violent action, on the predominance of peaceful confrontation methods, organizations playing a role, and the societies losing fear of dictatorship by continued non-violent protest. Despite its limitations, particularly its restricted geographic coverage, the SCAD dataset proved to be an invaluable source of useful information for studying large scale conflict processes.

Chapter 5

In Chapter 5, a description of an 'abstract' ABM which extends Epstein's ABM is presented, together with a series of six computer experiments devised to test the model's explanatory power and show how the newly introduced mechanisms influence the complexity of the solutions.

The ABM is based on the same two types of agents ('populations') as Epstein's ABM, namely 'citizens' and 'cops', and its novel features are: (*i*) a more general form of the estimated arrest probability with a parameter ρ_c which can be viewed as a threshold of 'massive fear loss' (or sudden generalized drop of risk perception); (*ii*) a simplified representation of grievance as a function of RD, based on a Pareto Type I distribution of 'value', with a parameter for representing emotional sensitivity to deprivation (and thus different forms of RD); (*iii*) endogenous legitimacy feedback, inspired on Gilley's theoretical framework [44]; and (*iv*) network influence effects, considering two types of networks, one called `group` and another called `infl` ('influentials'), for representing distinct forms of influence. The model was described using the ODD protocol [48].

The computer experiments were idealized to study the influence of parameter values, effects and mechanisms on the qualitative and quantitative properties of the solutions, and comparing them with those of real events in the AS to the extent possible. The sequence was set so that the plausible values for the parameters suggested by the results of each experiment were used in subsequent simulations.

The exploration of the model started with an analytical study of the 'citizens' decision rule $G - N > T$ in Epstein's original model for different forms of the estimated arrest probability function P_a. This study provided an explanation of why some forms of P_a lead to large intermittent peaks of rebellion whereas others do not, and suggested a more general form of P_a than used in previous models. This functional form includes the newly introduced parameter ρ_c, which is a critical threshold for the 'cop' to 'active' ratio below which the risk perception ('fear of retribution') drops to zero. This parameter was shown to have a strong influence on the solutions' behaviour, and to represent a mechanism of 'massive fear loss' within a society which has some support in theories and also in records of conflict events (chapter 4). A condition (inequality) between the population threshold, the legitimacy and the estimated arrest probability for a significant proportion of 'citizens' turning 'active' was also derived.

In the first computer experiment, the effect of the newly introduced parameter ρ_c

on the size, duration and recurrence (interval between successive bursts of activity) was studied, and the qualitative and quantitative properties of the solutions were discussed in comparison with the results of the analysis of the SCAD dataset in §4.1. The second computer experiment was dedicated to the study of the role and influence of the jail term (determined by the parameter J_{max}). The third experiment was set to study the stability and instability of the solutions for low values of legitimacy and varying levels of deterrence capability. The next three experiments were devised to study the influence of the newly introduced mechanisms/effects: RD (political/economic), legitimacy feedback and network influences. The results of each experiment were discussed and interpreted by comparison with previous experiments and with the analysis in §4.1.

6.2 Contributions to the State-of-the-Art

The contributions of the present work to the state-of-the-art can be grouped in four topics: (*i*) critical discussion of Epstein's Model I; (*ii*) integrated analysis of datasets of conflict events and international indicators for a real large scale conflict process (the AS); (*iii*) extension of Epstein's Model I to include the representation of political grievance as a function of RD and new mechanisms ('massive fear loss', legitimacy feedback, network influences and 'mass enthusiasm'); and (*iv*) model exploration, including role of parameters, effect of deterrence, uniformly distributed and RD-dependent hardship, impact of legitimacy feedback and network influence effects, using the analysis of the African AS countries for parametrization and validation, to the extent possible.

Discussion of Epstein's Model I

The qualitative discussion of Epstein's model in §3.3 led to the following conclusions:

- If the basic mechanisms described by the decision rule (conflict between grievance/anger and risk/fear, with lowering of the risk/fear dependent on the local relation between deterrence and collective support) are the same in peaceful and violent uprisings, then Epstein's model applies to both types of phenomena, although the values of the agents' attributes and the resulting patterns of conflict events (size, duration and recurrence) may be different.[62]

[62]This argument applies in the case of authoritarian regimes, in which participation in peaceful

– The Legitimacy (L) and threshold T affect the whole artificial population and thus are key parameters for determining stability or instability.

– The vision radii v and v' represent the influence space of 'citizens' and the information space of 'cops', respectively. The difference between these two parameters can be expected to have a significant impact in the solutions' behaviour.

– If the union of the 'cops' individual information spaces does not cover the whole space, rebellion bursts may start and grow undetected. Therefore, it is expected to find tipping points associated with the density of 'cops' and v'.

Analysis of Conflict Events and International Indicators for African AS countries

The exploration of datasets and indicators for the AS countries to obtain quantitative elements for parametrization and analysis of the solutions of Epstein's ABM and its extensions is one of the main improvements of the present work to the state-of-the-art.

The analysis of eight African countries affected by the AS (Algeria, Egypt, Libya, Mali, Mauritania, Morocco, Sudan and Tunisia) combining the SCAD database of conflict events, and FSI, FWI and Gini indicators, provided important insights on: (*i*) the AS itself; (*ii*) the significance of complexity for studying large scale conflict against central authorities; and (*iii*) plausible estimates for ABM parameters and size, duration and recurrence of simulated conflict events.

– <u>Exploration of the SCAD database [97]</u>

- There were massive demonstrations and riots before the beginning of the AS in several of the African countries analysed.

- The AS greatly increased the number and frequency of conflict events, particularly demonstrations. Egypt was the country with the highest number of demonstrations and riots, before and after the beginning of the AS.

- Demonstrations were the most important form of conflict event and the main drive of the AS was the fight for human rights and democracy. Riots

demonstrations can lead to physical harm, arrest or even death caused by police forces, as was confirmed by the analysis of conflict events for African AS countries in Chapter 4.

were of secondary importance and their motifs more heterogeneous than for demonstrations.

