Inequality: Driver or Inhibitor of Collective Action?

Christopher K. Frantz and Amineh Ghorbani

C. K. Frantz, Norwegian University of Science and Technology (NTNU), Norway, E-mail: cf@christopherfrantz.org (Corresponding author)

A. Ghorbani, Delft University of Technology (TU Delft), The Netherlands, E-mail: a.ghorbani@tudelft.nl

Abstract Inequality is considered one of the drivers for the emergence of collective action, but conventional wisdom suggests that it is equality among the stakeholders that helps sustain it. Nonetheless, more controversial findings in the collective action literature suggest that inequality can in fact be beneficial for the sustainability of collective action beyond its emergence. In this research, we use simulation to gain more insights into the relationship between inequality and collective action. We simulate an abstract common-pool resource system to model collective action and consider different types of inequality (e.g., wealth, social influence) to study its correlation with the sustainability of the system in terms of resource well-being, wealth levels and distribution. Preliminary results suggest that equality promotes sustained collective action, but also highlight that factors such as social influence and individual behavioural characteristics may be more decisive in determining the overall well-being.

Keywords: inequality, wealth, social influence, social-value orientation, clustering, DBSCAN, collective action

1 Introduction

Modern societies are characterised by rapid developments in areas including environmental and social awareness, as well as technological development. As a result of this, individual participation in the governance of the society and engagement in its development is once again taking momentum in the form of bottom-up collective action. Collective action provides the opportunity to deal with sustainability and to guarantee the expression of equal and democratic opinion (Chatterton 2016).

In addition, the overt display of socio-economic inequalities, as a side effect of modern societal developments, can also be considered a trigger for collective action movements. Most of those movements either highlight the symptoms of inequality (recall the 1-percent debate and the associated Occupy movements from 2011 onwards), or drive concrete policy solutions (here the discussion around the universal basic income comes to mind).

Besides being a trigger for collective action, conventional wisdom suggests that inequality has negative effects on the success and durability of collective action (Alesina and La Ferrara 2000; Lijphart 1997). Yet, literature offers a more differentiated picture. For example, Baland and Platteau (2006) identify circumstances in which inequality can act as a driver and inhibitor of collective action. They suggest that influential stakeholders of common-pool resources (CPR) have strong incentives to initiate the management of shared resources in order to preserve the latter (and thus their influence), while less influential stakeholders benefit from shared governance (and thus equal influence) as a means to prevent overexploitation, and thus to secure their stake.

The question therefore is, if collective action is triggered by inequalities, and acts as a means to promote equal rights and opportunities in a society, can we gain more insight into the circumstances under which inequality can sustain shared governance regimes that are to the benefit of all participants?

This work represents an initial step towards developing an integrated understanding of the influence factors (e.g., resource redistribution preferences, social structures) that drive various types of inequality, including economic inequality in the form of wealth and income, as well as structural inequality based on disparity in social influence.

The structure of the paper is as follows. Section 2 gives some theoretical background on inequality. Section 3 describes an abstract CPR model that we use to study inequality, followed by an overview of the experimental setup in Section 4. Section 5 presents some initial analysis of the simulation results, and finally, Section 6 concludes our findings.

2 Inequality and Collective Action

The topic of inequality has received attention in a wide area of scientific disciplines, especially since it is seen as a predictor for social disruption and violent conflict, a relationship Lichbach refers to as “economic inequality – political conflict nexus” (Lichbach 1989).

Looking at the drivers of emerging inequality, Tilly (1998) provides a comprehensive long-term overview on the development of inequality, but also explores a broad set of influence factors and social dimensions of inequality (including physical, demographic and economic dimensions). Looking at quantitative evidence, Berman et al. (2016) use empirical data to provide a systematic analysis of policy influence on the dynamics of inequality.

