Risk Transfer Policies and Climate-Induced Immobility among Smallholder Farmers

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Abstract

Climate change will likely impact smallholder farmer livelihoods substantially. However, empirical evidence is inconclusive regarding how increased climate stress affects smallholder farmers' deployment of various livelihood strategies, including rural-urban migration. Here we use an agent-based model to show that in a South Asian agricultural community experiencing a $1.5^{o}C$ temperature increase by 2050, climate impacts are likely to decrease household income in 2050 by an average of 28 percent, with fewer households investing in both economic migration and cash crops, relative to a stationary climate. Pairing a small cash transfer with risk transfer mechanisms significantly increases the adoption of migration and cash crops, improves community incomes, and reduces community inequality. While specific results depend on contextual factors such as risk preferences and climate risk exposure, these interventions are robust in improving adaptation outcomes and alleviating immobility by addressing the intersection of risk aversion, financial constraints, and climate impacts.

Climate change is likely to impact the livelihoods of many of the world's 500 million smallholder farming households [1], particularly with projected increases in drylands populations [2]. Migration represents one of several adaptation strategies that farmers could deploy in the face of climate stress [3], and there is mixed evidence on the extent to which climate change may positively or negatively impact migration flows [4, 5, 6]. Uncertainty regarding future climate adaptation policies [7], including new financial instruments to help poor households cope with natural disasters [8, 9], further cloud projections about how climate will impact rural households' use of migration as a risk management strategy. Conversely, policymakers seeking to promote climate resilience need to better understand the complex ways in which potential interventions may impact the dynamics of household adaptation decisions. This study seeks to better understand how rural-urban migration relates to other on-farm livelihood strategies and risk-transfer mechanisms as smallholder farming households cope with increasing climate stress.

While previous econometric studies have built our understanding of how climatic factors have influenced migration patterns [10, 4, 6], they typically have limited ability to account for dynamic interactions between changing climatic and societal variables. Recently, experimental economics has elucidated some causal factors of climate migration decisions [11], but under a limited set of conditions. One additional set of tools for investigating these questions includes agent-based models (ABMs). ABMs simulate how individual decision-makers (generally at the person or household scale) make choices based on pre-defined decision-making rules, complex interactions between agents, and feedbacks between agent actions and their environment [12, 13, 14].

To address gaps in these methods (Box 1) this study investigates three main research questions. First, how does increased climate stress, both as a general trend and through increased frequency of extreme drought, impact livelihood strategy choices of smallholder farmers over time? Second, what decision-making factors (i.e., risk preferences, financial constraints) have the most impact on these adaptation pathways? Third, how are various risk-transfer mechanisms likely to impact adaptation outcomes for smallholder farmers?

Box 1 | ABM Contributions to Climate-Migration Literature

ABMs have been deployed to investigate decision-making regarding household adaptation to evolving flood risks [15] and the potential for consequent outmigration [16]. A further body of literature has explored farmer decision-making and economic outcomes under various climate and policy scenarios [17, 18, 19, 20]. A subset of these ABMs has explored smallholder farmer migration decisions and dynamic push-pull factors, including changing environmental conditions [21, 22, 23, 24, 25, 26, 14]. Such models highlight conditions in which future climatic trends may increase rural outmigration, such as the case of Ethiopian pastoralists facing increased frequency of extreme droughts [25], or conditions in which climate change may decrease planned migration [23]. These and other models also identify other demographic variables that are likely to influence future migration trends, including the response to increased climate stress [24, 21] (see SI Section 1 for more details).

The novelty of this study lies in exploring the interactions between multiple livelihood options, policy approaches, and climatic effects that are relevant to smallholder farming decision-making, particularly in South Asia. In order to achieve this, we develop a new ABM that makes three main contributions. First, agents in our model choose between multiple livelihood strategies, including cropping strategies with different risk-reward profiles. Previous ABMs also explored migration in the context of multiple rural livelihood options (e.g. [23, 19, 25, 26]), but did not specifically include multiple crop options with planned migration. Yet, South Asian farmers are increasingly planting diverse sets of crops with different yield potentials and drought tolerances [27], which may have unforeseen effects on migration decisions. Second, while some ABMs explore the potential for risk-sharing policies to build farmer resilience (e.g. [19]), here we examine three different means of doing so - cash transfers, index insurance, and a bank that smooths remittance income. This enables us to identify potential complementarities between different instruments of risk transfer. Finally, while other ABMs have explored farmer migration responses to a non-stationary climate (e.g. [21, 23]) or extreme shocks [25, 26], this study includes both types of climatic effects. This allows us to account for multiple pathways in which climate influences farmer decisions, including changes in the perceptions of strategy payoffs, the financial resources to afford adaptation strategies, and the willingness to pay for insurance.

An Agent-Based Model to Simulate Farmer Livelihood Decisions

We develop an ABM that examines livelihood decisions among smallholder farming households under increasing climate stress. Households are the main decision-making entity, and choose between multiple livelihood strategies characterized by different income distributions, including on-farm options and rural-urban migration (Fig. 1a). Decision-making is grounded in the theory of the New Economics of Labour Migration (NELM), which posits that households diversify livelihood strategies as a means of reducing risks to collective household income, as well as reducing the self-perception of relative deprivation compared to others in their reference group [28, 29]. Along the lines of pattern-oriented modelling [30], the ABM is built in four layers of increasing complexity: economic rationality, bounded rationality and social network impact, demographic stratification, and climate impacts (see Methods for more details).

The ABM consists of N agents in a farming community (here, $N = 100$), each representing a household consisting of 5 working-age people [31]. At each time step, households can either farm low-risk, low-cost and low-reward cereal crops (e.g. rice or maize) in the Business-as-Usual (BAU) livelihood, or farm higher-risk, higher-cost, and higher-reward commercial crops (e.g. legumes and fruits) in the Cash Crop livelihood. Households can also decide to deploy one or more individuals as rural-urban migrants who earn remittances in the Migrate livelihood. This livelihood is characterized by an up-front cost in the first timestep of migration, reflecting the expense of travelling and establishing oneself in the city, and moderate-reward, high-variance remittances in subsequent timesteps, reflecting the inter-annual variability in job prospects and wages of urban migrants. The three livelihood types serve as principal components to form 11 distinct strategy options for households: farming BAU crops while sending between 0 - 4 migrants; farming Cash Crop crops while sending between 0 - 4 migrants, or sending all 5 working-age members as migrants. While simplified, these options represent a broader suite of smallholder farming livelihood choices that differ based on their expected income, income volatility, and up-front costs (see Methods for the decision-making utility function and SI Section 2 for how these entities are parameterized). The ABM is framed in terms of economic drivers in order to better isolate the effects of risk transfer policies, and to parameterize the model with real-world data. We note several additional factors that can affect migration decisions in the Discussion.

