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Prosocial preferences improve climate risk management in subsistence farming communities

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Contents

1 Modelling Framework

1.1 Background on Evolutionary Game Theory

The concept of evolutionary games (EGs) was first developed as a tool to explain patterns of animal behaviour in contexts where an animal's fitness depends on (i) its behavioural strategy and (ii) that of others in its population [1]. Similar to classical game theory from economics, EGs are typically used to identify one or more strategies that are selected when played against other individuals acting strategically. However, EGs differ from classical economic game theory in several important respects that are relevant to our research questions. Whereas non-cooperative games typically examine a limited number of interactions between a limited number of agents, EGs are used to evaluate the equilibria emerging from many repeated interactions with many other individuals in a population. As such, whereas traditional game theory usually evaluates agent payoffs in static or sequential conditions (i.e. each agent can only make one or a limited number of moves), agents in an EG can continually update their strategies based on payoffs that change dynamically as a function of the distribution of strategies played in a population. Thus, whereas the main outcome of a classical game is an individual's best-response strategy (the Nash equilibrium), the main outcome of EGs is the population-level distribution of strategies that arises as equilibria, termed evolutionarily stable strategies (ESS). These properties of EGs make them especially useful for our case study, in which farmers are likely to repeatedly assess whether to purchase insurance, participate in a community revenue-sharing pool, and/or pursue migration as a function of other community members' decisions, and we are especially interested in the equilibrium distribution of risk management strategies.

While EGs were initially developed for ecological applications, they have more recently been applied to the study of human populations. Ecological EGs are often constructed for infinite populations, allowing for analysis using differential equations. In our analysis, we model a finite population of discrete individuals to mimic real-world conditions in subsistence farming villages, and agents can choose between eight discrete strategy options, which thus leads us to develop a simulated EG. In our setting, it is not immediately clear which behaviours can be considered as cooperation vs. defection. While we analyze which strategy options lead to optimal collective outcomes, these may change depending on agents' risk and loss aversion preferences.

The proposed EG makes use of agent-based methods and models explicitly each individual household [2]. In the EG, each agent only considers one other option at a time - the strategy of the household to which they are randomly matched. This resembles a boundedly-rational agent that is limited in their ability to consider multiple strategies simultaneously; however, repeated interactions allow agents to continue updating their strategies as they encounter other options. In this EG, we assume agents have perfect information about the strategy option they are considering at any given time. Finally, strategy updates are done one agent at a time, so that each agent can assess the utility of their strategy against a relatively stable strategy distribution in the population.

1.2 Model notation

Supplementary Table 1 | Model parameters

Symbol	Description	Baseline Value
general		
$\mathbf{x}$	state of the population	–
N	number of households	100
T	number of time steps	20000
utility variables		
$\pi_i(\mathbf{x}, t)$	expected payoff	–

$u_i(\mathbf{x}, t)$	utility of self-interested household at time t playing strategy i	–
$u_i^{\mathrm{F}}(\mathbf{x}, t)$	utility from farming of self-interested household at time t	–
$u_i^{\mathrm{M}}(t)$	utility from migration of self-interested household at time t	–
$v_i(\mathbf{x}, t)$	utility of household with non-negative altruism at time t playing strategy i	–
$w_i(\mathbf{x}, t)$	utility of household with non-negative solidarity at time t playing strategy i	–
$z_i(\mathbf{x}, t)$	utility of pro-social household at time t playing strategy i	–
$Z_i(\mathbf{x}, t)$	aggregated utility of pro-social household at time t playing strategy i	–
utility parameters		
I	average farm income/cycle	163 USD
σ_I	farm income standard deviation	199 USD
C^{F}	farming costs/cycle	170 USD
η	migrant farm productivity adjustment	0.9
R	average remittance/cycle	600 USD
σ_R	remittance standard deviation	650 USD
C^{M}	up-front migration cost	700 USD
S	income from formal and informal risk transfer	–
β	proportion of income shared in pool	0.2
r	discount rate	0.1
h	time horizon (crop cycles)	10
risk parameters		
ϱ	correlation between household incomes	0.35
ϱ^M	correlation between farming and migration	0.0
p	drought probability	0.35
preferences		
b	risk weight	0.5
γ	re-scaled loss aversion	1.33
α	altruism index	0.3
κ	solidarity index	0.3
policy		
S	premium subsidy factor	0.0
evolutionary mechanism		
ζ	selection strength	27.7
ν	mutation rate	0.01

1.3 Moments of the Income Distributions for Different Strategies

Based on Eqn. 1 in the Main Text, the elements of expected strategy payoffs $\pi_i(\mathbf{x}, t)$ are displayed in Table 2 for each strategy i. Table 3 displays the variances of each strategy, σ_i^2.

type	Strategy	I_i	R_i	$S_i(\mathbf{x})$	C_i
1	F	I	0	0	C^{F}
2	F+I	I^{nd}	0	0	$C^{\text{F}} + p(I^{\text{nd}} - I^{\text{d}})$
3	F+S	I	0	$\beta \cdot \frac{x_3 I + x_4 I^{\text{nd}} + x_7 \eta I + x_8 \eta I^{\text{nd}}}{x_3+x_4+x_7+x_8}$	$C^{\text{F}} + \beta I$
4	F+S+I	I^{nd}	0	$\beta \cdot \frac{x_3 I + x_4 I^{\text{nd}} + x_7 \eta I + x_8 \eta I^{\text{nd}}}{x_3+x_4+x_7+x_8}$	$C^{\text{F}} + p(I^{\text{nd}} - I^{\text{d}}) + \beta I^{\text{nd}}$
5	FM	$\eta \cdot I$	R	0	$C^{\text{F}} + C^{\text{M}}$
6	FM+I	$\eta \cdot I^{\text{nd}}$	R	0	$C^{\text{F}} + C^{\text{M}} + p\eta(I^{\text{nd}} - I^{\text{d}})$
7	FM+S	$\eta \cdot I$	R	$\beta \cdot \frac{x_3 I + x_4 I^{\text{nd}} + x_7 \eta I + x_8 \eta I^{\text{nd}}}{x_3+x_4+x_7+x_8}$	$C^{\text{F}} + C^{\text{M}} + \beta\eta I$
8	FM+S+I	$\eta \cdot I^{\text{nd}}$	R	$\beta \cdot \frac{x_3 I + x_4 I^{\text{nd}} + x_7 \eta I + x_8 \eta I^{\text{nd}}}{x_3+x_4+x_7+x_8}$	$C^{\text{F}} + C^{\text{M}} + \beta\eta I^{\text{nd}} + p\eta(I^{\text{nd}} - I^{\text{d}})$

Supplementary Table 2 | Expected payoff of strategy options. Strategies are combinations of either farming only (F) or farming and mMigration (FM), participating in a revenue-sharing collective (S), and purchasing formal insurance (I).

type	variance
1	σ_I^2
2	$(1-p)\sigma_{I^{\text{nd}}}^2 + p\sigma_{I^{\text{d}}}^2$
3	$(1-\beta)^2\sigma_I^2 + \frac{\beta^2}{(x_3+x_4+x_7+x_8)^2} \cdot \left(x_3\sigma_I^2 + x_4\sigma_{\text{IFI}}^2 + x_7\sigma_{\text{IM}}^2 + x_8\sigma_{\text{IMFI}}^2\right) + 2(1-\beta)\frac{\beta}{x_3+x_4+x_7+x_8}\sigma_I^2$
4	$(1-\beta)^2\sigma_{\text{IFI}}^2 + \frac{\beta^2}{(x_3+x_4+x_7+x_8)^2} \cdot \left(x_3\sigma_I^2 + x_4\sigma_{\text{IFI}}^2 + x_7\sigma_{\text{IM}}^2 + x_8\sigma_{\text{IMFI}}^2\right) + 2(1-\beta)\frac{\beta}{x_3+x_4+x_7+x_8}\sigma_{\text{IFI}}^2$
5	$\eta^2\sigma_I^2 + \sigma_R^2$
6	$\eta^2[(1-p)\sigma_{I^{\text{nd}}}^2 + p\sigma_{I^{\text{d}}}^2] + \sigma_R^2$
7	$[1-\beta]^2\sigma_{\text{IM}}^2 + \frac{\beta^2}{(x_3+x_4+x_7+x_8)^2} \cdot \left(x_3\sigma_I^2 + x_4\sigma_{\text{IFI}}^2 + x_7\sigma_{\text{IM}}^2 + x_8\sigma_{\text{IMFI}}^2\right) + 2(1-\beta)\frac{\beta}{x_3+x_4+x_7+x_8}\sigma_{\text{IM}}^2$
8	$[1-\beta]^2\sigma_{\text{IMFI}}^2 + \frac{\beta^2}{(x_3+x_4+x_7+x_8)^2} \cdot \left(x_3\sigma_I^2 + x_4\sigma_{\text{IFI}}^2 + x_7\sigma_{\text{IM}}^2 + x_8\sigma_{\text{IMFI}}^2\right) + 2(1-\beta)\frac{\beta}{x_3+x_4+x_7+x_8}\sigma_{\text{IMFI}}^2$

Supplementary Table 3 | Variance of strategy options under independent risk. To shorten notation, σ_{IFI}^2 and σ_{IM}^2 represent the variance for the farming + formal insurance and the farming + migration strategies, respectively. Similarly, σ_{IMFI}^2 represents the variance for the farming + migration + formal insurance strategy. σ_{II}^2 represents the variance for the farming + informal revenue-sharing strategy.

1.4 Loss Aversion Re-Scaling

To conserve the core feature of loss aversion, we calculate the loss aversion parameter under mean-variance theory (MVT), λ, such that the ratio of the drought to non-drought utilities for the Farm strategy under MVT are equivalent to the ratio of utilities for the same strategy under cumulative prospect theory (CPT), given a loss aversion parameter γ. Formally, this is calculated as

$$\lambda \frac{U^{\text{MVT}}(I^{\text{d}})}{U^{\text{MVT}}(I^{\text{nd}})} = \frac{U^{\text{CPT}}(I^{\text{d}})}{U^{\text{CPT}}(I^{\text{nd}})} \tag{S1}$$

or in terms of model parameters

$$\lambda \frac{(I^{\text{d}} - C^{\text{F}}) - b \cdot \sigma_{I^{\text{d}}}}{(I^{\text{nd}} - C^{\text{F}}) - b \cdot \sigma_{I^{\text{nd}}}} = -\gamma \frac{[-(I^{\text{d}} - C^{\text{F}})]^{\alpha_{\text{CPT}}}}{(I^{\text{nd}} - C^{\text{F}})^{\alpha_{\text{CPT}}}} \tag{S2}$$

where α_{CPT} represents the CPT utility curvature parameter. Using typical values for γ (2.25) and α_{CPT} (0.88) from Tversky and Kahneman [3], along with a risk factor of $b = 0.5$ in MVT, we calculate a unique λ for each risk scenario. For the Medium Risk scenario ($p = 0.35$), with $C^{\mathrm{F}} = 221$, $I^{\mathrm{nd}} = 280$, $\sigma_{I^{\mathrm{nd}}} = 247$, $I^{\mathrm{d}} = 26$, and $\sigma_{I^{\mathrm{d}}} = 235$, we calculate the rescaled loss aversion factor $\lambda = 1.33$.

1.5 Estimation of Parameters

Model parameters listed in Table 4 are calibrated with empirical data from two relevant contexts: crop farming in the Chitwan Valley of Nepal, and a combination of crop farming and pastoralism in the Borena region of Ethiopia. Both case studies share several characteristics that make them ideally suited for our research questions: (1) in both regions, subsistence agriculture constitutes the dominant livelihood; (2) farmers and pastoralists in each location are often subject to climate-driven hazards, such as droughts; (3) migration is a commonly employed livelihood diversification strategy in both contexts; (4) index insurance has been considered by national policymakers in Nepal [4] and was introduced in Ethiopia's Borena region starting in 2012 [5]; and (5) both case studies come with high-frequency data, collected over several years, on farmers' livelihood choices and incomes [6, 7].