However, when attempting to develop a systematic relationship between both inequality and resulting collective action, the focus on the macro-level perspective can obscure the fundamental micro-level dynamics that are decisive to bring collective action about.[1] In this context, the inequality acts as a seed for disruptive behaviour based on its negative social effects (e.g., reducing the level of social participation and thus development of social capital (Alesina and La Ferrara 2000); undermining democratic processes by increasing the risk of vote-buying (Lijphart 1997)).

Exploring this relationship further, literature provides a more differentiated picture. Given the documented role of inequality as driver for collective action (both in the positive sense, e.g., establishing resource governance, and negative sense, e.g., violent conflicts), Baland and Platteau (2006) help us identify circumstances in which inequality can act as a driver and inhibitor of collective action in the context of common-pool resource allocation. They suggest that influential stakeholders of common-pool resources have strong incentives to initiate the management of the shared resource in order to preserve it (and thus their influence), while less influential stakeholders benefit from governance as means to prevent overexploitation, and thus secure their share.

This is contrasted with challenges rooted in inequality. Problems arise if the cost of governance (e.g., monitoring) exceeds the benefits drawn from the resource, which, in consequence, can lead to violation of governance commitments by the disadvantaged party. A further challenge arises if the dominating party does not depend on the managed resource (e.g., because of abundant private resources), in which case it can simply exploit the common resource without concern of long-term subsistence. High levels of inequality further drive the risk of bargaining, thus leading to

[1] A convincing account for the case of Rwanda is provided by André and Platteau (1998), who suggest that regional redistribution problems ignited the nation-wide ethnic conflict.

inefficient resource allocation (Bardhan 2005) and concentration of political influence (North et al. 2009).

Looking at this brief overview of related literature, we find that a clear-cut account on the relationship between inequality and collective action processes is hard to establish. To integrate selected documented accounts, we aim to develop an initial model that reflects some of the discussed characteristics to provide a basis for the systematic study of the influence of inequality on the durability and success of collective action.

3 Model Overview

Given the well-established literature on collective action around common-pool resources, we build an abstract model of a common-pool resource management system to study the relationship between inequality and collective action. At this stage, the model primarily concentrates on wealth inequality (as opposed to income inequality), since it offers a more accurate reflection of socio-economic reality (see e.g., Keister and Moller (2000)). In addition, we explore the impact of social influence differences (represented as a tendency to imitate successful individuals' strategies (Bandura 1977)).

The model consists of one shared resource (which has an initial amount and a growth rate) and a collection of agents who appropriate from and contribute to the resource. For this exploration, the resource has a logistic growth rate, such as found in the context of natural resources (e.g., forestry). The agents in the simulation are heterogeneous in terms of initial wealth, social value orientation (SVO) (Griesinger and Livingston 1973), the social influence they have on others, as well as productivity, all of which are operationalised as described below:

- Wealth: Agents are initialised with values drawn from a given distribution. Besides appropriating from the resource, which adds to their wealth, the agents also contribute to it. The level of contribution is dependent on their SVO and the behaviour of their neighbours.
- Social Value Orientation: To model agents' social values with respect to cooperation, we model altruistic, competitive, individualistic and cooperative orientations (Griesinger and Livingston 1973). The proposed model operationalises these as probability ranges that determine an agent's preferred value distribution between itself and others (similar to Murphy et al. (2011)). An agent's orientation is chosen at the beginning of the simulation in the form of a distribution ratio with extreme values that favour altruistic redistribution (Value: 0) or selfish behaviour (Value: 1). It is used to define an agent's resource contribution and appropriation behaviour.
- Social Influence: As an alternative to operating based on their own social value preferences, agents can copy the behaviour of their successful and influential neighbours. The social influence of an agent increases every time others copy its behaviour.