We use the ABM to evaluate the dynamics of several community outcomes of interest, including: the final distribution of household strategy choices, average community income, proportion of the community that migrates, GINI coefficient, and proportion of households whose savings are less than the cost of migration (which we term the "immobility threshold"). While we focus here on planned migration that is primarily motivated by economic opportunity; we also note that socio-cultural migration (e.g. for marriage or amenity reasons) or distress migration as an option of last resort are also of interest to policymakers, and may follow different patterns from the results presented here. The most relevant model parameters affecting mentioned output variables are the status-quo parameter λ indicating when the current household strategy needs to be re-evaluated, the risk aversion b_i penalizing income volatility relative to expected income in agent utility functions, the information preference parameter ω_i balancing social versus public information sources, the household memory length m_i affecting the perceived income and volatility of different strategies, the time horizon h_i over which households evaluate the utility of strategy options (here, m_i and h_i are both set to 10 cropping cycles for all households), the household exponential discount rate ρ_i, and the temperature increase ΔT. Heterogeneity between households is included in the ABM, indicated by the index i corresponding to each household in the farming community.

To ground the model in a policy-relevant context and partially demonstrate its validity, we parameterize it with a variety of climate and socioeconomic data from South Asia. Smallholder farming villages in this region tend to exhibit several shared characteristics that make it especially relevant to this study: (1) rainfed, smallholder agriculture is currently the main livelihood option, (2) alternative livelihood options (e.g. cash crops and migration) tend to be costlier and riskier than subsistence farming, and (3) future climate change is likely to decrease crop yields across most non-mountain regions, threatening the viability of current farming livelihoods [27].

Specifically, household-level economic data collected between 2006-2015 from the Chitwan Valley Family Study (CVFS) in Nepal [32] is used to characterize the mean and variance of income for each strategy (Fig 1a). We parameterize farming costs using data on district-level seed and labor costs in Nepal [33], and migration costs reflect an average of low-cost migration to India and high-cost migration to Persian Gulf countries [34]. We note that this average tends to reflect longer-range, economically-driven migration, and is not likely to capture short-distance migration.

Parameterization of agent risk aversion is based on household-level survey data of Nepali tea farmers' risk aversion [35] (SI 2.2.1). Data on the distribution of household educational status is collected at the district scale from the Nepali Census [31]. The model is initialized using CVFS data on the distribution of households by livelihood strategies in 2007 and run for 44 years to 2050, with two time steps per year in which households can update their strategy decisions (representing major cropping cycles). We conduct partial validation of the model by comparing results in year 9 of the model with CVFS data on household strategy choices in 2015 (SI 3.3). In the Base Case Scenario, we assume an increase $\Delta T = 1.5^{o}C$ from 2007-2050, consistent with the mean of Coupled Model Intercomparison Project (CMIP) 6 projections for South Asian region [36]. To assess the robustness of our conclusions, we conduct a series of sensitivity analyses to key parameters (Section 3.2 and SI 3.4), and explore two alternative scenarios that differ based on the degree of climate risk and community risk aversion (Sections 3.2 and 3.3).

Sources of Immobility in Climate Adaptation

The layered structure of the ABM allows us to compare results as we progressively add sources of model complexity: economic rationality, bounded rationality and social networks, demographic stratification, and climate stress. We refer to these as model layers, to distinguish from scenarios that feature different combinations of model parameters under a given layer of model complexity. Figure 2 presents the evolution of household strategy decisions, average number of migrants per household, and adaptation outcomes for each model layer over the model time horizon. Under economic rationality, 75 and 78 percent of households opt for the Cash Crop and Migrate strategies, respectively, by terminal time (Fig. 2a, left). The average community income rises to approximately 870 USD/household/cropping cycle, and 44 percent of the community's working-age population ultimately migrates (Fig. 2a, right). Because the same strategy options are adopted by most households, the GINI coefficient drops to 0.17.

Bounded rationality characteristics (i.e., risk aversion and partial reliance on one's social network for information) decrease the proportion of households that adopt Cash Crop and Migrate strategies to 45 and 70 percent of households, respectively, by terminal time (Fig. 2b, left), as households now penalize the higher volatility of these strategies. Agents' reliance on social networks for information also leads to varying perceptions of strategy income and volatility (SI 3.2). While most households continue to engage in some migration, the majority now send 2 or less migrants per household (Fig. 2b, centre).

The stratification of the population by educational attainment further depresses the adoption of the Cash Crop and Migrate strategies to 42 and 58 percent of households, respectively (Fig. 2c, left). This particularly affects households with primary education: poor access to information, higher risk weighting, and lack of financial resources combine to keep the majority of smallholder farming households in the relatively low-income, low-risk BAU strategy, while more elite groups of the community take advantage of higher-risk, higher-cost, and higher-return strategies (SI 3.3).

A 1.5^0C increase in mean annual temperature by 2050 further depresses the adoption of the Cash Crop strategy to 19 percent of households by terminal time, and lowers migration to 52 percent of households (Fig. 2d, left). Owing to decreased crop yields and increased extreme droughts, some households switch back from Cash Crop to BAU crops (especially after year 23, approximately corresponding to the year 2030). Climate stress increases the risk of this strategy, which relies on water-intensive crops, through increased frequency of extreme droughts. Additionally, the negative effect of climate stress on both Cash Crop and BAU crop yields make it more difficult for households to accumulate sufficient resources to afford the up-front cost of migration. While fewer households overall engage in migration, a few households who have sufficient assets ultimately send additional migrants by terminal time (Fig. 2d, centre). The finding of differential capacities to adapt through migration echo empirical findings from Bangladesh, which indicate that while crop failures reduce migration for households who experience direct financial losses, they increase migration for other households in drought-prone districts who are not directly affected [10]. At the community level, climate stress further lowers average income by 28 percent compared to the scenario without climate effects, to 380 USD/household/cycle (Fig. 2d, right), and slightly increases the GINI coefficient to 0.27, while the overall migrant proportion remains unchanged at 24 percent of the community. As this final layer is intended to be the most representative of real-world complexity, we use it as the basis for a partial validation of the model, based on the CVFS survey data. We find that the model accurately predicts the distribution of household cropping strategies, though it under-predicts the total level of migration relative to real-world data (for more details, see SI 3.4).

