Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Evolution of altruistic punishments among heterogeneous conditional cooperators

Balaraju Battu (Balaraju.Battu@eui.eu)
European University Institute

Research Article

Keywords: evolution, altruistic punishments, conditional cooperators

Posted Date: March 10th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-224808/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Version of Record: A version of this preprint was published on May 18th, 2021. See the published version at https://doi.org/10.1038/s41598-021-89563-z.

Evolution of altruistic punishments among heterogeneous conditional cooperators

Balaraju Battu
Department of Political and Social Sciences
European University Institute, Florence, Italy

&

Centre of Behavioural and Cognitive Sciences
University of Allahabad, Allahabad, India

Address correspondence to:
Balaraju Battu, Department of Political and Social Sciences, European University Institute, 50014 San Domenico di Fisole, Italy. Email: Balaraju.Battu@eui.eu & bala@cbcs.ac.in

Abstract

Although altruistic punishments solve the free rider problem in repeated public good games, it has been a puzzle why altruistic punishers willing to incur personal costs in order to improve the group benefits. It has been shown that when the population consists of a finite set of pure strategies along with altruistic punishers, altruistic punishments evolve in the population. These models the population consists of a finite set of strategies and the strategies do not depend on the past strategies of the population. Unlike assumptions made in these models, the population is heterogeneous in their conditional cooperative strategies and the individuals who are more willing to donate also are more willing to punish the free riders. I propose an evolutionary agent-based model, each agent's donation depends on the difference between the number of donations in the past and the threshold value and a propensity value. Altruistic punishment depends on the difference between the threshold value of altruistic punisher and random matched another agent. The proposed model overcomes the unrealistic assumptions made in the previous models and altruistic punishments evolve for a large set of parameters. The simulations show that, for certain inflicted costs of punishments, generous altruistic punishments evolve in the population and establish stable cooperation. The conditional nature of cooperation implies that, unlike previous models, it is not necessary to punish all free riders equally, but it is necessary to do so in the case of the selfish free riders but not in the case of negative reciprocators.

Introduction

Unlike other species, humans cooperate with genetically unrelated individuals, even if these are individuals they had never met in the past. In the literature several mechanisms have been proposed to understand suitable conditions to establish cooperation in dyadic interactions[1]. The mechanism focuses on the conditions required to offset the current cost of cooperation with future obtainable benefits. Unlike, dyadic interactions, in public good provision, an individual incurs personal costs by contributing to the public good and the benefits are diffused among the group members because public goods are 'non-excludable,' i.e., each individual can share them equally, irrespective of their contributions. Contrary to the assumptions of standard economic theory, laboratory[2–4] and field studies[5] suggest that, in repeated public good games, the majority of the population willing to punish the free riders, even at incurring substantial personal costs[6]. Remarkably, the punishments are implemented even if the interactions are anonymous, with no gain in personal payoff and reputation[4]. Neurobiological studies show that altruistic punishment has been linked to the reward centers of the brain, suggesting that in the past such behavior was rewarded and evolved in populations[7]. An individual incurs personal costs by punishing free riders and the benefits are diffused. The free riders gain relatively higher payoff than the punishing individuals. In evolutionary biology costs and benefits are measured in terms of fitness; altruistic punisher reduces his/her fitness in order to improve the group's fitness. Why altruistic punishments proliferate in human societies has been an evolutionary puzzle because natural selection supposes to favor free riding rather than costly punishments.

How to explain the evolutionary emergence of altruistic punishment, two important class of models have been proposed based on group selection[8–10] and individual selection[11] to explain altruistic punishments in public good settings. The group selection models have shown that in certain conditions altruistic punishment do evolve and evolutionarily stable when the punishment is common but does not explain how the altruistic punishment emerges within the group or when individual selection operates within the group. To explain altruistic punishments within the group, an individual selection model has been proposed. It has been shown that when the population consists of altruists, unconditional defectors or free riders, non-participants, and altruistic punishers, the altruistic punishers dominate the population. The two approaches ignore conditional nature of cooperation observed in many social dilemma[12] and the models suffer from the following considerations. In both the models, the behaviour of individuals does not depend on the past behaviour of other individuals in their groups, or the strategies not interdependent. These assumptions are odd with the behavioural regularities observed in experimental repeated public goods games[13,14] and field studies,[125] which suggest that individuals actions are interdependent and the individuals in the population behave like conditional cooperators and the population is heterogeneous in their conditional nature[13,1514]. Further, there are no separate altruists and altruistic punishers and the individuals who are more willing to donate to the public good are also more willing to punish the free riders[2,12] or are involved in costly monitoring of them[5]. Considering the prehistory of humans, a strategy like nonparticipation is not a reasonable assumption, rather a theoretical convention to achieve cooperation. Clearly, the assumption made in the existing models is far from the reality, therefore these models do not explain the evolution of altruistic punishments in the population of heterogeneous conditional cooperators.

I propose a third explanation that does not suffer from the assumptions made in the previous individual and group selection models. By considering the behavioural regularities observed in repeated public good games in the field and experimental settings, I propose an evolutionary agent-based model with a population of heterogeneous conditional cooperators. Unlike the previous models[9–11,16], in the proposed model, (*a*) the majority of the population behave like conditional cooperators, (*b*) the more individuals willing to donate are also willing to punish free riders, and (*c*) the population is heterogeneous[141215175]. The proposed model involves three stages: individuals or agents make donations occasionally to public good game according to their conditional cooperative strategies, after a couple rounds of the game, reciprocators potentially punish the potential free riders, and agents imitate successful role models' social behavior. In all three stages agents may commit mistakes. Whenever an agent donates, the agent incurs certain cost and whenever an agent is punished the agent incurs inflected cost and inflected cost is more than the cost of altruistic punishment. The simulations show that populations of heterogeneous conditional cooperators establish high levels of cooperation in repeated public good games and the altruistic punishers dominate the population for certain inflected costs. The cooperation is stable against occasional mutations in the population. Further, for certain inflected costs, evolution favors generous altruistic punishment strategies than strict punishment strategies, i.e., agents punish the occasional free riders with less frequently and the selfish free riders with high frequency.

Method

The above developed intuition is converted into an agent-based evolutionary model in the context of public goods provision. In the proposed evolutionary agent-based model[18], all the agents play a linear public goods game by using conditional cooperative strategies, enforcing altruistic punishments based on relative differences in their cooperation tendencies, and imitating successful role models' social behavior with certain errors. The process is iterated several thousands of generations.

Population type

In the previous models, population consists of finite set of discrete strategies and the strategies do not depend on the past strategies of the population, whereas experimental and field studies suggest that in repeated public good games, the strategies of individuals are interdependent; individuals in the population behave like conditional cooperators and the population is heterogeneous. In the proposed model, the individuals in the population behave like conditional cooperators. The individuals may commit mistakes in their donations and altruistic punishments and the population is heterogeneous. Further, individuals do not punish other individuals only based on previous immediate free riding but punish based on frequency of free riding. In the proposed model, there are no strategies like loners and separate altruistic punishes, free riders, and altruists.

The population consists of heterogeneous conditional cooperators. Each individual born with an arbitrary conditional cooperative criterion (CCC) and a propensity, β. Both are positive values. Each agent's CCC value is drawn from a uniform distribution (0, N), where N is the population size, and β is drawn from a uniform distribution (0, 3). With β =0 the actions of the individuals is random and with β = 3 the individuals behave like ideal conditional cooperator. Intermediate values the individuals behave like non-ideal conditional cooperators. The consideration is equal to the natural selection designing the conditional cooperative strategies. The combinations of CCC and β create heterogeneous populations with varieties of propensities. The consideration is close to the conditional nature of population observed in experimental settings[5,14].

Conditional cooperative decision

The conditional cooperative decision of the agent is operationalized in the following way[19,20]. For instance, in the r^{th} round, an agent i (with CCC = CCC_i value) donates to the public goods with probability, q_d,

$$q_d = \frac{1}{1+\exp\left(-(n_C - CCC_i)\times\beta_i\right)} \quad (1)$$

n_C indicates the number of donations in the $(r\text{-}1)^{th}$ round. The parameter β_i controls the steepness of the probability function. For the higher β_i, the agent is highly sensitive to the (n_C-CCC_i). For instance, as $\beta_i \to \infty$, the q_d is sensitive to the sign of the (n_C-CCC_i), i.e., if (n_C-CCC_i)> 0 then q_d =1 and if (n_C-CCC_i)< 0 then q_d =0. Either with (n_C-CCC_i) = 0 or with β_i=0 and both are zero, the agent donates to PGG with 50% time. In the model $0<\beta_i< 3$. With $\beta_i >2$, the agent is more sensitive to the conditional rule. For β_i = 0, the agent ignores the rule and behaves randomly. In β_i <2 and (n_C-CCC_i)<2 the individual does not follow the conditional rule, occasionally. In this construction both agents with the same *CCC* value may act differently with different β_i values. For example, an agent with n_C = 25, CCC_i = *24,* and β_i >2 donates with probability close to one and β_i < 2, donates with the probability less than one. With a non-zero amount of cooperation in the zeroth round, very low CCC value agents potentially behave like altruists, middle CCC value agents behave like conditional cooperators and very high CCC value agents behave like free riders. In the model the population and the conditional cooperators are heterogeneous. The assumption is similar to the experimental and field observations in repeated public goods[2,5,12,21].

