Supplementary information
Evolutionary dynamics of behavioral motivations for cooperation

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Supplementary Note 1: Model

The population structure is described by a network comprising N nodes, which are denoted by $\mathcal{N} = \{1, 2, \cdots, N\}$, and $\{w_{ij}\}_{i,j\in\mathcal{N}}$ as the edge weights between nodes. The total degree of node i is defined as the sum of its edge weights, denoted by w_i, and is given by $w_i = \sum_{j\in\mathcal{N}} w_{ij}$.

Each individual i has a set of L action options denoted by $\mathcal{L} = \{1, 2, \cdots, L\}$. In each round, every individual selects an action to play a game with each of their neighbors. The payoff for using action k against action ℓ is denoted by $M_{k\ell}$. Let s_i denote individual i's selected action, i.e. $s_i \in \mathcal{L}$. The edge-weighted payoff for individual i in round t is given by the equation:

$$u_i(t) = \sum_{j\in\mathcal{N}} \frac{w_{ij}}{w_i} M_{s_i s_j}. \tag{S1}$$

The accumulated payoff pattern for each individual can be analyzed in a similar way.

In addition to their action choices, each individual also has a unique behavioral motivation characterized by a set of probability functions denoted by $\mathcal{G}_i = \left\{g_i^{k\ell}\left(\delta\left(u - \alpha_i^{k\ell}\right)\right)\right\}_{k,\ell\in\mathcal{L},k\neq\ell}$. Function $g_i^{k\ell}\left(\delta\left(u - \alpha_i^{k\ell}\right)\right) \in (0,1)$ represents the probability that individual i forgoes action k and switches to adopt action ℓ when they receive a payoff of u. The term $u - \alpha_i^{k\ell}$ indicates how much i's payoff exceeds their need threshold $\alpha_i^{k\ell}$ for transitioning from action k to action ℓ. The parameter δ (> 0) measures the extent to which the payoff difference influences the action updating process. When $\delta = 0$, the action updating process is completely random and payoff-independent, with every individual choosing any action with equal probability, i.e. $g_i^{k\ell}(0) = 1/L$ for any $\ell \neq k$. We focus on the week selection, i.e. $\delta \ll 1$. Generally, the transition function $g_i^{k\ell}$ and the need threshold $\alpha_i^{k\ell}$ vary across individuals i, current action k, and potential action ℓ.

At the end of each round t, an individual i is selected randomly to update their action from k to another action ℓ (where $\ell \neq k$), based on a comparison between their payoff $u_i(t)$ and the need threshold $\alpha_i^{k\ell}$, and switch to action ℓ with probability $g_i^{k\ell}\left(\delta\left(u_i(t) - \alpha_i^{k\ell}\right)\right)$. Otherwise, they continue using action k in the next round with probability $1 - \sum_{\ell\neq k,\ell\in\mathcal{L}} g_i^{k\ell}\left(\delta\left(u_i(t) - \alpha_i^{k\ell}\right)\right)$.

After T rounds of interactions and action updating, each individual i has an averaged payoff over the last T rounds, given by $\bar{u}_i = \sum_{t=1}^{T} u_i(t)/T$. Then, a random individual i is selected to update their behavioral motivation, represented by the set of probability functions $\mathcal{G}_i$, based on the death-birth updating rule. Specifically, individual i replaces their current behavioral motivation $\mathcal{G}_i$ with neighbor j's behavioral motivation with probability proportional to neighbor j's averaged payoff

$\bar{u}_j$. The probability of i adopting j's behavioral motivation is given by

$$e_{ji}(\mathcal{G}) = \frac{w_{ij}\bar{u}_j}{\sum_{\ell \in \mathcal{N}} w_{i\ell}\bar{u}_\ell}, \tag{S2}$$

where $\mathcal{G}$ represents the current population state, with the i_{th} element set to be $\mathcal{G}_i$.

Supplementary Note 2: Methods

2.1 Strategy evolution under fixed behavioral motivation

We begin by analyzing the global abundance of a specific action ℓ in the long run, i.e., when T is sufficiently large. We study how this abundance depends on the probability functions and need values. Assuming that $0 < g_i^{k\ell}\left(\delta\left(u-\alpha_i^{k\ell}\right)\right) < 1$ for any i,k,ℓ, and $0 < 1-\sum_{\ell\neq k} g_i^{k\ell}\left(\delta\left(u-\alpha_i^{k\ell}\right)\right) < 1$ for any i,k, the system has no absorbing state in terms of actions taken, i.e., there is no situation where all individuals adopt the same action from a certain point in time onwards. Let x_i^ℓ denote the abundance of individual i taking action ℓ, such that $\sum_{k\in\mathcal{L}} x_i^k = 1$. The expected payoff for individual i when using action k is given by

$$u_i^k = \sum_{j\in\mathcal{N},\ell\in\mathcal{L}} \frac{w_{ij}}{w_i} x_j^\ell M_{k\ell}. \tag{S3}$$

Regarding the action abundance, we have

$$x_i^\ell = \sum_{k\in\mathcal{L},k\neq\ell} x_i^k g_i^{k\ell}\left(\delta\left(u_i^k-\alpha_i^{k\ell}\right)\right) + x_i^\ell\left[1-\sum_{k\in\mathcal{L},k\neq\ell} g_i^{\ell k}\left(\delta\left(u_i^\ell-\alpha_i^{\ell k}\right)\right)\right], \tag{S4}$$

where the first term on the right-hand side represents the probability of switching to action ℓ conditioned on using action k in the current round, and the second term is the probability of continuing to use action ℓ conditioned on using the same action in the current round.

For weak selection with $\delta \ll 1$, we can express the effect of small perturbations of δ around 0 in terms of a first-order Taylor expansion, yielding

$$\begin{aligned} g_i^{k\ell}\left(\delta\left(u_i^k-\alpha_i^{k\ell}\right)\right) =& \frac{1}{L} + \left.\frac{\mathrm{d}g_i^{k\ell}(y)}{\mathrm{d}y}\right|_{y=0}\left(u_i^k-\alpha_i^{k\ell}\right)\delta + O(\delta^2), \\ x_i^\ell =& \frac{1}{L} + a_i^\ell\delta + O(\delta^2), \end{aligned} \tag{S5}$$

where a_i^ℓ is an expression that is independent of δ. We denote $\left.\frac{\mathrm{d}g_i^{k\ell}(y)}{\mathrm{d}y}\right|_{y=0}$ by $\lambda_i^{k\ell}$. Substituting Eqs. S3 and S5 into Eq. S4 and comparing coefficients of terms with δ, we obtain

$$a_i^\ell = \frac{1}{L}\sum_{k\in\mathcal{L},k\neq\ell}\left[\lambda_i^{k\ell}\left(\frac{1}{L}\sum_{m\in\mathcal{L}} M_{km} - \alpha_i^{k\ell}\right) - \lambda_i^{\ell k}\left(\frac{1}{L}\sum_{m\in\mathcal{L}} M_{\ell m} - \alpha_i^{\ell k}\right)\right]. \tag{S6}$$

The global abundance of every action ℓ is given by

$$x^{\ell} = \frac{1}{N}\sum_{i\in\mathcal{N}} x_i^{\ell} = \frac{1}{L} + \frac{\delta}{N}\sum_{i\in\mathcal{N}} a_i^{\ell} + O(\delta^2). \tag{S7}$$

The condition for the abundance of action ℓ is higher under weak selection than in the neutral case, i.e. $x^{\ell} > 1/L$, is

$$\sum_{i,k\neq\ell}\left[\lambda_i^{k\ell}\left(\frac{1}{L}\sum_{m\in\mathcal{L}} M_{km} - \alpha_i^{k\ell}\right) - \lambda_i^{\ell k}\left(\frac{1}{L}\sum_{m\in\mathcal{L}} M_{\ell m} - \alpha_i^{\ell k}\right)\right] > 0. \tag{S8}$$

where the term $\sum_{m\in\mathcal{L}} M_{km}/L - \alpha_i^{k\ell}$ measures how satisfied an individual is with their payoff in terms of the need to switch from action k to ℓ. The other term $\lambda_i^{k\ell}$ measures to what degree they are motivated to switch from action k to action ℓ. Thus, the satisfaction level of an individual with their current payoff and the degree to which they are motivated to switch, jointly determine the abundance of each action.

