# Extending the Civil Violence Model: Heterogeneous Legitimacy and Mean-field Approach

Sheng Gao[a], Jiawei Liao[a] and Julius Wagenbach[a]

[a] *University van Amsterdam, Science Park 904, Amsterdam, 1098 XH, The Netherlands*

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ABSTRACT

This report presents and extends an agent-based computational model of civil violence based on the 2002 paper *Modeling civil violence: An agent-based computational approach* by Epstein (2002). We extend the basic model by changing the legitimacy from a global constant to a global or regional heterogeneous internal variable. Additionally, we modify the legitimacy update mechanism by employing a mean-field approach, where the legitimacy of a citizen is influenced by the average legitimacy of their neighbors. Within this framework, we investigate the evolutionary process through which initially heterogeneous citizen legitimacy gradually converges towards homogeneity. We also consider varying deterrent effects of different jail terms on citizens, and the possible changing of citizen's perception of regime legitimacy when they are jailed. We discuss how our extensions impact the model, and compare our models against the original basic one in terms of legitimacy and active citizens, and conduct a sensitivity analysis of significant parameters.

## 1. Introduction

As a historically relevant phenomenon, civil violence arises through the complex interplay of socio-political and economic factors. Goldstone (1980) Epstein introduced an agent-based model to explore the conditions under which civil violence emerges and evolves. Epstein's model uses grievance and perceived legitimacy (L) as observable variables in simulating a potential rebellion against a central authority.

However, the basic model doesn't consider the heterogeneity of citizen's L, citizen's exchange of views, the deterrent effects of different jail terms, and changing of citizen's L after arrest. Our extension model designs two forms of L heterogeneity: global heterogeneity and regional heterogeneity, to simulate a society in which citizens with different L are randomly mixed together, or citizens with the same L are clustered within the same community. We also design a mean-field computation to simulate citizen's L updating over time. We introduce a new parameter $\alpha$ to research the deterrent effects of jail terms, $jailfactor$ to research the effects of imprisonment on arrested citizens L. We analyze the active citizen ratio by varying these new parameters and compare the results to the basic model. We also conduct a sensitivity analysis examining how variations in key parameters affect the outcome of the model. These extensions aim to provide a more comprehensive understanding of the factors that influence civil violence which can help predict the potential outcomes of different policy interventions and provide guidance for policymakers in different scenarios.

## 2. Shortcomings of the Basic Model

The basic civil violence model is not fully suited to describe how a central authority seeks to suppress decentralized rebellion in real life for the following reasons:

### 2.1. L as an Environmental Constant

In the basic model, L is assumed to be uniform across all citizens and remains constant throughout one simulation. This simplification overlooks the significant variations in how individuals perceive legitimacy in real-world scenarios. In practice, citizens' views on legitimacy are shaped by a multitude of factors, including personal experiences, socio-economic status, cultural background, and exposure to information. For instance, individuals who have directly benefited from a regime's policies may view its legitimacy more favorably, while those who have suffered under the same regime might see it as fundamentally illegitimate. By ignoring these individual differences, the model fails to capture the complex nature of legitimacy in a society.

### 2.2. Lack of Consideration for Interaction Between Citizens

The basic civil violence model does not account for how interactions between citizens can lead to shifts in their perceptions of regime legitimacy. In reality, the way individuals view the legitimacy of a regime is not formed in isolation, it is heavily shaped by their social environment. Discussions with family, friends, colleagues, or acquaintances often influence people's opinions. This social interaction plays a crucial role in the spread of both support for and dissent against a regime Kuran (1989).

### 2.3. Neglect of the Differential Deterrent Effects of Varying Jail Terms

The basic model fails to account for the varying deterrent effects that different jail terms can have on citizens. In reality, the length and severity of imprisonment play a crucial role in shaping how effective these punishments are in deterring rebellious behavior Jourdan (2015).

### 2.4. Neglect of Impacts of Imprisonment on Incarcerated Citizens' L

The civil violence model also neglects to consider the impact that imprisonment itself can have on an individual citizen's perception of regime legitimacy. In real-world scenarios, the experience of being imprisoned can profoundly alter a person's view of the government and its authority Jourdan (2015).

## 3. Extensions of the Basic Model

Based on the described shortcomings, we implemented multiple extensions to the basic model which will be described in this section.

### 3.1. L as an Internal Variable

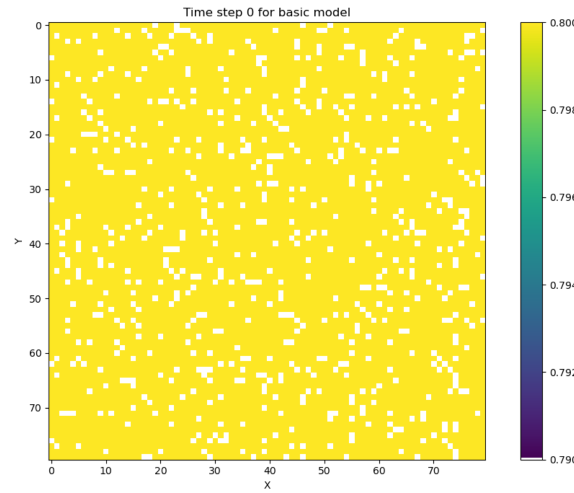
For the initialization of the legitimacy variable of each citizen, we design two extended models, the global heterogeneous model and the regional heterogeneous model.