Additionally, there are several important differences between the two contexts that can help to generalize our analysis. With respect to livelihoods, farming of cereal crops (including rice, maize, and wheat) is the main option in the Chitwan Valley, whereas pastoralism (selling of camels, goats, sheep, and/or their milk) predominates in Borena. From a climatic perspective, the Chitwan Valley is exposed to a variety of hazards, including drought, floods, and hail. Over the past twenty years, Chitwan has faced such hazards at a relatively high frequency, approximately once every two cropping cycles. On the other hand, drought is the main hazard affecting Borena, which happens with relatively lower frequency - approximately one event every four years (SI 1.5.2). Finally, the breadth and temporal coverage of panel data differs substantially between the two contexts. The Chitwan Valley Family Study (CVFS) provides annual data on household livelihood decisions (including migration), crop production, and remittance incomes over a 12-year period, from 2006-2017 [6]. The Index Based Livestock Insurance (IBLI) Borena Household Survey provides seasonal data on household livelihood choices and income (excluding migration), household social networks and informal lending, and formal insurance purchases from 2012-2014 [7]. We can therefore exploit differences in these two case studies to test the robustness of our conclusions to different subsistence agricultural contexts. Below, we describe the estimation of our Base Case economic parameters and multiple covariate risk scenarios.

Symbol	Parameter Description	Base Case	Source	Sensitivity Analysis
N	Number of Households	100	Assumed	SI Section 2.5
T	Time Steps	20,000	Assumed	N
I	Avg. Farm Income/Cycle	163 USD	[6]	N
σ_I	Farm Income Std Dev.	199 USD	[6]	N
C^{F}	Farming Costs/Cycle	170 USD	[8]	N
η	Migrant Farm Productivity Adjustment	0.9	Assumed	N
R	Avg. Remittance/Cycle	600 USD	[9]	SI Section 2.3
σ_R	Remittance Std Dev	650 USD	[9]	SI Section 2.3
C^{M}	Up-front Migration Cost	700 USD	[9]	SI Section 2.3
β	Proportion of Income Shared in Pool	0.2	Assumed	SI Section 2.6
ϱ	Correlation between Household Incomes	0.35	[6]	Main Text 3.2
ϱ^M	Corr. between Farming and Migration	0.0	Assumed	N
p	Drought Probability	0.35	[10]	Main Text 3.2
r	Discount Rate	0.1	Assumed	SI Section 2.6
h	Time Horizon (crop cycles)	10	Assumed	N
b	Risk Weight	0.5	[11]	SI Section 2.6
α	Altruism Factor	0.0	Assumed	Main Text 3.3
κ	Solidarity Factor	0.0	Assumed	Main Text 3.3
γ	Re-scaled Loss Aversion	1.33	[3]	SI Section 2.6
S	Premium Subsidy Factor	0.0	Assumed	Main Text 3.4
ζ	Selection Strength	27.7	Calculated	SI Section 1.6
ν	Mutation Rate	0.01	Calculated	N
τ	Consumption Threshold	84.43 USD	[6]	N

Supplementary Table 4 | List of Model Parameters

1.5.1 Base Case Economic Parameters

Owing to its wider temporal coverage and higher granularity in terms of economic inputs and outputs, we use CVFS data to derive values for our Base Case farming parameters. Specifically, the CVFS Agriculture and Migration Survey Calendar Data consists of 2,255 households in the Chitwan District from the years 2006-2017, and includes annual data at the household scale on the land area dedicated to various crops, crop production, number of household migrants, and remittance income earned. This allows us to estimate several key economic parameters for the Base Case, including the mean and standard deviation of farming incomes (I and σ_I, respectively) and the correlation between farming incomes (ϱ, SI 1.4.2).

While the CVFS data does not explicitly include income earned from farming of staple crops, we convert observed data on crop production to revenues using 2010 crop prices for Nepal from Food and Agricultural Organization data [12]. Total farm revenue (TFR_{it}) is calculated for each observation (household*year) in the CVFS dataset by aggregating revenues earned from all crops produced, I_{itk}, and standardizing to the average household farm size (0.56 ha) as follows

$$TFR_{it} = \frac{\sum_k A_{itk} \cdot Y_{itk} \cdot w_k}{\bar{A}} \tag{S3}$$

where A_{itk} represents the cropping area that household i dedicates to crop k in year t, $\bar{A}$ denotes the average farm size for households in the CVFS dataset, Y_{itk} denotes the yield of crop k for household i in year t, and w_k denotes the FAO 2010 USD price for crop k. TFR_{it} thus gives a standardized measure of farming income that controls for variation in farm sizes among Chitwan Valley farmers. We use this metric to calculate the mean and variance of farming incomes (I and σ_I^2, respectively) across all household*year observations in the CVFS dataset. Here we monetize all household crop production, including that which would be consumed by the household itself. We assume that any subsistence consumption offsets food that would otherwise have to be purchased at the same market price that is reflected in the FAOSTAT data.

To calculate remittance income parameters, we rely on Nepali outmigration data from [9], which presents a decomposition of migration costs, mean remittances, and variance in remittance income by different destinations. More specifically, we calculate R, σ_R, and C_M for local destinations only (Nepal + India, which does not require a visa for Nepali migrants), international destinations (all other countries), and a weighted composite of these destinations, which informs our Base Case parameters. More details can be found in Supplementary Information 2.3.

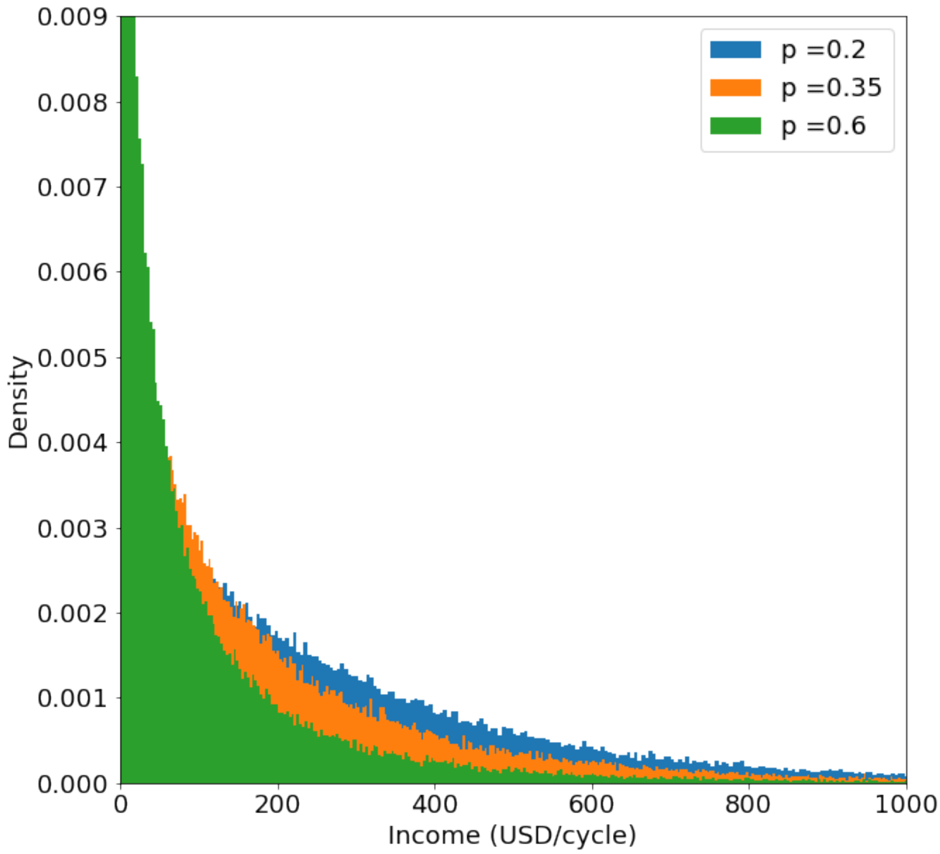
1.5.2 Covariate Risk Parameters

We now turn to estimation of the parameters governing covariate risk faced by farmers: the drought risk p and income correlation ϱ. For this analysis, we develop composite Low and Medium Risk scenarios from the Chitwan Valley and Borena case studies, and extrapolate from observed conditions to develop an additional High Risk scenario. A possible interpretation for these scenarios is as follows. The Low Risk scenario represents the lower bound for the two covariate risk parameters that are currently observed in the Chitwan Valley and Borena region ($p = 0.2$ and $\varrho = 0.1$). Climate risks are likely to only increase over the remainder of the century [13], and it is unlikely that farming incomes will become less correlated than the already low value we observe. The Medium Risk scenario roughly represents the average covariate risk currently faced by such communities ($p = 0.35$, $\varrho = 0.35$), and could serve as a future scenario for current Low Risk communities, if climate risks increase and household incomes become more correlated over time. The latter condition may occur, for example, if households pursue similar climate adaptation strategies (e.g. planting similar seed varieties and/or adjusting timing in similar ways), or if small-scale farms begin to consolidate with a transition to commercial-scale agriculture. Finally, the High Risk scenario ($p = 0.6$, $\varrho = 0.5$) represents a potential future where climate risks have become extreme, and farming households have few viable adaptation options, leaving them to mostly pursue similar strategies.

Climate risks for the Low and Medium Risk scenarios are calculated using the Standardized Precipitation and Evapotranspiration Index (SPEI) database, which estimates soil moisture conditions at a 0.5 x 0.5 degree grid cell scale (approximately 50 km x 50 km at the Equator) at a monthly frequency [10]. These estimates are then normalized to a historical baseline for the specified grid cell for various time horizons, ranging from 1-48 months. SPEI values therefore indicate how many standard deviations current soil moisture conditions are above or below the historical baseline for a given grid cell. Here, we take the 3-month SPEI as an indicator of soil moisture conditions for the duration of a typical growing season in both Nepal and Ethiopia. For example, the 3-month SPEI value in July 2020 for the grid cell containing the Chitwan Valley (27.75^0 N, 84.25^0 W) was 0.167; this indicates that soil moisture conditions from mid-April through mid-July 2020 were 0.167 standard deviations wetter than the historical baseline in the region for this time period.

To estimate climate risks currently faced by subsistence farming communities in both the Chitwan Valley and Borena contexts, we examine 3-month SPEI values for the years 2000-2019, and calculate the number of months with severe drought or wet conditions during this time period. In the Chitwan Valley, the dry season typically corresponds to the months of January - May, while the rainy monsoonal season comes from June - November. The Borena region is characterized by two cycles of wet/dry seasons: the long wet (dry) season is from March-May (June-September), and the short wet (dry) season occurs from October - November (December - February) [7]. For the purposes of this analysis, we generate a range of extreme event risks for each region by calculating the proportion of wet season months that were characterized by severe moisture, and the proportion of dry season months that were characterized by extreme drought. Specifically, if the minimum 3-month SPEI in any given year is below -1.0, we classify this as a severe drought occurrence; conversely, we characterize a severe wet event as a 3-month SPEI value greater than 1.0. This is in line with the standard used by the Index-Based Livestock Insurance (IBLI) program in Ethiopia, which compensates policyholders if a vegetation index is below 1 standard deviation of a historical baseline [7]. We then calculate a central tendency of the climate risk, p, as the total number of months with SPEI values outside the interval $[-1, 1]$ divided by the total number of months. During this time period, the Chitwan Valley was characterized by a high number of months with both severe wet events (38.3 percent of wet season months and severe drought-like conditions (55.8 percent of dry season months), for a total of 47.1 percent of months in which there was a severe event, or $p = 0.47$. In Borena, 10.8 percent of wet season months exhibited severe wet conditions, and 21.7 percent of dry season months exhibited drought-like conditions, leading to a total of $p = 0.16$ months with extreme events.