2.2 Evolutionary dynamics with behavioral motivation

In this section, we investigate the competition and evolution of two behavioral motivations, denoted as motivation A with $\left\{g_A^{k\ell}(\delta(u-\alpha_A^{k\ell}))\right\}_{k,\ell\in\mathcal{L},k\neq\ell}$ and motivation B with $\left\{g_B^{k\ell}(\delta(u-\alpha_B^{k\ell}))\right\}_{k,\ell\in\mathcal{L},k\neq\ell}$. Let $\mathbf{z}$ denote the state of individuals' behavioral motivation, where the i_{th} entry $z_i = 1$ (respectively $z_i = 0$) means individual i uses behavioral motivation A (respectively B). The average payoff that individual i obtains after long-term repeated interactions and action updating is given by

$$\bar{u}_i = \sum_{k\in\mathcal{L}} x_i^k u_i^k = \frac{1}{L^2}\sum_{k,\ell\in\mathcal{L}} M_{k\ell} + \frac{\delta}{L}\sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left(\sum_{j\in\mathcal{N}}\frac{w_{ij}}{w_i}a_j^{\ell} + a_i^k\right). \tag{S9}$$

We define

$$\beta_X^{\ell} = \frac{1}{L}\sum_{k\in\mathcal{L},k\neq\ell}\left[\lambda_X^{k\ell}\left(\frac{1}{L}\sum_{m\in\mathcal{L}} M_{km} - \alpha_X^{k\ell}\right) - \lambda_X^{\ell k}\left(\frac{1}{L}\sum_{m\in\mathcal{L}} M_{\ell m} - \alpha_X^{\ell k}\right)\right], \tag{S10}$$

where $X \in \{A, B\}$. With this, we can rewrite Equation (S9) to be

$$\begin{aligned}\bar{u}_i(\mathbf{z}) =& \frac{1}{L^2}\sum_{k,\ell\in\mathcal{L}} M_{k\ell} + \frac{\delta}{L}\sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left[\sum_j \frac{w_{ij}}{w_i}\left(z_j\beta_A^{\ell} + (1-z_j)\beta_B^{\ell}\right) + \left(z_i\beta_A^k + (1-z_i)\beta_B^k\right)\right] \\ =& \frac{1}{L^2}\sum_{k,\ell\in\mathcal{L}} M_{k\ell} + \frac{\delta}{L}\sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left[\left(\beta_A^{\ell} - \beta_B^{\ell}\right)\sum_j \frac{w_{ij}}{w_i}z_j + \left(\beta_A^k - \beta_B^k\right)z_i + \beta_B^k + \beta_B^{\ell}\right].\end{aligned} \tag{S11}$$

Note that Eqs. S5 and S6 indicate that the abundance of each action ℓ by every individual is independent of the network structure. Nonetheless, an individual i's payoff is structure-dependent. We define $\pi_i = w_i / \sum_{j\in\mathcal{N}} w_j$, $p_{ij} = w_{ij}/w_i$, and $p_{ij}^{(n)}$ to be the probability that an individual starting from node i terminates in node j after an n-step random walk.

Theorem 2 in Ref. [1] provides the fixation probability of a mutant A taking over a population of residents B under any initialization. For additive games, the fixation probability of mutant A with the uniform initialization is

$$\rho_A = \frac{1}{N} + \delta \sum_{i,j,n\in\mathcal{N}} \pi_i c_n^{ji} \left(\eta_{in} - \eta_{jn}\right) + O(\delta^2), \tag{S12}$$

where

$$\left.\frac{\mathrm{d}}{\mathrm{d}\delta}\right|_{\delta=0} e_{ij}(\mathbf{z}) = \sum_{n\in\mathcal{N}} c_n^{ij} z_n, \tag{S13}$$

and

$$\eta_{ij} = \begin{cases} 0, & i = j, \\ \frac{1}{2} + \frac{1}{2}\sum_{k\in\mathcal{N}} \left(p_{ik}^{(1)}\eta_{kj} + p_{jk}^{(1)}\eta_{ik}\right) & i \neq j. \end{cases} \tag{S14}$$

Substituting Eq. S11 into Eq. S2, we have

$$\begin{aligned}\left.\frac{\mathrm{d}}{\mathrm{d}\delta}\right|_{\delta=0} e_{ij}(\mathbf{z}) = \frac{L p_{ji}^{(1)}}{N\sum_{k,\ell\in\mathcal{L}} M_{k\ell}} \Bigg[&\left(z_i - \sum_{n\in\mathcal{N}} p_{jn}^{(1)} z_n\right) \sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left(\beta_A^k - \beta_B^k\right) \\ &+ \left(\sum_{n\in\mathcal{N}} p_{in}^{(1)} z_n - \sum_{n\in\mathcal{N}} p_{jn}^{(2)} z_n\right) \sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left(\beta_A^\ell - \beta_B^\ell\right)\Bigg]\end{aligned} \tag{S15}$$

which gives

$$\begin{aligned} c_n^{ij} = \frac{L p_{ji}^{(1)}}{N\sum_{k,\ell\in\mathcal{L}} M_{k\ell}} \Bigg[&\left(p_{in}^{(0)} - p_{jn}^{(1)}\right) \sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left(\beta_A^k - \beta_B^k\right) \\ &+ \left(p_{in}^{(1)} - p_{jn}^{(2)}\right) \sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left(\beta_A^\ell - \beta_B^\ell\right)\Bigg]. \end{aligned} \tag{S16}$$

Substituting c_n^{ij} into Eq. S12 gives

$$\rho_A = \frac{1}{N} + \frac{\delta}{N}\left(\eta_2 \frac{\sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left(\beta_A^k - \beta_B^k\right)}{\sum_{k,\ell\in\mathcal{L}} M_{k\ell}} + (\eta_3 - \eta_1)\frac{\sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left(\beta_A^\ell - \beta_B^\ell\right)}{\sum_{k,\ell\in\mathcal{L}} M_{k\ell}}\right), \quad \text{(S17)}$$

where $\eta_n = \sum_{i,j\in\mathcal{N}} \pi_i p_{ij}^{(n)} \eta_{ij}$. We then have the condition for the fixation probability of behavioral motivation A exceeding $1/N$, given by

$$\eta_2 \frac{\sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left(\beta_A^k - \beta_B^k\right)}{\sum_{k,\ell\in\mathcal{L}} M_{k\ell}} + (\eta_3 - \eta_1)\frac{\sum_{k,\ell\in\mathcal{L}} M_{k\ell}\left(\beta_A^\ell - \beta_B^\ell\right)}{\sum_{k,\ell\in\mathcal{L}} M_{k\ell}} > 0. \quad \text{(S18)}$$

Equation S18 also predicts when selection favors behavioral motivation A over B, with the constant term in the second expression of Eq. S14 replaced by 1.

