Human-environment feedback and the consistency of proenvironmental behavior

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Abstract

Addressing global environmental crises such as anthropogenic climate change requires the consistent adoption of proenvironmental behavior by a large part of a population. Here, we develop a mathematical model of a simple behavior-environment feedback loop to ask how the individual assessment of the environmental state combines with social interactions to influence the consistent adoption of proenvironmental behavior, and how this feeds back to the perceived environmental state. In this stochastic individual-based model, individuals can switch between two behaviors, 'active' (or actively proenvironmental) and 'baseline', differing in their perceived cost (higher for the active behavior) and environmental impact (lower for the active behavior). We show that the deterministic dynamics and the stochastic fluctuations of the system can be approximated by ordinary differential equations and a Ornstein-Uhlenbeck type process. By definition, the proenvironmental behavior is adopted consistently when, at population stationary state, its frequency is high and random fluctuations in frequency are small. We find that the combination of social and environmental feedbacks can promote the spread of costly proenvironmental behavior when neither, operating in isolation, would. To be adopted consistently, strong social pressure for proenvironmental action is necessary but not sufficient – social interactions must occur on a faster timescale compared to individual assessment, and the difference in perceived environmental impact must be small. This simple model suggests a scenario to achieve large reductions in environmental impact, which involves incrementally more active and potentially more costly behavior being consistently adopted under increasing social pressure for proenvironmentalism.

Keywords: Global change, stochastic model, social pressure, timescales, fluctuations, payoffs, cooperation, social dilemma

Introduction

Why don't we all act more decisively in the face of global environmental crises such as climate change or biodiversity loss? Achieving climate and biodiversity targets set by international agreements (e.g. Paris accord, Aichi convention) ultimately requires consistent behavioral changes within and across societies. At the level of individuals, limiting climate change or biodiversity loss requires consistent consumer choices with reduced net environmental impact. As citizens, individuals must consistently promote governmental policies that favor proenvironmental actions. Leaders and senior managers, as individuals, should make consistent decisions to influence greenhouse gas emissions and natural resource use by large organizations and industries.

For individuals, adopting a proenvironmental behavior can be a hard decision. Indeed the decision amounts to accepting certain short-term costs and reductions in living standards in order to mitigate against higher but uncertain losses that may be far in the future [15]. Individual behavioral responses to this collective-risk social dilemma [36] are not all-or-nothing, however. Between those who unconditionally accept or unconditionally deny the need for action towards environmental sustainability, the vast majority of people do not engage consistently in either way. Rather, non-ideologically polarized individuals tend to show inconsistent behavior as they change opinion, revise their intention, or switch behavior during their lifetime [1], possibly on very short timescales [8].

Such a behavioral inconsistency can be due to various mechanisms. Individuals who engage in some kind of proenvironmental action may lose motivation to "take the next step". In this case, action limits intention for more, a pattern called *tokenism* [15]. In the same vein, the *rebound effect* occurs when some mitigating effort is diminished or erased by the individual's subsequent actions [16]. For example, after acquiring a more fuel-efficient vehicle (an active mitigating behavior), owners tend to drive them farther, in effect reverting to their baseline environmental impact [31]. Other patterns of inconsistent behavior involve responses to extreme climatic events. Exposure to a climate-related hazard such as wildfires increases support for costly, pro-climate ballot measures in subsequent local elections [23]; but the degree of personal concern about climate change is related to the temperature anomaly only over a few months in the past [12]. Thus, outside of the most politically polarized groups, the influence of environmental anomalies can be strong, but it decays rapidly [21].

Mathematical modeling of human-environment dynamics can help identify pathways toward proenvironmental behavior consistency. Game-theoretic models with environmental feedbacks, or eco-evolutionary games, have been developed to study coupled environmental and behavior dynamics [34, 17, 50, 22, 47]. Specific examples address the use of a natural resource such as farmland [14], water [45] or forest [5]. A key aspect of these behavior-environment models [48, 9, 50] based on 'imitation dynamics' [24] is that individuals' behavioral decisions are only

made in the context of their interaction with others. Yet factors that are not tied to social encounters, such as the individual's own experience and perception of the environmental state, may play a key role in environmental decisions. This is core to the conceptual framework that Schill et al. (2019) [42] recently put forth, building on behavioral economics and cognitive psychology, for understanding human behavior in the face of sustainability challenges. In this framework, individuals create social and environmental contexts that change dynamically with continuous feedback to their behavior. Following Schill et al. (2019) [42] we hypothesize that the dynamics of environmental behavior are shaped both by social context and the individuals' private environmental experience.

Here we implement this hypothesis by constructing a simple mathematical stochastic model based on individual-level rules. Individuals perceive having an impact on the environment to a degree that is determined by their behavior. Individuals can change their behavior in response to both social interactions and their own perception of the environment. The environment and the individuals' behavior are considered as continuous and discrete variables, respectively, and the different processes affecting the state of the behavior-environment system play out on different time scales. We use the model to investigate the determinants of proenvironmental behavior consistency. We say that a behavior is adopted consistently when its frequency at stationary state is high and the stochastic fluctuations in frequency are small. Our model analysis addresses how the individual assessment of environmental actions combines with social interactions to determine the consistent adoption of proenvironmental behavior, and how this feeds back to the perceived environmental state. In particular, we ask whether larger costs of, or weak social pressure on, proenvironmental behavior make the consistent adoption of proenvironmental behavior less likely; and whether a slower pace of change in the perceived environmental state can promote consistency.

Results

Model overview

We consider a population of N agents that interact among themselves and perceive the state of the environment (more or less degraded) through a single environmental variable, e. Individual behavior and perceived environmental state are modeled on a short enough timescale so that N remains constant. The e variable measures the perceived environmental state on a continuous scale, with larger e corresponding to an environment perceived as more degraded. At any time t each individual can express one of two behaviors: baseline (denoted by B) or active (denoted by A). When expressing behavior A, an agent actively seeks to reduce its environmental impact compared to the baseline impact of behavior B. This is modeled by assuming that an agent in state A increases the perceived environmental impact of the population by an amount l_A, which is less than the environmental impact, l_B, of behavior B (per capita). We also assume that l_A is positive meaning that the population influences the environment by its own existence.

Agents can switch between behaviors A and B.

In the Methods we expound the mathematical derivation of a model for the joint dynamics of the population frequency of behavior A and the perceived environmental state. Notations are listed in Table 1. We assume that the dynamics of the perceived environnemental state follows a deterministic continuous process. We define parameter ℓ as representing the timescale at which individuals' behavior affects the perceived environmental state: the higher ℓ, the faster the perceived environmental state changes due to individuals' behavior. In a population where all agents express behavior A (B, respectively), the rate of change of the environment perceived as minimally (maximally) degraded is proportional to l_A (l_B) and the stationary value of the perceived environmental state is l_A (l_B). In a population where both behaviors are expressed, the perceived environmental state varies between l_A and l_B.

Any agent may switch at any time between behaviors A and B first as a result of encounters with other agents (modeling social interactions). We define κ as a scaling parameter controlling the rate of switching behavior via social interactions (modeled as encounters with other agents). The rate at which an agent changes its behavior upon encountering another agent depends on the attractiveness of the alternate behavior, which is determined by the perceived payoff differential between the two behaviors, and the social pressure. We use parameters γ_i, $i = A$ or B, the payoff from adopting behavior i, and δ_i, the social pressure for behavior i. We denote the payoff difference between behaviors A and B, or payoff differential, by $\beta = \gamma_A - \gamma_B$. We say that the active behavior A is *costly* when the payoff differential, β, is negative. The payoff differential may be positive if, for example, the active behavior A is actually incentivized through public policy.

Second, any agent may also switch behavior at any time based on their assessment of the value of the state variable representing the perceived environment. Agents tend to adopt the alternate behavior when they perceive the environmental impact of their current behavior as relatively large, compared to the alternate behavior. We use parameter τ to set the timescale of behavioral switch based on individual assessment.

The dynamics of the coupled behavior-environment process are stochastic, driven by the probabilistic events of behavior switch between A and B, under the joint effects of encounters among agents and individual assessment, and the deterministic response of the perceived environmental state. The mathematical model we obtain is a Piecewise Deterministic Markov Process where the population state (frequencies of behaviors) probabilistically jumps at each change in individual behavior while the environmental state deterministically and continuously changes between jumps. Note that the model assumes that the perceived environmental state and social context are the same for all individuals, and individuals do not differ in personality, in the sense that all individuals have the same intrinsic propensity to change their behavior (or not) across time.