Risk Aversion and Financial Constraints Mediate Adaptation

While Nepal's Chitwan Valley serves as a case study to partially validate our model, risk preferences and the degree of expected temperature change may vary widely across South Asian farming communities [36, 35, 37]. Here we show how these two parameters (b_i and ΔT) interact with financial constraints to mediate climate adaptation outcomes, with particular attention to the proportion of the community that resides away from the village at terminal time, as an approximation for long-term migration (SI Section 3.2). This proportion varies widely for different combinations of risk aversion and degrees of temperature change, from 0 to 50 percent of the community (Fig. 3a). Generally, higher values of average risk aversion $\bar{b}$ result in lower migration, as this strategy involves a high degree of income volatility. Risk aversion also mediates the relationship between temperature change and migration. Under low average risk aversion (roughly $\bar{b} < 0.5$), increases in temperature change lead to higher community migration. However, there is no clear relationship between temperature and labour migration for higher values (roughly $\bar{b} > 0.5$): here, the effect of risk aversion on migration is dominant, even for values of ΔT beyond the range of expected temperature changes for the region.

We further illustrate these interactions through three example scenarios reflecting potential combinations of risk aversion and climate risk exposure: (A) a high risk ($\Delta T = 4.5^o C$), low average risk aversion ($\bar{b} = 0.25$) scenario; (B) our Base Case, reflecting a relatively low risk ($\Delta T = 1.5^o C$), medium risk aversion ($\bar{b} = 0.5$) scenario; and (C) a medium risk ($\Delta T = 3.0^0 C$), high risk aversion ($\bar{b} = 1.25$) scenario (Fig. 3b). Despite high variation across scenarios, two robust relationships emerge. First, the combined effect of risk aversion and financial constraints (blue bar for "Risk Aversion") consistently drives down the use of migration as an adaptation strategy, which decreases average community income (SI 3.6). What is not immediately intuitive is that the main driver of this effect differs based on the scenario. In Scenario A, risk aversion on its own would actually increase net migration (Fig. 3b, left, first orange bar): sending more migrants helps reduce household income volatility relative to keeping most household members in the higher-risk Cash Crop strategy. However, financial constraints prevent some households from doing so, driving them to the BAU strategy with fewer migrants. By contrast, in Scenarios B and C, risk aversion substantially decreases the use of migration even in a world with perfect access to credit (Fig. 3b, centre and right, first orange bars). Here, the inherent risk of migration is sufficient to dissuade some households from adopting this strategy.

A second robust pattern is that in the absence of financial constraints, climate impacts would consistently increase migration relative to a counterfactual without climate impacts (Fig. 3b, orange bars for Climate), as the viability of farming strategies decreases. However, climate change erodes household financial assets through decreased crop yields and increased droughts, preventing some households from affording alternative livelihood options in the presence of financial constraints. This interaction provides further nuance to findings of divergent migration patterns in the face of climate risk [6], including climate immobility [5, 38], particularly when there are multiple adaptation options with different risk-reward profiles. Still, the robust effects of risk aversion and financial constraints on reducing community migration and average income suggest a role for risk transfer policies and interventions such as cash transfers that help households overcome such constraints.

Risk and Cash Transfer Policy Improve Community Outcomes

Policymakers at various governance scales can design incentives to influence farmer risk perceptions of various livelihood strategy choices, as well as their capacity to implement such strategies. Here we assess the impact of three such interventions: index-based insurance, a remittance bank that smooths volatility of migrant incomes, and cash transfers, assuming an identical government subsidy for each policy of 30 USD/household/cropping cycle. Each of these policies has been implemented in real-life contexts in South and Southeast Asia [39, 29, 40, 41, 27]. We also test a package of the three policies, subsidized at 30 USD/household/cropping cycle. Here, we assume that such interventions are generally implemented at the national scale, but we focus our analysis on how they impact the following community-scale outcomes: average community income (Fig. 4, left panels), inequality as measured by the GINI coefficient (Fig. 4, centre panels), the number of households below an immobility threshold (Fig. 4, right panels), and overall community migration (SI 3.7, Fig. 10). In the Supplementary Information Section 3.8, we also present a conceptual model for exploring the impacts of information policies on farmer household decision-making.

The impacts of these policies are assessed for the three illustrative scenarios described above (see Methods for more detail on the modelling of the policies). While each intervention exhibits some potential to improve community outcomes relative to a no-policy baseline, their relative effectiveness depends on community risk preferences and exposure to climate risk. For example, in Scenario A, index insurance and cash transfers exhibit greater potential to increase average community incomes and reduce inequality, relative to the remittance bank (Fig. 4a). Under these conditions, migration is the most resilient livelihood strategy to such high climate risks, and the main obstacle to greater adoption of this strategy is the financial constraints that are exacerbated by increasingly frequent droughts. Both cash transfers and index insurance address these by either directly providing households with additional income (cash transfers), or protecting households against the erosion of financial assets due to droughts (insurance), enabling a higher proportion of households to engage in migration (Fig. 5a). By contrast, in Scenario C, the remittance bank is the most effective individual policy in increasing average income while reducing inequality (Fig. 4c). Here, high risk aversion is the largest barrier to households engaging in migration. A remittance bank most directly addresses this obstacle by reducing the variance associated with this strategy, increasing the proportion of households engaging in migration relative to other policies (Fig. 5c). In Scenario B, each policy exhibits roughly equal ability to improve community outcomes (Fig. 4b). There is some empirical evidence that risk transfer policies such as index insurance indeed incentivize subsistence farmers in South Asia to adopt higher-risk cropping strategies [41], though these studies have only tracked outcomes for a few cropping seasons. Similarly, early evidence indicates cash transfers can help households deploy additional coping strategies, though the very poor may still be limited in achieving these benefits [42]. To our knowledge, no evidence has been collected on the effects of collective remittance banks on development outcomes in recent decades.

One robust finding across all scenarios is that a combination of all three policies is always at least as effective, and often more effective, than any individual policy in increasing average income and reducing inequality (Fig.4, left and centre panels, all scenarios). For example, in Scenario B, this policy package increases average household incomes by 88 percent relative to the no-policy baseline (352 to 660 USD/hh/cycle), while reducing inequality by 45 percent, as measured by the GINI coefficient. This policy package also has substantial impacts on increasing incomes and reducing inequality for Scenario A, and more limited, but still significant effects on these outcomes in Scenario C. The consistent improvement in community outcomes suggests that under a variety of community risk preferences and climate risk exposure, policymakers seeking to promote climate-resilient livelihoods can exert the most leverage by pairing policies addressing financial constraints (i.e., cash transfers) with those transferring some risk from individual households to collective scales (i.e., index insurance and a remittance bank).