Public goods game

In the first round of linear PGG[12], each agent is given an initial endowment *E* and individuals potentially donate an amount u_i by using eq.1. After all the individuals make their decisions, the collective amount is enhanced by a factor (α >1) and the resulting public goods are distributed equally among all the agents, irrespective of their contributions towards public accounts. After each round of PGG, the agent's total payoff from the linear public goods game is

$$\pi_G = (E - u_i) + \frac{\alpha}{N}\left(\sum_{i=1}^{N} u_i\right), \; i = 1, 2, 3, \dots . N, \alpha > 1, \frac{\alpha}{N} < 1 \quad (2)$$

The first term $(E - u_i)$ indicates the payoff from what was not contributed to the public goods (the private payoff). The second term indicates payoff from the public goods. Each unit donated becomes worth $\alpha > 1$ unit. Due to the 'non-excludable' nature of public good, all the agents gain equal payoff from the public good game. Clearly, all the individuals by donating can create an efficient PGG and by free riding increase his/her private payoff but reduce the group's payoffs. Overall, the free riders gain relatively higher payoffs than the donors if the game starts with few initial donations. Given the same amount of cooperation level, the higher *CCC* agents donate less frequently and gain relatively higher payoffs than the payoffs of the lower *CCC* agents who donate more frequently.

Altruistic Punishments

The assumptions of the model allow the following two rules: (***i***) the agents who are more willing to donate are also more willing to punish[2,5,12]. (***ii)*** the agents punish the free riders more frequently than the occasional free riders[5,12]. The *CCC* value of an agent acts as a proxy measure of an individual's donation tendency and punishment tendency. The individuals enforce altruistic punishment based on relative CCC difference of randomly matched pairs. An agent *i* (with CCC_i) has the potential to punish another agent *j* (with CCC_j) with probability q_p.

$$q_p = \frac{1}{1+\exp\left(-(CCC_j - CCC_i)\times\beta_i\right)} \quad (3)$$

With $(CCC_j\text{-}CCC_i)>1$ and $\beta_i>2$ *or with* $(CCC_j\text{-}CCC_i)>2$ and $\beta_i>1$, the agent *i* punishes the agent *j* with high probability. With $(CCC_j\text{-}CCC_i)\times\beta_i<1$, the agent *i* punishes the agent *j* occasionally. In this construction, a lower CCC agent with $\beta>2$ punishes a higher CCC agent more accurately than a slightly lower CCC agent. A lower CCC agent with $\beta<2$ punishes a higher CCC agent less accurately and may not punish a slightly lower CCC agent. For example, in a random pair, with $(CCC_j\text{-}CCC_i)=1$ with $\beta_i>2$ agent *i* punishes the agent *j* with a high probability close to one and $\beta_i<2$ punishes rarely. Depending on the differences in CCC values and β many possibilities exist. The above considerations are different from the existing models of altruistic punishments[8,11] and close to the experimental observations in public goods provision[512]. In the population of heterogeneous conditional cooperators, the lower CCC agents donate and punish frequently, the moderate CCC agents occasionally free ride and punish, and very high CCC agents mostly free ride and do not punish.

Reproduction

After altruistic punishments, each agent's total payoff equals to the sum of the payoff from the PGG and the potential costs incurred in imposing altruistic punishments (π_{alt}) and the cost paid if the punishment is received (π_{in}). For instance, i^{th} agent' payoff will be $\pi_i=\pi_G+\pi_{alt}+\pi_{in.}$ All the agents occasionally update their strategies by pairing another randomly matched agent and adapting the role model's strategy with a probability proportional to the payoff difference[22,23]. In terms of cultural evolution each individual imitates the successful agent's social behavior; all the agents update their CCC and β_i values simultaneously with certain mutations. The updating is done by the following procedure[24]. An agent *i* potentially imitates successful individual *j's* social behavior (*CCCj*) and β_i with probability, $q_{r,}$

$$q_r=\frac{1}{1+\exp\left(-(\pi_j-\pi_i)\times\beta_i\right)} \qquad (4)$$

Where $(\pi_j\text{-}\pi_i)$ is the cumulative payoff difference of agents *j* and *i* respectively. β_i is i^{th} agent's propensity, which controls the steepness of eq.4. An agent with a higher β_i more accurately imitates the social behavior of the role model. In each generation the population undergoes 10% mutations, i.e., each individual miscopies successful role models' properties with probability 0.1.

Simulations

In the simulations, the initial propensity (β) values are drawn from uniform distribution [1, 3] and CCC values are drawn from [1, *N*], where *N* is the population size =100. Agents enter into the PGG with the initial payoff (u) = 10 units. Each agent decides their donation by using a stochastic conditional decision rule, eq.1. The donation cost is 1 unit and the enhancing factor of the collected donation is $\alpha=3$ units. The total payoff of an agent is given by eq. 2. A generation consists of three rounds of PGG. After each generation, altruistic punishments were implemented and, subsequently, the population updates or reproduces by using eq.3 with 10% mutations.

Mutations are created by adding a random value, drawn from a Gaussian distribution with ***mean*** zero and ***s.d.***= 5 (max = 50 and min = −50). Each agent in the population miscopies role model properties with a probability 0.1. After updating by using eq. 4, a randomly drawn *CC*C value is added to the updated CCC value and a β value is replaced by a randomly drawn value from uniform distribution of (0, 3). If the updated *CCC* value is greater than *N*, it is rounded off to *N*; if the resultant

CCC value is negative, it is rounded off to zero. This allows the population to have unconditional free riders ($CCC = N$) and unconditional cooperators ($CCC = 0$).

To reduce individual trial variations, each experimental condition (a fixed set of parameters) is iterated 10 times and the average data is used to plot the results. We observed that there is no difference in the results after the first few thousand generations; therefore, we have plotted the results for the first 10,000 generations. We plotted the distribution of CCC and β values for different experimental conditions in the last 10,000th generation. We measured donation fractions, i.e., the fraction of donations in a specified number of generations. Asymptotic donation fractions are computed by taking donations in the last 1000 generations of the 10,000th generation. We computed the distribution of CCC of the population and β values, which indicates the composition of population (or strategies). In simulations, we kept the following parameters constant: the donation cost (u) =1, enhancing factor of collected donations (α) =3. The probability of altruistic punishments after each generation is designated by w. Simulations are performed with varies $w(w<1)$ and inflected costs. In the model, if the punishing cost is x, inflicted punishment cost will be $3x$.

Results

Agents starting with arbitrary CCC and β values, donating to public good by using eq.1, enforcing altruistic punishments using eq.2., and updating strategies using eq.4, for certain punishment costs, altruistic punishment evolved in the population. Evolution of altruistic punishments crucially depends on the inflected cost of the punishment and the opportunities given to the individuals to enforce punishments.

Figure 1 represents donation fractions (fraction of population donated to PGG) for various inflected costs across generations with $w = 1$ and $w = 0.5$. The donations are much higher with $w = 1$ than with $w = 0.5$ for the same inflected costs. With w=1, the donation fractions decline as the cost of the inflected punishment also declines.

