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Prosocial preferences improve climate risk management in subsistence farming communities

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Several governments have tested formal index-based insurance to build climate resilience among smallholder farmers. Yet, adoption of such programmes has generated concerns that insurance may crowd out long-established informal risk transfer arrangements. Understanding this phenomenon requires new analytic approaches that capture dynamics of human social behaviour when facing risky events. Here we develop a modelling framework, based on evolutionary game theory and empirical data from Nepal and Ethiopia, to demonstrate that insurance may introduce a new social dilemma in farmer risk management strategies. We find that while socially optimal risk management is achieved when all farmers pursue a combination of formal and informal risk transfer, a community of self-interested agents is unable to maintain this co-existence under rising climate risks. We find that a combination of prosocial preferences—moderate altruism and solidarity—helps farmers overcome these concerns and achieve the social optimum. In our model, behavioural interventions that cue such preferences can reduce farmer expected losses by 26% and save approximately 5% of community agricultural income through reduced premium subsidies under climate risk levels likely to emerge in the coming decades.

Rising climate risks threaten the livelihoods of many of the world's 500 million smallholder farming households[1], most of which lack financial protection against climate-driven agricultural losses[2]. To cope with the risks of droughts, floods and heat waves, development agencies and several national governments have tested formal risk transfer mechanisms, such as index-based crop and livestock insurance[3–5]. Whereas indemnity insurance generally entails high administrative costs to accurately measure specific losses suffered by individual policyholders, index insurance achieves cost reductions by linking payouts to an exogenous indicator that measures seasonal weather variables and/or crop yields at a regional scale. As climate-driven risks to rural livelihoods increase in coming decades[6], index insurance programmes may therefore be a promising tool for climate adaptation.

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Yet, initiatives to promote index insurance are often deployed in contexts in which subsistence farming communities have already developed mechanisms to manage longstanding livelihood risks[7–9]. These mechanisms include intrahousehold strategies, such as diversifying household income streams through migration remittances[10,11] and community-wide risk transfer mechanisms, including informal lending and revenue-sharing cooperatives[12–14]. However, although informal mechanisms may effectively reduce independent risks (such as individual health shocks) and provide other societal benefits[15,16], their capacity to manage climate-driven risks may depend on the level of social capital in a community[17], as well as the degree to which risks are covariant[18].

Recent literature has sought to understand the potential for index insurance programmes to either complement or substitute informal community risk transfer mechanisms[19]. Experiments in India[20] and Ethiopia[12–14] demonstrate that formal insurance and informal lending can serve as complementary mechanisms, especially if basis risk is high (that is, a high potential mismatch between a climatological index and actual damages experienced by a policy-holder)[20]. However, these studies were only able to exploit data over short timeframes (1–2 years). Theoretical frameworks exploring these interactions suggest that while index insurance and informal revenue transfers may initially serve as complements, over the long term, insured households acting out of self-interest may be tempted to reduce or even abandon their commitments to informal revenue transfers[21], unless some form of peer monitoring is able to enforce them[22]. Such findings indicate that self-interested agents acting strategically may not be able to reach a socially optimal outcome without additional incentives or sanctions[23].

Yet, a growing body of empirical evidence suggests that observed levels of human cooperation cannot be explained by completely self-interested, homo economicus preferences[24–26]. In particular, ref. 26 identifies fundamental mechanisms, including an intrinsic desire for equity, the desire to reciprocate others' behaviour and self-image as a prosocial actor, that may compel individuals to comply with social norms, even when doing so impinges on their material self-interest[26]. In a similar vein, others demonstrate that a combination of selfishness and morality (the desire to 'do the right thing') is an evolutionary stable preference[27,28]. Additionally, direct experimental and empirical evidence indicates that altruism—the consideration of others' well-being in an individual decision-maker's objectives—plays a significant role in shaping interhousehold risk transfer in rural farming communities[29,30]. Together, such frameworks and evidence call for incorporating more realistic alternatives to purely rational, self-interested preferences in explaining the emergence of cooperative behaviour[31].

Our aim in this analysis is to investigate the role that alternative decision-making preferences may play in the ability of a smallholder farming community to maintain socially optimal risk management strategies under various levels of climate risk. Specifically, we develop this analysis in four steps. First, we demonstrate that in subsistence farming communities, a combination of formal and informal risk management mechanisms provides the most robust protection to extreme events. Second, through a new evolutionary game theory model, we illustrate that communities of self-interested farmers will find it difficult to maintain co-existence of formal and informal risk management as climate risks increase in the coming decades. Third, we find that moderate levels of prosocial preferences in a farming community can maintain this co-existence, at least under moderate climate risk. Fourth, we demonstrate that a combination of financial incentives and behavioural interventions cultivating prosocial preferences can serve as complements to more feasibly promote robust climate risk management.

Risk management choices under bounded rationality and prosociality

We consider an agricultural community where farmers choose between different risk management strategies at three different scales. These are (1) intrahousehold risk transfer, whether to exclusively farm or combine farming with rural–urban migration; (2) informal risk transfer, whether to take part in a revenue-sharing pool at the community scale; and (3) formal risk transfer, whether to purchase index insurance covering households at the regional scale (leading to $2^3 = 8$ discrete strategy options). We set up a population game based on evolutionary game theory (Supplementary Section 1.1) to improve our understanding of how strategy choices change over time as a result of repeated interactions across a large population of agents that simultaneously make strategic decisions[32], as illustrated in Fig. 1a–c. The population game allows for the integration of bounded rationality. For example, households make decisions by imitating the strategic choices of peers who receive higher utility, rather than by rationally optimizing their actions across the full strategy set.

In our model, farmers evaluate strategies using a utility function that accounts for risk aversion, loss aversion and time discounting (Fig. 1d). Grounded in the New Economics of Labour Migration (NELM)[11], agents in the model seek to improve expected profits while reducing the volatility of their income streams. In addition to penalizing income volatility, agents in our model also exhibit loss aversion; that is, they assign a higher penalty to perceived losses than the benefits experienced from gains of a similar magnitude. This is especially relevant in the context of insurance decisions, in which one of the most salient motivations is to protect against a possible loss[33,34]. Agents considering migration strategies exponentially discount expected future remittance income relative to immediate migration costs and also apply loss aversion to these costs. Finally, agents in the evolutionary game seek to minimize perceived gaps between their utility and that of their peers.

We investigate how social preferences affect the share of chosen strategies in the population. Here we examine the consequences of two different types of prosociality: (1) altruism, which includes the utility of peers in the evaluation of personal utility, and (2) solidarity, which represents the assumption of coordinated action between like-minded households, resulting from a union of purpose (Fig. 1e). These are parameterized through α and κ, which each range from 0 to 1 and indicate the respective degrees of altruism and solidarity in agent utility functions (Methods). We assume that these preferences are homogeneous throughout the population and remain stable over the modelled timeframe, although in our results we assess sensitivities of equilibrium strategy outcomes under different combinations of prosocial preferences.

Existing informal risk management strategies are limited in their capacity to address covariate risks (in the case of this analysis, drought risk) affecting an entire community at once. Here we use the base-level correlation ϱ between household farming incomes before any risk management strategies are applied and drought probability P to create three scenarios of covariate risk: low ($P = 0.2$, $\varrho = 0.1$), medium ($P = 0.35$, $\varrho = 0.35$) and high ($P = 0.6$, $\varrho = 0.5$; Supplementary Section 1.5). We also test for the effects of different types of government interventions, including subsidies for insurance premiums[2,12,14] and informational policies that may cue prosocial preferences[35,36].

Diversified risk transfer is socially optimal

Identifying an optimal risk management strategy for subsistence farming communities is complex and involves tradeoffs between multiple objectives. As a first-order approximation, we simulate collective-scale outcomes of farming communities pursuing monomorphic strategies, that is, boundary cases in which all households opt for the same strategy, over 1,000 cropping cycles with stochastic drought events and income draws. As shown below, most equilibrium outcomes that arise from strategic interactions between farming households involve combinations of four risk management strategies: (1) farming and migration (FM); (2) farming, migration and community revenue-sharing (FM + S); (3) farming, migration and formal insurance (FM + I); and (4) farming, migration, revenue-sharing and insurance (FM + S + I).

