Cooperative Norms and the Growth of Threat: Differences Across Tight and Loose Cultures

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***Abstract*—Cultural differences in conformity pressures play a critical role in whether and how a society can effectively adopt a cooperative norm and fight against an evolving threat. Using an agent-based evolutionary game theoretic model, our results show that in general, tight societies with stronger conformity pressures adopt a cooperative norm faster than loose societies. As a consequence, the threat ends up lower in tight societies. However, high conformity pressures in tight societies are also a double-sided sword. Sometimes, a tight society may conform to a defective norm at the beginning of a threat, leading to a faster escalation of threat at the early stage of a threat. Nevertheless, as threat increases, tight societies are able to switch to a cooperative norm quickly and slow down the growth of threat, so eventually the threat levels in tight societies are close to or lower than that in loose societies. Our findings bring insight into how cultural differences in conformity pressures influence different societies' success in dealing with collective threats.**

***Index Terms*—cultural tightness-looseness, cooperation, threat, conformity pressure, evolutionary game theory**

I. Introduction

Societal threats are ubiquitous. Threats, whether they are earthquakes, floods, warfare or pandemics, diminish people's resources and well-being [1]. To overcome collective threats, *cooperation* is essential. The COVID-19 pandemic is a case in point. Seventeen science and medical academies have issued a statement emphasizing the urgency of international cooperation in responding to the global pandemic [2]. Cooperative behaviors on the individual level, such as wearing a face mask [3] and practicing social distancing [4]–which are costly for an individual to make but have a greater benefit for others–are also critical for slowing down the spread of the threat.

However, not all societies are equally successful in dealing with threats [5], raising the question of what factors are critical for fostering cooperation in such conditions. Here we focus on social norms, or unwritten rules for behavior, and argue that they play a *double-sided* role in the evolution of cooperation that is beneficial for the society. On the one hand, when an individual believes there is a cooperative norm in the society, the fear of social ostracism can effectively constrain them from free-rider behavior [6], [7]. On the other hand, social norms sometimes lead people to adopt maladaptive behaviors. For instance, teenagers may consume an excessive amount of alcohol or engage in irresponsible sexual behavior because they believe others endorse these behaviors [8], [9].

The strength of social norms and the pressure to conform to them further amplify the double-sided effect of social norms. Some societies have a *tighter* culture, wherein people feel more pressure to conform with the social norms while some other societies have a *looser* culture, where there is less pressure to conform [10]–[12]. If the social norm is a beneficial one, strong pressure to conform with the norm in a tight society amplifies adherence to it. However, if the norm is maladaptive, the strong pressure to conform to it may also lead to its widespread adaption, inhibiting the population from pursuing more beneficial behaviors. For example, [13], [14] compared the norm change in a tight vs. a loose society and found that when the majority of the population are given a choice to adopt a behavior that has higher economic value, the pressure to conform with the current norm hampers the norm change in a tight society. However, once the optimal behavior has become the norm, the pressure to conform with the new norm motivates people in a tight society to adopt the beneficial behavior very rapidly.

Therefore, cultural differences in tightness-looseness play a critical role in whether and how a society can effectively adopt a cooperative social norm and fight against an evolving threat. Indeed, a recent study has indicated that cultural tightness is associated with early success in dealing with the COVID-19 pandemic threat. With an agent-based model, [5] indicated that the conformity pressure in a tight society is helpful for the forming of a cooperative norm especially under medium to high levels of threat, while it is not as needed under low levels of threat.

Although [5] has revealed the role of cultural tightness-looseness in the evolution of cooperative norms under threat, it has some limitations in its model framework. First, in the model in [5], the threat in the environment increases at a constant speed and this speed is independent of people's cooperative behavior. This assumption, however, is not always realistic. In many situations, cooperative behavior may help slow down the growth of threat or even decrease the level of

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threat. For example, practicing social distancing helps flatten the curve in a pandemic [15], and reducing one's carbon footprint helps alleviate climate change [16]. It is important to take into consideration the impact of cooperation on threat to the extent this may be one of the reasons that lead different societies to have different levels of threat.