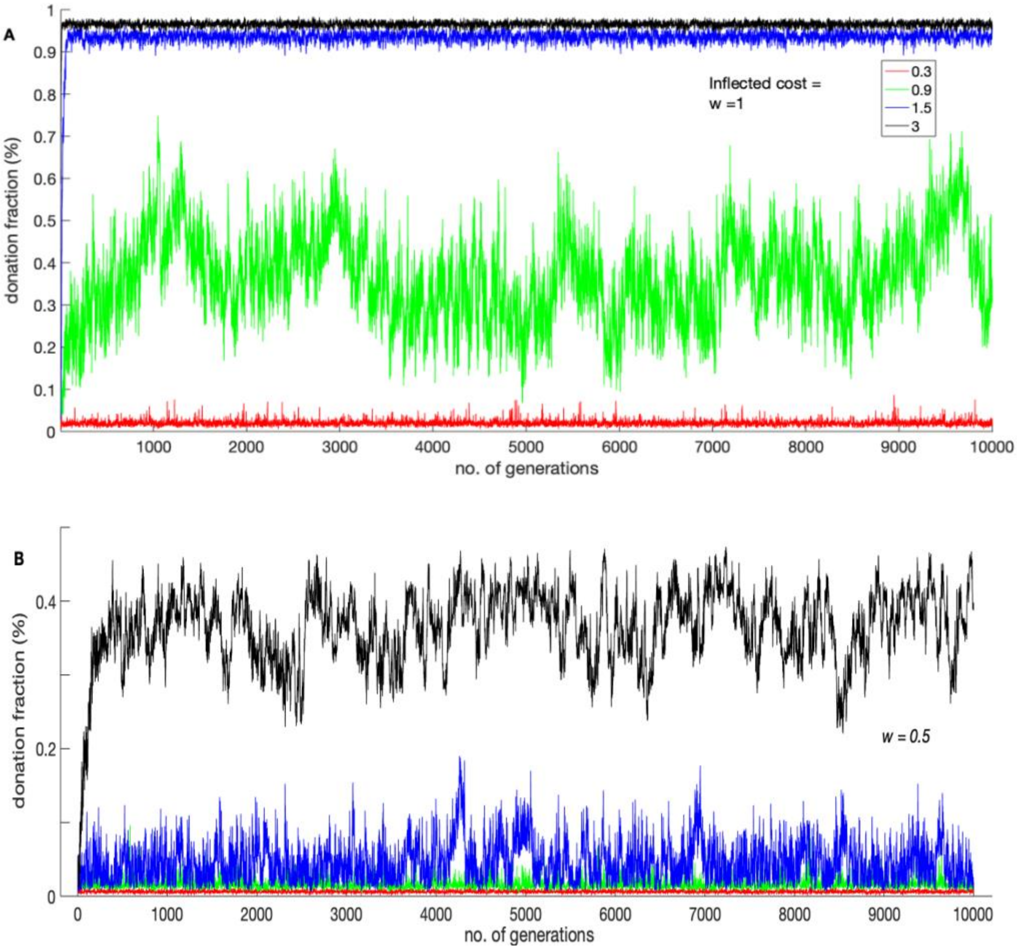

Figure 1. Donation rates for **A** (w) = 1 and for **B** (w) = 0.5 for various cost values for the first 10,000 generations.

In Figure 2, asymptotic donation rates are shown across different costs of inflected punishments with w =1(when the agents have been given more opportunities to punish after every few rounds) and with w = 0.5 (when the agents punish randomly) respectively. With w=1 the donation rates are higher after inflected cost > 0.9. With w=0.5, the donation fractions are higher only for higher inflected costs.

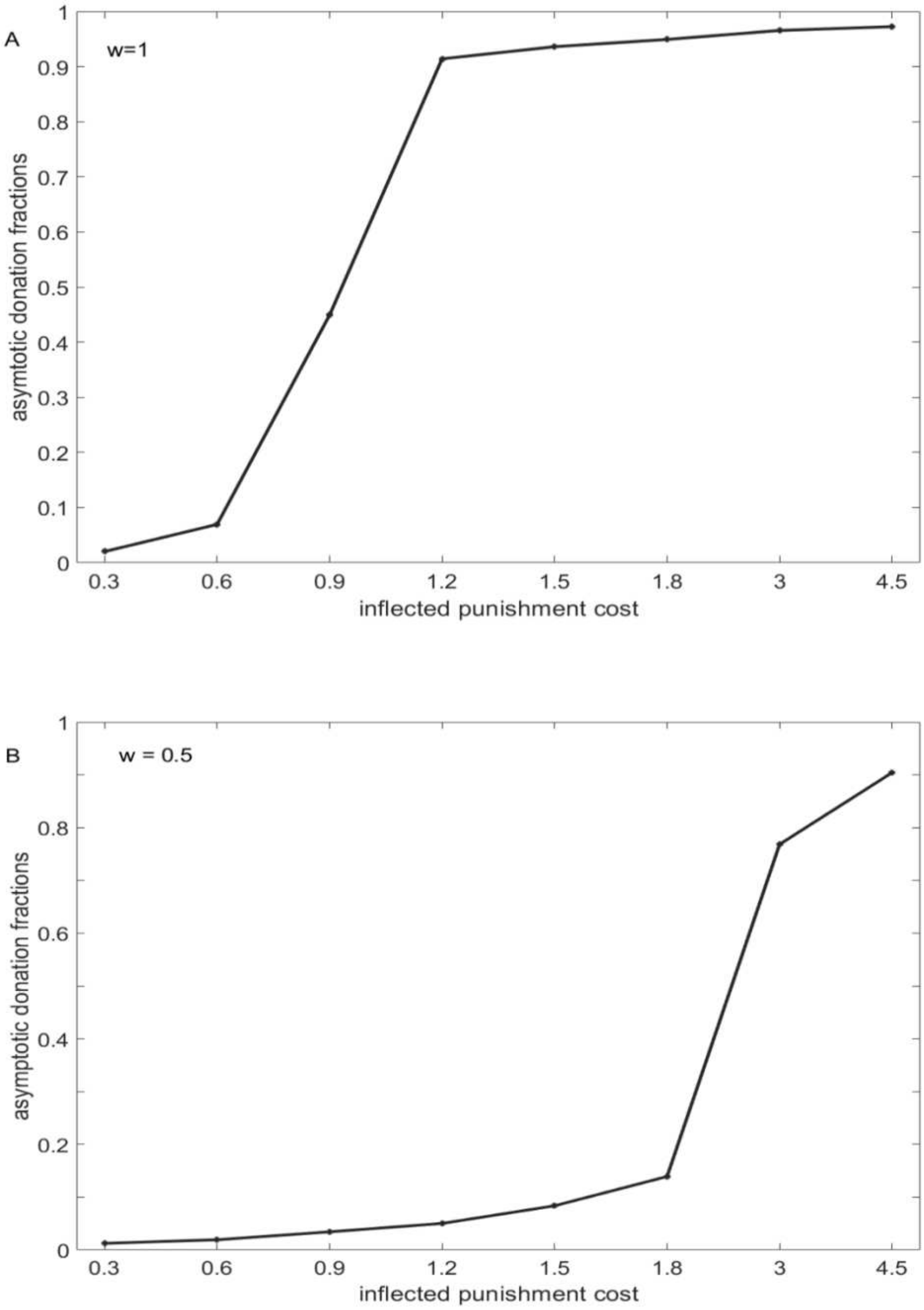

Figure 2. Asymptotic donations fractions of population with various punishment costs. Figure **A** (*w*) = 1 and Figure **B** (*w*) = 0.5.

In Figure 3, the distribution of CCC values of the population shown for various inflected costs. With *w* = 1 and with inflected cost =3, the frequency of punishments is high, therefore high CCC agents are penalized substantially. The higher CCC agents become extinct from the population because the score of these agents is lower than the mean population score and the population. As the generations increase, with cost = 3, the population moves towards lower CCC agents (mean =10.06) and, with inflected cost = 0.9, the population moves towards moderate CCC value agents (mean=24.23).