#### *3.1.1. Global Heterogeneous L Initialization*

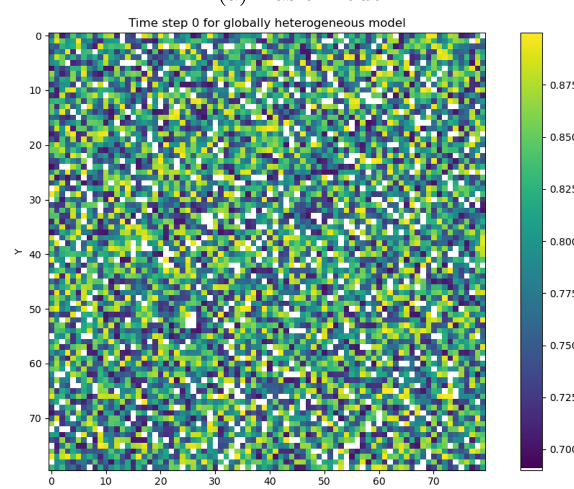
The global heterogeneous model assumes L of all citizens is initialized randomly within a specified range, which means the perception of regime legitimacy varies across individuals but is distributed uniformly across the entire domain, irrespective of geographic factors. Specifically, $L$ for each citizen is initialized within a range defined by $[L_0 - \Delta L, L_0 + \Delta L]$, where $L_0$ represents the average legitimacy and $\Delta L$ is the legitimacy range. Legitimacy width reflects the variability in individuals' perceptions of the regime's legitimacy.

The rationale behind this method is individuals within a society often hold differing views about the regime's legitimacy. These differences can arise from a variety of factors including personal experiences, media influence, social interactions, and more. By assuming that these perceptions are uniformly distributed and independent of geographic location, we can model scenarios where the variation in legitimacy is present across the entire population without any regional clustering.

Figure 1 shows an example to compare the initial (time step = 0) L distribution for the basic model and the global heterogeneous model. Figure 1a shows a heatmap for the basic model, where legitimacy values are initialized uniformly across the domain with no variation. As expected, the heatmap is all yellow (white representing blank lattice or cops), showing the homogeneity of citizen L in the basic model. In contrast, Figure 1b presents a heatmap of the globally heterogeneous model. The color scale ranges from purple, indicating lower legitimacy values, to yellow, indicating higher legitimacy values, demonstrating the heterogeneity in legitimacy across the citizens, with no discernible regional clustering.




(a) Basic Model




(b) Global Heterogeneous Model

**Figure 1:** Heatmap of L across domain at time step 0 for the basic and global heterogeneous model. Colors indicate the level of L, with yellow representing higher L, purple representing lower L, and White representing lattice occupied by cops(since we assume cops don't have L) or blank.

The introduction of global heterogeneous legitimacy is expected to influence the dynamics of civil unrest. Citizens with lower legitimacy values are more likely to become discontented and, consequently, more prone to participate in rebellious activities. Conversely, citizens with higher legitimacy values may act as stabilizing forces within the society, resisting movements toward rebellion. The uniform distribution of legitimacy across the domain ensures that potential hotspots of unrest are not geographically localized but rather dispersed throughout the population.

This model also allows for the examination of how different initial distributions of legitimacy can impact the emergence and spread of civil unrest. By manipulating the central legitimacy value $L_0$ and the legitimacy width $\Delta L$, we can explore various scenarios, from highly homogeneous societies with minimal variation in legitimacy to volatile environments with significant disparity in public opinion.

### 3.1.2. Regional Heterogeneous L Initialization

The regional heterogeneous model assumes citizens' L is determined by the region they occupy within the domain. Unlike the global heterogeneous model, it introduces spatial variation in regime legitimacy, reflecting the reality that different regions may have varying levels of support or opposition to the regime. It allows us to model scenarios where geographic factors play a significant role in the distribution of legitimacy across a population. Specifically the domain is divided into multiple subregions, with each subregion assigned a specific, predetermined L value. All citizens within a given region share the same initial L value, which reflects the collective sentiment of that region towards the regime. The boundaries between regions are clearly defined, ensuring that each region has a uniform perception of legitimacy that differs from adjacent regions.

This model simulates real-world situations where geographic areas may have different levels of support for a government due to historical, socio-economic, or political reasons **?**. For example, urban areas might show higher legitimacy due to better access to government services, while rural or marginalized regions might display lower legitimacy Schama (1989).

Figure 2 illustrates the initial legitimacy distribution across the domain in the regional heterogeneous model. The domain is divided into six subregions. Each subregion is represented by a distinct color corresponding to its predetermined L value, from purple to yellow as well. This model effectively demonstrates the regional differences in legitimacy, with each region showing a uniform color that reflects the homogeneous legitimacy assigned to all agents within that region. The figure highlights how these predetermined legitimacy values vary across regions which might result in potential regional disparities in civil unrest dynamics. By analyzing different configurations of regional legitimacy, we can simulate a variety of political and social scenarios, providing insights into how regional factors contribute to the emergence and escalation of civil unrest.

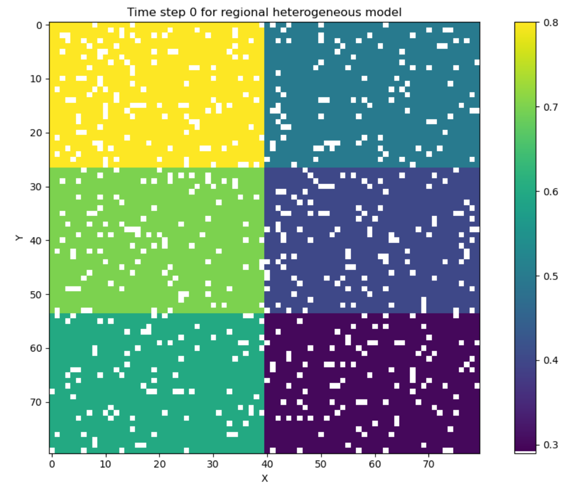



**Figure 2:** Heatmap of regime legitimacy across the domain at Time Step 0 for the regional heterogeneous model. Colors indicate the level of legitimacy, with yellow representing higher L and purple representing lower L.