Second, [5] assumes that threat increases linearly as a function of time. However, many threats, such as a pandemic threat like COVID-19, escalate exponentially. They increase at a low speed at the beginning but start to increase dramatically after some time. It is important to take this non-linear nature of threat escalation into account because in an exponentially increasing threat, the timing of interventions is important. If a society fails to take rapid and intense enough actions to reduce threat at an early stage, they may miss the best timing to control it [17]. [5] showed that although a tight society tends to have more cooperation than a loose society, this difference is not pronounced until threat increases to a medium-to-high level. Moreover, [5] found that when threat is low, tight societies may have even less cooperation than loose societies because the people in them may conform to a wrong norm (i.e., defective norm). In this case, a tight vs. loose society may have very different trajectories of threat escalation and thus have different levels of threat eventually. Therefore, accounting for the nonlinear increase of threat and the dynamic influence of cooperative behaviors on the rates of change of threat is essential for understanding how tight vs. loose societies may be differently successful in their collective fight against threat. The different trajectories of threat change, consequently, will have further effects on the cooperative norms in different societies [18]. Thus, we are interested in how the levels of threat and cooperative norms *co-evolve* in different societies.

Using an agent-based evolutionary game theoretic (EGT) model, this paper combines previous work on social norms, cooperation, and threat, and aims to understand the following questions: 1) Under an escalating threat where collective cooperation can help slow down the escalation of threat, how will cooperative norms change in tight vs. loose societies? 2) How will the threat levels change in tight vs. loose societies as a consequence of their different cooperative norms?

This paper will be based on the model in [5] but will expand it by assuming a dynamic threat, the increasing rate of which varies as a function of the evolving cooperation rate in the population. Specifically, we assume that the more people cooperate in the population, the slower the threat increases. If everyone in the population is practicing a cooperative norm, the rate-of-increase of threat will be very low, or may even be negative. On the other hand, if few people cooperate, the rate-of-increase will be high. We run multiple simulations in which people (i.e., agents) play cooperation games with each other in societies with different levels of conformity pressure. In all the simulations, threat starts at a very low level but dynamically changes across time depending on the proportion of cooperative behavior that agents perform in their cooperation games (i.e., cooperation rate). We compare the cooperation rates and the trajectories of threat escalation in these societies in order to study the impact of cultural tightness-looseness on the evolution of cooperative norms under threat as well as how the levels of threat change as a consequence of the change in cooperative norms.

II. Methods

A. An Introduction to EGT

In this paper, we use an agent-based EGT simulation model to address the research questions. An EGT model is an application of population dynamical methods to game theory. It was introduced by evolutionary biologists but has been increasingly used to model the evolution of human behavior [19]. A typical process of an agent-based EGT simulation is as follows: A population of agents start with some assigned strategies. In each iteration, agents will interact with each other in a formal game, such as a cooperation game. Agents' actions in the game will be decided by their strategies and they will get their corresponding payoffs from the game. The game's payoffs represent the individuals' evolutionary fitness–as with natural selection in biological evolution, in each generation, some agents die and some agents are born, but agents with higher fitness are more likely to reproduce their strategies to the next generation. By repeating the game iterations (i.e., generations), we will be able to observe the evolutionary trajectories of different strategies and thus understand the change of behaviors in the population. An EGT simulation also allows us to manipulate the characteristics of the interaction environment, such as changing the threat and conformity pressure in the environment [18]. Thus, we will be able to observe how different behaviors evolve under different environmental circumstances.

B. Agent Interaction and Strategy Updating

In our EGT model, we start a simulation with 400 agents embedded in a 20×20 wrap-around grid. An agent has either a *cooperate* or *defect* strategy, with both strategies being equally likely at the beginning of the simulation. Then the simulation repetitively performs the following steps as in [5]:

1) *Immigration*: At a randomly chosen empty site in the grid, if there is any, an agent with a random strategy appears.[1]

2) *Interaction*: Agents play a typical cooperation game with all their immediate neighbors on the grid and get payoffs from the interactions, as shown in Table I. All the pairs in the grid play the game in a random order.