Deterministic approximation of the dynamics and stochastic fluctuations

When the population size N is very large and under assumptions on the rates stated below, the behavior-environment dynamics can be approximated (in a sense made rigorous in the Methods and Supplementary information) by the unique solution of the following system of ordinary differential equations for the active behavior frequency, x, and perceived environmental state, e,

$$\begin{aligned} \frac{dx_t}{dt} &= p(x_t, e_t) = \kappa x_t(1-x_t)(\lambda_A(x_t) - \lambda_B(x_t)) + \tau_A(e_t)(1-x_t) - \tau_B(e_t)x_t \\ \frac{de_t}{dt} &= h(x_t, e_t) = \ell e_t(l_A x_t + l_B(1-x_t) - e_t) \end{aligned} \tag{1}$$

with initial conditions (x_0, e_0) in $[0,1] \times [l_A, l_B]$. The first equation governs the frequency x of the active behavior, A. In the right hand side of $p(x,e)$, the first term measures behavior switching due to encounters (social interactions), with B switching to A at rate $\lambda_A(x)$ and A switching to B at rate $\lambda_B(x)$, given by

$$\begin{aligned} \lambda_A(x) &= \gamma_A + \delta_A x \\ \lambda_B(x) &= \gamma_B + \delta_B(1-x) \end{aligned} \tag{2}$$

(following from Eq. (10), (11) and (8), see Methods). The second term measures behavior switching due to individual assessement of the environmental state. The corresponding rates of switching from B to A and from A to B respectively are

$$\begin{aligned} \tau_A(e) &= \tau(e - l_A) \\ \tau_B(e) &= \tau(l_B - e) \end{aligned} \tag{3}$$

(following from Eq. (13) in the Methods). The second equation in System (1) drives the dynamics of the perceived environmental state, e. An equilibrium point (x^*, e^*) is a (x,e) pair that nullifies both functions $p(x,e)$ and $h(x,e)$.

Even though the rates of behavior switching are deterministic functions, the individual switching events occur probabilistically. As a consequence, given that the population size is finite, the actual frequency of the behaviors fluctuates randomly, even asymptotically around the equilibrium values predicted by the deterministic model. In the Methods and Supplementary information, we show that the variance of the random fluctuations in frequency is equal to the total rate of behavior switching between A and B, elicited by social interactions and individual assessment of the environment. This total rate, denoted by Ω, is equal to

$$\Omega(x,e) = \kappa x(1-x)(\lambda_A(x) + \lambda_B(x)) + \tau_A(e)(1-x) + \tau_B(e)x \tag{4}$$

given the values of the A frequency, x, and perceived environmental state, e. The total rate Ω measures the intensity of switching between behaviors across the population. Thus, the

higher Ω, the larger the probability that some agent switches behavior. We characterize A as being consistently adopted when the A equilibrium frequency, x^*, is high (close to one) and the corresponding total rate of behavior switching, $\Omega(x^*, e^*)$, is low (close to zero).

In the following subsections we first describe the deterministic dynamics of the large-population model in the absence of environmental feedback ($\tau = 0$ in Eq. (1)). When the environmental feedback is included, we investigate the effect of all parameters to identify those that control the value and stability of equilibria: payoff differential, β, social norm threshold, individual environmental impacts and environmental impact differential, $l_B - l_A$, individual sensitivity to the environmental state, τ, and reactivity of the environment, ℓ. We then identify conditions for the spread and consistent adoption of the A behavior. Finally, we qualitatively discuss how incremental variation in the proenvironmental behavior could affect the behavior-environment system dynamics and lead to a robust reduction of the individuals' perceived environmental impact.

Behavior dynamics without environmental feedback

In the absence of environmental feedback (i.e. no individual assessment, $\tau = 0$), agents may switch behavior only upon encountering other agents, i.e. through social interactions. Equation (1) then reduces to the standard imitation dynamics (or replicator) equation

$$\begin{aligned} \frac{dx_t}{dt} &= \kappa x_t(1-x_t)[\beta + \delta_A x_t - \delta_B(1-x_t)] = p_0(x_t), \\ \frac{de_t}{dt} &= h(x_t, e_t) = \ell e_t(l_A x_t + l_B(1-x_t) - e_t) \end{aligned} \tag{5}$$

Assuming $l_A > 0$ and e_0 between l_A and l_B, the only possible equilibrium value for the environmental state is $e^* = l_A x^* + l_B(1-x^*)$. The model admits three equilibria, $x_0^* = 0$, $x_1^* = 1$ and $x^* = \frac{\delta_B - \beta}{\delta_A + \delta_B}$. If $x^* < 0$ (resp. $x^* > 1$), then $x_1^* = 1$ (resp. $x_0^* = 0$) is globally stable. If $0 < x^* < 1$, then the system is bistable; convergence to $x_1^* = 1$ occurs if the initial frequency of the active behavior is higher than x^* (Fig. 1). Note that when the payoff differential β is null, the outcome is entirely determined by social pressures and in this case, the frequency threshold x^* is equal to $\nu = \frac{\delta_B}{\delta_A + \delta_B}$, a term that we call *social norm threshold*.

At stable equilibrium ($x_0^* = 0$ or $x_1^* = 1$) the total rate of behavior switching, Ω (Eq. (4)), is always equal to zero, which means that the prevailing behavior, A or B, is adopted consistently. Thus, if the active behavior A spreads, it will necessarily be adopted consistently; but the spread of A from low frequency requires A to be perceived as sufficiently rewarding compared to B (i.e.$\gamma_A > \gamma_B + \delta_B$).

Effect of environmental feedback on active behavior frequency

As expected, environmental feedback alone can prevent the active behavior from spreading to high frequency. By taking $\tau > 0$ and $\kappa = 0$ in Eq. (1), individual behavior is influenced by the perceived environmental state and not by social interactions. In this case, Eq. (1) possesses only one stable equilibrium, $(x^*, e^*) = (\frac{1}{2}, \frac{l_B+l_A}{2})$. With no social interactions ($\kappa = 0$) the payoffs γ_A and γ_B have no influence on the equilibrium frequency of the active behavior, since the payoffs only play a role in the behavior dynamics when agents can compare them, which requires contact.

By setting both $\tau > 0$ and $\kappa > 0$ in Eq. (1), the effect of environmental feedback combines with the effect of social interactions. As in the case without environmental feedback (cf. previous subsection), the model predicts up to three internal equilibria (i.e. $0 < x^* < 1$, see Methods). The stability analysis shows that the product of individual sensitivity to the environment, τ, and environmental impact differential, $l_B - l_A$, is a key determinant of the system dynamics. When $\tau(l_B - l_A)$ is small enough, there is one (globally stable) or three (two stable, one unstable) equilibria, depending on the payoff differential, β, and social norm threshold, ν (Fig. 2a-c). The stable equilibrium is always close to $x^* = 0$ or $x^* = 1$ while the two stable equilibria are close to $x^* = 0$ and $x^* = 1$, respectively. When the product $\tau(l_B - l_A)$ is large enough, there is only one equilibrium. For a given payoff differential, β, and social norm threshold, ν, this equilibrium can be stable or unstable (here necessarily a limit cycle) depending on environmental reactivity, ℓ (Fig. 2d-i). Thus, parameter ℓ, the environmental reactivity, does not affect the number of equilibria but it affects their stability (Fig. 2d-f).

The environmental feedback thus has two main consequences for the spread of the active behavior A from low frequency. On the one hand, under the condition that the product $\tau(l_B - l_A)$ is small enough (Fig. 2a-c), the increase of A frequency from very low to an equilibrium close to 1 becomes possible even if A is costly ($\beta < 0$) or at least low-incentivized (small $\beta > 0$), provided that the environmental feedback be combined with strong social pressure for the active behavior (low ν due to large δ_A, Fig. 2a-c to be compared with Fig. 1). On the other hand, for large values of the product $\tau(l_B - l_A)$, the environmental feedback dominates the effect of social conformism for the active behavior. As a consequence, most active behaviors can reach a frequency close to 0.5 irrespective of their cost and the intensity of social pressure (Fig. 2g-i). High frequency (close to one) can be reached but only under very strong social pressure, even for active behavior that are strongly beneficial (large $\beta > 0$).

The spread from low to high frequency of a *costly* active behavior ($\beta < 0$) cannot occur in the absence of environmental feedback. The effect of the environmental feedback can be explained as follows. In a population where the active behavior is rarely expressed (x close to zero initially), the perceived environmental state is essentially set by the baseline behavior B. Thus, the environmental state is perceived as degraded, the environmental feedback promotes

the behavioral switch from B to A, hence the frequency of A rises. If the social pressure of individuals expressing behavior A is strong enough (i.e., if δ_A is sufficiently larger than δ_B) the initial pull of the A frequency by the environmental feedback will be enough to drive it above the social norm threshold, ν. Once the A frequency exceeds the ν tipping point, social interactions pick up and drive A toward its equilibrium frequency, close to 1.