- Spontaneous demonstrations and riots were more numerous than organized events. Escalation to riots in initially peaceful demonstrations was significant, but riots did not evolve into more violent conflict manifestations (e.g. anti-governmental violence).[63] This confirms the conceptual framework sketched in figure 1.1 and the relevance of complexity for studying large scale conflict processes.
- The % of the time with calm and activity is important for comparing with ABM simulations, because it is independent of the time scale. For demonstrations, the characteristic % of time with activity was 14% (Egypt) - 16% (all countries) before and 26% (Egypt) - 57% (all countries) after the beginning of the AS. For riots, the corresponding values were 4% (Egypt) - 4% (all countries) before and 3% (Egypt) - 7% (all countries) after the beginning of the AS.
- In general demonstrations were short events, with median one day and 75% of the cases with duration less than ten days. However, some countries (Egypt, Mauritania, Morocco, Tunisia) experienced exceptionally long demonstrations, which in fact resulted from long successions of shorter events related to particular situations.
- The time interval between events was very heterogeneous among the eight countries, particularly before the beginning of the AS, for both demonstrations and riots. After the beginning of the AS, a characteristic value was 15-20 days.
- The analysis of the time lines of the range of estimated % of the population participating in demonstrations and riots, showed intermittent events in both cases, which were larger and more frequent for demonstrations. This favours the conjecture on the scope of Epstein's model discussed in §3.3.1. The % of the population participating in demonstrations was smaller for more populous countries (e.g. Egypt and Argelia) than for less populous countries. Typical ranges of these % are [0.5,4.0] and [1,10], respectively, meaning that activity peaks involving than 10% or more of the population are unlikely.

[63]The analysis of SCAD is consistent with the existence a "dividing line" between demonstrations and riots, and more violent forms of conflict (which require permanently organized militias or military forces).

– Analysis of the FSI indicators [96]

- Before the beginning of the AS, the scaled FSI "Legitimacy of the State" scores were below 0.4 (in a scale 0-1) for all countries analysed except Mali, with very low values for Sudan and Egypt.

- The FSI scores have no significant predictive value, because their variations prior to the AS were small. Also, the uprisings did not start in one of the countries with lowest legitimacy score, as would be expected.

- In some countries, the scaled "Legitimacy of the State" and "Human Rights and Rule of Law" scores deteriorated after the beginning of the AS. This supports the conjecture that legitimacy feedback is significant, with characteristic variations in the range [20%,40%]. These estimates are useful for analysing plausible implementations of this mechanism in ABM.

– Analysis of the FWI indicator [37]

- The "Freedom Rating" of the FWI indicator by Freedom House provides essentially the same qualitative information of the FSI "Human Rights and Rule of Law" score, but with larger variations in response to the evolution of the situation in each country. As with the FSI, this indicator has no significant predictive value for anticipating processes like the AS.

– Analysis of the "All the Ginis" database [13]

- The analysis of the "All the Ginis" database showed that a characteristic value of the Gini index (related to welfare inequality) for the countries analysed is 0.4 (or 40%). This characteristic value was used to model RD in the ABM.

Proposed ABM. Extensions of Epstein's Model I

The innovations of the proposed ABM with respect to existing 'abstract' models of the same type are:

– Analysis of the 'citizens' decision rule: The analytical study of the pdf of $G-N$ in the 'citizens' decision rule in Epstein's ABM provided an explanation of why some previously proposed forms the estimated arrest probability function P_a lead to large rebellion peaks whereas others do not. It was shown that large rebellion peaks are possible if $P_a = 0$ below a critical value of the ratio ρ_c of the number of visible 'cops' to visible 'active' citizens. A relationship was derived between T, L and P_a for significant rebellion peaks to occur, which shows that permanent rebellion does not occur for low L if T is set to a suitable value.[64]

– Extension of the 'citizens' decision rule: The decision Rule A was extended to include network influences and 'mass enthusiasm' via the mechanism of *dispositional contagion*. This formulation was inspired in Epstein [32], and is a more consistent approach for modelling network influences than in previous works (e.g. [60]).

– 'Massive fear loss': A new form of P_a with a threshold parameter ρ_c, which encompasses the forms of the estimated arrest probability function proposed in previous works. This new form provides an abstract representation of the mechanism of 'massive fear loss'.[65]

– RD (economic & political): The model describes hardship as a function RD which incorporates two key propositions (I.2 and I.4) of Ted Gurr's frustration-aggression theory. This formulation is based on (*i*) setting a Pareto-distributed `value` attribute of 'citizen' agents; (*ii*) computing RD as the difference between the median of 'value' of visible agents and the agent's own 'value'; and (*iii*) using a power function to model the emotional intensity of the response to the distance (gap) between expectation and own 'value' (to represent the difference between political and economic RD).

– Legitimacy feedback: The mechanism of (endogenous) legitimacy feedback was implemented using a simple linear function of the proportions of 'quiet', 'active' and 'jailed' citizens inspired in Gilley's theoretical framework on the measurement of legitimacy [43, 44], combined with memory effects (to represent a delay between bursts of rebellion and legitimacy drops). Two different forms of the legitimacy feedback mechanism were implemented, homogeneous (global) and heterogeneous (variable among 'citizens').

– Network Influences: Network influence effects were implemented via the mechanism of dispositional contagion [32]. Two different networks were considered: (*i*) 'group' represented by a union of small undirected cliques, and (*ii*) 'infl' (for 'influentials') represented by a union of directed star networks with randomly

[64] This allowed simulations with intermittent peaks of rebellion of plausible sizes for values of legitimacy characteristic of the FSI scores for the African AS countries, instead of the relatively high values of legitimacy used in previous studies (e.g. [33, 31], [35]).

[65] Variations of the threshold parameter ρ_c can be used to simulate the effect of the society losing fear of repression by continued protest, postulated in Gene Sharp's theory of non-violent action.

chosen ‘citizen’ agents as hubs. The two networks provide an abstract representation of two important influence modes in a society, one associated with highly cohesive small scale communities connected by strong undirected links (two-way influence), and another associated with (weaker, one-way) directed links through which influential agents (‘activists’) shape global perceptions.

– ‘Mass enthusiasm’: This effect, described by many authors in the context of crowd behaviour [12, 67], was also implemented via the mechanism of dispositional contagion.

Model Exploration

The simulation experiments described in chapter 5 led the following contributions:

– The use of dimensionless quantities such as the relative % of the population involved in conflict events and the % of total time with calm and rebellion is useful to relate (up to some extent) the scales of time and size in real events and simulations.

– The parameter ρ_c in the functional expression of P_a has a strong impact on the size of rebellion peaks, and also in the interval between successive outbursts. This parameter is a mathematical representation of the mechanism of ‘massive fear loss’, and has associated tipping points.

– The parameter J_{max} (maximum jail term) mainly controls the waiting time between successive events. If the ratio between J_{max} and the duration of rebellion bursts is sufficiently large, the former parameter has a small influence on the peak size. The simulation results suggest that (at least) in this latter case there are no tipping points associated with J_{max}.

– The ABM developed in the present work can produce solutions with three distinct regimes or long term behaviours – permanent rebellion, complex (i.e. with intermittent peaks of rebellion) and permanent calm (stability of the society), even for relatively low values of the legitimacy L (typical of authoritarian regimes), if inequality (5.10) is used to set suitable values of the threshold T.

– The solutions’ behaviour is very sensitive to the ‘cop’ density and vision radius (input parameter `vision-c`), as well as on the size of the artificial society.