Supplementary Note 3: Examples

3.1 Two-action game

We consider the classic two-player two-action game with a payoff structure

$$\begin{array}{c} \\ C \\ D \end{array} \begin{array}{c} \begin{array}{cc} C & D \end{array} \\ \begin{pmatrix} R & S \\ T & P \end{pmatrix} \end{array}, \tag{S19}$$

where C and D respectively represent cooperation and defection, respectively. Let $g_i^{CC}\left(\delta(u-\alpha_i^{CC})\right)$ denote the probability of individual i taking cooperation in the next round conditioned on their cooperative action, and $1-g_i^{CC}\left(\delta(u-\alpha_i^{CC})\right)$ the probability of individual i choosing defection. Similarly, let $g_i^{DC}\left(\delta(u-\alpha_i^{DC})\right)$ denote the probability of individual i taking cooperation in the next round conditioned on their previous defection, and $1-g_i^{DC}\left(\delta(u-\alpha_i^{DC})\right)$ the probability of individual i choosing defection. By substituting the switching function and payoff structures in Eq. S7, we obtain the abundance of the cooperative action

$$x_C = \frac{1}{2} + \frac{\delta}{4N}\sum_{i\in\mathcal{N}}\left[\lambda_i^{CC}\left(R+S-2\alpha_i^{CC}\right)+\lambda_i^{DC}\left(T+P-2\alpha_i^{DC}\right)\right]. \tag{S20}$$

When it comes to the competition between two behavioral motivations, say A with a switching function and need threshold $\left(g_A^{CC}(y), g_A^{DC}(y), \alpha_A^{CC}, \alpha_A^{DC}\right)$ and B with $\left(g_B^{CC}(y), g_B^{DC}(y), \alpha_B^{CC}, \alpha_B^{DC}\right)$, substituting the switching function and payoff structure into Eqs. S17 and S18 gives

$$\rho_A = \frac{1}{N} + \frac{\delta(\beta_A-\beta_B)}{2N(R+S+T+P)}\left[(R+S-T-P)\eta_2+(R-S+T-P)(\eta_3-\eta_1)\right], \tag{S21}$$

which is the fixation probability of a single individual with motivation A in a population of individuals with motivation B, where $\beta_A = \lambda_A^{CC}(R+S-2\alpha_A^{CC})+\lambda_A^{DC}(T+P-2\alpha_A^{DC})$ and $\beta_B = \lambda_B^{CC}(R+S-2\alpha_B^{CC})+\lambda_B^{DC}(T+P-2\alpha_B^{DC})$. The selection favoring motivation A occurs when

$$\frac{\beta_A-\beta_B}{R+S+T+P}\left[(R+S-T-P)\eta_2+(R-S+T-P)(\eta_3-\eta_1)\right] > 0. \tag{S22}$$

Note that the cooperation abundance in a population of individuals with behavioral motivation $X \in \{A, B\}$ is $x_C(\mathbf{X}) = 1/2 + \delta\beta_X/4$, Eq. S22 can be rewritten to be

$$\left(x_C(\mathbf{A}) - x_C(\mathbf{B})\right)\left[\frac{R+S-T-P}{R+S+T+P}\eta_2 + \frac{R-S+T-P}{R+S+T+P}(\eta_3-\eta_1)\right] > 0. \tag{S23}$$

The example presented in the main text, with an action-independent need threshold and sigmoid-like action updating function, can be replicated by using the following setting $g_A^{CC}(y) = g_A^{DC}(y) = 1/\left(1+\exp\left[-\lambda_A y\right]\right)$, $g_B^{CC}(y) = g_B^{DC}(y) = 1/\left(1+\exp\left[-\lambda_B y\right]\right)$, $\alpha_A^{CC} = \alpha_A^{DC} = \alpha_A$, $\alpha_B^{CC} = \alpha_B^{DC} = \alpha_B$. Note that in the main text, we simplify the expression by denoting $\delta\lambda_X$ by λ_X, which measures both the motivation type (by the sign of value λ_X) and the motivation intensity (by the absolute value of λ_X).

We analyze the representative snowdrift game with payoff structure

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} b-\frac{1}{2} & b-1 \\ b & 0 \end{pmatrix}, \end{array} \tag{S24}$$

where $b > 1$. Substituting the payoff structure into Eq. S23, we have the condition for selection favoring the motivation A over B, given by

$$\left(x_C(\mathbf{A}) - x_C(\mathbf{B})\right)\left[b\left(\eta_2+\eta_3-\eta_1\right) - \frac{1}{2}\left(3\eta_2-\eta_3+\eta_1\right)\right] > 0. \tag{S25}$$

Particularly, in the random regular networks with size N and node degree d, selection favors the undemanding philanthropists or demanding aspirationalists over demanding philanthropists or undemanding aspirationalists if

$$b > \frac{(3d-1)N - 4d}{2(d+1)N - 8d}. \tag{S26}$$

Analogously, we analyze the representative stag-hunt games with payoff structure

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} b & 0 \\ 1 & 1 \end{pmatrix}, \end{array} \tag{S27}$$

where $b > 1$. We have the condition for selection favoring the motivation A over B, given by

$$\left(x_C(\mathbf{A}) - x_C(\mathbf{B})\right)\left[b\left(\eta_2+\eta_3-\eta_1\right) - 2\eta_2\right] > 0. \tag{S28}$$

In the random regular networks with size N and node degree d, selection favors the undemanding philanthropists or demanding aspirationalists over demanding philanthropists or undemanding

aspirationalists if

$$b > \frac{(2N-4)\,d}{(d+1)\,N-4d}. \tag{S29}$$

Our general model can also recover the prior studies about aspiration-based action updating as a specific case [2–7], by taking $g_i^{CC}(y) = g_i^{DD}(y) = 1/\left(1+\exp\left[-y\right]\right)$, $g_i^{CD}(y) = g_i^{DC}(y) = 1/\left(1+\exp\left[y\right]\right)$. As such, one is more likely to keep the action unchanged when one's payoff exceeds the threshold and switches to the other action otherwise. The cooperation abundance and the fixation probability can analogously be derived from Eq. S20 and S23 respectively.

3.2 Multiple-action game

We extend the two-action donation name to a L-action variation, where action k means paying a cost to c_k to bring the opponent a benefit b_k. We begin with the linear donation game, with $c_k = c(k-1)/(L-1)$ and $b_k = b(k-1)/(L-1)$, which gives payoff structure $M_{k\ell} = -c(k-1)/(L-1) + b(\ell-1)/(L-1)$. As such, action 1 corresponds to be defective, and action L fully cooperative, namely paying a cost c to yield a benefit b to the opponent. The degree to be cooperative increases with the increasing action label. There is a large body of choices of need thresholds and probability functions. A representative case is

$$\alpha_i^{k\ell} = \begin{cases} \frac{\ell\alpha_i}{L-1}, & \ell < k, \\ \frac{(\ell-1)\alpha_i}{L-1}, & \ell > k, \end{cases} \tag{S30}$$

and

$$g_i^{k\ell}\left(\delta\left(u-\alpha_i^{k\ell}\right)\right) = \begin{cases} \frac{2}{L\left(1+\exp\left[\lambda_i\delta\left(u-\alpha_i^{k\ell}\right)\right]\right)}, & \ell < k, \\ \frac{2}{L\left(1+\exp\left[-\lambda_i\delta\left(u-\alpha_i^{k\ell}\right)\right]\right)}, & \ell > k. \end{cases} \tag{S31}$$

Substituting payoff structure, need thresholds, and action updating functions into Eqs. S6 and S7 gives x^ℓ. Furthermore, we have the global cooperation abundance, given by

$$x_C = \sum_{\ell\in\mathcal{L}} \frac{\ell-1}{L-1} x^\ell = \frac{1}{2} + \frac{\delta(L+1)}{12NL}\left[(b-c)\sum_{i\in\mathcal{N}}\lambda_i - \frac{L}{L-1}\sum_{i\in\mathcal{N}}\lambda_i\alpha_i\right]. \tag{S32}$$

When it comes to the competition between two behavioral motivations, namely A with $\left(g_A^{k\ell}(y), \alpha_A^{k\ell}\right)$ and B with $\left(g_B^{k\ell}(y), \alpha_B^{k\ell}\right)$, substituting the need thresholds and action updating functions into

Eq. S18, we have the condition for the evolution of behavioral motivation A, given by

$$\left[\lambda_A\left(b-c-\frac{L}{L-1}\alpha_A\right)-\lambda_B\left(b-c-\frac{L}{L-1}\alpha_B\right)\right](-c\eta_2+b(\eta_3-\eta_1))>0. \quad \text{(S33)}$$