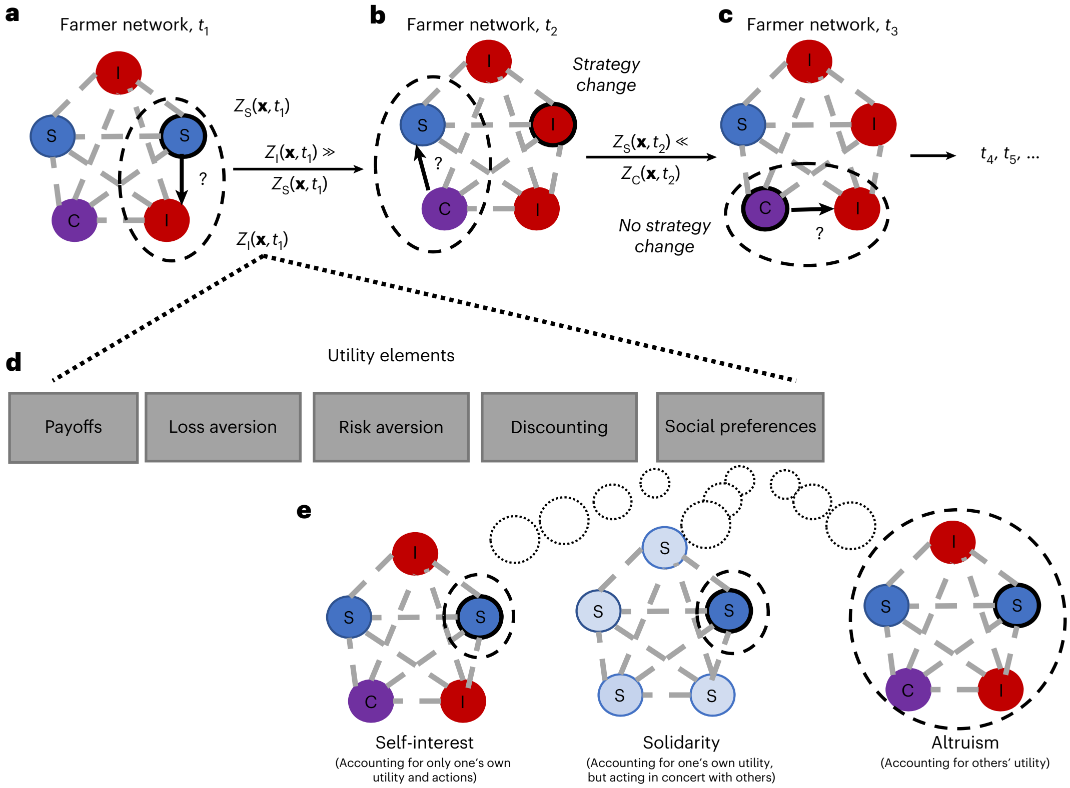


Fig. 1 | Overview of the evolutionary game theory model. We illustrate the evolutionary game theory framework developed for this analysis using a simplified network of five households. **a**, Households (represented by circles) are connected via social ties (dashed lines), which govern with whom households share part of their income and whose strategies they may imitate. Household risk management strategies are indicated by colour (blue, informal revenue-sharing, S; red, formal insurance, I; purple, combination of revenue-sharing and insurance, C). In any given time step, one household is selected as the focal agent (in time t_1, this agent deploys strategy S) and another household is selected as the comparison agent (in this case, this agent deploys strategy I). The focal agent compares the utility of its strategy, $Z_S(\mathbf{x}, t_1)$, given the distribution of strategies deployed across the community, $\mathbf{x}$, at time t_1, to that of the comparison agent. **b**, In this example, the utility of I is substantially higher than that of S, so the focal agent adopts insurance in t_2 with high probability. Two more households—deploying strategies C and S—are randomly selected as the focal and comparison agent, respectively. **c**, Now, the utility of S is substantially less than that of C, so the focal agent does not change strategies. Another focal and comparison agent are selected at random and this sequence repeats for T time steps. **d**, The elements that constitute utility evaluation include payoffs (parameterized as $\pi_i(\mathbf{x}, t)$), loss aversion (λ), risk aversion (b), discounting (r) and the social preferences (α and κ). **e**, Social preferences consist of self-interest, in which the focal agent considers only their own utility and actions; altruism, in which the focal agent considers the utilities of every other agent playing their current strategies; and solidarity, in which the focal agent considers its own utility if other households (represented by light blue nodes) also adopt the same strategy of the focal agent. The degree to which altruism and solidarity are incorporated in utility evaluation is determined by the values of α and κ, respectively.

Under the medium risk scenario, layering formal and informal risk transfer effectively shields farming communities against extreme outcomes in drought cropping cycles (Fig. 2; see Supplementary Section 2.2 for results under different risk and migration scenarios). While risk management options do not change the expected income across cropping cycles, formal insurance in particular reduces downside risks to income during drought years (orange), including cycles in which the mean community income falls below the poverty line (Fig. 2a, dashed line). Combining formal insurance with informal revenue-sharing further reduces to some degree this collective-scale volatility. However, the reduction of downside risk comes at the cost of foregoing the potential for high community incomes in non-drought years (green) due to costly premiums. The combination of informal and formal risk transfer also limits inequality over long time horizons by providing households with more stable and equal farming revenues (Fig. 2b). The tradeoffs inherent in deploying risk transfer mechanisms are most apparent in evaluating poverty rates (Fig. 2c). Without formal insurance, an average of 63% of households fall under the poverty threshold in drought years. Deploying formal insurance reduces these rates in drought years but costly insurance premiums increase the proportion of households falling into poverty during non-drought years, relative to the absence of such mechanisms. Still, such mechanisms may be preferable if a community wishes to avoid extremely high poverty levels in any given cropping cycle, and pairing insurance with informal revenue-sharing can help mitigate this effect by allowing for some interhousehold income transfers.

While pairing formal and informal risk transfer leads to complex tradeoffs at the collective scale, the benefits of layering these mechanisms are evident at the individual household scale (Fig. 3). By construction, all four risk management strategies involving migration lead to the same expected income (Fig. 3, left column) but pairing formal insurance with informal revenue-sharing slightly lowers income volatility across cropping cycles (Fig. 3, middle column). Most importantly, household income losses in communities that deploy both formal insurance and informal revenue-sharing are on average 60% of losses in communities without either risk transfer mechanism and significantly better than either mechanism on its own (Fig. 3, right column, $P < 0.01$). On the basis of its ability to reduce inequality and attenuate extreme poverty at the collective scale and to minimize income volatility and expected losses at the household scale, we designate the diversified risk management strategy consisting of migration, informal revenue-sharing and formal insurance as the socially optimal strategy for risk- and loss-averse decision-makers.

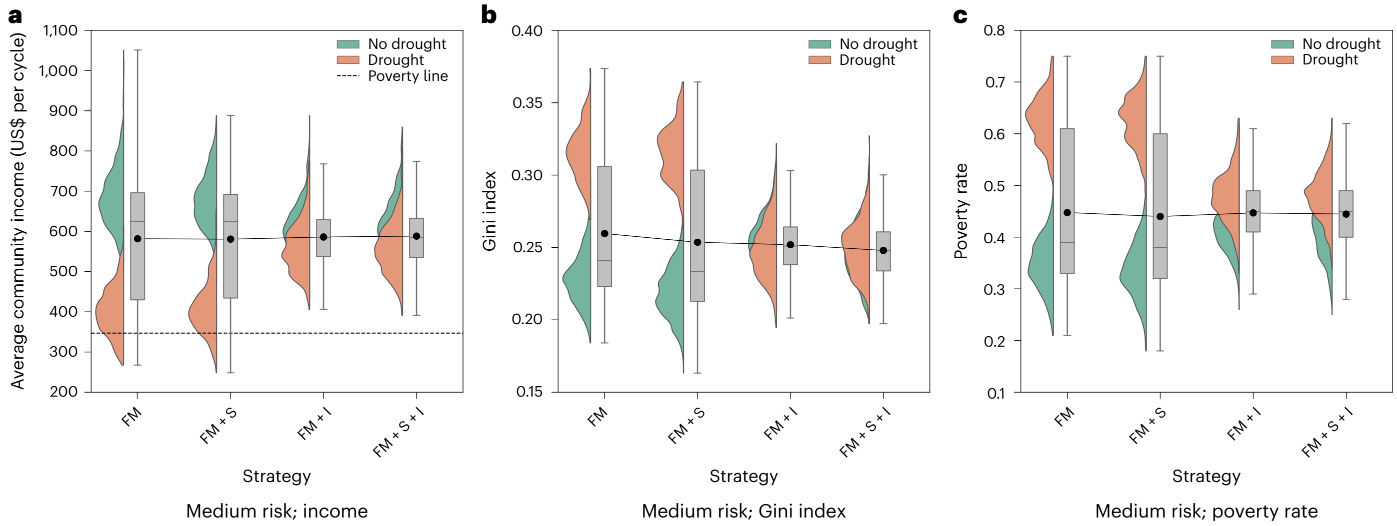


Fig. 2 | Community outcomes for monomorphic risk management strategies. **a**–**c**, We assess how a community of 100 households would fare when all households adopt one of the eight possible risk management strategies, with random income draws and drought events under the medium risk scenario ($P = 0.35$, $\varrho = 0.35$). Here we compare the distributions of average community income (**a**), Gini index (**b**) and poverty rate (**c**) when the community adopts each of four strategies involving migration: farming and migration (FM); farming, migration and informal revenue-sharing (FM + S); farming migration and formal insurance (FM + I); and a combination of all strategies (FM + S + I). Each data point in the distribution represents the results from one independent simulation with randomized income draws, averaged over the 100 households ($n = 1{,}000$ simulated crop cycles for all panels). Distributions are shown separately for outcomes in drought years (orange) and non-drought years (green), with boxplots summarizing the total distribution over both drought and non-drought years (whiskers represent 1.5× the interquartile range, shaded boxes represent the interquartile range and centre lines represent the median of each distribution). Black dots connected by the line plot indicate mean values for each strategy. Results for other risk levels and non-migration strategies are shown in Supplementary Section 2.2.