Throughout the simulation, the agents operate in a static spatial environment with a randomly initialised maximum vision radius (*visionRadius*). In a later variation of the model, agents are segregated into dynamic clusters (i.e., neighbourhoods) based on their relative level of contribution and appropriation (referred to as *contribution-appropriation ratio*). This segregation influences the social influence patterns of agents, since they would only copy others in their own cluster (social proximity), rather than the population as a whole. The clustering is performed using the density-based DBSCAN algorithm (Ester et al. 1996).

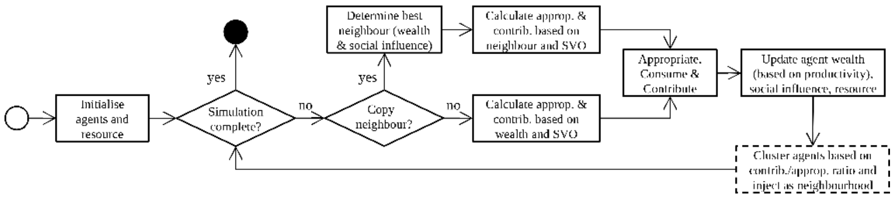
The detailed agent execution is as follows:

After the initialisation with wealth and social value orientation at the beginning of each round as well as random placement within the spatial environment, agents use a parameterised probability (*random action probability*) to determine their resource appropriation based on a random value between 0 and a parameterised maximum appropriation value, which is multiplied by the agent's SVO ratio. Agents then make use of their overall wealth based on a productivity factor that can both have negative and positive values, reflecting both inefficient and efficient use of resources. As an alternative to the autonomous behaviour based on the random action probability, agents identify neighbours in their spatial environment. They copy the appropriation behaviour of the neighbour with the highest combination of wealth and social influence within their vision radius. In this case, the social influence metric of the copied agent is incremented. Following this, a fixed value of wealth (10 units) is deducted to emulate consumption behaviour. Finally, the agent contributes a fraction of its wealth back to the common pool. Equivalent to the decision-making in the case of appropriation, the agent either acts autonomously (based on the random action probability), return a value between 0 and maximum contribution weighted by (1 – *svoRatio*), or by copying the most successful neighbour in their environment.

As mentioned before, variations of this cycle include the consideration of a dynamic environment, in which neighbours are not determined based on spatial proximity, but rather based on the similarity of their contribution-appropriation ratio determined at the end of each round.

The simulation model is outlined in Figure 1 in flow chart notation, with dashed boxes indicating the scenario-dependent additional activity.

Figure 1: Model Overview



4 Experimental Setup

The model behaviour has been explored through systematic exploration of the parameter ranges. The ranges were chosen based on manual identification of sensible value boundaries. The model parameters and the explored ranges are shown in Table 1. Exploration occurred across 600 individual parameter configurations for six scenarios (normal and beta wealth distributions, each with and without consideration of social value orientation and clustering). Each individual simulation configuration is run for 3,000 rounds.

Table 1: Parameters

Parameter	Value Range
Number of Agents	50 – 100
Random Action Probability	0.1 – 0.2
Minimum Productivity	-1 – 0
Maximum Productivity	0 – 1
Reservation Outlook	50 – 250
Resource Growth Rate	0.25 – 0.35
Initial Resource Amount	10,000 – 50,000
Maximum Contribution	30 – 40
Maximum Appropriation	30 – 40
Minimum Vision Radius	2 – 5
Maximum Vision Radius	Min. Radius + (20 - Min. Radius)
Minimum Initial Wealth	100
Maximum Initial Wealth	1,500
Consumption per Round	10
Maximum Distance (Clustering)	0 – 0.25
Minimum Number of Cluster Members	3

5 Model Results and Evaluation

In order to explore the relation between inequality and collective action in a common-pool resource setting, we have formulated some initial hypotheses which we explored with the model. We observe inequality in two different ways in our experiments: in terms of wealth and in terms of social influence. Our goal is to see whether any of these inequalities' distributions have any relation with the state of the CPR system. The state of the system is defined in terms of the well-being of the resource, and the average wealth and its distribution across the individuals in the system.