This confirmed some of the points mentioned in the qualitative discussion of Epstein's model in §3.3.

– The study of RD-dependent hardship with commitment to value expressed by a power law to represent political vs economic deprivation, for variable deterrence capability of the central authority, led to the following findings:

 - The solutions showed the same three distinct regimes as in the case of uniformly distributed hardship, using values of legitimacy and Gini index characteristic of the indicators for the African AS countries analysed in chapter 4;

 - The system's stability is much more sensitive to the parameter γ than to the deterrence capability of the central authority, which is consistent with political deprivation being more important than economic deprivation as a source of large scale social conflict [92, 11]. The value 0.15 was identified as a possible approximation for a tipping point associated with γ. This provides a possible explanation for the fact that once the sensitivity to RD surpasses a certain limit, there will be social unrest even for strong levels of repression (as suggested by Gene Sharp's theory of non-violent action [92] and also by the results in chapter 4);

 - When the solutions are plotted in the phase space {RD, % 'active',% 'jailed'} it is observed that as the value of γ drops below the tipping point, the orbits change from calm stability (0 % 'active' and 'jailed') with oscillating deprivation, to trajectories in the phase space whose shape depends on the size of the artificial society.

– Introduction of the legitimacy feedback mechanism had an important effect on the solutions' behaviour and led to the following conclusions:

 - When legitimacy feedback is combined with RD-dependent hardship the solutions show the same three regimes as in the simulations of the RD-dependent hardship, for the same ranges of γ and 'cop' density;

 - The system was more unstable when legitimacy feedback was introduced;

 - When the solutions are plotted in the two 3-D phase spaces {RD, % 'active',% 'jailed'} and {RD, % 'active',L}, it is observed that for certain combinations of the sweeping input parameters (`gamma` = γ and `initial-cop-density`) the orbits are approximately described by line segments characteristic of stable solutions with oscillating deprivation and permanent calm, whereas for other combinations the orbits describe trajectories of more complicated shape in both phase spaces;

  - Under certain conditions, legitimacy feedback introduces a tendency for generating solutions with alternating periods of calm and turmoil.

- In the present formulation (based on dispositional contagion and linear superposition), network influences due to both the 'group' and 'infl' networks introduce instability in otherwise stable solutions, by greatly amplifying the maximum peak size and duration of the simulated conflict events.

Chapter 7

Future Work

The present work can be improved in many different ways. The most obvious improvement would be to overcome the limitations of the model explorations due to time constraints, computational resources and number of parameters. Another possible avenue for exploration is the extension of the model to ethnic and religious conflict. Other ways of improving the model are the consideration of more sophisticated agent types, architectures and decision rules.

7.1 Improvements of Model Exploration

The model explorations described in Chapter 5 were limited due to time constraints, the large number of input parameters, and the multiple mechanisms that can interact and influence the solutions' behaviour. Therefore, a straightforward way of improving the present work would be to run more simulations of the experiments for which one one long run (10,000 cycles) was performed, to improve the statistics of the patterns of size, % of time with calm and rebellion, duration, and recurrence of conflict events.

Another way of improving the exploration of the model is to set up other experiments to investigate important effects not considered in the present work. The following paragraphs describe some possibilities.

Size and Density of the Artificial Society

The behaviour of the ABM solutions depends on the number of agents. The discussion in §3.3 and the study of Fonoberova and collaborators [35] showed that the agents' density is also an important issue. Thus, it is interesting to repeat the explorations described in Chapter 5 for larger grid sizes and varying agent densities, and try to relate these with data on population sizes and densities in real countries.

Vision and Move Radii

In some models (e.g. Ilachinsky's ABM of land combat [53]) the vision and move radii are different. Thus, a straightforward and interesting way of exploring the model is to use different vision and move radii, as well as different values of these parameters for 'citizen' and 'cop' agents.

Time Varying Patterns of RD

In the simulations described in §5.2.5 the 'citizens' `value` attribute was constant throughout the simulations. One interesting exploration of the model would be to investigate the model's response the time varying RD patterns shown in figure 2.1. This can be implemented by changing the `value` over the simulation time, in several possible ways. For instance, it is possible to simulate the result of increasing RD for the majority of 'citizens' with low welfare by reducing the `value` of the poorest, of all agents, or according to some other criterion.

Network Influence Effects

The exploration of network effects in §5.2.7 was very limited, and raised interesting questions. To further explore this mechanism, it will be necessary to run the simulations for the 'large society' case ($\sim 10,000$ agents) to compare with the results for the 'small society'. Also, it would be interesting to both widening and refining the parameters' ranges (size and influence weight of each network, and `num-infl` for the 'infl' network).

Another possibility of improvement is to implement more realistic models, with time-varying links or network structures, complemented by the use of networks with more realistic sizes and topologies. This could be done by using theoretical networks (such as random, small-world or scale-free) or networks with topology synthesised using real data (e.g. from Facebook or Twitter). The implementation of this exploration would require keeping the network size within manageable limits and using a larger number of agents for the proportion of the network size(s) to the whole population to be closer to real situations.

7.2 Improvements of Model Capabilities

Cop Density, Information Exchange and Limited Arresting Capability

In all simulations in Chapter 5 the density of 'cop' agents is much higher than in real cases.[66] This is because the modelling of the 'cop' agents' behaviour in the present model is rather crude. In real processes, 'cops' can exchange information and converge on 'hot spots' where bursts of rebellion are forming, instead of moving at random. This can be implemented by defining one or more networks for 'cops', endow them with some form of purposeful movement, and observe how these improvements of efficiency would result in maintaining stability with smaller 'cop' densities.

Another important aspect is that in reality there should be a limit to the maximum number of 'citizens' that can be arrested. Denoting by N_{MJC} the maximum jail capacity, this can be implemented by replacing Rule C by the following modified rule:

Rule C': Inspect all sites within v' and arrest a random 'active' citizen with probability $P_a = 1 - N_{jailed}/N_{MJC}$.

Peaceful and Violent Uprisings

One interesting improvement of the proposed model is the definition of an additional 'violent' state for 'citizen' agents. This will allow the modelling of large scale peaceful and violent uprisings (i.e. massive demonstrations and riots, respectively) as well as escalation.