TABLE I
Payoff Matrix of the Cooperation Game

	Cooperate	**Defect**
Cooperate	(2, 2)	(-1, 3)
Defect	(3, -1)	(0, 0)

In addition to this *interaction payoff*, agents also receive a *base payoff* from the environment. The level of threat is

[1]At the beginning of a simulation, there is no empty site. However, there will be some empty sites as the simulation goes on because of Step 4.

manipulated as a reduction of τ from everyone's payoff, as in [18]. Thus, the final payoff of an agent, π, is as defined in (1). The value of threat τ dynamically changes depending on the cooperation rate in the population, which will be elaborated in the next section.

$$\pi = \textit{base payoff} + \textit{interaction payoff} – \tau \tag{1}$$

This final payoff is transformed into an agent's fitness, $f(\pi)$, based on the principle of diminishing marginal utility [20], [21] as shown in (2):

$$f(\pi) = \begin{cases} 1 - e^{-0.1 \cdot \pi} & \text{if } \pi \geq 0; \\ 0 & \text{if } \pi < 0. \end{cases} \tag{2}$$

3) *Reproduction*: Each agent is chosen in a random order and given a chance to reproduce with a probability equal to its fitness $f(\pi)$. Reproduction means creating an offspring agent in a randomly selected adjacent neighboring empty site, if there is any. This offspring usually has the same strategy as their parent agent but with a small probability $\mu = 0.05$, this offspring's strategy will be randomly set as either "cooperate" or "defect", resembling the mutation dynamics in evolution.

4) *Death*: Each agent has a probability d to die. The death probability d of an agent is a function of its fitness, $f(\pi)$, as defined by (3). The lower one's fitness is, the higher probably this agent will die. A dead agent will be removed from the grid, leaving an empty site until a new-born agent takes the place.

$$d = \mathrm{e}^{-2.3 \cdot f(\pi)} \tag{3}$$

5) *Conform*: Each agent has a probability of l to conform to the modal strategy in their neighborhood, independent of the fitness of the strategies. This process resembles the conformity pressure in a society. A larger l represents a tighter society which has greater conformity pressure. The neighborhood of an agent is defined as the eight grid sites that located around the agent. If there are equal numbers of cooperators and defectors in the neighborhood, the agent randomly selects from the multiple modal strategies to adopt.

We ran the above five steps repeatedly for 15000 iterations in each simulation run.

C. Change of Threat

We manipulate the level of threat τ in the environment based on the assumption that cooperative behavior in the population influences the rate of change of threat. The level of threat starts from a low level $\tau_0 = 5$ and changes stepwise every 500 iterations. For example, the first time that threat changes is when Iteration = 500, the second time that threat changes is when Iteration = 1000, and the last time that threat changes is when Iteration = 14500. At each changing time, the new level of threat can be represented by (4) and (5):

$$\tau_{i+1} = \tau_i \cdot (1 + \delta_i) \tag{4}$$

$$\delta_i = \frac{\delta_{max} - \delta_{min}}{\ln 2} \cdot \ln(2 - \kappa_i) + \delta_{min} \tag{5}$$

τ_i denotes the threat level at the current time. τ_{i+1} denotes the new level of threat throughout the following 500 iterations. The rate of change of threat, δ_i, varies as a function of the cooperation rate κ_i at the moment, where $0 < \kappa_i < 1$. (5) is a monotonic decreasing function depicting that when the cooperation rate is higher in the population, the rate of change of threat is lower. We choose a concave function between κ_i and δ_i based on the assumption that as more and more people start to cooperate, the impact of cooperation proliferates. However, we will show the robustness of our findings using a linear function between κ_i and δ_i, too.