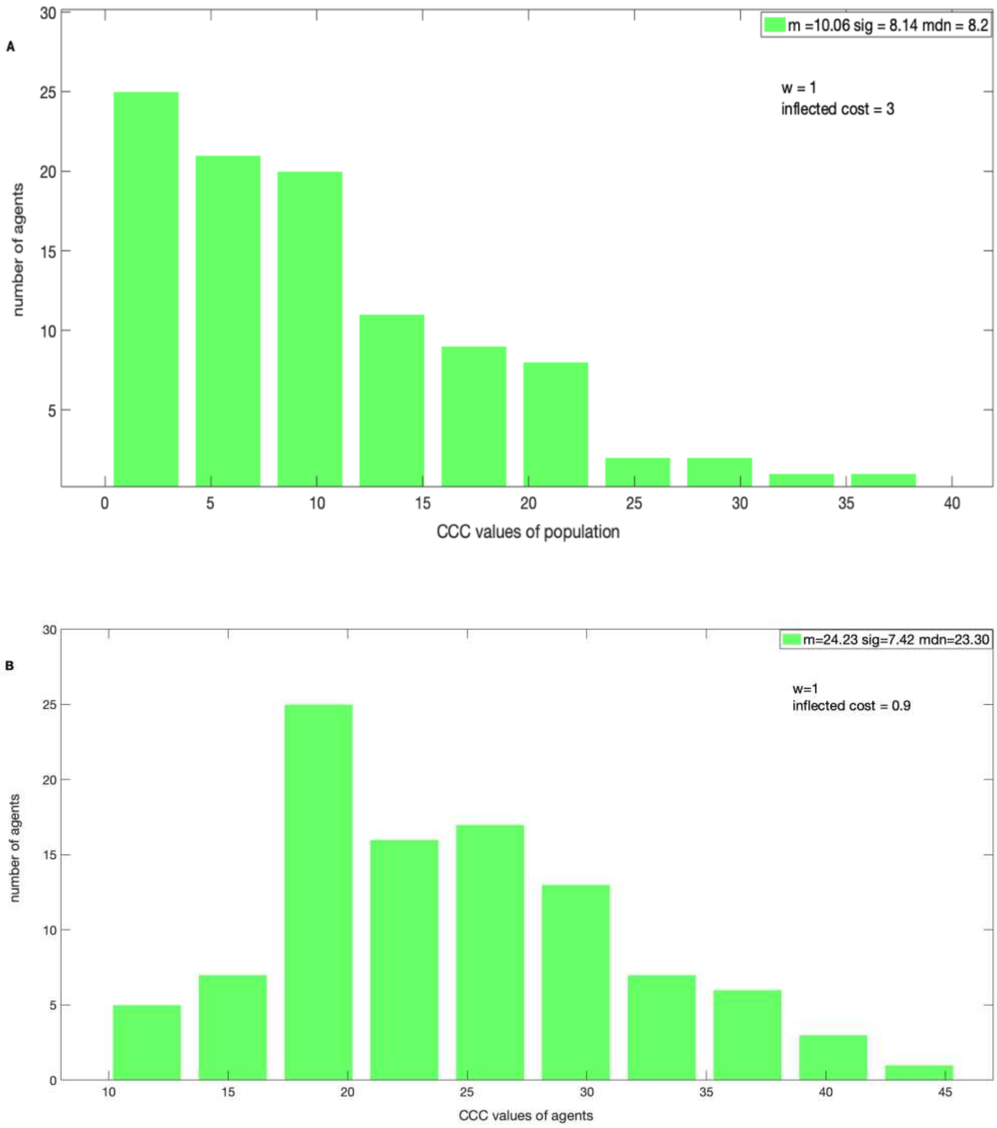

Figure 3. The distribution of CCC values in the 10,000th generation with a bin size of 10.
With *w* =1 Figure **A** (cost) = 3 and with **B** (cost) = 0.9.

In Figure 4, the distribution of CCC values of the population shown for various inflected costs. The results show that lower CCC agents proliferate in the population with higher inflected costs, these individuals not only donate to public good but also enforce altruistic punishments. The population remains heterogeneous.

With *w* = 0.5 and with inflected cost =3, the frequency of punishments is low, therefore high CCC agents are not penalized substantially thus, moderate CCC agents still remain in the population. The population moves towards moderate CCC agents (mean =17.75). With inflected cost = 0.9, the population moves towards larger CCC value agents (mean=32.81).

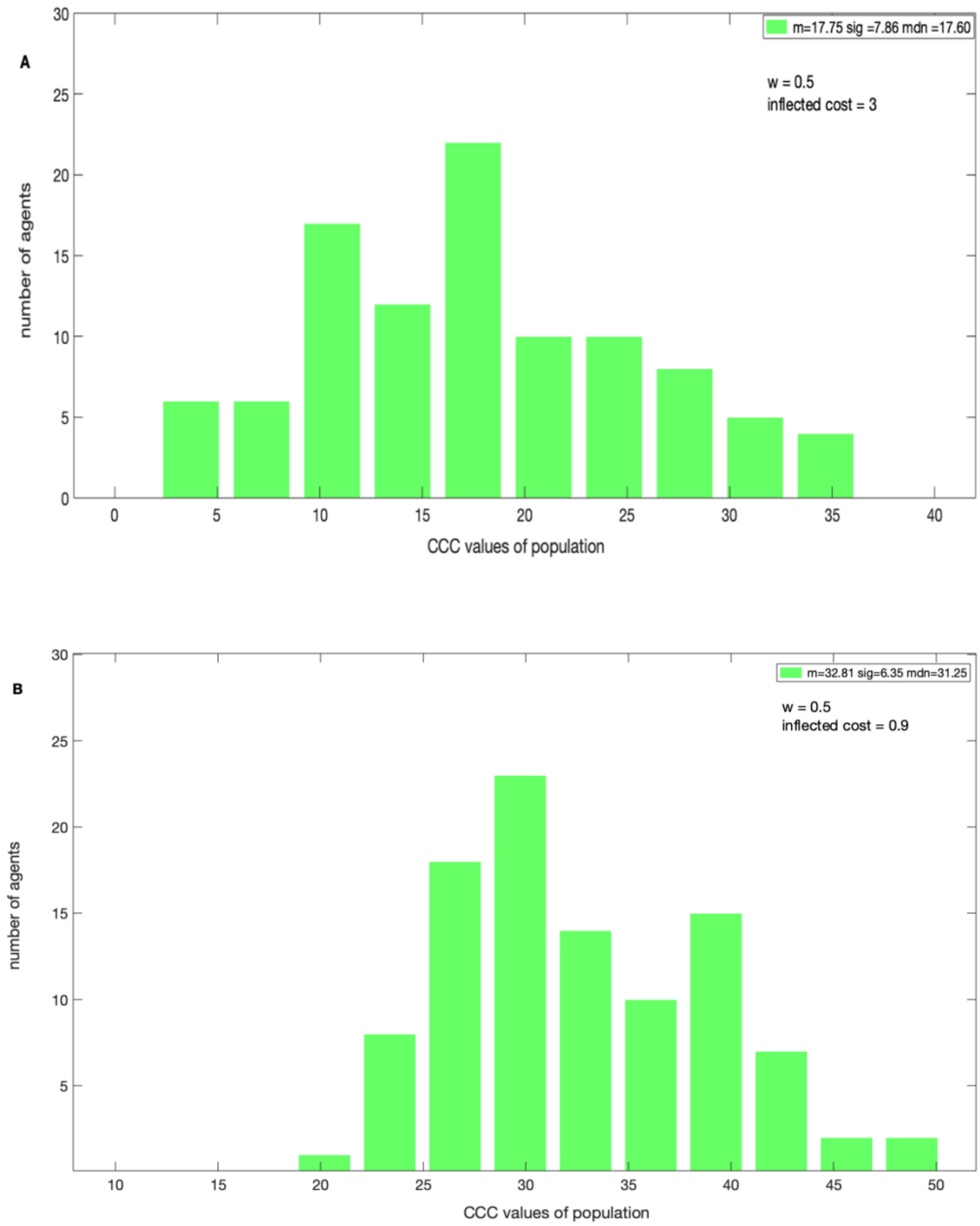

Figure 4. The distribution of CCC values in the 10,000th generation with a bin size of 10.
With w = 0.5 Figure **A** (cost) = 3 and with **B** (cost) = 0.9.

In Figure 5 the average β values of the population shown for various inflected costs with $w = 1$ and with $w = 0.5$. For higher inflected costs the average values of β decline, i.e., the population adapted to probabilistic donations and punishments. With $w = 0.5$, β values increase only for higher costs of inflected punishment; the population adapted relatively higher β values than in the previous condition.