In §3.3.1 it was argued that the 'citizens' decision rule could be used to model peaceful demonstrations and violent large scale uprisings, because the mechanism

[66] In [104] it is found that the median of police officers per 100,000 inhabitants is 300. In the same reference, the only country of interest for which information is provided is Algeria, with a median of 413 police officers per 100,000 inhabitants (in 2009). In an ABM with 10,000 agents, the number of 'cops' would be about 30-40, which would correspond to much smaller 'cop' densities than used in the experiments reported in this work.

of conflict between opposing drives (grievance/anger and risk/fear, with lowering of the risk/fear dependent on deterrence and collective support) is the same in both cases. The grievance is the driving term in both cases, but the risk perception and government's repression should obviously be higher for 'violent' than for 'active' states. Combining these ideas, the 'active' and 'violent' states can be implemented using the following decision rule:

$$\begin{array}{lll} \text{Rule A':} & \text{Default state:} & \text{be 'quiet'} \\ & \text{if } G - N \cdot P_a(\rho_a) > T_a \quad ; & \text{be 'active'} \\ & \text{if } G - N \cdot P_v(\rho_v) > T_v \quad ; & \text{be 'violent'} \end{array}$$

where $P_a(\rho_v)$ and $P_v(\rho_v)$ are the estimated arrest probabilities for 'active' and 'violent' states, $\rho_a = (C/A)_v$, $\rho_v = (C/V)_v$, C_v is the number of visible 'cops', A_v is the number of visible 'active' citizens, V_v is the number of visible 'violent' citizens, T_a is a threshold for turning 'active' and T_v a threshold for turning 'violent'. The higher level of repression for civil violence can be modelled by setting $T_v > T_a$. The increased risk perception for turning 'violent' can be modelled using equation (5.1) with different values for ρ_c (critical threshold for 'massive fear loss').

The introduction of a 'violent' state requires two extra input parameters, which complicates the parametrization, validation and exploration. The `escalation` field in SCAD can provide useful information for such an undertaking.

Introduction of Cognitive, Emotional and Social Components

In reference [32], Epstein proposed the decision rule described by equations (3.1)-(3.3), which includes cognitive, emotional (affective) and social components and is more general than the one used in the present model.

A promising way of improving the model would be a reformulation of the decision rule, taking the grievance as the 'cognitive' component and modelling the 'affective component' using the Rescorla-Wagner equation (3.4). This change introduces new mechanisms of activation and inhibition, with time scales determined by the learning constants [32]. One potential advantage is that inhibition would result from both individual fear conditioning and arrests, so that the interval between successive rebellion bursts would be less dependent on the jail term.

Extension of the Model to Ethnic and Religious Conflict

Ethnic and religious conflicts are extremely important and can be very violent. These types of conflict differ from the one considered in this work in some significant ways.

One important difference is that ethnic and religious conflicts involve social identity [95]. Social RD arises from comparison between in-group and out-group status and capabilities. Modelling social RD (inclusion-exclusion) involves other mechanisms and variables than modelling political or economic RD.

Another important difference is that in ethnic (or religious) conflict 'citizens' interact with both members of the rival ethnic and the 'cops', and 'cops' mediate those interactions. Therefore, the action rules are more complicated. Since these conflicts tend to be more violent than those considered in this work, it is usual to model killings of the rival ethnic, and introduce some population dynamics to compensate for the resulting decays [33]. Spatial patterns of unrest (e.g. genocide or the formation of safe havens) are important, even for ABM of 'abstract' type.

Religious conflicts pose additional challenges. The formation of religious identity involves both beliefs and rituals, which will have to be modelled in some way in an ABM. This implies that new model entities will have to be considered, such as 'religious leader' agents and 'place of worship', and their effect on other agents must be modelled.

The methodology of development for this extension can be the same used in the present work. First, the relevant mechanisms and variables must be identified from theories such as 'Sacred Values' [93] and 'Devoted Actor' [4]. The fundamental mechanisms of deterrence and group support are present, but deterrence now involves both 'cops' and members of the rival ethnic. Then, the definition of the agents' possible states, their action and interaction rules will have to be cast in mathematical form.

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Appendices

Appendix A

ABM of Civil Violence. ODD Description

A.1 Purpose

The purpose of the model is to simulate large scale conflict processes against a central authority, including relative deprivation as a factor of political grievance and the mechanisms of ‘massive fear loss’, legitimacy feedback, network influence effects and ‘mass enthusiasm’.

A.2 Entities, State variables and Scales

The model was implemented in NetLogo [106] and has four entities: ‘observer’, agents, networks and environment (consisting of a grid of cells, or patches in NetLogo’s terminology). Figure A.1 shows the class diagram for all entities.[67] The agents, networks and model space will be described in this section. The ‘observer’ is a special entity in the NetLogo system which represents the model user.

Agents
There are two types of agents, ‘citizens’ and ‘cops’. ‘Citizens’ represent the population and may actively contest the central authority or not. ‘Cops’ are the law enforcing

[67]In NetLogo, all agent types are subclasses of a generic ‘turtle’ class and all links are subclasses of a ‘link’ class, via the `breed` and `directed-link-breed`/`undirected-link-breed` primitives, respectively [106].