However, a second robust finding provides some grounds for caution in relying too heavily on migration and risk transfer mechanisms to promote climate adaptation. In all three scenarios, the remittance bank leaves a significantly higher proportion of households with savings below an immobility threshold (the average up-front cost of migration without help from migrant networks) relative to the other policies (Fig 4, right panel, all scenarios). Essentially, this policy creates two classes of households - those that are able to afford the upfront migration cost and thus benefit from it, and those that cannot reach this threshold and are left behind. This finding reinforces the recommendation that policymakers consider packaging interventions that address risk transfer with those addressing financial constraints to promote climate-resilient livelihood decisions.

Discussion

Increasingly severe climate impacts are likely to challenge the viability of smallholder farmer livelihoods in the coming decades, forcing farming households and policymakers alike to make complex decisions. Several contributing factors influence these decisions and their ramifications for climate adaptation outcomes, including climate risk exposure, risk preferences, financial constraints, access to information, and government incentives. To promote resilient livelihoods, policymakers must account for non-linear interactions between these factors.

Through a novel agent-based model, we illustrate how future climate impacts, absent any policy intervention, are likely to reduce average household incomes and increase inequality among smallholder farming households in South Asian contexts. Climate change directly reduces incomes through diminished crop yields and increased frequency of extreme droughts, which affects all households who maintain farming livelihoods. Indirectly, increased climatic stress also restricts the range of higher-cost, higher-reward livelihoods that households may deploy, including labour migration, by preventing them from accumulating sufficient resources. These factors contribute to increased inequality, as households with lower access to financial and social capital will be even less likely to diversify livelihoods through planned migration and thereby protect against increasing climate risks. The feedback loop of increased climate stress, diminished financial assets, and higher household immobility introduces an additional poverty trap [43, 5] that may become increasingly common across many developing country contexts.

Consequently, climate adaptation policies in the agricultural sector should consider the combination of factors through which climate directly and indirectly impacts farming resilience. Directly providing households with financial resources through cash transfers may help alleviate some of these financial constraints, and improve household incomes, while reducing inequality. However, they may not be sufficient for some households to diversify livelihoods, particularly if alternate options (migration and cash crops) are seen as too risky. Alternatively, risk transfer mechanisms (index insurance and remittance banks) may attract more risk-averse farmers to diversify livelihoods, but on their own may not overcome the financial constraints that keep farmers in lower-income, lower-risk strategies. While the relative effectiveness of these interventions vary based on community risk aversion and climate risk exposure, a package of both cash and risk transfer mechanisms is robust in its ability to increase community income and reduce inequality, beyond the ability of any single policy approach on its own.

We note that several factors with the potential to influence smallholder farmers' climate adaptation responses are outside the scope of this study, yet merit further study. First, there are several additional push-pull factors that are not incorporated in this model, including hedonic attachment to one's home, life history events (e.g. marriage), civil conflict and human trafficking, and border-related policies that directly impact the ability to migrate.

Second, our analysis does not account for the effect of natural disasters on distress migration, which has been found to temporarily increase migration in some regions, though typically does not lead to a sustained change in migration patterns [4]. Third, we do not explore informal, bottom-up risk-sharing mechanisms that farmers themselves may employ to secure livelihoods in the face of increasing risk [44]. Fourth, we do not investigate the ramifications of livelihood decisions and the policies that influence these on local food security, which may be a prevailing concern in many subsistence farming communities in South Asia [45]. Finally, we also assume a static population with respect to demographic parameters e.g. education levels and social connections, as well as constant technological and economic conditions. These are likely to evolve over time, changing how smallholder farmers cope with increased climatic risks. As well, the values, social norms, and perceived capacities that inform farmers' decision-making processes may themselves change as climate risks become more severe [46].

There exist several fruitful avenues for further exploration across scales of decision-making factors. At the micro-scale, extensions of this model could allow agents to evaluate the utilities of time-varying strategies, e.g. by alternating crop choices or explicitly accounting for circular migration. Currently, these patterns only emerge if agents select different strategy options in subsequent timesteps. At the meso-scale, future work could explore the effects of different network structures and network dynamics on the transmission of information and household adaptation decisions. At the macro-scale, the Shared Socioeconomic Pathways [47] provide useful socioeconomic and climate scenarios that could be downscaled to further explore smallholder farmer adaptation decisions under dynamic demographic variables. For some contexts, including Nepal, it may also be of interest to disaggregate migration channels and gain insight on how various climate and policy scenarios may impact the distribution of migrants by destination.

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Methods

In each timestep, households select the strategy that maximizes their utility over a given time horizon h, on condition that the household savings $S_i(t)$ exceed the cost of the selected strategy. The profit of household i employing strategy k in the strategy set $\mathscr{K}$ is given by $\pi_{ik}(t) = I_{ik}(x_k, t) + R_i(x_k, t) - C_{ik}(t)$, where $I_{ik}(x_k, t)$ represents the income of household i corresponding to strategy k with x_k on-farm household members, $C_{ik}(t)$ represents the cost of strategy k, and $R_i(x_k, t)$ represents the remittances received from migrants. We construct the utility function as the difference of expected profit and profit volatility

$$U(\mu_{\pi,ik}(t), \sigma_{\pi,ik}(t)) = \mu_{\pi,ik}(t) - b_i \cdot \sigma_{\pi,ik}(t)\,, \tag{1}$$

with $\mu_{\pi,ik}(t) = \mathbb{E}[\pi_{ik}(t)]$ and $\sigma_{\pi,ik}(t) = \sqrt{\mathbb{E}\big[(\pi_{ik}(t) - \mu_{\pi,ik}(t))^2\big]}$ the expected value and standard deviation of strategy k's profit distribution, as perceived by household i at time t, and b_i the risk weighing of household i. The risk weight in Equation 1 therefore reflects the penalty that households associate with income variance, relative to the utility assigned to maximizing expected income. This type of utility function is derived from modern portfolio theory [1, 2], and is consistent with NELM, in which households are concerned with minimizing risks to income [3, 4, 5].

The decision-making process of a rational household at time t can be formulated as the following optimization problem

$$\underset{k}{\operatorname{argmax}} \quad \sum_{s=t}^{s=t+h} \frac{U\big(\mu_{\pi,ik}(s), \sigma_{\pi,ik}(s)\big)}{(1+\rho)^{s-t}} \tag{2}$$

$$\text{s.t.} \quad C_{ik}(t) \le S_i(t)\,, \tag{3}$$

where ρ represents the discount rate in evaluating strategy costs and payoffs and $S_i(t) = S_i(t-1) + \pi_{ik}(t-1)$ represents the wealth of household i at time t (measured in liquid savings). We make the simplifying assumption that the entirety of a household's profits go to its savings.

The ABM [6] is built in four layers of increasing complexity. This modelling strategy enables us to isolate the effects of modelling assumptions by progressively introducing new sources of complexity in each layer.