Spread and consistent adoption of a costly active behavior

The consistent adoption of a costly active behavior requires the equilibrium frequency, x^*, to be close to one and the total switching rate, Ω (Eq. (4)), to be close to zero. Figures 2 and 3 illustrate conditions under which this is the case. According to the previous subsection, a general condition for a costly (or low-incentivized) active behavior to spread from low to high frequency (x^* close to 1) is that the social pressure for A be strong enough (large δ_A hence small ν, Fig. 2). When that is the case, the product $\tau(l_B - l_A)$ fully determines consistency, since for x^* close to 1, the total rate of behavior switching is approximated by

$$\Omega(1, l_A) = \tau(l_B - l_A). \tag{6}$$

Thus, with a relatively weak sensitivity to the environment (i.e. τ low) and a small environmental impact differential (i.e. l_A close to l_B), costly active behaviors can spread from low to high frequency provided the social pressure for active behavior is strong enough (Fig. 2a-c), and consistent adoption is expected (Fig. 3a). In contrast, if the individual sensitivity to the environment is strong enough (large τ) and/or the environmental impact differential is large (large $l_B - l_A$), behavioral inconsistency is expected, with agents frequently switching between active and baseline behaviors (Fig. 3b-c), even if the predicted equilibrium frequency of the active behavior is high (see lower (yellow) regions in Fig. 2d-i, where the social pressure for A, δ_A, is high hence the social normal threshold, ν, is low).

For intermediate values of $\tau(l_B - l_A)$, low environmental reactivity, ℓ, may be an additional cause of behavior inconsistency. In this case, decreasing environmental reactivity can destabilize the unique positive equilibrium and turn it into a limit cycle (Fig. 2d-f). Individuals will thus switch behavior at a total rate that is itself changing over a slower timescale set by the environmental reactivity. The slow timescale of environmental reactivity creates a time lag between the perceived environmental state and individuals' behavior, generating periodic oscillations in the switching rates.

Robust environmental impact reduction through incremental behavior change

Starting from an environment perceived as degraded, can an active behavior with much smaller environmental impact than the baseline behavior (i.e. large $l_B - l_A$) drive a robust improvement of the environmental state (from high to low e at stationary state)? Such an active

behavior could rise to high frequency provided the social pressure for proenvironmentalism is very strong (Fig. 4a), with a concommitent drop in environmental impact (Fig. 4d). But stochastic fluctuations in this case are large (Fig. 4g), indicating that the active behavior may not be adopted consistently.

In contrast, environmental impacts and feedback such that $\tau(l_B - l_A)$ is small allow for the unconditional spread and consistent adoption of low-incentivized or even costly active behavior (i.e., β close to 0 or even negative) (Fig. 4b,h). Even though the effect of such behavioral change on the environmental state is small (Fig. 4e), this sets the stage for a scenario of incremental behavioral change towards robust environmental impact reduction (Fig. 4b-i) whereby increasingly more active behaviors would spread and be adopted consistently, each behavioral change imparting a small reduction of environmental impact. Once behavior A is established, it becomes the common baseline behavior where individuals may start expressing a new active behavior A', with lower environmental impact, and potentially a larger cost. In the latter case, a stronger social pressure (higher δ_A hence lower ν) may compensate for the larger cost and ensure that the active behavior A' spreads and becomes adopted consistently, in lieu of A. Thus, in a system where social conformism for active behavior can increase (increasing δ_A hence decreasing ν) in relation with more effective active behavior (lower l_A) and/or the perception of reduced environmental impact (lower e^*), a substitution sequence of gradually more active (lower l_A) and more costly (more negative β) behaviors can take place, driving a potentially substantial decrease in the perceived environmental impact (* decreasing to arbitrarily low levels).

We hypothesize that such an incremental scenario might be triggered even for active behaviors that are initially costly, and with weak social pressure for them (small δ_A hence high ν) – as long as their cost is not too large so that bistability remains possible (upper areas of black regions in Fig. 4b). In this case, random fluctuations in behavior frequency may cause the system to switch from the low-frequency to the high-frequency A equilibrium (Fig. 5), where it may reside long enough for some new behavior A' more active than A to spread and take over. The study of such dynamics, involving the effect of individual stochasticity on alternate equilibria, is beyond the scope of this model and warrants further mathematical investigation.

Discussion

We developed a simple mathematical model to study how social and environmental feedbacks jointly influence the consistent adoption of proenvironmental behavior. The treatment of individual assessment of the perceived environment and social interactions as two separate factors of individual decisions differentiate our model from evolutionary games with environmental feedbacks, in which the influence of the environment is entirely mediated by the payoffs of the strategic interactions [34, 17, 50, 22, 47]. In contrast, our model assumes that the payoffs are constant and that the perception of the environmental state can influence an individual's

behavioral choice independently of their interactions with others. This structure allows us to separate the behavioral effect of individual assessment of the environment from the effect of social interactions. Our model thus aligns with the conceptual framework of Schill et al. (2019) [42] for connecting environmental behavior with both social and perceived biophysical contexts.

The importance of timescales for behavioral consistency

The assumed invariance of the payoff difference (unaffected by variation in the environmental state variable) is rooted in the short timescale involved in the behavior-environment dynamics. Because the environmental state variable captures perceived information, shaped by behavioral intentions or actions, it is plausible that the timescale of environment-behavior change be short relative to the timescale over which the true state of the physical environment changes. Under this timescale separation, the payoff difference remains constant as the perceived environmental information changes, without precluding change in payoffs that could occur over the slower timescale of a changing physical environment.

When the timescale of individual assessment is fast relative to social interactions, the environmental feedback dominates the system dynamics, leading to inconsistent behavior. The relatively fast individual assessment timescale may originate from individuals having more confidence in their own evaluation of costs and benefits than in others' influence. This is known to occur, for instance, when the decision to be made carries a lot of personal weight [4, 37] or when individuals have grown up in a very favorable environment [27]. When individual assessment is slow compared to social interactions, the social feedback dominates. This raises the question, whether, in practice, social influence could be stronger among individuals who engage in proenvironmental behavior than among individuals who do not. One can speculate that this could be the case if the active behavior is individually costly and perceived as a moral duty. In this case, the active individuals behave as cooperators whose efforts (measured in terms of opportunity cost) are influenced the most by the observation of the others' efforts [39, 6].

Overall, the timescale of perceived environmental change has little effect on the behavior-environment dynamics. Thus, whether individuals assume that their actions are environmentally meaningful in the short term (high environmental reactivity, ℓ) or the long term (low environmental reactivity, ℓ) generally has no significant effect on behavior consistency. The case of social interactions and individual assessment occurring on similar timescales is special, however. In this case, low environmental reactivity, ℓ, creates a time lag between behavioral and perceived environmental changes, causing behavior-environment cycles when the proenvironmental behavior is costly and levels of conformism are not too different between behaviors. A similar effect of slow environmental reactivity relative to social interactions promoting oscillations was also detected by [44] in their model of forest growth and conservation opinion dynamics. Contrasted environmental impacts of behaviors A and B (i.e. large $l_B - l_A$) favor the limit cycle regime over bistability which is reminiscent of previous findings of behavior-environment cycles

replacing bistability when the human influence on the environment is strong [26].

Consistent adoption of incrementally more active behavior

A question of interest is how the consistent adoption of an active behavior depends on the magnitude of environmental impact reduction associated with that behavior. The model shows that for active behaviors causing only a small environmental impact reduction, the bistable regime is favored, which leads to consistent behavior adoption (of A or B). In fact, a small environmental impact reduction by the active behavior has the same effect on the system dynamics as a slow timescale of individual assessment. Once a 'small step' active behavior is adopted consistently, the perceived level of environmental degradation is only decreased by a small amount; but if more behavioral options were available, the socio-environmental context would be set to promote individuals engaging consistently in 'the next small step'. If the process were repeated, leading to the consistent adoption of active behaviors of gradually smaller environmental impact, we would expect the perceived level of environmental degradation to decrease. Interestingly, this might happen even if the relative cost of active behavior was increasing, provided the social pressure for active behavior increased concommitently.

Our consideration of gradual behavioral change through a sequence of 'small steps' raises the empirical question of whether the perceived change in environmental state could in turn affect the repertoire of individual behaviors, and in particular motivate behaviors more active than A. In practice, the existence and direction of such an additional feedback may depend on whether each small step is individually beneficial and thus considered by people as a self-serving decision, or individually costly and considered as a form of cooperation. In the first case, there is no obvious reason for the perceived change in environmental state to affect individual decisions, so it is unlikely that such feedback would exist. In the second case, however, the question relates to the rich empirical literature on the influence of the perceived environmental state on cooperation. The majority of studies in this field, and in particular the highest powered studies, report a positive relationship between the quality of the environment experienced by individuals and their level of investment in cooperation [28, 43, 3, 38, 33, 41, 52, 29]; although some studies report opposite effects [2, 30, 40] or no effect at all [46, 51]. We may thus hypothesize the existence of the additional positive feedback whereby the perception of an improved environmental state would enlarge the behavioral repertoire and motivate more active behaviors. The improvement or, on the contrary, the deterioration of the perceived environment could lead individuals to invest more, or, on the contrary, less in proenvironmental behavior, thus generating the kind of behavioral sequence that we envisioned in this analysis.