Averaging between these two regions, we take $p = 0.31$ as a Base Case value of the probability of severe weather events. This informs how we re-scale the income distribution function as a function of p. Using CVFS data, we fit a Weibull distribution to characterize the farm income earned by households, with the scale parameter $\lambda_w = 0.88$ and shape factor $\kappa_w = 203$. Given the averaged probability of severe events, we define the severe event income threshold, I_{thresh}, as the 31st percentile of the income distribution, which occurs at $I_{\text{thresh}} = 63$ USD. We interpret this value to be the upper limit of farming income earned during an severe event. For each covariate risk scenario, we re-scale the Weibull distribution such that a proportion p of the distribution lies below $I_{\text{thresh}} = 63$; for example, in the High Risk scenario, $p = 0.6$ and 60 percent of the distribution lies below $I_{\text{thresh}} = 63$. As the Weibull distribution is defined by two parameters, we also fix an extreme point corresponding to the 99.99 percentile of the distribution at $I_{\max} = 2500$ for all risk scenarios, reflecting the highest observed TFR in the Chitwan dataset. This gives us two points of the distribution with two percentiles, from which we can calculate a re-scaled λ_w and κ_w. For the Low risk scenario, $p = 0.2$, $\lambda_w = 1.01$ and $\kappa_w = 278$; for the Medium risk scenario, $p = 0.35$, $\lambda_w = 0.83$ and $\kappa_w = 174$; for the High risk scenario, $p = 0.6$, $\lambda_w = 0.63$, and $\kappa_w = 73$. Supplementary Figure 1 displays histograms of the farm income distribution under each of these risk scenarios.



Supplementary Figure 1 | Histogram of farm income distributions under Low (blue), Medium (orange), and High (green) covariate risk scenarios.

Income correlation for the Low and Medium Risk scenarios is calculated from the CVFS and IBLI datasets, respectively, by calculating a Pearson's correlation matrix of agricultural income among households in each dataset. For the Chitwan Valley context, this is calculated using the total farm revenue (TFR_{it}) metric described in equation (S3). We restrict the calculation to only those households that reported a non-zero income for all eight years of the survey, leading to a panel dataset of 610 households.

For the Borena case study, the IBLI dataset directly reports income from different livelihood activities (including sales of crops and livestock). Likely owing to the predominance of pastoralism in this region, the IBLI dataset does not disaggregate data by type of crop. On the other hand, income is disaggregated temporally according to four sequential seasons: the long rain (March - May), long dry (June - September), short rain (October - November), and short dry (December - February) seasons. Therefore, for each household, we construct a panel dataset by aggregating the total income earned from agricultural activities (specifically, sale of crops, sale of livestock, and sale of livestock products) across each annual sequence of dry and rainy seasons. As the IBLI data is reported for four years, from 2012-2015, we restrict our analysis to only those households that were captured for each year of the survey; this leads to 458 household observations.

Both the Chitwan Valley and Borena datasets sampled respondents from multiple villages: the Chitwan dataset includes respondents from 151 neighbourhoods, and the Borena dataset includes respondents from 17 Reeras (the smallest administrative unit in that context). As we are concerned with the interaction of insurance and informal revenue-sharing within a village, we would like to obtain a proxy of within-village income correlation, which is likely to be higher than correlation across the multiple villages represented in each dataset. Although specific neighbourhoods (Reeras) of respondents are not included in the public dataset of the Chitwan (Borena) studies, we can estimate a range of within-village correlation by bootstrapping village-sized samples from the full sample size. Specifically, we calculate a mean number of sampled households per village in each study as $N_v = N/V$, where N_v is the mean number of sample respondents per village, N is the total sample size in our correlation matrix, and V is the number of neighbourhoods (Reeras) in the Chitwan (Borena) dataset. We then take 1000 random samples of size N_v of the correlation matrix for each study in order to estimate the range of potential within-village correlation. For the Chitwan dataset, this results in a mean correlation of 0.035, with the 67 percent confidence interval (-0.12, 0.26) and 95 percent confidence interval (-0.26, 0.54). For the Borena dataset, this results in a mean correlation of 0.08, with the 67 percent confidence interval (0.018, 0.15) and 95 percent confidence interval (-0.018, 0.24). Note that the mean correlation is likely to be lower than the actual within-village income correlation in both contexts, as most samples in the bootstrap procedure likely include farmers from different villages. We thus set $\varrho = 0.1$ as the Low Risk estimate of income correlation, $\varrho = 0.35$ as the Medium Risk estimate, and $\varrho = 0.5$ as the High Risk estimate. To indicate the likely range of covariate risks for both the Chitwan and Borena regions in Figure 4 in the Main Text, we use the 67 percent confidence interval of income correlation.

1.6 Approximation for Utility Function Including Solidarity

The *homo moralis* has a utility function given by

$$\begin{aligned} w_i(\mathbf{x}, t) &= \mathbb{E}_{\tilde{\mathbf{x}}}\left[u_i(\tilde{\mathbf{x}}, t)\right] \\ &= \mathbb{E}_{\tilde{\mathbf{x}}}\left[u_i^{\mathrm{F}}(\tilde{\mathbf{x}}, t)\right] + u_i^{\mathrm{M}}(t) \end{aligned} \tag{S4}$$

This utility function can be computed numerically by averaging over enough realizations of the vector $\tilde{\mathbf{x}}$. To improve the numerical tractability, we propose here an approximation of $w_i(\mathbf{x}, t)$ that does not require the simulation of multiple vectors $\tilde{\mathbf{x}}$.

Only in case of revenue-sharing (in 4 of the 8 strategies), the utility function is a function of $\mathbf{x}$, and therefore the analysis is limited to these strategies. Nor the expected revenue, nor the standard deviation are linear in $\mathbf{x}$. The linear approximation in the first term of (S4) can be written as

$$\begin{aligned} &\mathbb{E}_{\tilde{\mathbf{x}}}\left[u_i^{\mathrm{F}}(\tilde{\mathbf{x}}, t)\right] \approx u_i^{\mathrm{F}}(\mathbb{E}[\tilde{\mathbf{x}}], t) \\ &\qquad = H(I_i(t) + S_i(\mathbb{E}[\tilde{\mathbf{x}}], t) - C^{\mathrm{F}}) \cdot \Big(I_i(t) + S_i(\mathbb{E}[\tilde{\mathbf{x}}], t) - C^{\mathrm{F}} - b \cdot \sigma_{I,i}(\mathbb{E}[\tilde{\mathbf{x}}], t)\Big) \\ &\qquad\quad + H(C^{\mathrm{F}} - I_i(t) - S_i(\mathbb{E}[\tilde{\mathbf{x}}], t)) \cdot \lambda \cdot \Big(I_i(t) + S_i(\mathbb{E}[\tilde{\mathbf{x}}], t) - C^{\mathrm{F}} - b \cdot \sigma_{I,i}(\mathbb{E}[\tilde{\mathbf{x}}], t)\Big), \end{aligned} \tag{S5}$$

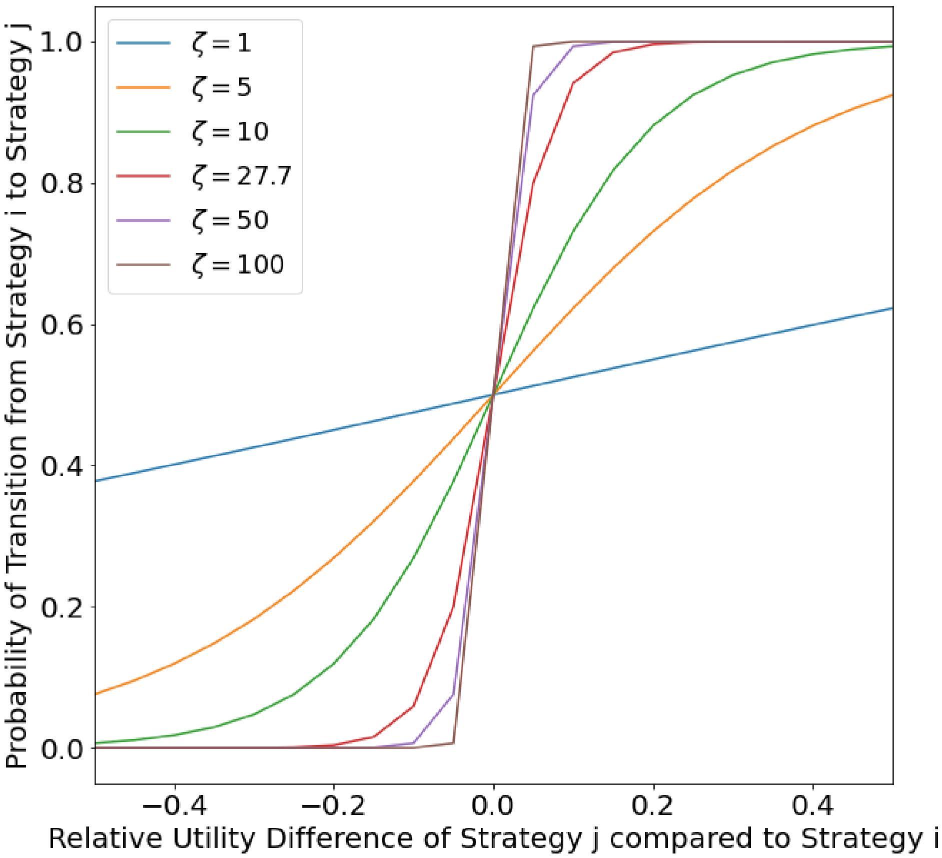
where $H(\cdot)$ is the Heaviside function. Taking as an example the calculation for the utility of strategy 3, the average number of households following strategy i are given by

$$\begin{aligned} &\mathbb{E}[\tilde{x}_1] = x_1 - \kappa x_1 = (1-\kappa)x_1 \\ &\dots \\ &\mathbb{E}[\tilde{x}_3] = x_3 + \kappa(N - x_3) \\ &\dots \\ &\mathbb{E}[\tilde{x}_8] = (1-\kappa)x_8 \end{aligned} \tag{S6}$$

We find that the utility given in (S6) provides an accurate approximation of the first term in (S4).

1.7 Transition Probability and Selection Strength

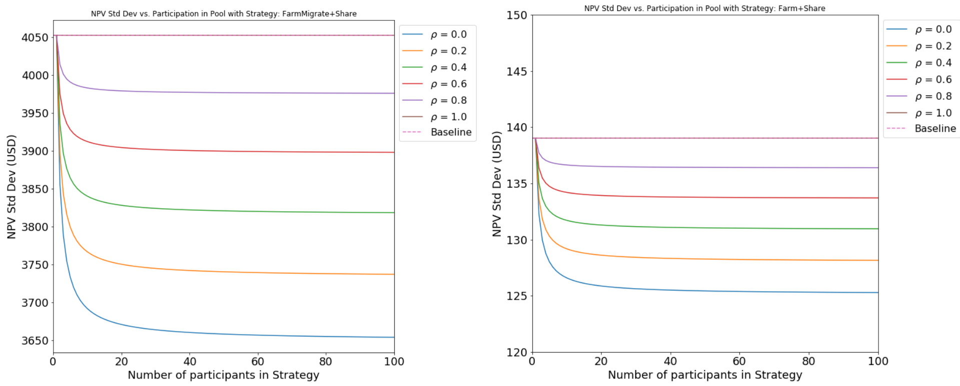
In the simulation results, the probability of transition between two strategies, $T_{i \to j}$, depends on the selection strength parameter ζ, as well as the relative difference in the utilities of the two strategies, f_i and f_j (see Main Text, Eqn 14). Here, we display $T_{i \to j}$ as a function of both of these components. For a relative gap in utilities of 0.1 (i.e. 10 percent difference), a selection strength $\zeta = 10$ leads to a probability of transition, $T = 0.8$. For a selection strength $\zeta = 50$, this probability approximates 1.0.



Supplementary Figure 2 | Transition probabilities between two strategies as a function of the relative difference in utility (x-axis) and selection strength parameter, ζ (represented by different lines). For Base Case results, we use $\zeta = 27.7$ (red line).