δ_{max} and δ_{min} are constants. δ_{max} is a positive number, representing the maximum rate of change of threat. $\delta_i = \delta_{max}$ when $\kappa_i = 0$. This set-up depicts that if no one in the population cooperates at the current moment, threat will increase at its maximum rate. In all the simulations, we set $\delta_{max} = 0.1$. δ_{min}, which is smaller than δ_{max}, represents the minimum rate of change of threat. $\delta_i = \delta_{min}$ when $\kappa_i = 1$. This set-up depicts that if everyone in the population cooperates at the current moment, threat will change at its minimum rate. δ_{min} can be either a positive or a negative number. If δ_{min} is negative, it depicts the situation where if everyone cooperates, they will be able to decrease the level of threat. If δ_{min} is positive, it depicts the situation where even if everyone cooperates, the threat will still escalate, just at a lower rate. This depicts the situations where mass cooperation can only help slow down the escalation of a very severe threat but not fully stop or reduce it. We will try different values of δ_{min} in different simulations, which will be elaborated in the next section.

D. Key Variables and Simulation Runs

There are two key variables in this model. The first one is cultural tightness-looseness, which is manipulated by the different levels of conformity pressure l. In this paper, we implemented a number of cultural tightness-looseness values, $l = [0.05, 0.1, 0.15, 0.2, 0.3]$.

The second variable is the type of threat, which is manipulated by δ_{min}. We implemented two different values of δ_{min}. One is positive and the other is negative, $\delta_{min} = [-0.01, 0.01]$. When $\delta_{min} = -0.01$, it depicts a reversible threat where when everyone cooperates, threat will *decrease* by 1% per 500 iterations. When $\delta_{min} = 0.01$, it depicts an ever-increasing threat where even if everyone cooperates, the threat still *increases* by 1%. Under this ever-increasing threat, full cooperation in the population can only slow down the escalating of threat, but not stop it.

For both types of threat, we ran 40 simulation runs under each level of cultural tightness-looseness. Therefore, we have $40 \times 2 \times 5 = 400$ simulation runs in total. Each simulation contains 15000 iterations. In each simulation, we track the proportion of cooperative behavior and the level of threat at each time point, so that we can track the trajectories of the evolution of cooperative behavior and threat growth in different societies.[2]

III. Results

A. Overall Cooperation Rates and Threat Growth

Fig. 1 shows the change of cooperation rates and threat across time in societies with different levels of tightness-looseness. A larger l represents a tighter society. Each line depicts the average of 40 simulation runs. Our results support the findings of [5]. The overall cooperation rates are low at the early stage of a threat but increase as threat escalates. Tighter societies switch to a cooperative norm earlier than looser societies, and ultimately, cooperation rates are higher in tighter societies. Moreover, tighter societies overall have lower levels of threat as time passes.

B. Two Patterns Among Tight Societies

As noted above, conformity pressures may play a double-sided role in the adoption of cooperative norms. [5] has indicated that when threat is low, tight societies may show two different patterns of trajectories of cooperative behavior, wherein they may either be highly cooperative or highly defective at the early stage of a threat, depending on which norm they randomly conform to early on. As a consequence, the two kinds of tight societies may show very different patterns in their trajectories of threat change, too.

To address this, in the 40 simulation runs under each level of tightness, we separated the single simulation runs which have a cooperative norm at the beginning from the runs which have a defective norm at the beginning. The criterion is as follows: in a single simulation run, if the average cooperation rate among the first 10000 iterations is above or equal to 0.5, this run is categorized as having a cooperative norm at the beginning. If the average cooperation rate among the first 10000 iterations is below 0.5, this run is categorized as having a defective norm at the beginning.

Table II shows the number of runs with cooperative vs. defective norms at the beginning of the simulations under each condition. When tightness level is low (l = 0.05 or 0.1), all of the single runs have a defective norm at the beginning. However, when tightness level is high, some of the single runs have a cooperative norm while the others have a defective norm at the beginning.

TABLE II
Number of Runs with Cooperative vs. Defective Norms

l	$\delta_{min} = 0.01$		$\delta_{min} = -0.01$	
	Cooperative	*Defective*	*Cooperative*	*Defective*
0.05	0	40	0	40
0.1	0	40	0	40
0.15	8	32	9	31
0.2	12	28	13	27
0.3	17	23	19	21

[2]All the codes for the simulations are available at https://osf.io/enxum/?view_only=091870735c80491b85ce814e4ee1d5a5

C. Cooperation Rates and Threat Growth in Tight vs. Loose Societies

We averaged the two kinds of runs among tight societies separately. In Fig. 2, the yellow line depicts the average of the simulation runs with a cooperative norm at the beginning in a tight society, where $l = 0.2$ (Tight-C). The red line depicts the average of the simulation runs with a defective social norm at the beginning (Tight-D). The shadows depict the standard deviations of these runs.