To study the correlation between the parameters, we used Spearman's ρ[2], significance level 0.01. Significance tests for different initial wealth distributions are performed using the Mann-Whitney-Wilcoxon test with a confidence level of 0.95. Table 2 shows correlations for selected variables for all explored model variations and different initial wealth distributions.[3] In the following subsections, we discuss selected results of relevance for our exploration.

[2] We chose Spearman's ρ due to its rank-based operation that offers a robust analysis of normal vs. non-parametric distributions as well as tolerance against outliers.

[3] For the sake of brevity, social influence is referred to as influence in the table.

Table 2: Correlations for different model variants (base model, SVO-enabled and cluster-enabled) for wealth initialisation based on normal and beta distributions

Correlated Variables	normal	beta	normal, SVO	beta, SVO	normal, SVO, clustering	beta, SVO, clustering
Resource μ vs. wealth μ	0.46	0.5	0.53	0.47	0.54	0.55
Resource μ vs. wealth gini	−0.33	−0.39	−0.33	−0.29	−0.27	−0.32
Resource σ vs. wealth μ	0.46	0.5	0.53	0.47	0.54	0.55
Influence σ vs. resource μ	0.35	0.4	0.46	0.4	0.5	0.55
Influence σ vs. resource σ	0.35	0.4	0.46	0.4	0.5	0.55
Influence μ vs. resource μ	0.47	0.52	0.49	0.42	0.49	0.51
Influence μ vs. wealth μ	0.83	0.84	0.92	0.91	0.9	0.9
Influence σ vs. wealth gini	−0.52	−0.61	−0.49	−0.52	−0.53	−0.56
Initial resource μ vs. resource μ	0.99	0.99	0.97	0.97	0.97	0.97
SVO σ vs. wealth μ			−0.18	−0.05	−0.09	−0.07
SVO σ vs. wealth gini			−0.07	−0.15	−0.22	−0.18
SVO σ vs. resource μ			−0.05	0.05	0.05	0.06
SVO σ vs. resource σ			−0.05	0.05	0.05	0.06
Individualistic SVO vs. resource μ			0.02	−0.01	0.01	−0.05
Cooperative SVO vs. resource μ			0.08	0	−0.05	−0.02
Competitive SVO vs. resource μ			−0.12	−0.14	−0.05	−0.11
Altruistic SVO vs. resource μ			0.07	0.11	0.03	0.11
Individualistic SVO vs. resource σ			0.02	−0.01	0.01	−0.05
Cooperative SVO vs. resource σ			0.08	0	−0.05	−0.02

Competitive SVO vs. resource σ	−0.12	−0.14	−0.05	−0.11
Altruistic SVO vs. resource σ	0.07	0.11	0.03	0.11
Individualistic SVO vs. influence μ	0.28	0.24	0.2	0.1
Cooperative SVO vs. influence μ	0.12	−0.01	0.1	0.1
Competitive SVO vs. influence μ	0.12	0.11	0.19	0.16
Altruistic SVO vs. influence μ	−0.34	−0.35	−0.44	−0.35
Individualistic SVO vs. influence σ	0.13	0.08	0.29	0.2
Cooperative SVO vs. influence σ	0.08	0.01	0.09	0.09
Competitive SVO vs. influence σ	−0.05	0.01	0.07	0.02
Altruistic SVO vs. influence σ	−0.02	−0.06	−0.23	−0.14
Cluster count vs. wealth μ			0.39	0.43
Cluster count vs. resource μ			0.35	0.43
Cluster count vs. resource σ			0.35	0.43
Cluster count vs. clustered gini			0.43	0.47
Cluster size vs. clustered gini			0.48	0.5
Cluster count vs. non-clustered gini			0.6	0.63
Cluster size vs. non-clustered gini			0.62	0.65

5.1 Experiment 1: No social value orientation, no segregation

In the first experiment, social value orientation was not considered in the agents' decision making. Furthermore, the agents were not segregated into clusters, and therefore, either acted autonomously, or copied the behaviour of the "best" individuals in their vision radius.