2 Supporting Results and Sensitivities

2.1 Income Variance and Informal Risk Pool



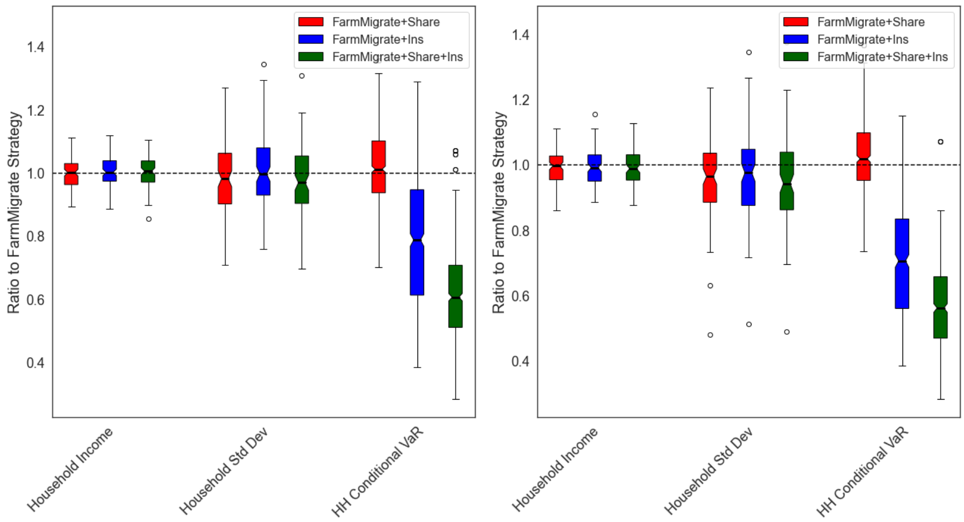
(a) Farm+Migrate **(b)** Farm Only

Supplementary Figure 3 | Net Present Value of Standard Deviation of a) FarmMigrate+Share strategy and b) Farm+Share strategy as a function of number of households in pool, for different levels of covariance between household income, ϱ. NPV is assessed over a time horizon $h = 10$ crop cycles, with discount rate $r = 0.1$.

2.2 Comparison of Individual- and Collective-Scale Outcomes of Risk Management Strategies

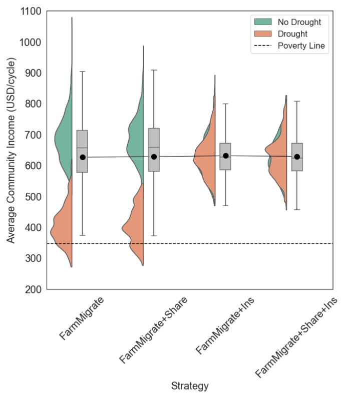
As a companion to Figure 2 in the main text, Section 3.1, here we present individual- (Supplementary Figure 4) and collective-scale outcomes (Supplementary Figure 5) for the four monomorphic strategies with migration, under Low ($p = 0.2$, $\varrho = 0.1$) and High ($p = 0.6$, $\varrho = 0.5$) covariate risk. General patterns are similar to those presented in the main text for the Medium Risk ($p = 0.35$,$\varrho = 0.35$) scenario. At an individual scale, the FarmMigrate+Share+Insurance strategy leads to substantial reductions in expected losses compared to the other risk management strategies. At the collective scale, this strategy option leads to lower inequality compared to other strategy options, though this benefit becomes attenuated under high climate risk.

We further explore the collective-scale outcomes of monomorphic strategies without migration (Supplementary Figure 6). There are two main differences between outcomes under these strategies compared to those presented for strategies with migration. First, outcomes for average income and poverty are uniformly worse for strategies without migration compared to those that include migration as a livelihood diversification strategy. Without remittance income, households' earning potential through farming strategies alone is quite limited and leaves many households at or near the poverty line, even in cases of Low covariate risk ($p = 0.2$, $\varrho = 0.1$). If covariate risks increase to Medium ($p = 0.35$, $\varrho = 0.35$) or High ($p = 0.6$, $\varrho = 0.5$) levels, then nearly all households earn incomes below the poverty line, even in non-drought crop cycles. The one exception is the GINI metric; because farming incomes are limited in both expectation and variance, strategies without migration remittances lead to less variance across household incomes, and therefore lower inequality levels compared to the strategies with migration. Note that incomes in drought cycles under Medium and High Risk are so limited that without insurance, GINI ≈ 0.0 and Poverty ≈ 1.0, as every household earns a negligible income.

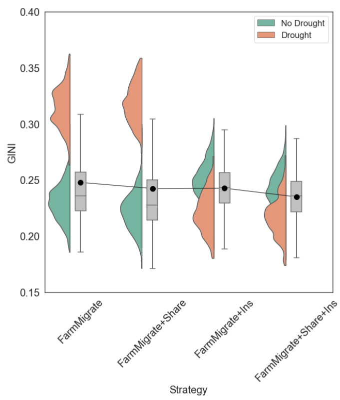


(a) Low Risk, Ratio **(b)** High Risk, Ratio

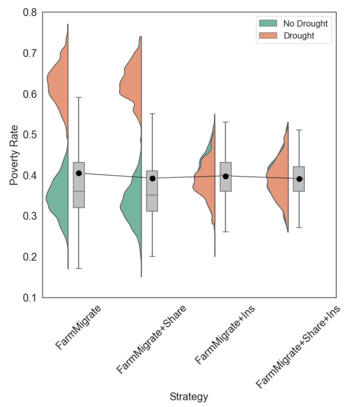
Supplementary Figure 4 | Disaggregation of farmer utility components. The ratios of three elements of farmer utilities - average household income, standard deviation of income, and losses expressed as conditional value at risk - are shown with respect to the FarmMigrate strategy for the **a)** Low and **b)** High Risk scenarios. Each column in both plots reflect a distribution of outcomes for n = 100 agents averaged over 1000 simulated crop cycles, in which each agent deploys the specified risk management strategy. For each boxplot, whiskers represent 1.5 times the interquartile range of the distribution, colour shaded areas represent the interquartile range, and centre line represents the median of the distribution.



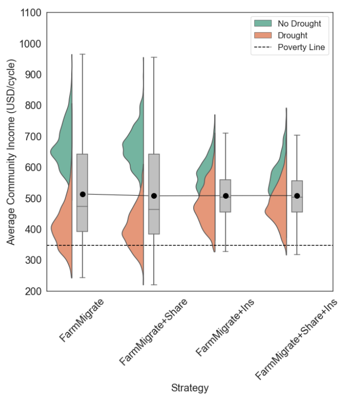
(a) **Low Risk; Avg Income**



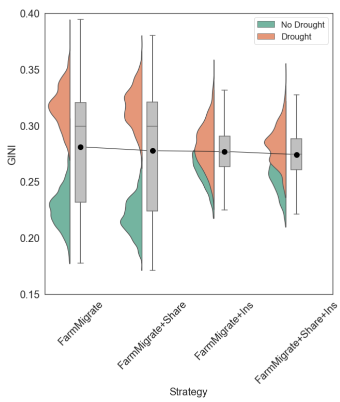
(b) **Low Risk; GINI**



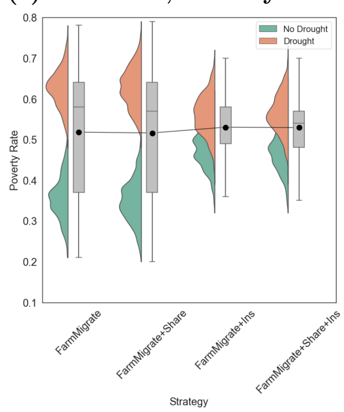
(c) **Low Risk; Poverty Rate**



(d) **High Risk; Avg Income**

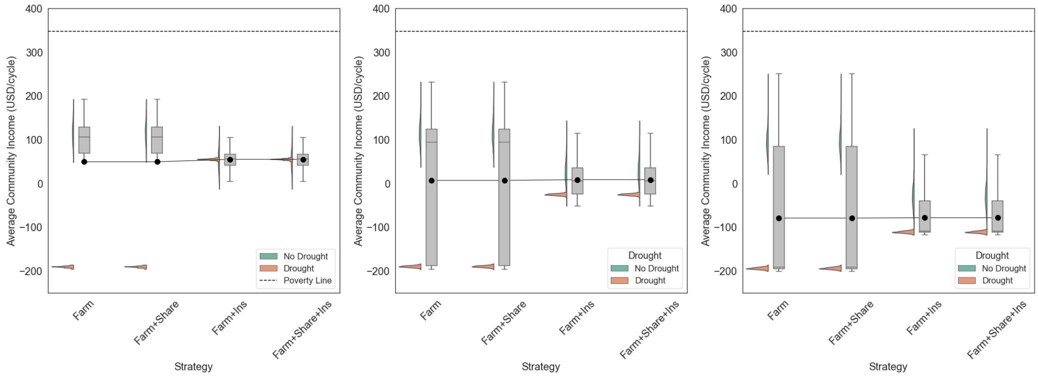


(e) **High Risk; GINI**

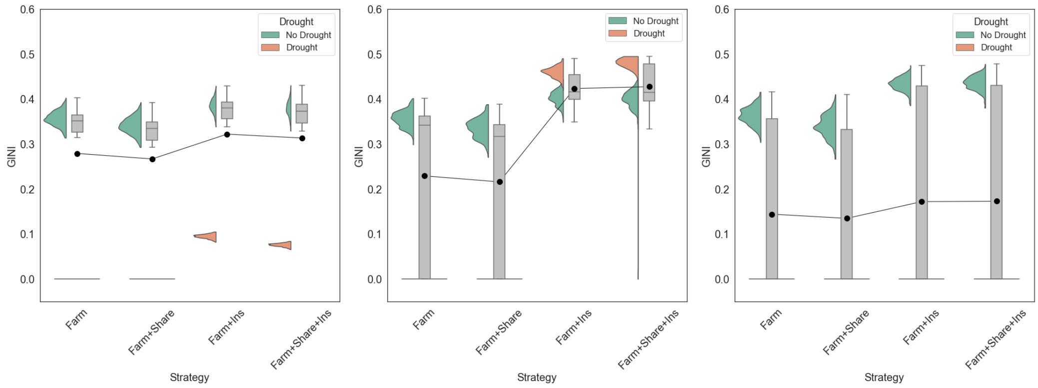


(f) **High Risk; Poverty Rate**

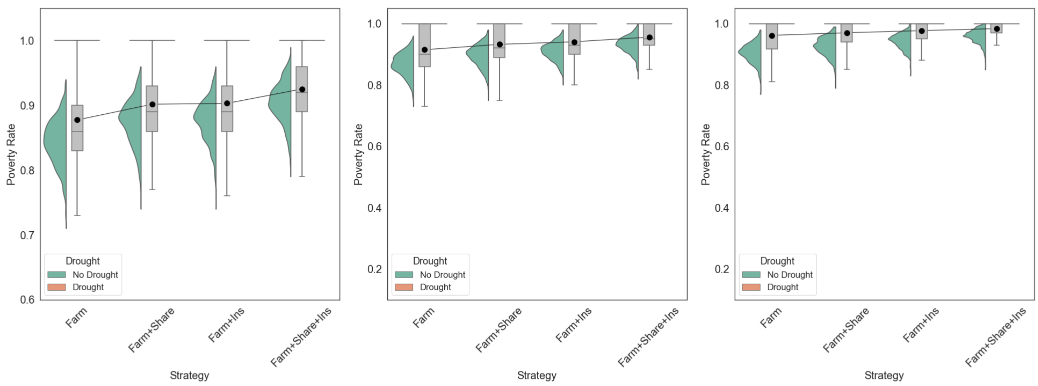
Supplementary Figure 5 | Community Outcomes for Monomorphic Risk Management Strategies. We assess how a community of 100 households would fare over 1,000 simulations with random income draws and drought events. The risk management strategies deployed by farming households may have significant ramifications for community-wide development outcomes under different risk levels. Here, the distributions of average community income (left column), GINI coefficient (middle column), and poverty rate (right column) are shown for four monomorphic strategies under Low (top row, $p = 0.2$, $\varrho = 0.1$) and High (bottom row, $p = 0.6$, $\varrho = 0.5$) risk levels. In each panel, outcomes are generated from 1000 simulations of a cropping cycle for 100 households, given the specified drought risk and income correlation. Each data point in the distribution represents community-scale results from one of n = 1000 simulations. 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 times 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.