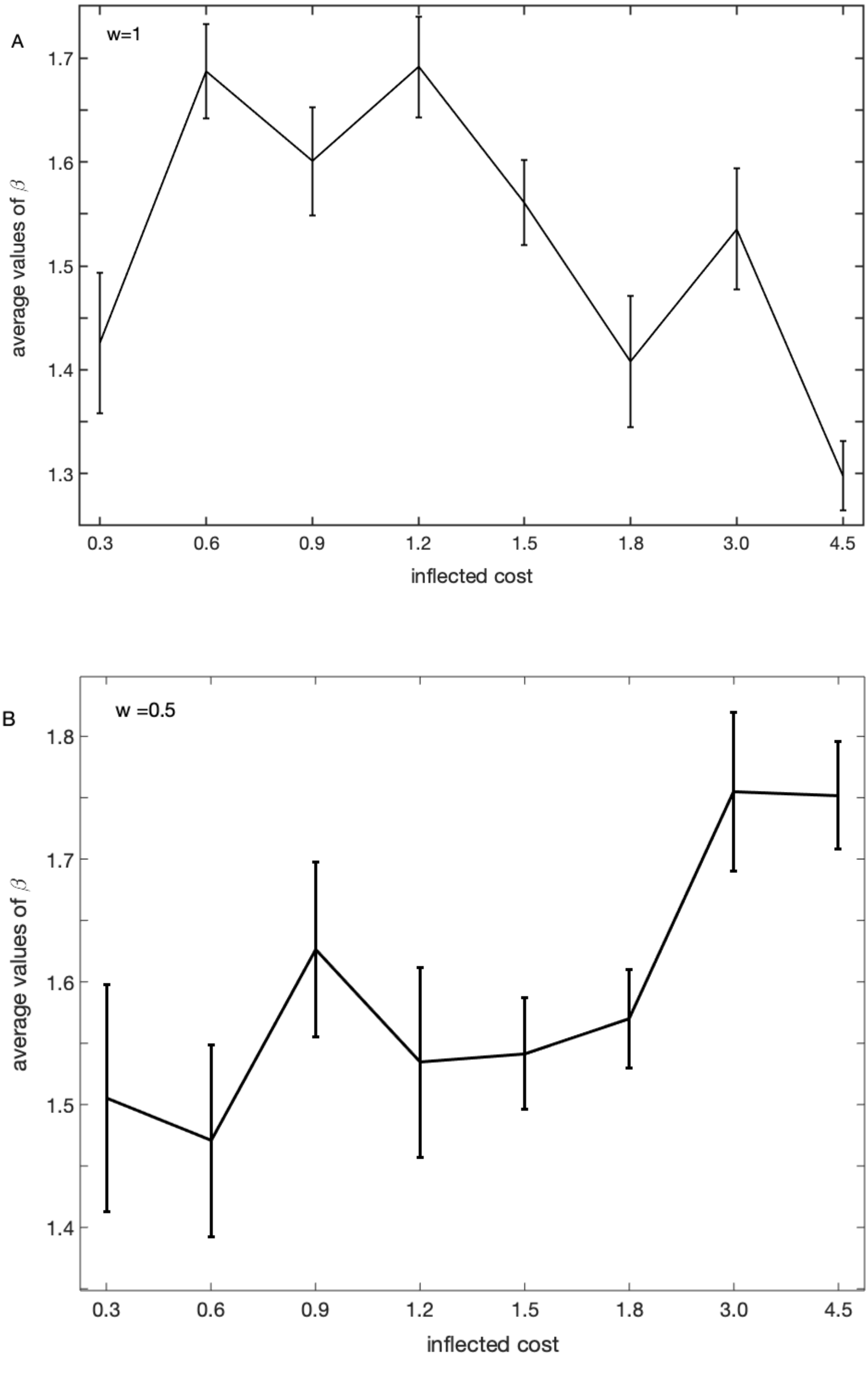

Figure 5. Population average β values for various costs in the 10,000th generation. **A** (*w*) = 1 and **B** (*w*) = 0.5.

Discussion

The results of the simulations show that a population starting with arbitrary conditional cooperative strategies, enforcing altruistic punishments based on relative differences in *CCC* values, and adapting successful role models' social behavior, altruistic punishments evolve in the population. The altruistic punishments establish stable and high levels of cooperation with certain inflected costs. Interestingly, certain infected costs, population adapted to generous altruistic punishment strategies. By using these strategies, the agents punishe selfish free riders frequently and punish occasional free riders or negative reciprocators less frequently. However, the evolution of generosity of the population crucially depends on the cost of altruistic punishment or inflicted punishments and the opportunities given to the population to enforce altruistic punishments. The recognition that conditional cooperators are adapting to generous altruistic punishments rather than strict altruistic punishments has important consequences in enforcing altruistic punishments [12525] and in understanding the evolution of altruistic punishments in social dilemmas[2,3]. Showing generosity towards occasional free riders allows the individuals to cooperate in the next interaction and it has been shown that generosity is a superior strategy when the good-intentioned players commit mistakes occasionally[26].

In the standard PGG without altruistic punishments, the free riders (high CCC agents) proliferate in the population because these agents score relatively higher payoffs than the reciprocators (lower CCC agents), thus no cooperation is established. Suppose, a population consists of pure strategies such as altruists, free riders, and reciprocators who not only cooperate but also punish the free riders, clearly the reciprocators score lesser payoffs than the altruists who donate but do not punish free riders. For sufficient costs of inflicted punishments, altruists proliferate in the population. In this stylistic model, the cooperation is not stable; in the sea of altruists, when an occasional mutant, a free rider, enters into the population, the free riders destroy the cooperation. Whereas when the population consists of heterogeneous conditional cooperators, the free riders do not gain a very high payoff, thanks to altruistic punishments and the heterogeneity of the population. If an occasional free rider, a mutant, gets into the population, the cooperation is not destroyed as the population remains heterogeneous and consists of reciprocators who also act as altruistic punishers. However, the composition of the population depends on the inflected costs and number of opportunities given for the implementation of altruistic punishments. Lower inflected costs and rare opportunities to punish free riders do not establish cooperation.

In the model, with w =1, all the agents have an opportunity to punish potential free riders in the population. Typically, the lower *CCC* agents potentially punish the higher *CCC* agents or potential free riders (eq.3). For certain critical inflected punishment costs, after punishments are implemented, the relative payoff of the higher CCC agents is less than the payoff of the lower CCC agents. It is important to note that because of the heterogeneity of the population, the donation levels are not high in the initial rounds. The process prevents the free riders from gaining higher payoffs and proliferating in the population. Due to the imitation process, the population creates a critical amount of cooperation or lower CCC agents gradually and this helps to establish cooperation. The heterogeneity of the population is preserved after even thousands of generations and the population does not turn into unconditional cooperators. The altruistic punishments are only effective if the population punishes the free riders more frequently and occasional free riders less frequently. Suppose if the occasional free riders were punished frequently, the population would wipe out many moderate CCC agents who are helpful in creating critical levels of cooperation and involved in altruistic punishments against the selfish free riders. For example, with w =1 and inflected punishment cost =3 units, the population starting with arbitrary CCC values, after several thousands of generations, the population is adapted to lower CCC values (mean= 10.06) (Figure 3(A)) and also adapted to lower β values (Figure 5(A)). With the lower *β* values and with lower CCC values, from the eqn.3 the reciprocators punish the selfish free riders frequently (due to high CCC values). These conditions help to establish cooperation by enforcing generous altruistic punishments. In these conditions, the cooperation levels are high (Figure 1(A) and 2(A)). When the inflected cost is lower, the population is adapted to relatively higher CCC and higher *β* values (see Figure 3(A) and 5(A)), cooperation is established but not high. Population does not establish conditional cooperation if the inflected costs are too low (Figure 2(A)).

When the punishments were enforced in a probabilistic manner, i.e., $w<1$, the agents get rare opportunities to punish free riders, thus higher CCC agents dominate the population, and thus no cooperation is established. For the same punishment cost with $w<1$, the population is adapted to relatively higher *β* values and higher *CCC* agents than the above condition ($w=1$). For instance, with $w = 0.5$ with inflected cost = 3, the population is dominated by moderate CCC values (mean = 17.75) (see Figure 3(B)), higher *β* values (see Figure 5(B)), and the cooperation levels are higher but not higher as with $w=1$. Unless inflected costs are more than a certain value, no cooperation is established. With $w = 0.5$ and with lower inflected cost = 0.9 (see Figure 2(B), the donation levels are close to zero and the CCC values of the population are higher (mean = 32.81 with cost = 0.9. Switching punishments on and off (w = 0.5) does not reduce the payoff of the higher CCC agents (free riders) substantially, therefore moderate or higher CCC agents dominate the population, thus no cooperation is established and such behavior has been observed in experiments elsewhere[28]. In the model, the occasional mutations do not destroy the conditional cooperation when the cost of inflected punishment and w is high or $w = 0.5$. For instance, a mutant *CCC* =N gets into population, with $w=1$ and sufficient inflected cost, the mutant will be punished quickly as the population is dominated by lower *CCC* agents. On the other hand, if the population consists of only altruists (*CCC*=0) and suppose an occasional mutant happens to be an unconditional free rider (*CCC* = N), the mutant can take over the population because free riding gives more advantages than the population average.

The proposed model is placed in the generic settings of conditional cooperation, yet some aspects of the model do not eliminate the few shortcomings. For example, an agent who reciprocated in PGG can be punished by other reciprocators in the group because the altruistic punishments are implemented by random pairings and based on relative *CCC* values, not based on the actions of individuals. Punishing reciprocators or negative reciprocators might lead to retaliation against the reciprocators or free riding in the next round. However, such occasions are rare in the long run because the difference in CCC values of reciprocators is small and *β* is not very high. The model does not consider other psychological aspects of agents such as 'warm glow [29]' the influence of partners and strangers[3], and beliefs about other agents [15].