Layer 1: Economically Rational Optimization

In Layer 1, households optimize the expected net present value of their income over a given time horizon under perfect information, while accounting for their financial assets.In this layer, each household i has perfect information about the future income distributions of each strategy k, corresponding to unbiased values of $\mu_{\pi,ik}(t)$ and $\sigma_{\pi,ik}(t)$. Moreover, in Layer 1 households only maximize expected profit, and therefore $b_i = 0$.

The strategies available to farming households are BAU, Cash Crop, and Migrate, each with its own expected income, risk, and cost. BAU farming is largely for subsistence with limited expected potential for income generation but also low costs C_{BAU}. Alternatively, farmers can diversify to cash crops that may generate commercial income $I_{i\mathrm{CashCrop}}$, but are also likely to come with higher initial costs C_{CashCrop} and a higher income variance. Finally, households can send a migrant to an urban location; this has an up-front cost $C_{i\mathrm{Migrate}}$, but households can subsequently benefit from remittances. Incomes derived from the two farming strategies, BAU and Cash Crop, vary across households according to a Weibull distribution, while incomes from Migrate vary according to a log-normal distribution, based on a best fit with data available from the Nepal CVFS Labor Outmigration, Agricultural Productivity, and Food Security survey [7]. Costs related to BAU and Cash Crop strategies are taken from a survey on Costs and Returns of Grain and Vegetable Crop Production in Nepal's Mid-Western Development Region [8], and Migrate strategy costs are approximated as an average of migration costs from Nepal to India and Gulf countries [9].

In all cases, an important feature of the income distributions is that a few agents earn relatively high incomes, while the majority of agents receive less than the mean income. We incorporate two economic feedbacks related to farming incomes and migration remittances. First, we assume that when a household sends a migrant to the city, the remaining members continue farming using either the BAU or Cash Crop strategy. However, migration reduces the amount of labor available for farming, and therefore farm productivity declines according to a saturation function (SI 2.1). Similarly, we assume that payoffs from migration tend to exhibit decreasing marginal returns as a function of the number of migrants from the same household.

We do not include a migrant's additional income beyond remittances as part of our utility function. We assume this income is spent by the migrant to meet consumption needs at the destination, and does not enter household decision-making regarding the utility of livelihood strategies at the household level. We note that a household with migrants would also likely have lower consumption needs relative to a full household in a given timestep. However, as households may continue to provide income for the needs of migrant family members [3], we define household net profit as the aggregate of remittances and household farm incomes, less the strategy costs, without adjusting consumption needs based on the number of household migrants. Modifying these assumptions (e.g. accounting for migrant profit beyond remittances, and/or altering household consumption needs as a function of the number of migrants) may also be a valid approach to modelling the profit of migration as an adaptive strategy, and may slightly change the results presented here. More information about the specific utility, Weibull and log-normal functions used for this layer, as well as the Base Case parameter values used to initialize the model, can be found in SI, Section 2.1.

Layer 2: Bounded Rationality and Social Network Impact

The behavioural psychology literature has established several mechanisms through which decision-makers deviate from rational (*homo economicus*) behaviour assumed in Layer 1. In particular, Simon [10] defines three aspects of bounded rationality that characterize many real-world decisions: (1) an agent may have incomplete information and is therefore unable to assess all possible decision options; (2) there may be decision-making goals, e.g. satisficing, that deviate from traditional utility maximization; and (3) agents may have limited cognitive capacity to fully calculate strategy utilities.

Layer 2 (Bounded Rationality and Social Network Impact) seeks to account for this behaviour by relaxing some of the assumptions made in Layer 1. In this layer, households optimize expected profit corrected for profit volatility across the strategy set $\mathscr{K}$. This is consistent with empirical and theoretical literature from NELM, which views migration as one way in which households spread risk and smooth consumption across highly variable economic conditions [3, 4, 11]. Households may differ with respect to the relative weight b_i, such that a higher value of b_i indicates a lower willingness to trade-off risk for expected return [12]. For Layer 2, we assume agents are randomly assigned a risk weighting from a normal distribution, with mean parameter value $\bar{b}_i = 0.5$, indicating that on average they penalize the perceived profit volatility of a strategy with half the weight they assign to its expected profit. Based on the average incomes and volatility of the livelihood options included in the model, this average risk weighting is approximately equivalent to a constant relative risk coefficient of 1.0 (SI 2.2.1).

In this layer, households receive imperfect information about the income distributions, resulting in biased values of the expected income and income standard deviation. To simulate information flow across limited social networks, farming households are placed on a randomized, scale-free network [13], through which a few households are connected to several other households, while most households have only a few connections to other households. Each agent's connections define the peers with which it compares income and gathers information about alternative strategies. The number of connections for each household follows a power law distribution such that a few households have a high number of connections and serve as key hubs of community information, while most agents have only a few connections (SI 2.2.2).

Household social connections alter the decision-making process in three ways. First, households must pass a status quo threshold before evaluating whether to change strategies. This test consists of comparing the household current profit with a reference point that accounts for the profits earned by their social connections and their own profits in recent years. Households that perceive they are below this reference point are motivated to re-evaluate their strategy, consistent with empirical research that points to the perception of relative deprivation compared to one's neighbors as a key migration push factor [14]. If the status quo threshold is passed, a second way in which social connections influence the household behavior is by altering the perception of expected strategy profit $\mu_{\pi,ik}(t)$ and standard deviation $\sigma_{\pi,ik}(t)$. Specifically, households observe a limited number of strategy payoffs from their own limited memories and social networks. For each strategy k, households take the mean and standard deviation of these observations as proxies for the perceived income distributions. This social network information is bounded by households' limited memories, such that only the observations from the past m_i time steps are included in forming perceptions of $\mu_{\pi,ik}(t)$ and $\sigma_{\pi,ik}(t)$. (In cases where a household has no observations available for a particular strategy k, it will search its social network until it finds a household whose perception of k's mean and standard deviation it can copy.) They then take a convex combination of these perceived values with objective information on the mean and standard deviation of each strategy's income distribution from public sources; the latter values are weighted with factor ω_i. Finally, social connections to households with migrants contributes to reduced migration costs. Empirical studies in several migration contexts have established that potential migrants are significantly more likely to migrate with increasing connections to current or returned migrants [15, 16]. Section 2.2.2 in SI contains more details on how each of these three feedbacks is operationalized.

Layer 3: Demographic Stratification

In previous layers, households are assumed to share similar demographic characteristics, and important parameters such as starting wealth, risk preferences, and weighting of public information sources were randomly distributed. However, demographic variables, especially educational attainment, have significant correlations with the ability to process information and adapt to climate risks [17, 18], and assumptions regarding these variables significantly impact projections regarding the future composition of societies [19]. While this model does not seek to account for all sources of demographic heterogeneity, in Layer 3 we correlate risk preferences, initial wealth, and access to accurate information with households' educational attainment, which is intended to better mimic the correlation of such economic decision-making factors in a real-world South Asian farming community.