(a) **Low Risk; Income** (b) **Med Risk; Income** (c) **High Risk; Income**



(d) **Low Risk; GINI** (e) **Medium Risk; GINI** (f) **High Risk; GINI**

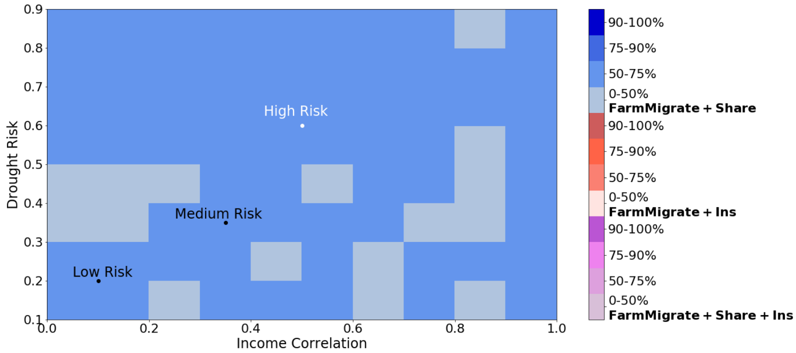


(g) **Low Risk; Poverty Rate** (h) **Med Risk; Poverty Rate** (i) **High Risk; Poverty Rate**

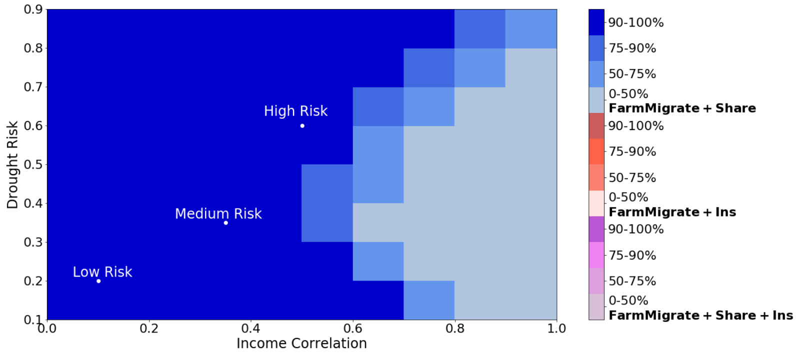
Supplementary Figure 6 | Community Outcomes for Monomorphic Risk Management Strategies without Migration. The distributions of average community income (top row), GINI coefficient (middle row), and poverty rate (bottom row) are shown for four monomorphic strategies without migration under three risk levels (left-right: Low, $p = 0.2$, $\varrho = 0.1$; Medium, $p = 0.35$, $\varrho = 0.35$; High, $p = 0.6$, $\varrho = 0.5$). Outcomes are generated from 1000 simulations of a cropping cycle for 100 households, given the specified drought risk and income correlation. Each data point in the distribution represents community-scale results from one of n = 1000 simulations. Distributions are shown separately for outcomes in drought years (green) and non-drought years (orange), with boxplots summarizing the total distribution over both drought and non-drought years (whiskers represent 1.5 times 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.

2.3 Effect of Decision-Making Parameters, Social Capital, and Migration Type on Equilibria Strategies

The evolutionary game theory model presented in the main text incorporates several complex interactions between farmers' risk and loss preferences on the one hand and migration options on the other hand that shape the risk management strategies emerging as equilibria from farmers' strategic interactions. In this section, we provide more detail on how each of these factors define results by comparing the equilibria strategies presented in Section 3.2 of the main text with results from simplified versions of the model. In Supplementary Fig. 7, we illustrate equilibria results for models in which agents have neither risk nor loss aversion (a), and risk aversion, but no loss aversion (b). This allows us to isolate the effects of each decision-making attribute on our baseline results. Notably, we find that without either attribute, a plurality of households would choose informal revenue-sharing (FarmMigrate+Share) under a wide range of drought risks and baseline income correlations. Accounting for risk aversion, but no loss aversion, further entrenches informal revenue-sharing as the dominant risk management strategy. By contrast, our main text results from the model incorporating both risk and loss aversion lead to richer behaviour across a range of covariate risks: a combination of formal and informal revenue-sharing emerges at lower risks, followed by a narrow range of drought risks over which formal insurance is preferred, followed by informal mechanisms at higher covariate risks.



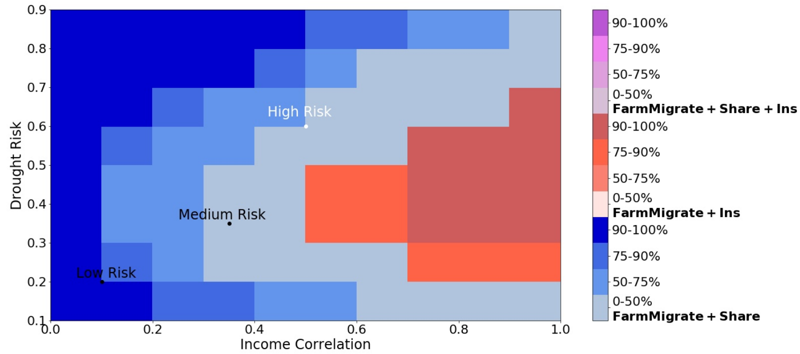
(a) No Risk Aversion, No Loss Aversion



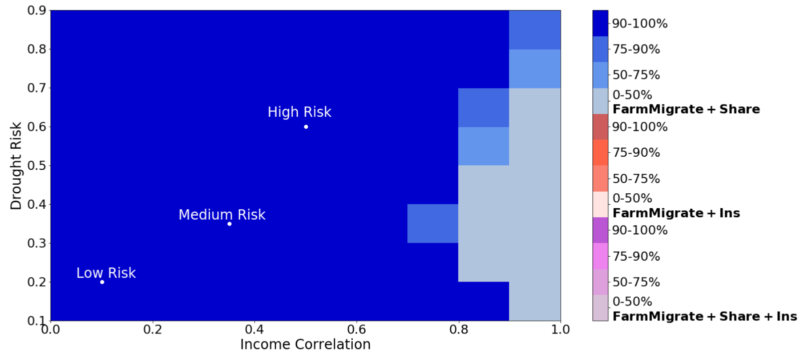
(b) Risk Aversion, No Loss Aversion

Supplementary Figure 7 | Equilibria Risk Management Strategies as a Function of Risk and Loss Preferences. The inclusion of farmer risk and loss aversion in the evolutionary game theory model substantially changes which risk management strategies emerge as equilibria from strategic interactions. For illustrative purposes, here we display equilibria strategies emerging from a version of the model with simplified decision-making behaviour for different drought risks and baseline income correlations. Colour gradients indicate the percentage of the population adopting a particular strategy. **a)** Without risk aversion or loss aversion (i.e. $b = 0.0$ and $\gamma = 1.0$), informal revenue-sharing is the most prominent risk management strategy for all of this parameter space. However, its adoption never exceeds 75 percent of the population, indicating that other risk management strategies e.g. FarmMigrate and FarmMigrate+Insurance are also present. **b)** With Base Case risk aversion but no loss aversion (i.e. $b = 0.5$, $\lambda = 1.00$), informal revenue-sharing becomes an even more dominant strategy over the parameter space, especially for low values of income correlation. Results are calculated as averages of terminal time strategy distributions over 100 simulations.

The effect of one of the dimensions of social capital, the level of contributions to the revenue-sharing pool, is illustrated in Supplementary Figure 8. In the Main Text, we set the Base Case value at $\beta = 0.2$, such that households share 20% of their income with others in a revenue-sharing pool. From the empirical literature on informal revenue sharing, we find values of β ranging from 0.05-0.1 in Ethiopia [14, 15] to 0.25 in Cambodia [16]. Here, we find that both lower ($\beta = 0.1$) and higher ($\beta = 0.4$) revenue-sharing contributions reduce the coexistence of formal and informal risk management.



(a) $\beta = 0.1$



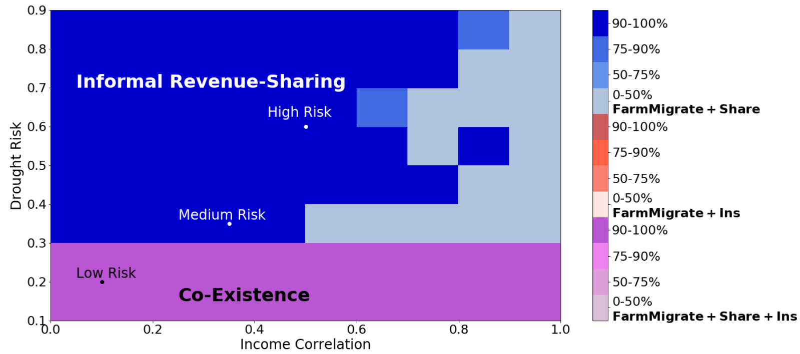
(b) $\beta = 0.4$

Supplementary Figure 8 | Equilibria Risk Management Strategies as a Function of Social Capital Parameters. The most common strategy emerging at terminal time for different degrees of drought risk (y-axis) and income correlation (x-axis) is shown for a community in which households share 10 percent of their income in an informal revenue-sharing pool (**a**) and households sharing 40 percent of their income in such a pool (**b**).

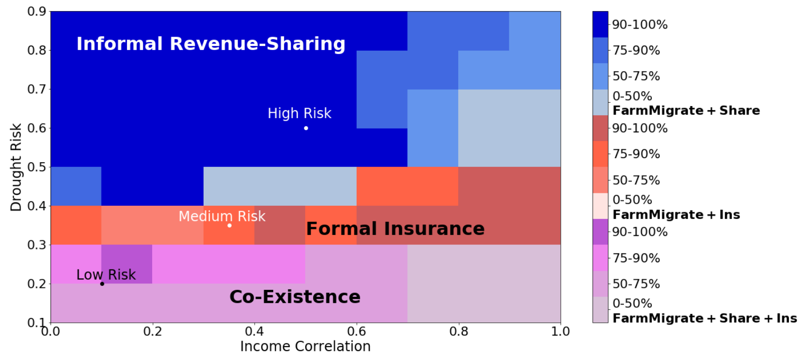
Rural-urban migration represents one form of intra-household risk transfer, and the migration options available to each household may influence the risk management equilibria that emerge from strategic interactions between households. For example, farming households may choose to send a migrant to a local destination within the same country, which is often characterized by relatively low up-front costs, mean remittance incomes, and variance in remittance incomes. Alternatively, households can attempt to send a migrant to an international destination, which often is characterized by higher upfront costs, mean remittance incomes, and variance in remittance incomes. In the main text, we present results for a composite migration option that reflects a weighted average of migration costs and incomes based on the composition of Nepali outmigration streams (40 percent local, 60 percent international) [9]. As a sensitivity analysis, here we present risk management equilibria for different levels of covariate risks if only local (Supplementary Figure 9a) or international (Supplementary Figure 9b) migration options were available. Specific parameterization of these migration options are detailed in Supplementary Table 4.

Parameter	**Local Migration**	**International Migration**	**Composite**
Avg Remittance/cycle (USD)	200.0	872.2	600.8
Remittance Std Dev (USD)	190.0	825.8	648.8
Up-front Cost (USD)	62.5	1133	700.6

Supplementary Table 5 | Parameters for Different Migration Options.