Strategic interactions lead to suboptimal risk management

In the absence of a legal framework to impose socially optimal strategies, we assess which risk management choices are likely to emerge as a result of strategic interactions between self-interested farming households. For all covariate risk scenarios, households consistently choose migration as an intrahousehold risk diversification strategy. Migration serves as an effective means of buffering household incomes against both covariate and independent shocks. However, migration remittance incomes are themselves subject to uncertainty and may indirectly affect which risk transfer strategies emerge (Supplementary Section 2.3). Equilibrium outcomes exhibit further sensitivity to the level of covariate risk faced by such communities. The co-existence of formal index insurance and informal revenue-sharing can emerge under low levels of covariate risk (Fig. 4a, $0 < P < 0.23$, $0 < \varrho < 0.8$). Despite the low degree of covariate risk, farmers' loss aversion motivates the purchase of insurance to avoid losses in drought years and risk aversion motivates farmers' participation in income-sharing cooperatives to reduce volatility in both drought and non-drought years. While we are unaware of farming contexts in which such widespread adoption of both crop insurance and informal revenue-sharing has been attained over the long term, early data from Ethiopia's index-based livestock insurance suggest that the introduction of insurance may induce increased interhousehold income transfers[13,14]. Indeed, our estimate of the current covariate risk faced by Ethiopian farmers in the Borena region (Supplementary Section 1.4), which has demonstrated relative success in pairing high adoption of index insurance with informal lending[12–14], lies in this range.

As covariate risk increases to moderate levels, self-interested participants in the cooperative will benefit even more from the stable income that insured members contribute and will have less of an incentive to purchase insurance themselves. At the same time, purchasing insurance at actuarially fair premiums is also more expensive in scenarios with higher drought risk. This social dilemma drives a collapse in the co-existence of formal and informal risk management at a threshold drought risk of approximately $P = 0.23$ (Supplementary Section 2.4), with formal insurance emerging as the dominant form of risk management. For the region of high covariate risk, households stay in the revenue-sharing pool but do not purchase formal insurance. For drought risks $P > 0.4$, insurance premiums are now sufficiently costly (>US$97 per cycle) that households would perceive a greater average loss in utility from purchasing insurance compared to remaining uninsured. Thus, households are left with participating in informal revenue-sharing cooperatives as the equilibrium risk management strategy. However, such mechanisms are especially ineffective under conditions of high covariate risk. Our estimates of covariate risks faced by farmers in the Chitwan Valley of Nepal largely lie in this range and recent empirical research demonstrates that index insurance adoption in Nepal is very low, despite strong government subsidies[37]. While several factors may contribute to low insurance adoption, including low familiarity with and/or trust in insurance products, our analysis suggests that at sufficiently high covariate risks, high premiums and strategic interactions will discourage farmers from adopting formal insurance.

A scan of sensitivities to other key decision-making parameters—including farmer risk aversion, loss aversion, discount rates, social network connections, migration remittances and the proportion of income contributed to the revenue-sharing pool—indicates that other risk management outcomes are also possible (Supplementary Sections 2.3 and 2.5). Overall, the shift away from optimal risk management over increasing drought risk and income correlation indicates the limits to adaptation. Indeed, subsistence farming communities will find it difficult to organize effective risk management strategies in the absence of policy intervention.

Moderate prosociality improves risk management outcomes

Can strategy selection be modulated by prosocial preferences? In our model, we represent altruistic preferences via the index α ($0 \leq \alpha \leq 1$) to indicate the degree to which individuals weigh others' utilities in their

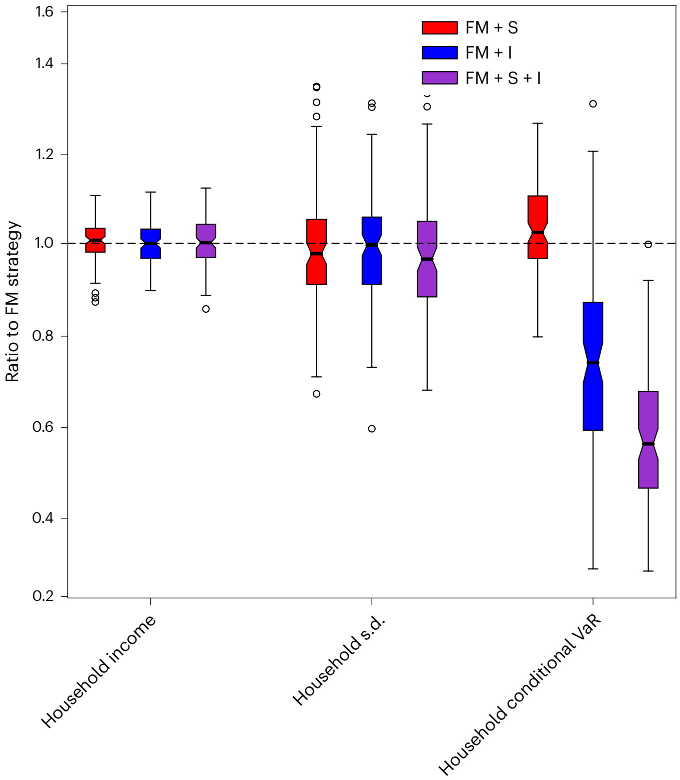


Fig. 3 | Decomposition of household utility components. Individual household strategy decisions are governed by a utility function that incorporates expected income, volatility (measured as standard deviation) and potential losses. The last metric is expressed as the conditional value at risk (VaR) or the weighted probabilistic average of losses below a farming household's break-even point. Here we decompose household utilities into these three components for four monomorphic strategy distributions (that is, every household adopting the same strategy). The average household income, standard deviation and loss for each of three risk management strategies involving risk transfer (FM + S, FM + I, FM + S + I) are displayed relative to the FM strategy. Results are generated by simulating random income draws for 100 households adopting the specified strategy over 1,000 independent crop cycles. Each point in the boxplot represents a value for one household averaged over the crop cycles, such that distributions are composed of $n = 100$ points. For each boxplot, whiskers represent 1.5× the interquartile range of the distribution, colour-shaded areas represent the interquartile range and centre line represents the median of the distribution. While average incomes are almost identical across the four monomorphic strategies, median volatility is slightly lower for all strategies that incorporate some form of risk transfer and losses are significantly lower for strategies incorporating insurance. In particular, the combination of informal revenue-sharing and insurance significantly reduces expected losses compared to the other strategies (two-tailed t-test, t-statistic = −8.96, $P = 2.49 \times 10^{-16}$).

own decision-making and solidarity-based worldviews with the index κ ($0 \leq \kappa \leq 1$) to indicate the degree to which a household trusts that others in their community will make the same strategic decision. Altruism has been measured through both statistical inference[29] and experimental[30] methods, with $\alpha = 0.6$ representing an upper bound for this parameter in most settings. While we know of no empirical work specifically measuring solidarity, studies in many settings demonstrate the prevalence of false consensus (that is, a bias that most other community members act and think in a similar fashion as oneself)[38,39], lending credence to a similar value as a feasible condition. In addition, cross-national surveys demonstrate that moderate amounts of community trust are common across several cultures[40,41].

Neither altruism nor solidarity by themselves is sufficient to promote high adoption of both formal insurance and informal revenue-sharing under the medium risk scenario (Fig. 5a). Although altruistic farmers consider how their choices affect the utilities of their peers, their own individual strategy choices do not have sufficient impact on the collective utility to overcome a coordination threshold. Even a community composed entirely of perfect altruists ($\alpha = 1.0$) is not likely to sustain high levels of both formal and informal risk transfer due to perceived limited impact. By contrast, communities in which farmers act out of solidarity do reach a different type of equilibrium, known as a limit cycle. In this case, the community continually cycles between mixes of informal revenue-sharing, formal insurance and a combination of both strategies, periodically approaching, then leaving, states where collective utility is maximized (Fig. 5b, centre). In principle, periodical cycling may help subsistence communities learn about the relative ability of different strategy mixes to contend with drought risks. In practice, over time communities may anticipate this cyclic behaviour and proactively adjust their decisions, leading to more stable strategies.

