Navigating a Warming World: Rural-Urban Migration in The Context of Smallholder Farmer Climate Adaptation

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Abstract

Over the 21st century, climate change is likely to substantially threaten the viability of many of the world's smallholder farmer livelihoods through increased risks of extreme droughts, floods, heatwaves, and other hazards. How farmers manage these risks will have significant consequences for several public policy issues, including rural-urban migration. In this dissertation, I employ a mixed-methods framework to explore the fundamental mechanisms by which climate risk and policy interventions shape the migration behavior of smallholder farmers. To do this, I integrate agent-based modelling, evolutionary game theory, survey research, and robust decision-making tools to investigate three multifaceted questions. First, how is climate change likely to affect the use of rural-urban migration by farming households, relative to other adaptation strategies like diversifying crops? Second, how do various decision-making factors, including risk aversion, loss aversion, and pro-social preferences, shape the climate adaptation strategies that are likely to be pursued by farmers? Third, how can policymakers at local and national governance scales design robust policies to improve smallholder farmer resilience to climate shocks?

To address these questions, I focus on data and case studies from South Asia, a region that is characterized by a high dependence on small-scale farming, costly livelihood alternatives to subsistence farming (including migration), and high exposure to climate impacts. This dissertation finds that future climate change is likely to exacerbate poverty traps, both by directly reducing crop yields and by constraining farming households' ability to pursue livelihood alternatives, including migration. Furthermore, while climate risks are already salient to farmers' economic decision-making, these also increase the perceived riskiness of alternative livelihoods to farming, including international migration and off-farm wage labor. Complementary policy packages, such as pairing cash transfers with risk transfer mechanisms, and combining insurance subsidies with interventions cueing pro-social

preferences, can be effective in providing farmers with the financial stability and capital to make effective adaptation investments. However, a lack of coordination across governance scales may impede the ability to meet key policymaking objectives across a range of climate futures. Therefore, effective adaptation interventions need to find complementarities across traditional policy spheres and bureaucratic divisions.

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It is a common misconception that doctoral research is done in isolation, head buried in books or glued to a computer screen. In reality, it takes a whole community to support one's PhD work. I am very grateful to have been part of so many amazing communities at Princeton University and outside its gates. There is no way to do justice to the wide array of support I received on this journey in a few pages, but here is a short attempt to do so.

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I still remember meeting Simon during my first visit to Princeton as a prospective student. That moment convinced me that Princeton would be a special place to do interdisciplinary research, and he is a large part of creating that environment. Simon is a role model not just in his Epicurean knowledge of science, music, and sports, but also his willingness to deploy his vast social networks to the benefit of a naïve graduate student. I know of no other professor who so casually invites academic giants to his lab meetings, transitions from a technical question about a differential equation to a thought-provoking ethical question by way of a joke, and lets new conversations emerge from complex interactions among his lab members.

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To a more just, secure, and empathetic world.

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Introduction

1.1 Motivation: Navigating a Warming Planet

Over the course of the 21st century, global mean temperatures are likely to rise by 1.5 - 4 ^{0}C relative to pre-industrial baselines, even if governments implement stringent new greenhouse gas emissions mitigation policies [1]. This level of climate change is almost certain to fundamentally reshape ecosystems and the human societies that inhabit them. Climate change has already driven more frequent extreme events, including droughts, floods, and heatwaves, that have exposed millions of people to food and water insecurity, particularly in Africa and Asia [1]. Among other impacts, a 2^{0}C rise in mean temperatures is likely to decrease global snowmelt and glacial melt by 20 percent and reduce yields of key staple crops (including rice, wheat, and maize) by 10-20 percent [2–4], severely threatening agricultural livelihoods for many of the world's 2 billion smallholder farmers [5, 6]. Furthermore, rising sea levels, stronger storm surges, and more intense heat waves are likely to make it more difficult or impossible to live in several highly-populated regions, particularly for populations that have few resources to cope with shocks [7].

Against this sober backdrop, individuals, communities, and institutions will have to navigate their way through several decades of climate-driven systemic risks. In some cases, adaptation to a climate-shaped world may involve literal navigation: the World Bank predicts that slow-onset climate change will result in 31 million - 143 million additional internal migrants in sub-Saharan Africa, South Asia, and Latin America [8]. Rural-urban migration has long been one of the most effective strategies for farmers to manage inherently uncertain livelihoods, even without accounting for emerging climate risks. Sending one or more household members to earn income in urban settings helps to diversify household incomes across geographies and economic sectors [9–11]. Indeed, there is strong empirical evidence that migrants adjust the remittances they send to their households in response to income shocks suffered by family members in origin communities [12, 13], indicating that migration is an intentional strategy to manage livelihood risks. Yet, it is less clear how new climate-driven sources of livelihood risk will affect such migration decisions. Increased climate pressures may serve as an additional factor that further incentivizes the use of rural-urban migration as a risk management strategy [14, 15]. Alternatively, climate-linked shocks may drain subsistence farming households of the financial and physical capital needed to afford the high up-front costs of migration, especially to international destinations that typically offer more economic opportunity [16–18]. Furthermore, there may be non-linear relationships between farmers' deployment of migration and other on-farm adaptation strategies, including diversifying the types of crops grown and improving water management techniques [19, 20]. Here again, migration could either serve as a complement to on-farm adaptation by providing additional financial capital to purchase new inputs and technologies, or it may serve as a substitute, if farmers perceive on-farm adaptation as sufficient in managing existing and future climate risks.

A further source of complexity in predicting how climate is likely to shape rural-urban migration is the role played by public policies and investments. The climate adaptation governance architecture is still nascent, with local and national governments piloting a variety of mechanisms to manage uncertain climate risks [21–24]. Such mechanisms include new short-term financial instruments to help individuals cope with imminent natural disasters [25], medium-term investments to assist communities in preparing for looming climate risks [26], and longer-term initiatives to guide more climate-resilient development pathways [27]. Interventions at each of these stages are likely to change farmers' incentives for various adaptation strategies. The set of policies and new governance institutions that are likely to emerge from these pilot stages is still unclear. Yet, the current state of adaptation governance also presents an opportunity to design new policies and institutions in a way that "crowds in" effective climate risk management strategies at all levels of decision-making.

To better understand the many ways in which climate change is likely to reshape rural-urban migration patterns, we need to develop frameworks that situate migration within the wider portfolio of livelihood strategies available to farmers. Much empirical and theoretical research over the past 15 years has contributed to our understanding of how climate has influenced migration patterns around the world. Yet, traditional methods for assessing the climate-migration relationship have often focused on these variables in isolation of other factors that affect farmer decision-making. Especially as climatic conditions in future decades become qualitatively different from the conditions experienced in the past, additional variables are likely to shape how individuals and communities navigate such changes. These include: on-farm adaptation mechanisms that farmers can take to attenuate (or in some cases, benefit from) the effects of climate change on crop productivity; non-farm economic and livelihood opportunities that can help farmers diversify their income streams, including but not limited to migration; farmers' risk and economic preferences that condition their decision-making objectives; social networks and information flows that influence the strategy options considered by farmers; and policy interventions at multiple levels - local, national, and international - that may constrain or expand the set of economic opportunities available to farmers. While each of these factors introduces substantial sources of complexity, developing a framework that integrates these considerations would provide a useful set of tools for various decision-makers as they explore the implications of various climate adaptation pathways.

This dissertation seeks to contribute decision-making tools that can assist decision-makers at multiple scales - including households, communities, and various levels of government - navigate uncertain climate futures in the subsistence agricultural sector. Through the four chapters of this work, I build an interdisciplinary framework that integrates insights from agent-based modelling (Chapter 2), evolutionary game theory (Chapter 3), survey research (Chapter 4), and robust decision-making (Chapter 5) to better understand how climate change is shaping the fundamental drivers of adaptation decisions among farmers. For most of my work, I focus on data and case studies in South Asia, a region that is characterized by high dependence on small-scale agriculture, costly livelihood alternatives to subsistence farming (including migration), and high exposure to climate impacts [28]. In particular, most chapters use and/or contribute new data from Nepal's Chitwan Valley [29]. The agricultural sector in Nepal represents an important case study to better understand how climate change is re-shaping farming livelihoods, and how smallholder farming communities can adapt to such changes. While the country is undergoing a rapid urbanization process, agriculture still accounts for 21.3 percent of Nepal's GDP [30] and employs 64 percent of its population [31], far higher than both regional and global averages. Nepal also faces several substantial climate risks, ranging from changing monsoonal patterns that affect the timing and volume of precipitation [28], temperature rise at higher-than-global averages that affect soil fertility [32], and rising potential for catastrophic events [33]. Gaining a better understanding of how climate change influences Nepali farmer risk perceptions, and the factors that shape their adaptation decisions, can provide useful insights for other agricultural contexts that may face similar climate threats in the coming decades.

1.2 Research Questions: Situating Rural-Urban Migration in Smallholder Farmer Climate Adaptation

The main research objective of this dissertation is to develop a more holistic framework of how rural-urban migration fits into the broader context of smallholder farmer climate adaptation. This objective has theoretical importance, in order to understand how climate change is likely to reshape migration processes. It also has policy relevance, in order to develop systemic interventions that provide vulnerable farming communities with the most tools possible to navigate uncertain climate risks. While each analytical chapter of this dissertation investigates a particular puzzle regarding rural-urban migration and climate adaptation, there are three over-arching questions that are woven throughout this work. These are:

- *How is climate change likely to affect the use of rural-urban migration as a livelihood strategy, relative to other adaptation options?* Climate change will almost certainly introduce more uncertainty to farm-based livelihoods, including higher potential for income losses [5], and rural-urban migration is one strategy that can help farmers cope with such risks. However, climate impacts on agriculture may also deprive farmers of the capital needed to afford long-distance labor migration. While much work has sought to clarify this relationship across several regions of the globe, here I seek to contribute new insights by analyzing how and when migration is deployed in the context of farmers' broader adaptation portfolios. These include other livelihood strategies, e.g. diversifying crops, engaging in off-farm wage labor, and investing in livestock [6]; as well as financial mechanisms, e.g. formal insurance and informal revenue-sharing arrangements, that can help farmers manage climate-driven risks to their household incomes.

- *How do decision-making factors condition the relationship between climate change and migration?* While improvements in climate modelling allow the scientific community to provide increasingly fine-grained climate information to farmers and policymakers, it is clear that several cognitive biases and heuristics mediate the way in which information ultimately shapes decisions. Previous work has demonstrated that simply increasing farmer access to climate information services may not lead to anticipated benefits in climate adaptation. In this dissertation, I seek to systematically assess how decision-making preferences, e.g. risk aversion, loss aversion, and pro-social preferences; strategic interactions amongst farmers and between farmers and policymakers; and differential access to informational and social capital fundamentally alter strategy decisions beyond what is predicted by rational, *Homo economicus* models of decision-making.

- *How can policymakers at local and national scales design robust policies to improve smallholder farmer resilience to climate shocks?* While several governments, multilateral organizations, and non-governmental organizations have experimented with policy interventions to promote smallholder farmer resilience, these interventions have generally been implemented in isolation from other policy levers, and have only benefited from a few years of data to evaluate their impact. In developing an integrated framework of smallholder farmer climate adaptation, I investigate how policies across several domains - including cash instruments, risk transfer mechanisms, migration supports, informational policies, and behavioral interventions - can leverage each other to provide more robust protection to farmers against climate uncertainty. In so doing, these policy packages may help expand the suite of strategy options available to farmers as they navigate a climate-shaped world.

1.3 Thesis Outline: An Integrated Framework for Multi-Faceted Governance Challenges

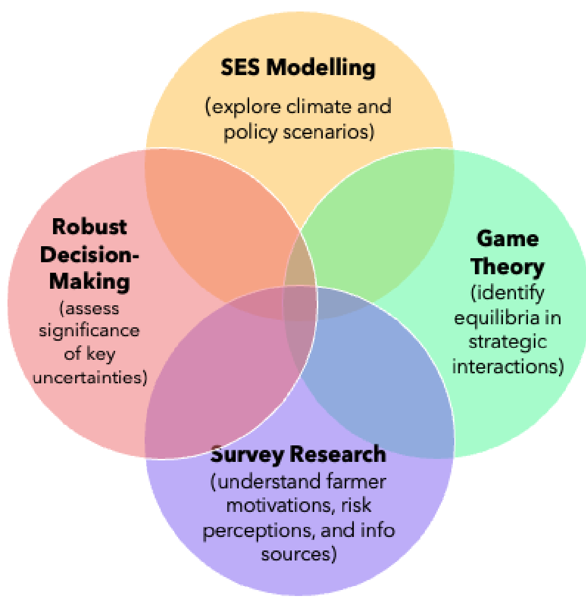

Figure 1.1: Methodological Framework for Dissertation Research.

To address the multi-faceted nature of these research questions, each chapter of this dissertation integrates insights from different methodological tools and theoretical frameworks to address a policy-relevant challenge in climate adaptation governance (Fig.

1.1). One such tool is social-ecological systems (SES) modelling. SES models comprise a broad range of applications, but generally seek to understand dynamic interactions between human societies and their environments. A key objective of this tool is to better understand how diverse system components relate to each other through direct and indirect interactions and across different temporal and geographic scales [34, 35]. This feature makes SES modelling especially useful as a tool to understand the climate-migration relationship: it can allow for a fuller investigation of the complex relationships that might lead climate change to increase migration flows for certain populations and timescales, while also suppressing migration flows in other contexts and timescales [15, 16, 36–38]. Among other uses, this type of tool also allows researchers and decision-makers to systematically explore how policy interventions are likely to cascade across a complex system. In Chapter 2 of this dissertation (in collaboration with M. Wildemeersch, M. Oppenheimer, and S.A. Levin), I develop a particular kind of SES model, known as an agent-based model (ABM), to investigate how smallholder farmer livelihood choices are likely to be shaped by changing climatic conditions and dynamic interactions between heterogeneous farmers. We use the ABM to identify key factors that are most influential in driving farmers' climate adaptation decisions, and assess the effects of three possible risk transfer policy interventions on farmers' economic outcomes across a range of climate and socioeconomic scenarios.

A second relevant tool for this research is evolutionary game theory (EGT). Although initially developed to understand how certain behavioral traits evolved as stable outcomes in non-human animal populations, EGT has more recently been applied to the study of cooperation in human social systems [39–42]. EGT is particularly useful in identifying the long-term equilibria outcomes of repeated, strategic interactions between decision-makers. In Chapter 3 of this dissertation (in collaboration with M. Wildemeersch, F.P. Santos, S.A. Levin, M. Oppenheimer, and E. Weber), I develop an EGT model to investigate the conditions in which both formal and informal risk management strategies can co-exist in equilibrium in subsistence farming communities. This responds to a recent policy challenge that has emerged across many subsistence societies: as smallholder farmers generally lack formal insurance for livelihood risks, several governments and non-governmental organizations have sought to promote index-based insurance as an inexpensive way to provide farmers with formal financial protection against climate shocks [43–45]. Yet, even with strong subsidies, most such programs have struggled with low adoption rates among farmers [46–49]. One hypothesized barrier is that most farming communities have already developed informal risk-sharing arrangements, e.g. informal lending and revenue-sharing cooperatives, that reduce demand for formal insurance [41, 47, 50]. While such informal arrangements help farmers cope with idiosyncratic shocks (i.e. those that are not correlated across individual households), they may prove insufficient in helping farmers cope with rising climate risks that impose covariate shocks across a farming community. Whether a community can maintain a combination of formal and informal insurance mechanisms depends in part on how one farming household's payoffs are affected by the risk management decisions of other households in its community. Here, we use EGT to identify which types of risk management strategies are likely to emerge as long-term equilibria based on the degree of covariate risk faced by a farming community, farmers' economic preferences, and the financial incentives provided for insurance.

While both ABM and EGT models are powerful tools to explore long-term outcomes arising from interactions between strategic decision-makers, and between decision-makers and their environment, their usefulness is dependent in part on assumptions regarding how agents make decisions. Understanding how climate change shapes farmers' decision-making processes is also critical for governments and non-governmental organizations seeking to promote adaptation in the agricultural sector through climate information services [51–53]. Particularly relevant questions for this research are how farmers perceive climate risks, what information sources and social networks influence their beliefs about strategy options, and how perceptions of climate and livelihood risks shape their decisions regarding climate adaptation. Household surveys and experiments can be valuable tools to test the applicability of different decision-making theories to the context of smallholder farmer climate adaptation, and to collect data on key uncertain parameters in modelling tools. In Chapter 4 of this dissertation (in collaboration with D. Ghimire, R. Ghimire, I. Chaudhaury, D. CK, and M. Oppenheimer), I develop a novel survey instrument and policy vignette to better understand how previous exposure to climate hazards, differential access to informational and social capital, and potential policy interventions shape farmers' perceptions of climate risks. We also use this tool to assess the salience of climate risks to observed differences in farmers' adaptation and livelihood decisions.

One of the most significant challenges to climate adaptation decision-making is the nature of "deep uncertainty" - a condition in which probability distributions of future conditions are unknowable or when experts disagree on probability distributions, and/or when stakeholders across governance scales do not agree on key objectives or the nature of a system [54, 55]. Subsistence agriculture under climate change is precisely such a system: while long-term climate change is likely to negatively impact crop yields in most parts of the world [2, 3, 7], the timing and nature of such impacts are difficult to characterize by crisp probability distributions. This is especially true of regional and global tipping points that may fundamentally alter agricultural conditions, e.g. glacial melting and changing monsoonal patterns. Furthermore, decision-makers at different governance scales are likely to have different ideals of what constitutes "good" climate adaptation. National policymakers might seek to ensure that climate change does not hamper economic growth;

local policymakers may wish to bolster food security and avoid high in- or out-migration from their region; and farming households may wish to be protect themselves against income volatility and shocks. Robust decision-making (RDM) is a useful framework for systematically analyzing potential tradeoffs among stakeholder objectives, and the impacts of deeply uncertain processes on the ability of stakeholders to negotiate such tradeoffs. RDM has historically been used to evaluate the robustness of infrastructure decisions, including building flood walls and irrigation systems, against deeply uncertain climate variables, including future emissions pathways [56–58]. In Chapter 5 (in collaboration with F. Errickson, A.B. Pokhrel, M. Oppenheimer, and K. Keller), I propose a new application of RDM to evaluate climate adaptation governance principles in the Nepali agricultural sector - an especially relevant case study given the country's recent transition to a decentralized federal governance structure. As national and local governance agencies are still navigating the distribution of competencies in this sector [59], RDM frameworks can help stakeholders identify governance design principles, e.g. realistic targets for local district self-sufficiency in food production, that are more likely to provide robust outcomes to climate, political, and socioeconomic uncertainty.

One methodological objective of this dissertation is to identify ways to integrate each method's relative strengths such that the cohesive whole provides new insights that would have been difficult to derive through each method individually. For example, ABM and RDM models can identify key decision-making parameters that drive important sensitivities in long-term outcomes, and merit further study through empirical surveys. In turn, surveys may reveal evidence supporting or suggesting modifications to certain decision-making theories that can lead to more realistic modelling frameworks in ABMs and EGT. ABMs and EGT can also be used in conjunction with surveys and empirical experiments to identify whether existing patterns of cooperative behavior are likely to remain stable in the face of changing environmental conditions and social relationships. In the dissertation's concluding chapter, I re-assess potential complementarities between these tools in light of the results from my research, and propose a future research agenda to more intentionally integrate multiple methods in developing a holistic understanding of climate adaptation decision-making. Overall, these projects highlight opportunities to connect policy instruments in new ways to provide smallholder farmers, farming community groups, and policymakers with the tools to navigate the uncharted waters of future climate change.

Chapter 2

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^oC *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.

2.1 Introduction

Climate change is likely to impact the livelihoods of many of the world's 500 million smallholder farming households [5], particularly with projected increases in drylands populations [60]. Migration represents one of several adaptation strategies that farmers could deploy in the face of climate stress [14], and there is mixed evidence on the extent to which climate change may positively or negatively impact migration flows [15, 36, 38]. Uncertainty regarding future climate adaptation policies [21], including new financial instruments to help poor households cope with natural disasters [25, 61], 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 [36–38], 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 [62], 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 [35, 63, 64].

To address gaps in these methods 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?

ABMs have been deployed to investigate decision-making regarding household adaptation to evolving flood risks [65] and the potential for consequent outmigration [66]. A further body of literature has explored farmer decision-making and economic outcomes under various climate and policy scenarios [67–70]. A subset of these ABMs has explored smallholder farmer migration decisions and dynamic push-pull factors, including changing environmental conditions [20, 35, 71–75]. 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 [20], or conditions in which climate change may decrease planned migration [73]. These and other models also identify other demographic variables that are likely to influence future migration trends, including the response to increased climate stress [71, 74] (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. [20, 69, 73, 75]), 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 [28], 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. [69]), 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. [71, 73]) or extreme shocks [20, 75], 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.

2.2 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. 2.1a). 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 [76, 77]. Along the lines of pattern-oriented modelling [78], 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 [79]. 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 Appendix A 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 [28].

Specifically, household-level economic data collected between 2006-2015 from the Chitwan Valley Family Study (CVFS) in Nepal [29] is used to characterize the mean and variance of income for each strategy (Fig 2.1a). We parameterize farming costs using data on district-level seed and labor costs in Nepal [80], and migration costs reflect an average of low-cost migration to India and high-cost migration to Persian Gulf countries [81]. 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 [82] (Appendix A2.2.1). Data on the distribution of household educational status is collected at the district scale from the Nepali Census [79]. 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 (Appendix A3.3). 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 [83]. To assess the robustness of our conclusions, we conduct a series of sensitivity analyses to key parameters (Section 2.4 and Appendix A3.4), and explore two alternative scenarios that differ based on the degree of climate risk and community risk aversion (Sections 2.4 and 2.5).

2.3 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 2.2 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. 2.2a, 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. 2.2a, right). Because the same strategy options are adopted by most households, the GINI coefficient drops to 0.17.

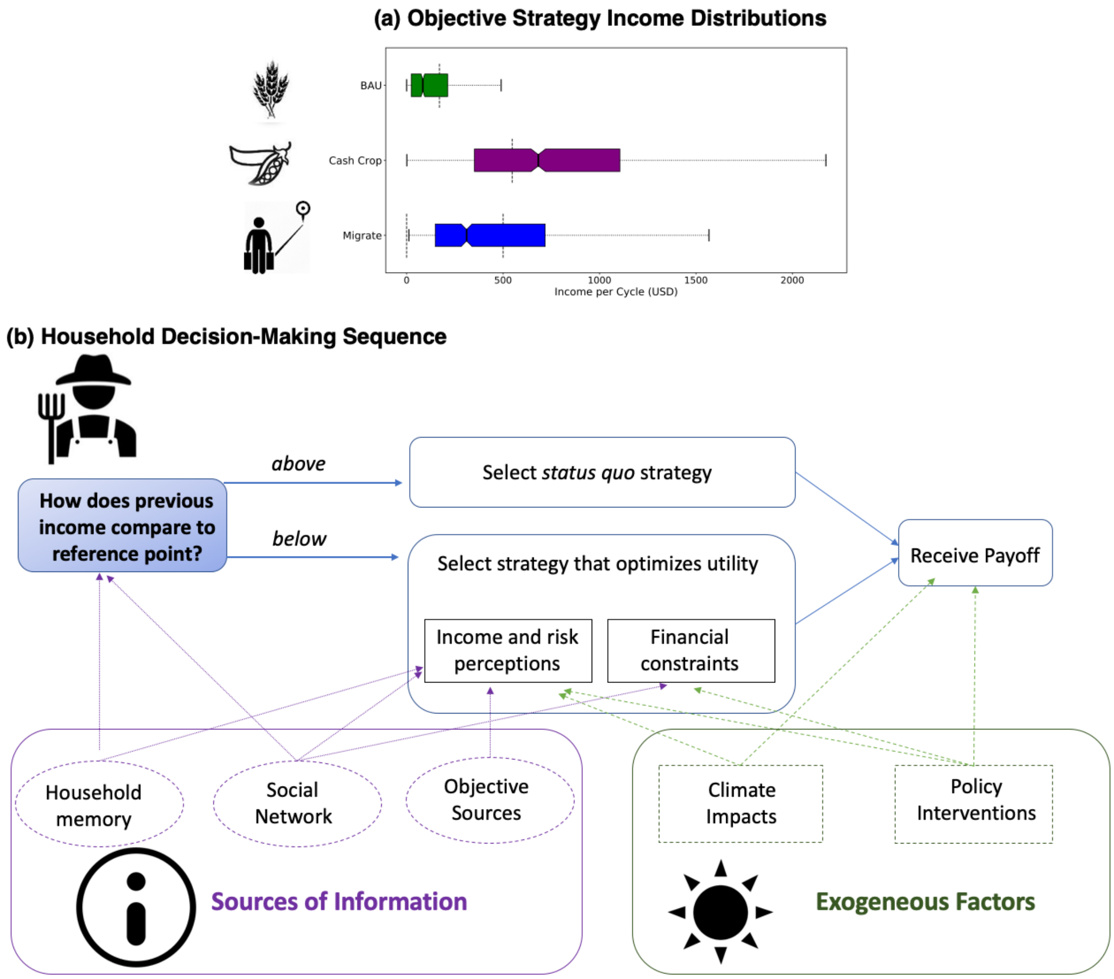


Figure 2.1: Schematic overview of ABM structure. (a) Boxplots indicate the median, interquartile region, and range of income distributions for each strategy. Costs for each strategy are indicated by the dashed vertical lines. For each migration trip, households incur a one-time cost of 500 USD, but then 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.