(a) Local Migration



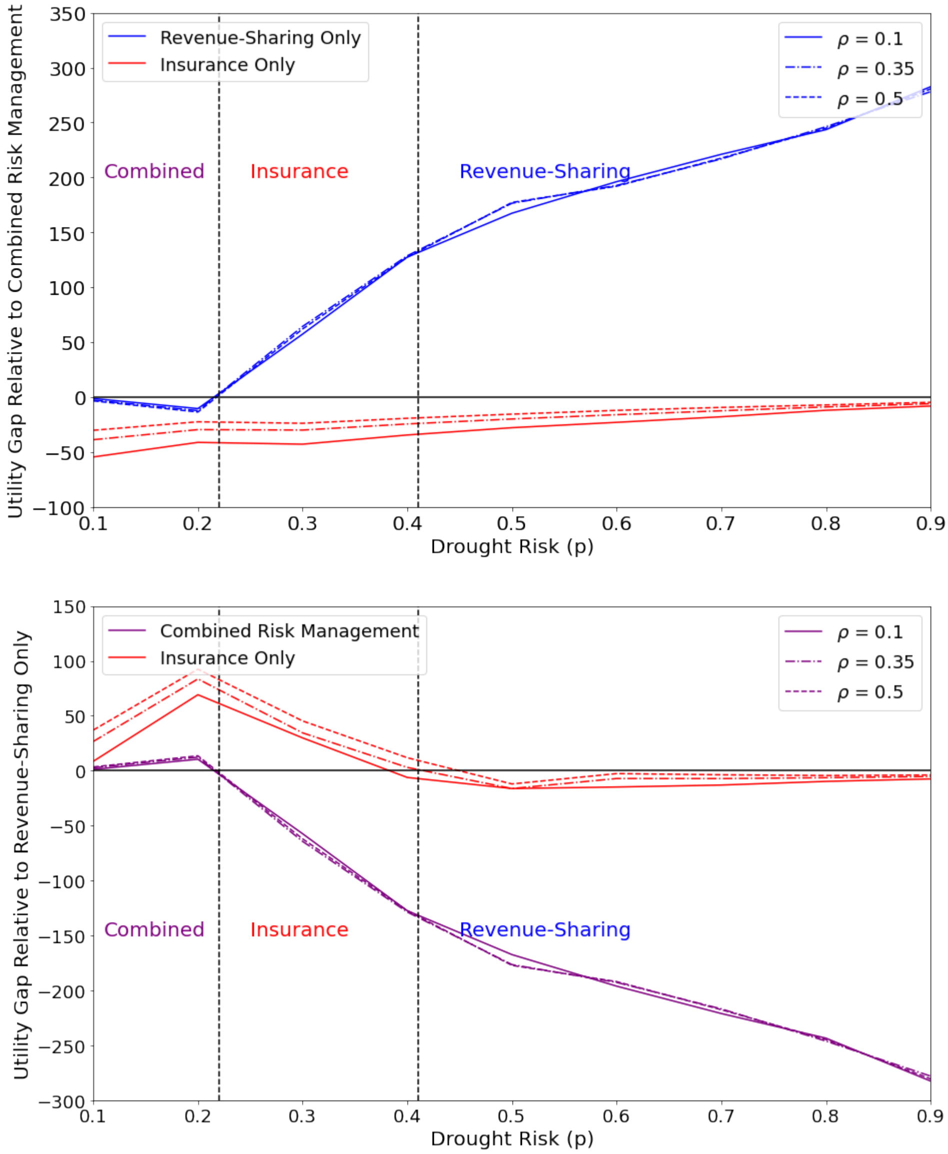
(b) International Migration

Supplementary Figure 9 | Equilibria Risk Management Strategies as a Function of Covariate Risk and Migration Type. The most common strategy emerging at terminal time for different degrees of drought risk (y-axis) and income correlation (x-axis) is shown for a community with only local migration options (left panel) and a community with only international migration options (right panel). Colour gradients indicate the percentage of the population adopting this strategy. **a)** With only local migration options, informal revenue-sharing emerges as the dominant risk management strategy for most of the parameter space. **b)** With only international migration options, formal insurance emerges as a stable strategy for moderate drought risk and high income correlation. Results are calculated as averages of terminal time strategy distributions over 100 simulations.

2.4 Effect of Drought Risk on Strategy Invasion Potential

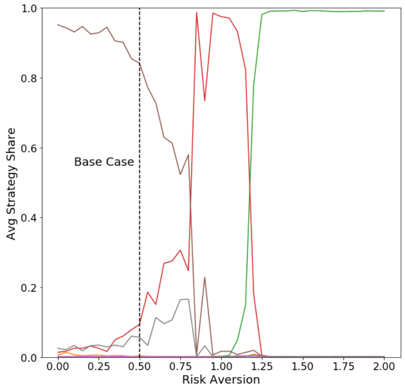
The invasion potential refers to the ability of an alternative strategy to take root in a community that is monomorphic in a baseline *status quo* strategy. For example, the potential of FarmMigrate+Share to invade FarmMigrate+Share+Insurance can be calculated as the incremental utility earned by one household if it switches to FarmMigrate+Share, while all other households adopt the FarmMigrate+Share+Insurance strategy. If incremental utility is positive, that strategy has the ability to invade the monomorphic FarmMigrate+Share+Insurance community. Put another way, the monomorphic FarmMigrate+Share+Insurance equilibrium is unstable, and one or more households are likely to deviate from this strategy. Here, we plot the invasion potential of FarmMigrate+Share (blue) and FarmMigrate+Insurance (purple) against FarmMigrate+Share+Insurance for different drought risks p. We also display the invasion potential of The FarmMigrate+Insurance strategy in a monomorphic FarmMigrate+Share community (red). Dashed lines indicate different farm income correlations, ϱ.

We note three main regimes related to drought risk. For risk $p < 0.23$, neither the FarmMigrate+Share (blue) nor the FarmMigrate+Insurance (purple) strategies can invade the FarmMigrate+Share+Insurance strategies; both of these lines are negative. Therefore, the combined strategy emerges as a stable equilibrium. From $0.23 < p <\sim 0.41$ (depending on the level of income covariance), the FarmMigrate+Share strategy can invade the FarmMigrate+Share+Insurance strategy (i.e., the blue line is positive), reflecting the temptation to free-ride on other community members' insurance purchases. However, the FarmMigrate+Insurance strategy can subsequently invade the FarmMigrate+Share strategy (red line), so the insurance-only strategy emerges as an equilibrium. For risks of $p >\sim 0.41$, the FarmMigrate+Insurance strategy can no longer invade the FarmMigrate+Share strategy - reflecting the cost of high insurance premiums under elevated covariate risk - so informal revenue-sharing emerges as the equilibrium strategy. Note that higher income covariance allows the FarmMigrate+Insurance strategy to invade the FarmMigrate+Share strategy over a slightly higher range of drought risks, owing to the diminished benefit of informal revenue-sharing to mitigate income variance in highly-correlated communities.

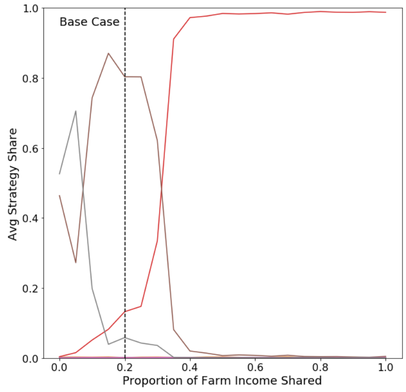


Supplementary Figure 10 | Invasion Potential of Risk Management Strategies vs. Drought Risk.

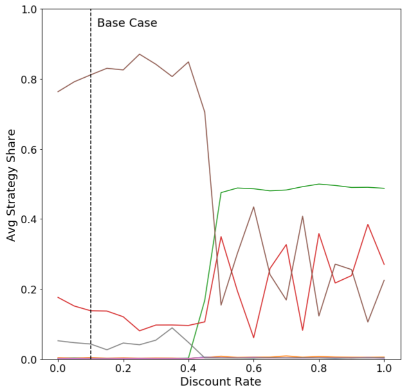
2.5 Sensitivities



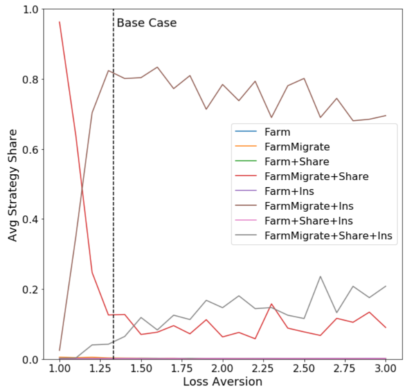
(a) b



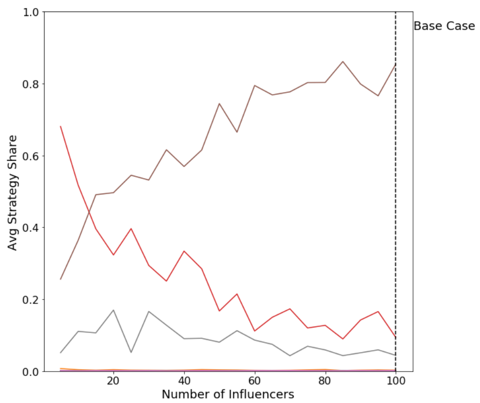
(b) β



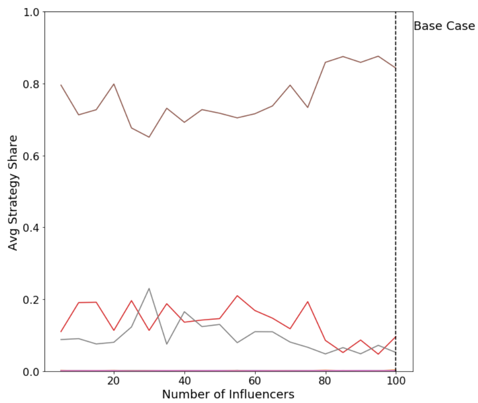
(c) r



(d) λ

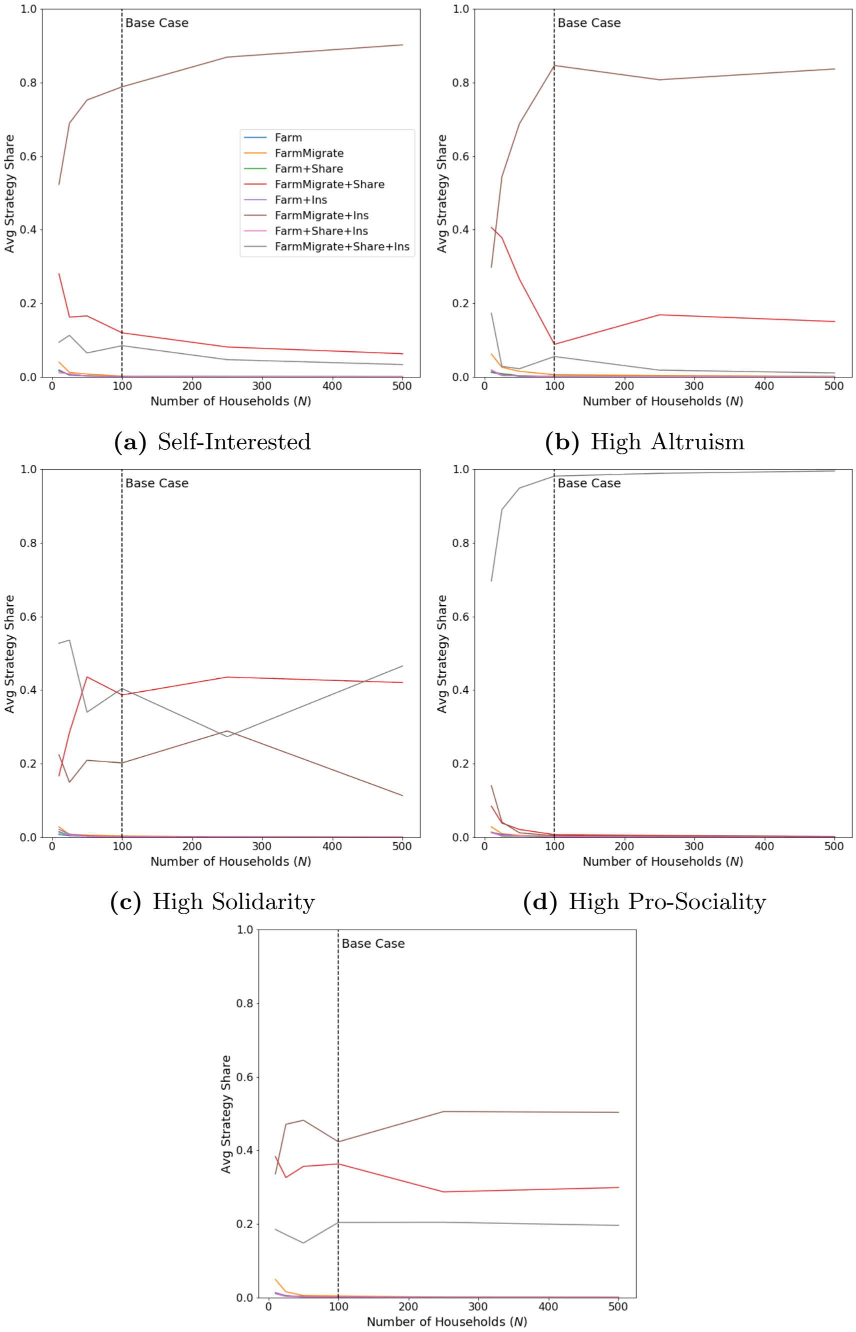


(e) Number of Top Performers (Fixed)



(f) Number of Top Performers (Updated)

Supplementary Figure 11 | Sensitivities to Decision-Making Parameters. Sensitivities of risk management strategies to parameters for **a)** risk preference, b, **b)** proportion of farm income shared, β, **c)** discount rate, r, **d)** loss aversion, λ, **e)** number of top performers by utility (assessed at the start of the model timeframe) to which farmers compare strategies, and **f)** number of top performers by utility, which are re-assessed every generation (where on average, every household has one opportunity to update its strategy). Each panel displays the average terminal time distribution of risk management strategies in the agricultural community after 20,000 time steps. Results are averages over 100 simulations, while keeping all other parameters at their Base Case values. In each plot, the vertical dashed line indicates the Base Case value of the focal parameter.