In summary, the consideration that individuals in repeated public good games behave like conditional cooperators – i.e. individuals who are more willing to donate are also more willing to punish free riders –, and that these conditional cooperators are heterogeneous, throws new light on the evolution of altruistic punishments in a heterogeneous population. The essential feature of conditional cooperation rests on the population's ability to create a critical amount of cooperation in the initial rounds and to create conditions in which reciprocators cooperate and establish cooperation. The simulations show that when conditional cooperators make occasional mistakes in their punishment strategies, evolution prefers generous altruistic punishment strategies rather than strict punishment strategies; these strategies not only save the overall payoff of the group but also help to initiate cooperation from conditional cooperators. Unlike previous models[8–11,27], the current model, provides new mechanisms to establish conditional cooperation and the evolution of altruistic punishments.

Conditional cooperation operates with reciprocity, fairness, and retaliation[7] but without using payoff maximizing strategies[6]. The model shows that to establish cooperation in public good scenarios, implementing stern altruistic punishments against negative reciprocators is not required but it is necessary to punish selfish free riders to create sufficient cooperation in each round and build cooperation in the subsequent rounds. In the sense that punishing free-riding in the initial rounds one can facilitate conditions to establish cooperation but also help to stabilize cooperation by using feedback loops[30,31].

Reference

1. Nowak, M. A. Five Rules for the Evolution of Cooperation. **314**, (2006).
2. Fehr, E. & Gächter, S. Altruistic punishment in humans. *Nature* **415**, 137 (2002).
3. Fehr, E. & Gächter, S. Cooperation and punishment in public goods experiments. *Am. Econ. Rev.* **90**, 980–994 (2000).
4. Fehr, E. & Fischbacher, U. Third-party punishment and social norms. *Evol. Hum. Behav.* **25**, 63–87 (2004).
5. Rustagi, D., Engel, S. & Kosfeld, M. Conditional cooperation and costly monitoring explain success in forest commons management. *Science.* **330**, 961–965 (2010).
6. Fehr, E. & Gächter, S. Fairness and retaliation: The economics of reciprocity. *J. Econ. Perspect.* **14**, 159–181 (2000).
7. De Quervain, D. J. F., Fischbacher, U., Treyer, V. & Schellhammer, M. The neural basis of altruistic punishment. *Science.* **305**, 1254 (2004).
8. Boyd, R., Gintis, H., Bowles, S. & Richerson, P. J. The evolution of altruistic punishment. *Proc. Natl. Acad. Sci.* **100**, 3531–3535 (2003).
9. Gintis, H. The hitchhiker's guide to altruism: Gene-culture coevolution, and the internalization of norms. *J. Theor. Biol.* **220**, 407–418 (2003).
10. Janssen, M. A. & Bushman, C. Evolution of cooperation and altruistic punishment when retaliation is possible. *J. Theor. Biol.* **254**, 541–545 (2008).
11. Fowler, J. H. Altruistic punishment and the origin of cooperation. *Proc. Natl. Acad. Sci.* **102**, 7047–7049 (2005).
12. Gächter, S. *Conditional cooperation: Behavioral regularities from the lab and the field and their policy implications*. (2006).
13. Keser, C. & Van Winden, F. Conditional cooperation and voluntary contributions to public goods. *Scand. J. Econ.* **102**, 23–39 (2000).
14. Fischbacher, U., Gächter, S. & Fehr, E. Are people conditionally cooperative? Evidence from a public goods experiment. *Econ. Lett.* **71**, 397–404 (2001).
15. Fischbacher, U. & Gachter, S. Social preferences, beliefs, and the dynamics of free riding in public goods experiments. *Am. Econ. Rev.* **100**, 541–556 (2010).
16. Mesterton-Gibbons, M. *et al.* Altruistic punishment in humans. *Phys. Rev. E* **325**, 137 (2010).
17. Fehr, E. & Fischbacher, U. The nature of human altruism. *Nature* **425**, 785–791 (2003).
18. Bowles, S. & Gintis, H. *A cooperative species: Human reciprocity and its evolution*. (Princeton University Press, 2011).
19. Battu, B. & Srinivasan, N. Evolution of conditional cooperation in public good games. *R. Soc. Open Sci.* **7**, 191567 (2020).
20. Battu, B., Pammi, V. S. C. & Srinivasan, N. Evolution of Cooperation with Heterogeneous Conditional Cooperators. *Sci. Rep.* **8**, 4524 (2018).
21. Fischbacher, U., Gächter, S. & Fehr, E. Are People Conditionally Cooperative ? Evidence from a Public Goods Experiment. *Econ. Lett.* **71**, 397–404 (2001).
22. Riolo, R. L., Cohen, M. D. & Axelrod, R. Evolution of cooperation without reciprocity. *Nature* **414**, 441–443 (2001).
23. Nowak, M. A. & Sigmund, K. Evolutionary dynamics of biological games. *Science (80-.).*

303, 793–799 (2004).
24. Szabó, G. & Fath, G. Evolutionary games on graphs. *Phys. Rep.* **446**, 97–216 (2007).
25. Bowles, S. Policies designed for self-interested citizens may undermine" the moral sentiments": Evidence from economic experiments. *Science.* **320**, 1605–1609 (2008).
26. Nowak, M. A. & Sigmund, K. Tit for tat in heterogenous populations. *Nature* **355**, 250 (1992).
27. Hauert, C., De Monte, S., Hofbauer, J. & Sigmund, K. Volunteering as red queen mechanism for cooperation in public goods games. *Science.* **296**, 1129–1132 (2002).
28. Milinski, M., Semmann, D. & Krambeck, H.-J. Reputation helps solve the 'tragedy of the commons'. *Nature* **415**, 424–426 (2002).
29. Andreoni, J. Impure altruism and donations to public goods: A theory of warm-glow giving. *Econ. J.* **100**, 464–477 (1990).
30. Gächter, S., Kölle, F. & Quercia, S. Reciprocity and the tragedies of maintaining and providing the commons. *Nat. Hum. Behav.* **1**, 650–656 (2017).
31. Miller, J. H. & Page, S. E. *Complex adaptive systems: An introduction to computational models of social life*. (Princeton university press, 2009).

Additional information

I declare I have no competing financial interest.

The author has not received any funding from any agency for this work

Acknowledgments

We thank Prof. Arnout van de Rijt, Vijaya, and Alyson Price for helping with the manuscript.

We declare I have no competing financial interest.