Our null hypothesis was that highly skewed wealth distributions (i.e., high inequality) have a positive effect on the state of the resource. We used beta distributions to represent skewed wealth distributions, and contrast those with wealth initialisation based on normal distributions. Our findings for this base model are as follows:

- For a skewed wealth distribution, we can observe a low negative relationship (-0.39) between wealth inequality and the state of the resource. For a normal wealth distribution, in contrast, the correlation is smaller (-0.33).
- For a skewed wealth distribution, wealth level has a low positive correlation (0.5) to resource level, which is slightly more pronounced compared to the relationship between wealth and resource levels for normal distributions (0.46).

Observing the relationship between wealth and resulting distribution of social influence, we can see that:

- Social influence inequality has a low positive correlation with resource state, with slightly stronger relationships for beta distributions (0.4) compared to normal distributions (0.35).
- Inequality in social influence furthermore has the same correlation with wealth inequality as for wealth levels (beta: 0.4; normal: 0.35).
- The social influence level has a moderate positive correlation with resource level (normal: 0.52; beta: 0.52).

These initial results show that when the community is not segregated, and when agents make decisions on appropriation and contribution levels without the consideration of their own social values, the unequal distribution of wealth has a negative relationship to the overall resource state. This is the case both for initial distributions based on non-skewed and skewed distributions, but slightly more pronounced for skewed initial distributions. However, given the minimal differences in selected metrics for both distributions, any claims that point to a specific distribution type should be considered with reservation.

Social influence level, in contrast, has a positive relationship to resource metrics, irrespective of the underlying initial wealth distribution, and a very high correlation with wealth levels (which is of little surprise, given its self-reinforcing role in partner selection). Along with this, however, the wider spread of social influence is positively correlated (but to a more moderate extent than influence and wealth level) with wealth equality. As such, some level of diversity in social influence and wealth spread may have a moderating relationship.

5.2 Experiment 2: Social value orientation, but no segregation

Extending the focus of the base model, in this experiment agents consider their SVO when making decisions about their appropriation and contribution behaviour.

Exploring the impact of the introduction of SVOs on the configuration of the previous experiment, we could not observe significantly differing correlation values for initial wealth distribution and resulting resource state. However, the systematic stratification of behaviour based on SVOs offers grounds for further exploration avenues. Our first hypothesis was that a highly divergent society in terms of SVO has a positive influence on the wealth distribution of agents and the state of the resource.

Observing the results, diversity in social value orientation did have a low negative relationship to wealth level for normally-distributed initial wealth (-0.18). For beta wealth distributions, in contrast, we could observe that SVO diversity is weakly related to wealth equality (0.15). Although the reported figures are low, we see that the introduction of SVOs emphasises the role of the initial wealth distribution, which had been rather limited in the first experiment.

While SVO diversity did not render conclusive insights with respect to the resource state, selected SVO components (i.e., altruistic, cooperative, individualistic, competitive) did. The state and variation of the resource is weakly negatively correlated with increasing the fraction of competitive agents (normal: -0.12; beta: -0.24). More significant, however, is the relationship of the fraction of individualistic agents and the mean level of social influence (normal: 0.28; beta: 0.24), thus driving the establishment of influence structures based on the higher fraction of individually appropriated resource. Complementing this observation is the relationship between the fraction of altruistic agents and social influence levels; in our model altruism limits the emergence of a social influence structure.

In contrast to the first experiment, an interesting general observation is that the variation of social value orientations appears to have more pronounced effects on social configurations that have non-skewed (here: normal) wealth distributions. As such, more balanced wealth distributions appear more sensitive to diversity of social behaviour, suggesting that skewed distributions may be more robust against significant shifts in cooperation behaviour.