## 3.2. Mean-Field Method for Updating Citizens' L

In real-life scenarios, the network of citizen interactions plays a critical role in the evolution of perceptions of legitimacy, and thus, in the escalation or de-escalation of conflicts **?**.

In our model, we utilize a two-dimensional square lattice with a lattice spacing of 1 to represent the spatial distribution of agents. Each site on the lattice, denoted as $\alpha$ (i,j), represents a possible position of an individual agent. To capture the interactions among citizens, for each interior lattice site $\alpha$ (i , j), we define its neighboring sites $\beta(\alpha)$ using the Moore neighborhood, which includes the eight adjacent cells surrounding each site:

$$\begin{aligned}\mathcal{B}(\alpha) = \{&(i-1,j-1),(i,j-1),(i+1,j-1),\\ &(i-1,j),(i+1,j),\\ &(i-1,j+1),(i,j+1),(i+1,j+1)\}\end{aligned} \tag{1}$$

And we introduce a new parameter "legitimacy impact" to quantify the extent to which a citizen's perception of regime legitimacy is influenced by the legitimacy perceptions of their neighbors. It determines the weight of the neighboring legitimacy average $L^0_{\overline{\beta(\alpha)}}$ on the citizen's new legitimacy value $L^1_\alpha$.So for $\alpha$ (i,j) at T=1 we have the formula for $L^1_\alpha$:

$$L^1_\alpha = L^0_\alpha + \left(L^0_{\overline{\beta(\alpha)}} - L^0_\alpha\right) \times \text{legitimacy\_impact} \tag{2}$$

$$\begin{aligned}L^0_{\overline{\beta(\alpha)}} = \frac{1}{8} \times (&L^0_{i-1,j-1} + L^0_{i,j-1} + L^0_{i+1,j-1} + L^0_{i-1,j}\\ &+ L^0_{i+1,j} + L^0_{i-1,j+1} + L^0_{i,j+1} + L^0_{i+1,j+1})\end{aligned} \tag{3}$$

We expect that with a high value of the legitimacy impact, a citizen's legitimacy perception is heavily influenced by their neighbors. This scenario reflects a society where peer influence, social networks, and community opinions strongly affect individual beliefs. For instance, in tightly-knit communities or societies with high social cohesion, individuals are more likely to conform to the prevailing views of their neighbors. A low legitimacy impact value signifies that citizens are less influenced by their neighbors, suggesting a more independent or individualistic approach to forming legitimacy perceptions. This might be seen in more fragmented or diverse societies where personal experiences and individual factors play a more significant role in shaping beliefs Fortunato (2010).

By using the mean-field method and incorporating the legitimacy impact parameter, our model better captures the complexities of social interactions and their influence on citizens' perceptions of regime legitimacy, providing a more nuanced understanding of how legitimacy evolves within a population Baker and Simpson (2010).

### 3.3. Influence of $\alpha$ and Jail Factor

The basic model assumes the agent's net risk $N = RP$, while R is the agent's level of risk aversion and P is the likelihood of arrest. However, it doesn't consider the influence of the jail term. So in our model, we assume $N = RPJ^{\alpha}$, while J is the jail term, $\alpha$ modifies the influence J on the agent's net risk N ($\alpha$=0 in the basic model, indicating that the jail term does not affect the agent's net risk, correspond to a situation where the length of the jail term is irrelevant to the agent's decision-making process.) In our extended model, we use varying $\alpha$ values to compare the number of active citizens in different modes.

Besides, the basic model assumes that agents leave jail exactly as aggrieved as when they entered. However, for many individuals, imprisonment is not just a physical punishment but also a psychological and social ordeal that can reshape their beliefs about the fairness and justice of the regime Goldstone (1980). So in our extension model, we introduce a parameter called the jail factor. This parameter modifies the legitimacy of a citizen upon their release from prison. Specifically, the legitimacy $L^*$ of an imprisoned citizen when they leave jail is given by formula:

$$L^* = L \times \text{jail factor} \tag{4}$$

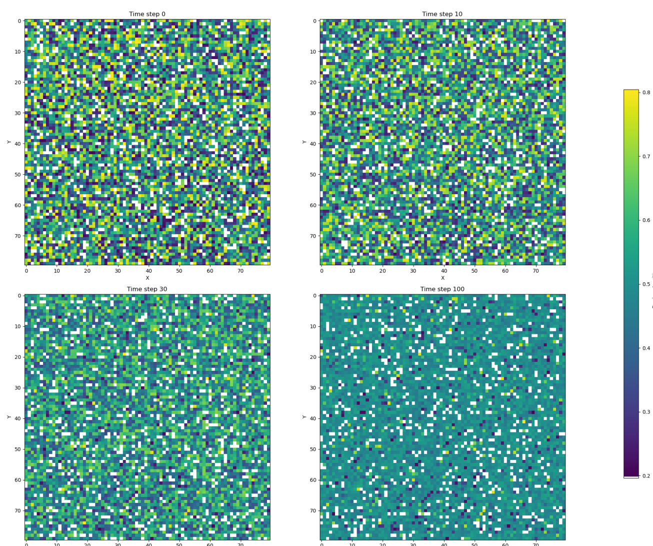
The jail factor is a positive number. When $0 < \text{jail factor} < 1$, it indicates that imprisonment has exacerbated the individual's dissatisfaction with the regime, making them view the regime as even less legitimate. This perception is often exacerbated by harsh prison conditions, mistreatment, or the perceived arbitrariness of the legal system. Instead of deterring future dissent, imprisonment can foster a sense of victimization and alienation from the state Goldstone (1980). Conversely, when $\text{jail factor} > 1$, it suggests that imprisonment has had a positive effect, increasing the individual's recognition of the regime's legitimacy, possibly due to political education or other rehabilitative efforts while in prison. By incorporating the jail factor, our model aims to better capture the nuanced effects of imprisonment on regime legitimacy, reflecting both potential negative and positive outcomes.