Limits and perspectives

Our work builds on the fundamental distinction between the individual's stable characteristics and the subset of situational characteristics which capture the social and environmental

situatedness of behavior [11]. In the model, all parameters, except the rate of environmental reactivity, ℓ, are set as individual characteristics. A key assumption is that all individuals are identical in their stable characteristics. Our framework could be extended to relax this assumption and investigate the consequences of diversity in individual social status or personalities [10, 49]. For example, the same objective cost of the active behavior (e.g. buying or maintaing an electric car) may be perceived very differently depending on the individual's wealth [35, 19]. Likewise, individuals of different social status may vary in their experience of social pressure from individuals expressing the active vs. baseline behavior; this in the model would manifest through inter-individual variation of δ_A and δ_B [27].

Given the predicted importance of the individual sensitivity to the environment, τ, and environmental impact differential, $l_B - l_A$, the outcome (consistent adoption of the active behavior) is likely to be influenced by inter-individual heterogeneity in these two parameters. It is known that individuals can differ greatly in their perception and assessment of the state of degradation of their environment, due to differences in social origin, education, or information [19, 18]; and in their potential proenvironmental response to perceived environmental degradation [18]. This heterogeneity could result in wide variation of both τ and $l_B - l_A$ among individuals, with contrasted personalities such as being little responsive and acting weakly (small τ and $l_B - l_A$), or responding fast and strongly (large τ and $l_B - l_A$).

In previous models of coupled human behavior and natural environment dynamics, the environment typically is measured by a variable such as the abundance of a renewable resource (e.g. forests [5], fisheries [32]), or a physical variable such as atmospheric greenhouse gases concentration or temperature [7]. In these models, the environmental dynamics are driven by their own endogenous processes and impacted by human activities (gas emissions, harvesting...). These models ask how human behavioral feedbacks alter the stability properties of the perturbed (polluted, exploited...) ecosystem. An important difference between our approach and previous human-environment system models lies in our definition of the environmental state in terms of perceived information, rather than any physical component (atmospheric CO_2 level, abundance of a natural resource...) of the environment. This information changes under the influence of individuals' intentions or behaviors; the physical environment may also change as a consequence, but we assume that the change would occur on a much slower timescale and therefore has no influence on the individual decisions that the model describes.

This representation of the environment allowed us to make the assumption that the payoff difference is insensitive to environmental change. Note, however, that a feedback of the environment to the payoff difference can be seen as implicit in our scenario for the consistent adoption of incrementally more active behavior. This could be due to institutional intervention responding - on a slow timescale - to change in the environmental stationary state, as defined here, and altering the payoff difference through incentives (reducing the payoff difference) or by promoting more effective behaviors that would also be more costly (increasing the payoff

difference). Another significant difference with most previous human-environment models is that here the environment, being purely informational, does not have its own intrinsic dynamics. A similar assumption was made by Weitz et al. (2016) [50] in a game-theoretic model where the environmental feedback was positive and governed by a tipping point. Future work could address the effect of a positive feedback in our model, to capture positive reinforcement (improved environmental state encourages to do more [25, 19]) and "giving up" (an environment assessed as degraded leads to less effort, rather than more [25, 19]).

Concluding remarks

In this minimal model of behavior-environment feedback, individuals intend proenvironmental action when they perceive their environment as degraded, and relax their effort as they perceive environmental improvement. This negative environmental feedback, by itself, opposes the consistent adoption of costly proenvironmental behavior, but opens the possibility for such behavior to rise from very low frequency and reach a tipping point at which social interactions and conformism will pick up and drive its consistent adoption. This suggests a scenario to achieve large reductions in environmental impact, which involves the consistent adoption of incrementally more active and potentially more costly behavior. The theoretical conditions for this to occur (social interactions timescale faster than individual assessment timescale, strong social pressure for proenvironmental action) raise empirical questions regarding why individuals' environmental intentions would rely more on others' influence than on their own assessment of the environmental state, and what factors (individual or collective) can make the social pressure of conformism stronger for proenvironmentalism.

Methods

In a population of finite size N, at any time t, the perceived environmental state and the numbers of individuals who are performing A or B are denoted by E_t^N, $N_t^{A,N}$ and $N_t^{B,N}$, respectively. Since the population size is constant we have $N_t^{B,N} = N - N_t^{A,N}$. Hereafter we derive a stochastic model for the joint dynamics of the frequency of behavior A in the population, $X_t^N = \frac{N_t^{A,N}}{N}$, and the perceived environmental state, E_t^N. The list of parameters and their default values is given in Table 1.

Environment dynamics

We assume that the dynamics of the perceived environnemental state E_t^N follows a deterministic continuous process. Each individual in the population has the same perception of the environment. The dynamics of E_t^N is driven by the ordinary differential equation

$$\dot{E}_t^N = h(X_t^N, E_t^N),$$

where h captures the environmental impact of the two behaviors given their frequency, according to

$$h(x, e) = \ell e(l_A x + l_B(1 - x) - e) \tag{7}$$

for any (x, e) in $[0, 1] \times [l_A, l_B]$.

The function h is chosen such that in a population where all individuals express behavior A (B, respectively), the rate of change of the environment perceived as minimally (maximally) degraded is proportional to l_A (l_B) and the stationary value of the perceived environmental state is l_A (l_B).

Behavior dynamics

Two factors influence the decision process of modeled agents: frequency of encounters with other modeled agents, and the value of the state variable representing some environmental factor.

Social interactions

We further assume

$$\begin{aligned} g_A(X^N) &= X^N \\ g_B(X^N) &= 1 - X^N. \end{aligned} \tag{8}$$

An agent with behavior i switches to behavior j via social interactions at rate

$$\lambda^N_{i\to j}(X^N) = N^2 \kappa g_i(X^N) g_j(X^N) \lambda^N_j(X^N), \tag{9}$$

where $\lambda^N_i(x)$ is the individual attractiveness of behavior i, $N^2\kappa g_i(X^N)g_j(X^N)$ is the number of potential encounters. Note that the number of potential encounters is symmetrical, $g_i(X^N)g_j(X^N) = X^N(1 - X^N)$. The difference between behavior i's and j's rate rely on the individual attractiveness of behavior. The individual attractiveness of behavior i is taken of the form

$$\lambda^N_i(X^N) = \frac{1}{N}\left(\gamma_i + \delta_i g_i(X^N)\right). \tag{10}$$

As a result, the individual rate of behavioral switch from i to j is

$$\lambda^N_{i\to j}(X^N) = N\kappa X^N(1 - X^N)(\gamma_j + \delta_j g_j(X^N)). \tag{11}$$

The term $\delta_j g_j(X^N)$ reflects that social influence is a coercive mechanism which encourages conformism.

Individual assessment

Behavior switching based on the assessment of the state of the environment occurs at the individual rate

$$\tau^N_{i\to j}(X^N, E^N) = N g_i(X^N)\tau_j(E^N), \tag{12}$$

where $g_A(X^N) = X^N$ and $g_B(X^N) = 1 - X^N$ (as above) and the environmental perception of individual i is measured by $\tau_j(E^N)$, which captures the difference between the environmental state, e, and the contribution of behavior j to the degradation of the environmental state.

The simplest form then is

$$\begin{aligned} \tau_A(E^N) &= \tau(E^N - l_A) \\ \tau_B(E^N) &= \tau(l_B - E^N). \end{aligned} \tag{13}$$

Thus, the larger the difference between the perceived environmental state, E^N, and the individual environmental impact of behavior i, l_i, the faster an agent expressing j behavior switches to i behavior.