5.3 Experiment 3: Social value orientation and clustering (segregation)

In the third set of experiments, our goal was to see if the segregation of a society based on their ratio of contribution and appropriation affects metrics of well-being in the system (wealth levels, resource level). Apart from the focus on stratified contribution behaviour (modelled using SVOs), the iterative use of clustering represents dynamic social structures based on changing group relationships – in contrast to the static neighbourhood configurations of the previous experiments.

A central hypothesis is that the introduction of neighbourhood clusters has a positive impact on wealth levels and distribution, as well as the resource state. As with all previous experiments, we further explore how clustering interacts with varying initial wealth distributions. So far, we have observed the following:

- Introducing segregation itself has a minor positive relationship with overall wealth levels, irrespective of the underlying initial wealth distribution. Looking at the results in more detail, we can observe that the number of clusters has a moderate correlation with wealth levels (normal: 0.39; beta: 0.43).

- While clustering itself, and the number of clusters specifically, appear related to stronger levels of inequality, the impact varies for individuals that are members of any cluster (normal: 0.43; beta: 0.47) and for individuals that are not a member of any cluster (normal: 0.6; beta: 0.63).
- In contrast to earlier experiments, the diversity of social value orientation has a stronger influence on the resulting wealth inequality (normal: -0.22; beta: -0.18).

These findings, specifically with respect to clustering, the differentiation between clustered and unclustered agents, as well as social value orientation, suggest that clustering per se introduces greater inequality. However, while overall inequality increases, the relative homogeneity of individuals within clusters may moderate this effect, especially when compared to all remaining unclustered agents. When combined with clustering, the influence of diversity in social value orientation appears to become more pronounced: Since agents' cooperation behaviours are characterised by their respective social value orientation, their economic stratification will be influenced by the initial SVO, and consequently, drive the formation of economically homogeneous clusters.

Overall, these findings suggest that clusters of homogeneous self-reinforcing behaviour based on SVO can lead to an overall improvement in societal well-being, both in terms of wealth as well as resource level. The flip side is that the combined use of SVOs and clustering manifests the overall wealth inequality in situations of unequal wealth distribution. The correlations between resource level and social influence further suggest the stronger role of social influence structures. However, whether this occurs within or outside of clusters is inconclusive at this stage.

To arrive at firm conclusions, this model still requires further exploration, involving questions such as: What is a desirable number and size of clusters to manage the trade-off between wealth levels and inequality? Furthermore, how do the individual clusters differ structurally? Specifically this latter question requires the analysis of cluster-specific characteristics (e.g., size, wealth, social influence levels and distributions).

6 Discussion and Outlook

This paper presents an initial step in our research on the role of inequality on the sustainability of collective action. We built a theoretical agent-based model, which is based on theories of CPR systems to study the correlation between inequality and well-being of the system (see Ghorbani and Bravo (2016) for details of a similar model). In addition to wealth and social influence as behavioural determinants, we instantiated agents with varying social value orientations and introduced segregation based on socio-economic variables to emulate the emergence of social structure. The model is further instantiated using different distribution functions that represent both balanced wealth distribution and skewed wealth distribution in order to analyse the impact of initial wealth distributions on the result.

While the first experiment shows that inequality increases with increasing resource and wealth levels (which bears limited surprise), it also shows that an increase in resource level is linked to stratification of social influence. In the second experiment, we explored the impact of social value orientation on resource, wealth and social influence metrics.

The results show that diversity in social value orientation is weakly associated with more balanced final wealth distributions. However, focusing on individual SVO components, we find that specific social value orientations are more decisive in determining the resulting wealth distribution than diversity per se, especially when involving individualistic agents. Another finding is that behavioural diversity (whatever the specific choice of parameter values) has a stronger impact on social configurations with non-skewed initial wealth distributions, leading to the suggestion that skewed configurations may be more robust against bottom-up dynamics.