Next, we consider an alternative L-action donation game with cost $c_k = -c(k-1)/(L-1)$ and benefit $b_k = b(1-\omega^{k-1})/(1-\omega^{L-1})$. The cost c_k is linearly related to the action label k, while the benefit b_k is nonlinearly related to the action label. The nonlinearity describes a possible situation where (i) action k corresponds to making donations for $k-1$ times, with each donation incurring a cost of $c/(L-1)$, and (ii) the benefit produced by the first donation is r and the benefit produced by every following donation is discounted or enhanced by a factor ω. Therefore, $k-1$ donations respectively generate benefits of $r, r\omega, r\omega^2, \cdots, r\omega^{k-2}$, where r is a constant. Discounting and synergetic effects prevail in various living systems [8]. Action k leads to an accumulated benefit of $r(1-\omega^{k-1})/(1-\omega)$. Aligning the benefit produced by a fully cooperative action to that in the linear donation game, we have $r = b(1-\omega)/(1-\omega^{L-1})$, and $b_k = b(1-\omega^{k-1})/(1-\omega^{L-1})$. Analogously, we have the global cooperation abundance:

$$x_C=\sum_{\ell\in\mathcal{L}}\frac{\ell-1}{L-1}x^\ell=\frac{1}{2}+\frac{\delta(L+1)}{12NL}\left[\left(\frac{2\sigma}{L}b-c\right)\sum_{i\in\mathcal{N}}\lambda_i-\frac{L}{L-1}\sum_{i\in\mathcal{N}}\lambda_i\alpha_i\right], \quad \text{(S34)}$$

where $\sigma = \left[L(1-\omega)-(1-\omega^L)\right] / \left[(1-\omega)(1-\omega^{L-1})\right]$.

For multi-action nonlinear games, the condition for selection favoring one motivation over the other is complicated, which does have a formalization like Eq. S33, except for specific cases. For example, substituting the payoff structure and action updating function $\left(g_A^{k\ell}(y), \alpha_A^{k\ell}\right)$ and $\left(g_B^{k\ell}(y), \alpha_B^{k\ell}\right)$ into Eq. S18, for the three-action nonlinear donation game, the condition for the evolution of behavioral motivation A is given by

$$\begin{aligned}&\eta_2 c\left[\lambda_A\left(\mathcal{C}_1-\mathcal{C}_2\alpha_A\right)-\lambda_B\left(\mathcal{C}_1-\mathcal{C}_2\alpha_B\right)\right]\\&+(\eta_3-\eta_1)b\left[\lambda_A\left(\mathcal{B}_1-\mathcal{B}_2\alpha_A\right)-\lambda_B\left(\mathcal{B}_1-\mathcal{B}_2\alpha_B\right)\right]>0,\end{aligned} \quad \text{(S35)}$$

where

$$\begin{aligned}\mathcal{C}_1&=-\frac{2b\omega-3c\omega+4b-3c}{9(\omega+1)},\quad \mathcal{C}_2=\frac{1}{2},\\ \mathcal{B}_1&=\frac{8b\omega-15c\omega+16b-9c}{36(\omega+1)},\quad \mathcal{B}_2=-\frac{7\omega+5}{12(\omega+1)}.\end{aligned} \quad \text{(S36)}$$

In the case of $\lambda_A = \lambda_B > 0$, the condition can be simplified to be $(\alpha_B-\alpha_A)\left[\eta_2\mathcal{C}_2 c+(\eta_3-\eta_1)\mathcal{B}_2 b\right] > 0$.

Supplementary Note 4: Extensions

Here, we extend our analysis of the evolutionary dynamics of behavioral motivations beyond weak selection intensities, focusing on the two-action donation game. The probability of an individual's likelihood to cooperate is described by the sigmoid function $g(u) = 1/\left(1+\exp\left[-\delta\lambda(u-\alpha)\right]\right)$, where u, α, and λ represent the individual's payoff, need threshold, and motivation intensity, respectively. We consider an infinite well-mixed population and assume all individuals have need threshold α and motivation intensity λ. By analyzing the stationary state, we can determine the stationary cooperating probability x for an individual, which is given by the following equation

$$x = \frac{x}{1+\exp\left[-\delta\lambda(bx-c-\alpha)\right]} + \frac{1-x}{1+\exp\left[-\delta\lambda(bx-\alpha)\right]}, \tag{S37}$$

where the first (respectively, the second) term in the right-hand side represents the cooperating probability in the next round conditioned on adopting cooperation (respectively, defection) in the current round. We can obtain the value of x by solving the following equation

$$x = \frac{1+\exp\left[\delta\lambda(bx-c-\alpha)\right]}{2+\exp\left[-\delta\lambda(bx-\alpha)\right]+\exp\left[\delta\lambda(bx-c-\alpha)\right]}. \tag{S38}$$

If a mutant with a different behavioral motivation intensity λ' and need threshold α' appears in the population, its effect on the cooperating probability of the other individuals is negligible for a sufficiently large population size. The mutant's stationary cooperation probability is x', which can be determined from the following equation

$$x' = \frac{x'}{1+\exp\left[-\delta\lambda'(bx-c-\alpha')\right]} + \frac{1-x'}{1+\exp\left[-\delta\lambda'(bx-\alpha')\right]}, \tag{S39}$$

which gives

$$x' = \frac{1+\exp\left[\delta\lambda'(bx-c-\alpha')\right]}{2+\exp\left[-\delta\lambda'(bx-\alpha')\right]+\exp\left[\delta\lambda'(bx-c-\alpha')\right]}. \tag{S40}$$

We can then determine whether the mutant can evolve by comparing the average payoffs of the residents and the mutant respectively, i.e. $\bar{u} = -cx + bx$ and $\bar{u}' = -cx' + bx$. To find the most advantageous mutant for a given value of x obtained from Eq. S38, we define a function $\phi(x,\alpha,\lambda)$ as follows

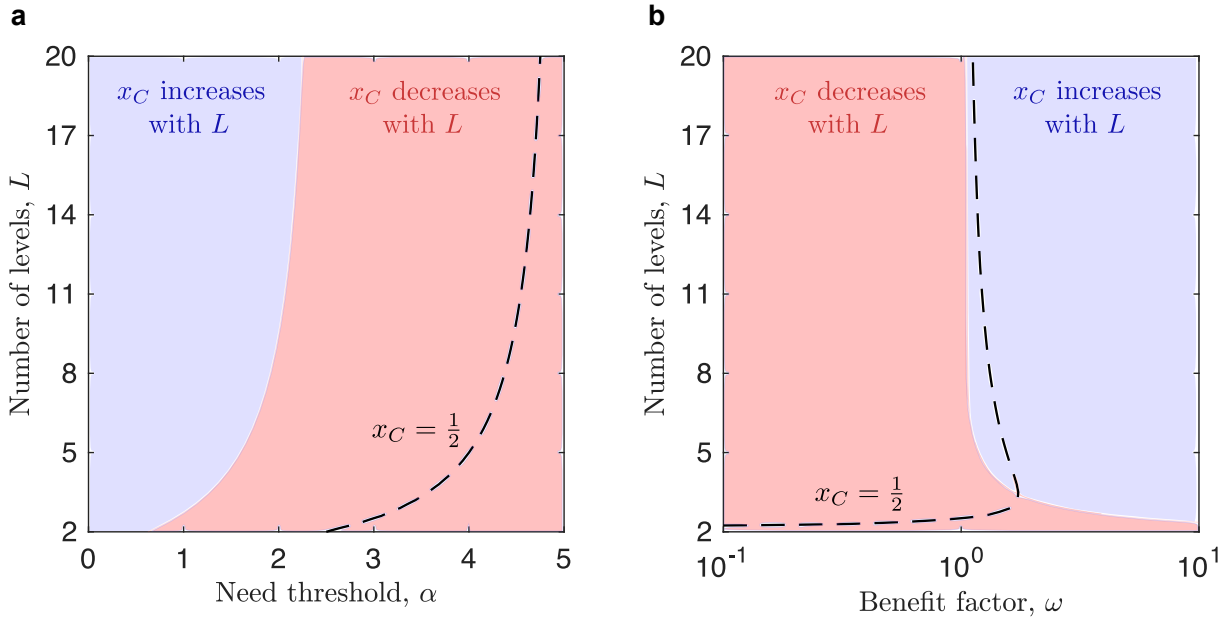
$$\phi(x,\alpha,\lambda) = \frac{1+\exp\left[\delta\lambda(bx-c-\alpha)\right]}{2+\exp\left[-\delta\lambda(bx-\alpha)\right]+\exp\left[\delta\lambda(bx-c-\alpha)\right]}, \tag{S41}$$