The effect of education is operationalized in the demographic stratification layer by assigning each household an educational attainment level E_i according to Primary (representing no education - completed primary), Secondary (representing some secondary - completed secondary), and Tertiary (representing any post-secondary education), consistent with categorizations that are typically used in population projections [19]. Educational levels are assigned based on data from the 2011 Nepal Population and Housing Census [20]. For simplicity, these educational levels remain constant over the course of the considered time horizon. While attainment may differ between male and female heads of household, and between parents and their children, it is assumed in this model that the highest education level of any household member is the most relevant for shaping future livelihood decisions.

In this layer, the education parameter E_i is correlated with the following parameters: Initial savings, $S_i(0)$ (positive correlation), [21]; Risk weighting factor, b_i (negative correlation) [22, 23]; and weight given to public information on strategy payoffs, ω_i (positive correlation) [24]. Table 3 in Section 2.3 of the SI displays the specific values used to parameterize the effects of education on these variables.

Layer 4: Climate Impacts

In the previous layers, the agricultural community experiences a stationary income distribution for each strategy k. In the climate impacts layer, we relax the assumption of income stability over time to better reflect the potential impact of increasing climate risk on farming-based livelihoods [25, 26]. We do this by introducing two related climate phenomena: the effect of long-term change in mean temperature on crop yields [27, 28, 29, 26, 30], and the impacts of increasing frequency of extreme events (e.g. droughts) on crop yields [31, 32, 30]. We keep the mean and variance of income from the Migrate strategy unchanged in this layer, such that its risks are uncorrelated with those of the farming strategies.

The first climate phenomenon assumes that the annual mean temperature of the agricultural community increases linearly between 2007 and 2050. While the rate of change in global mean temperature is projected to be non-linear over long time horizons, a linear rate of change is a fairly accurate approximation over shorter timeframes [33]. For the representative South Asian farming community in this model, we assume an average decrease in crop yield of 10 percent for every 1^o C of warming, consistent with the observed global average impact of temperature increases on cereal crops that are prevalent in this region, i.e. rice, wheat, and maize [26]. This effect is operationalized by adjusting the mean annual income of the BAU and Cash Crop strategies as a function of temperature (for more details, see SI 2.4).

In addition to a gradual decrease in the viability of farming strategies, increasing climate change may also threaten agricultural livelihoods through an increase in the frequency of catastrophic natural disasters, e.g. droughts [34, 31, 32, 30]. Thus, smallholder farmers may make adaptation decisions not only in response to long-term trends, but also to cope with more frequent shocks to their livelihoods. To account for this possibility, a second climate phenomenon represents the possibility of increasingly frequent natural disasters that may more drastically affect income from farming-based strategies. This effect is modelled using a peaks-over-threshold approach under a non-stationary distribution. First, we employ the Standardized Precipitation and Evapotranspiration Index (SPEI) as an indicator of drought conditions. The SPEI is a normalized index based on historical data (ranging from 1901 to present day) in which 0 represents the mean hydrological balance for any region in a given calendar time span, and increases/decreases of 1 unit represents one standard deviation in the historical distribution of the monthly hydrological balance [35]. We assign an SPEI value of -2 as threshold for an extreme drought for BAU crops, historically representing a 1-in-40 year drought event that would likely wipe out most of the crop yield in a particular growing season. We assume that crops used in the Cash Crops strategy are more water-dependent and thus more sensitive to drought risks in rain-fed agricultural areas; we use an SPEI value of -1.5 to delineate an extreme drought for this strategy (roughly historically equivalent to a 1-in-15 year drought). In a drought year for crop strategy k, each household i planting such a crop receives a random income drawn from the bottom portion of a truncated income distribution for crop k.

In each timestep of the model, we assign the community an SPEI number by randomly sampling from the SPEI distribution. We account for the effects of changing mean annual temperature on drought frequency by adjusting the mean of the SPEI distribution as a function of mean annual temperature. This relationship was obtained by regressing the lowest SPEI 3-month index in each year of the SPEI dataset (1901-2014) on mean annual temperature for the 0.5^o x 0.5^o grid cell that contains Bharatpur, in Nepal's Chitwan Valley. Thus, the probability of drought increases over time with increasing temperature, but does so differently for the BAU and Cash Crop strategies, given their different thresholds. More information on on calculations related to droughts are available in SI 2.4.

While the introduction of climate stress in Layer 4 does not fundamentally change the decision-making process of household agents, the nature of the bounded rationality characteristics described in Section 4.2 holds several interesting implications for how households evaluate the suitability of strategy options under non-stationary climatic conditions. First, because of the *status quo* bias, households employing strategies that were successful in the recent past will be less likely to re-assess the fitness of these strategies under deteriorating climatic conditions in the future. This leads to the emergence of an optimism bias among more successful households. However, this is partially mitigated by the fact that as climatic conditions for farming worsen, a household is increasingly likely to receive lower income compared to previous years, more frequently triggering a re-evaluation of strategy options. Second, we assume agents have relatively myopic time horizons ($h = 10$ cropping cycles), limiting their ability to forecast large climatic changes. Finally, as we assume that households have limited cognitive capacity to evaluate all potential decision options, they do not evaluate possible time-varying strategy options (e.g. "If I employ strategy X at time t, I will gain enough income to employ strategy Y at time $t+1$"). This limits households' ability to think strategically about ideal time frames for various strategy options under a changing climate.

Policy Interventions

We model the impact of three types of policy interventions - cash transfers, index-based insurance, and a remittance bank - on household strategy choices and community outcomes. Modelling these policies allows us to more broadly compare interventions that mostly target the expected income of livelihoods (cash transfers) vs. interventions that mostly target their volatility (index insurance and the remittance bank). In order to evaluate each individual policy option on an equivalent basis, we assume that the government subsidizes the insurance option and the remittance bank option by the same amount as the cash transfer program, such that both the index insurance premium and remittances in the remittance bank are subsidized by 30 USD/household/cycle. Finally, we evaluate a policy package in which all three options are implemented simultaneously; in this case, we assume that the insurance premium and remittances are unsubsidized, but that each household receives the 30 USD/household/cycle cash transfer. Details on the modelling of each of these three interventions are presented below.