The final set of experiments introduces segregation into the model based on density-based clustering using the ratio of contribution and appropriation as social-economic metric. The results show that clustering introduces higher level of social inequality, but also highlight that this effect is more pronounced for non-clustered agents, in contrast to ones that are organised in clusters. This suggests a moderating effect of clustering for larger societies and larger clusters, an aspect that will be subject of further exploration. Clustering further interacts with social value orientation by affording a segregation of groups with shared characteristics, potentially contributing to the aforementioned homogeneity within clusters. However, to provide more conclusive insights, a detailed investigation of the intra- and inter-cluster characteristics is needed.

An observation that applies across all experiments is that the initial wealth distribution appears less decisive in determining the final distribution than the behavioural characteristics, such as the injected social values or the emergent social structures based on social influence and clustering. This is particularly observable for cases where different input distributions produced marginal variations in resulting metrics, which is potentially rooted in characteristics of the specific chosen distributions, as opposed to reflecting characteristics of skewed vs. non-skewed distributions more generally.

This leaves us with the opportunity to explore empirically-grounded wealth distributions found in contemporary human societies, in contrast to the idealised normal and beta distributions explored as part of this work. Beyond these analytical refinements, the model does not yet consider monitoring and sanctioning mechanisms found in real societies. Furthermore, we plan to validate our findings by comparing the model input and outcomes with a dataset on common-pool resource institutions.

References

Alesina, A. and La Ferrara, E. (2000). Participation in heterogeneous communities. Quarterly Journal of Economics, 115(3):847–904.

André, C. and Platteau, J.-P. (1998). Land relations under unbearable stress: Rwanda caught in the malthusian trap. Journal of Economic Behaviour and Organisation, 34:1–47.

Baland, J.-M. and Platteau, J.-P. (2006). Collective action on the commons: the role of inequality. In Baland, J.-M., Bardhan, P., and Bowles, S., editors, Inequality, Cooperation, and Environmental Sustainability, pages 10–35, Princeton University Press, Princeton (NJ).

Bandura, A. (1977). Social Learning Theory. General Learning Press, New York (NY).

Bardhan, P. (2005). Scarcity, Conflicts, and Cooperation. MIT Press, Cambridge (MA).

Berman, Y., Ben-Jacob, E., and Shapira, Y. (2016). The dynamics of wealth inequality and the effect of income distribution. PLOS ONE, 11(4):1–19.

Chatterton, P. (2016). Building transitions to post-capitalist urban commons. Transactions of the Institute of British Geographers, 41(4):403–415.

Ester, M., Kriegel, H.-P., Sander, J., and Xu, X. (1996). A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. In Simoudis, E., Han, J., and Fayyad, U., editors, Second International Conference on Knowledge Discovery and Data Mining, pages 226–231, Portland, Oregon. AAAI Press.

Ghorbani, A. and Bravo, G. (2016). Managing the commons: a simple model of the emergence of institutions through collective action. International Journal of the Commons, 10(1).

Griesinger, D. W. and Livingston, J. W. (1973). Toward a model of interpersonal motivation in experimental games. Behavioral Science, 18(3):173–188.

Keister, L. A. and Moller, S. (2000). Wealth inequality in the united states. Annual Review of Sociology, 26:63–81.

Lichbach, M. I. (1989). An evaluation of does economic inequality breed political conflict? studies. World Politics, 41(4):431–470.

Lijphart, A. (1997). Unequal participation: Democracy's unresolved dilemma. American Political Science Review, 91(1):1–14.

Murphy, R. O., Ackerman, K. A., and Handgraaf, M. J. J. (2011). Measuring social value orientation. Judgment and Decision Making, 6(8):771–781.

North, D. C., Wallis, J. J., and Weingast, B. R. (2009). Violence and Social Orders: A Conceptual Framework for Interpreting Recorded Human History. Cambridge University Press, New York (NY).

Tilly, C. (1998). Durable Inequality. University of California Press, Berkeley (CA).