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. 2.2b, 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. 2.2b, 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. 2.2c, 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 (Appendix A3.3).

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. 2.2d, 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. 2.2d, 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 [37]. 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 2.2d, 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 Appendix A3.4).

2.4 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 [82–84]. 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 (Appendix A3.2). This proportion varies widely for different combinations of risk aversion and degrees of temperature change, from 0 to 50 percent of the community (Fig. 2.3a). Generally, higher values of average risk aversion $\bar{b}$ result in lower migration, as this strategy involves a high degree of income

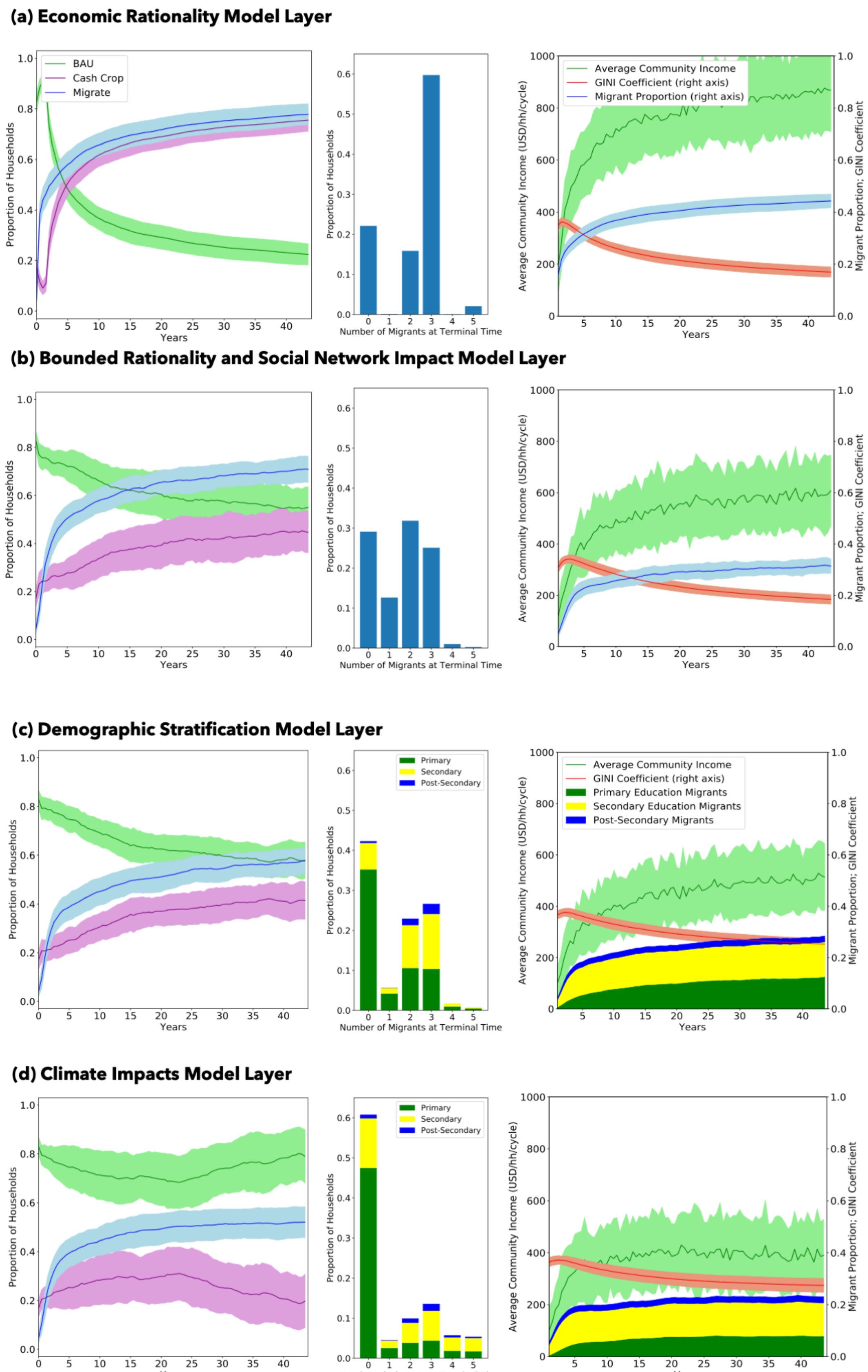

(a) Economic Rationality Model Layer
BAU
Cash Crop
Migrate
Proportion of Households
Years
Number of Migrants at Terminal Time
Average Community Income
GINI Coefficient (right axis)
Migrant Proportion (right axis)
Average Community Income (USD/hh/cycle)
Migrant Proportion; GINI Coefficient
(b) Bounded Rationality and Social Network Impact Model Layer
(c) Demographic Stratification Model Layer
Primary
Secondary
Post-Secondary
Primary Education Migrants
Secondary Education Migrants
Post-Secondary Migrants
(d) Climate Impacts Model Layer

Figure 2.2

Figure 2.2: (Previous page.) **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 $1.5^0 C$ 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.

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. 2.3b). 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 (Appendix A3.6). 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. 2.3b, 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. 2.3b, 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. 2.3b, 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 [36], including climate immobility [15, 85], 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.

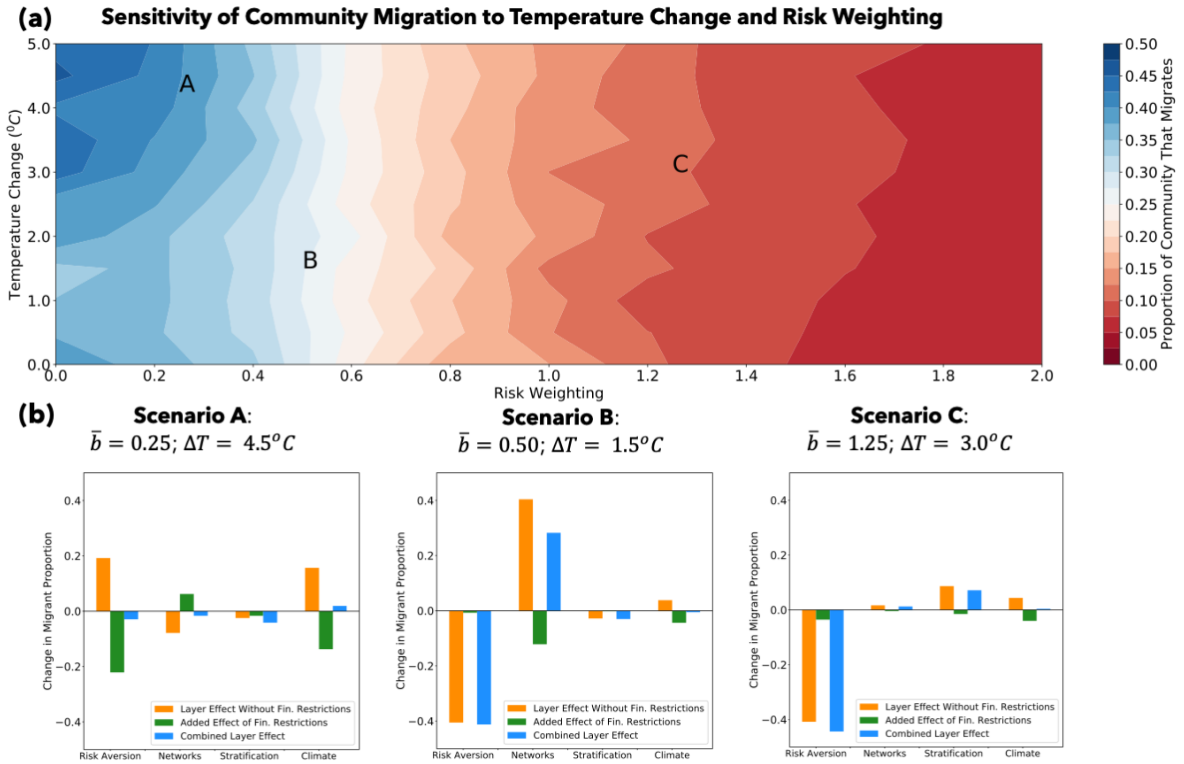


Figure 2.3: Drivers of Migration Outcomes for Different Risk and Climate Scenarios. Adaptation outcomes are driven by complex interactions between financial constraints and several decision-making factors in the model. **(a)** The intersection of different average risk weightings $\bar{b}$ and the degree 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.

2.5 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 [28, 77, 86–88]. 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. 2.4, left panels), inequality as measured by the GINI coefficient (Fig. 2.4, centre panels), the number of households below an immobility threshold (Fig. 2.4, right panels), and overall community migration (Appendix A3.7, Fig. A.11). In Appendix A3.8, 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 Section 2.7 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. 2.4a). 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. 2.5a). By contrast, in Scenario C, the remittance bank is the most effective individual policy in increasing average income while reducing inequality (Fig. 2.4c). 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. 2.5c). In Scenario B, each policy exhibits roughly equal ability to improve community outcomes (Fig. 2.4b). 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 [88], 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 [89]. 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. 2.4, 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 2.4, 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.

2.6 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.

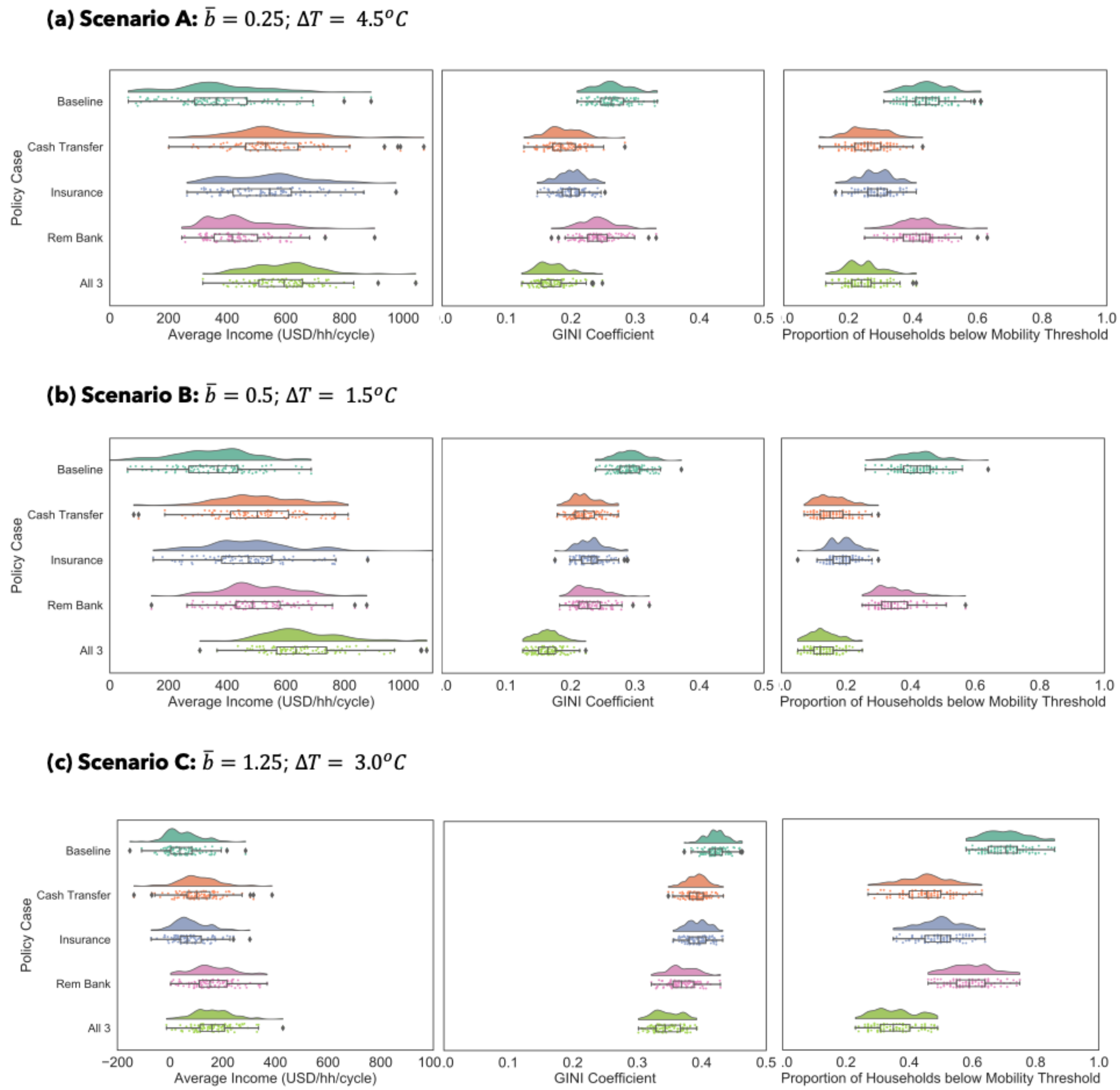


Figure 2.4

To promote resilient livelihoods, policymakers must account for non-linear interactions between these factors.

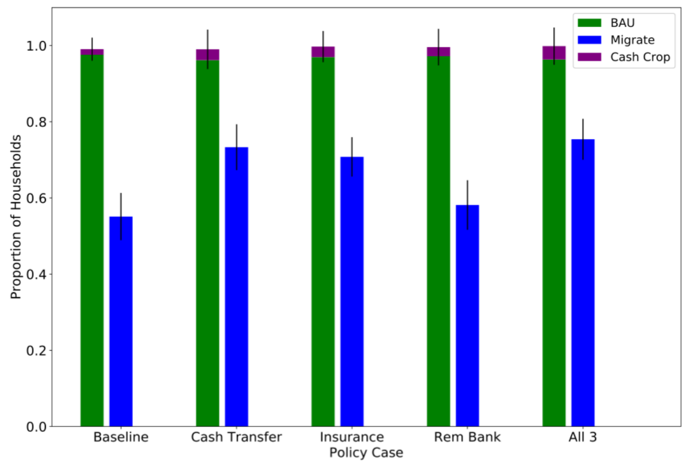
Through a novel agent-based model, we illustrate how future climate impacts, absent any policy intervention, are likely to reduce average household incomes and increase inequality among smallholder farming households in South Asian contexts. Climate

Figure 2.4: (Previous page.) **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.

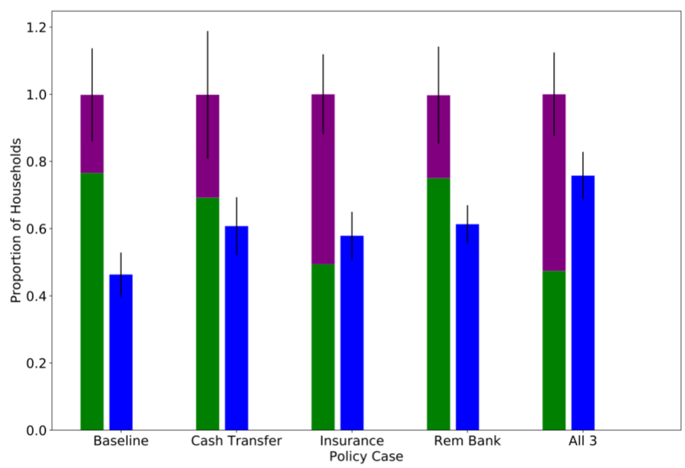
change directly reduces incomes through diminished crop yields and increased frequency of extreme droughts, which affects all households who maintain farming livelihoods. Indirectly, increased climatic stress also restricts the range of higher-cost, higher-reward livelihoods that households may deploy, 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 [15, 90] 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

a) $\bar{b} = 0.25;\ \Delta T = \ 4.5^{o}C$



b) $\bar{b} = 0.5;\ \Delta T = \ 1.5^{o}C$



c) $\bar{b} = 1.25;\ \Delta T = \ 3.0^{o}C$

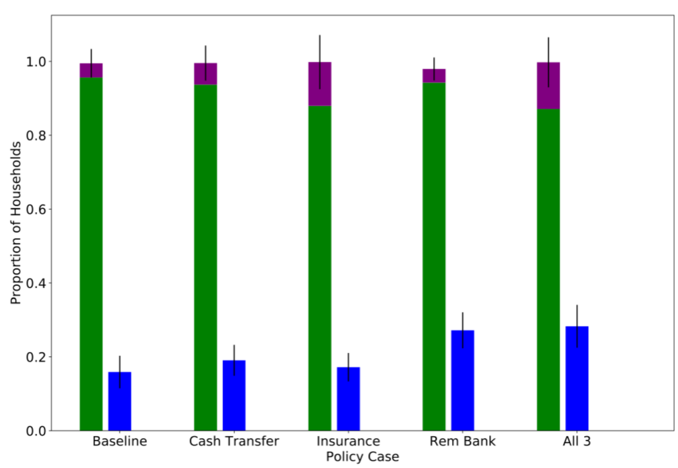


Figure 2.5

Figure 2.5: (Previous page.) **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.

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 [38]. 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 [91]. 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 [92]. 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 [93].

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 [94] 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.

2.7 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

$$U(\mu_{\pi,ik}(t), \sigma_{\pi,ik}(t)) = \mu_{\pi,ik}(t) - b_i \cdot \sigma_{\pi,ik}(t)\,, \tag{2.1}$$

with $\mu_{\pi,ik}(t) = \mathbb{E}[\pi_{ik}(t)]$ and $\sigma_{\pi,ik}(t) = \sqrt{\mathbb{E}\left[(\pi_{ik}(t) - \mu_{\pi,ik}(t))^2\right]}$ 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 [95, 96], and is consistent with NELM, in which households are concerned with minimizing risks to income [12, 76, 77].

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

$$\underset{k}{\text{argmax}} \quad \sum_{s=t}^{s=t+h} \frac{U\big(\mu_{\pi,ik}(s), \sigma_{\pi,ik}(s)\big)}{(1+\rho)^{s-t}} \tag{2.2}$$

$$\text{s.t.} \quad C_{ik}(t) \leq S_i(t)\,, \tag{2.3}$$

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 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 $I_{i\text{CashCrop}}$, 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 $C_{i\text{Migrate}}$, 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 [29]. 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 [80], and Migrate strategy costs are approximated as an average of migration costs from Nepal to India and Gulf countries [81].

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 (Appendix A2.1). 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 [12], 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 Appendix A2.1.

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 [97] 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 $\mathcal{K}$. 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 [12, 13, 77]. 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 [98]. 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 (Appendix A2.2.1).

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 [99], 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 (Appendix A2.2.2).

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 [11]. 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 [100, 101]. Appendix A2.2.2 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 [102, 103], and assumptions regarding these variables significantly impact projections regarding the future composition of societies [104]. 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 [104]. Educational levels are assigned based on data from the 2011 Nepal Population and Housing Census [79]. 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), [105]; Risk weighting factor, b_i (negative correlation) [106, 107]; and weight given to public information on strategy payoffs, ω_i (positive correlation) [108]. Table A3 in Appendix A2.3 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 [4, 5]. We do this by introducing two related climate phenomena: the effect of long-term change in mean temperature on crop yields [4, 109–112], and the impacts of increasing frequency of extreme events (e.g. droughts) on crop yields [112–114]. 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 [115]. 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 [4]. 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 Appendix A2.4).

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 [112–114, 116]. 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 [117]. 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 Appendix A2.4.

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 Layer 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 [87, 118] and also roughly equivalent to the current levels of government subsidies for index insurance [119].

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 Layer 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

$$L_k(t) = \mu_{I,k,\text{nd}}(t) - \mu_{I,k,\text{d}}(t)\,, \tag{2.4}$$

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 [119].

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

$$C_{k,\text{pr}}(t) = p_{k,\text{d}}(t) \cdot L_k(t) - I_{\text{subs}}\,, \tag{2.5}$$

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 $p_{k,\mathrm{d}}(t)$ 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

$$\tilde{\mu}_{I,k}(t) = (1 - p_{k,\mathrm{d}}(t)) \cdot \mu_{I,k,\mathrm{nd}}(t) + p_{k,\mathrm{d}}(t) \cdot \big(\mu_{I,k,\mathrm{d}}(t) + L_k(t)\big) = \mu_{I,k,\mathrm{nd}} \tag{2.6a}$$

$$\tilde{\sigma}_{I,k}(t) \approx (1 - p_{k,\mathrm{d}}(t)) \cdot \sigma_{I,k}(t)\,, \tag{2.6b}$$

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 Appendix A2.5.

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 $\rho_{\mathrm{rem}} = 0.25$). 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

$$
\begin{aligned}
R_{i,\text{dep}}(x_i, t) &= \rho_{\text{rem}} \cdot R_i(x_i, t) \\
R_{i,\text{po}}(x_i) &= \rho_{\text{rem}} \cdot \mu_R(x_i)\,,
\end{aligned}
\tag{2.7}
$$

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

$$
\begin{aligned}
\tilde{\mu}_R(x_i, t) &= (1 - \rho_{\text{rem}}) \cdot \mu_R(x_i) + \rho_{\text{rem}} \cdot \mu_R(x_i) = \mu_R(x_i) \\
\tilde{\sigma}_R(x_i, t) &= (1 - \rho_{\text{rem}}) \cdot \sigma_R(x_i)\,,
\end{aligned}
\tag{2.8}
$$

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.

Chapter 3

Pro-Social Preferences Improve Climate Risk Management in Subsistence Farming Communities

In preparation as: N. Choquette-Levy*; M. Wildemeersch*; F.P. Santos; S.A. Levin; M. Oppenheimer; and E. Weber (2022). Pro-social preferences improve climate risk management in subsistence farming communities.

Abstract

Several governments have piloted formal index-based insurance as a tool to build climate resilience among smallholder farmers. Yet, adoption of such programs has generally fallen short of expectations and generated concerns that insurance may crowd out long-established informal risk transfer arrangements. Here, we develop an evolutionary game theory framework, with empirical data from Nepal and Ethiopia, to demonstrate that insurance *may introduce a new social dilemma in risk management strategies deployed by smallholder farmers. We find that while farmers enjoy more robust protection against climate risks if all community members pursue a combination of formal and informal risk transfer, a community of self-interested agents is unable to maintain this coexistence at moderate-high covariate risks due to free-riding concerns. We also find that a combination of pro-social preferences - namely, moderate altruism and solidarity - are able to promote socially optimal risk management strategies more efficiently than either preference in isolation. Behavioural interventions that cue such preferences can offer a "pro-social dividend", rendering financial incentives (e.g. premium subsidies) more efficient in promoting optimal risk management.*

3.1 Introduction

Rising climate risks threaten the livelihoods of many of the world's 500 million smallholder farmers [5], the vast majority of whom lack financial protection against climate-driven agricultural losses [120]. To cope with the risks of droughts, floods, and heat waves, development agencies and several national governments have piloted formal risk-transfer mechanisms, such as index-based crop and livelihood insurance [43–45]. Whereas indemnity insurance generally entails high administrative costs to accurately measure specific losses suffered by individual policyholders, index insurance ties payouts to an exogenous indicator that measures seasonal weather variables and/or crop yields at a regional scale. If such an index is breached, all policyholders in a given region receive a pre-specified payout, foregoing the need to assess individual damages and reducing costs. As climate-driven risks to rural livelihoods increase in coming decades [1], index insurance programs may therefore be a promising tool for climate adaptation.