Dynamics of the behavior-environment stochastic process

The dynamics of the coupled behavior-environment process $\left(X^N_t, E^N_t\right)$ are stochastic, driven by the probabilistic events of agents switching between the baseline (B) and active (A) behaviors, under the joint effects of encounters and individual assessment, and the deterministic response of the perceived environmental state. Mathematically, the effects of all possible events (agents' behavior switches, change in perceived environment) on the state of the Markovian system $\left(X^N_t, E^N_t\right)_{t\geq 0}$ are captured by the infinitesimal generator L^N of the stochastic process $\left(X^N_t, E^N_t\right)$. For $(x, e) \in [\![0, \frac{1}{N}, \cdots, 1]\!] \times \mathbb{R}^+_*$ and a test function $f \in \mathcal{C}^1_b([\![0, \frac{1}{N}, \cdots, 1]\!] \times \mathbb{R}^+_*, \mathbb{R})$, we have

$$\begin{aligned} L^N f(x,e) =& N^2\kappa x(1-x)\lambda^N_A(x)\left[f\left(x+\frac{1}{N}, e\right) - f(x,e)\right] \\ &+ N^2\kappa x(1-x)\lambda^N_B(x)\left[f\left(x-\frac{1}{N}, e\right) - f(x,e)\right] \\ &+ N(1-x)\tau_{B\to A}(x,e)\left[f\left(x+\frac{1}{N}, e\right) - f(x,e)\right] \\ &+ Nx\tau_{A\to B}(x,e)\left[f\left(x-\frac{1}{N}, e\right) - f(x,e)\right] \\ &+ h(x,e)\frac{\partial f(x,e)}{\partial e}. \end{aligned} \tag{14}$$

Agents switch behavior at a given time t for a given state of the system (X_t, E_t) with a probability given by Eq. (14). In this expression, the first and second rows account for individual behavior switches due to encounters (from B to A or A to B, respectively). For instance, the rate at which a $B \to A$ switch occurs because of encounters (first row) is proportional

to $N(1-x)$, the number of agents adopting behavior B; $\kappa N x$, the encounter rate between a single agent adopting B and agents adopting A; and $\lambda_A(x)$, the social attractiveness of a single agent adopting A. The third and fourth rows account for switches because of individual assessment of the perceived environment state. For instance, the rate at which a $B \to A$ switch occurs because of the environmental state variable (third row) is proportional to $N(1-x)$, the number of agents adopting B; and $\tau_{B\to A}(x,e)$, the rate at which an agent in state B adopts the alternate behavior A after assessing the impact of its behavior on the perceived state of the environment. Finally, the last row accounts for changes in the perceived environmental state depending on the frequency. By taking $f(x,e) = x$ and $f(x,e) = e$, we obtain the deterministic part in Supplementary Eq. (2) (see Supplementary Note [13]) while $f(x,e) = x^2$ gives the quadratic variation in Supplementary Eq. (4). The process whose law is characterized by Eq. (14) is a Piecewise Deterministic Markov Process where the population state (frequencies of behaviors) probabilistically jumps at each change in agent behavior while the environmental state deterministically and continuously changes between jumps.

Dynamical system approximation for large populations

In the Supplementary Note [13], we explain that, assuming the population size N very large and under Assumptions (10-15), the sequence of stochastic processes $(X^N, E^N)_{N\in\mathbb{N}^*}$ converges in distribution to the unique solution of the system Eq. (1). By plugging Eq. (2), (3) and (**??**) into Eq. (1), we obtain Eq. (15)

$$\begin{aligned}\frac{dx_t}{dt} &= p(x_t,e_t) = \kappa x_t(1-x_t)[\beta + \delta_A x_t - \delta_B(1-x_t)] + \tau\left[e_t - l_A(1-x_t) - l_B x_t\right]\\ \frac{de_t}{dt} &= h(x_t,e_t) = \ell e_t(l_A x_t + l_B(1-x_t) - e_t)\end{aligned} \tag{15}$$

with initial conditions x_0 between 0 and 1 and e_0 between l_A and l_B. The first equation governs the frequency x of the active behavior, A. The second equation drives the dynamics of the perceived environmental state variable, e.

The model predicts up to three equilibria given by the zeros of

$$p(x, l_A x + l_B(1-x)) = p_0(x) + \tau(l_B - l_A)(1-2x), \tag{16}$$

(p_0 defined in Eq. (6)), that are nonegative and less than (or equal to) one. By setting both $\tau > 0$ and $\kappa > 0$ in Eq. (15), the effect of the environmental feedback on its own can be highlighted by comparing Eq. (15) at its stable equilibria with the value of Eq. (16) at the same state (i.e. $x^* = 0$ or $x^* = 1$). Since $p(0, l_B) = \tau(l_B - l_A) > 0$ and $p(1, l_A) = -p(0, l_B) < 0$, the environmental feedback moves the equilibria of the system away from 0 and 1 (Fig. 2). The roots of Eq. (16) also show that the number of equilibria is likely influenced by the encounter rate, κ, the payoff differential, β, the social norm threshold, $\nu = \frac{\delta_B}{\delta_A+\delta_B}$, and the combination (product) of the individual sensitivity to the environment, τ, and the differential environmental

impact, $l_B - l_A$.

Quantifying the effect of individual stochasticity

To analyse the fluctuations of the stochastic model around the deterministic limit, we generalize the central limit theorem to the convergence of the stochastic process $(X_t^N, E_t^N)_{t\in[0,T]}$ to the deterministic solution of Eq. (1). We therefore introduce $(\eta_t^N)_{t\in[0,T]} = (\eta_t^{A,N}, \eta_t^{E,N})_{t\in[0,T]} = (\sqrt{N}(X_t^N - x_t, E_t^N - e_t))_{t\in[0,T]}$, where $((x_t, e_t), t \leq T)$ is the deterministic solution of Eq. (1) and (X^N, E^N) is the stochastic process. Assuming that η_0^N converges in law to η_0, when $N \to \infty$, the process $(\eta_t^N)_{t\in[0,T]}$ converges in law to a Ornstein-Uhlenbeck type process $(\eta_t)_{t\in[0,T]} = (\eta_t^A, \eta_t^E)_{t\in[0,T]}$ and we have

$$(X_t^N, E_t^N) = (x_t, e_t) + \frac{1}{\sqrt{N}}(\eta_t^A, \eta_t^E) + o\left(\frac{1}{\sqrt{N}}\right).$$

For all t in $[0, T]$, the process $(\eta_t)_{t\in[0,T]} = (\eta_t^A, \eta_t^E)_{t\in[0,T]}$ satisfies

$$\begin{aligned}
\eta_t^A &= \eta_0^A + \int_0^t [(\kappa(1-2x_s)(\gamma_A - \gamma_B - \delta_B + (\delta_A + \delta_B)x_s) - \tau(l_B - l_A))\eta_s^A + \tau\eta_s^E]ds \\
&\quad + \int_0^t \sigma(x_s, e_s)dW_s, \\
\eta_t^E &= \eta_0^E + \int_0^t \ell[(l_A - l_B)e_s\eta_s^A + (l_A x_s + l_B(1-x_s) - 2e_s)\eta_s^E]ds.
\end{aligned} \tag{17}$$

where

$$\sigma(x, e) = \sqrt{\kappa x(1-x)(\lambda_A(x) + \lambda_B(x)) + \tau_A(e)(1-x) + \tau_B(e)x}, \tag{18}$$

and W is a standard Brownian motion (see Supplementary Note [13] for mathematical detail).

Note that the drift and variance are functions of the solution of the deterministic system (1). The stochastic part of the fluctuation process given by Eq. (18) is the square root of the total rate Ω (see Eq. (4)) of behavior switching in the population. According to Eq. (17), it only affects the fluctuations in behavior frequency (not in the perceived environmental state).

Simulations and numerical analysis

For the stochastic process, the dynamics of agent behaviors' frequency (by stochastic jumps) is jointly simulated with the dynamics of the perceived environment (by deterministic changes, continuously in time between the stochastic population jumps). Random times are for any N drawn according to an exponential distribution of parameters ξ^N, where

$$\xi^N > N \sup_{(x,e)\in[0,1]\times[l_A,l_B]} (\kappa(\lambda_A(x) + \lambda_B(x)) + \tau_A(e) + \tau_B(e)). \tag{19}$$

At each of these times, we update our variables of interest. There are three possible cases: either no agent changes their behavior in the population, or one agent switches from B to A, or one agent switches from A to B. The perceived environment is changed using a Euler scheme between two events in the population.

Without loss of generality, parameters κ and l_B are fixed to 1 (default values for parameters used in numerical analyses are reviewed in Table 1). We analyse the properties of the stochastic and deterministic models for values of δ_A and γ_A spanning the whole range of possible values while keeping δ_B and γ_B constant. Parameters are varied across a discrete grid. We search for fixed points by computing the zeros of the polynomial given by Eq. (16). Local stability is tested by computing the Jacobian matrix of the system. We use the Poincaré-Bendixson theorem to check the absence of limit cycle (Th.1.8.1 in [20], see also Supplementary Material [13]). When the existence of a stable limit cycle in addition to an attractive fixed point cannot be excluded, we simulate the dynamical system for different initial conditions. Would there be a limit cycle crossing the trajectory of the simulations, the trajectory would be trapped around the limit cycle and not converge to its stable fixed point. Otherwise, all trajectories converge to the equilibrium, thus excluding the existence of a limit cycle.

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References

[1] Alexandra Alvergne and Rose Stevens. "Cultural change beyond adoption dynamics: Evolutionary approaches to the discontinuation of contraception". In: *Evolutionary Human Sciences* 3 (2021), e13.

[2] Dorsa Amir, Matthew R Jordan, and David G Rand. "An uncertainty management perspective on long-run impacts of adversity: The influence of childhood socioeconomic status on risk, time, and social preferences". In: *Journal of Experimental Social Psychology* 79 (2018), pp. 217–226.

[3] James Andreoni, Nikos Nikiforakis, and Jan Stoop. *Are the rich more selfish than the poor, or do they just have more money? A natural field experiment.* Tech. rep. National Bureau of Economic Research, 2017.