In communities with high amounts of both altruism and solidarity ($\alpha = \kappa = 0.6$), which we term 'high prosociality', all households purchase formal insurance and participate in the revenue-sharing cooperative in steady state (Fig. 5b, right). Here altruism and solidarity have a synergistic effect in promoting optimal risk management. Altruism leads to the desire to contribute to others' utility and solidarity provides farmers with the confidence that combining formal and informal risk transfer will have a material impact on collective utility. While it may not be realistic to expect all members of a farming community to act with high altruism and high solidarity, even moderate amounts of both preferences (for example, $\alpha = \kappa = 0.3$) promote equilibria with some households deploying a combination of insurance and revenue-sharing (Fig. 5a). While not as socially beneficial as the equilibrium that emerges under high prosociality, it is notable that moderate prosociality comprises a value of altruism that is in line with observed values in many subsistence societies, at least in experimental settings[29]. Similarly, it is plausible that in a typical community, an average decision-maker would trust at least 30% of his or her neighbours to also act in a similar fashion.

An implicit assumption of this analysis is that agents' economic preferences remain stable and are not endogenous to risk management decisions around migration and purchasing formal insurance. Here we do not incorporate such endogenous feedbacks but Fig. 5a may still serve as a useful guide to assess how shifts in baseline preferences affect the ability of a community to maintain the combination of formal and informal risk transfer mechanisms. In the next section, we turn to the efficacy of financial and behavioural interventions in promoting this outcome.

Pairing financial and behavioural interventions

One way in which governments can promote socially optimal risk management is through financial incentives. Here we consider the effects of insurance premium subsidies, a tool already widely used to promote index insurance with mixed results on observed patterns of adoption[19,42,43]. Under the medium risk scenario, different economic preferences of a community can require notably different subsidies (Fig. 6a). For example, in communities of self-interested agents, a subsidy of approximately 15% of premiums (US\$13.40 per household per crop cycle) would be required to achieve widespread adoption (≥90% of households) of the socially optimal strategy. Widespread adoption of socially optimal risk transfer would reduce farmer expected losses by 26%, compared to the self-interested equilibrium without intervention. This subsidy is slightly lower than the threshold of a 23% subsidy that was found to promote high index insurance uptake in Bangladesh[43], although it is unclear if farmers in that case study also participated in an informal risk-sharing arrangement. By contrast, for communities espousing moderate prosociality ($\alpha = \kappa = 0.3$), only a 5% subsidy (US\$4.50 per household per crop cycle) is needed to achieve the same objective. This reflects the complementary nature of prosocial preferences and financial incentives in overcoming the social dilemma

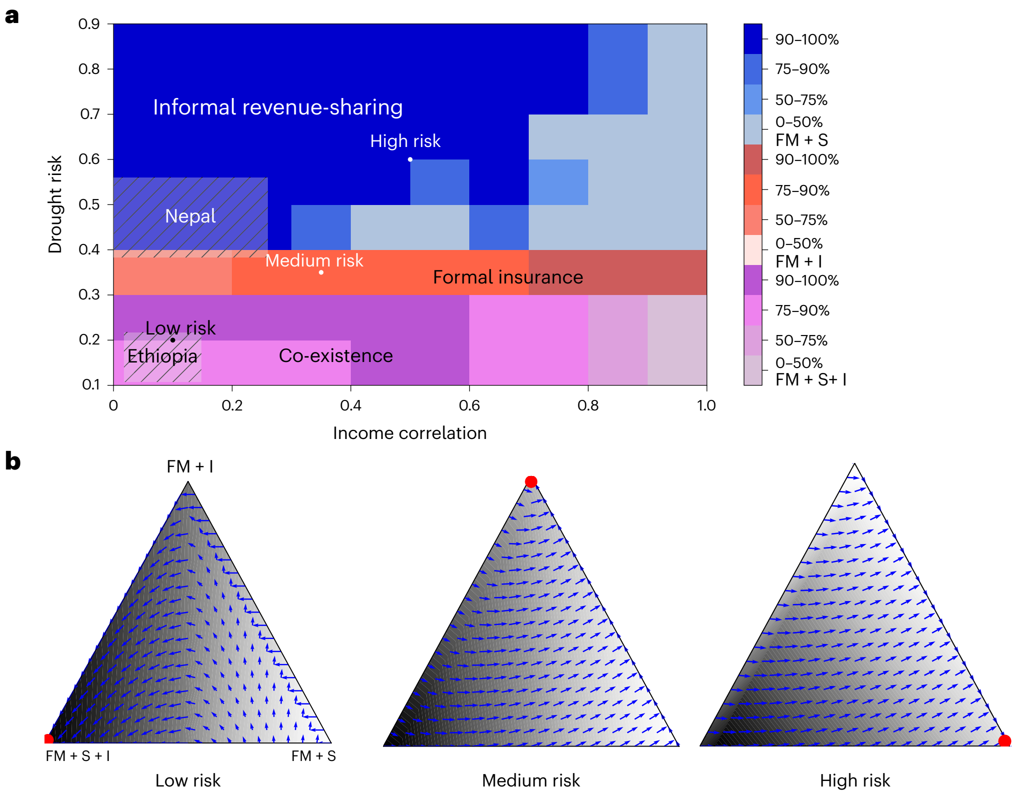


Fig. 4 | Equilibrium risk transfer strategies for self-interested farmers. In communities of purely self-interested farmers, co-existence of formal and informal risk management can emerge at low covariate risk but collapses at higher levels of risk due to free-riding concerns. **a**, We assess which risk management strategies are most likely to emerge as a function of farm income correlation (*x* axis) and drought risk (*y* axis). Colours indicate the the most common strategy at terminal time (averaged over 100 independent simulations), with gradations indicating the percentage of the population adopting this strategy. While households choose between all eight risk management strategies in these simulations, only three options emerge as the most common strategy at terminal time based on different risk levels. Shaded boxes indicate current estimated levels of covariate risks for Ethiopia and Nepal (Supplementary Section 1.4). **b**, For three risk scenarios, utility gradient plots identify the equilibrium points (red dots) between the three risk transfer strategies that are most likely to emerge at terminal time. Each point in the triangle represents the distribution of households according to the proportion of farmers adopting FM + S, FM + I and FM + S + I. Blue arrows indicate the incremental direction of highest utility, given the distribution of strategies in the population at that coordinate. Grey shading indicates the aggregate utility of the population (darker grey, higher utility) for the given distribution of strategies. Under the low risk scenario, the equilibrium point corresponds with the point of highest aggregate utility at [0,0] (representing 100% of households adopting FM + S + I). Under the medium and high risk scenarios, the equlibrium point shifts to all farmers pursuing FM + I and FM + S, respectively, while the highest aggregate utility remains at the origin. In this analysis, we assume that migration remittances are unaffected by drought risk, either because destinations are remote from the drought-stricken area or because migration incomes are typically earned in non-agricultural sectors.

that arises when formal insurance is introduced in communities with informal risk-sharing arrangements. Premium subsidies provide an incentive for individual households to purchase insurance and prosocial preferences partially overcome the temptation to free-ride on others' insurance purchases.

Pairing financial incentives for climate risk management with behavioural interventions promoting prosociality merits strong consideration as climate-driven risks increase in the coming decades. Interventions could include approaches that have been demonstrated in real-world settings to address collective action problems in climate mitigation. Examples include mass informational campaigns that promote a shared identity and cue affective modes of decision-making[35,44,45], more controlled settings in which decisions can be framed as contributions to community and future well-being[46], and campaigns that target a subset of community influencers to adopt a prosocial behaviour, which may lead to broader community adoption through social tipping points[36]. Such policies can contribute to cultivating altruism and solidarity as general values that predominate in farming communities and/or activating such values in targeted decision environments and time periods, for example, community meetings in which farmers have the opportunity to purchase insurance and contribute to revenue-sharing pools. In Supplementary Section 2.7, we present additional analysis to demonstrate that a targeted influence campaign may generate some limited benefits under the medium risk scenario.