Yet, initiatives to promote index insurance are often deployed in contexts in which subsistence farming communities have already developed informal mechanisms to manage long-standing livelihood risks [9**?** , 10]. These mechanisms include intra-household strategies, such as diversifying household income streams through migration remittances [12, 121], and community-wide risk transfer mechanisms, e.g. informal lending and revenue-sharing cooperatives [46–48]. However, although informal mechanisms are effective in reducing idiosyncratic risks, they may exhibit diminished capacity to protect livelihoods in the face of rising climate-driven covariate risk [122].

Recent literature has sought to understand the potential for new index insurance programs to either serve as complements (i.e. "crowd in") or substitutes (i.e. "crowd out") to informal community risk transfer mechanisms [123]. Experimental studies of index insurance pilot programs in India [49] and Ethiopia [46–48] demonstrate that formal insurance and informal lending can serve as complementary mechanisms, especially for lending among relatives or close neighbours [48], and if basis risk is high (i.e. a high potential mismatch between a climatological index and actual damages experienced by a policyholder) [49]. However, these studies were only able to exploit data over short time frames (1-2 years). Theoretical frameworks exploring these interactions suggest that while index insurance and informal revenue transfers may initially serve as complements, over the long term, insured households may be tempted to reduce or even abandon their commitments to informal revenue transfers [50], unless some form of peer monitoring is able to enforce them [41]. Such findings indicate that self-interested agents acting strategically may not be able to reach a socially optimal outcome without some form of coordination [40].

Yet, a growing body of empirical evidence suggests that observed levels of human cooperation cannot be explained by completely self-interested, *homo economicus* preferences [124–126]. In particular, Fehr and Shurtenberger identify fundamental mechanisms, including an intrinsic desire for equity, the desire to reciprocate others' behaviour, and self-image as a pro-social actor, that may compel individuals to comply with social norms, even when doing so impinges on their material self-interest [126]. In a similar vein, Alger and Weibull demonstrate that a combination of selfishness and morality (the desire to "do the right thing") is an evolutionary stable preference [127, 128]. Additionally, direct experimental and empirical evidence indicates that altruism - the consideration of others' well-being in an individual decision-maker's objectives - plays a significant role in shaping inter-household risk transfer in rural farming communities [129, 130]. Together, such frameworks and evidence call for the incorporation of more realistic alternatives to purely rational, self-interested preferences in the emergence of cooperative behaviour [131].

Our aim in this analysis is to provide an expanded framework by which governments, non-governmental organizations, and insurance agencies can evaluate policy strategies to promote insurance uptake while mitigating the potential of crowding out informal risk-sharing arrangements. In this regard, we investigate the role that alternative decision-making preferences may play in the ability of a smallholder farming community to maintain socially optimal risk management strategies under various levels of climate risk. Specifically, we address four research questions. First, what are the implications of different risk management strategies on long-term community development outcomes, including average community income, inequality, and poverty rates? Second, do different levels of climate-driven covariate risk affect whether formal index insurance is likely to crowd out and/or complement informal revenue-sharing as a long-term risk management strategy? Third, how do alternative economic preferences affect the risk management choices that emerge from farming communities? Fourth, how might financial and informational policies aimed at promoting various climate adaptation strategies affect the risk management equilibria?

Second, we investigate how different assumptions about behavioral and economic preferences alter predicted levels of farmer cooperation on risk transfer mechanisms. Here, we focus on the role of moral values in decision-making and are especially interested in comparing equilibria states of (in)formal risk sharing adoption under three different types of utility functions self-interested, altruistic, and solidarity-based. Traditionally, game theoretic approaches assume households act out of self-interest (*homo economicus*); consequently, the Nash equilibria in most situations tend to predict lower-than-optimal levels of cooperation. However, there is evidence that at least some decision-makers may act out of altruistic concern for others' welfare, particularly in small and/or tight-knit communities e.g. smallholder farmer villages, which promotes higher levels of cooperation [39, 125]. In this alternative utility function, an agent incorporates the effect of his or her strategy choice on others in the community, whereas a self-interested agent would not consider such externalities. As well, recent work in economics has formalized a *homo moralis* worldview [127], in which agents seek to maximize their own utility, including the probability that others in their community will follow suit. Such preferences may help explain observed pro-social behaviour, particularly an individual decision may appear costly and insignificant in achieving a common goal, such as in taking a pro-environmental action, or some other contribution to a public good.

To address these questions, we develop a novel game theoretic framework that integrates empirical data from South Asian and East African farming contexts to investigate household decision-making on risk management strategies under climatic uncertainty.

In this framework, household strategies are determined via three binary decisions that represent different scales of risk management: whether to diversify livelihoods through migration, participate in an informal community revenue sharing pool, and purchase index insurance (see Section 2 and Methods for more details). We apply this model to different risk scenarios to investigate the conditions under which informal, formal, or both types of risk management strategies emerge as a result of strategic decision-making by individual farming households. We also assess model results under different assumptions about agents' economic preferences to explore how pro-sociality and policy interventions may impact the strategies that emerge at equilibrium.

Through this work, we make three contributions at the intersection of emerging literatures on risk management, climate adaptation, and cooperation. First, we expand the conditions under which the relationship between formal insurance and informal revenue-sharing is examined, paying specific attention to how this relationship changes under different degrees of covariate risk, migration options, and economic preferences in subsistence farming communities. Second, we evaluate the relevance of two distinct preferences, altruism and solidarity, that work in concert to promote pro-social outcomes, and assess the degree to which these preferences may change predicted levels of co-existence between formal and informal risk management. Third, we evaluate the efficacy of both financial-based policy incentives to promote desired risk management decisions, and informational-based campaigns that may help shape decision-making preferences.

3.2 Risk management choices under bounded rationality and different social preferences

The core question underpinning this study is to find what risk management strategies are likely to emerge in a community of subsistence farmers, each making strategic decisions in response to those of their peers. We consider an agricultural community where farmers choose between different risk management strategies at three different scales. We consider (i) intra-household risk transfer: whether to exclusively farm, or combine farming with rural-urban migration, (ii) informal risk transfer: whether to take part in a revenue-sharing pool at the community scale, and (iii) formal risk transfer: whether to purchase index insurance covering households at the regional scale. We set up a population game based on evolutionary game theory to improve our understanding of how strategy choices change over time as an outcome of repeated interactions across a large population of agents that simultaneously make strategic decisions [132]. The population game allows for the integration of bounded rationality. For example, households can imitate the strategic choices of peers who are receiving higher utility, rather than being fully rational and optimizing their actions. Further background on evolutionary game theory is provided in Appendix B1.1.

In our model, farmers evaluate strategies based on a utility function that accounts for risk aversion, loss aversion, and time discounting, based on established theories of decision-making under uncertainty [98]. Borrowing from the New Economics of Labor Migration (NELM) [76, 121], agents in the model seek to improve expected profits while minimize the volatility of their income streams. In addition to penalizing income volatility, agents in our model also exhibit loss aversion; i.e. they assign a higher penalty to perceived losses than the benefits experienced from gains of a similar magnitude. This is especially relevant in the context of insurance decisions, in which one of the most salient motivations is to protect against a possible loss [133, 134]. Agents considering migration strategies exponentially discount expected future remittance income relative to immediate migration costs, and also apply loss aversion to these costs. Finally, agents in the evolutionary game seek to minimize perceived gaps between their well-being and that of their peers, which echoes findings from NELM and the importance to decision-makers of meeting basic aspiration levels from the Security-Potential/Aspiration framework [135].

We investigate how social preferences affect the share of chosen strategies in the population. Here, we examine the consequences of two different types of prosociality: (i) altruism, which includes the utility of peers in the evaluation of personal utility, and (ii) solidarity, which incorporates the awareness that partial cooperation is necessary to improve collective outcomes. These are parameterized through α and κ, which each range from 0-1 and indicate the respective weights of altruism and solidarity in agent utility functions (Methods). We assume these preferences are homogeneous throughout the population and remain stable over the modelled timeframe, though we assess sensitivities of equilibrium strategy outcomes under different combinations of pro-social preferences (Section 3.3.3).

Existing informal risk management strategies are limited in their capacity to address covariate risks (in the case of this analysis, drought risk) affecting an entire community at once. Here, we use the base-level correlation between household farming incomes before any risk management strategies are applied, ϱ, and drought probability p to create three risk scenarios of covariate risk: Low ($p = 0.2$, $\varrho = 0.1$), Medium ($p = 0.35$, $\varrho = 0.35$), and High ($p = 0.6$, $\varrho = 0.5$). Note that a higher covariate drought probability also implies a higher farming income correlation, hence the increase in ϱ for higher risk scenarios.

The Low risk parameters are a composite of the lowest observed drought risk and income correlations from the two considered regions (Nepal's Chitwan District and the Borena region in Ethiopia), and likely serve as a lower bound of covariate risk in most subsistence farming contexts, given the prospect of increased frequency of extreme events as a result of global climate change [1]. By contrast, the Medium risk scenario is parameterized using the highest drought risks and income correlations observed from the considered regions (Appendix B1.4). We focus on results from this scenario in the main text, as it likely best describes the types of risks that farmers in both the Chitwan District and Borena region will face in the coming 1-2 decades. Finally, the High risk scenario is a speculative case of a context where climate-driven risks have substantially increased, and also led to higher correlation among household incomes. We establish this as a potential upper bound of covariate risk in which insurers may still wish to offer formal index insurance, and also conduct sensitivity analyses of equilibrium strategy choices to both drought risk and income correlation.

Governments may intervene in multiple ways to shape incentives for household risk management decisions. For example, several national governments are already experimenting with various levels of subsidies for insurance premiums, in order to encourage uptake of new index-based insurance products [46, 47, 120]. Alternatively, policymakers may also wish to overcome information asymmetries between households and governments or insurance agencies. This can for instance be achieved by releasing aggregate information about risk management preferences and choices in a community. Making this type of information observable may enable households to more easily coordinate on strategies that contribute to well-being, but might otherwise be subject to free-riding concerns [136, 137].

3.3 Results

3.3.1 Combining Formal and Informal Risk Transfer Provides More Robust Protection to Drought Risks

Identifying an optimal risk management strategy for subsistence farming communities is complex and involves tradeoffs between multiple objectives at multiple scales of decision-making. As a first-order approximation, we compare the collective-scale outcomes of farming communities pursuing monomorphic strategies (i.e. boundary cases in which all households in a community opt for the same strategy) for the four strategy options involving migration. As shown below, most equilibrium outcomes that arise from strategic interactions between farming households fall into one of these monomorphic cases. We include a comparison of strategies without migration in Appendix B2.4.

The collective-scale implications of these strategy options are measured against three development outcomes: average community income, inequality (measured by the GINI coefficient), and poverty rate (measured by the World Bank threshold of an income of less than 1.90 USD/household/day). Specifically, we simulate how a community of 100 households deploying the same risk management strategy would fare if each household received a random income draw, given a specified drought risk, p, and base correlation between household incomes, ρ based on the Risk scenarios described in Section 2. We repeat these simulations for each of four strategies - FarmMigrate, FarmMigrate+Share, FarmMigrate+Insurance, and FarmMigrate+Share+Insurance. As individual income draws and the occurrence of droughts are stochastic, we conduct 1000 simulations for each combination of drought risk and strategy to generate an overall distribution of these development metrics. The resulting distributions, including means, median, ranges, and skewness, may be interpreted as the plausible properties of outcomes for one community across many cropping cycles.

Our results indicate that layering formal and informal risk transfer effectively shields farming communities against extreme outcomes in drought cropping cycles, although it entails trading off positive outcomes in non-drought cycles (Fig. 3.1). Generally, community incomes may range widely from one cropping cycle to the next, especially between drought (green) and non-drought (orange) cycles (Fig. 3.1, a-c). As risks increase (left-right), the mean income for any given cropping cycle decreases, from a mean of 637 USD/cycle under Low Risk to 509 USD/cycle under High Risk. This 20 percent decrease stems from both a higher proportion of time spent in drought years and slightly worse income in non-drought years. While risk management options do not change the expected income across cropping cycles, formal insurance in particular reduces downside risks to income during drought years, including cycles in which the mean community income falls below the poverty line (dashed line). Combining formal insurance with informal revenue-sharing further reduces this collective-scale volatility, at the expense of foregoing the potential for high community incomes (e.g. an average greater than 700 USD/cycle) in non-drought years (final column of each panel).

The combination of informal and formal risk transfer also limits inequality over long time horizons (Fig. 3.1, d-f). Without any risk transfer, increased climate risks drive higher inequality, from an average GINI of 0.245 under Low Risk to 0.275 under High Risk. Again, this trend reflects a higher frequency of droughts and the high inequality in such occurrences, absent any risk transfer mechanisms (average GINI = 0.32). Droughts drastically reduce all households' farming incomes, which leaves them mostly dependent on highly-variable migration remittances. In any given year, some households earn a high amount of remittances, while most households earn moderate to low remittances.

Risk transfer mechanisms, particularly the combination of formal and informal options, attenuate this inequality, especially for Low-Medium risk levels. However, as risk levels increase, costlier premiums lead to greater inequality in non-drought years compared to strategies without formal insurance. Here again, household revenues are increasingly composed of highly-variable remittances, as most farming revenues are used to pay for high premiums. Subsistence communities therefore face a tradeoff between protecting against extreme inequality in drought years through a combination of risk layering, and accepting slightly higher inequality in non-drought years.

The tradeoffs inherent in deploying risk transfer mechanisms are most apparent in evaluating poverty rates (Fig. 3.1, g-h). In the absence of any such mechanism, an increase in risk from the Low to High scenarios substantially increases the mean poverty rate, from 39.4 to 50.6 percent of the community, representing a 28 percent increase in poverty. Without formal insurance, droughts are particularly damaging for raising poverty levels (an average of 64 percent of households fall under the poverty threshold in drought years under High Risk). Deploying formal insurance attenuates poverty rates in drought years at all risk levels; however, insurance premiums increase the proportion of households falling into poverty during non-drought years, relative to the absence of such mechanisms. Pairing insurance with informal revenue-sharing can help mitigate this effect by allowing for some inter-household income transfers, but its efficacy declines as income correlation increases. Consequently, at Medium and High risk levels, mean poverty rates are actually slightly higher if a community adopts insurance with unsubsidized premiums, relative to risk management strategies without insurance. Still, such mechanisms may be preferable if a community wishes to avoid extremely high poverty levels in any given cropping cycle.

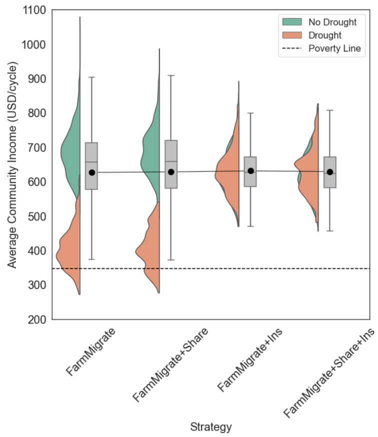
While formal and informal risk transfer leads to complex tradeoffs at the collective scale, the benefits of layering these mechanisms are evident at the individual household scale (Fig. 3.2). Here, we focus on the Medium risk level as a focal case, reflective of current drought risk conditions in Nepal and potential future risks in Ethiopia (Appendix B1.5), and include analyses of the Low and High risk levels in Appendix B2.2. By construction, all four risk management strategies involving migration lead to the same expected income (Fig. 3.2a, blue bars, and Fig. 3.2b, left column), but layering formal insurance and informal revenue-sharing slightly lowers income volatility across cropping cycles (Fig. 3.2a, orange bars, and Fig. 3.2b, middle column). Most significantly, pairing these two mechanisms substantially lowers the expected loss incurred by farming households (Fig. 3.2a, purple bars); household income losses in communities that deploy both formal insurance and informal revenue-sharing are on average 60 percent those of losses in communities without either risk transfer mechanism, and significantly better than either mechanism on its own (Fig. 3.2b, right column). Insurance helps mitigate covariate household losses in drought years, and informal revenue-sharing reduces expected losses from idiosyncratic shocks in non-drought years. Therefore, pairing formal insurance and informal revenue-sharing would be the optimal monomorphic strategy for households that are both risk-averse (i.e. wishing to avoid income volatility) and loss-averse (i.e. wishing to avoid strong losses).

The combination of formal and informal risk transfer generally reduces extreme outcomes and leads to more stability in both collective and household-level outcomes. This is because such mechanisms counteract income correlation between households, and transfer some income from non-drought to drought years. In identifying this as a socially optimal outcome, we assume that subsistence community leaders and household decision-makers are generally risk- and loss-averse, have the luxury of evaluating outcomes over long time horizons, and care equally about the welfare of each member of the community. However, in some situations, policymakers may wish to gamble on maximizing outcomes over a short time horizon, and/or favour the well-being of a particular societal group, thereby preferring the absence of risk transfer mechanisms. For example, this may especially be the case in governance systems that are based on "competitive federalism", in which local policymakers are evaluated against each other for promotions, often over short time scales, a limited set of outcome metrics, and a specific subset of the population [138].

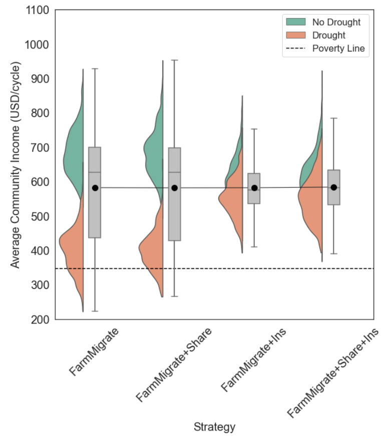
3.3.2 Strategic Interactions among Households Lead to Risk Management Dilemma

Having analyzed implications of risk management strategies for collective and individual outcomes, we next assess which strategies are likely to emerge as a result of strategic interactions between self-interested agents. As index insurance programs are still relatively unknown in most subsistence farming communities [44, 120], we first examine which strategies emerge in the absence of formal insurance, and then assess how the introduction of formal insurance may affect this distribution of strategies. We are especially interested in understanding whether different risk management strategies emerge as households face different degrees of climate risk to their farming incomes.

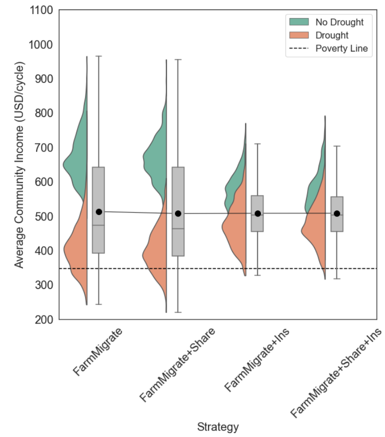
As a general principle, we find that the co-existence of formal index insurance and informal revenue-sharing can emerge under low levels of covariate risk (Fig. 3.3a-b, $0.0 < p < 0.23$, $0.0 < \rho < 0.8$). In this region, it is in farmers' own self-interest to both purchase insurance and participate in a revenue-sharing cooperative. Despite the low degree of covariate risk, farmers' loss aversion motivates the purchase of insurance to avoid losses in drought years, and risk aversion motivates farmers' participation in income-sharing cooperatives to reduce volatility in both drought and non-drought years. This leads to a stable equilibrium point of 100 percent of the population playing the



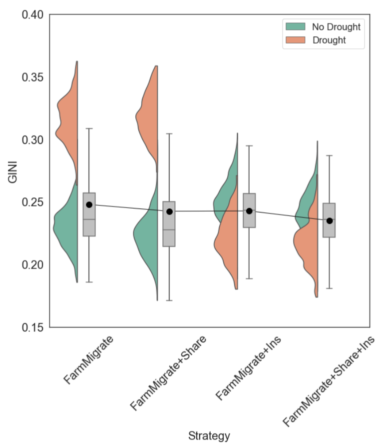
(a) Low Risk; Income



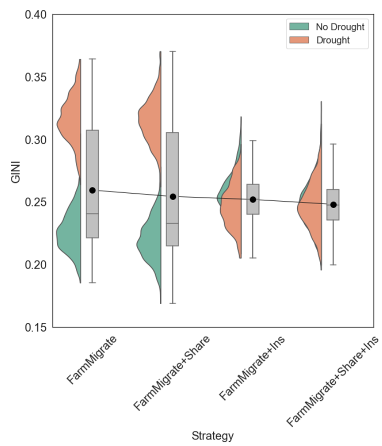
(b) Med Risk; Income



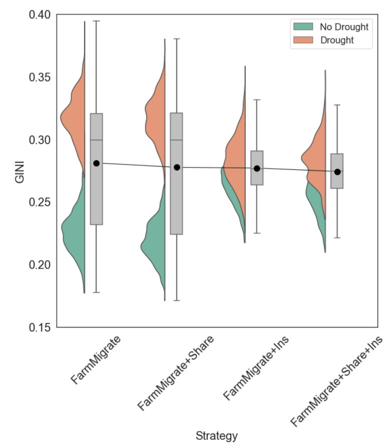
(c) High Risk; Income



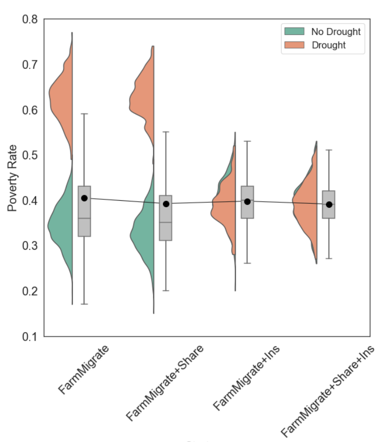
(d) Low Risk; GINI



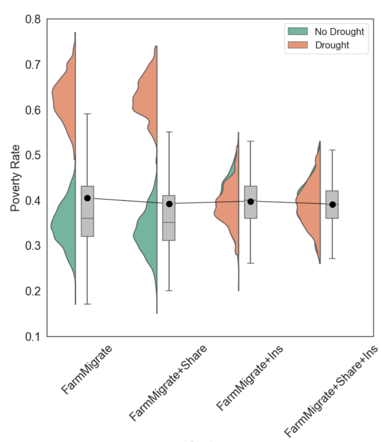
(e) Medium Risk; GINI



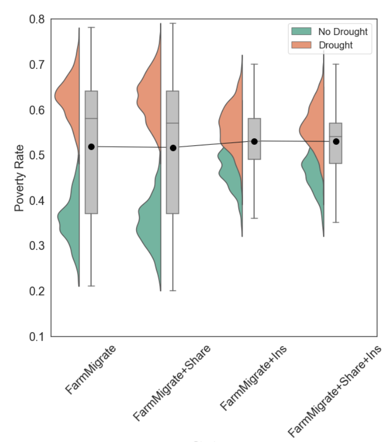
(f) High Risk; GINI



(g) Low Risk; Poverty Rate



(h) Med Risk; Poverty Rate



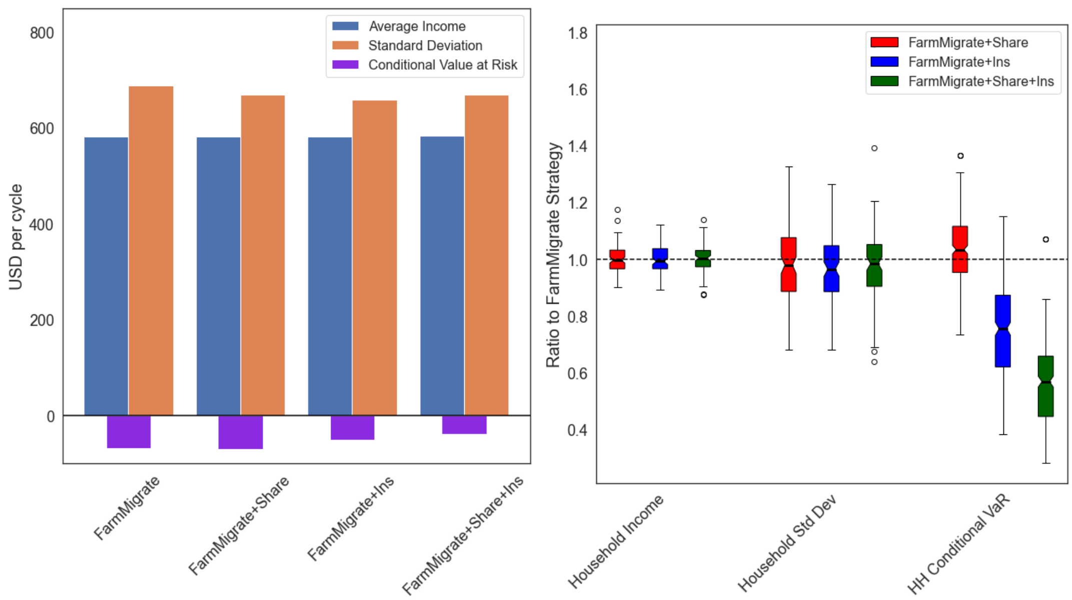
(i) High Risk; Poverty Rate

Figure 3.1

Figure 3.1: (previous page) **Community Outcomes for Monomorphic Risk Management Strategies.** 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 (top row), GINI coefficient (middle row), and poverty rate (bottom row) are shown for four monomorphic strategies under three risk levels (left-right: Low, $p = 0.2$, $\rho = 0.1$; Medium, $p = 0.35$, $\rho = 0.35$; High, $p = 0.6$, $\rho = 0.5$). 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 the results from one simulation, averaged over the 100 households. Distributions are shown separately for outcomes in drought years (green) and non-drought years (orange), with boxplots summarizing the total distribution (drought and non-drought years). Black dots connected by the line plot indicate mean values for each strategy.