Cash Transfer

In the Cash Transfer intervention, we model an unconditional transfer of funds to farming households. Households are given these funds at the beginning of every cropping cycle, and make decisions on their preferred strategy options knowing that they will receive such a transfer. When receiving information on the incomes of their social network, households also account for the cash transfers received by their connections in forming perceptions of strategy incomes. In this analysis, we model a cash transfer of 30 USD/household/cycle, in line with other forms of cash transfers that have been introduced in Nepal [36, 37] and also roughly equivalent to the current levels of government subsidies for index insurance [38].

Index-Based Insurance

Index-based insurance is a specialized form of insurance that gives policyholders a pre-specified payout based on whether a measurable index exceeds a threshold (e.g. a specific wind speed or drought indicator), as opposed to indemnity insurance, which pays each policyholder based on the assessed level of damages sustained. In this analysis, the index-based insurance uses the 3-month SPEI value as the indicator. This indicator is a random variable with a non-stationary probability distribution, as detailed in Section 4.4. In each cropping cycle, a random draw is taken from this distribution; if the value is lower than the BAU and/or Cash Crop drought threshold ($\tau_{\text{BAU}} = -2.0$; $\tau_{\text{CashCrop}} = -1.5$), then the insurance policy is triggered and policyholders are automatically paid the expected loss for their crops in a drought event. Expected losses are calculated as a function of the mean income derived from each type of crop, which is also a non-stationary distribution based on long-term climate impacts on yields

$$L_k(t) = \mu_{I,k,\text{nd}}(t) - \mu_{I,k,\text{d}}(t)\,, \tag{4}$$

where $\mu_{I,k,\text{nd}}(t)$ represents the mean income for strategy k at time t in a non-drought year, and $\mu_{I,k,\text{d}}(t)$ represents the mean income for strategy k at time t in a drought year. In every time step, each household farming BAU or Cash Crops has the option of purchasing an insurance policy for that crop cycle. Premiums are set at actuarially-fair values, and to establish a comparison to the cash transfer intervention, we assume that a government subsidizes premiums by 30 USD/cycle. For comparison, the Nepali government currently subsidizes such premiums by 75 percent, which is approximately equal to 26 USD/ha/cycle for rice, and 23 USD/ha/cycle for wheat [38].

Let I_{subs} represent the government subsidy, then premiums $C_{k,\text{pr}}(t)$ are calculated at each time t as

$$C_{k,\text{pr}}(t) = p_{k,\text{d}}(t) \cdot L_k(t) - I_{\text{subs}}, \tag{5}$$

where $p_{k,\text{d}}(t)$ represents the probability of a drought for crop k at time t. Because households assign different weight to public information, and receive different information from their social networks, they form their own different perceptions of $p_{k,\text{d}}(t)$ and $L_k(t)$. In addition to different levels of wealth at any time t, this leads to different decisions among households about whether to purchase insurance. Under perfect information, households opting for insurance see the expected income $\mu_{I,k}(t)$ from farming strategy k and volatility $\sigma_{I,k}(t)$ of these strategies adjusted as follows

$$\tilde{\mu}_{I,k}(t) = (1 - p_{k,\text{d}}(t)) \cdot \mu_{I,k,\text{nd}}(t) + p_{k,\text{d}}(t) \cdot \left(\mu_{I,k,\text{d}}(t) + L_k(t)\right) = \mu_{I,k,\text{nd}} \tag{6a}$$

$$\tilde{\sigma}_{I,k}(t) \approx (1 - p_{k,\text{d}}(t)) \cdot \sigma_{I,k}(t), \tag{6b}$$

where the right-hand side of (6b) is a close approximation of the standard deviation adjusted for index insurance. Note that since the drought portions of these distributions are relatively small, we assume households do not perceive variance in the income they project to receive during a drought. The perfect information on the income distribution is combined with social information and information from memory to yield the perceived income distribution, expressed by $\tilde{\mu}_{I,ik}(t)$ and $\tilde{\sigma}_{I,ik}(t)$. More details on the decision-process to acquire index-based insurance can be found in the SI 2.5.

Remittance Bank

While the Migrate strategy leads to a relatively high expected income, it also is characterized by high volatility, which may dissuade some households from adopting this strategy. As one intervention to make this strategy more attractive, we model a hypothetical remittance bank that reduces income volatility for this strategy by pooling a portion of migration remittances from households in the community. Under this policy, all households engaging in migration deposit a specified proportion ρ_{rem} of their remittances in each cycle (for this analysis, we set $\rho_{\text{rem}} = 0.25$). The bank then pays each migrating household the same proportion ρ_{rem} of the expected remittance income for the number of migrants in a household. To establish a comparison with the cash transfer and index insurance, we assume that a government subsidizes deposits to the remittance bank by a remittance subsidy R_{subs} of 30 USD/cycle. In each cropping cycle, a household deposits to the bank $R_{i,\text{dep}}(x_i, t)$ and receives a payout from the bank $R_{i,\text{po}}(x_i)$, which are defined as

$$
\begin{aligned}
R_{i,\text{dep}}(x_i, t) &= \rho_{\text{rem}} \cdot R_i(x_i, t) \\
R_{i,\text{po}}(x_i) &= \rho_{\text{rem}} \cdot \mu_R(x_i)\,,
\end{aligned}
\tag{7}
$$

where $R_i(x_i, t)$ is the random income for a household engaging in migration (scaled by the number of migrants per household $x_{\text{hh}} - x_i$, with x_{hh} the household size) and $\mu_R(x_i)$ is the expected income for this strategy for a given number of migrants per household. For simplicity, under the Remittance Bank policy intervention, we assume all households engaging in migration participate in such a remittance bank. Similar to the effects of index insurance for the farming strategies, the presence of a remittance bank adjusts the expected income and standard deviation of Migrate as follows

$$
\begin{aligned}
\tilde{\mu}_R(x_i, t) &= (1 - \rho_{\text{rem}}) \cdot \mu_R(x_i) + \rho_{\text{rem}} \cdot \mu_R(x_i) = \mu_R(x_i) \\
\tilde{\sigma}_R(x_i, t) &= (1 - \rho_{\text{rem}}) \cdot \sigma_R(x_i)\,,
\end{aligned}
\tag{8}
$$

where $\sigma_R(x_i)$ is the standard deviation of the Migrate income distribution in the absence of a Remittance Bank.

Code Availability

The code for the agent-based model developed in this study is available via a public GitHub repository at: https://github.com/nchoquettelevy/RiskTransferClimateImmobilityABM.

Data Availability

The agent-based model from which results are generated is available via a public GitHub repository at: https://github.com/nchoquettelevy/RiskTransferClimateImmobilityABM.

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Author Contribution

NCL and MW conceived of and developed an initial design for the study. MO and SL proposed modifications incorporated in the final design. NCL wrote the model code.