To help governments evaluate the value of such interventions, we define a metric called the prosocial dividend, which reflects the monetary benefit of cultivating prosocial preferences with respect to improved efficiency of financial policies relative to a community without such preferences. The prosocial dividend represents the difference in subsidy levels required to achieve optimal risk management in a community espousing moderate prosociality versus a community of self-interested farmers. Under medium risk, this prosocial dividend is equal to US\$8.90 per household per cycle or US\$1,790 per year for a community of 100 households. For subsistence farming communities, this is a non-negligible sum, equal to approximately 4.6% of the community's total annual farming income. Further, this prosocial dividend is likely to increase with increasing climate risk (Fig. 6b). Under such conditions, higher climate risks drive higher premiums while also reducing farmers' disposable incomes, increasing the temptation to free-ride on other community members' insurance purchases. While the benefits of cultivating prosocial preferences under rising climate risk appear substantial, we note two caveats. First, the prosocial dividend may accrue to insurance companies and/or different levels of governments and may not be fully re-invested

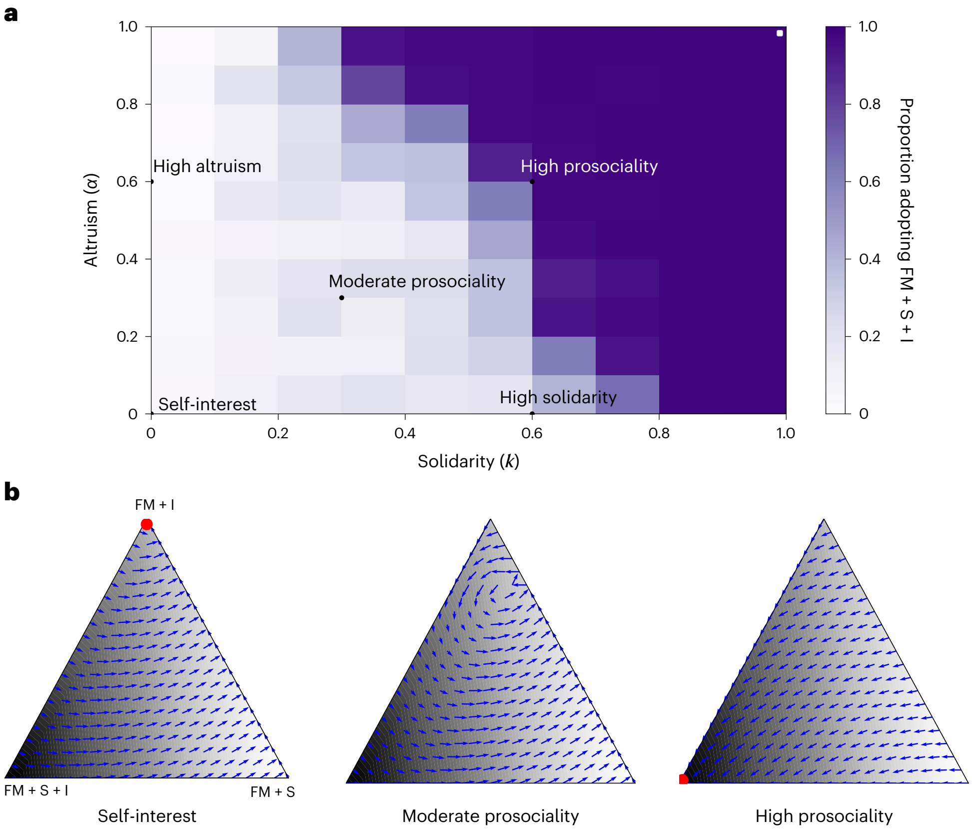


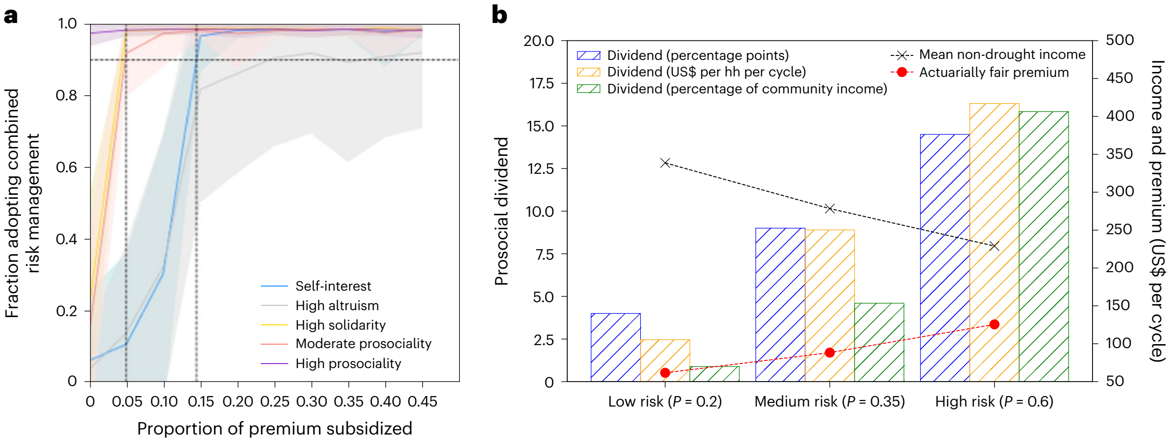
Fig. 5 | Effect of alternative social preferences on risk management equilibria. Alternatives to purely self-interested preferences may shift the risk management equilibria that emerge in a subsistence farming community. We focus here on the medium risk scenario ($P = 0.35$, $\varrho = 0.35$), while results for other scenarios are included in Supplementary Section 2.6. **a**, Various combinations of altruism- and solidarity-based preferences can support a socially optimal combination of index insurance and informal revenue-sharing. Here, for different degrees of solidarity (κ, x axis) and altruism (α, y axis), the proportion of the community adopting the socially optimal strategy (FM + S + I) is indicated by the violet colour bar, with darker shadings indicating higher adoption of this strategy. The displayed proportion is an average over 100 independent simulations in which households choose between all eight strategy options. Generally, adoption increases with increasing levels of altruism and/or solidarity. Downward-sloping diagonal gradients indicate that prosocial preferences exhibit a synergistic effect: the presence of some altruism reduces the threshold level of solidarity needed to achieve high adoption of the socially optimal strategy and vice versa. **b**, Different ideal types of social preferences can lead to substantially different equilibrium points among the three main risk management strategies that are most likely to emerge at terminal time. Here equilibria are shown under the medium risk scenario for self-interest ($\alpha = 0$, $\kappa = 0$), moderate prosociality ($\alpha = 0.3$, $\kappa = 0.3$) and high prosociality ($\alpha = 0.6$, $\kappa = 0.6$) (also indicated by the points in **a**). Under self-interest and high prosociality, a single equilibrium point emerges in which 100% of farmers adopt insurance only and a combination of insurance and revenue-sharing, respectively. Under moderate prosociality, a limit cycle emerges in which the equilibrium distribution of strategies shifts between different proportions of all three strategies, all with at least 60% of farmers adopting insurance only. Similar plots for other social preference types and risk scenarios can be found in Supplementary Section 2.6.

in the community itself. Second, as rising climate risks increase the temptation to free-ride, behavioural interventions that were successful in promoting prosocial preferences under lower climate risks may lose effectiveness.

Discussion

Rising climate risks are likely to impose increased losses on subsistence farming communities over the remainder of the twenty-first century, threatening the viability of rural livelihoods. Such a future calls for risk transfer instruments that enable households and communities to deploy livelihood strategies with more stable economic outcomes. A diversification approach to risk management offers farming communities more complete protection against climate-driven losses: migration and informal revenue-sharing help households cope with independent shocks to their incomes, while insurance helps communities manage covariate shocks that could otherwise limit the effectiveness of informal revenue-sharing mechanisms. However, we demonstrate that different levels of shared climate risk are likely to drive different types of emergent risk management behaviour. As such risks increase, smallholder farmer communities will probably encounter more difficulty in maintaining the co-existence of formal and informal risk management mechanisms. Additionally, we integrate insights from social psychology into a mechanistic agent-based framework[47] and find that prosociality plays an important role in overcoming a coordination problem in risk management. This is particularly true for moderate levels of climate risk, similar to those currently observed in Nepal and which may represent future risks in Ethiopia. These prosocial preferences can render pecuniary incentives, for example, premium subsidies, more efficient in their ability to promote optimal risk management.