FarmMigrate+Share+Insurance strategy (Fig. 3.3c), which is stable to individual attempts to free-ride by foregoing either insurance purchases or contributions to the cooperative (Fig. 3.3b). We find that such an equilibrium would typically be reached after approximately 20 years, with an intermediate stage in which the majority of farmers first purchase formal insurance before also re-engaging in a revenue-sharing cooperative (Fig. 3.3f).

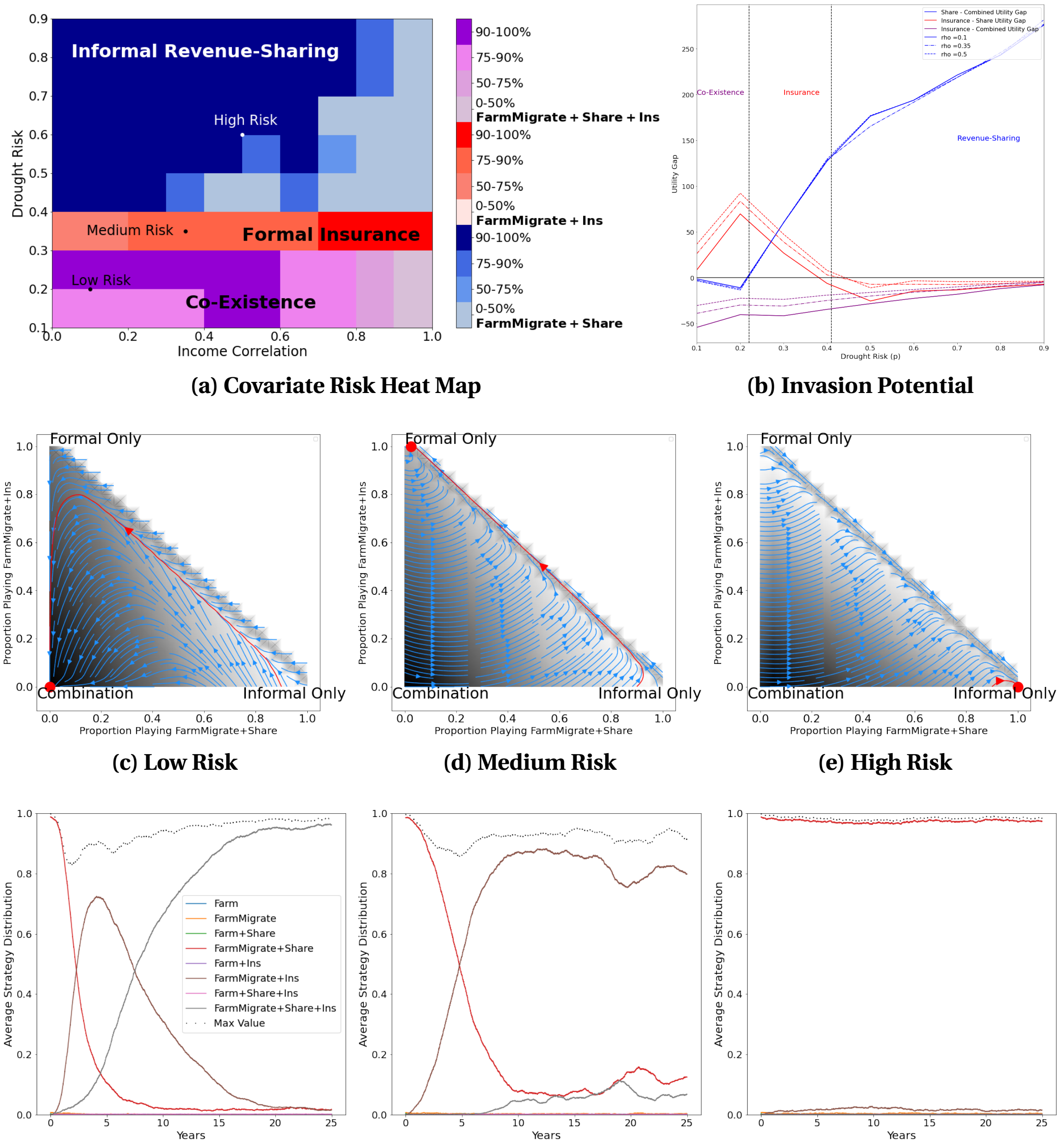
As covariate risks increase to moderate levels, the co-existence of formal insurance with informal revenue-sharing cooperatives becomes increasingly tenuous, with formal insurance emerging as the dominant form of risk management (Fig. 3.3a). If the majority of households in a revenue-sharing cooperative forego purchase formal insurance, other self-interested participants will benefit from the stable income that insured members contribute, and will have less of an incentive to purchase insurance themselves. As drought risks increase, the positive externality of one household's insurance purchase on the rest of the pool increases; at the same time, the cost of purchasing insurance also increases with the expected loss. This social dilemma drives a collapse in the co-existence of formal and informal risk management at a threshold of approximately $p = 0.23$ (Fig. 3.3b). For the region of moderate drought risk and/or high income correlation (e.g. the Medium Risk scenario), households leave the informal revenue-sharing pool within 5-10 years after



(a) Utility Decomposition, Aggregate **(b) Utility Decomposition,Relative**

Figure 3.2: Decomposition of Household Utility Components. Individual household strategy decisions are governed by a utility function that incorporates expected income, volatility (measured as standard deviation), and potential losses, expressed as the conditional value at risk. Here, we decompose household utilities into these three components for four monomorphic strategy distributions (i.e. every household adopting the same strategy). The average household income, standard deviation, and loss are displayed **a)** in absolute terms and **b)** relative to the FarmMigrate strategy. Results are generated by simulating random income draws for 100 households adopting the specified strategy over 1000 cycles. In **b)**, each point in the boxplot represents a value for one household, averaged over 1000 simulations. While average incomes are almost identical across the four monomorphic strategies, median volatility is slightly lower for all strategies that incorporate some form of risk transfer, and losses are significantly lower for strategies incorporating insurance. In particular, the combination of informal revenue-sharing and insurance substantially reduces losses compared to the other strategies.

insurance is introduced, and mostly rely on their own purchases of formal insurance as the main risk management strategy (Fig. 3.3d,g). Under high income correlation, the revenue-sharing pool is relatively ineffective in managing risks, as all participants are likely to contribute low income during drought years.



(a) Covariate Risk Heat Map **(b) Invasion Potential**

(c) Low Risk **(d) Medium Risk** **(e) High Risk**

(f) Low Risk **(g) Medium Risk** **(h) High Risk**

Figure 3.3

For the region of high covariate risk, households stay in the revenue-sharing pool but do not purchase formal insurance (Fig. 3a). Under drought risks $p > 0.4$, insurance premiums are now sufficiently costly (> 97 USD/cycle) that households would perceive a greater loss from purchasing insurance compared remaining uninsured, even though

Figure 3.3: (previous page) **Equilibrium Risk Transfer Strategies for Self-Interested Farmers.** In communities of purely self-interested farmers, co-existence of formal and informal risk management can emerge at low covariate risk, but collapses at higher levels of risk. **(a)** We assess which risk management strategies are most likely to emerge as a function of farm income correlation (x-axis) and drought risk (y-axis). Colours indicate the the most common strategy at terminal time (averaged over 100 simulations), with gradations indicating the percent of the population adopting this strategy. **(b)** The stability of a co-existence equilibrium depends in large part on drought risk (p). For $p < 0.23$, the marginal utility of combining both insurance and revenue-sharing is greater than either insurance (purple line) or revenue-sharing (red line) alone. From $0.23 < p <\approx 0.4$, an individual household derives higher utility from free-riding off of others' insurance purchases, causing the co-existence of both mechanisms to collapse. However, the marginal utility of purchasing insurance is higher than that of relying on revenue-sharing alone (blue line), leading to an equilibrium of formal insurance. At higher drought risks ($p > 0.4$ for $\rho = 0.35$), the utility of insurance becomes less than that of revenue-sharing due to high premiums, leading to an equilibrium of informal revenue-sharing alone. **(c-e)** For three risk scenarios, utility gradient plots identify the equilibrium points (red dots) between the three most common risk management strategies: FarmMigrate+Insurance, FarmMigrate+Share+Insurance, and FarmMigrate+Share. Each point in the triangle represents the distribution of households according to the proportion playing FarmMigrate+Share (x-coordinate), FarmMigrate+Insurance (y-coordinate), and the remainder playing FarmMigrate+Share+Insurance. Blue arrows indicate the incremental direction of highest utility and grey shading indicates the aggregate utility of the population (darker grey = higher utility) for the given distribution of strategies. **(f-h)** Here, we illustrate the dynamics of households choosing between the eight different risk management options as a function of the distribution of strategies in the population. Proportions represent the average across 100 simulations with stochastic mutations and initial conditions.

their utility would still be maximized if everyone combined insurance and informal revenue-sharing. Thus, households are left with participating in informal revenue-sharing cooperatives as the equilibrium risk management strategy (Fig. 3.3e). However, such mechanisms are especially ineffective under conditions of high climatic risks: in most years, the revenue-sharing pool will have few contributions as its members suffer covariate climate shocks. This parameter space can therefore be viewed as a region of limits to adaptation - without policy intervention, subsistence farming communities would find it difficult to organize effective risk management strategies.

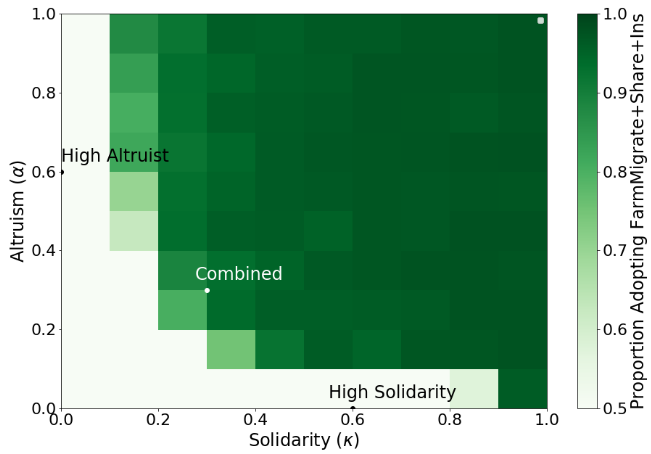
For all covariate risk scenarios, households consistently choose migration as an intra-household risk transfer strategy. Migration serves as an effective means of buffering household incomes against both covariate and idiosyncratic shocks. However, migration remittance incomes are themselves subject to uncertainty, and may indirectly affect which risk transfer strategies emerge. For example, if only local migration options are available - characterized by lower expected income and lower income volatility - formal insurance on its own does not emerge as a dominant strategy under any conditions, although the co-existence of insurance with informal risk-sharing still emerges at low drought risks ($p \leq 0.3$) (Appendix B2.4). By contrast, if only international migration options are available - characterized by high upfront cost, high expected income, and high volatility - then either formal insurance or the combination of insurance and informal revenue-sharing is a preferred strategy for a broader range of drought risks ($0 < p < 0.5$). Here, insurance and migration serve as complementary mechanisms: migration helps to increase household incomes, while insurance indirectly reduces some of the additional income volatility introduced by migration.

A scan of sensitivities to other key decision-making parameters - including farmer risk aversion, loss aversion, discount rates, and the proportion of income contributed to the revenue-sharing pool - indicates that other risk management outcomes are also possible. For example, in communities with highly risk-averse farmers ($b > 0.8$), households are likely to forego relatively volatile migration income, and rely instead on a combination of formal insurance and revenue sharing to manage risks (Appendix B2.5). Similarly, farming communities featuring high discount rates ($r > 0.5$) may also opt to forego migration, which requires a costly up-front investment in return for future remittances, but rely only on informal revenue-sharing as the main risk management strategy. Finally, communities in which households contribute lower proportions of their income to a revenue-sharing pool ($\beta < 0.2$) are more likely to see either a combination of insurance and revenue-sharing or formal insurance emerge as dominant strategies. In such cases, contributions to a revenue-sharing pool may be too small to yield the same benefit of stabilizing farmers' incomes relative to formal insurance options.

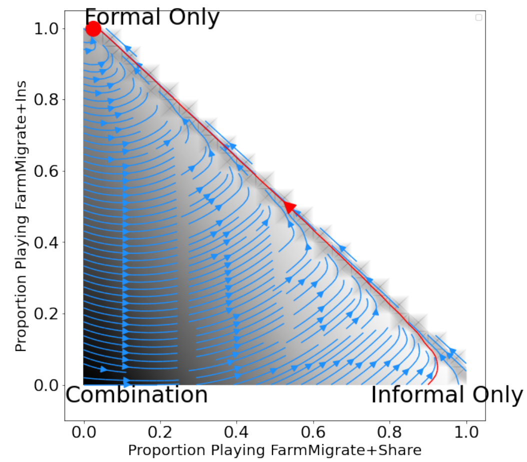
In sum, while self-interested agents are able to achieve optimal risk management under low covariate risk, free-riding concerns and high insurance premiums inhibit their ability to manage co-existence of formal and informal risk management under higher covariate risk. Ironically, this is just the level of risk at which combining formal insurance with informal revenue-sharing becomes especially important in order to limit extreme poverty and inequality in drought cycles.

3.3.3 Moderate Pro-Sociality Can Promote Socially Optimal Risk Management

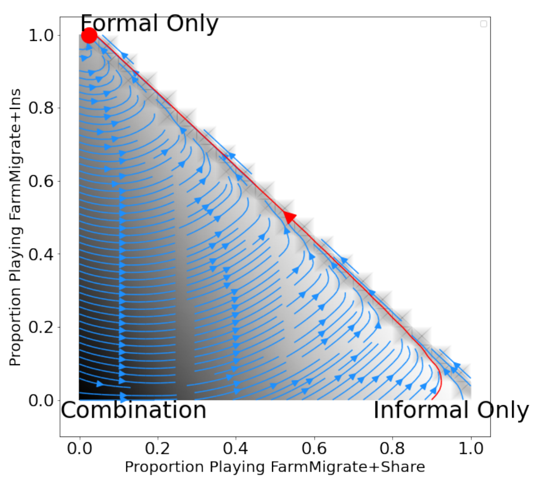
In the previous section, we analyzed the factors that may drive different risk management strategy decisions for communities of self-interested farmers. Here, we turn to how these decisions may be shaped by pro-social preferences - including utilities based on altruism and solidarity - and their interaction with the degree of climate risk. Specifically, we represent altruistic preferences by Equation 3.6 as described in Section 3.5.3, and set the altruism factor $\alpha = 0.6$ as an example of high altruism. This level of altruism is at the highest end of the ranges estimated in laboratory experiments [130] and statistical inference [129]. Similarly, we represent solidarity-based worldviews with Equation 3.7 in Section 3.5.3, and set the solidarity factor $\kappa = 0.6$ as an example of high solidarity. One interpretation



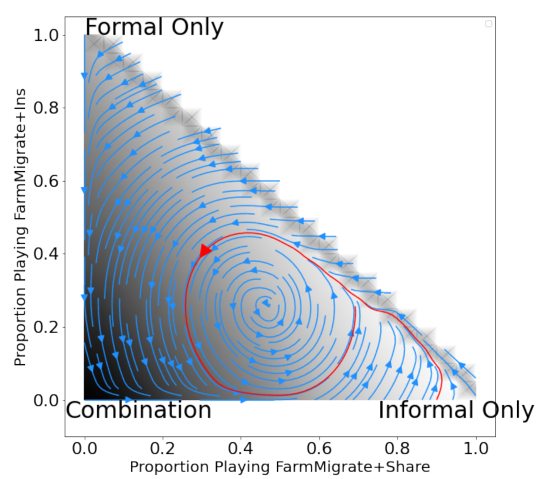
(a) Heat Map



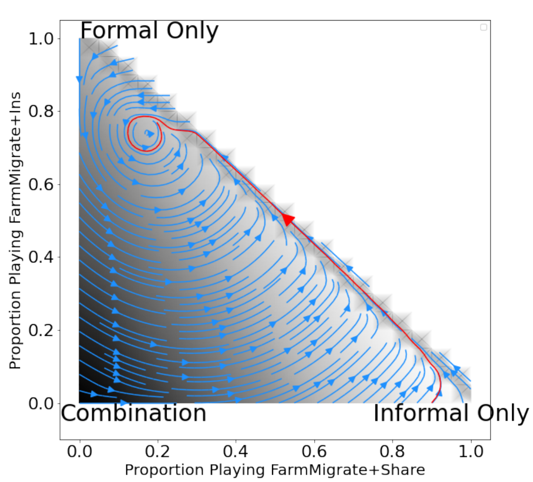
(b) Self-Interest



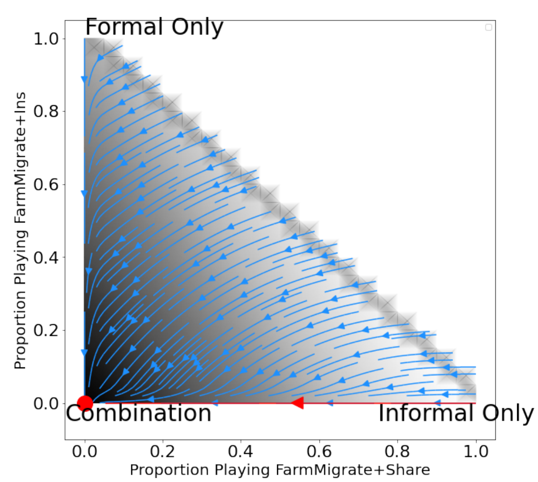
(c) High Altruism



(d) High Solidarity



(e) Moderate Pro-Sociality



(f) High Pro-Sociality

Figure 3.4

Figure 3.4: (previous page) **Effect of Alternate Social Preferences on Risk Management Equilibria.** Alternatives to purely self-interested preferences may shift the risk management equilibria that emerge in a subsistence farming community. **a)**Various combinations of altruism- and solidarity-based preferences can support a socially optimal combination of index insurance and informal revenue-sharing. Here, for different degrees of solidarity (κ, x-axis) and altruism (α, y-axis), the proportion of the community playing the Farm-Migrate+Share+Insurance strategy is indicated by the green colourbar. This sensitivity is displayed for the Medium risk level ($p = 0.35$, $\rho = 0.35$). **b-f)** Different ideal types of social preferences can lead to substantially different equilibrium points among the three main risk management strategies. Here, equlbria are shown under the Medium Risk scenario for Self-Interest ($\alpha = 0$, $\kappa = 0$), High Altruism ($\alpha = 0.6$, $\kappa = 0.0$), High Solidarity ($\alpha = 0$, $\kappa = 0.6$), and Moderate Pro-Sociality ($\alpha = 0.3$, $\kappa = 0.3$), and High Pro-Sociality ($\alpha = 0.6$, $\kappa = 0.6$) preferences types (also indicated by the points in **a)**. In each panel, the red line traces the equilibrium path from initial conditions at the point insurance is introduced (99 percent of population participating in informal revenue-sharing). Similar plots for other risk scenarios can be found in the SI.

of this value is that a decision-maker trusts that 60 percent of other households in their community will make the same utility-maximizing decision. While we know of no empirical work specifically measuring solidarity, studies demonstrating the prevalence of "false consensus" (i.e. a bias that most other community members act and think in a similar fashion as oneself) in several settings [136, 139] lend credence to this value as a feasible, if not common, condition. Further, cross-national surveys demonstrate that moderate amounts of community trust are common across several cultures [140, 141]. Here, we focus on the effects of pro-social preferences on risk management equilibria under the Medium risk scenario.

As boundary conditions, we compare the equilibria that emerge under ideal types of subsistence farming communities, in which all members espouse the same type of preference. In these conditions, we see that altruism or solidarity by themselves are not sufficient to promote a high adoption of both formal insurance and informal revenue-sharing (Fig. 3.4a). Perhaps counterintuitively, farmers acting out of high altruism reach the same equilbrium strategy as those espousing self-interest: a monomorphic strategy where all farmers only pursue formal insurance (Fig. 3.4 b-c). Although altruistic farmers consider how their choices affect the utilities of their peers, their own individual strategy choices do not have sufficient impact on the collective utility to move from this equilibrium. By contrast, communities in which farmers act out of solidarity do reach a different type of equilibrium. In this case, the community cycles between mixes of informal revenue-sharing, formal insurance, and a combination of both strategies, periodically approaching, then leaving, states where collective utility is maximized (Fig. 3.4d). This level of solidarity is enough to partially overcome the free-riding problem that prevents a combination of both risk transfer mechanisms from emerging in communities of self-interested farmers. However, it is not sufficient to prevent free-riding when a substantial proportion of the community has adopted both insurance and revenue-sharing. Only around $\kappa = 0.8$ would solidarity be sufficiently high to overcome this social dilemma on its own.

Communities in which farmers combine altruism and solidarity as pro-social preferences display further differences in risk management equilibria. If farmers exhibited high amounts of both preferences ($\alpha = \kappa = 0.6$), which we term "high pro-sociality", then the equilibrium state features all households purchasing formal insurance and participating in the revenue-sharing collective, thereby maximizing overall utility (Fig. 3.4f). While neither high altruism nor high solidarity on their own are sufficient to reach this state, they have a synergistic effect in promoting optimal risk management. High solidarity helps farming communities approach the coordination threshold at which households are incentivized to pursue the combination of formal and informal risk management, at which point high altruism sufficiently weights the utilities of others to incentivize farmers to pursue the socially optimal strategy. Put another way, high altruism prompts farmers to consider the effect of their strategy choices on the utilities of others in the community, and high solidarity provides the confidence that other households will also act in an altruistic manner.