[4] Robert S Baron, Joseph A Vandello, and Bethany Brunsman. "The forgotten variable in conformity research: Impact of task importance on social influence." In: *Journal of personality and social psychology* 71.5 (1996), p. 915.

[5] Chris T Bauch et al. "Early warning signals of regime shifts in coupled human–environment systems". In: *Proceedings of the National Academy of Sciences* 113.51 (2016), pp. 14560–14567.

[6] Mélusine Boon-Falleur et al. "Leveraging social cognition to promote effective climate change mitigation". In: *Nature Climate Change* 12.4 (2022), pp. 332–338.

[7] Thomas M Bury, Chris T Bauch, and Madhur Anand. "Charting pathways to climate change mitigation in a coupled socio-climate model". In: *PLoS computational biology* 15.6 (2019), e1007000.

[8] Robert B Cialdini. *Influence: The psychology of persuasion.* Vol. 55. Collins New York, 2007.

[9] Colin W Clark. "Mathematical bioeconomics". In: *Mathematical Problems in Biology: Victoria Conference.* Springer. 1974, pp. 29–45.

[10] Susan Clayton et al. "Psychological research and global climate change". In: *Nature climate change* 5.7 (2015), pp. 640–646.

[11] Sara M Constantino and Elke U Weber. "Decision-making under the deep uncertainty of climate change: The psychological and political agency of narratives". In: *Current Opinion in Psychology* 42 (2021), pp. 151–159.

[12] Simon D Donner and Jeremy McDaniels. "The influence of national temperature fluctuations on opinions about climate change in the US since 1990". In: *Climatic change* 118.3 (2013), pp. 537–550.

[13] Claire Ecotière et al. "Supplementary materials". In: (2022).

[14] Joana Figueiredo and Henrique M Pereira. "Regime shifts in a socio-ecological model of farmland abandonment". In: *Landscape ecology* 26.5 (2011), pp. 737–749.

[15] Robert Gifford. "The dragons of inaction: psychological barriers that limit climate change mitigation and adaptation." In: *American psychologist* 66.4 (2011), p. 290.

[16] Robert Gifford, Karine Lacroix, and Angel Chen. "Understanding responses to climate change: Psychological barriers to mitigation and a new theory of behavioral choice". In: *Psychology and climate change*. Elsevier, 2018, pp. 161–183.

[17] Chaitanya S Gokhale and Christoph Hauert. "Eco-evolutionary dynamics of social dilemmas". In: *Theoretical Population Biology* 111 (2016), pp. 28–42.

[18] Aurore Grandin, Melusine Boon-Falleur, and Coralie Chevallier. "The belief-action gap in environmental psychology: How wide? How irrational?" In: (2021).

[19] Aurore Grandin et al. "Socioeconomic status, time preferences and pro-environmentalism". In: *Journal of Environmental Psychology* 79 (2022), p. 101720.

[20] John Guckenheimer and Philip Holmes. *Nonlinear oscillations, dynamical systems, and bifurcations of vector fields*. Vol. 42. Springer Science & Business Media, 2013.

[21] Lawrence C Hamilton and Mary D Stampone. "Blowin'in the wind: Short-term weather and belief in anthropogenic climate change". In: *Weather, Climate, and Society* 5.2 (2013), pp. 112–119.

[22] Christoph Hauert, Camille Saade, and Alex McAvoy. "Asymmetric evolutionary games with environmental feedback". In: *Journal of theoretical biology* 462 (2019), pp. 347–360.

[23] Chad Hazlett and Matto Mildenberger. "Wildfire exposure increases pro-environment voting within democratic but not republican areas". In: *American Political Science Review* 114.4 (2020), pp. 1359–1365.

[24] Josef Hofbauer, Karl Sigmund, et al. *Evolutionary games and population dynamics*. Cambridge university press, 1998.

[25] Mehran Homayounfar, Rachata Muneepeerakul, and John Anderies. "Resilience-performance trade-offs in managing social-ecological systems". In: *Ecology and Society* 27.1 (2022).

[26] Clinton Innes, Madhur Anand, and Chris T Bauch. "The impact of human-environment interactions on the stability of forest-grassland mosaic ecosystems". In: *Scientific reports* 3.1 (2013), pp. 1–10.

[27] Pierre O Jacquet et al. "The ecological roots of human susceptibility to social influence: A pre-registered study investigating the impact of early-life adversity". In: *Royal Society open science* 6.1 (2019), p. 180454.

[28] Martin Korndörfer, Boris Egloff, and Stefan C Schmukle. "A large scale test of the effect of social class on prosocial behavior". In: *PloS one* 10.7 (2015), e0133193.

[29] Niels Lettinga et al. "Environmental adversity is associated with lower investment in collective actions". In: *PloS one* 15.7 (2020), e0236715.

[30] Daniel Lim and David DeSteno. "Suffering and compassion: The links among adverse life experiences, empathy, compassion, and prosocial behavior." In: *Emotion* 16.2 (2016), p. 175.

[31] Joshua Linn. “The rebound effect for passenger vehicles”. In: *The Energy Journal* 37.2 (2016).

[32] Jean-Denis Mathias et al. “Exploring non-linear transition pathways in social-ecological systems”. In: *Scientific reports* 10.1 (2020), pp. 1–12.

[33] Michael E McCullough et al. “Harsh childhood environmental characteristics predict exploitation and retaliation in humans”. In: *Proceedings of the Royal Society B: Biological Sciences* 280.1750 (2013), p. 20122104.

[34] John M McNamara. “Towards a richer evolutionary game theory”. In: *Journal of the Royal Society Interface* 10.88 (2013), p. 20130544.

[35] Hugo Mell, Nicolas Baumard, and Jean-Baptiste André. “Time is money. Waiting costs explain why selection favors steeper time discounting in deprived environments”. In: *Evolution and Human Behavior* 42.4 (2021), pp. 379–387.

[36] Manfred Milinski et al. “The collective-risk social dilemma and the prevention of simulated dangerous climate change”. In: *Proceedings of the National Academy of Sciences* 105.7 (2008), pp. 2291–2294.

[37] Olivier Morin. “Is cooperation a maladaptive by-product of social learning? The docility hypothesis reconsidered”. In: *Biological Theory* 9.3 (2014), pp. 286–295.

[38] Daniel Nettle, Agathe Colléony, and Maria Cockerill. “Variation in cooperative behaviour within a single city”. In: *PloS one* 6.10 (2011), e26922.

[39] Karine Nyborg. “No man is an island: social coordination and the environment”. In: *Environmental and Resource Economics* 76.1 (2020), pp. 177–193.

[40] Paul K Piff et al. “Having less, giving more: the influence of social class on prosocial behavior.” In: *Journal of personality and social psychology* 99.5 (2010), p. 771.

[41] Lou Safra et al. “Neighborhood deprivation negatively impacts children’s prosocial behavior”. In: *Frontiers in psychology* 7 (2016), p. 1760.

[42] Caroline Schill et al. “A more dynamic understanding of human behaviour for the Anthropocene”. In: *Nature Sustainability* 2.12 (2019), pp. 1075–1082.

[43] Stefan C Schmukle, Martin Korndörfer, and Boris Egloff. “No evidence that economic inequality moderates the effect of income on generosity”. In: *Proceedings of the National Academy of Sciences* 116.20 (2019), pp. 9790–9795.

[44] Ram P Sigdel, Madhur Anand, and Chris T Bauch. “Competition between injunctive social norms and conservation priorities gives rise to complex dynamics in a model of forest growth and opinion dynamics”. In: *Journal of theoretical biology* 432 (2017), pp. 132–140.

[45] Murugesu Sivapalan and Günter Blöschl. “Time scale interactions and the coevolution of humans and water”. In: *Water Resources Research* 51.9 (2015), pp. 6988–7022.

[46] Angelos Stamos et al. “Having less, giving more? Two preregistered replications of the relationship between social class and prosocial behavior”. In: *Journal of Research in Personality* 84 (2020), p. 103902.

[47] Andrew R Tilman, Joshua B Plotkin, and Erol Akçay. “Evolutionary games with environmental feedbacks”. In: *Nature communications* 11.1 (2020), p. 915.

[48] Danielle FP Toupo et al. “Evolutionary game dynamics of controlled and automatic decision-making”. In: *Chaos: An Interdisciplinary Journal of Nonlinear Science* 25.7 (2015), p. 073120.

[49] Ralph H Turner. “Personality in society: Social psychology’s contribution to sociology”. In: *Social Psychology Quarterly* (1988), pp. 1–10.