NCL and MW analysed model results. All authors contributed to drafting the manuscript, responding to reviewer comments, and producing the final version. Correspondence and requests for materials should be addressed to NCL (nc8@princeton.edu) and MO (omichael@princeton.edu).

Competing Interests Statement

The authors declare no competing interests.

Figure Legends/Captions

Figure 1

Schematic overview of ABM structure. (a) Boxplots indicate the median, interquartile region, and range of income distributions for each strategy. Costs for each strategy are indicated by the dashed vertical lines. For each migration trip, households incur a one-time cost of 500 USD, but then no additional costs in subsequent timesteps. (b) At each time t, households enter a two-step decision-making sequence. First, they compare their income at time $t-1$ with their reference point income, which reflects a mix of their own bounded memories and the incomes at time $t-1$ from other households in their social networks. If the previous time step's income is above this reference point, households retain the same strategy. If the previous income is below this reference point, households re-evaluate strategies and select the option that optimizes their utility, based on their perceptions of the income distribution and drought risk resulting from each strategy. Households are also subject to financial constraints that may prevent them from deploying costly strategies, if they do not have sufficient savings. Sources of information include households' own memories, social networks, and objective sources. Climate impacts and policy interventions may affect households' perceptions of strategy incomes and risk, as well as the actual payoffs households receive. Certain policy options also ease financial constraints through subsidies.

Figure 2

Evolution of Household Strategy Choices and Community Outcomes under Four Model Layers. (a) Under Economic Rationality, the vast majority of households adopt both Cash Crop and Migrate strategies over the course of the considered timeframe (left), and most deploy 3 of their 5 working-age members as migrants (centre). These strategies lead to steadily increasing average community income over time (green line, right), while the proportion of community migrants also increases as more households gain financial resources to afford this strategy (blue line). **(b)** The introduction of Bounded Rationality and Social Network effects decreases the adoption of Cash Crop and Migrate over time, decreases the average number of migrants per household, and limits the growth in average income and migration proportion. **(c)** Stratification of risk weighting, information access, and financial resources along educational lines further reduces the proportion of households who adopt Cash Crop and/or Migrate, while most households that engage in Migrate generally send 2 or 3 migrants. Although primary-educated households make up 65 percent of the community, most households sending multiple migrants have secondary or post-secondary education (yellow and blue bars in centre panel, respectively), and these account for over 63 percent of all migrants by terminal time (right-hand panel). **(d)** With a 1.5^0C temperature increase over the considered time horizon, the proportion of households switching to Cash Crops is limited, and decreases after about year 23. Fewer households engage in migration, and multiple-migrant households skew further towards higher educational status (centre panel). This further lowers average community income, and increases community inequality (right). Results for each plot represent average values for each time step over 100 model simulations; shaded values indicate +/- 1 standard deviation.

Figure 3

Drivers of Migration Outcomes for Different Risk and Climate Scenarios. Adaptation outcomes are driven by complex interactions between financial constraints and several decision-making factors in the model. **(a)** The intersection of different average risk weightings $\bar{b}$ and the degree of temperature change ΔT leads to different outcomes for the proportion of the community that migrates. **(b)** The drivers of these outcomes are further analyzed for three distinct scenarios. Each panel demonstrates the incremental effect of risk aversion, social networks, demographic stratification, and climatic impacts on the final proportion of the community that migrates. We compare the effect of these model layers, where households must afford the up-front cost of alternative strategies (blue bars), to a version of the model where households adopt their preferred strategies without regard to financial constraints (orange bars). This allows for quantification of the added effect of financial constraints on each factor (green bars). In Scenario A, risk aversion and social networks somewhat decrease community migration relative to previous model layers. In the absence of the financial constraint, climate effects would lead to a more than 15 percentage point increase in community migrants, but this is mostly attenuated by the presence of financial constraints, for a net increase of 3 percentage points in the migration rate. In Scenario B, risk aversion substantially drives down migration, but social networks somewhat counter this effect. In the absence of financial constraints, climate effects would increase migration by 4 percentage points, but financial constraints actually lead to a net decrease in migration of 1 percentage point. In Scenario C, risk aversion significantly reduces the migration rate, to the point that social networks are unable to counter this effect. Without constraints, climate effects would increase migration by 5 percentage points, but this is mostly erased by the presence of financial constraints.

Figure 4

Comparison of Policy Effects on Community Adaptation Outcomes. Each panel demonstrates the distribution of community outcome metrics by model terminal time over 100 simulation runs (from left to right: average household income, community GINI coefficient, and proportion of households below an immobility threshold, i.e. the initial migration cost without assistance from migrant networks). For each panel, individual rows represent the effect of the policy condition specified on the y-axis. Dots indicate individual simulation outcomes, with the smoothed data distribution indicated above these dots; boxplots indicate the median of the distribution and the interquartile range. **a)** In Scenario A (low risk aversion, high climate risk), cash transfer and index insurance demonstrate the best ability to increase average income, decrease the GINI coefficient, and reduce the proportion of households below the immobility threshold, relative to a no-policy baseline. **b)** In Scenario B (moderate risk aversion, low climate risk), all three policies demonstrate roughly equal abilities to increase average incomes and reduce inequality. **c)** In Scenario C (high risk aversion, moderate climate risk), the remittance bank demonstrates the best ability to increase average incomes and reduce inequality. Two robust findings are consistent across all three scenarios: a remittance bank by itself would leave more households below an immobility threshold relative to the other policies, and a package of all three policies leads to the highest average income and lowest inequality by these metrics.

Figure 5

Comparison of Policy Effects on Community Adaptation Outcomes. Each panel demonstrates the distribution of community outcome metrics by model terminal time over 100 simulation runs (from left to right: average household income, community GINI coefficient, and proportion of households below an immobility threshold, i.e. the initial migration cost without assistance from migrant networks). For each panel, individual rows represent the effect of the policy condition specified on the y-axis. Dots indicate individual simulation outcomes, with the smoothed data distribution indicated above these dots; boxplots indicate the median of the distribution and the interquartile range. **a)** In Scenario A (low risk aversion, high climate risk), cash transfer and index insurance demonstrate the best ability to increase average income, decrease the GINI coefficient, and reduce the proportion of households below the immobility threshold, relative to a no-policy baseline. **b)** In Scenario B (moderate risk aversion, low climate risk), all three policies demonstrate roughly equal abilities to increase average incomes and reduce inequality. **c)** In Scenario C (high risk aversion, moderate climate risk), the remittance bank demonstrates the best ability to increase average incomes and reduce inequality. Two robust findings are consistent across all three scenarios: a remittance bank by itself would leave more households below an immobility threshold relative to the other policies, and a package of all three policies leads to the highest average income and lowest inequality by these metrics.

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