While it may not be realistic to expect all members of a farming community to act with high altruism and high solidarity, even moderate amounts of both preferences ($\alpha = \kappa = 0.3$), which we term moderate pro-sociality, promote equilibria that include some households deploying a combination of insurance and revenue-sharing (Fig. 3.4e). As with the high solidarity case, communities in this condition alternate between different equilibria states, although these states always feature at least 65 percent of households relying exclusively on formal insurance. While not as socially optimal as the equilibrium that emerges under high pro-sociality, it is notable that moderate pro-sociality comprises a value of altruism that is in line with observed values in many subsistence societies, at least in experimental settings [129]. Similarly, it is plausible that in a typical community, an average decision-maker would trust at least 30 percent of his or her neighbours to also act in a similar utility-maximizing fashion.

3.3.4 Pairing Financial and Behavioural Interventions Yields a Pro-Social Dividend

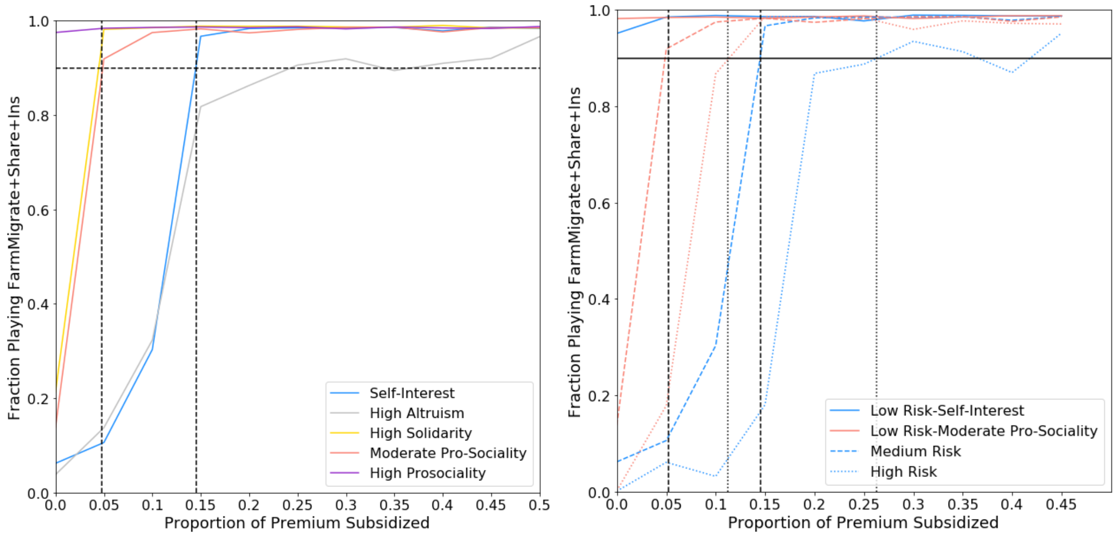
One way in which governments can promote socially-optimal risk management choices in agricultural communities is through financial incentives. Here, we consider the effects of insurance premium subsidies, a tool already widely used to promote adoption of index insurance, with mixed results on observed patterns of insurance uptake [88, 123, 142]. In particular, we compare how a subsidy's efficacy in promoting widespread adoption of this strategy may change based on the economic preferences that predominate in a subsistence farming community. As even heavy subsidies may not promote 100 percent uptake of both insurance and revenue-sharing, we set a threshold of 90 percent adoption in the community as a point of comparison. For analytical tractability, we compare "boundary conditions" in which all agents are homogeneous in their economic preferences; communities that are heterogeneous in their preferences are likely to require subsidy levels between these extremes.

We find that subsidies may be effective in promoting widespread adoption of both index insurance and informal revenue-sharing, but economic preferences and risk levels can substantially influence the level of subsidy required to achieve this goal. Under the Medium risk scenario, different economic preferences of a community can lead to significantly different subsidies (Fig. 3.5a). For example, in communities of Self-Interested agents, a subsidy of approximately 15 percent of premiums (equivalent to 13.40 USD/household/crop cycle) would be required to achieve widespread adoption of the socially optimal strategy. This is slightly lower than the threshold of a 23 percent subsidy that was found to promote high index insurance uptake in Bangladesh [88], though it is unclear if farmers in that case study also participated in an informal risk-sharing arrangement. By contrast, for communities in which High Pro-Sociality ($\alpha = \kappa = 0.6$) predominates, no premium subsidy is needed; pro-social preferences are already sufficient in promoting near-universal uptake of insurance and informal revenue-sharing. Even in communities espousing Moderate Pro-Sociality ($\alpha = \kappa = 0.3$) or High Solidarity ($\alpha = 0.0$, $\kappa = 0.6$), a subsidy of only 5 percent of premiums (4.50 USD/household/crop cycle) is needed to achieve the same objective.

This reflects the complementary nature of pro-social preferences and financial incentives in advancing robust risk management in subsistence farming communities. Pro-social preferences partially overcome the temptation of participants in a revenue-sharing pool to free-ride on others' insurance purchases, and premium subsidies also provide an incentive for individual households to purchase insurance. Together, these two mechanisms can assist farmers in overcoming the social dilemma that arises when formal insurance is introduced in communities with informal risk-sharing arrangements. However, communities with High Altruism ($\alpha = 0.6$, $\kappa = 0.6$) would require even higher subsidies than communities of Self-Interested agents (24 percent of premiums, or 21.40 USD/household/crop cycle). This is another example of how altruism by itself may not be sufficient in overcoming social dilemmas. Although altruistic agents make strategy decisions while accounting for their peers' well-being, without solidarity, farmers may not believe that their individual actions are sufficient to materially affect others' utilities. Further, as altruistic agents consider their own well-being with less weight than self-interested agents, a higher personal gain (i.e. higher subsidy) is needed for pecuniary policies to have the same effect.

For governments that are limited in resources, pairing financial incentives with policies that cue or cultivate pro-social preferences may be an effective strategy to overcome social dilemmas and promote optimal risk management. Interventions could include strategies that have been used to address collective action problems in climate mitigation, including: mass informational campaigns that promote a shared identity and injunctive norms, more targeted campaigns that frame specific actions (e.g. purchasing index insurance and contributing to revenue-sharing pools) as contributing to a public good, and communication outlets through which farmers can gain awareness of their peers' risk management intentions (e.g. a campaign that shares a descriptive norm of the number of farmers interested in purchasing insurance) [143, 144]. Such policies could contribute to cultivating altruism and solidarity as general values that predominate in farming communities, and/or activating such values in specific decision environments, e.g. community meetings in which farmers have the opportunity to purchase insurance and contribute to revenue-sharing pools.

To help governments evaluate the value of such interventions, we define a metric called the "pro-social dividend", which reflects the monetary benefit of cultivating pro-social preferences with respect to improved efficiency of financial policies, e.g. insurance subsidies, relative to a community without such preferences. In this case study, we calculate the pro-social dividend as the difference in subsidy levels required to achieve optimal risk management in a community espousing moderate pro-sociality vs. a community of self-interested farmers. Under Medium risk, this pro-social dividend is equal to 8.90 USD/household/cycle, or 1790 USD per year for a community of 100 households. For subsistence farming communities, this is a non-negligible sum, equal to approximately 4.6 percent of the community's total annual farming income. Further, this pro-social dividend is likely to increase with increasing climate risk (Fig. 3.5b). Under High risk, a 14 percent subsidy would be required to promote widespread adoption of insurance and revenue-sharing in a community characterized by moderate pro-sociality, whereas a community of self-interested agents would require a subsidy of 27 percent. Under these conditions, the pro-social dividend is equal to 16.30 USD/household/cycle, or 3260 USD/year for the community - roughly double the dividend under Medium risk conditions. Further, as high climate risks depress crop yields, this dividend is equivalent to 15.8 percent of average annual farming income. Under such conditions, higher climate risks drive higher premiums, which in turn increase the temptation to free-ride on other community members' insurance purchases, making pro-sociality even more important in promoting optimal risk transfer. Pairing financial incentives for climate risk management with behavioural interventions promoting pro-sociality is a strategy that merits strong consideration as climate-driven risks increase in the coming decades.



(a) Medium Risk, All Preferences **(b) Selected Preferences, All Risks**

Figure 3.5: Effect of Financial Policy Incentives and Pro-Social Preferences on Risk Management Strategy Choices. a) For the Medium risk scenario ($p = 0.35$, $\rho = 0.35$), the proportion of households pursuing the socially optimal strategy (FarmMigrate+Share+Insurance) is displayed as a function of the insurance subsidy (x-axis), expressed as a proportion of the total premium, for communities exhibiting five types of economic preferences: Self-Interested ($\alpha = 0.0$, $\kappa = 0.0$); Altruist ($\alpha = 0.6$, $\kappa = 0.0$); Moralist ($\alpha = 0.0$, $\kappa = 0.6$); and Moderate Pro-Sociality ($\alpha = 0.3$, $\kappa = 0.3$), and High Pro-Sociality ($\alpha = 0.6$, $\kappa = 0.6$). The horizontal line indicates 90 percent of the population, and vertical lines indicate the subsidy level at which the Moderate Pro-Sociality and Self-Interested preferences cross this line, enabling a comparison of the "prosocial dividend" - i.e. how much is saved in subsidies required to achieve a socially optimal goal, given prosocial preferences. **b)** The effect of subsidies on the Self-Interested (blue) and Moderate Pro-Sociality (red) preferences is shown for three risk scenarios: Low (solid line), Medium (dashed line), and High (dotted line). Dashed vertical lines indicate the subsidy levels at which the two preferences reach 90 percent adoption of FarmMigrate+Share+Insurance under the Medium risk scenario, and dotted vertical lines indicate these levels under the High risk scenario. All results display the average terminal time frequency of households pursuing this strategy over 100 simulations.

3.4 Discussion

Rising climate risks, including extreme droughts and floods, are likely to impose increased losses on subsistence farming communities over the remainder of the 21st century, threatening the viability of rural livelihoods. Such a future calls for risk transfer instruments that offer farmers protection against climate-driven losses, thereby enabling households and communities to deploy livelihood strategies under more stable economic outcomes. In this analysis, we investigated how risk management strategies at three levels - household (rural-urban migration), community (informal revenue-sharing pool), and regional (index insurance) - may either co-exist or crowd out each other through strategic interactions among smallholder farming households. To do so, we developed a novel evolutionary game theoretic framework that accounts for household decisions at these three levels, and seeded the model with climate and socioeconomic data from two countries, Nepal and Ethiopia, that face high climate vulnerability and whose governments are currently experimenting with index insurance instruments.

Our analysis contributes four major findings. First, we confirm that combining the three levels of risk management - migration, informal revenue-sharing, and index insurance - offers farming households and communities more complete protection against climate-driven losses than any other combination of strategies. This is because migration and informal revenue-sharing helps households cope with idiosyncratic shocks to their farming incomes, while insurance helps communities manage covariate shocks that could otherwise limit the effectiveness of informal revenue-sharing mechanisms. Second, we find that the combination of insurance with informal revenue-sharing introduces a new social dilemma: households in a revenue-sharing pool must contend with the temptation to free-ride off the stable income that insured households contribute. In fact, just as climate-driven risks increase beyond currently observed levels in Ethiopia and Nepal (i.e. a roughly 1-in-4 or greater probability of extreme drought), our model predicts that the co-existence of formal and informal mechanisms would collapse in a community of purely self-interested agents, with farming households either pursuing index insurance or informal revenue-sharing depending on climate risks and income correlation. Third, the presence of pro-social preferences, namely altruism and solidarity, can change the equilibria risk management states that arise from strategic interactions among farmers. In particular, a combination of moderate altruism and solidarity, in line with empirically-measured values, can be sufficient to promote at least some uptake of optimal risk management layering. Fourth, we demonstrate that pro-social preferences can render pecuniary incentives, e.g. premium subsidies, more efficient in their ability to promote optimal risk management. We develop the concept of a "pro-social dividend" to help policymakers evaluate the value of behavioural interventions, e.g. informational campaigns and commitment fora, that may help activate pro-social behaviour among farmers.

This analysis contributes to two emerging strands of literature: one examining the ability of index insurance to help smallholder farmers manage livelihood risk, and one examining the role of pro-sociality in the provision of public goods. Regarding the role of index insurance, we echo conclusions from previous empirical [46–48, 86, 88, 133] and theoretical [41, 50, 145] studies that while such programs may offer many advantages, widespread adoption is likely to be constrained by several challenges. Our study adds to this literature by demonstrating that formal insurance may crowd out informal risk-sharing arrangements, and vice versa, as climate risks rise and if farmers primarily act out of self-interest. We also note previous work that demonstrated the potential for new insurance programs to be maladaptive by crowding out existing informal lending arrangements [146]; our finding that insurance adoption may slightly increase average poverty rates offers support for this concern. Regarding the role of pro-sociality, we contribute to growing literature that demonstrates its importance in providing public goods. However, whereas pro-sociality is typically conceptualized as the incorporation of others' well-being in one's decision-making objectives [147], or the adherence to social norms [126], here we highlight two distinct preferences that underlie this concept: altruism (regard for others' well-being) and solidarity (willingness to "do the right thing", and trust that others will do the same). Crucially, we demonstrate that altruism alone is not sufficient to solve this dilemma: even a community composed entirely of perfect altruists ($\alpha = 1.0$) is not likely to sustain high levels of risk management co-existence, as individuals assess that their own actions as insufficient to overcome a coordination threshold. By contrast, a combination of both altruism and solidarity, in moderate amounts, may help overcome the social dilemma of under-provisioning of risk transfer. While solidarity in particular is difficult to measure empirically, experimental evidence suggests that altruism levels in subsistence communities approximate these values [129, 130]. Further, previous studies have also found that behavioural interventions can increase community trust, leading low-income individuals to be less myopic in making inter-temporal decisions [148].

While our conclusions are generally robust to sensitivities in risk levels, household risk and loss aversion preferences, and community size, there are several additional considerations that add nuance to our findings. As with any model, our framework includes some abstractions from real-world risk management decision-making that merit closer study. High basis risk, which has been explored in other work [41, 49, 50], may inhibit widespread adoption of index-based insurance, but increase the complementarity of formal and informal mechanisms. Another substantial barrier to smallholder farmer adoption of index insurance, even when premiums are heavily subsidized, appears to be a lack of trust in receiving timely payouts [142]. In particular, future work could explore how solidarity and trust preferences may assume different forms when applied to peers (e.g. other farmers) versus institutions (e.g. governments and insurance companies). Furthermore, while we include communities with heterogeneous preferences in this analysis, an extension could be to assess the impact of assortative interactions on the effect of such preferences. For example, agents exhibiting high solidarity and/or altruism may be more likely to interact with similar agents over time, and less likely to engage with purely self-interested farmers. This pattern is found to be one regularity in experimental evidence on cooperative games [126]. Similarly, such preferences may be dynamic and endogenous to farmer observations of material payouts; agents that initially espouse high altruism may reduce their altruism over time if they do not perceive it to be reciprocated [124, 128].

From a financial perspective, our model generally assumes that any farming household that wishes to engage in migration or purchase insurance either has enough savings or access to credit to so. In reality, subsistence farming communities typically have imperfect access to credit and limited ability to save [10], making it difficult to deploy strategies that provide long-term benefits for an upfront cost. In an extension of the model, we impose restrictions on the strategies households can deploy if they do not accumulate sufficient savings; our analysis demonstrates that such restrictions may delay the dynamics with which risk management strategies are adopted in a community and lead to qualitatively different long-term equilibria (Appendix B2.8).

Our analysis also indicates that migration is an essential livelihood and risk management strategy among subsistence households - under nearly all conditions we examined, farming households would choose to engage in migration as part of their risk management portfolio. This in fact approximates real-world conditions in at least one of our case studies: approximately 70 percent of farming households in Nepal's Chitwan Valley reported at least one migrant in 2015 [29] (migration rates were not collected in the Borena survey). Yet, a heavy reliance on this strategy carries important implications at the household and community scales that are difficult to capture with our model. At the household scale, a reliance on migration as a necessary risk management option, rather than an aspirational choice that households can make out of a position of high agency, can lead to farm labor shortages and strain family relationships, among other impacts [149]. At the community and regional scales, widespread migration may lead to significant demographic shifts and a cycle of relying on economic remittances for well-being, which can itself be subject to boom-bust cycles [150].

This points to a final consideration that our analysis is unable to fully capture: risk management strategies that may be optimal for households and small communities may not scale to larger regions or entire countries. For example, while it may be feasible and perhaps even desirable for certain communities in Nepal and Ethiopia to withstand high outmigration rates in order to receive remittance income and alleviate population pressures, high national outmigration rates could lead to large-scale economic and food security shocks. Further, in this analysis, we assume that insurance programs cover a sufficiently diversified population such that they can remain solvent when all households in a focal community experience a climate shock and require a payout. In reality, many nascent index insurance programs are administered at the national or regional scale, and may themselves face significant financial risks if their client pool exhibits highly covariate risks. As well, behavioural interventions that promote altruism and/or solidarity are likely to be more effective in smaller community settings, where repeated interactions and a shared identity among households contribute to pro-sociality. At larger governance scales, anonymity and even rivalry between farmers from different regions are likely to challenge the ability to draw out such preferences. Such issues point to another fruitful avenue for further research: assessing the potential tradeoffs in risk management objectives at different governance scales, and the ability of polycentric governance structures (i.e., overlapping institutions at multiple scales) to coordinate these tradeoffs (see Chapter 5 for a fuller exploration of these tradeoffs).

3.5 Methods

The evolutionary dynamics of strategy choices are governed by imitation, and households within the population interact with each other through their utility functions. The state of the population is represented by the vector $\mathbf{x} \in \mathbb{N}^N$, where the ith element of the vector, x_i, represents the number of households that selects pure strategy i. At any given time, households can select one of the eight strategy options representing different combinations of livelihood strategies (farming w/ or w/o migration) and risk reduction strategies (informal revenue-sharing and formal insurance). Households selecting strategy i receive an expected profit $\pi_i(,t)$, but are risk- and loss-averse as they are sensitive to the variance $\sigma_i^2(,t)$ of strategy i and negative net income, respectively. To incorporate different decision-making preferences, we first consider the payoff function $u_i(,t)$ of the risk-averse *homo economicus*, and add an altruism index in $v_i(,t)$ and a solidarity index in $w_i(,t)$. These preferences may be combined into one generalized utility function, $z_i(,t)$ incorporating both altruism and solidarity.

We construct a Base Case to compare how different levels of risk and pro-social preferences shape predictions about the risk management strategies most likely to emerge, given a consistent set of assumptions. In this analysis, we assume a community of $N = 100$ households, and simulate results for $T = 20{,}000$ time steps to mimic the process of households re-evaluating strategies in each cropping cycle. Such a timeframe allows us to explore the long-term dynamics as households update their risk management strategies, in relation to those espoused by others in their community. To mimic real-world conditions such as those in Nepal and Ethiopia, in which formal climate insurance is not yet common, we further assume that the initial distribution of strategies in the community does not include formal insurance. That is, households are initially distributed among the four strategy options without formal insurance, and only consider insurance options if there is a mutation in a household's decision-making process. Once a few households in the community adopt strategies with insurance, it then becomes more likely that other households will observe this option and consider adopting the same strategy.

We parameterize our model with economic and risk preference data from Nepali farming communities (Appendix Table B.3). Data on expected incomes and standard deviations of farming and migration livelihoods are taken from the Chitwan Valley Family Study [29], a longitudinal survey of farming households in one of Nepal's most prominent agricultural regions. The correlation between farming incomes is also estimated from this source (Appendix B1.5). Risk parameters were derived from a composite of drought data from the Standardized Precipitation and Evapotranspiration Index (SPEI) [117] and socioeconomic data from two regions of subsistence farming communities whose governments are experimenting with index insurance programs. These are the Borena region of Ethiopia, home to subsistence pastoralist communities and one of the main sites for the Index Based Livelihood Insurance pilot project [151], and Nepal's Chitwan District, one of the main agricultural regions of the country [29]. Data on farming costs are taken from Katovich and Sharma [80], and migration costs come from Shrestha [81]. Farmer risk preferences are derived using data from Mohan [82]. Data on exposure to drought risks is estimated from historical data obtained from the SPEI Global Drought Monitor [117] (Appendix B1.5).

3.5.1 Material payoff functions

Although the material payoff of an agent is random, we assume that each agent following strategy i has the same expected payoff $\pi_i(\mathbf{x}, t)$, which can be written as

$$\pi_i(\mathbf{x}, t) = I_i(t) + R_i(t) + S_i(\mathbf{x}, t) - C_i(t)\,. \tag{3.1}$$

The expected income from farming $I_i(t)$ at time t for strategy i accounts for the number of farming household members in case of migration through the migration adjustment factor η. The variance of the farming income is represented by $\sigma^2_{I,i}$. A drought occurs in any cropping cycle with probability p, and the expected income in a non-drought (drought) year are represented by I^{nd} (I^{d}), with corresponding variance $\sigma^2_{I^{\mathrm{nd}}}$ ($\sigma^2_{I^{\mathrm{d}}}$). $R_i(t)$ are the expected remittances of strategy i with corresponding variance σ^2_R. $S_i(t)$ represents the income originating from risk sharing in strategy i, and β represents the proportion of total household income that is shared in an informal risk-sharing pool. $C_i(t)$ are the costs corresponding to strategy profile i, and can consist of the farming cost C_{f}, upfront migration cost C_{m}, revenue-sharing cost $\beta \cdot (I_i(t) - C_{\mathrm{f}})$, and formal insurance premium. An overview of the mean and variance of all strategy options can be found in the Appendix, Section B.1.2.

3.5.2 Utility including risk- and loss-aversion

Grounded in the theory of the new economics of labour migration (NELM), we assume that households diversify their strategies to reduce the risk to their livelihood. To this purpose, the utility can be defined as the difference of the expected profit and the weighted profit volatility, given by $\pi_i(, t) - b \cdot \sigma_i(, t)$ where b represents the risk-aversion parameter. However, as decision-makers tend to be more sensitive to experiencing losses versus gains of a similar magnitude [152], any potential loss is penalized with factor λ, with $\lambda > 1$

for most decision-makers. According to the loss aversion framework, decision-makers interpret payoffs in terms of gains and losses relative to a reference point W_i. In the particular decision-making context of subsistence farming, the salient reference point is average farming cost, C_f. That is, households will perceive farming investments as a loss if the net farming revenues they accrue (including costs and payouts from insurance and/or the revenue-sharing pool) do not cover their initial expenses for a cropping season. Conversely, net farming revenues above those expenses are considered gains. This is equivalent to the status quo reference point evaluated by Lampe and Wurtenberger in their study of loss aversion and demand for index insurance [133], and allows us to evaluate the gains and losses of all farming risk management options on an equivalent basis. Households account for migration decisions separately from farm management decisions. Here, the relevant reference point for evaluating gains or losses from migration is 0. That is, if a household has not yet engaged in migration, then it will perceive an initial loss of C_m, representing the upfront cost of migration. On the other hand, if a household has already engaged in migration, we assume there are no additional upfront costs borne by the household, and the expected remittance income $R_i(t)$ is seen as a gain.