The direction in which the mutant would be most advantageous is given by $-\frac{\partial \phi}{\partial \alpha}$ and $-\frac{\partial \phi}{\partial \lambda}$, as follows

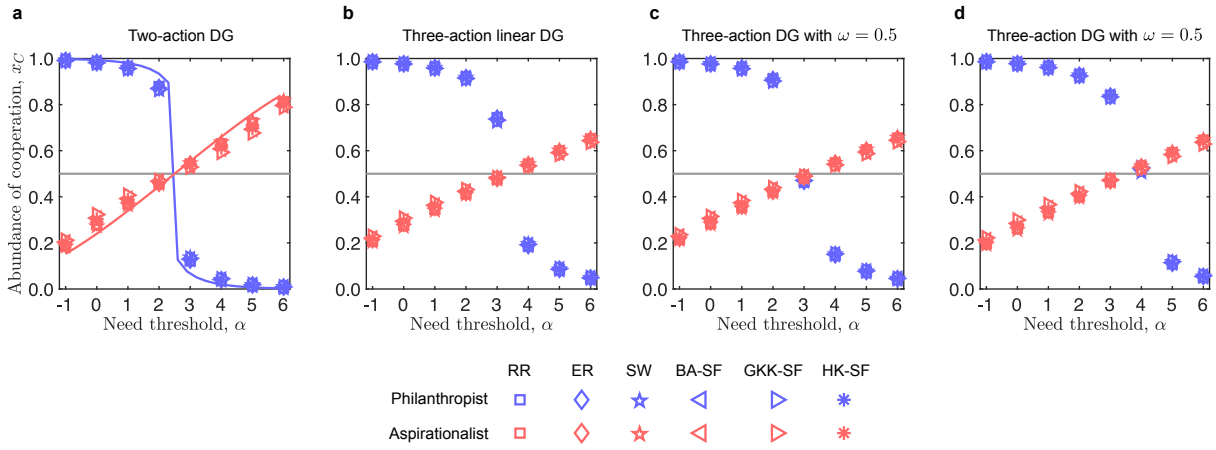
$$\begin{aligned}\frac{\partial \phi}{\partial \alpha} =& -\frac{\delta\lambda\left(2\exp\left[-\delta\lambda c\right]+\exp\left[\delta\lambda(bx-c-\alpha)\right]+\exp\left[-\delta\lambda(bx-c-\alpha)\right]\right)}{\left(2+\exp\left[-\delta\lambda(bx-\alpha)\right]+\exp\left[\delta\lambda(bx-c-\alpha)\right]\right)^2},\\ \frac{\partial \phi}{\partial \lambda} =& \frac{\delta\exp\left[-\delta\lambda c\right]\left(\exp\left[\delta\lambda(bx-\alpha)\right](xb-c-\alpha)+\exp\left[\delta\lambda(c+\alpha-bx)\right](bx-\alpha)+2xb-c-2\alpha\right)}{\left(2+\exp\left[-\delta\lambda(bx-\alpha)\right]+\exp\left[\delta\lambda(bx-c-\alpha)\right]\right)^2}.\end{aligned} \tag{S42}$$

We note that the sign of the gradient with respect to α depends only on the sign of $\delta\lambda$, whereas the sign of the gradient with respect to λ depends on x, b, c and α. If the need threshold α is fixed, with λ allowed to evolve, this can give rise to multi-stabile selection intensity (Supplementary Figure 5).