## 4. Experiments and Analysis

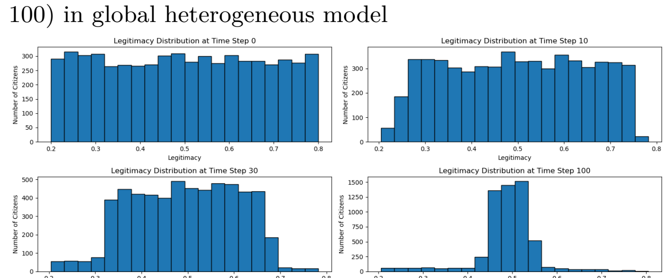
### 4.1. Changes in Legitimacy (L) Over Time

#### *4.1.1. Global Heterogeneous Model*

In this experiment, we investigate the dynamics of L over time in the global heterogeneous model. Figure 3a shows an example heatmap of regime legitimacy at various time steps, ranging from the initial time step to time step 100. Figure 3b displays the corresponding histograms of the legitimacy distribution at the same time steps, averaged over a large number of model simulations. These histograms provide a quantitative view of how the distribution of legitimacy among agents evolves over time.




(a) Heatmaps of L across the domain at time steps (0, 10, 30, 100) in global heterogeneous model




(b) Histograms of the citizens' average L distribution at time steps (0, 10, 30, 100) in the global heterogeneous model. The x-axis represents legitimacy values, and the y-axis represents the number of citizens.

**Figure 3:** Heatmaps and histograms of L distribution at time steps (0, 10, 30, 100) in the global heterogeneous model.

- **Early Time Steps (Time Steps 0 to 30)**: In the early stage, the first and second heatmaps show a gradual smoothing of the color variations, indicating that L are beginning to converge. The histograms at these time steps show a modest reduction in the extremes of the distribution, with more citizens clustering around the central values of legitimacy.

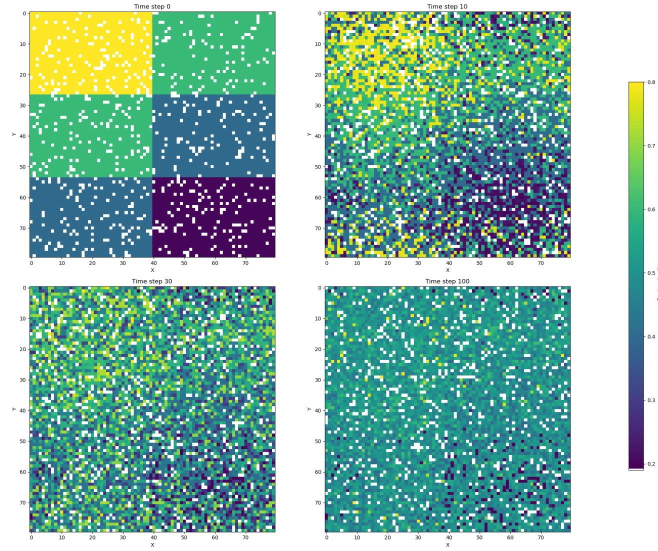
- **Mid Time Steps (Time Steps 30 to 80)**: By the mid-point of the simulation, the convergence becomes more pronounced. The third heatmap depicts a more uniform distribution of L across the domain, with fewer regions showing extreme L. The histograms further confirm this trend, as the distribution begins to take on a more peaked shape, centered around the mean L.

- **Later Time Steps (Time Steps 80 to 100)**: In the later stages of the simulation, the L distribution continues to narrow. The last heatmap shows that most of the domain now exhibits a relatively homogeneous L level, with fewer individuals displaying significant deviations from the mean. The histograms at these time steps reveal a clear centralization of L, with the distribution becoming increasingly Gaussian in shape, centered around a specific L range.

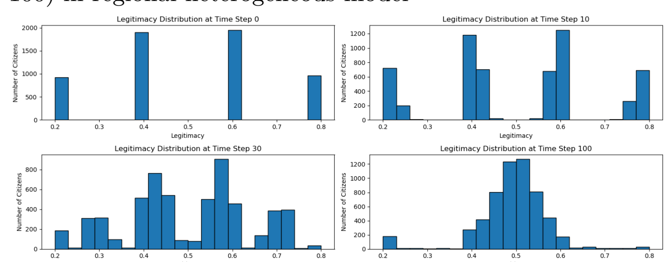
The results from this experiment indicate that when L is initialized heterogeneously across the entire population, there is a natural tendency for the distribution of L to converge towards a central value over time. This convergence is due to the interactions between citizens, where those with extreme L are influenced by their neighbors, leading to a more homogeneous distribution. The narrowing of the L distribution suggests a stabilization of public opinion, with fewer agents holding extreme views about the regime's legitimacy as the simulation progresses. This outcome highlights the potential for societal consensus to emerge even in the presence of initially diverse opinions, provided there is sufficient interaction between individuals within the population. This finding has important implications for understanding how public opinion may stabilize in the face of diverse individual beliefs.