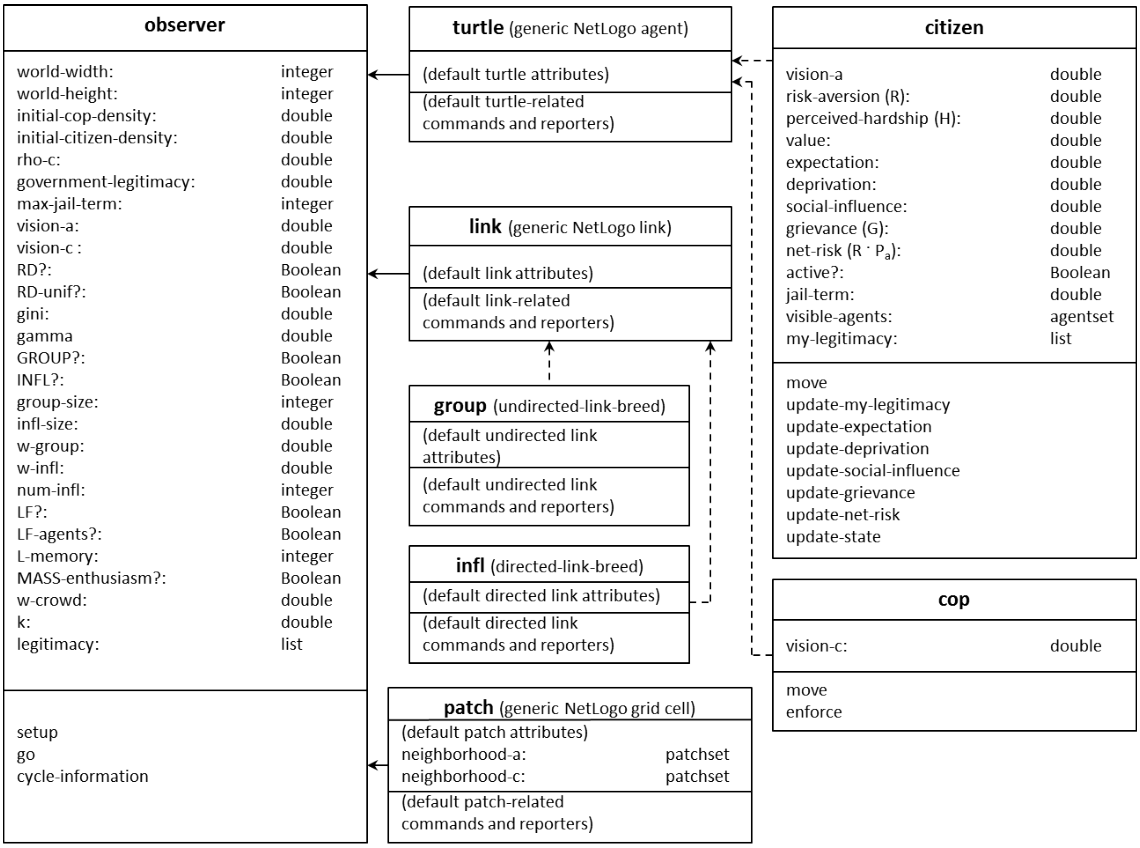

Figure A.1: Class diagram for the entities in the NetLogo implementation of the ABM. (Source: author)

officers and try to keep the order by arresting 'active' citizens. Both 'citizens' and 'cops' have one move and one action rule.

'Citizen' Agent Specification

Table A.1 shows the attributes for 'citizen' agents. There are two subtypes of citizens, 'normal' and 'activist', which are defined using the default `turtle` attribute `label`.

'Citizen' agents can be in one of three states, 'quiet', 'active' (or 'rebellious') or 'jailed'. 'Activist' citizens are the hubs of the `infl` network. They are defined only if the input variable `INFL?` is set to *true*. 'Citizens' that are not 'jailed' move and change state between 'quiet' and 'active' according to their move and action rules. 'Activist' citizens (if present) differ from 'normal' ones only in their move rule.

The default move rule for 'citizen' agents is the same as in Epstein's ABM:

$$\text{Rule M}_1 \;:\; \begin{array}{ll} \textbf{if} & \texttt{jail-term} = 0 \land \mathcal{E}_v \neq \emptyset \textbf{ then } \text{move to a random cell } c_r \in \mathcal{E}_v \\ \textbf{else} & \text{stand still} \end{array}$$

Table A.1: Attributes of 'citizen' agents. (Source: author)

Variable name	Meaning	Description
`label`	Agent subtype	{ "normal","activist" }
`vision-a`	Vision radius v	'citizen' vision radius
`risk-aversion`	Risk-aversion R	$\sim \mathcal{U}(0,1)$
`perceived-hardship`	Hardship H	$=$ `RD` if `RD?` $=$ *true*; $\sim \mathcal{U}(0,1)$ if `RD?` $=$ *false*
`value`	Value capability	$\sim \mathcal{U}(0,1)$ if `RD-unif?` $=$ *true*; Pareto-distributed if `RD-unif?` $=$ *false*
`expectation`	Median of `value` of other visible 'citizens'	Median of `value` of other visible 'citizens'
`deprivation`	RD - a function of the difference between expectation and `value`	$\texttt{RD} = \texttt{max}(0, \texttt{expectation} - \texttt{value})^{\gamma}$ (see text)
`grievance`	grievance G	$= RD \cdot (1 - L_p)$ if `RD?` $=$ *true*; $= H \cdot (1 - L_p)$ if `RD?` $=$ *false*
`social-influence`	social influence	Weighted sum of dispositional contagion influences (see text)
`net-risk`	net risk R	$\sim \mathcal{U}(0,1)$
`active?`	'citizen' state	*true* if 'active'; *false* if 'quiet' or 'jailed'
`jail-term`	jail term	$\sim \mathcal{U}(0, J_{max})$
`visible-agents`	agentset of other agents within vision radius	Used as a cache to speed up computations
`my-legitimacy`	list (vector) of perceived legitimacy, L_p	perceived legitimacy in previous 1 to `L-memory` cycles

where $\mathcal{E}_v$ is the set of empty cells whose centre lies within the agent's vision radius.[68] The move rule for 'activist' citizens is:

$$\begin{array}{lll} \text{Rule M}_2 \;:\; \textbf{if} & \texttt{jail-term} = 0 \wedge \mathcal{E}_v \neq \emptyset \textbf{ then} \\ & \textbf{if } \mathcal{A}_v \neq \emptyset \textbf{ then } \text{move to one } c_r \in \mathcal{E}_v \text{ with } \texttt{min}(d(\hat{x}_g, \hat{y}_g)) \\ & \textbf{else } \text{move to a random cell } c_r \in \mathcal{E}_v \\ \textbf{else} & \text{stand still} \end{array}$$

where $\mathcal{A}_v$ is the set of visible 'citizens' that are 'active' and $d(\hat{x}_g, \hat{y}_g)$ is the distance to the centroid $(\hat{x}_g, \hat{y}_g)$ of $\mathcal{A}_v$. Thus, if 'activists' see no 'active' citizens they follow the default move rule, otherwise they try to approach concentrations of rebellious citizens. This departure from random movement in 'abstract' ABM is a simple representation of the 'agenda setting bias' of 'activists' and traditional media towards showing protests and violence.[69]

'Citizen' agents change state according to the threshold rule

[68] A cell is considered empty if there is no agent inside it, or if it contains only jailed 'citizen' agents. In the NetLogo implementation, 'jailed' agents are hidden from view and do not interfere with the other agents' movement, but cannot be removed from the model space.

[69] The theoretical concepts on agenda setting and an ABM implementation of purposeful movement to simulate this effect can be found in [10] and [60], respectively.

$$\text{Rule A:} \quad \textbf{if} \quad G - N + \mathscr{S} + \mathscr{M} > T \ \textbf{then} \text{ be 'active'}$$
$$\textbf{else} \quad \text{be 'quiet'}$$

where

$G \quad = H \cdot (1 - L_p)$ is the level of grievance;

$N \quad = R \cdot P_a(\rho_v)$ is the net risk perception;

$\mathscr{S} \quad = \texttt{w-group} \cdot \sum_{\mathscr{A}_k \in \mathcal{AG}_i} (G_{\mathscr{A}_k} - N_{\mathscr{A}_k}) + \texttt{w-infl} \cdot \sum_{\mathscr{A}_l \in \mathcal{AINFL}_i} (G_{\mathscr{A}_l} - N_{\mathscr{A}_l})$

is the sum of network influences;

$\mathscr{M} \quad = \texttt{w-crowd} \cdot \sum_{\mathscr{A}_j \in \mathcal{A}_v} (G_{\mathscr{A}_j} - N_{\mathscr{A}_j})$ is the 'mass enthusiasm' term.