While our conclusions are generally robust to sensitivities in household risk- and loss-aversion preferences and community size, there are several additional considerations that add nuance to our findings. High basis risk, which has been explored in other work[20–22], may inhibit widespread adoption of index-based insurance but increase the complementarity of formal and informal mechanisms. We also assume that the insurer is pooling sufficient independent risks to remain solvent but increasing climate risks might require it to enlarge the geographical scale of risk pooling[48]. Another substantial barrier to adoption of index insurance, even when premiums are



Medium risk; all preferences

Prosocial dividend; all risks

Fig. 6 | Effect of financial policy incentives and prosocial preferences on risk management strategy choices. a, Under the medium risk scenario ($P = 0.35$, $\varrho = 0.35$), the proportion of households pursuing the socially optimal strategy (FM + S + I) is displayed as a function of the proportional insurance subsidy (*x* axis) for communities exhibiting five types of economic preferences: self-interested (blue, $\alpha = 0.0, \kappa = 0.0$), high altruism (grey, $\alpha = 0.6, \kappa = 0.0$), high solidarity (yellow, $\alpha = 0.0, \kappa = 0.6$), moderate prosociality (red, $\alpha = 0.3, \kappa = 0.3$) and high prosociality (purple, $\alpha = 0.6, \kappa = 0.6$). The horizontal line indicates an objective of attaining 90% adoption of this strategy and vertical lines indicate the subsidy levels at which the moderate prosociality and self-interested preferences reach this threshold, enabling a comparison of the 'prosocial dividend'—that is, the savings in subsidies required to achieve a socially optimal goal as a result of the presence of prosocial preferences. In this scenario, the dividend is equal to approximately 10% of the actuarially fair premium or US$8.90 per household (hh) per crop cycle. Solid lines indicate the average terminal time frequency of households pursuing this strategy over 100 independent simulations and shaded regions indicate ±1 s.d. of this proportion. **b**, The value of the prosocial dividend depends substantially on risk level and is displayed here under low ($P = 0.2$, $\varrho = 0.1$), medium and high ($P = 0.6$, $\varrho = 0.5$) risk. We compare the dividend by three related metrics: the percentage point difference in subsidy levels required to attain 90% adoption of the socially optimal strategy between self-interested and moderate prosocial communities (blue), the monetary difference between these subsidy levels per household and per cropping cycle (orange) and the aggregate community-wide monetary difference between these subsidy levels per cropping cycle, expressed as a percentage of total community farming income (green). The ratio of the dividends under high versus low risk is higher when they are expressed as a monetary difference and as a percentage of total community income, as higher covariate risks increase the actuarially fair premium (red dashed line, circle markers) and reduce mean farming income (black dashed line, 'x' markers).

heavily subsidized, appears to be a lack of trust in receiving timely payouts[42]. Furthermore, the importance of preference heterogeneity in communities and the impact of network effects can alter the selection of risk management strategies[26]. A specific set of such cases arises if preferences are at least partly endogenous to risk management decisions themselves, for which there is some limited experimental evidence[17,40]. Preferences may then change in different directions and at different rates for members of a community based on their strategy decisions; this represents a promising area for integrated modelling and empirical work. From a financial perspective, our model generally assumes that any farming household wishing to engage in migration or purchase insurance has sufficient savings or credit to do so. In reality, subsistence farming communities typically have imperfect access to credit and limited ability to save[8], making it difficult to deploy strategies that provide long-term benefits for an upfront cost. These conditions may leave households exposed to other substantial risks, including human smuggling and indentured labour arrangements, which were salient risks for both Nepali and Ethiopian migrants working in Qatar on World Cup infrastructure[49,50]. In an extension of the model, we impose restrictions on the strategies households can deploy if they do not accumulate sufficient savings; our analysis demonstrates that such restrictions may delay the dynamics with which risk management strategies are adopted in a community and lead to qualitatively different long-term equilibria (Supplementary Section 2.7).

Risk management strategies that may be optimal for households and small communities may not scale to larger regions or entire countries. For example, while it may be feasible and perhaps even desirable for certain communities in Nepal and Ethiopia to withstand high outmigration rates to receive remittance income and alleviate population pressures, high national outmigration rates could lead to large-scale demographic, economic and food security shocks. As well, behavioural interventions that promote altruism and/or solidarity are likely to be more effective in smaller community settings, where repeated interactions and a shared identity among households contribute to prosociality. At larger governance scales, anonymity and even rivalry between farmers from different regions are likely to challenge the ability to draw out such preferences. Another fruitful avenue for further research is therefore to assess the potential tradeoffs in risk management objectives at different governance scales and the ability of polycentric governance structures (that is, overlapping institutions at multiple scales) to coordinate these tradeoffs.

Methods

In the proposed modelling framework, the evolutionary dynamics of strategy choices are governed by imitation and households within the population interact with each other through their utility functions. The state of the population is represented by the vector $\mathbf{x} \in \mathbb{N}^S$, with S as the number of strategies and where the ith element of the vector, $\mathbf{x}_i$, represents the number of households that selects pure strategy i. At any given time, households can select one of the eight strategy options representing different combinations of intrahousehold livelihood strategies (farming with or without migration), informal risk transfer (revenue-sharing) and formal risk transfer (index insurance). Households selecting strategy i receive an expected profit $\pi_i(\mathbf{x}, t)$ but are risk- and loss-averse as they are sensitive to the variance $\sigma_i^2(\mathbf{x}, t)$ of strategy i and negative net income, respectively. To incorporate different decision-making preferences, we first consider the payoff function $u_i(\mathbf{x}, t)$ of the risk- and loss-averse homo economicus and add an altruism index in $v_i(\mathbf{x}, t)$ and a solidarity index in $w_i(\mathbf{x}, t)$. These preferences may be combined into one generalized utility function, $z_i(\mathbf{x}, t)$ incorporating both altruism and solidarity. An overview of the notation of all model variables and parameters can be found in Supplementary Section 1.2.

Material payoff functions

Each agent following strategy *i* has an expected payoff $\pi_i(\mathbf{x}, t)$, which can be written as

$$\pi_i(\mathbf{x}, t) = I_i(t) + R_i(t) + S_i(\mathbf{x}, t) - C_i(t)\,. \qquad (1)$$

We assume that households consider one strategy at a time and have perfect information about the expected income and variance of these strategy options, which may change on the basis of the strategy choices selected by other households in the community. The expected income from farming $I_i(t)$ at time *t* for strategy *i* accounts for the number of farming household members in case of migration through the migration adjustment factor η. The variance of the farming income is represented by $\sigma^2_{I,i}$. A drought occurs in any cropping cycle with probability *P* and the expected income in a non-drought (drought) year is represented by I^{nd} (I^{d}), with corresponding variance $\sigma^2_{I^{\mathrm{nd}}}$ ($\sigma^2_{I^{\mathrm{d}}}$). We assume all households farm mostly cereal crops based on a weighted average of crop production data from Nepal's Chitwan Valley (Supplementary Information), although previous work has demonstrated that risk transfer policies may lead farmers to shift cropping strategies over the long term[51]. $R_i(t)$ are the expected remittances of strategy *i* with corresponding variance σ^2_R. $S_i(t)$ represents the income originating from informal and formal risk transfer in strategy *i*. In case of informal revenue-sharing, β represents the proportion of household farming income that is shared in an informal risk-sharing pool. $C_i(t)$ are the costs corresponding to strategy profile *i* and can consist of the farming cost C^{F}, upfront migration cost C^{M}, revenue-sharing cost $\beta \cdot (I_i(t) - C^{\mathrm{F}})$ and formal insurance premium C^{FI}. An overview of the mean and variance of all strategy options can be found in Supplementary Section 1.3.

Utility including risk and loss aversion

Grounded in the theory of NELM, we assume that households diversify their strategies to reduce the risk to their livelihood. To this purpose, the utility can be defined as the difference of the expected profit and the weighted profit volatility, given by $\pi_i(\mathbf{x}, t) - b\sigma_i(\mathbf{x}, t)$ where *b* represents the risk-aversion parameter. However, as decision-makers tend to be more sensitive to experiencing losses versus gains of a similar magnitude[52], any potential loss is penalized with factor λ, with $\lambda > 1$ for most decision-makers. According to the loss-aversion framework, decision-makers interpret payoffs in terms of gains and losses relative to a reference point. In the particular decision-making context of subsistence farming, the salient reference point is average farming cost, C^{F}. That is, households will perceive farming investments as a loss if the net farming revenues they accrue (including costs and payouts from insurance and/or the revenue-sharing pool) do not cover their initial expenses for a cropping season. Conversely, net farming revenues above those expenses are considered gains. This is equivalent to the status quo reference point evaluated by others in their study of loss aversion and demand for index insurance[33] and allows us to evaluate the gains and losses of all risk management options on an equivalent basis. Households account for migration decisions separately from farm management decisions. Here the relevant reference point for evaluating gains or losses from migration is 0. That is, if a household has not yet engaged in migration, then it will perceive an initial loss of C^{M}, representing the upfront cost of migration. On the other hand, if a household has already engaged in migration, we assume there are no additional upfront costs borne by the household and the expected remittance income $R_i(t)$ is seen as a gain.