### *4.1.2. Regional Heterogeneous Model*

In this experiment, we investigate the dynamics of L over time in the regional heterogeneous model. The figures presented illustrate the changes in legitimacy over time. Figure 4a) shows a heatmap of regime legitimacy at various time steps, ranging from the initial time step to time step 100. Figure **??**) displays the corresponding histograms of the L distribution at the same time steps, which are averaged over a large number of model simulations, reflecting the changes within and between the regions.




(a) Heatmaps of L across the domain at time steps (0, 10, 30, 100) in regional heterogeneous model




(b) Histograms of the citizens' average L distribution at time steps (0, 10, 30, 100) in regional heterogeneous model. The x-axis represents legitimacy values, and the y-axis represents the number of citizens.

**Figure 4:** Heatmaps and histograms of L distribution at time steps (0, 10, 30, 100) in the regional heterogeneous model.

- **Early Time Steps (Time Steps 0 to 30)**: As time progresses, interactions between citizens at the borders of regions lead to a gradual blending of L. The first and second heatmap show that the sharp boundaries between subregions begin to blur as L start to diffuse across subregions. The histograms during these time steps show a broadening of the peaks, indicating that the previously uniform L within each subregion is starting to diversify.

- **Mid Time Steps (Time Steps 30 to 80)**: By the mid-point of the simulation, L within each subregion continues to mix, resulting in a more continuous distribution of L across the entire domain. The third heatmap depicts a further reduction in the distinctness of regional boundaries, while the histograms illustrate a shift towards a more integrated distribution, with multiple peaks merging into fewer, broader ones.

- **Later Time Steps (Time Steps 80 to 100)**: In the later stages of the simulation, the distribution of L approaches a more homogeneous state, although regional influences remain visible. The last heatmap shows a significant reduction in regional differences, with L more evenly distributed across the domain. The histogram at these time steps indicates that L is converging towards a central range but with lingering effects of the initial regional heterogeneity.

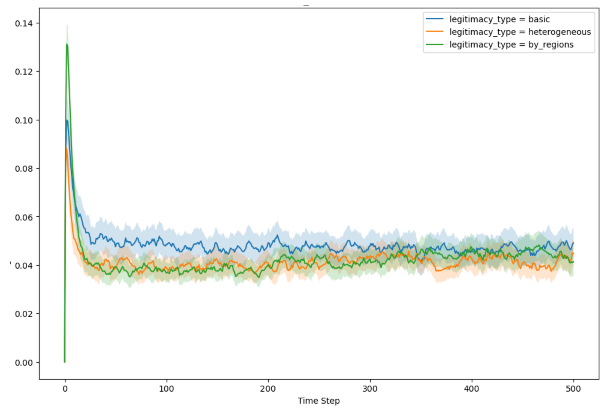
The results from this experiment demonstrate that regional heterogeneity in L leads to a slower convergence compared to global heterogeneity. The presence of initial regional differences creates persistent effects that influence the dynamics of civil unrest over time. This persistence of regional characteristics in legitimacy distribution suggests that geographic and social boundaries play a significant role in shaping the evolution of public opinion. The blending of legitimacy values at regional borders highlights the importance of interaction between different spatial groups in mitigating or exacerbating civil unrest.

## 4.2. Comparison of the Active Citizens Ratio in Different Models

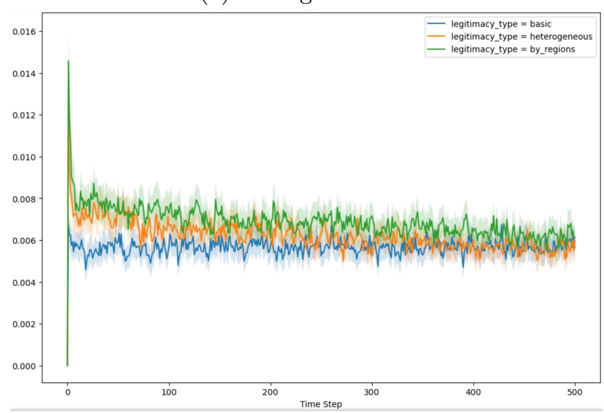
We observe the change in active citizens across a large number of runs between the base model and our extensions while keeping all other parameters constant. The result shown in Fig.5, exhibits significant differences across various average system legitimacy (L) levels.

When the average L is low (0.7), after the initial spike, the basic model stabilizes at the highest level compared to the other two models, the global heterogeneous model stabilizes at a middle level, and the regional heterogeneous model stabilizes at the lowest level. And the active citizens ratios in the three models gradually converge over time.

In the low average L society, a uniform low L across all citizens (basic model) leads to sustained high levels of rebellion, as everyone's L is low enough to be active, so discontent is widespread and persistent. The random distribution of L (global heterogeneous model) allows at least some citizens to have higher L, showing that even in a highly discontented society, there are still some individuals who remain fervent supporters of the regime, which slightly reduces the overall active citizen ratio. For the regional heterogeneous model, the regional differences in initial L create pockets of higher L, leading to localized pockets of stability, significantly reducing the overall active citizen ratio. This can be observed in a big regime system where some communities have a better relationship with the regime than others. However, with frequent communication and exchange of opinions among citizens, the L in the global heterogeneous model and regional heterogeneous model gradually evolves from heterogeneous to homogeneous.