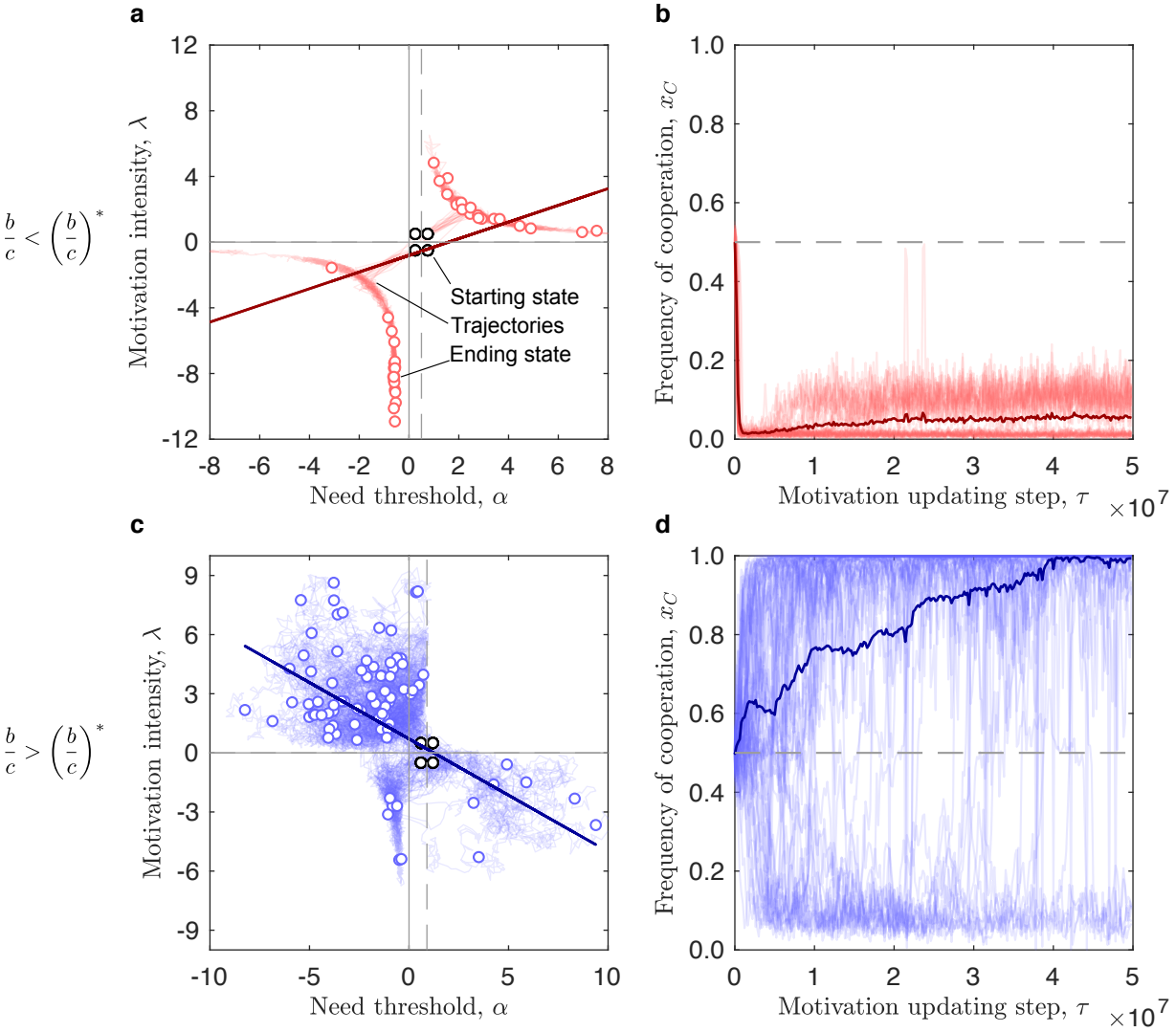
Supplementary Figures



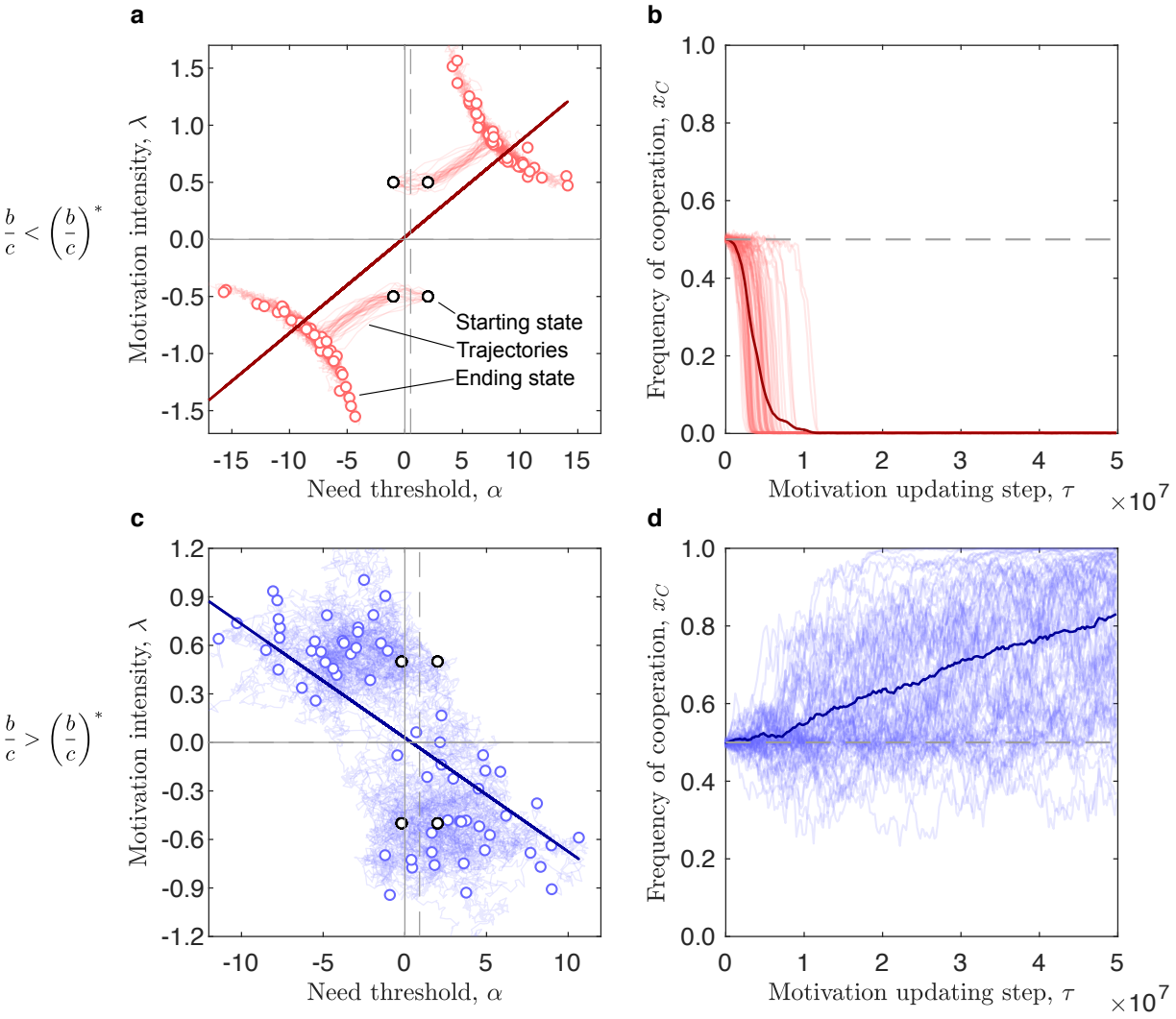
Supplementary Figure 1: Breaking down the high need into small pieces can make cooperation favorable. Different from Fig. 4 in the main text, here we consider a population of aspirationalists. **a**, Abundance of cooperation x_C as a function of the need threshold α and the number of available actions L in the multi-action linear donation game. In the red zone, the cooperation abundance x_C decreases monotonously with L, and a large L can make cooperation less favorable. In the blue zone, the increasing L monotonously increases the cooperation abundance x_C. The solid dashed line marks the level of $x_C = 1/2$. Thus, for behavioral motivations with a low need threshold $\alpha < 1/2$, increasing the number of available actions can increase the cooperation abundance. **b**, Abundance of cooperation x_C as a function of the benefit factor ω and the number of available actions L in the multi-action nonlinear donation game. Generally, the cooperation abundance increases with L for $\omega > 1$ and decreases with L for $\omega < 1$. Similarly, for $\omega > 1$, increasing the number of available actions can make cooperation favorable, i.e., $x_C > 1/2$. Parameter values: $b = 6$, $c = 1$, $\lambda = -0.01$, and $\alpha = 3$ (**b**).



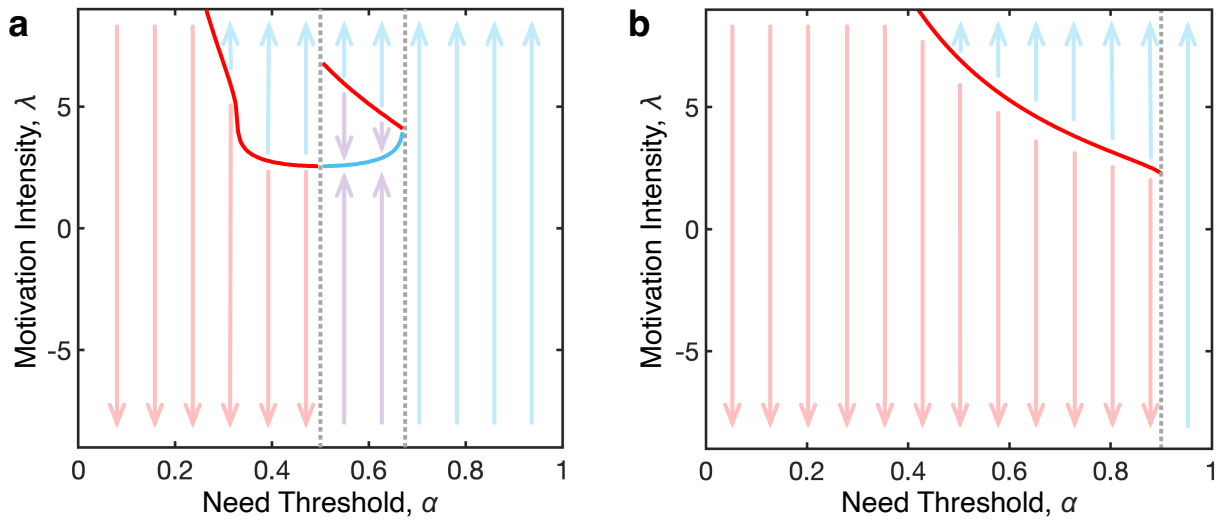
Supplementary Figure 2: Undemanding philanthropic and demanding aspirational behavioral motivations promote cooperation beyond weak motivation intensity. We consider the motivation intensity $\lambda = 1.0$ and $\lambda = -1.0$, and identical motivation threshold α for all individuals. All other parameter settings and notation using follow Fig. 3 in the main text. Solid lines are analytical results by Eq. (S32) (blue for philanthropists and red for aspirationalists). Results show that cooperation thrives in the population of undemanding philanthropists and demanding aspirationalists while perishes in the population of demanding philanthropists and undemanding aspirationalists. Besides, the effects are consistent in all population structures we studied. Here we provide a few intuitions about the non-linearity of the cooperation abundance x_C in relation to the need threshold α for philanthropists, and the linearity for aspirationalists. Although both of them are threshold-based behavioral motivations, they result in different evolutionary processes, especially under high motivation intensity, such as for $|\lambda|$=1. In a population of undemanding philanthropists (small α), individuals are easily satisfied and thus choose to cooperate. This brings high payoffs to individuals taking defection, driving them to switch to cooperation. This switching from defection to cooperation further increases the payoffs for others, leading to more transitions to cooperation, resembling positive feedback. This mechanism explains the nearly full cooperation observed in a population of undemanding philanthropists. However, when philanthropists are demanding (large α) and not easily satisfied, the choice of defection induces more individuals to switch to defection, until all individuals choose defection. Overall, the positive feedback leads to global cooperation in a population of undemanding philanthropists and to global defection in a population of demanding philanthropists, corresponding to the sharp decrease and non-linearity. Conversely, aspirational motivation results in negative feedback. When the aspirationalists are undemanding, they easily switch to defection, but this decreases their payoffs, promoting a transition back to cooperation. Therefore, compared to philanthropists, it is harder for aspirationalists to reach a state of full cooperation or full defection, corresponding to the observed linearity.