Loss aversion is typically measured empirically using a cumulative prospect theory (CPT) utility function. Since the utility function is derived from mean-variance theory (MVT), rather than CPT, the loss-aversion parameter is re-scaled such that it retains the same meaning in an MVT framework. We do this by comparing the ratio of farming utilities in a drought vs. non-drought year under both CPT and MVT (see Appendix, Section B.1.3 for more details). Accounting for loss aversion related to farming and migration losses, the utility at time t from farming and migration of a self-interested, risk- and loss-averse household following strategy i can be written as

$$u_i^{\mathrm{F}}(,t) = \begin{cases} I_i(t) + S_i(,t) - C_f - b \cdot \sigma_{I,i}(,t) & \text{if } I_i(t) + S_i(,t) \geq C_{\mathrm{f}} \\ \lambda \cdot \left[I_i(t) + S_i(,t) - C_{\mathrm{f}} - b \cdot \sigma_{I,i}(,t) \right] & \text{if } I_i(t) + S_i(,t) < C_{\mathrm{f}} \end{cases} \tag{3.2}$$

and

$$u_i^{\mathrm{M}}(t) = \begin{cases} R_i(t) - b \cdot \sigma_{\mathrm{R}}(t) & \text{if } C_{\mathrm{m}}(t) = 0 \\ -\lambda \cdot C_{\mathrm{m}}(t) & \text{if } C_{\mathrm{m}}(t) > 0 \end{cases} \tag{3.3}$$

Using (3.2) and (3.3), the total utility of a self-interested household at time t is given by

$$u_i(,t) = u_i^{\mathrm{F}}(,t) + u_i^{\mathrm{M}}(t), \tag{3.4}$$

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

$$\mathbb{E}[u_i(,t)] = p \cdot u_i^{\mathrm{d}}(,t) + (1-p) \cdot u_i^{\mathrm{nd}}(,t), \tag{3.5}$$

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

3.5.3 Utility under pro-social preferences

Building on frameworks from Foster and Rosenzweig [129], Tilman et al. [39], and Lin et al. [130], we introduce an altruism index, α, which governs the degree to which individual households prioritize the collective well-being of the community over their individual utility. Different levels of altruism can be captured as follows in the utility function

$$\begin{aligned} v_i(,t) &= (1-\alpha)\cdot u_i(,t) + \alpha \cdot \frac{1}{N} \cdot \sum_j x_j \cdot u_j(,t) \\ &= (1-\alpha)\cdot u_i(,t) + \alpha \cdot \frac{W(,t)}{N}\,, \end{aligned} \tag{3.6}$$

where α takes values in the interval $[0,1]$, and $W(,t) = \sum_j u_j(,t)$ represents the social welfare function. For $\alpha = 0$, the decision-maker coincides with the self-interested household (*homo economicus*) defined in (3.4), while for $\alpha = 1$, the decision-maker is a complete altruist, attaching equal weight to the utility of each individual in the population, including him- or herself. In this case, $v_i(,t)$ reflects the average per capita utility of the community; that is, the sum of all individual utilities normalized by the population size, N.

We next introduce a solidarity parameter, κ, which specifies the degree to which a decision-maker takes actions that he or she wishes to be universalized. Different levels of solidarity are captured as follows in the utility function

$$w_i(,t) = [u_i(\tilde{},t)]\,. \tag{3.7}$$

In this utility function, the expectation is taken over the random vector $\tilde{}$ where the strategy of m out of the remaining $(N-1)$ households is replaced by strategy i with probability $\kappa^m \cdot (1-\kappa)^{N-m-1}$. The parameter κ takes values in the interval $[0,1]$, with higher values of κ indicating a greater propensity to adopt the strategy that household i wishes were universalized. An alternative interpretation of κ is a trust parameter, in which higher values of κ indicate greater trust that other households will also act in solidarity with the focal household. For $\kappa = 0$, this decision-maker coincides with a *homo economicus* household, while for $\kappa = 1$ the decision-maker acts as if all households select the same strategy. A high value of κ therefore corresponds with the concept of *homo moralis*, i.e. a decision-maker that defines what is 'the right thing to do' from a self-regarding perspective [127].

The self-interested, altruist, and solidarity preferences can be captured by a single generalizing utility function as follows

$$z_i(, t) = \left[(1-\alpha) \cdot u_i(, t) + \alpha \cdot \frac{1}{N} \cdot \sum_j x_j \cdot u_j(, t) \right], \tag{3.8}$$

which allows us to model combinations of different levels of altruism and solidarity. An interpretation of households evaluating strategy options using $z_i(, t)$ with non-zero α and κ, is that households in a community display some ability to coordinate with their peers to deploy strategies that collectively improve utility. This utility function may resemble the strategy of conditional cooperation [126], in which agents are predisposed to cooperate towards a pro-social goal, provided they have some confidence that other agents are also likely to cooperate. Note that if $\alpha = 0$, (3.8) reduces to the *homo moralis* preference in (3.7). Similarly, if $\kappa = 0$, $z_i(, t)$ reduces to the altruist preference in (3.6), and if both $\alpha = \kappa = 0$, the same equation reduces to the risk-averse *homo economicus* household of (3.4).

In their decision-making, households consider the aggregated utility over time, which in case of a self-interested household is defined as

$$U_i(, t) = \sum_{s=t}^{s=t+h} \frac{u_i(, s)}{(1+r)^{s-t}}. \tag{3.9}$$

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

3.5.4 Accounting for Idiosyncratic and Covariate Risk

An important element of the model is to determine how different levels of idiosyncratic and covariate risk affect the risk management strategies that emerge from farmer decision-making. The risk is determined through the parameters σ_i, covering the idiosyncratic risk of livelihood strategy i; ρ, capturing the correlation between household farming incomes; and p, capturing the probability of a shock event, e.g. drought, represented by a threshold frequency of the income distribution below which income is assumed to be the result of an extreme event. Note that p also affects the expected income by re-shaping the income distribution as described in the SI, Section **??**). Generally, idiosyncratic risk increases with σ_i, whereas covariate risk increase with p and ρ. The precise level of risk faced by each household depends on its risk management strategy and those of its fellow community members.

Income correlation is relevant in case of revenue sharing, which is only applied to the portion of the income originating from farming. A household pursuing revenue sharing receives the following revenue from farming

$$I_{i,k}^{\mathrm{RS}}(,t) = (1-\beta) I_{i,k} + \beta \cdot \frac{1}{|\mathscr{P}(t)|} \sum_{l \in \mathscr{P}(t)} I_{i,l}\,, \tag{3.10}$$

where $I_{i,k}$ is the income from farming for household k following strategy i, potentially in combination with formal insurance. The income can be found by adding to the income of household k the proportional share of the total contributions by the revenue sharing pool

$\mathscr{P}(t)$. The mean farming income under revenue sharing can be written as

$$\mu_{I_i^{\text{RS}}}(t) = (1-\beta)\mu_{I_i} + \frac{\beta}{|\mathscr{P}(t)|} \cdot |\mathscr{P}(t)| \cdot \mu_{I_i} = \mu_{I_i}\,, \tag{3.11}$$

$$\tag{3.12}$$

and income variance under revenue sharing can be written as

$$\sigma^2_{I_i^{\text{RS}}}(t) = \Big((1-\beta)^2 + 2(1-\beta)\frac{\beta}{|\mathscr{P}(t)|}(1+\rho(|\mathscr{P}(t)|-1)) + \frac{\beta^2}{|\mathscr{P}(t)|}(1+\rho(|\mathscr{P}(t)|-1))\Big)\sigma^2_I\,, \tag{3.13}$$

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

3.5.5 Policy Interventions

In this analysis, we model two financial interventions and analyze their relative effectiveness in (i) encouraging households to adopt socially-optimal risk management strategies; and (ii) promoting household resilience to climate shocks. In the first intervention, we model the effect of a government providing a monetary subsidy, I_{s}, to purchasers of formal insurance. We assume that such subsidies are provided immediately upon purchase of the insurance product in each cropping cycle, and take the form of a fixed cash amount, such that the cost of insurance in each cycle can be written as

$$C_{ins} = p * (I^{nd} - I^d) - I_{\text{s}} \tag{3.14}$$

That is, insurance premiums equal the expected loss of farming income due to a climatic shock, which is a function of the drought probability, less the government subsidy. This type of intervention raises the expected profit of risk management strategies that include formal insurance, which increases their utility relative to strategies without formal insurance, *ceteris paribus.*

In contrast, the second modelled intervention promotes the relative attractiveness of informal revenue-sharing as a form of risk management. Here, we consider a policy in which governments match household donations to a revenue-sharing pool by contributing I_{m} per participating household, per cycle. For ease of comparison to the insurance subsidy, we also assume this matching takes place instantaneously and that households contributing to informal revenue-sharing are aware of this option. They therefore evaluate the expected income received from the shared income pool in each cycle as

$$S_i(x) = \beta \cdot \frac{x_3 I + x_4 I^{\mathrm{nd}} + x_7 \eta I + x_8 \eta I^{\mathrm{nd}}}{x_3 + x_4 + x_7 + x_8} + I_{\mathrm{m}} \tag{3.15}$$

As with the premium subsidy, this intervention also increases expected income of households, but in this case focuses on strategies incorporating informal revenue-sharing. In both the premium subsidy and matching interventions, the variance of risk-management strategies remains unaffected: each intervention simply shifts the expected income higher for the targeted risk management strategies, while conserving the shape of their income distributions. As such, these interventions allow us to compare the relative effectiveness of the risk management options themselves (i.e. index insurance and informal revenue-sharing), which reduce the variance of farming income, with policy mechanisms that change the expected income of this livelihood.

Finally, we compare the effectiveness of these two policies in shifting risk management decisions for communities espousing different decision-making preferences. Specifically, we examine the effects of such policies for communities of agents characterized by high self-interest, high altruism, high solidarity, and a combination of moderate altruism and moderate solidarity. We also assess the potential impact of these policies in communities that are heterogeneous in their preferences. This analysis permits us to identify potential complementarities in financial inducements and informational interventions that may help shape community preferences. While we cannot reliably quantify costs for the latter category of policies, we can at least quantify a threshold financial inducement needed to achieve a certain objective under different combinations of decision-making preferences.

3.5.6 Evolutionary selection mechanism

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

$$
\begin{aligned}
T_{i\to j} &= (1-\mu)\cdot\frac{1}{1+\exp\beta\cdot\frac{U_j(,t)-U_i(,t)}{U_i(,t)}} \\
T_{i\to k} &= \mu\cdot\frac{1}{S-1}, \qquad k\neq i \\
T_{i\to i} &= 1-(1-\mu)\cdot\frac{1}{1+\exp\beta\cdot\frac{U_j(,t)-U_i(,t)}{U_i(,t)}}-\mu\cdot\frac{1}{S-1}\,,
\end{aligned}
\tag{3.16}
$$

where $1/(1+\exp\beta\cdot(U_j(,t)-U_i(,t)/U_i(,t))$ is the logistic function with steepness β and utility functions U_i and U_j.

Chapter 4

How Does Heterogeneity in Social and Informational Capital Affect Nepali Farmer Climate Risk Management?

In preparation as: N. Choquette-Levy, D. Ghimire, R. Ghimire, I. Chaudhaury, D. CK, and M. Oppenheimer. How does heterogeneity in social and informational capital affect Nepali farmer climate risk management?

Abstract

Increasing climate risks are likely to threaten the livelihoods of many of the world's 500 million smallholder farming households. Previous scholarship has demonstrated that access to accurate climate information may enhance farmers' adaptive capacity, including adaptive rural-urban migration, but evidence is mixed on how farmers actually integrate such information in their decision-making. In this study, we analyze how farmers' information *sources, social networks, and previous exposure to hazards shape climate risk perceptions and livelihood decisions. Informed by the New Economics of Labour Migration, Protection Motivation Theory, and Security-Potential Aspiration frameworks, we collected data from 500 households in Nepal's Chitwan Valley on farmers' livelihood choices from 2015-2021, climate risk perceptions, and access to informational and social capital. We find that climate risks are highly salient to farmers' perception of general livelihood risks, including non-farm livelihoods. The effects of climate on perceived risks of non-farm livelihoods, including migration and off-farm labor, may be one factor tempering adaptation responses to climate hazards. For some hazards, including droughts and groundwater risks, access to greater informational and social capital may decrease risk perceptions, but also contribute to an increased propensity to adopt adaptation strategies. Finally, we find that while farming households generally maintain diversified income portfolios, they tend to rely even more on perceived high-risk strategies during climate-driven shocks. Our results indicate that efforts to build farmers' resilience should especially account for risk perceptions of livelihood alternatives and loss-averse behavior in response to income shocks.*

4.1 Introduction

Increasing climate risks over the coming decades are likely to threaten the livelihoods of many of the world's 500 million smallholder farming households (i.e., those who farm on less than 2 ha of land) [1, 153, 154]. More frequent extreme events have already exposed millions of people to food and water insecurity, which is likely to intensify with increased intensity and frequency of droughts, floods, and heatwaves across many regions of the world [1]. Over the longer term, a 2^oC or greater rise in global mean temperatures is likely to diminish the average yields of most staple crops by 10-20 percent [3] and erode the viability of some agricultural livelihoods [6], especially for farmers without the financial means to adapt to such changes [5]. As most smallholder farmers rely primarily on agriculture for subsistence, climate shocks may further entrench poverty traps [90] and lead to maladaptive strategies that can cascade to societal-wide shocks, e.g. involuntary displacement, deforestation, and food insecurity. Therefore, developing a better understanding of tools that can build smallholder farmer adaptive capacity is a key part of developing societal-level climate resilience.

While subsistence farmers have had to contend with high income volatility and natural hazards for decades [9, 10], climate change introduces new sources of uncertainty to farmer livelihood decisions. First, farmers face uncertainty regarding the degree to which natural hazard risks are changing over time, and the timing and scale of such changes. This is especially true regarding slow-onset climate changes, e.g. increasing mean temperatures and changing water availability, which may be difficult for farmers to notice by just relying on one's memory [53, 155]. This kind of uncertainty may affect decisions regarding whether to invest in coping strategies to manage short-term shocks or longer-term adaptive strategies to fundamentally transform how farming households earn a livelihood [156]. A second source of uncertainty is how climate risks may affect farmers' physical, financial, informational, and social capital. Over short time horizons, climate change may actually increase farmers' capital, e.g. through longer growing seasons or a particularly wet season that increases yields of staple crops [157]. However, over the longer term, climate impacts are likely to erode farmers' assets, further constraining the capacity to respond to livelihood shocks. In some cases, short-term investments to protect against climate risks, e.g. increasing pesticide use and building irrigation canals, may prove maladaptive for longer-term climate change [156]. Another source of uncertainty is how to make use of emerging climate information services to proactively respond to climate change. While advances in climate science have significantly improved scientists' abilities to down-scale the projected impacts of global climate models, there are still substantial gaps in making this information useful for end users e.g. smallholder farmers [51]. For example, seasonal climate forecasts may still be too broad for individual farm-level decisions, and/or may be too late in reaching farmers for them to materially change strategies [52]. Furthermore, such forecasts are still characterized by a high degree of uncertainty [158], and common cognitive biases may push farmers to discount the possibility of extreme scenarios or the entire forecast altogether [52, 53].

Over the past two decades, research conducted in different parts of the world has elucidated a few stylized facts regarding farmer perceptions of climate risks. First, despite high inter-annual variability in weather conditions, there is evidence that farmers accurately perceive long-term climatic trends, even if they do not directly attribute this to anthropogenic climate change. For example, 84 percent of a sample of Sri Lankan rice farmers indicated that droughts had become somewhat or much worse than historical norms [159], 90 percent of coffee farmers in Nicaragua perceived some form of long-term climatic change [107], and farmers in the Nepal Himalaya and Terai plains regions accurately reported long-term climatic trends over the past 30 years [157]. However, perceived climate risks may not directly lead farmers to take adaptive actions; several other factors may mediate this relationship. Few Nicaraguan coffee farmers took adaptive actions to protect against climatic changes, especially those experiencing food insecurity [107]. A study of farmers across 14 districts in Malawi found that less than 40 percent have taken a single adaptive action, despite near-universal experience with hazards including droughts, floods, pests, and hailstorms [108]. Similarly, a survey of Indian farmers demonstrated that those with sufficient assets to afford seeds over the next two years were more likely to take adaptive actions than those without [156]. Finally, government interventions seeking to provide farmers with climate information appear to have had limited success thus far. In Zimbabwe, few farmers decided to switch from water-intensive maize to drought-resistant millet in predicted dry seasons; farmers in Lesotho seemed especially averse to using forecasts that called for negative impacts on yields [52, 160]. In Vietnam, farmers with access to public information sources generally perceived lower climate risks to their livelihoods, partially out of a belief that public adaptation measures would be sufficient to manage these risks [161]. In Ethiopia, access to agricultural extension services increased the likelihood of farmers adopting a technical strategy e.g. increased fertilizer use, but did not affect the uptake of other strategies, e.g. changing crop types or planting/harvesting times [162]. However, access to climate information was one of the most significant predictors of Malawian farmers choosing to diversify crops and/or delay planting [108].

Despite this rich body of evidence, there are still several puzzles regarding the processes by which climate change affects smallholder farmer decision-making. One such puzzle is how climate change shapes perceptions not only of farming risks, but the risks of other adaptation strategies and livelihood alternatives. Previous studies provide evidence that farmers may be reluctant to adopt new technologies, crop varieties, and farming practices out of high perceived risk [162, 163], which may be accentuated by climate change. For example, alternative crops, livestock raising, and local off-farm labor options may also be susceptible to the same heat, drought, and flood risks affecting the main staple crops that are grown in a region. While smallholder farming households often deploy rural-urban migration as a way to diversify income streams across economic sectors and geographies [77], climate risks to agriculture may erode farmers' abilities to afford this option in the future [16], and the migration trip itself may become more perilous during a period of increased climate stress. Another puzzle is the role of informational and social capital in mediating (i) climate risk perceptions and (ii) the likelihood of taking adaptive strategies.

In a complex and uncertain environment, access to diverse social networks and sources of information should provide decision-makers with more accurate risk perceptions and the resources to manage these effectively. However, empirical studies suggest that various information sources may have differential effects on whether farmers perceive climate change as a serious risk [52, 156, 161] and whether they take adaptive action [108].

To help address these puzzles, in this study we analyze how farmers' information sources, social networks, and previous experience with climate hazards shape perceptions of climate risks and adaptation strategy choices. Specifically, through a cross-sectional survey of 500 farming households in the Chitwan Valley of south-central Nepal, this study investigates four main research questions:

- How does access to diverse sources of informational and social capital influence perceptions of climate risks to farming?
- How salient is climate change to farmers' perceptions of livelihood risks, relative to other established risk factors e.g. access to financial and human capital, availability of farming inputs, and access to markets?
- How do smallholder farmers' information sources, social networks, and risk perceptions affect their choices of adaptation strategies?
- How do perceptions of climate risk and risks of livelihood alternatives condition their income diversification strategies?

By addressing these questions, we seek to make three main contributions to the literatures on climate adaptation, decision-making under uncertainty, and rural-urban migration. First, we assess how differential access to several types of information sources and social networks – including conventional radio/TV/print media, digital media, government offices, farmer social networks, and migrant networks – shape perceptions of climate risks to various livelihood strategies. Second, we investigate how risk perceptions influence both short-term and longer-term responses to climate hazards, including migration. Third, we seek to test the applicability of various theories of decision-making under uncertainty to smallholder farmer climate adaptation. In so doing, we hope that our analysis may help inform the design of more effective climate information services for this context.

4.2 Theoretical Framework and Hypotheses

In addressing our research questions, this study tests hypotheses emerging from three theoretical frameworks that are especially relevant to questions of how subsistence farming households perceive and act on climate risk. The New Economics of Labor Migration (NELM) postulates that households engaged in rural livelihoods seek to minimize risks to their livelihoods and overcome constraints in access to financial capital [121]. Additionally, households aim to minimize their sense of relative deprivation, or a perceived gap between their well-being and that of others in their social network [76]. A common strategy to cope with risk is to diversify sources of household income by engaging in multiple livelihood strategies, including rural-urban migration [12]. Based on these principles, if households perceive elevated risks to their livelihoods due to climate change, especially in emerging market contexts with limited access to financial services, then they should be more likely to diversify their livelihood portfolios. Furthermore, we hypothesize that households with larger social networks are more likely to be aware of alternative livelihood strategies and may be more likely to feel a sense of relative deprivation, further amplifying the likelihood of changing strategies. Conversely, households with smaller social networks may be less motivated to change livelihood strategies. Therefore, our first two formalized hypotheses are:

- H1: *Farmers' perception of overall climate risk to their livelihoods will be positively correlated with (a) their past experience of climatic events and (b) the size of their social networks.*
- H2: *The degree to which household incomes are diversified away from farming will be positively correlated with farmers' overall perception of climate risk to their livelihoods.*

A second relevant theory from the decision sciences is Protection Motivation Theory (PMT), which states that decision-makers generally seek to mitigate the risk of perceived threats [53, 155, 164]. The degree to which they act in accordance with this principle depends on two main variables: the perceived severity of a threat and the perceived capacity to mitigate this risk. A more generalized framework, the Theory of Planned Behavior (TPB), also frames individuals' actions in terms of their attitudes towards a behavior and their perceived control in carrying out that behavior, and also adds that social norms shape how strongly an individual considers a behavior [165]. Therefore, we should expect that the more farming households perceive climate change as a threat, and/or the more that households believe they have sufficient resources to mitigate climate hazards, the more likely they should be to take observable forms of climate adaptation (including planting different crops, changing the timing of planting and harvesting seasons, and/or engaging in migration) [160]. We hypothesize that households with recent experience with climate hazards are more likely to perceive climate change as a salient threat to their livelihoods. Furthermore, access to diverse sources of information is likely to increase the perceived severity of climate change, as well-informed households are more likely to hear of and understand climate information. We note that a possible counter hypothesis is that as households gain access to more diverse sources, the information they receive may reflect an average of climatic conditions across a broader geographic scope, and may not reflect the actual climate risks they face in the Chitwan District. For this analysis, we assume that the majority of information sources, with the exception of migrant networks, reflect local conditions. This could be more precisely explored in future survey waves. Finally, in contexts with limited access to formal institutions, households belonging to social groups, e.g. farmer cooperatives and women's groups, are more likely to believe they have the financial and social capital to address such risks, and also to be subject to social norms promoting climate adaptation. Our next set of formal hypotheses are thus:

- H3: *Farming households that (i) have experienced more natural hazards and (ii) have greater access to informational capital will be more likely to perceive climate change as a salient threat to their livelihoods.*
- H4: *Farmers' likelihood of taking an adaptive action to a climate event (e.g. switching crops or sending a household member as a migrant) will be positively correlated with (a) perceived climate risk, (b) the diversity of information sources to which they have access, and (c) the size of their social networks.*

While NELM and PMT provide testable implications for whether farming households take observable actions to reduce climate risk, they do not differentiate between the different risk management options that farmers may choose from. By contrast, Cumulative Prospect Theory (CPT) [152] and a related framework, Security-Potential/Aspiration (SP/A) [135], provide more granular theory on how decision-makers choose among a portfolio of risky options. Both frameworks start with the assumption that decision-makers interpret risky outcomes as either gains or losses relative to a subjective reference point. In both frameworks, individuals also exhibit risk aversion (i.e. decreasing marginal utility of gains) and loss aversion (i.e. losses are penalized with greater weight than gains of an equivalent magnitude). One additional component of SP/A is that decisions are framed as a dual-objective process: individuals assess their potential gains or losses relative to an aspiration (similar to the reference point in CPT), but may differ in terms of how much utility weight they assign to the worst possible outcomes (the security potential). If those outcomes are unlikely to meet a basic aspiration level, a security-minded individual may become risk-seeking in order to minimize or eliminate a loss. If the aspiration level has a good chance of being met, the individual then becomes risk-averse in evaluating additional gains. This framework may have particular relevance for farmers evaluating multiple adaptation options in light of climate shocks that threaten their basic subsistence. Specifically, when exposed to a shock e.g. a drought or flood, smallholder farmers may be expected to choose riskier adaptation strategies that have the potential to minimize or eliminate their losses, whereas in the absence of climate shocks, farmers may be expected to choose less risky strategies. Our last pair of formal hypotheses are thus:

- H5a: *In years without a climate shock, households' livelihood choices will be negatively correlated with their perceived risk of individual livelihood options.*
- H5b: *In years with a climate shock, households' livelihood choices will be positively correlated with their perceived risk of individual livelihood options.*

Table 4.1 summarizes the basic decision-making objectives, relevant factors, and limitations in applying each theoretical framework to smallholder farmer climate adaptation. While they focus on different scales and aspects of decision-making under uncertainty, all three frameworks broadly predict that farmers should mitigate climate risks to their livelihoods to various degrees. NELM and PMT also suggest that greater access to social and informational capital should be correlated with a higher propensity to take adaptive actions, both because these networks can highlight the salience of climate risks, and also because they may give farmers more confidence in their ability to implement an action. However, the PMT framework is unique in highlighting the salience of perceived climate threat as an important factor in decision-making, and SP/A uniquely focuses on the role of farmers' aspiration levels and security weighting in determining their choices among risky options.