(a) Average L = 0.7




(b) Average L = 0.88

**Figure 5:** Active average citizens ratio over time for different models. The time step is denoted as x-axis, the active citizens ratio is denoted as y-axis. The plot displays the active citizens' ratio with different models within low and high-average L systems. Each subplot represents the average of 100 simulations with a 90% confidence level.

Consequently, the active citizen ratios in all three models eventually converge over time.

When the system average L is high (0.88), after the initial spike, the three models exhibit different performances. The regional heterogeneous model stabilizes at the highest level, the global heterogeneous model still stabilizes at the middle, and the basic model stabilizes at the lowest. This phenomenon is not difficult to explain, uniform high L across all citizens minimizes dissent as everyone's L is high enough to be quiescent. Similarly, the global heterogeneous model creates some spatially dispersed citizens with lower L, slightly increasing overall dissent. It reflects even in societies with generally high L, variability can introduce some levels of dissent, for example in pluralistic societies where most groups support the regime, but minority grievances exist. The regional heterogeneous model creates some areas of lower L, increasing overall dissent the most. This is observed in countries with strong regional identities where most regions support the central government, but some have distinct issues. The active citizen ratios in all three models also converge over time in the high average L system.

### 4.3. The Influence of $\alpha$

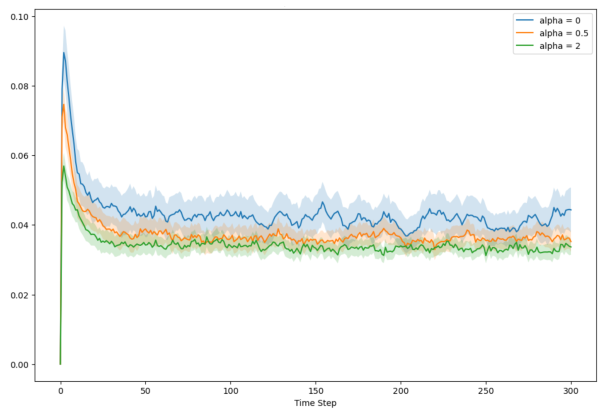
We keep all other parameters constant and vary $\alpha$ value as 0, 0.5 and 2 in each model to observe and compare the ratio of active citizens. The result is shown in Fig.6. All three subplots exhibit a consistent general pattern where the active citizens' ratio spikes initially and then stabilizes. Higher $\alpha$ values consistently result in lower numbers of active citizens across all models.

When $\alpha = 0$, it shows the highest active citizens ratio level, indicating a lower $\alpha$ implies a weaker deterrent effect of jail terms on citizens' decision to become active. Citizens are less influenced by the risk of arrest and longer jail terms, leading to higher participation in active protests or unrest.

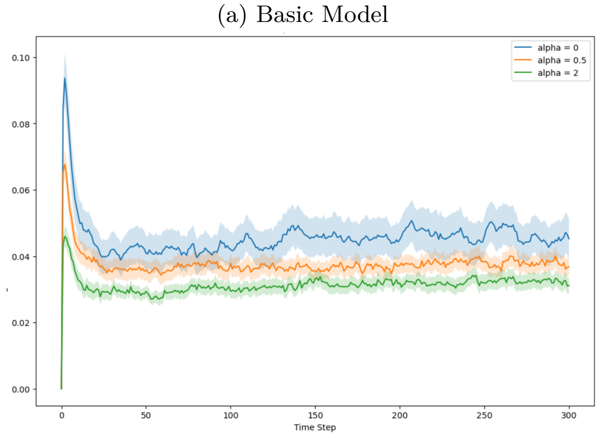
When $\alpha = 0.5$, it shows lower peaks, and an intermediate $\alpha$ indicates a moderate deterrent effect. The jail terms and arrest risk have a more substantial impact on reducing active participation. The lower active ratio suggests citizens are more cautious, as the potential consequences (jail) temper their willingness to participate.

When $\alpha = 2$, it shows the lowest levels of active citizens, and a high $\alpha$ represents a strong deterrent effect, where the fear of long jail terms significantly suppresses active participation. The very low levels of active citizens suggest that most are deterred by the high risks associated with being active, leading to minimal outbursts.

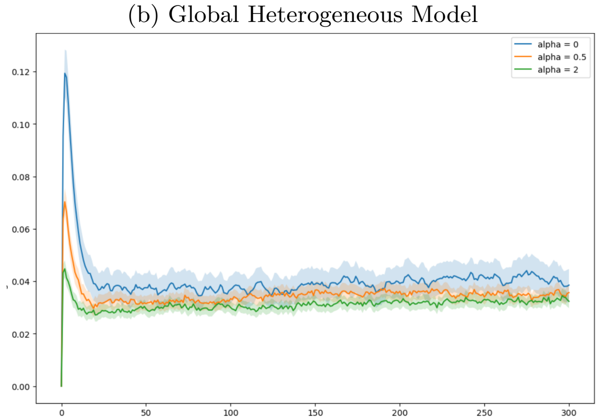
We've already known that when $\alpha = 0$, the jail term has no effect on the agent's perceived risk. This is equivalent to a risk-neutral scenario where agents do not consider the consequences of their actions in terms of potential jail time. When $\alpha > 0$, the jail term increasingly influences the agent's decision. Higher values of $\alpha$ increase the deterrent effect, leading to fewer active agents as the fear of long jail terms suppresses the willingness to participate in rebellious activities. Different $\alpha$ can help policymakers gauge the potential effectiveness of different levels of deterrence through judicial measuresAdhickari (2016). A higher $\alpha$ might be more effective in maintaining order but could also suppress legitimate protests, while a lower $\alpha$ could encourage more active civic participation, possibly at the cost of higher unrest.