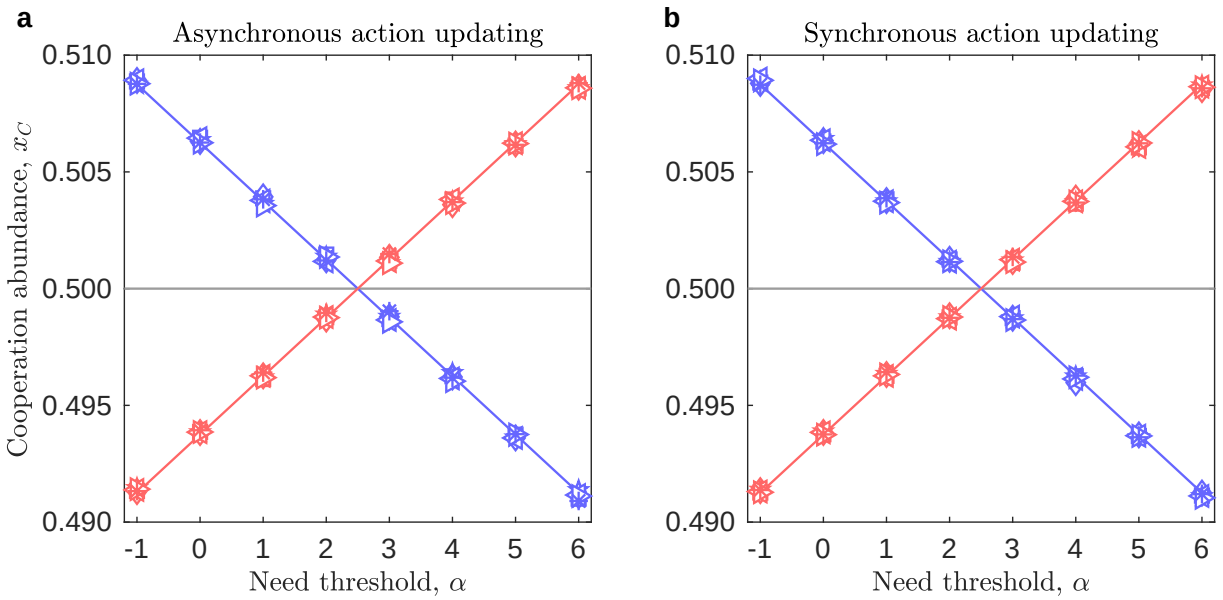
Supplementary Figure 3: Evolution of behavioral motivation beyond weak motivation intensity. All other parameter settings and notation using follow Fig. 6 in the main text, except for the initial behavioral motivations (0.25,0.5), (0.25,-0.5), (0.75,0.5), (0.75,-0.5) for $b/c < (b/c)^*$, and (0.6,0.5), (0.6,-0.5), (1.2,0.5), (1.2,-0.5) for $b/c > (b/c)^*$. **a**, When the benefit-to-cost ratio b/c is below the critical ratio $(b/c)^*$, all individuals eventually evolve into demanding philanthropists or undemanding aspirationalists. **b**, Cooperation abundance decreases to zero. **c**, When the benefit-to-cost ratio b/c exceeds the critical ratio $(b/c)^*$, all individuals eventually evolve into undemanding philanthropists or demanding aspirationalists. **d**, Evolution sees an increase in cooperation abundance. Results here are qualitatively consistent with the case of weak motivation intensity, as Fig. 6 in the main text.



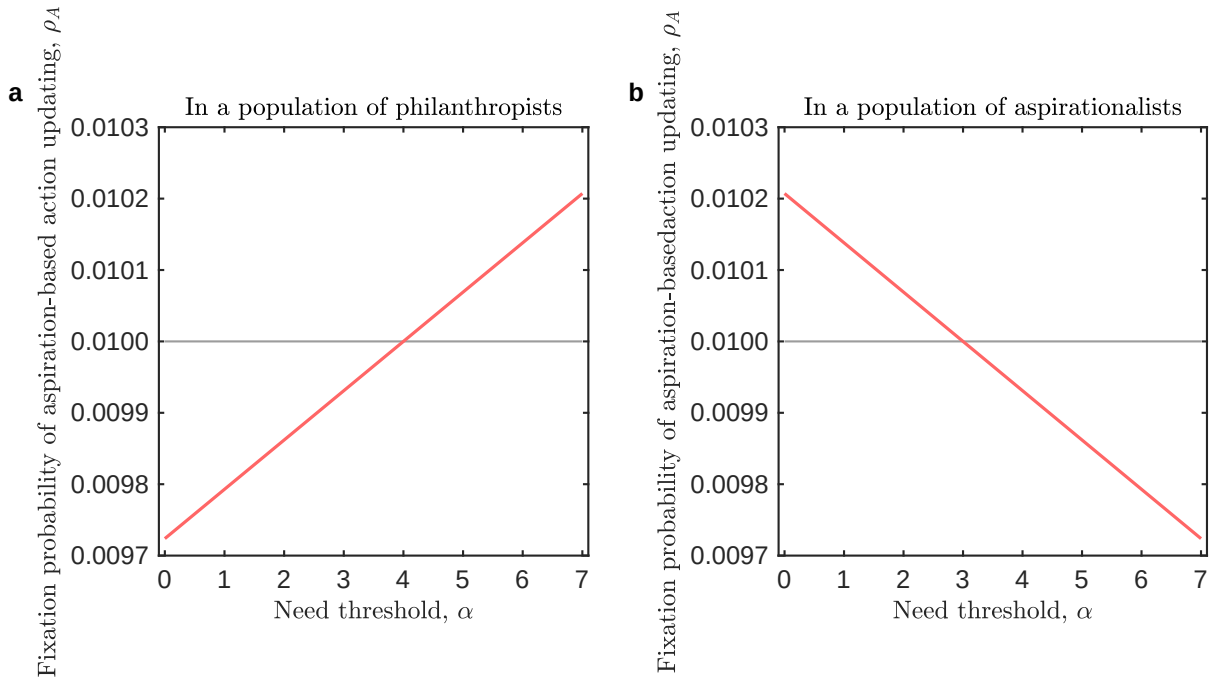
Supplementary Figure 4: Evolution of behavioral motivation under extreme initial configurations. We consider four behavioral motivations (α, λ) given by (2,0.5), (-1,0.5), (2,-0.5), and (-1,-0.5) (open black dots) for the case of $b/c < (b/c)^*$ and (2,0.5), (-0.2,0.5), (2,-0.5), and (-0.2,-0.5) for the case of $b/c > (b/c)^*$. The initial behavioral motivations deviate further from the neutral motivation $((b-c)/2, 0)$ in comparison to those in Fig. 6 in the main text. All other parameter settings and notation using follow Fig. 6. **a**, When the benefit-to-cost ratio b/c is below the critical ratio $(b/c)^*$, all individuals eventually evolve into demanding philanthropists or undemanding aspirationalists. **b**, Cooperation abundance decreases to zero. **c**, When the benefit-to-cost ratio b/c exceeds the critical ratio $(b/c)^*$, all individuals eventually evolve into undemanding philanthropists or demanding aspirationalists. **d**, Evolution sees an increase in cooperation abundance. Results here are qualitatively consistent with the case of weak selection, as Fig. 6 in the main text.