In these expressions, $P_a(\rho_v)$ is the estimated arrest probability; $\rho_v = (C_v/A_v)$, C_v is the number of visible 'cops'; A_v is the number of 'active' citizens visible to a generic 'citizen' $\mathscr{A}_i$; $\mathcal{A}_v$, $\mathcal{AG}_i$ and $\mathcal{AINFL}_i$ are the sets of visible 'active - activist' citizens, 'active' citizens in the `group` network and 'active' citizens in the `infl` network for citizen $\mathscr{A}_i$, respectively; and the remaining variables and parameters are described in tables A.1 and A.4. The terms $\mathscr{S}$ and $\mathscr{M}$ are zero if network influences and 'mass enthusiasm' are turned off, respectively.

'Cop' Agent Specification

'Cop' agents have one move rule and one action rule. The move rule for 'cops' is:

$$\text{Rule M}_3 \ : \ \textbf{if} \quad \mathcal{E}_{v'} \neq \emptyset \ \textbf{then} \text{ move to a random cell } c_r \in \mathcal{E}_{v'}$$
$$\textbf{else} \quad \text{stand still}$$

and the action rule is:

Rule C : **if** $\mathcal{A}_{v'} \neq \emptyset$ **then**
select one random $\mathscr{A}_i \in \mathcal{A}_{v'}$
set `'active?'`$_{\mathscr{A}_i} = \textit{false}$
set `jail-term`$_{\mathscr{A}_i} = J \sim \mathcal{U}(0, J_{max})$
move to $(x_{\mathscr{A}_i}, y_{\mathscr{A}_i})$
endif

where $\mathcal{A}_{v'}$ is the set of visible 'active' citizens and $\mathscr{A}_i$ is a random 'citizen' in this set.

Networks The model includes two networks called `group` and `infl` (for 'influentials'), which are intended to represent two different types of social influence. The former is related to strong influence in small and highly cohesive social groups, and the latter to influence of 'activists' (which are influential agents) in a society. In the present version of the model the two networks do not change during the whole simulation.

The `group` network is set up by forming cliques of undirected links of type `group-member` between 'citizens', created using the `undirected-link-breed` NetLogo primitive. The clique (group) size is defined via the `group-size` input parameter (Table A.4).

The `infl` network is set by connecting each 'activist' (randomly chosen 'citizen') to a proportion of the population defined by the `infl-size` input parameter, via directed links of `infl-follower` type created using the `directed-link-breed` NetLogo primitive. The `infl` network is a union of `num-infl` directed star networks, each with one 'activist' as central hub. One 'citizen' can be connected to more than one 'activist' agent.

Environment
The scenario is a 2D homogeneous torus space, which combined with the random movement of ('normal') 'citizen' and 'cop' agents ensures that the probability of interaction between these two populations is independent of the position (i.e there is no clustering or formation of "sanctuaries").

A.3 Process Overview and Scheduling

The model is implemented in two main procedures, `setup` and `go`, which initialize a new run and implement the main cycle, respectively. The `setup` procedure clears all variables from the previous run, resets the simulation clock (`ticks`), initializes the global variables, creates the agents and sets their attributes, builds the networks (`group` if `GROUP?` = *true* and `infl` if `INFL?` = *true*, respectively), and displays the simulation space. The `go` procedure consists of the following steps:

1. Activate all agents except 'jailed' citizens by random order and execute their move and action rule;
2. For all 'jailed' agents, decrement the `jail-term` variable by one. If `jail-term` = 0, 'release' the 'jailed' agent by moving it to an empty cell, in the 'quiet' state, and making it visible;
3. If `LF?` = *true* update the global legitimacy (see "Submodels" below for the details);
4. Advance the simulation clock;

5. Display the simulation space, and update the plots and monitors of the NetLogo interface.

For 'cops', the first step is a straightforward application of Rules M_3 and C described above. For 'citizens', the application of Rule A requires the following operations:

- Scan the environment and cache the visible 'citizens';[70]
- If `LF?` $=$ *true* update the perceived legitimacy L_p with the `update-my-legitimacy` command (figure A.1; §5.1.4 below describes the details);
- If `RD?` $=$ *true* set the hardship as the relative deprivation (RD), using with the commands `update-expectation` and `update-deprivation` (figure A.1; §5.1.4 below describes the details);
- If `GROUP?` $=$ *true* and/or `INFL?` $=$ *true*, compute the social influence term $\mathscr{S}$;
- Compute G and N with the commands `update-grievance` and `update-net-risk` (figure A.1);
- Update the state according to $G - N + \mathscr{S} + \mathscr{M} > T$, where $\mathscr{M} \neq 0$ only if `MASS-enthusiasm?` $=$ *true*.

A.4 Design Concepts

Basic Principles

The basic principles used in the development of the ABM are:

- Preserve the basic simplicity and 'minimalist generative capacity' of Epstein's original ABM (i.e. keep the same types of agents and simple threshold action rule for 'citizens');
- Model the newly introduced mechanisms of network influences and 'mass enthusiasm' via the mechanism of *dispositional contagion* instead of *behavioural imitation* (as in [32]);

[70] This speeds up the calculations because the numbers of 'active', 'jailed' and 'quiet' agents are used more than once.

- Consider that only ‘active’ citizens influence dispositional contagion (like in models of epidemics);
- Formulate all new features using the simplest formulae possible that are consistent with some applicable theory or have some empirical basis.

Emergence

The emergent properties of interest are the long term behaviour of the solutions (stability, intermittent bursts of rebellion, or permanent unrest), the patterns (distributions of size, duration and waiting time between successive events) of bursts of rebellion, and also the time variation of the number (or %) of ‘jailed’ citizens, RD (if `RD?` = *true*) and legitimacy (if `LF?` = *true*).

Although the model is based on simple agents and rules, the multiplicity of parameters and mechanisms leads to complex behaviour. Some parameters are expected to be associated with tipping points. Also, the occurrence of large peaks of rebellion is expected to be associated with some specific combinations of parameter values.

Adaptation

Agents have no adaptation capabilities.

Objectives

In the present ABM the agents’ objectives (goals) are encoded in a very simple way in their action rules. In the case of ‘activist’ citizens, the additional goal of approaching concentrations of ‘active’ citizens is encoded in their move rule. Since agents do not have cognitive capabilities or adaptive behaviour they do not rank decision alternatives according to some utility or fitness function.

Learning

Agents have no learning capabilities.