(a) Basic Model




(b) Global Heterogeneous Model



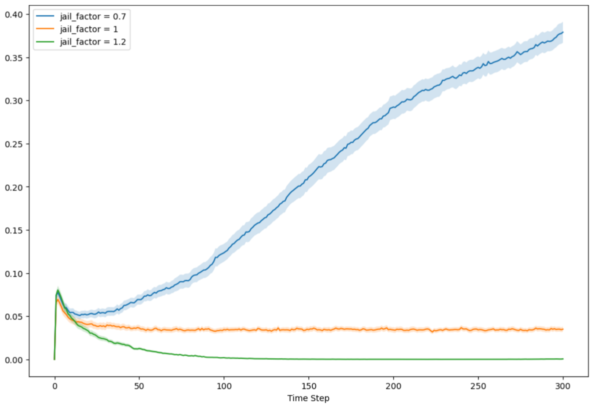

(c) Regional Heterogeneous Model

**Figure 6:** Active average citizens ratio over time for different $\alpha$ values in three modes. The time step is denoted as x-axis, and the active citizens ratio is denoted as y-axis. The plot displays the ratio of active citizens with different $\alpha$ values (0, 0.5, 2) in each mode. Each subplot represents the average of 100 simulations with a 90% confidence level.

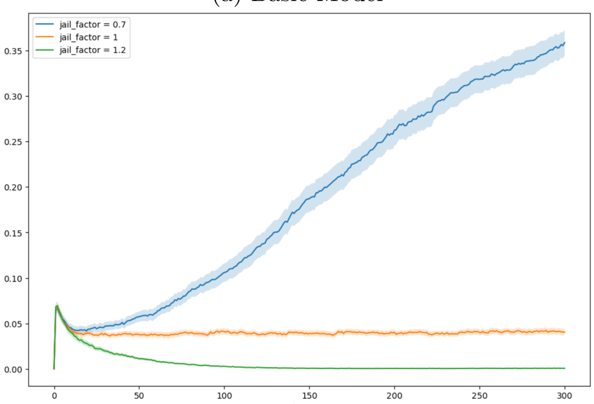
### 4.4. The Influence of Jail Factor

We keep all other parameters constant and vary our introduced jail factor value as 0.7, 1, and 1.2 in each model to observe and compare the ratio of active citizens. The result is shown in Fig.7.

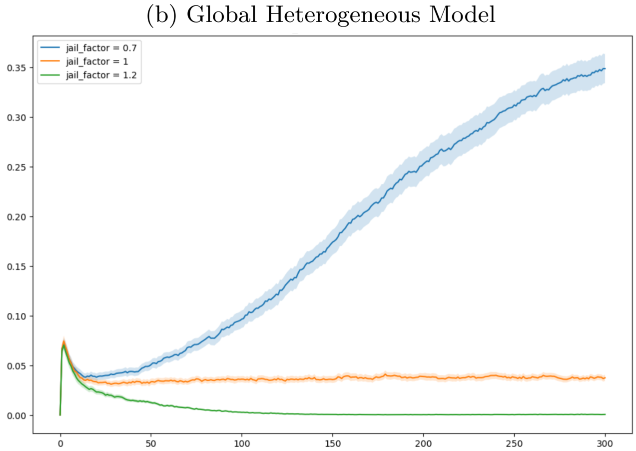
All three subplots exhibit a consistent general pattern of active citizens ratio after initial spikes. A jail factor of less than 1 indicates imprisonment has a harsh impact on citizens, exacerbating their dissatisfaction and increasing their willingness to engage in rebellion. When the jail factor = 0.7, it shows an increasing trend of active citizens over time, indicating escalating activity, in which the active citizens' ratio will increase to burst over time, leading to more active resistance and unrest. It reflects harsh prison conditions can deepen existing grievances and feelings of injustice among citizens, and create a cycle of resistance where




(a) Basic Model




(b) Global Heterogeneous Model




(c) Regional Heterogeneous Model

**Figure 7:** Average active citizens ratio over time for different jail factor values in three modes. The time step is denoted as x-axis, the active citizens ratio is denoted as y-axis. The plot displays the ratio of active citizens with different jail factor values (0.7, 1, 1.2) in each mode. Each subplot represents the average of 100 simulations with a 90% confidence level.

individuals become more determined to oppose the regime (harsh punitive measures lead to larger-scale rebellions), leading to higher levels of organized and sustained dissent.

A jail factor of 1 indicates a neutral impact of imprisonment, where the conditions don't significantly change L among citizens. When jail factor = 1, the stabilization of active citizens ratio at a moderate level suggests that neutral imprisonment policies neither effectively deter dissent nor significantly exacerbate it. In real life, maintaining a neutral stance can lead to policy stability, where citizens perceive the justice system as predictable and consistent, albeit without major shifts in public opinion.

A jail factor greater than 1 indicates that imprisonment has a rehabilitative or positive impact on citizens, improving their L. When jail factor = 1.2, it shows a decreasing trend of active citizens ratio over time, suggesting that rehabilitative imprisonment policies are effective in reducing active dissent. It reflects a rehabilitation imprisonment policy can improve arrested citizens' L, reducing the motivation for dissent. By focusing on rehabilitation, the regime can achieve long-term stability and social cohesion.