(a) Self-Interested

(b) High Altruism

(c) High Solidarity

(d) High Pro-Sociality

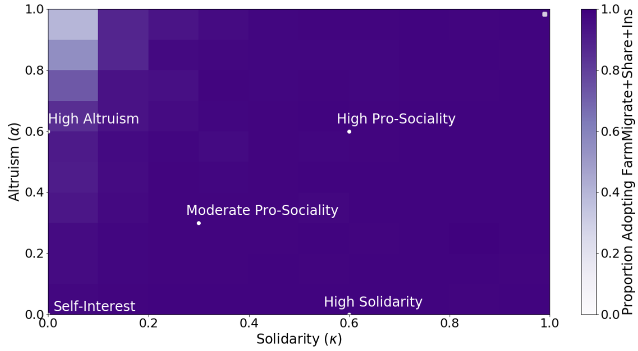
(e) Moderate Pro-Sociality

Supplementary Figure 12 | Sensitivity of terminal time strategy distributions to community household sizes, N. Lines display the average terminal time distribution of households by risk management strategy under different decision-making profiles: Self-Interested ($\alpha = 0.0$, $\kappa = 0.0$); High Altruism ($\alpha = 0.6$, $\kappa = 0.0$); High Solidarity ($\alpha = 0.0$, $\kappa = 0.6$); High Pro-Sociality ($\alpha = 0.6$, $\kappa = 0.6$); and Moderate Pro-Sociality ($\alpha = 0.3$, $\kappa = 0.3$). Results reflect averages over 100 simulations.

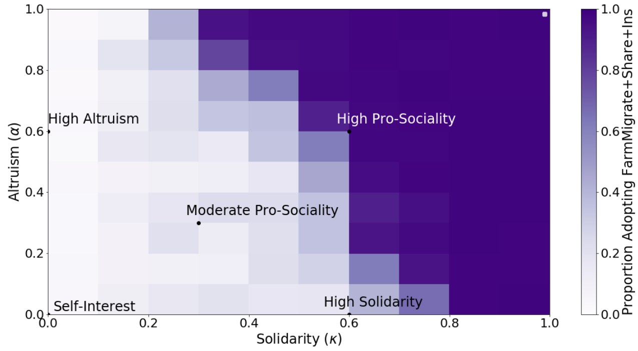
2.6 Interactions between Social Preferences and Covariate Risk

In the main text (Section 3.3), we assess the potential for pro-social preferences to shift the risk management equilibria that emerge from strategic interactions among farmers under a Medium Risk scenario ($p = 0.35$, $\varrho = 0.35$). In this section, we compare the effects of such preferences on the adoption of the socially optimal strategy, FarmMigrate+Share+Insurance, under Low ($p = 0.2$, $\varrho = 0.1$), Medium, and High ($p = 0.6$, $\varrho = 0.5$) Risk scenarios (Supplementary Figure 11). We find that moderate values of pro-social preferences have an especially noticeable effect on adoption of the optimal strategy under the Medium Risk Scenario, in which different preferences can lead to substantially different adoption rates. By contrast, under Low Risk, nearly all farmers would adopt the socially optimal strategy under almost any combination of pro-social preferences. Conversely, very few farmers would adopt this strategy under High Risk, except under near-perfect altruism and solidarity.

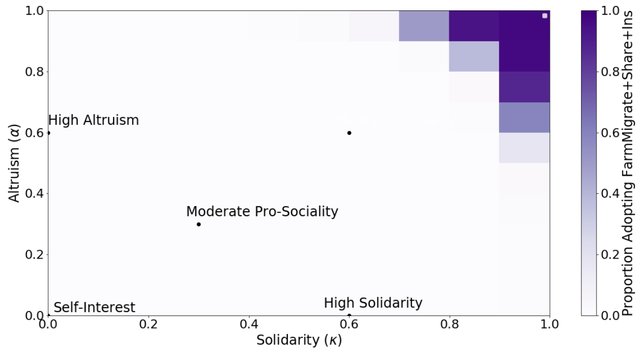
For each of the three risk scenarios (Supplementary Figures 12-14), we also compare the selection gradients and equilibria that emerge from interactions of the three most common strategies (FarmMigrate+Share, FarmMigrate+Insurance, and FarmMigrate+Share+Insurance) under five specific pro-social profiles: Self-Interest ($\alpha = 0.0$, $\kappa = 0.0$), High Altruism ($\alpha = 0.6$, $\kappa = 0.0$), High Solidarity ($\alpha = 0.0$, $\kappa = 0.6$), High Pro-Sociality ($\alpha = 0.6$, $\kappa = 0.6$), and Moderate Pro-Sociality ($\alpha = 0.3$, $\kappa = 0.3$). Here again, we find that selection gradients and equilibrium points (or limit cycles) change substantially between different profiles under Medium Risk. Equilibria are largely the same across profiles under both Low Risk (FarmMigrate+Share+Insurance) and High Risk (FarmMigrate+Share). Notably, under Low Risk, the selection gradients and paths taken to the equilibrium point may still differ substantially across the pro-social profiles.



(a) Low Risk

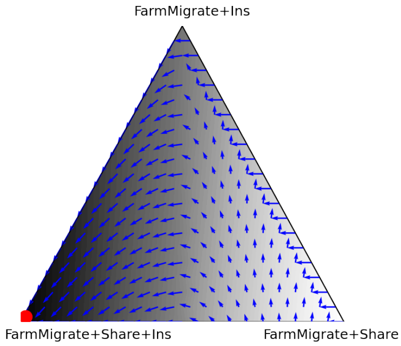


(b) Medium Risk

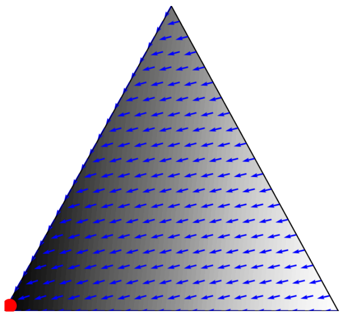


(c) High Risk

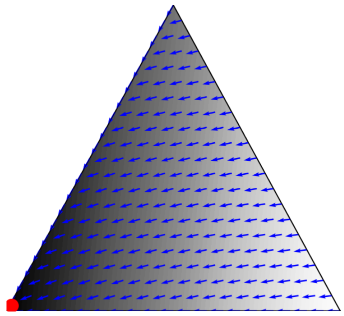
Supplementary Figure 13 | Effect of Pro-Social Preferences and Risk Levels on Adoption of Socially Optimal Strategy.



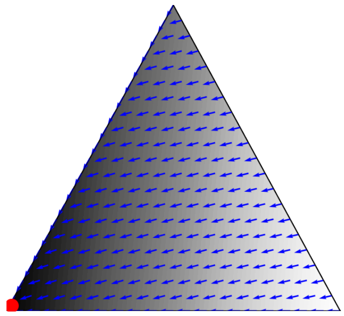
(a) Self-Interest



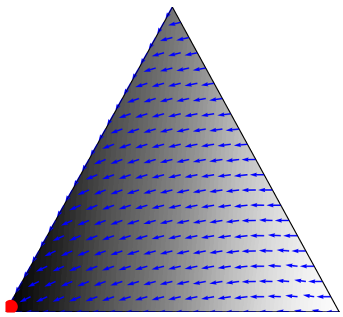
(b) High Altruism



(c) High Solidarity

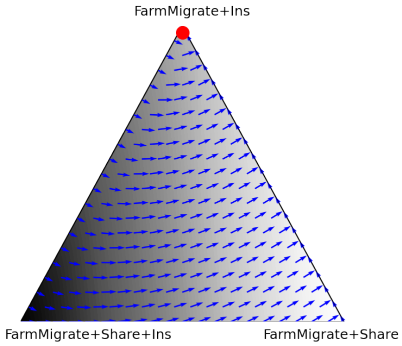


(d) High Pro-Sociality

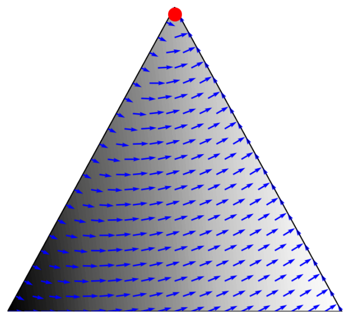


(e) Moderate Pro-Sociality

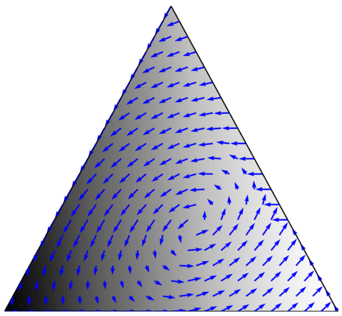
Supplementary Figure 14 | Risk Management Equilibria under Low Risk Scenario.