Fig. 2 also compares the cooperation rates and threat levels in these two kinds of tight societies with a loose society ($l = 0.05$). In the loose society, all the simulation runs have a defective norm at the beginning, so the average of them is represented by a single blue line.

In the Tight-C society, the cooperation rate is always high throughout the simulation. The Tight-D society has the lowest cooperation rate at the early stage, but as threat escalates to a moderate level, it quickly switches to a cooperative norm. The loose society starts with a moderate cooperation rate and eventually switches to a highly cooperative norm too, but the switch happens much later than the Tight-D society.

For the change of threat, the Tight-C society always has the lowest threat level. For an ever-increasing threat ($\delta_{min} = 0.01$) as shown on the left of Fig. 2, the threat level in the Tight-D society first increases fast and is higher than that in the loose society. However, as the Tight-D society starts to switch to a cooperative norm, the escalation of threat slows down and the threat level in the Tight-D society eventually gets closer to that in the loose society. Note that at the late stage, the cooperation rates in both Tight-D and loose societies fall to around 0.5 and become noisy. This is because the threat levels are very high at this point, and the majority of the population dies out at the end of this ever-increasing threat. For a reversible threat ($\delta_{min} = -0.01$) as shown on the right of Fig. 2, the threat level in the Tight-D society is the highest at the beginning, but as they switch to a cooperative norm, the escalation of threat is well controlled. On the contrary, in the loose society, though it has a relatively low threat at the beginning, because it fails to switch to a cooperative norm timely, the threat ends up the highest among the three kinds of societies.

In Fig. 2, we use the plots under $l = 0.05$ and $l = 0.2$ as examples for loose and tight societies. Other values of l generally show similar patterns. We also tested the robustness of the findings by replacing (5) with a linear function between cooperation rate κ_i and the rate of change of threat δ_i, as shown in (6). The findings remain robust.

$$\delta_i = \kappa_i \cdot \delta_{min} + (1 - \kappa_i) \cdot \delta_{max} \tag{6}$$

IV. Discussion

Cultural differences in conformity pressures play a critical role in whether and how a society can effectively adopt a cooperative norm and fight against an evolving threat. Using an agent-based EGT model, our results show that overall, under an evolving threat, tight societies with stronger conformity pressures adopt a cooperative norm faster than loose societies.

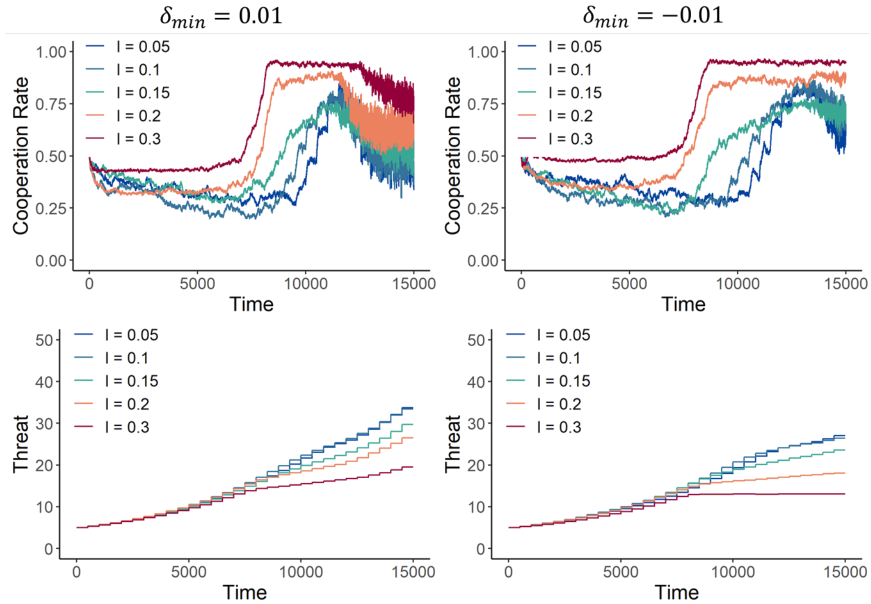

Fig. 1. Trajectories of cooperation rates and threat growth in different societies.