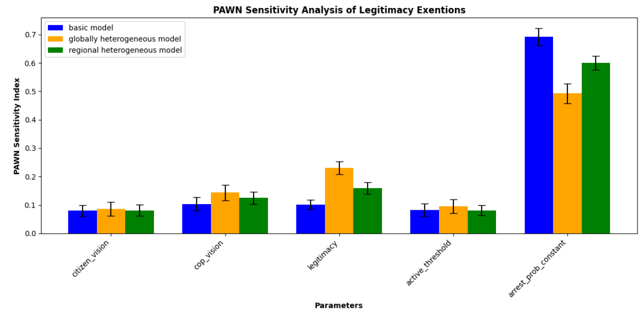



**Figure 8:** Sensitivity analysis for main parameters between the base model and our extended models

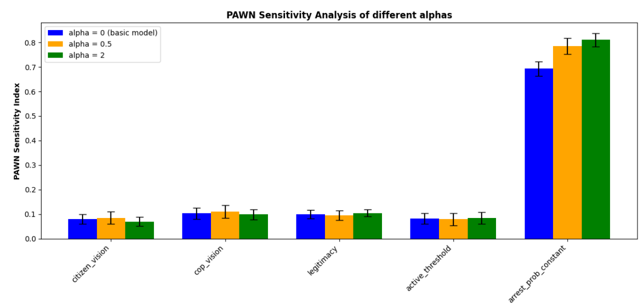



**Figure 9:** Sensitivity analysis for main parameters between the base model changed values of alpha

## 5. Sensitivity Analysis

### 5.1. Varying Model Types

Figure 8 shows the sensitivity analysis we conducted of the base model and our two extension models: global heterogeneous model and regional heterogeneous model, using PAWN (Pianosi and Wagener (2015)). In the base model, the arrest_prob_constant has the highest sensitivity index, which means that it is the most influential factor in determining the average size of outbursts. This is intuitive, since the higher this

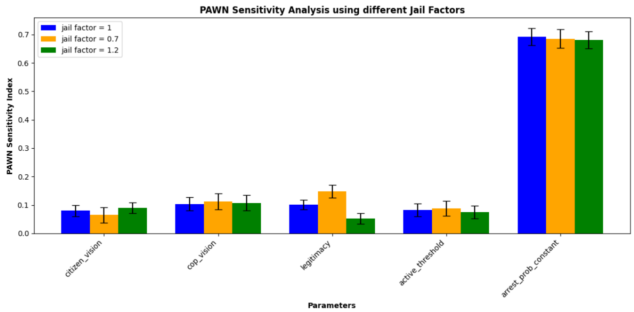



**Figure 10:** Sensitivity analysis for main parameters between the base model and our extended jail factor computation

value is, the more likely it is that citizens will be arrested, which directly impacts the outburst dynamics. The other four parameters citizen_vision, cop_vision, legitimacy, active_treshold and arrest_prob_constant have lower values, meaning their impact on the the size of the outburst is less. When compared to our extensions, the same trends are true, but we can observe some differences: For the global heterogeneous model and regional heterogeneous model, the variable legitimacy has a higher impact. This is to be expected because the legitimacy of the agents is being frequently readjusted. This is likely also why, arrest_prob_constant impact is lower for these two modes, because the legitimacy variable is more important in the overall model.

### 5.2. Varying Alpha

In the sensitivity analysis for varying alphas seen on Figure 9, we can observe a change in sensitivity for the arrest-prob-constant variable. The higher the alpha is, the higher the sensitivity of this value seems to be. This is likely because increasing alphas leads to greater variability in the likelihood of citizens participating in rebellious activities. If a higher alpha strongly deters rebellion by increasing the perceived risk of long jail terms, the arrest probability constant becomes more critical in influencing whether individuals decide to act or remain passive, thus increasing its sensitivity.

### 5.3. Varying Jail Factor

Figure 10 shows the sensitivity analysis for the extended jail factor for values 0.7, 1 and 1.2. In the sensitivity analysis for the jail factor, we can observe a change in sensitivity for the legitimacy variable. The higher the jail factor, the lower the sensitivity index for legitimacy is. This is likely because if the jail factor is set to make imprisonment a highly rehabilitative process with a high jail factor, legitimacy will become more stable across the population, and vice versa.

## 6. Conclusion

The global and regional heterogeneous models demonstrate that even when L is initially diverse across a population, the dynamic interactions between citizens can lead to a convergence of L over time, while the regional heterogeneous model has a more complex and prolonged stabilization process compared to the global heterogeneous model.

When the system average L is low, the basic model has the highest active citizen ratio, the global heterogeneous model stabilizes at a middle level, and the regional heterogeneous model is the lowest. When the system average L is high, the order is opposite. In both situations, the active citizens ratios in the three models gradually converge over time, as the heterogeneity of L dissipates over time due to interaction between citizens.

For the influence of $\alpha$, the smaller the $\alpha$, the higher the active citizen ratio. A bigger $\alpha$ represents a strong deterrent effect where the fear of long jail terms significantly suppresses active participation.

A jail factor of less than 1 indicates imprisonment has a harsh impact on citizens, leading to more active resistance and unrest. A jail factor greater than 1 indicates imprisonment has a rehabilitative impact on citizens, leading to a decreasing trend of active citizens ratio over time, suggesting that rehabilitative imprisonment policies are effective in reducing active dissent.

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