Loss aversion is typically measured empirically using a cumulative prospect theory (CPT) utility function. Since the utility function in this work is derived from mean-variance theory (MVT), rather than CPT, the loss-aversion parameter is rescaled such that it retains the same meaning in the MVT framework. We do this by comparing the ratio of farming utilities in a drought versus non-drought year under both CPT and MVT (Supplementary Section 1.4). Accounting for loss aversion related to farming and migration losses, the utility at time *t* from farming and migration of a self-interested and risk- and loss-averse household following strategy *i* can be written as

$$u_i^{\mathrm{F}}(\mathbf{x}, t) = \begin{cases} I_i(t) + S_i(\mathbf{x}, t) - C^{\mathrm{F}} - b\sigma_{I,i}(\mathbf{x}, t) & \text{if } I_i(t) + S_i(\mathbf{x}, t) \geq C^{\mathrm{F}} \\ \lambda\left[I_i(t) + S_i(\mathbf{x}, t) - C^{\mathrm{F}} - b\sigma_{I,i}(\mathbf{x}, t)\right] & \text{if } I_i(t) + S_i(\mathbf{x}, t) < C^{\mathrm{F}} \end{cases} \qquad (2)$$

and

$$u_i^{\mathrm{M}}(t) = \begin{cases} R_i(t) - b\sigma_{\mathrm{R}}(t) & \text{if } C^{\mathrm{M}}(t) = 0 \\ -\lambda C^{\mathrm{M}}(t) & \text{if } C^{\mathrm{M}}(t) > 0 \end{cases} \qquad (3)$$

Similar to the CPT framework, the loss-aversion factor is applied to the loss corrected for the risk penalty.

Using equations (2) and (3), the total utility of a self-interested household at time *t* is given by

$$u_i(\mathbf{x}, t) = u_i^{\mathrm{F}}(\mathbf{x}, t) + u_i^{\mathrm{M}}(t)\,, \qquad (4)$$

and the expected utility over drought and non-drought periods for each farming strategy *i* can be calculated as

$$\mathbb{E}[u_i^{\mathrm{F}}(\mathbf{x}, t)] = p u_i^{\mathrm{d}}(\mathbf{x}, t) + (1 - p) u_i^{\mathrm{nd}}(\mathbf{x}, t)\,, \qquad (5)$$

with $u_i^{\mathrm{d}}(\mathbf{x}, t)$ and $u_i^{\mathrm{nd}}(\mathbf{x}, t)$ as the utility in a drought and non-drought period, respectively.

Utility under prosocial preferences

Building on frameworks from refs. [29,30,53], we introduce an altruism index, α, which governs the degree to which individual households prioritize the collective well-being of the community over their individual utility. Different levels of altruism can be captured as follows in the utility function

$$\begin{aligned} v_i(\mathbf{x}, t) &= (1 - \alpha) u_i(\mathbf{x}, t) + \alpha \frac{1}{N} \sum_j x_j u_j(\mathbf{x}, t) \\ &= (1 - \alpha) u_i(\mathbf{x}, t) + \alpha \frac{W(\mathbf{x}, t)}{N}\,, \end{aligned} \qquad (6)$$

where α takes values in the interval [0, 1] and $W(\mathbf{x}, t) = \sum_j u_j(\mathbf{x}, t)$ represents the social welfare function. For $\alpha = 0$, the decision-maker coincides with the self-interested household (homo economicus) defined in equation (4), while for $\alpha = 1$, the decision-maker is a complete altruist, attaching equal weight to the utility of each individual in the population, including himself or herself. In this case, $v_i(\mathbf{x}, t)$ reflects the average per capita utility of the community.

We next introduce a solidarity index, κ, which specifies the degree to which a decision-maker takes actions that they wish to be universalized. Different levels of solidarity are captured as follows in the utility function

$$w_i(\mathbf{x}, t) = \mathbb{E}_{\tilde{\mathbf{x}}}\left[u_i(\tilde{\mathbf{x}}, t)\right]\,. \qquad (7)$$

In this utility function, the expectation is taken over the random vector $\tilde{\mathbf{x}}$ where the strategy of each household is changed to strategy *i* with probability κ. Higher values of $\kappa \in [0, 1]$ indicate a greater propensity to adopt the strategy that household *i* wishes were universalized. An alternative interpretation of κ is a trust parameter, in which higher values of κ indicate greater trust that other households will also act in solidarity with the focal household. For $\kappa = 0$, this decision-maker coincides with a homo economicus household, while for $\kappa = 1$ the decision-maker acts as if all households select the same strategy. A high value of κ therefore corresponds with the concept of homo moralis, that is, a decision-maker that defines what is 'the right thing to do' from a self-regarding perspective and overcomes a priori the coordination problem[27]. This utility function may resemble the strategy of conditional cooperation[26], in which agents are predisposed to cooperate towards a prosocial goal, provided they have some confidence that other agents are also likely to cooperate. To calculate the utility function including solidarity, we present an approximation in Supplementary Section 1.6.

The self-interested, altruist and solidarity preferences can be captured by a single generalizing utility function of a prosocial household

$$z_i(\mathbf{x},t) = \mathbb{E}_{\tilde{\mathbf{x}}}\left[(1-\alpha)u_i(\tilde{\mathbf{x}},t) + \alpha\frac{1}{N}\sum_j x_j u_j(\tilde{\mathbf{x}},t)\right], \tag{8}$$

which allows us to model combinations of different levels of altruism and solidarity. An interpretation of households evaluating strategy options using $z_i(\mathbf{x}, t)$ with non-zero α and κ is that households in a community consider their peers' well-being while trusting that a share κ of the community will follow the strategy choice of the focal household. Note that if $\alpha = 0$, equation (8) reduces to the homo moralis preference in equation (7). Similarly, if $\kappa = 0$, $z_i(\mathbf{x}, t)$ reduces to the altruist preference in equation (6) and if both $\alpha = \kappa = 0$, the same equation reduces to the risk- and loss-averse homo economicus household of equation (4).

In their decision-making, households consider the aggregated utility over time, which can be defined on the basis of the instantaneous prosocial utility function $z_i(\mathbf{x}, t)$ as follows

$$Z_i(\mathbf{x},t) = \sum_{s=t}^{s=t+h}\frac{z_i(\mathbf{x},s)}{(1+r)^{s-t}}. \tag{9}$$

The parameter h represents the time horizon over which farming households evaluate their strategy options and r is the discount factor. This is particularly relevant for evaluating strategy options that include migration. Here we assume that households engaging in migration pay an upfront cost C^{M} in the first time step and begin receiving remittances in subsequent time steps.

Accounting for independent and covariate risk

An important element of the model is to determine how different levels of independent and covariate risk affect the risk management strategies that emerge from farmer decision-making. The risk is determined through the standard deviations σ_i, covering the independent risk of livelihood strategy i; ϱ, capturing the base-level correlation between household farming incomes before any risk management strategies are applied; and P, capturing the probability of a shock event, for example, drought, represented by a threshold frequency in the income cumulative distribution function below which income is assumed to be the result of an extreme event. Note that P also affects the expected income by reshaping the income distribution as described in Supplementary Section 1.5.2. Generally, independent risk increases with σ_i, whereas covariate risk increases with P and ϱ. The precise level of risk faced by each household depends on their risk management strategy and those of their fellow community members.

Income correlation is relevant in case of revenue-sharing, which is only applied to the portion of the income originating from farming. The revenue of household k pursuing revenue-sharing is given by

$$I^{\mathrm{RS}}_{i,k}(\mathbf{x},t) = (1-\beta)I_{i,k} + \beta\frac{1}{|\mathcal{P}(t)|}\sum_{l\in\mathcal{P}_i(t),\, i\in\mathcal{S}^{\mathrm{RS}}} I_{i,l}, \tag{10}$$

where $I_{i,k}$ is the income from farming for household k following strategy i. The income of household k pursuing revenue-sharing can be found by adding the proportional share of the total contributions to the revenue-sharing pool $\mathcal{P}(t) = \bigcup_{i\in\mathcal{S}^{\mathrm{RS}}}\mathcal{P}_i(t)$, where $\mathcal{S}^{\mathrm{RS}}$ stands for the subset of strategies that include revenue-sharing. The mean farming income under revenue-sharing can be written as

$$I_i(t) + S_i(\mathbf{x},t) = \mu_{I_i^{\mathrm{RS}}}(\mathbf{x},t) = (1-\beta)\mu_{I_i} + \frac{\beta}{|\mathcal{P}(t)|}|\mathcal{P}(t)|\mu_{I_i} = \mu_{I_i}, \tag{11}$$

and income variance under revenue-sharing can be written as

$$\sigma^2_{I_i^{\mathrm{RS}}}(\mathbf{x},t) = \Big((1-\beta)^2 + 2(1-\beta)\frac{\beta}{|\mathcal{P}(t)|}(1+\varrho(|\mathcal{P}(t)|-1)) + \frac{\beta^2}{|\mathcal{P}(t)|}(1+\varrho(|\mathcal{P}(t)|-1))\Big)\sigma^2_I, \tag{12}$$

with ϱ as the Pearson correlation coefficient assumed constant over time and equal between all pairs of households.