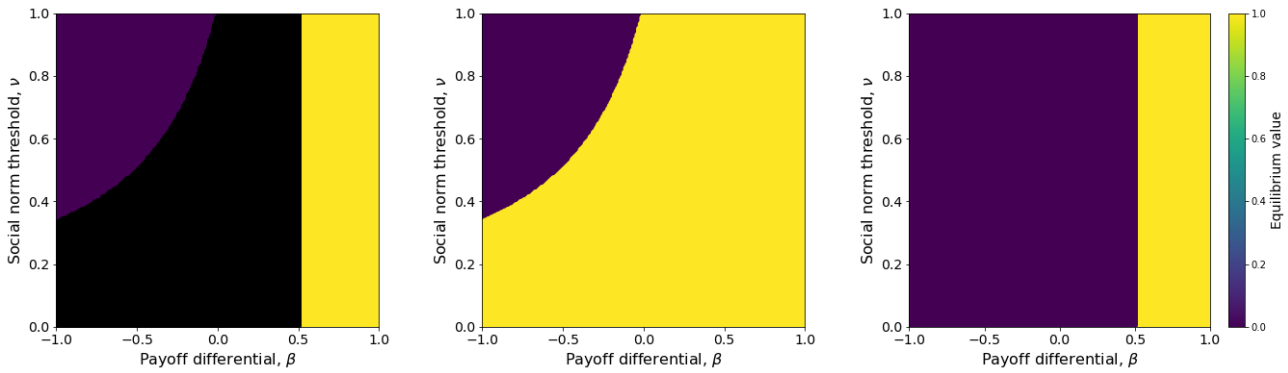
[50] Joshua S Weitz et al. “An oscillating tragedy of the commons in replicator dynamics with game-environment feedback”. In: *Proceedings of the National Academy of Sciences* 113.47 (2016), E7518–E7525.

[51] Junhui Wu et al. “Life history strategy and human cooperation in economic games”. In: *Evolution and Human Behavior* 38.4 (2017), pp. 496–505.

[52] Elena Zwirner and Nichola Raihani. “Neighbourhood wealth, not urbanicity, predicts prosociality towards strangers”. In: *Proceedings of the Royal Society B* 287.1936 (2020), p. 20201359.

Notation	Parameter description	Default value
A, B	Active vs. Baseline behaviors	
N	Size of the population	
$N_t^{A,N}, N_t^{B,N}$	Number of individuals expressing behavior A or B at time t	
X_t^N, E_t^N	Frequency of individuals with behavior A and Environment state at time t	
x_t, e_t	Deterministic frequency individuals with behavior A and environment state at time t	
κ	Encounter rate	1
τ	Individual sensitivity to the environment	
ℓ	Environmental reactivity	
γ_A (resp. γ_B)	Payoff of behavior A (resp. B)	$\gamma_B = 1$
δ_A (resp. δ_B)	Social pressure of behavior A (resp. B)	$\delta_B = 0.5$
l_A (resp. l_B)	Individual environmental impact of behavior A (resp. B)	$l_B = 1$
$\beta = \gamma_A - \gamma_B$	Payoff differential	
$\frac{\delta_B}{\delta_A+\delta_B}$	Social norm threshold (SNT)	
$l_B - l_A$	Environmental impact differential	

Table 1: **Parameter definitions and default values.**



(a) (b) (c)

Figure 1: **Frequency of active behavior at equilibrium in the absence of environmental feedback (Eq.** (5)**), with respect to the payoff differential (**β**) and social norm threshold (**$\nu = \frac{\delta_B}{\delta_A+\delta_B}$**).** (a) Bistability occurs in the black filled area (depending on the initial conditions, the equilibrium is either $x^* = 0$ or $x^* = 1$). (b) The upper equilibrium value ($x^* = 1$) is plotted across the bistability area (reachable for initial frequency $x_0 > \nu$). (c) The lower equilibrium value ($x^* = 0$) is plotted across the bistability area (reachable for initial frequency $x_0 < \nu$)
. Environmental sensitivity is $\ell = 0.1$ and other parameters are set to their default values (Table 1).

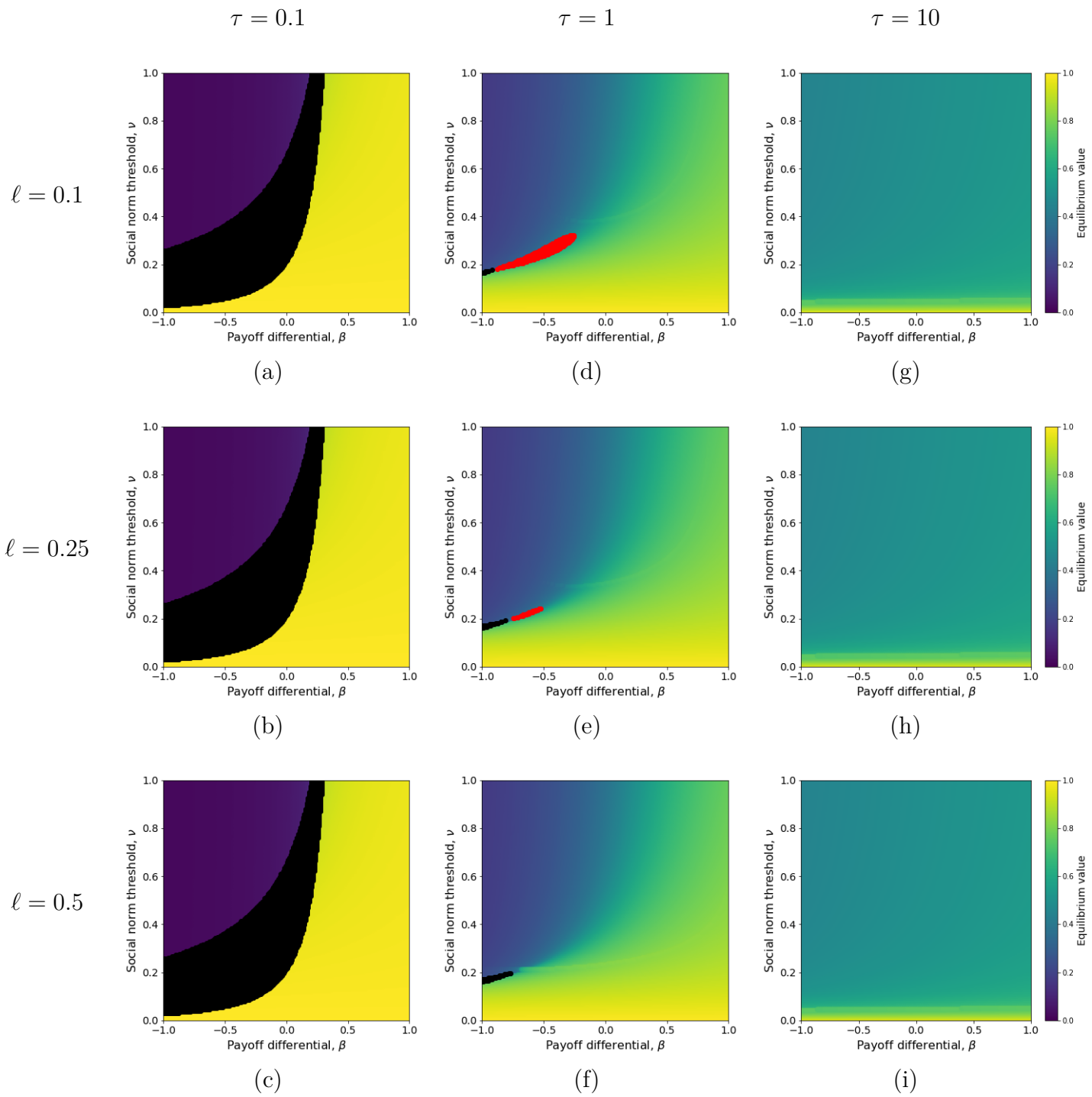


Figure 2: **Frequency of active behavior at equilibrium in the presence of environmental feedback (Eq. 16), with respect to the payoff differential (β) and social norm threshold ($\nu = \frac{\delta_B}{\delta_A+\delta_B}$)**, for low to high individual sentivity to the environment (τ) and environmental reactivity (ℓ). Bistability occurs in the black filled areas. Stable limit cycles occur in the red filled areas. The environmental impact differential is fixed ($l_B = 1, l_A = 0.7$). Other parameters (κ, δ_B) are set to their default values (Table 1).