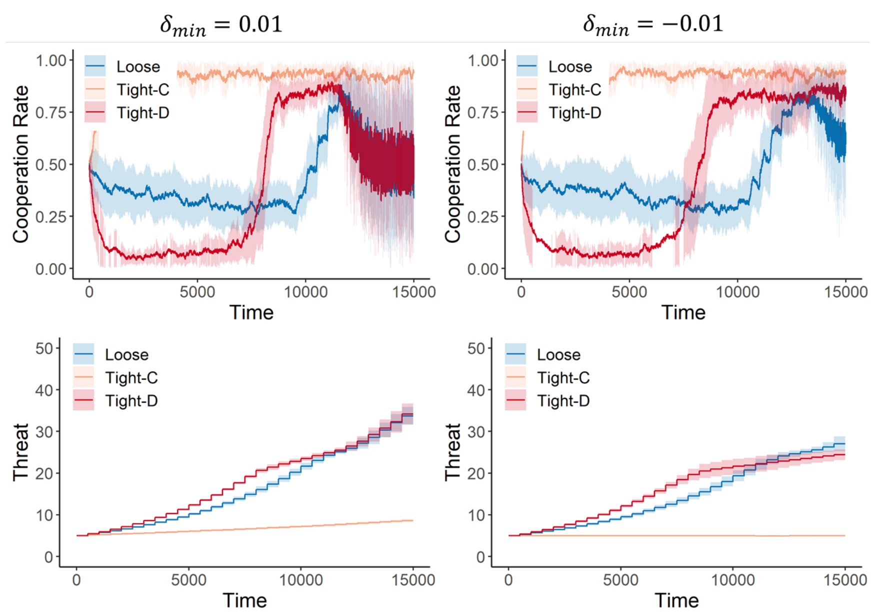

Fig. 2. Trajectories of cooperation rates and threat growth in tight vs. loose societies. Each line is the average trajectory of multiple runs. The shadows show standard deviations. In the tight societies, $l = 0.2$. In the loose society, $l = 0.05$.

As a consequence, in general, the threat ends up lower in tight societies. However, we also show that the high conformity pressures in tight societies is a double-sided sword especially at the early stage of threat. Sometimes, a tight society may conform to a defective norm at the beginning of a threat, which leads to a faster escalation of threat at the beginning. Nevertheless, as threat increases, tight societies are able to switch to a cooperative norm quickly and slow down the growth of threat, so eventually the threat levels in tight societies are close to or lower than those in loose societies. Our findings bring insight into how cultural differences in conformity pressures influence different societies' success in dealing with collective threats.

We note that our model has several limitations. First, our model is based on the assumption that cooperation among population helps slow down threat growth or reduce threat. In some cases, this is a justified assumption. For example, practicing social distancing helps flatten the curve in a pandemic [15]. However, in some other cases, this assumption may not be justified. Our model is not applicable for the situations where cooperation does not have a clear impact on threat. Second, we assume an exponentially increasing threat. We note that not all kinds of threats in the real world increase in this way. Third, in our model, we assume that cooperation rate is the only factor that influences changes in the rate of threat. This is obviously not necessarily realistic. In the real world, factors such as new technologies, vaccine, governmental interventions, changes in climate, availability of resources, etc., can all have substantial impacts on the trajectories of threat growth. These factors may interact with cultural tightness-looseness and cooperative norms, but this is beyond the scope of this paper. Finally, as any simulation work, this model is an oversimplification of the real world. The set-ups in this model, such as the manipulation of threat and the cooperation game, are highly abstract. We don't intend to represent any specific threat or behavior in real life. Neither do we intend to predict the threat change in any specific society. Validation with empirical data is needed if future research wants to compare the findings of this paper with real world phenomena.

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