The authors have not received any funding from any agency for this work

Figures

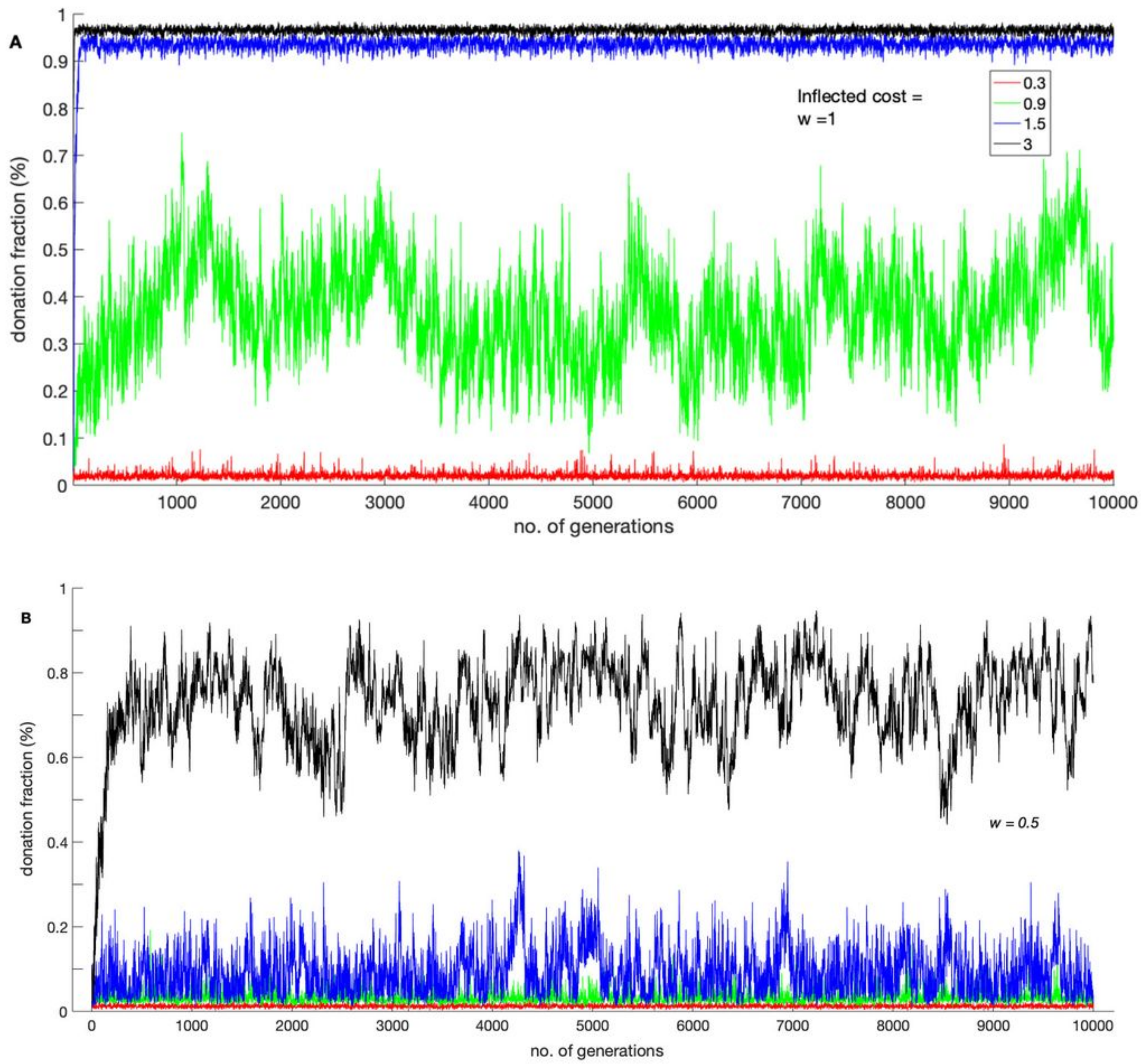

Figure 1

Donation rates for A (w) = 1 and for B (w) = 0.5 for various cost values for the first 10,000 generations.

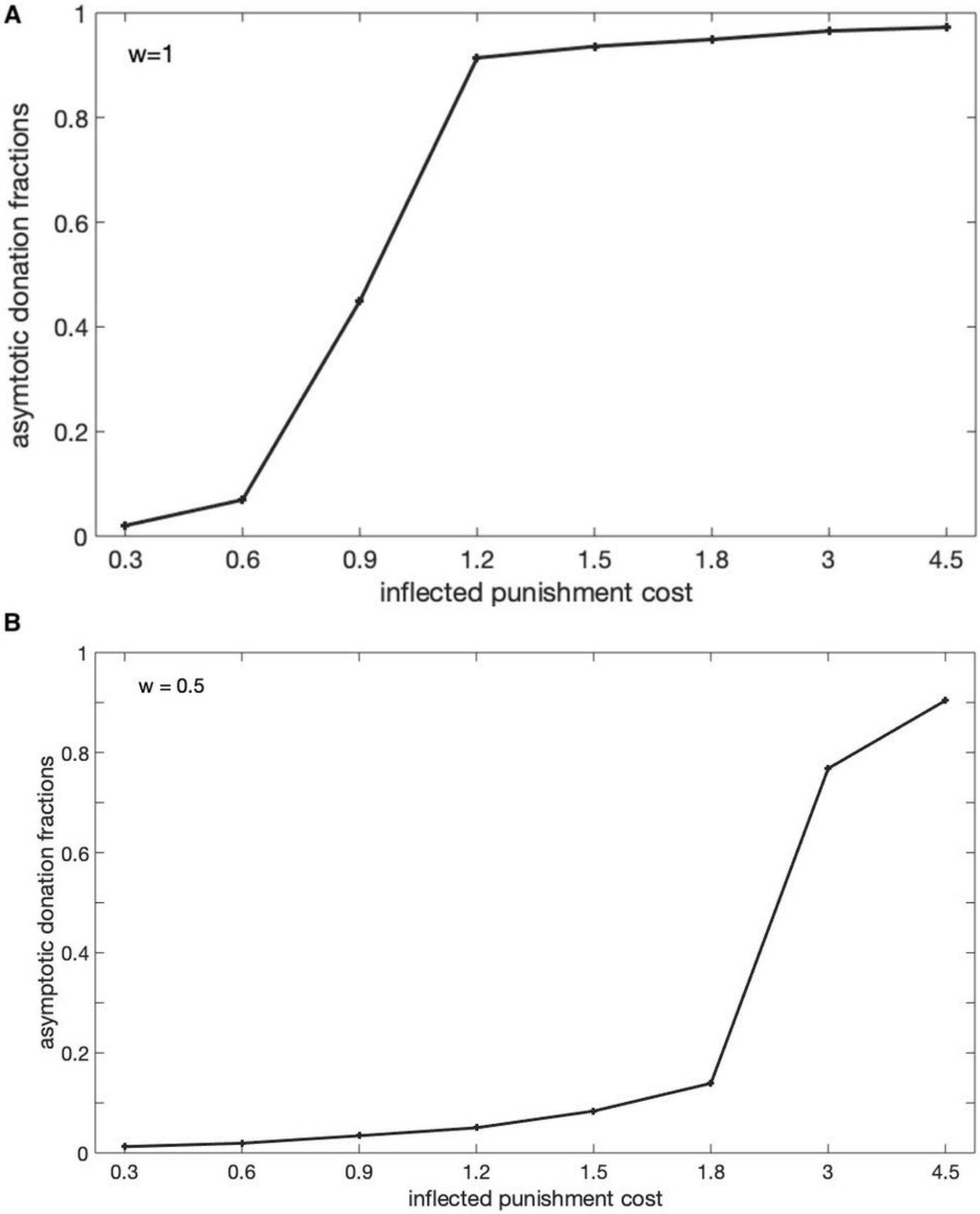

Figure 2

Asymptotic donations fractions of population with various punishment costs. Figure A (w) = 1 and Figure B (w) = 0.5.

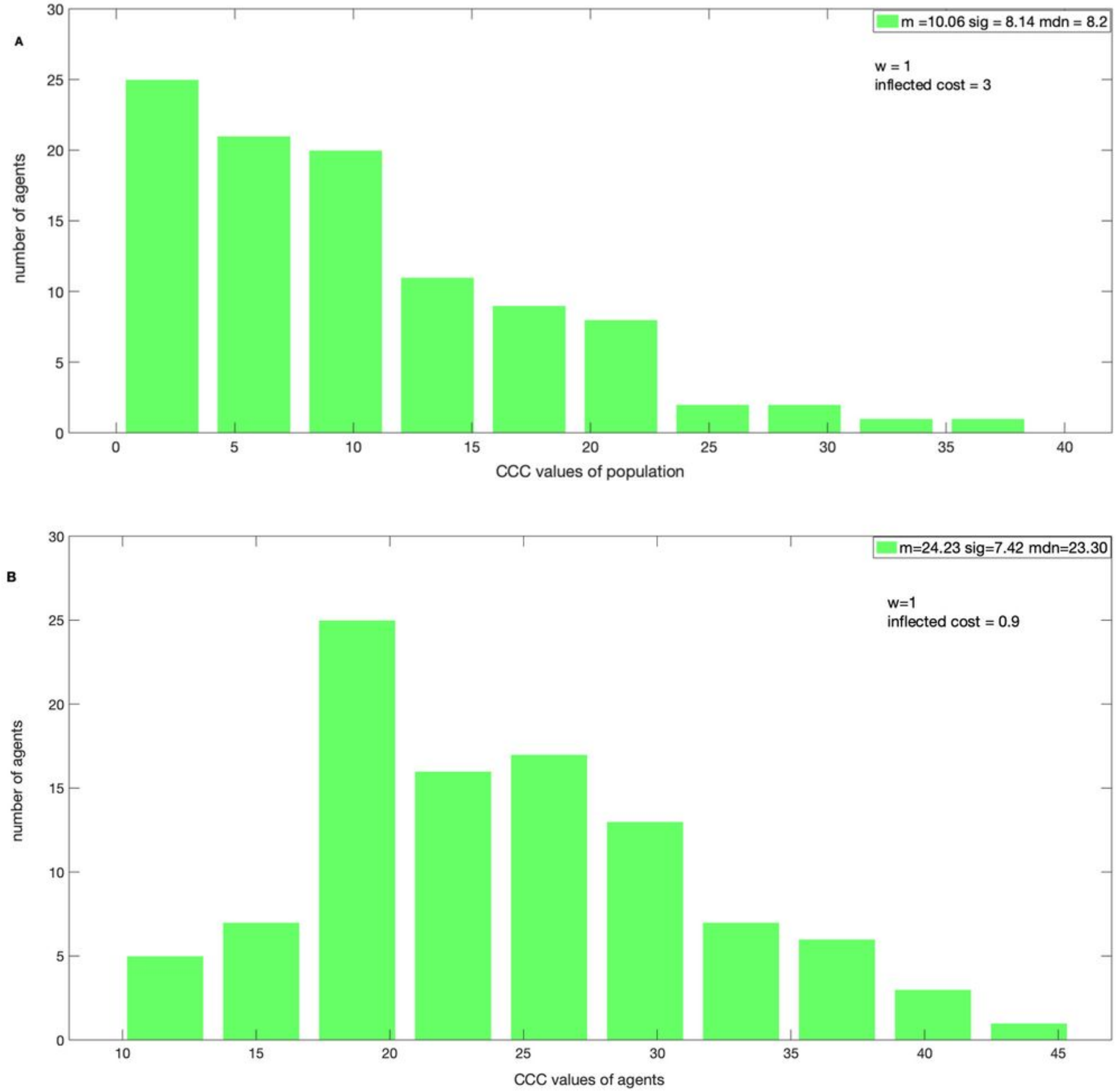

Figure 3

The distribution of CCC values in the 10,000th generation with a bin size of 10. With w =1 Figure A (cost) = 3 and with B (cost) = 0.9.