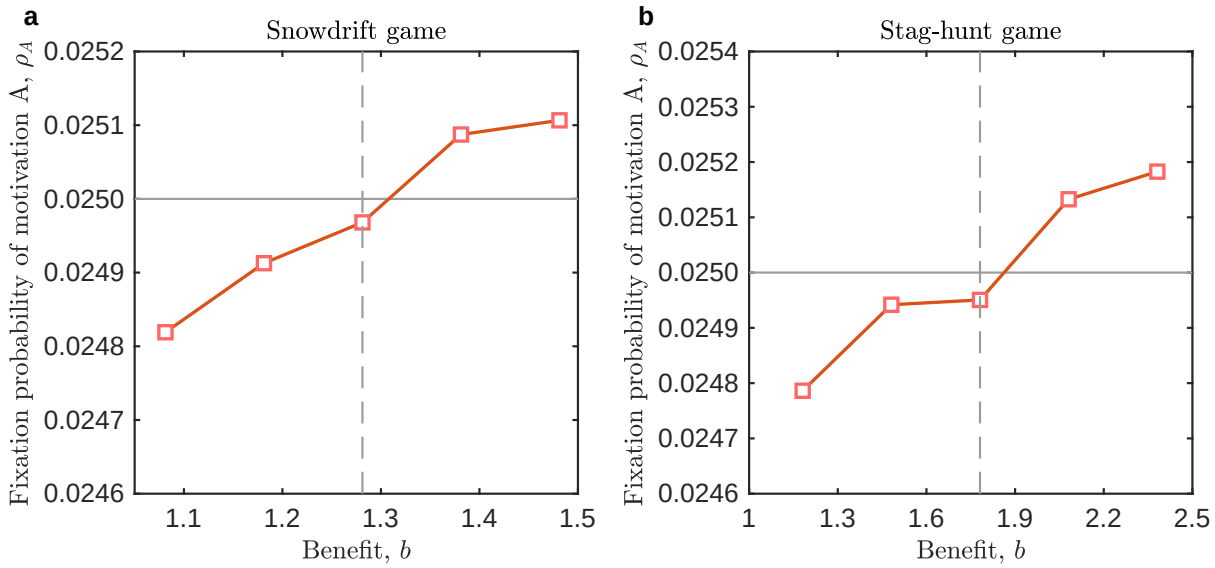
Supplementary Figure 5: The evolution of λ for different values of need threshold α. We numerically explored the evolution of λ for fixed behavioral motivations α. We employ evolutionary invasion analysis, in which the whole population is assumed to share the same behavioral motivations (i.e., the same λ and α) and then test the ability for a new behavioral motivation, that differs in the value of λ to invade. **a**, Results are shown for $b = 2$, and $c = 1$, with arrows indicating the direction of evolution of λ, red lines indicating unstable fixed points of the evolutionary dynamics and blue lines indicating stable fixed points. **b**, Results are shown for $b = 2$, and $c = 0.2$. Our findings in both panels indicate that in the well-mixed setup, and under strong motivation intensity, for a low threshold α, selection favors the aspirationalists (with negative λ); for a high threshold α, selection favors the philanthropists (with positive λ). However the intermediate equilibrium shown in panel **a** is lost when costs are lower. For comparison, we use Eq. (6) from the main text to analyze the evolutionary dynamics of behavioral motivations in a well-mixed population under weak motivation intensity. In this case, we find that $-c\eta_2 + b(\eta_3 - \eta_1) < 0$ for any positive values of b and c, indicating that weak selection consistently favors the evolution of the demanding philanthropists and undemanding aspirationalists. These results qualitatively align with the findings from the evolutionary invasion analysis.



Supplementary Figure 6: The evolutionary outcome remains consistent under both asynchronous action updating and synchronous action updating. We consider the random regular networks. All parameter settings follow Fig. 3**e** in the main text. **a**, Abundance of cooperation under asynchronous action updating, where only one individual updates his action in each round. **b**, Abundance of cooperation under synchronous action updating, where in each round all individuals update their actions. Results show that cooperation thrives in the population of undemanding philanthropists and demanding aspirationalists while perishes in the population of demanding philanthropists and undemanding aspirationalists. Besides, the effects are consistent under both asynchronous and synchronous action updating.



Supplementary Figure 7: Undemanding philanthropists and demanding aspirationalists can resist the invasion of mutants using aspiration-based action updating. Presented are the fixation probability of a mutant using aspiration-based action updating in a population of philanthropists (**a**) and aspirationalists (**b**), for a broad range of need threshold α. We consider the random regular networks with size $N = 100$ and node degree $d = 6$. Results show that mutants using aspiration-based action updating are disfavored against philanthropists with low need thresholds and aspirationalists with large need thresholds. Parameters: benefit $b = 8$, cost $c = 1$, motivation intensity $\lambda = 0.01$ for philanthropists and $\lambda = -0.01$ for aspirationalists, the selection intensity for aspiration-based action updating $\delta = 0.01$ (see Supplementary Note 3).



Supplementary Figure 8: Selection favors undemanding philanthropists over demanding philanthropists when the benefit of cooperation exceeds a critical value. We consider random regular networks of size $N = 40$ and node degree $d = 6$. Presented is the fixation probability of an undemanding philanthropist with $\lambda = 0.01$ $\alpha = 1.0$ (denoted by motivation A) in a population of demanding philanthropists with $\lambda = 0.01$ and $\alpha = 4.0$ as a function of benefit b, under snowdrift games (**a**, see Supplementary Note 3) and stag-hunt games (**b**). Squares represent the fixation probability by simulations and vertical dashed lines mark the critical benefit for selection favoring undemanding philanthropists over demanding philanthropists. The fixation probability is determined by the fractions of simulations where the beneficial motivation A reached fixation out of 2×10^7 generations.

Supplementary References

[1] A. McAvoy and B. Allen. Fixation probabilities in evolutionary dynamics under weak selection. *Journal of Mathematical Biology*, 82(3):14, 2021.

[2] J. Du, B. Wu, P. M. Altrock, and L. Wang. Aspiration dynamics of multi-player games in finite populations. *Journal of the Royal Society Interface*, 11(94):20140077, 2014.

[3] J. Du, B. Wu, and L. Wang. Aspiration dynamics in structured population acts as if in a well-mixed one. *Scientific Reports*, 5:8014, 2015.

[4] B. Wu and L. Zhou. Individualised aspiration dynamics: Calculation by proofs. *PLoS Computational Biology*, 14(9):1–15, 2018.

[5] L. Zhou, B. Wu, V. V. Vasconcelos, and L. Wang. Simple property of heterogeneous aspiration dynamics: Beyond weak selection. *Physical Review E*, 98(6):62124, 2018.

[6] M. R. Arefin and J. Tanimoto. Evolution of cooperation in social dilemmas under the coexistence of aspiration and imitation mechanisms. *Physical Review E*, 102(3):32120, 2020.

[7] L. Zhou, B. Wu, J. Du, and L. Wang. Aspiration dynamics generate robust predictions in heterogeneous populations. *Nature Communications*, 12(1):3250, 2021.

[8] C. Hauert, F. Michor, M. A. Nowak, and M. Doebeli. Synergy and discounting of cooperation in social dilemmas. *Journal of Theoretical Biology*, 239(2):195–202, 2006.