Table A.2: Agents' sensing: information space, type of influence, related state variables and percept (information used for decision/action). (Source: author)

Agent Type	Information Space	Type of Influence	Related State Variables	Percept
Citizen, "normal"	Cells within vision radius	Random citizens ("flock"/"mob")	v	# 'active', 'jailed','quiet'; # 'cop'
	`group` network	Group neighbours (two-way, strong ties)	`group-size`, `w-group`	"disposition", $G - N$
	`infl` network	'Activists', "influentials" (one-way, weak ties)	`infl-size`, `num-infl` `w-infl`	"disposition", $G - N$
Citizen, "activist"	Cells within vision radius	Random citizens ("flock"/"mob")	v	# 'active', 'jailed','quiet'; # 'cop'
	`group` network	Group neighbours (two-way, strong ties)	`group-size`, `w-group`	"disposition", $G - N$
Cop	Cells within vision radius	-	v'	'active' citizens

Prediction

In this model, 'citizen' agents predict the net risk of turning rebellions based on the estimated arrest probability. However, they do not have predictive ability for decision making in the sense of agents with cognitive or learning capabilities.

Sensing

Agents obtain information about the environment from two sources, the cells within their vision radius and, in the case of 'citizens', the `group` and `infl` networks (if present). These sources correspond to distinct information spaces and variables, as well as different types of influence and percepts. Table A.2 summarizes these aspects for the agent types and subtypes in the ABM.

Interaction

The interactions between the agents and the mechanisms related to them are summarized in table A.3.

Table A.3: Interactions between agents and related mechanisms. (Source: author)

	'Citizens'	**'Cops'**
'Citizens'	• fear threshold lowering (via P_a) • massive fear loss (via P_a) • dispositional contagion (via $\sum(G-N)$) due to nw influences + "mass enthusiasm"	-
'Cops'	• deterrence/fear threshold rising (via P_a) • imprisonment (via imposing a `jail-term`)	-

Stochasticity

Stochasticity is essential to the working of the ABM. Many processes are modelled using pseudo-random variables, in the initialization (`setup`) and in the model cycle (`go`).

In the initialization, pseudo-random variables are used to: (*i*) set up the initial positions of the agents; (*ii*) set up the 'citizens' attributes, namely hardship, value (if `RD?` = *true*), and risk-aversion; (*iii*) build the `group` network, by randomly selecting the nodes of the group cliques and setting undirected links between them; and build the complete `infl` network, by randomly selecting the 'activists' (hubs of directed star networks) and their 'audience' among 'citizen' agents. In the model cycle, pseudo-random variables are used to: (*i*) define the agents' activation order; (*ii*) select the target cell in the agents' move rule; (*iii*) select the 'active' citizen to be arrested and the jail term in 'cops' rule C.

The particular distributions of hardship, value, risk-aversion and jail term play a key role in the generation of complex solutions.[71] When exact reproducibility of the results is required, a random seed must be generated and stored in the output files. To reproduce a particular simulation, the user must set the random seed prior to running `setup`.

Collectives

The collectives represented in the ABM are the `group` and `infl` networks, described in §A.2.

[71] It would be interesting to investigate the effect of setting the vision radius according to some probability distribution and, in the case of the `infl` network, of selecting the 'activists' according to the distribution of `value`.

Table A.4: Description of the input parameters for the ABM of large scale conflict against a central authority. (Source: author)

Variable name	Description	Default value	Range
`world-width`	Width of model space	40	-
`world-height`	Height of model space	40	-
`initial-cop-density`	'cop' density (# cops/# cells)	4%	0% - 100%
`initial-citizen-density`	'citizen' density (# citizens/# cells)	70%	0% - 100%
`threshold`	Threshold (T)	0.1	0 - 1
`rho-c`	Critical C/A in P_a	0.5	0 - 5
`government-legitimacy`	Initial (or constant) legitimacy (L_0)	0.82	0 - 1
`max-jail-term`	Maximum jail term (J_{max})	30	0 - 400
`vision-a`	Vision radius for 'citizen' agents (v)	7	0 -30
`vision-c`	Vision radius for 'cop' agents (v')	7	0 - 30
`RD?`	*true* if $G = f(RD)$, *false* otherwise	*false*	*true,false*
`RD-unif?`	*true* for `value` $\sim \mathcal{U}(0,1)$, *false* otherwise	*false*	*true,false*
`gini`	Gini index for Pareto-distributed `value`	0.40	0 - 1
`gamma`	Exponent for power law RD (γ)	0.20	0.05 - 5.00
`GROUP?`	*true* if 'group' network is present, *false* otherwise	*false*	*true,false*
`INFL?`	*true* if 'infl' network is present, *false* otherwise	*false*	*true,false*
`group-size`	group size	5	0 - 10
`infl-size`	size of influence network associated with each 'activist' (% population)	5%	0% - 100%
`num-infl`	number of 'activists'	0	0 - 10
`w-group`	weight for 'group' dispositional contagion (if `GROUP?` = *true*)	0.05	0.00 - 0.10
`w-infl`	weight for 'infl' dispositional contagion (if `INFL?` = *true*)	0.05	0.00 - 0.10
`LF?`	*true* for legitimacy feedback, *false* otherwise	*false*	*true,false*
`LF-agents?`	*true* for heterogeneous legitimacy, *false* otherwise	*false*	*true,false*
`L-memory`	Number of time steps for averaging legitimacy (if `LF?` = *true*)	5	1 - 10
`MASS-enthusiasm?`	*true* for simulating 'mass enthusiasm', *false* otherwise	*false*	*true,false*
`w-crowd`	weight for 'crowd' dispositional contagion (if `MASS-enthusiasm?` = *true*)	0.01	0.00 - 0.02
`k`	arrest constant in P_a	2.3	2.3

Observation

The observation data for the ABM are of two types: international indicators on legitimacy, human rights, economic decline, etc. for model parametrization; and databases of conflict events for analysing and interpreting the solutions . In this work the FSI [96], FWI [37] and "All the Ginis" [13] indicators were used, as well as the SCAD database of conflict events [97].

Initialization

Model initialization is done in the `setup` procedure, as described in §A.3. Tables A.4 and A.1 describe the global variables and the agent attributes, respectively. The global variables are set in NetLogo's Interface tab using sliders and input boxes for real (double precision) variables, and switches for Boolean variables.

Input Data

The model does not require any input from external data files. Parameter sweeping can be done using NetLogo's `BehaviorSpace` tool, but a simple R script based on the RNetLogo package [99] was written for that purpose.

To run the model using this script, the user must: (*i*) set the values of all the input variables that should remain fixed in the NetLogo file; (*ii*) specify the names of the sweeping variables in a character vector, and the values of these variables as a list of vectors with the same length as the vector of variable names; (*iii*) add additional nested loops in the sweeping section of the script by hand if required. The script then runs the model with or without NetLogo's GUI active and writes the values of the input variables (plus the value of the random seed) and the output for all experiments in a `.RData` file. The advantage of using RNetLogo for parameter sweeping is that the results of an experiment can be directly imported into R.