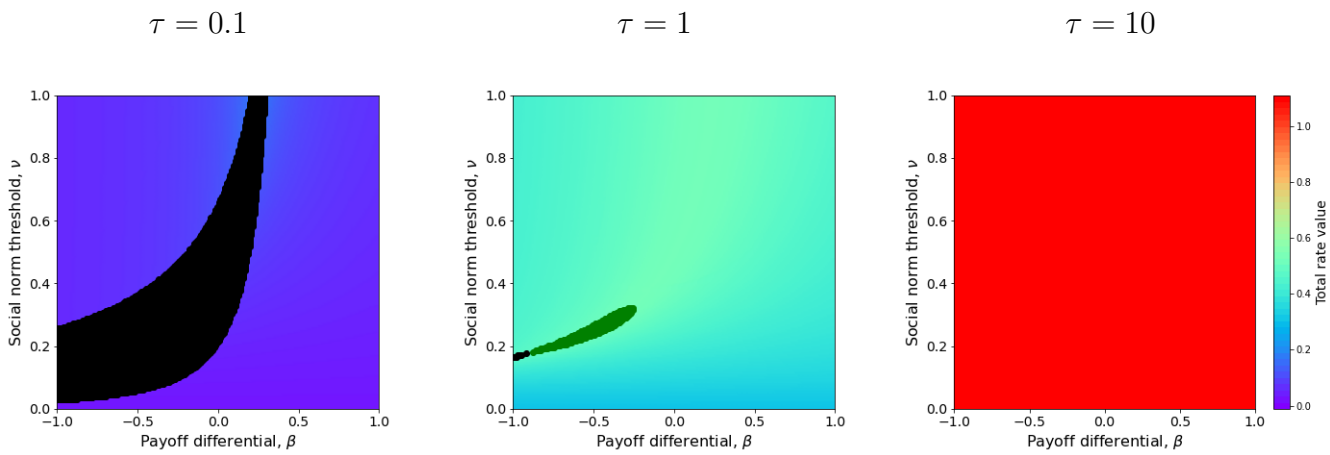


Figure 3: **Total switching rate at stationary state.** The total switching rate is equalt to the variance of the asymptotic fluctuations around the equilibrium x^* as given by Eq. 18. (a) Variance for $\tau = 0.1$. (b) Variance for $\tau = 1$. (c) Variance for $\tau = 10$. The environmental impact differential is fixed ($l_B = 1, l_A = 0.7$), environmental sensitivity is $\ell = 0.1$ and other parameters are set to their default values (Table 1).

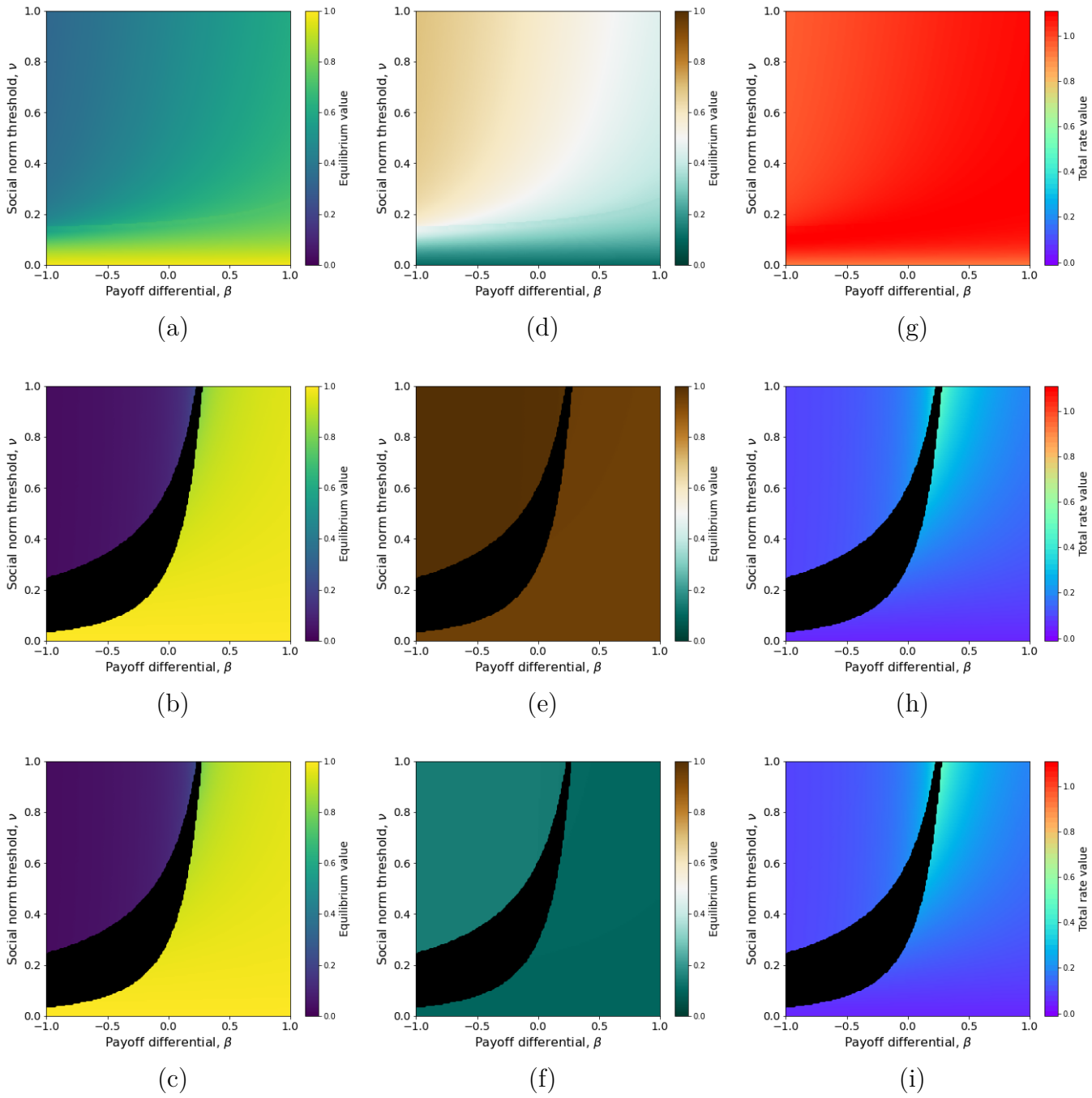
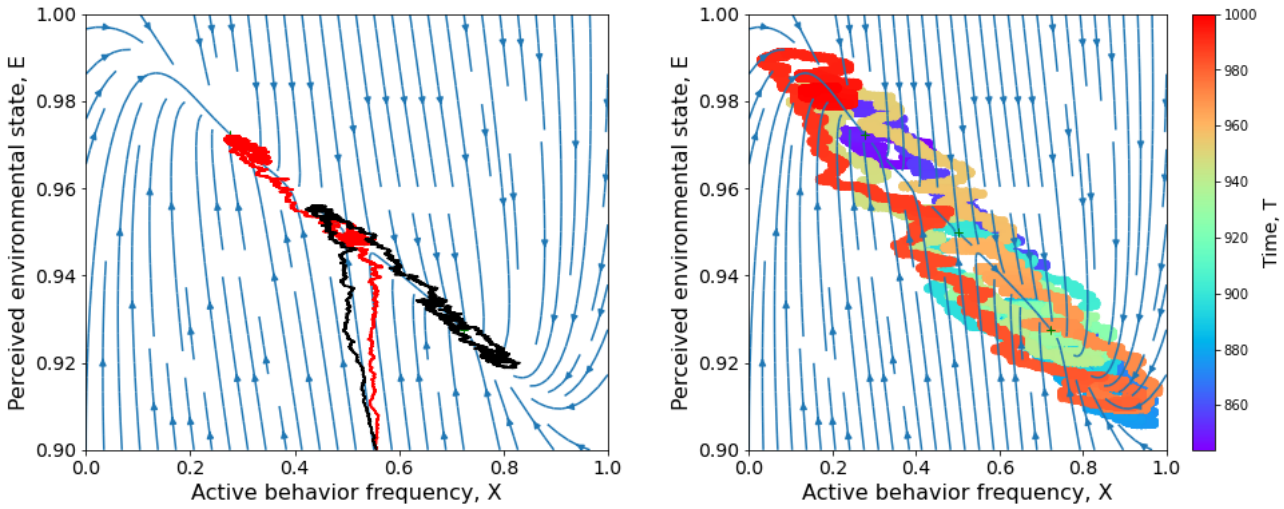


Figure 4: **Influence of the environmental impact differential, $l_B - l_A$, on the frequency of active behavior (a, b, c), perceived environmental state (d, e, f), and total switching rate (g, h, i) at equilibrium.** For (a), (d) and (g), the parameters are $l_B = 1$ and $l_A = 0.1$. For (b), (e) and (h), $l_B = 1$ and $l_A = 0.95$. For (c), (f) and (i), $l_B = 0.15$ and $l_A = 0.1$.
Individual sensitivity to the environment and environmental reactivity are set to $\tau = 1$ and $\ell = 0.1$. Other parameters are set to their default values (Table 1).



(a) (b)

Figure 5: **Effect of stochastic fluctuations on behavior-environment dynamics in the bistable case.** (a) Convergence of two trajectories issued from the same initial condition to alternate equilibria. (b) A single trajectory, with color coding for passing time, visits alternate equilibria, from the higher x^* (blue tones) to the lower x^* (green) to the higher x^* (orange) to the lower x^* (red). The stochastic simulation algorithm is described in the Methods. Environmental sensitivity $\ell = 0.1$ (as in Fig. 2a), payoff difference $\beta = -0.25$ and social norm threshold $\nu = 0.3$. Other parameters are set to their default values (Table 1).