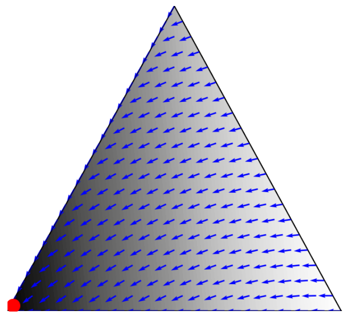
(a) Self-Interest



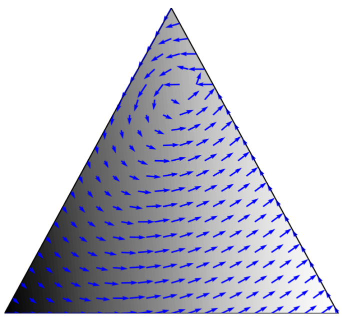
(b) High Altruism



(c) High Solidarity

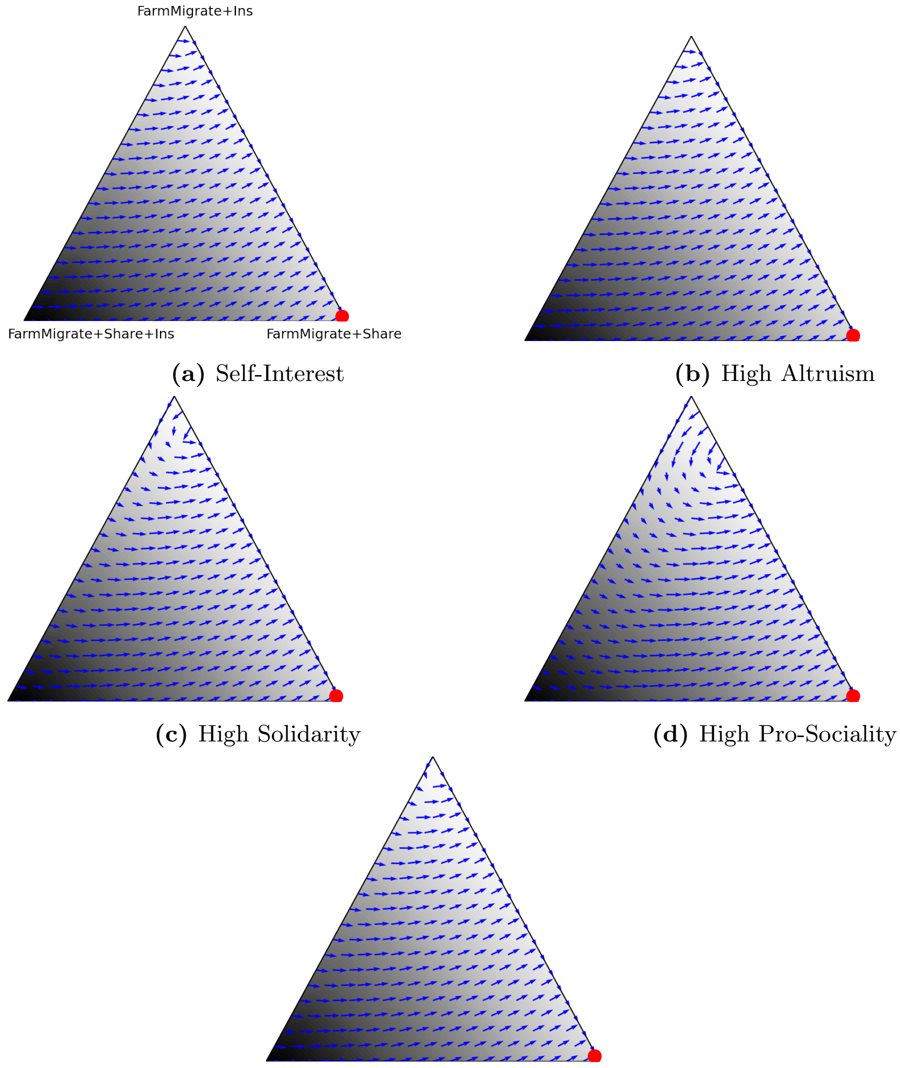


(d) High Pro-Sociality



(e) Moderate Pro-Sociality

Supplementary Figure 15 | Risk Management Equilibria under Medium Risk Scenario.



(a) Self-Interest (b) High Altruism (c) High Solidarity (d) High Pro-Sociality (e) Moderate Pro-Sociality

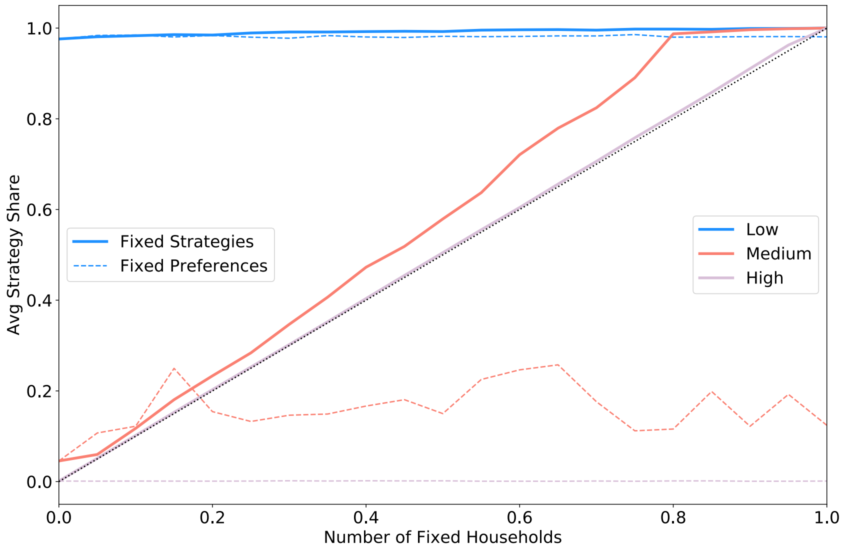
Supplementary Figure 16 | Risk Management Equilibria under High Risk Scenario.

2.7 Alternate Policy Mechanisms: Targeted Influencing

In addition to the combination of financial subsidies for insurance and community-wide policies cultivating pro-social preferences, another policy approach to promoting socially optimal climate risk management could be to target incentives to a subset of community households. In particular, there may be certain threshold levels of households pursuing a socially optimal strategy and/or acting out of prosocial preferences that lead other self-interested households to also adopt socially optimal behavior. Ideally, such policy approaches could be one way for resource-limited governments to promote effective collective action through a combination of targeted incentives and community strategic interactions.

Here, we present an initial analysis of such policies by comparing two forms of targeted incentives: one that leads to a subset of households consistently deploying a socially optimal strategy (in this case, the combination of formal and informal insurance, or FarmMigrate+Share+Insurance), and one in which a subset of households act out of prosocial preferences (in this case, Moderate Pro-Sociality, where $\alpha = \kappa = 0.3$), even while others act out of self-interest. Supplemental Figure 17 indicates that targeting may be an effective policy approach in limited circumstances. In particular, targeting a subset of households to deploy FarmMigrate+Share+Insurance under Medium covariate risk ($p = 0.35$, $\rho = 0.35$) leads to a non-linear increase in the proportion of households adopting this strategy. For example, incentivizing 50 percent of the population to consistently deploy FarmMigrate+Share+Insurance leads to 58 percent adopting this strategy, and incentivizing 60 percent of the population to adopt this strategy leads to 72 percent community-wide adoption. However, targeting a subset of households to act out Moderate Pro-Sociality leads to less-than-linear adoption of FarmMigrate+Share+Insurance in the community. Neither policy has a substantial effect at Low covariate risk levels, where community-wide adoption of FarmMigrate+Share+Insurance is already high without policy incentives. At High risk levels, directly targeting household adoption of this strategy has negligible effect on generating additional adoption, while Moderate Pros-Sociality is not sufficient to incentivize adoption of formal and informal insurance mechanisms, even when all households act out of this preference.

In this analysis, we do not account for potential inequalities in influence among community households. In reality, some households are likely to be more influential than others, and targeting such community leaders may lead to more efficient policy outcomes. This analysis also does not quantify the relative costs of incentivizing a subset of households to consistently adopt socially optimal risk management vs. cultivating pro-social preferences in the same subset. Both of these limitations are useful avenues for future work.

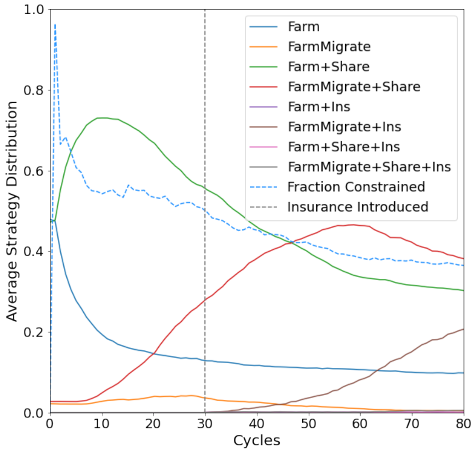


(a) Targeting Behaviors

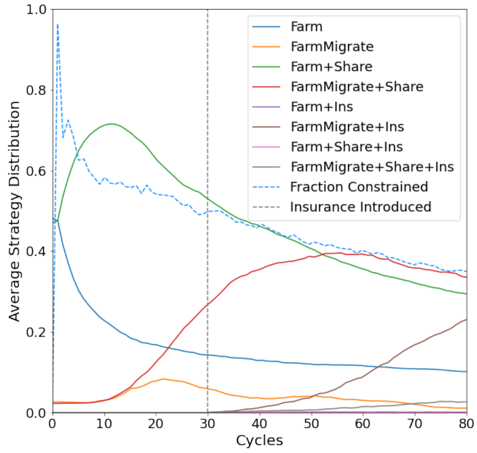
Supplementary Figure 17 | Effect of Household-Targeting Policies on Adoption of Optimal Climate Risk Management. Policies that target subsets of a farming community in order to influence their strategy choices or preferences may have non-linear effects on community-wide adoption of the socially optimal climate risk management strategy, FarmMigrate+Share+Insurance. Here, we display the proportion of the community adopting this strategy (y-axis) as a function of the proportion of households that either act out of moderate pro-sociality (dashed lines, $\alpha = 0.3$, $\kappa = 0.3$) or directly adopt of the optimal strategy (solid lines). Results are displayed for different covariate risk levels: Low (blue, $p = 0.2$, $\rho = 0.1$), Medium (red, $p = 0.35$, $\rho = 0.35$, and High (blue, $p = 0.6$, $\rho = 0.5$).

2.8 Policy Effectiveness under Financial Constraints

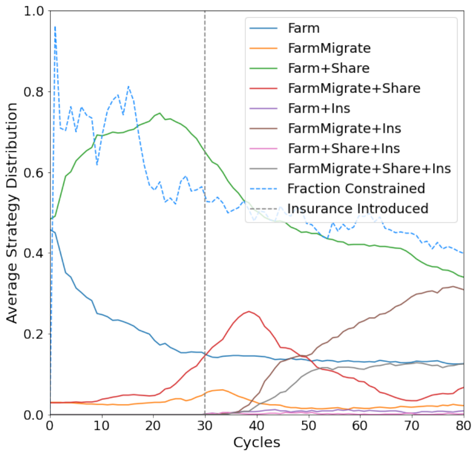
Plots below illustrate the dynamics of risk management strategy choices in a model extension in which households are constrained by the costs of various risk management strategies. In this scenario, if households do not have sufficient savings to afford the upfront costs of either migration or insurance, they are unable to pursue those strategies in a given time step. Further, we assume that all households must meet a basic income threshold to ensure food security (84 USD/household/cycle based on data from [6]). We assume that households with incomes above this level spend approximately 80 percent of their income on consumption, based on data from IBLI [7], leaving up to 20 percent of income as savings.



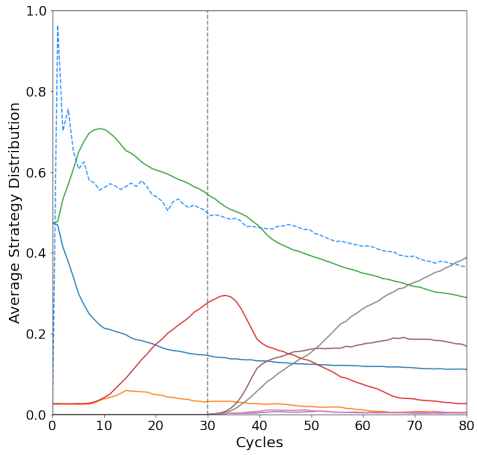
(a) Self-Interested; No Subsidy



(b) Moderate Pro-Sociality; No Subsidy



(c) Self-Interested; 20 Percent Subsidy



(d) Moderate Pro-Sociality; 20 Percent Subsidy

Supplementary Figure 18 | Effect of Financial Restrictions and Social Preferences on Strategy Choices. Financial restrictions slow down the dynamics of risk management strategy choices and attenuates the effects of prosocial preferences and financial subsidies on promoting optimal risk transfer. **a-b)** Without a subsidy, roughly 45 percent of households are unable to afford migration due to financial constraints (dashed blue line). The remaining households pair migration with either informal revenue-sharing (red line) or formal insurance (brown line), but not both. **c-d)** A 20 percent premium subsidy helps reduce the number of households that are constrained to approximately 40 percent. Further, the proportion of households adopting insurance increases to approximately 35 percent under Self-Interested preferences. Under Moderate Pro-Sociality, a substantial proportion of the population (approximately 40 percent) chooses the combination of formal insurance and informal revenue-sharing.

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