Submodels

There are three important submodels: estimated arrest probability (i.e. the form of P_a used in the ABM), relative deprivation (for expressing the hardship as a function of RD) and (endogenous) legitimacy feedback.

<u>Estimated Arrest Probability</u>
The estimated arrest probability is computed using the following expression:

$$P_a(\rho) = \begin{cases} 0 & \rho < \rho_c \\ 1 - \exp(-k\,\rho) & \rho \geq \rho_c \\ 1 & \rho = +\infty \quad (A_v = 0) \end{cases} \tag{A.1}$$

where $k = 2.3$, $\rho = C_v/A_v$, and C_v and A_v are the numbers of 'cops' and 'active' citizens within the agent's vision radius, respectively. Equation (A.1) is a generalization of one of the expressions considered by Fonoberova et al. [35], which contains equation (3.5) as a special case. The parameter ρ_c can be used to model the mechanisms of 'massive fear loss'.[72]

<u>Relative Deprivation</u>
The ABM developed in the present work includes a simplified representation of

[72] The meaning and theoretical justification of equation (A.1) is analysed in §5.2.1, in connection with the occurrence of solutions with cascades and large peaks of rebellion.

economic and political RD. The RD submodel is activated by setting the input variable `RD?` to `true`. In this case, the hardship for each 'citizen' is computed as follows. First, the 'citizen' agent computes its 'expectation' as the median of the `value` attribute of the other 'citizens' within its vision radius. Then, it computes a 'relative deprivation' as a function of the difference between its 'expectation' and `value`:

$$\mathtt{RD} = \max(\mathrm{median}(\mathtt{value})_v - \mathtt{value}, 0) \tag{A.2}$$

where $\mathrm{median}(\mathtt{value})_v$ is the 'expectation'. If the agent's `value` is lower than its 'expectation', the `RD` is proportional to the difference between 'expectation' and `value`, otherwise it is zero.

To compute the RD using (A.2) it is necessary to specify an heterogeneous distribution of `value`. In the ABM, this can be specified in two different ways, according to the Boolean input variable `RD-unif?`. For $\mathtt{RD\text{-}unif?} = true$, $\mathtt{value} \sim \mathcal{U}(0,1)$. For $\mathtt{RD\text{-}unif?} = false$, a Pareto Type I distribution is used [76]:

$$F_V(x) = \begin{cases} 1 - (\frac{x_m}{x})^\alpha & x \geq x_m \\ 0 & x < x_m \end{cases} \tag{A.3}$$

where $\alpha > 0$ is the shape parameter and $x_m > 0$ is the scale parameter.[73] The Pareto-distributed value for 'citizen' agents is generated using the formula

$$\mathtt{value} = \frac{x_m}{U^{1/\alpha}} \tag{A.4}$$

where $U \sim \mathcal{U}(0,1)$. In the code, $x_m = 2^{-(\alpha+1)/\alpha}$,[74] and the shape parameter is computed in terms of the input parameter `gini` using the equation

$$\alpha = \frac{\mathtt{gini} + 1}{\mathtt{gini}} \tag{A.5}$$

Equation (A.2) is a simplified model of economic deprivation, based on the hypothesis that deprivation is proportional to the difference between expectation and value. It can be viewed as a straightforward implementation of proposition I.2 in Ted Gurr's frustration-aggression theory of civil violence (Table 2.1, page 22).

[73]The scale parameter x_m is the minimum possible value/level of welfare, e.g. the minimum national income. The shape parameter determines the inequality of value. It is necessary that $\alpha > 1$ for finite mean value and variance of the distribution defined by equation (A.3).

[74]This value of x_m is chosen so that the median of the distribution of `value` is 1/2, which is equal to the mean value of $H \sim \mathcal{U}(0,1)$.

In the case political RD, the values at stake (democracy, political participation, individual liberties) are different, and so is commitment and the emotional factor of deprivation. Both theory (e.g. [49, 92, 11]) and the SCAD exploration of conflict events in §4.1 favour the hypothesis that people are more sensitive to the gap between expectation and value in the case political deprivation than in the case of economic deprivation. This can be implemented in a simple way by using the following modified form of equation (A.2)

$$\texttt{RD} = \{\max(\mathrm{median}(\texttt{value})_v - \texttt{value}, 0)\}^{\gamma} \tag{A.6}$$

where $\gamma > 0$ is another input parameter. $\gamma = 1$ corresponds to 'economic RD', or to a 'neutral' response to the gap between expectation and deprivation. If $0 < \gamma < 1$ the 'citizens' become more sensitive (less tolerant) to this gap, as occurs with political issues.[75] Equation (A.6) is a straightforward implementation of proposition I.4 in Ted Gurr's frustration-aggression theory on the psychological factors of civil violence ("The strength of anger tends to vary as a power function of the perceived distance between the value position sought and the attainable or residual value position", Table 2.1, page 22).

In summary, equations (A.2) and (A.6) extend Epstein's ABM by expressing the hardship in terms of a formulation of RD that incorporates two key propositions of Ted Gurr's frustration-aggression theory.

Legitimacy Feedback

The legitimacy feedback submodel was inspired in the theoretical framework of Gilley [43, 44] (§2.6). The perceived legitimacy L_p is expressed in terms of "views of legality" (L_{leg}), "views of justification"(L_{just}) and "acts of consent" (L_{cons}) as follows:

$$L_{leg} = 1 \tag{A.7}$$

$$L_{just} = \frac{n_{quiet}}{N_{citizens}} \tag{A.8}$$

$$L_{cons} = L_{just} \tag{A.9}$$

where $N_{citizens}$ is the population size and n_{quiet} is the total number of 'citizens' in the 'quiet' state. Thus, it is assumed that the government is fully legal but justification and consent are expressed by the proportion of 'citizens' that are not showing opposition. The legitimacy is computed using the 'weighted average' formula

[75] In the present work, social RD is not considered, because ethnic, religious or other conflicts related to identity are not modelled.

proposed by Gilley [43, 44]:

$$L = L_0 \cdot \left(\frac{1}{4} \cdot (L_{leg} + L_{cons}) + \frac{1}{2} L_{just} \right) \tag{A.10}$$

$$= L_0 \cdot \left(\frac{1}{4} + \frac{3}{4} \cdot \frac{n_{quiet}}{N_{citizens}} \right) \tag{A.11}$$

where L_0 is the value of the `government-legitimacy` input parameter. Equations (A.7)-(A.11) are a simplification of the formulation of legitimacy feedback described in [64].

For heterogeneous legitimacy perception (`LF-agents?` $=$ *true*), n_{quiet} and $N_{citizens}$ are replaced by the numbers of visible 'citizens' in the 'quiet' state and visible 'citizens', respectively.