Table 4.1: Theoretical Frameworks - Application to Smallholder Farmer Climate Adaptation

Framework	Decision Objectives	Relevant Factors	Limitations
New Economics of Labor Migration	Minimize livelihood risk; Minimize "relative deprivation"; Overcome credit constraints	Perceived income volatility; Comparison to social networks	Doesn't distinguish between adaptation options
Protection Motivation Theory	Mitigate risk of perceived threats	Perceived threat severity; Perceived capacity to mitigate; Social norms	Only applicable to perceived threats
Security-Potential /Aspiration	Meet basic aspiration level	Aspiration target; Security of meeting aspiration	Difficult to ascertain aspiration targets

4.3 Methods

4.3.1 Study Area and Survey Design

To test these hypotheses, we administered a cross-sectional, face-to-face survey of 500 farming households in Nepal's Chitwan District from May – July 2022. The agricultural sector in Nepal represents an important case study to better understand how climate change is re-shaping farming livelihoods, and how smallholder farming communities can adapt to such changes. While the country is undergoing a rapid urbanization process, as of 2021 agriculture still accounts for 21.3 percent of Nepal's GDP, higher than the regional average for South Asia (16.7 percent) and far higher than the global average (4.3 percent) [30]. More strikingly, 64 percent of the population is employed in the agricultural sector, the highest among any country outside of sub-Saharan Africa, and far higher than both regional (42) and global (27) averages [31]. Furthermore, shaped by its unique geography and location between the Tibetan Plateau and the Indo-Gangetic Plain, Nepal faces several substantial climate risks, ranging from changing monsoonal patterns that affect the timing and volume of precipitation [28], temperature rise at higher-than-global averages that affect soil fertility [32], and rising potential for catastrophic events that can wipe out harvests and homes, e.g. glacial lake outburst floods [33]. Most of the country's farmers operate small-scale farms (average size of 0.7 hectares) that rely on rainfed agriculture [166], limiting the resources and capital that they can deploy to adjust to changing environmental conditions. Gaining a better understanding of how climate change influences Nepali farmer risk perceptions, and the factors that shape their adaptation decisions, can provide useful insights for other agricultural contexts that may face similar climate threats in the coming decades.

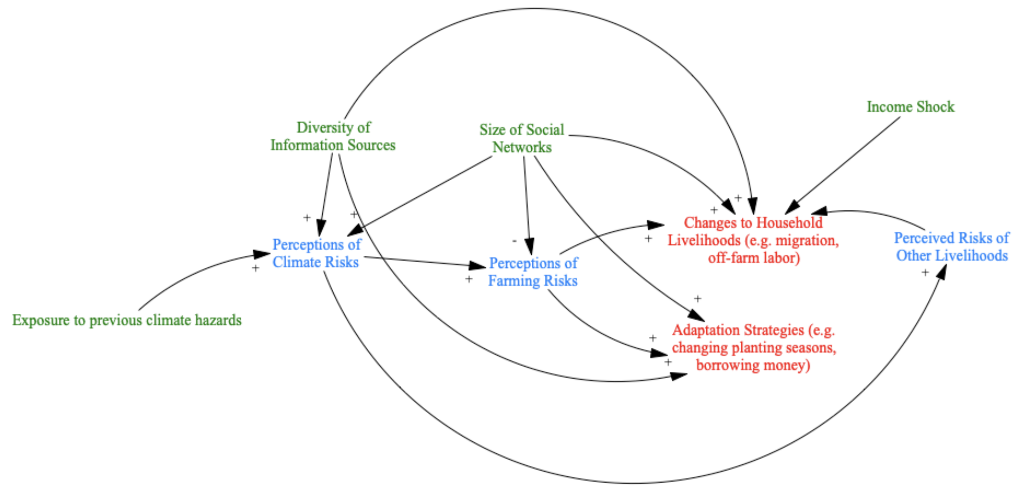
The Chitwan District is one of the country's main agricultural regions, cultivating a variety of subsistence and cash crops, and livestock ranging from capital-intensive buffalo and cows to less-expensive goats and chickens. In Nepal's 2010 National Adaptation Plan of Action, the Chitwan District ranked "High" (fourth out of five categories) on an index of overall vulnerability to climate change, reflective of its high exposure to increasing droughts, floods, and pests, among other hazards [167]. Demographically, the region is home to a diverse mix of ethnic and caste groups, including Brahmin, Chetri, Gurung, and Indigenous Tharu and Janjati populations. Additionally, over the last 20 years, the Chitwan District has seen a marked increase in outmigration to several countries, including India, Saudi Arabia, Qatar, and East Asian countries [29, 149, 168]. This study site therefore provides a high degree of variation in livelihood strategies, exposure to climate risks, ethnic/caste identity, connection to migrant and other social networks. These variations allow us to assess how multiple forms of demographic heterogeneity may translate to important differences in factors hypothesized to underlie risk perceptions and climate adaptation strategies.

Geographically, the 15 km by 30 km region is located in the Terai plains and is transected by two main rivers, the Narayani and East Rapti, with different propensities to flood during the monsoonal rains. Participants for our survey were recruited from two of the district's 29 wards, with one (Ward 26) bordering the larger, more flood-prone Narayani and the other (Ward 23) bordering the smaller, less flood-prone East Rapti. In each ward, we stratified the sample by randomly selecting 200 households within 1 km of the riverbank and 50 households at least 3 km from the river. This sampling strategy allows us to exploit localized variation in exposure to climate hazards while controlling for similar economic and political conditions, strengthening the potential power of our research design with respect to inferring causal effects of climate risks on livelihood choices.

Survey questions were designed to measure several categories of independent, intervening, and dependent variables, and were refined after pre-testing questions through 12 semi-structured interviews with farmers across the Chitwan District. Independent variables included basic demographic information on respondent gender, age, and educational attainment, as well as household-level information on family size, income, ethnic/caste group identity, and land tenure. Other key independent variables of interest included the the frequency and trust with which respondents consult various information sources, the social groups in which a respondent participates, and exposure to previous climatic hazards in each year from 2015-2021. This latter variable was assessed using a survey calendar design, in which respondents are presented with a physical calendar that contains Nepali years and cues of locally-relevant events (e.g. a local-level election). This design was refined in previous demographic surveys in the Chitwan District, which have demonstrated its efficacy in improving respondent recall of life history events [169].

Key intervening variables included respondents' perceptions of climate risks, and the salience of climate to perceptions of overall livelihood risks. Specifically, climate risk perceptions were assessed by asking respondents a series of Likert-scale questions on whether the impact of various hazards on crops (including droughts, floods, pests, etc.) would become worse, better, or about the same over the coming 5 years. The salience of climate risks was assessed by asking respondents to rate the importance of 14 economic, social, and physical factors (including market access, access to labor, long-term weather conditions, etc.) to their economic success, on a scale from 1-3. We constructed a salience index for each respondent by comparing the score assigned to "long-term weather conditions" with the average score the respondent gave to all other factors (see Section 4.3 for more details). Because the terminology of "climate change" was not well-understood during the pre-testing, we used the category "long-term weather conditions", defined for respondents as weather events lasting more than 2 weeks, as a proxy for climate risks. In each survey interview, respondents were asked to evaluate the importance of the 14 factors before moving on to climate-specific questions, in order to reduce the potential bias for anchoring to climate as a salient factor. Finally, respondents were asked to rate their general assessment of the riskiness of each of 12 livelihood strategies commonly deployed in the Chitwan District, including farming cereal crops, farming fruits/vegetables, raising livestock, engaging in local or international migration, and working off-farm jobs.

The main dependent variables of this study include respondents' self-reported adaptation actions taken intentionally as a response to a climate hazard, and the composition of their household income by livelihood. This latter variable was assessed by using the calendar instrument to ask respondents about the livelihood strategies their household deployed in each year from 2015-2021, as well as an estimate of the income earned from each livelihood. This allows us to evaluate the effect of independent and dependent variables not just on binary livelihood choices, but also on the relative proportions that each livelihood contributes to household income. Respondents who reported being exposed to a climate hazard at least once in the past seven years received a follow-up question regarding which of a list of 14 adaptation actions (including changing the timing of planting/harvesting, planting new crop varieties, borrowing money, etc.) they had taken as a response to the hazard. Respondents could also specify other strategies not on the list, or answer that they had taken no such actions. Further details on how survey responses were coded into variables can be found in Sections 4.4.2 - 4.4.4.



(a)

Figure 4.1: Conceptual Framework for Analytical Strategy. Arrows indicate hypothesized effects between independent variables (green), intervening variables (blue), and dependent variables (red). Where applicable, a + or – sign indicates the hypothesized directional effect of the variable at the tail of an arrow on the variable at the head of the arrow. While this framework proposes independent and dependent variables for the purposes of hypothesis testing, there also may be endogeneity in certain hypothesized relationships (e.g. strategy choices that affect climate risk perceptions. Such feedbacks are further noted in Section 4.6 and treated in Chapter 5.

4.3.2 Analytical Strategy

To test the hypotheses listed above, we employ a three-stage analytical design. First, we use a linear probability model to estimate the effects of three independent variables - social networks, access to information sources, and exposure to previous natural hazards - on farmers' perceptions of climate risks to their livelihoods, controlling for demographic factors e.g. gender, age, education, and caste identity. Next, we estimate the degree to which farmer climate risk perceptions are salient for their general risk perceptions of livelihood options, including farming cereal crops, engaging in migration, and seeking off-farm labor. Respondents rated their perceived risk of each of these livelihood options on a 3-point Likert scale, allowing us to use an ordered logistic model to predict which factors contribute to respondents rating a particular livelihood as "Not Risky", "Somewhat Risky", or "Highly Risky".

In the final step of the analysis, we assess the degree to which climate risk perceptions to farming, access to information sources, size of social networks, and perceived risk of alternative livelihoods shape the dependent variables of interest, farmers' livelihood and climate adaptation strategy choices. Here, we assume that social networks and access to information sources are not significantly influenced by livelihood and adaptation strategy choices. We address potential endogeneity issues between livelihood strategy choices and climate risk perceptions in the Discussion. Impacts of these variables on adaptation strategy choices are assessed using a series of logistic models to assess the effect of risk perceptions and other covariates on three categories of adaptation strategies (Farming strategies, Financial strategies, and Livelihood strategies, Section 4.4.3). Then, we use the survey calendar data on the income that each respondent household earned from different livelihoods in year t, as well as self-reported exposure to climate hazards, to assess how changes in income composition are related to information sources, social networks, climate risk perceptions, risk perceptions of alternative livelihoods, and potential income shocks. Section 4.4 provides more detail on the operationalization of key variables and the econometric models used to estimate their effects.

4.4 Key Variables and Descriptive Statistics

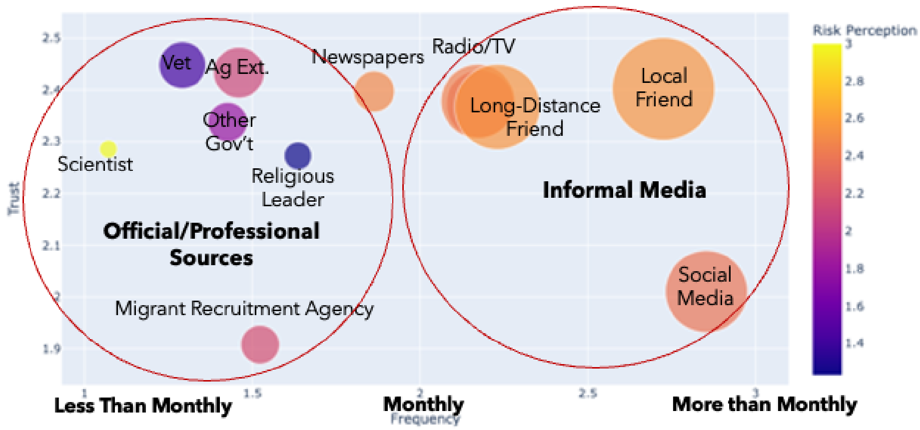
4.4.1 Demographic Variables

Table B.3 illustrates summary statistics on key demographic variables for the survey population, including gender, age, annual income, educational attainment, and caste identity. Where available, these are compared with demographic data from the 2011 Nepali Census for the Chitwan District, and for the country as a whole [79]. Note that the latest Nepali census was conducted in 2021, but updated demographic data was not publicly available at the time of writing.

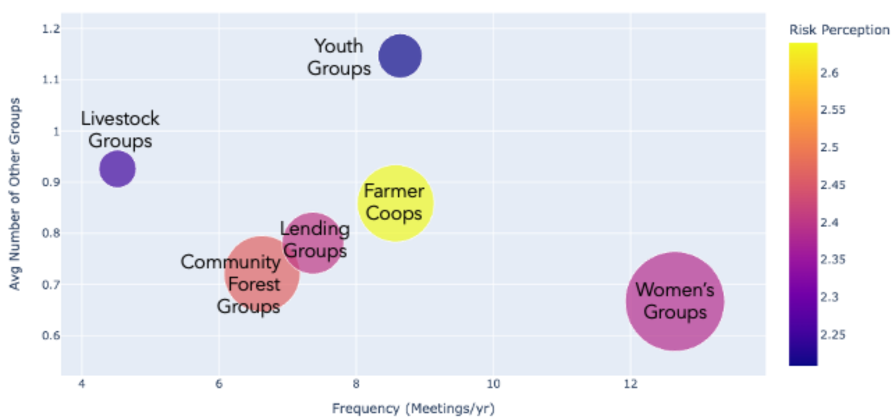
There are several important demographic differences between the survey population and the broader populations of the Chitwan District and Nepal, which can likely be attributed to common demographic processes in rural areas. First, there were markedly more female respondents in the survey (62.8 percent) compared to the sex composition of the broader society. This likely reflects highly-gendered migration patterns from rural areas, in which working-age men are more likely than other demographic groups to be living outside of the survey area. This is further supported by the age breakdown; survey respondents skewed older, with only 22 percent of respondents between 18-34 (whereas this age group comprises 48 percent of Chitwan adults). Respondents had less formal educational attainment than either Chitwan or Nepali residents as a whole, with roughly half the survey population not having received secondary education. With respect to caste identity, Dalit and Tharu/Darai/Kumal respondents were more highly represented in the survey population than the broader Nepali population. These castes have historically had lower socio-economic status compared to other caste identities. The analysis in this paper does not adjust data based on population weights, though this could be done in future work.

Table 4.2: Demographic Summary Statistics

Variable	Survey Population (2022)	Chitwan District Population (2011)	Nepal Population (2011)
Total Individuals	2,389	579,984	26,494,504
Households	500	132,462	5,427,302
Average Household Size	4.78	4.38	4.88
Gender			
Female	62.8	51.9	51.5
Male	37.2	48.1	48.5
Age (Pct of Adult Population)	45.0 (median)		
18-34	22.0	48.1	49.1
35-44	30.6	19.2	19.3
45-54	22.2	14.1	13.3
55-64	16.4	9.1	9.7
65+	7.4	9.3	8.5
Annual Income (NRs)	29,800 (average)	N/A	N/A
0- 100,000	17.4		
100,000 - 250,000	32.2		
250,000 - 500,000	31.8		
500,000 - 1,000,000	15.4		
1,000,000+	3.2		
Educational Attainment (Grade)	5.48 (avg grade)		
0-5	48.2	41.0	47.4
6-10	43.8	34.3	32.0
SLC-Intermediate	6.2	20.7	16.7
Bachelor's or above	1.8	3.9	3.8
Caste		N/A	
Brahmin-Chetri	35.8		29.3
Newar	1.8		5.0
Gurung-Magar-Tamang	12.4		14.9
Dalit	15.0		0.59
Tharu-Darai-Kumal	31.4		7.1
Other	3.6		43.1

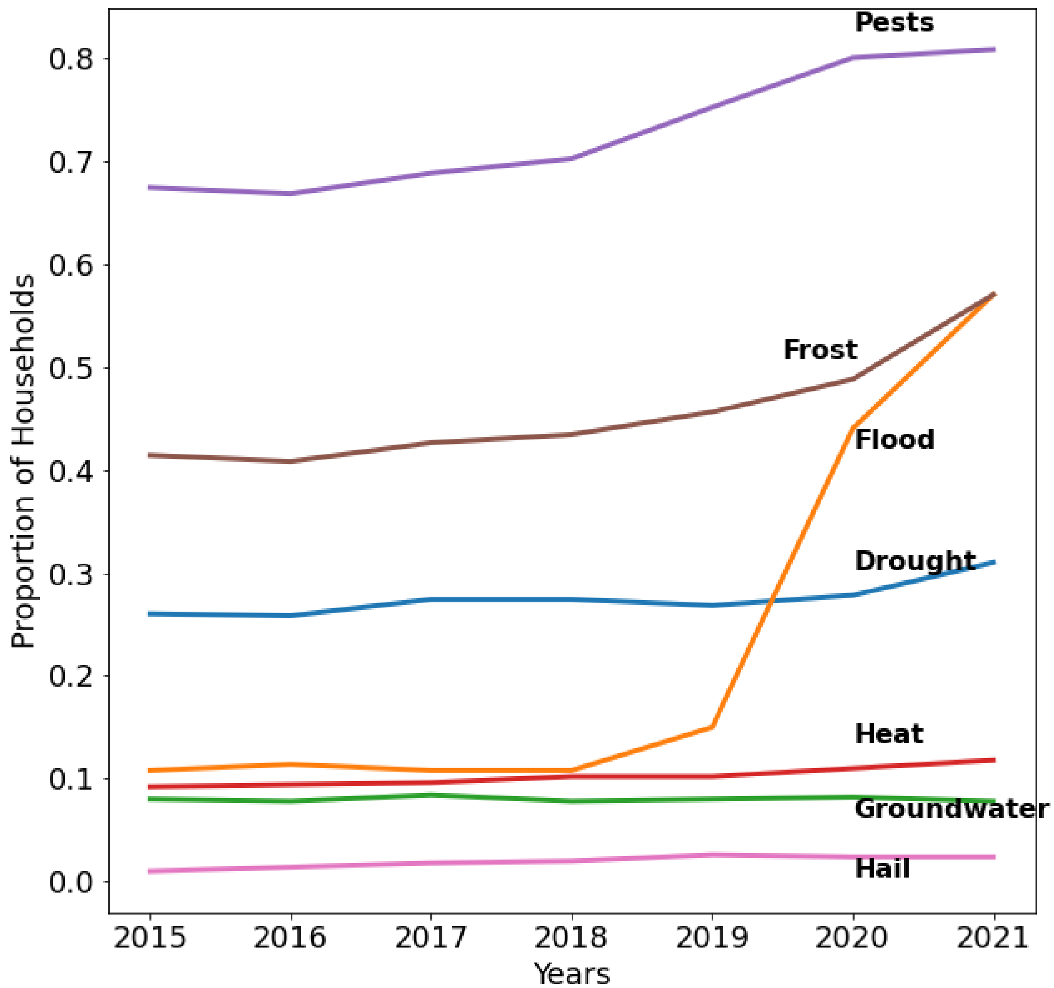


(a) Information Sources



(b) Social Networks

Figure 4.2: Breakdown of key information sources and social groups. **a)** Informational sources are positioned according to the average frequency with which they are consulted by respondents (x-axis) and the relative trust that respondents have in them (y-axis, 1 = "Low Trust", 3 = "High Trust"). The size of each bubble corresponds to the proportion of the survey sample that consulted a source at least once in a year. The color of each bubble corresponds to the average climate risk perception, P_i. **b)** Social groups are positioned in a similar fashion, with the x-axis representing the average number of times per year respondents participate in a group. The y-axis position for a group represents the average number of other groups to which its members also have membership. Bubble size corresponds to the proportion of respondents in given group, and color represents the average climate risk perception.



(a) Exposure to Hazards

Figure 4.3: Annual Self-Reported Exposure to Climate Hazards. The annual proportion of households who reported experiencing each of seven hazards is displayed for the seven years of the calendar instrument, 2015-2021.

4.4.2 Independent Variables: Access to Informational & Social Capital and Past Climate Exposure

In our survey design, each of the independent variables - social networks, access to information, and exposure to previous hazards - is assessed through a series of event frequency questions. For example, we ask respondents to identify how many times over the past seven years they have experienced each of seven climate-driven hazards (drought, flood or heavy rain, excess heat, pests, frost, hail, and lack of groundwater). Then, we asked respondents to indicate how many times per year someone from their household has participated in each of eight different types of social groups present in the Chitwan Valley, including formal groups e.g. a community forest user group, and farming cooperative, and other informal social groups e.g. a group of migrants. Finally, we ask respondents to identify how often they consult each of 12 types of information sources, including radio, television, agricultural offices, social media, and other information sources (See Appendix C.1 for full list of groups and information sources). For each of these variables, we are interested in measuring both the cumulative effect of the variable (e.g. how many different types of hazards one experienced, how many groups a household frequents, etc.), as well as the individual effect of each type of hazard, group, and information source.

To facilitate analysis, we create standardized indices to represent the number of sources (number of groups) that a respondent consults at least once per year. Alternative specifications could make use of different thresholds (e.g. consulting an information source once per season, or once per month), but some groups and information sources (e.g. agricultural extension offices) may be influential even if encountered relatively infrequently. For the hazard exposure index, we count the number of different types of hazards that a household reported experiencing for at least one year in our calendar range. One assumption here is that being exposed to a hazard at least once in the past seven years is sufficient to make it a salient event for current decision-making.

To compare each of these indices on an equal basis, we standardize them as follows:

$$\tilde{I}_i^k = \frac{I_i^k - \bar{I}^k}{\sigma_{I^k}} \tag{4.1}$$

where $\tilde{I}_i^k$ represents the standardized index value for household i for variable k (where k is the set [Hazards, Groups, Information Sources]). I_i^k represents the raw count of the index as specified above, and $\bar{I}^k$ represents the mean number of hazards, groups, or sources counted across the survey population. The factor σ_I^k represents the standard deviation of I^k across the survey population for variable k. The standardized index $\tilde{I}_i^k$ thus represents the number of standard deviations that household i is above (positive) or below (negative) the survey sample mean with respect to its exposure, access to information sources, and participation in social groups.

Summary statistics for the raw numbers of each of these variables are reported in Table 4.3, and further details are illustrated in Figures 4.2-4.3. With respect to information sources, there appears to be two broad categories: a set of informal sources (e.g. friends in Chitwan or abroad, social media) that are consulted frequently by the majority of the population, and a set of professional sources (e.g. agricultural extension services, veterinarians, migrant recruitment agencies) that are consulted less frequently, and by fewer farmers (Fig. 4.2a). However, the effect of consuming information from professionalized sources vs. informal sources on climate risk perceptions is not statistically significant (ANOVA test, $p = 0.30$). With respect to social groups, a substantial proportion of respondents belong to women's groups, which meet on average once per month (Fig. 4.2b). Other influential groups appear to be farmer cooperatives, lending groups, and community forest user groups, each meeting a few times per year.