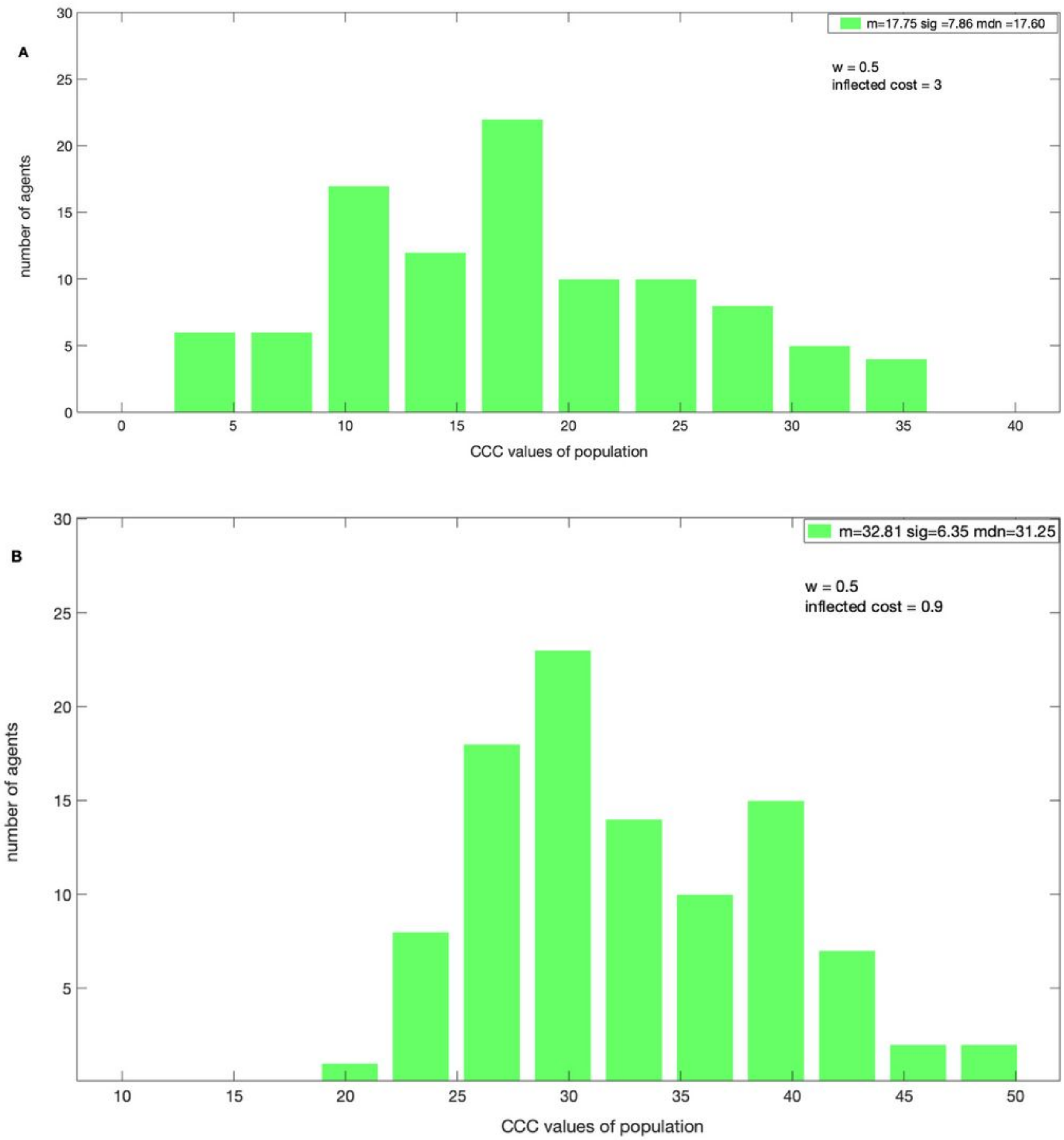

Figure 4

The distribution of CCC values in the 10,000th generation with a bin size of 10. With w = 0.5 Figure A (cost) = 3 and with B (cost) = 0.9.

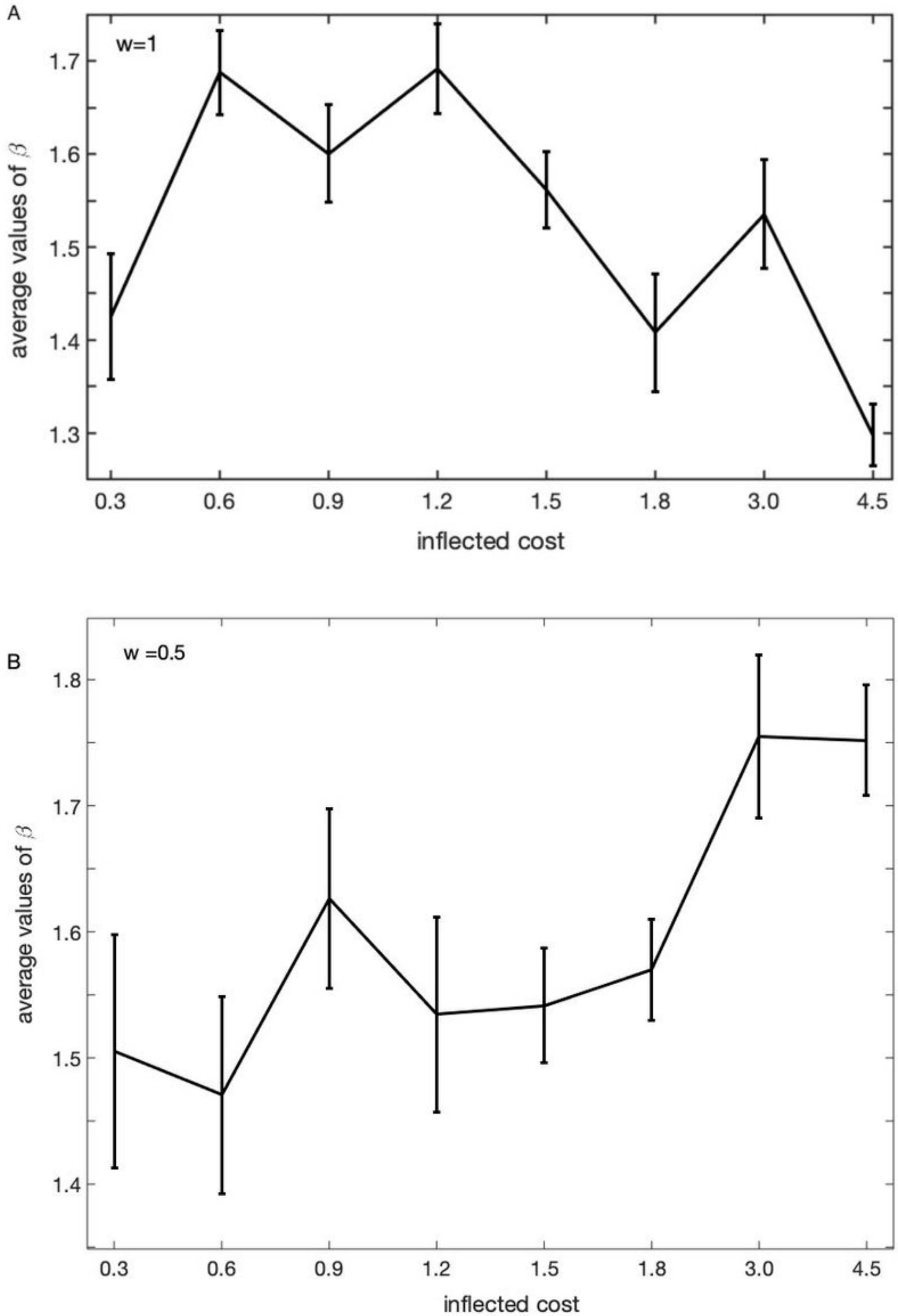

Figure 5

Population average β values for various costs in the 10,000th generation. A (w) = 1 and B (w) = 0.5.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- PGGPunishSupp.zip
- Supporting.pdf