Policy interventions

We model the effect of a government providing a monetary subsidy, I^{s}, to purchasers of formal insurance and analyse its relative effectiveness in encouraging household adoption of socially optimal risk management strategies. We assume that such subsidies are provided immediately upon purchase of the insurance product in each cropping cycle and take the form of a fixed cash amount. The premium for insurance in each cycle can be written as

$$C^{\mathrm{FI}} = p(I^{\mathrm{nd}} - I^{\mathrm{d}}) - I^{\mathrm{s}}. \tag{13}$$

This type of intervention raises the expected profit of risk management strategies that include formal insurance, which increases their utility relative to strategies without formal insurance, ceteris paribus. Note, however, that subsidies do not change the variance of strategies that include formal insurance.

Evolutionary selection mechanism

Considering a population of N households, each of which is following a strategy $i \in \{1,\cdots,S\}$, we simulate how the number of households $x_i(t)$ adopting strategy i evolves over time. In each time step, a household is matched with another household randomly and over one generation of N time steps the entire population has, on average, the opportunity to change strategy. We also allow for a small mutation probability $v = 1/N$ representing the random exploration of the strategy space. Mutations ensure that monomorphic states can be left. The matching process does not correspond to a physical meeting between households but could also stand for information that arrives at a given household. When a household of strategy i is matched with a household following strategy j, then we get the following transition probabilities $T_{i\to j}$ between strategies i and j

$$T_{i\to j} = (1-v)\frac{1}{1+\exp\left(-\zeta\frac{Z_j(\mathbf{x},t)-Z_i(\mathbf{x},t)}{|Z_i(\mathbf{x},t)|}\right)} \tag{14a}$$

$$T_{i\to k} = v\frac{1}{S-1}, \quad k \neq i \tag{14b}$$

$$T_{i\to i} = 1-(1-v)\frac{1}{1+\exp\left(-\zeta\frac{Z_j(\mathbf{x},t)-Z_i(\mathbf{x},t)}{|Z_i(\mathbf{x},t)|}\right)} - v\frac{1}{S-1}, \tag{14c}$$

where $1/(1+\exp(-\zeta\cdot x))$ is the logistic function with steepness ζ. The transition probability in equation (14a) is based on the relative, aggregate utility differential between household i and household j. The absolute value in the denominator of the relative utility differential is necessary to ensure consistency in case of negative utilities. Equation (14b) represents the probability of a random mutation and equation (14c) is the probability that the focal household does not change strategy.

Model setup

We construct a base case to compare how different levels of risk and prosocial preferences shape risk management strategies most likely to emerge, given a consistent set of assumptions. In this analysis, we assume a community of $N = 100$ households and simulate results for 200 generations of N decisions in which households are chosen at random to make a strategy decision. Such a timeframe allows us to explore the long-term dynamics as households update their risk management strategies, in relation to those espoused by others in their community. To mimic real-world conditions such as those in Nepal and Ethiopia, in which formal climate insurance is not yet common, we further assume that the initial distribution of strategies in the community excludes formal insurance.

We parameterize our model with economic and risk preference data from Nepali farming communities (Supplementary Section 1.5 and Supplementary Table 4). Data on expected incomes and standard deviations of farming and migration livelihoods are taken from the Chitwan Valley Family Study[54], a longitudinal survey of farming households in one of Nepal's most prominent agricultural regions. The correlation between farming incomes is also estimated from this source (Supplementary Section 1.5.2) and data from the index-based livestock insurance programme in Ethiopia's Borena region[55], two regions of subsistence farming communities whose governments are experimenting with index insurance programmes. We derived risk parameters from a composite of these correlation data and drought data for these two regions from the standardized precipitation and evapotranspiration index (SPEI)[56]. Data on farming costs are taken from ref. 57 and migration costs come from ref. 58. Farmer risk preferences are derived using data from ref. 59. Regarding transition dynamics, we assume a selection strength $\zeta = 27.7$ such that a 10% difference in relative utilities leads to a 90% probability of transition (Supplementary Section 1.7) and mutation rate $\mu = \frac{1}{N} = 0.01$, in line with typical parameters for evolutionary game theory models[60].

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Data sources used to support this analysis include Chitwan Valley Family Study—Labour Outmigration, Agricultural Productivity and Food Security, Nepal (ICPSR 36755) (https://www.icpsr.umich.edu/web/DSDR/studies/36755/versions/V5); IBLI Borena Household Survey R1-4 Stata 13 data (https://data.ilri.org/portal/dataset/ibli-borena-r1/resource/41b75ad5-71cd-4d23-911c-dcce53bc68a7); and SPEI (https://spei.csic.es/database.html).

Code availability

The game theory model for this study was developed via Python 3 software and is available via a Zenodo repository at https://doi.org/10.5281/zenodo.8347265.

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Author contributions

N.C.L. and M.W. conceived of and developed an initial design for the study and drafted the initial manuscript. F.P.S., S.A.L., M.O. and E.U.W. proposed modifications incorporated in the final design. N.C.L. wrote the model code. N.C.L. and M.W. analysed model results. All authors contributed to drafting the final manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Policy information about availability of computer code

Data collection	A novel evolutionary game theory model was developed via open-source Python 3 software to support this analysis. The code for that model is available via a Zenodo repository at DOI: 10.5281/zenodo.8347265.
Data analysis	All data was converted to .csv format and analyzed using open-source Python 3 software. Code to analyze the data is available in a Zenodo repository at DOI: 10.5281/zenodo.8347265

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Data to support this analysis was collected from open-source repositories, including:

- Chitwan Valley Family Study: Labour Outmigration, Agricultural Productivity, and Food Security, Nepal (ICPSR 36755): https://www.icpsr.umich.edu/web/DSDR/studies/36755/versions/V5
- IBLI Borena Household Survey R1-4 Stata 13 data: https://data.ilri.org/portal/dataset/ibli-borena-r1/resource/41b75ad5-71cd-4d23-911c-dcce53bc68a7
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Study description	This study develops an evolutionary game theory (EGT) model to simulate smallholder farmer risk management strategies under various climate and policy scenarios. The main method is a computational model, combined with analysis of publicly-available socioeconomic data from Nepal (Chitwan Valley Family Study) and Ethiopia (Borena Index-Based Livestock Insurance Study), as well as biophysical data from the Standardized Precipitation and Evapotranspiration Index. All data used in this study are quantitative.
Research sample	No new data was collected in this study. Publicly-available datasets that were used in this analysis surveyed smallholder farmers in the Chitwan District of Nepal and Borena region of Ethiopia, two agricultural regions that are experiencing significant climate change and are suitable case studies for studying risk management strategies under climate stress. Additionally, publicly-available global data on soil moisture balance was used to assess drought risk levels for these two case studies. Specifically, the following datasets were used in this analysis: - Chitwan Valley Family Study: Labour Outmigration, Agricultural Productivity, and Food Security, Nepal (ICPSR 36755): https://www.icpsr.umich.edu/web/DSDR/studies/36755/versions/V5. This is a panel dataset that reports farmers' cropping choices, migration trips, and income earned from 2006-2015 for the Chitwan Valley in Nepal. - IBLI Borena Household Survey R1-4 Stata 13 data: https://data.ilri.org/portal/dataset/ibli-borena-r1/resource/41b75ad5-71cd-4d23-911c-dcce53bc68a7. This is a dataset of herders' livestock possessions, income earned, and purchase of index-based insurance in the Borena Region of Ethiopia, collected over four waves from 2012-2015. - Standardized Precipitation and Evapotranspiration Index: https://spei.csic.es/database.html. This is a global raster database of soil moisture balance, reported at 0.5 degree grid cells for the years 1901-2019. For each grid cell, standardized water balance measures are reported at time scales ranging from 1 to 48 months.
Sampling strategy	No data were collected in this study. Rather, results were generated from an evolutionary game theory model that simulates farmers' risk management strategies under different climate and policy scenarios. Therefore, sampling methods for data collection (e.g. random, snowball, stratified, convenience) do not apply to this study.
Data collection	No data were collected for this study. Rather, results were generated from an evolutionary game theory model that simulates farmers' risk management strategies under different climate and policy scenarios. There was no experimental condition or study hypothesis.
Timing	No data were collected for this study. Rather, results were generated from an evolutionary game theory model that simulates farmers' risk management strategies under different climate and policy scenarios. Therefore, there was no timing of data collection.
Data exclusions	We parametrized the EGT model by fitting a Weibull distribution to estimated farmer incomes from survey data from the Chitwan

Data exclusions	Valley Family Study (described in Supplemental Information 1.4). Here, we excluded the top 1 percent of farm incomes in the survey so that the Weibull distribution converges.
Non-participation	No data were collected for this study. Rather, results were generated from an evolutionary game theory model that simulates farmers' risk management strategies under different climate and policy scenarios. No participants were involved in this study.
Randomization	No data were collected for this study. Rather, results were generated from an evolutionary game theory model that simulates farmers' risk management strategies under different climate and policy scenarios. Therefore, randomization techniques for data collection do not apply here.

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