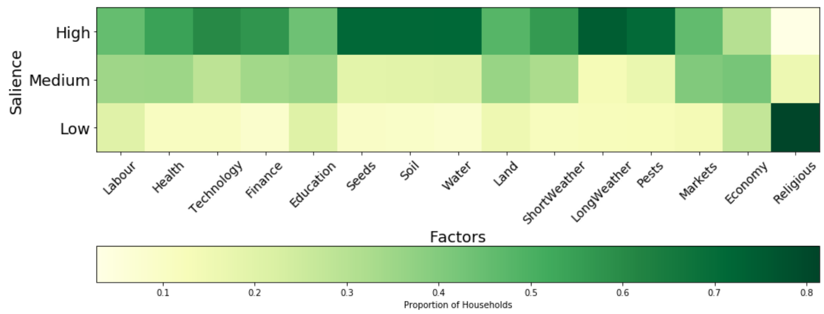
A high proportion of households reported repeated exposures to both pests and frost, reaching 81 and 57 percent, respectively, by 2021 (Fig. 4.3a). A sizable trend in the past three years has been a five-fold increase in flood exposure: 11 percent of households reported experiencing a flood in Nepali Year 2075 (April 2018 - March 2019), whereas 57 percent experienced a flood in Nepali Year 78 (April 2021 - March 2022). Finally, a smaller but relatively stable proportion of households, roughly 27 percent, reported experiencing drought conditions through the past 7 years.

Table 4.3: Independent Variables

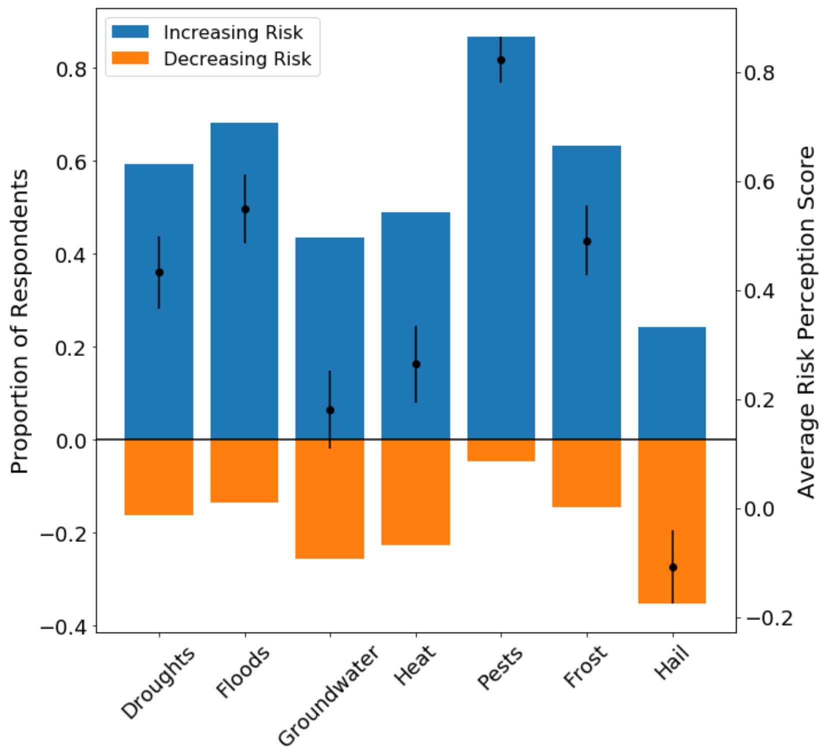
Factor	Range	Mean	Std. Dev.	IQR
Hazards Experienced at least Once	[0,7]	3.09	1.32	[2.00, 4.00]
Sources Consulted at least Once per Year	[0,12]	3.93	2.17	[2.00, 5.00]
Groups Participated in at least Once per Year	[0,5]	1.36	1.06	[1.00, 2.00]

4.4.3 Intervening Variables: Climate Risk Perceptions

The main intervening variable in our research design is farmers' perceptions of climate risk to their livelihoods. We operationalize this variable through two sub-measures: (i) the degree to which respondents perceive that climate-driven hazards are likely to improve or worsen over the near term, and (ii) the salience of climatic factors to respondents' economic decision-making. The first indicator is measured by asking survey respondents to assess how each of seven hazards (the same hazards used to construct the exposure index above) is likely to impact their crop harvests over the next five years. Respondents could answer whether they perceived these risks to become less severe, about the same, or more severe than current conditions. Here, we construct a directional risk perception index, P_i, by assigning a score of +1 to each hazard that household i identified as becoming more severe in the future, and -1 for each hazard the household identified as becoming less severe. Hazards identified as not significantly changing in the coming years were assigned a score of 0, with P_i equal to the sum of scores for each hazard. To maintain a distinction between respondents that generally perceived risks to be increasing (positive scores) and those perceiving risks to be decreasing (negative scores), an index $\tilde{P}_i$ was created by dividing each

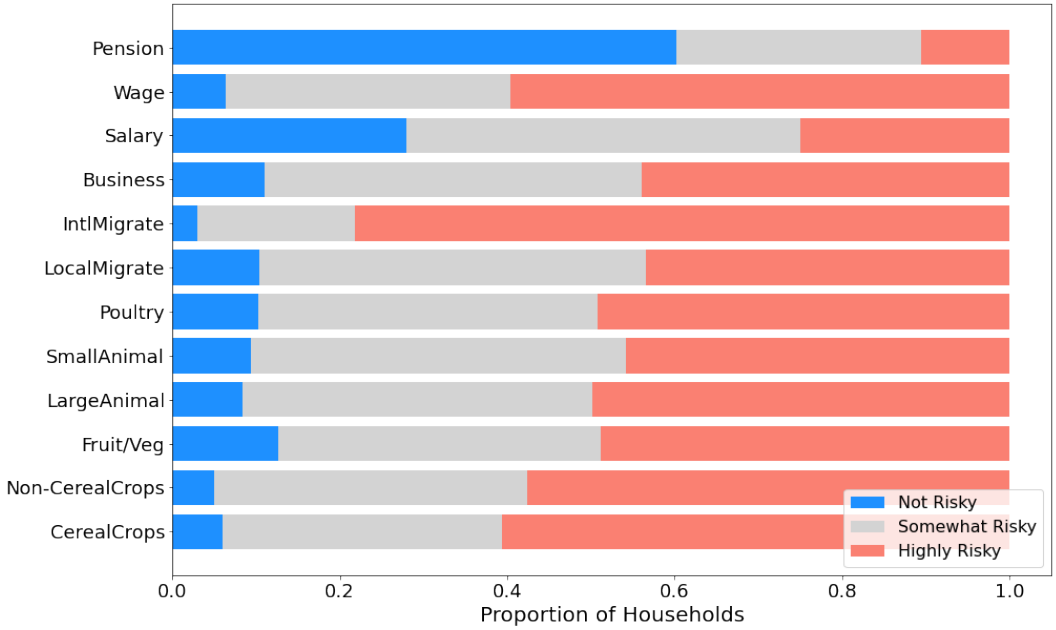


(a) Salience



(b) Risk Perceptions

Figure 4.4: Summary Statistics on Climate Risk Perceptions and Salience. a) The heat map illustrates the distribution of survey respondents by the level of salience assigned to each factor on the x-axis with respect to their economic success. For a given factor, the proportion of respondents assigning "Low", "Medium" or "High" importance to a given factor is illustrated by green shading. **b)** Survey respondents generally find that most climate hazards are likely to worsen in the near future. For each hazard on the x-axis, blue (orange) bars indicate the proportion of respondents projecting the hazard's impacts to become worse (better) over the next five years. Proportions may not add to 1, as respondents could also answer that "no change" was likely in the hazard. Black dots indicate the sample-wide mean score for each hazard, with 1 representing 100 percent of respondents believing a hazard will get worse, and -1 representing 100 percent of respondents believing hazards will get better. Error bars indicate the 95 percent confidence interval.



(a)

Figure 4.5: Perceptions of Livelihood Risk. For each of 12 livelihood categories, the proportion of respondents assessing a livelihood to be "Not Risky" (blue), "Somewhat Risky" (gray), and "Highly Risky" (red) are shown by the horizontal bars.

household's score by the theoretical maximum P_{max} (i.e. 7, in which each hazard is rated as +1). Note that in this case, $\tilde{P}_i$ can take on values in the interval [-1, 1], with negative values indicating a general perception that climate risks are likely to alleviate in the near future.

To calculate the salience of climate risks, respondents rated the degree to which each of 14 factors has influenced their level of success in growing crops. These included several non-weather related factors, e.g. access to labour/technology, level of education, quality of seeds, etc., as well as both short-term and long-term weather conditions. In the survey, we defined long-term weather conditions as events lasting more than two weeks, and used this as a proxy for the salience of climatic conditions. To avoid potential biases due to the availability heuristic (i.e. respondents may over-weigh factors that first come to mind), we asked respondents this set of questions before engaging in any climate- and weather-specific questions. For each factor, respondents answered on a Likert scale ranging from 1 (no influence) to 3 (a lot of influence). To assess the salience of climatic factors in respondents' decision-making, S_j, we compare the specific score that household j assigned to the long-term weather factor with the average across all other factors, as follows:

$$S_j = L_j^c - \bar{L}_j^{k \neq c} \tag{4.2}$$

where L_j^k represents the Likert score assigned by household j to factor k, and c represents the long-term weather factor specifically. This measure distinguishes the degree to which long-term weather factors are seen as influential to economic success from farming, relative to other factors. For example, if a respondent rated long-term weather as having "A lot of influence", and also rated all other factors in the same way, then $S_j = 0$. If households rated long-term weather and few other factors as "having a lot of influence", then $S_j > 0$, reflecting the outsized importance that j assigns to this factor. Conversely, if the household rated long-term weather as having some or no influence while rating several other factors as having "a lot of influence", then $S_j < 0$, reflecting the relatively minimal importance j assigns to this factor.

To facilitate the construction of a composite climate risk index (see below), we would like a standardized salience index, $\tilde{S}_j$, to take on only non-negative values. Therefore, we first translate the variable by 2 (as the lowest possible value of S_j is $1-3=-2$) and then standardize to the maximum observed value:

$$\tilde{S}_j = \frac{S_j + 2}{S_{j,max} + 2} \tag{4.3}$$

such that $\tilde{S}_j$ takes on values in the interval [0,1], with 0 representing low salience and 1 representing high salience.

To combine information on the salience of climate factors and the perception of future climate risks, a composite climate risk perception indicator, $\tilde{R}_i$, is defined as:

$$\tilde{R}_i = \tilde{P}_i * \tilde{S}_i \tag{4.4}$$

This composite index captures several features of respondent climate risk perceptions. First, $\tilde{R}_i$ takes on values in the interval [-1, 1], and the direction indicates whether the respondent believes climate risks will alleviate ($\tilde{R}_i < 0$) or worsen ($\tilde{R}_j > 0$) in the near future. Second, the magnitude is an indicator of how much of an effect a respondent believes future climatic conditions are likely to have on their farming success. A value $\tilde{R}_i \approx 1$ indicates that the respondent believes most climate-driven hazards will worsen in the coming years, and that this is highly salient to their farming success. However, if a respondent believes that only a few hazards may worsen, and/or that long-term weather conditions are not particularly salient to their farming success, then $\tilde{R}_j$ will take on some fraction between 0 and 1.

Summary statistics for the measures $\tilde{R}$, $\tilde{S}$, and $\tilde{P}$ are summarized in Table 4.4 below. Summary statistics for the distribution of survey respondents by both the risk perception and salience measures are illustrated in Figure 4.4. Generally, "long-term weather" rated the highest of all 14 factors regarding its impact on farmers' economic success, with 74 percent of respondents assigning it a "High" importance (Fig. 4.4a). Furthermore, for most hazards, the majority of respondents assessed that the impact of climate hazards on their economic success was likely to worsen over the coming 5 years (Fig. 4.4b). This was especially true for pests, which 87 percent of farmers expect to worsen in the coming years. Farmers also largely expected floods (68 percent of respondents), frost (63 percent), and droughts (59 percent) to worsen. One notable exception to this trend was hail, which more respondents expected to lessen in impact in the coming years. Although we did not follow up on reasons for these answers, there may be a general perception that warming temperatures will lead to fewer hailstorms.

To better understand how perceptions of farming risk compare to perceived risks of other livelihood alternatives, we asked respondents to rate the overall riskiness of each of 12 livelihood categories (Fig. 4.5). In this context, farming is perceived as one of the most risky livelihood strategies available to Chitwan farmers, with approximately 61 percent of respondents identifying farming cereal crops as "high risk". However, some of the most common alternatives, including international migration (78 percent) and off-farm wage labor (60 percent), were also perceived to be highly risky by the majority of respondents.

Table 4.4: Intervening Variables - Summary Statistics

Variable	**Range**	**Mean**	**Std. Dev.**	**IQR**
Risk Perception Index $\tilde{P}$	[-1,1]	0.407	0.395	[0.167, 0.667]
Salience Index $\tilde{S}$	[0.169,1]	0.655	0.138	[0.610, 0.746]
Composite Risk $\tilde{R}$	[-0.797,0.915]	0.268	0.270	[0.105, 0.455]

4.4.4 Dependent Variables: Adaptation Strategies and Livelihoods

There are two categories of dependent variables in this research design: farmers' intentional adaptation choices and the composition of household incomes by livelihood. In our survey, we used the calendar format to ask respondents whether they had deployed each of 14 types of livelihoods over the Nepali years 2072-2078 (roughly, 2015-2021), and if so,

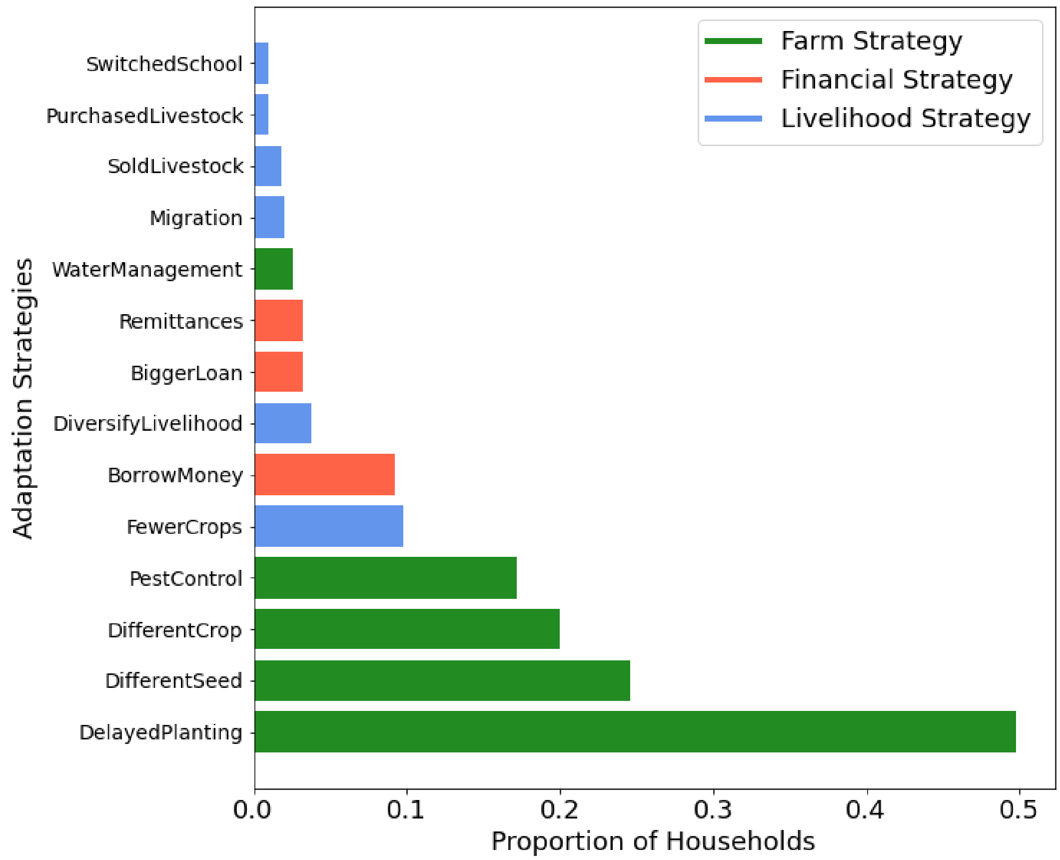
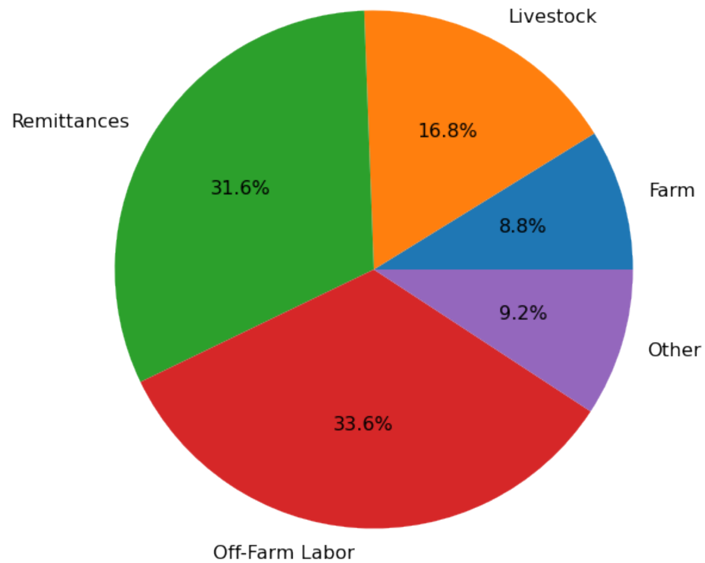
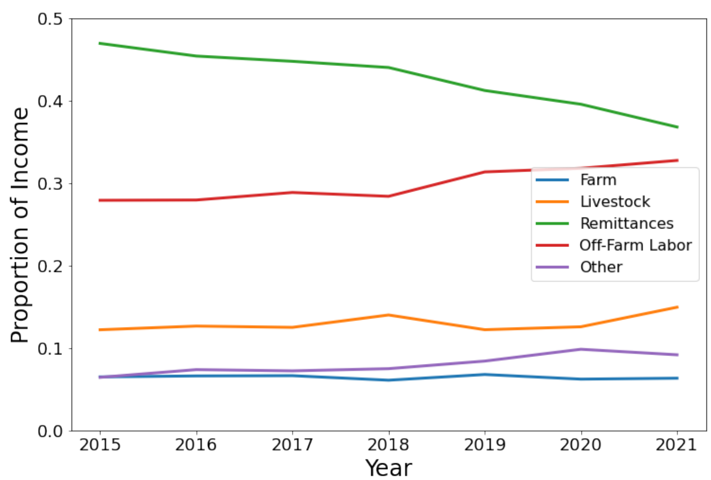


Figure 4.6: Adoption of Adaptation Strategies in Response to Climate Hazard. Bars display the proportion of respondents reporting the adoption of each of 14 strategies in response to a climatic hazard. Generally, these strategies can be clustered into three categories: on-farm management (green bars), financial strategies (red bars), and changing livelihoods (blue bars). Over 50 percent of respondents reported taking at least one on-farm management action in response to a climatic hazard, with fewer respondents reporting taking a financial or livelihood diversification strategy.

approximately how much income their household had earned from each livelihood for that year. This generated a panel dataset of livelihood choices and incomes for 500 farming households over seven years, which allows us to estimate the composition of household incomes as a function of the independent and intervening variables. For the purposes of analysis, we aggregated the 14 livelihoods into five general categories: farming, raising livestock, engaging in off-farm jobs within the Chitwan District, migration, and other (e.g.



(a) Household-Level Income Sources Averaged across Years



(b) District-Level Income Sources by Year

Figure 4.7: Distribution of farmer incomes by livelihood categories. **a)** Wedges represent the average proportion of household incomes coming from each of six livelihood sources over the entire 7-year survey calendar period. For example, an average household received 31.6 percent of its income from migration remittances from 2015-2021. **b)** Lines display the proportion of total district income coming from each livelihood category per year. For example, in 2021, 37 percent of all income reported by survey respondents came from remittances. Note that proportions may not match, as higher-income households may have different distributions than lower-income households.

government pensions).

Respondents were then asked whether they had ever taken each of 12 pre-specified actions (e.g. delaying crop planting, borrowing money, engaging in migration, etc.) in response to a natural hazard. Additionally, respondents were given the option to name other strategies they had adopted that were not included in the pre-specified list. This was a common response, with 20.6 percent of respondents providing at least one additional strategy; most of these responses could be categorized as either water management (e.g. "diverted a water source", "added water to the land") or pest control (e.g. "used insecticides"). After data collection was completed, we retroactively added these two categories to the list of adaptation strategies, though we note that their totals likely represent an under-count of their true adoption rate, given that respondents were not explicitly prompted to consider these options. In total, this provided us with 14 different adaptation strategies.

Figure 4.6 illustrates the adoption rates of each of these strategies, which range from 1.0 percent (switching children to a less expensive school) to 49.8 percent (delaying the planting of a crop by several days or weeks). To assist with analysis, we further categorize these strategies into three overarching categories of adaptation: farm-based strategies (Fig. 4.6, green bars), financial-based strategies (red bars), and livelihood diversification strategies (blue bars). This allows us to test whether our independent and intervening variables lead farmers to adopt different adaptation pathways - for example, whether access to greater informational capital might lead farmers to diversify livelihoods, rather than pursue on-farm adaptation techniques. We find that a large majority of respondents (82.4 percent) pursued at least one type of on-farm management strategy, while substantially fewer respondents pursued either financial management (14.4 percent) or livelihood diversification (17.2 percent) strategies. In particular, only 2.0 percent of respondents reported that their household engaged in migration in direct response to a climate hazard.

Beyond intentional adaptation strategies, households also generally maintained highly diversified income portfolios throughout the survey calendar period (Fig. 4.7). An average household derived 33.6 percent of its income from off-farm labor and 31.6 percent from migration remittances, with farming comprising only 8.8 percent of total income (Fig. 4.7a). However, household income portfolios are highly variable: roughly 50 percent of respondents received less than 10 percent of their income from remittances, whereas 20 percent of households received 80 percent or more of their income from this source (SI Fig. 9). Still, nearly all respondents relied on non-farming revenue sources for the majority of their income. There are also significant temporal trends across the study area: the proportion of income coming from migration remittances generally decreased from 2015-2021 (a 21.5 percent decline), while off-farm labor comprised an increasing proportion of incomes (a 17.2 percent increase). This may reflect increasing industrialization in the Chitwan District, providing farming households with more nearby economic opportunities to diversify income sources.

4.5 Econometric Analyses

This section presents econometric tests of the research questions and formal hypotheses introduced in Sections 4.1-4.2. Each of the following sections revisits one of the four research questions and relevant hypotheses. Then, we describe the statistical model constructed to address these questions. Unless otherwise stated, significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. A brief summary of our formal hypotheses and the evidence supporting/contradicting these hypotheses is provided in the Discussion (Section 4.6).

4.5.1 What Factors Shape Climate Risk Perceptions?

Our first research question concerns how access to social and informational capital shape farmers' climate risk perceptions. The relevant hypotheses derived from NELM and PMT include:

- H1: *Farmers' perception of overall climate risk to their livelihoods will be positively correlated with (a) their past experience of climatic events and (b) the size of their social networks.*
- H3: *Farming households that (i) have experienced more natural hazards and (ii) have greater access to informational capital will be more likely to perceive climate change as a salient threat to their livelihoods.*

Based on these hypotheses, we developed a linear probability model to test for the significance of (i) exposure to past hazards, (ii) access to diverse informational sources, and (iii) access to diverse social groups in affecting farmers' general perceptions of and salience of climate risk, while controlling for demographic variables. This model has the form:

$$Y_i = \beta_0 + \beta_1 \text{Gender}_i + \beta_2 \text{Age}_i + \beta_3 \text{Secondary}_i + \vec{\beta}_{4-8} \cdot \vec{\text{Caste}}_i + \beta_9 \tilde{H}_i + \beta_{10} \tilde{I}_i + \beta_{11} \tilde{G}_i + \epsilon_i \tag{4.5}$$

where Gender and Secondary are categorical variables taking on the value 1 if the respondent is a woman and has achieved at least some secondary schooling (i.e. greater than grade 5), respectively, and 0 otherwise. Caste is a vector of five categorical variables that take the value 1 if the respondent is a member of a specified caste, with Brahmin-Chetri serving as the baseline category. The variables $\tilde{H}_i$, $\tilde{I}_i$, and $\tilde{G}_i$ denote the hazard, information, and social group standardized indices, respectively, as described in Section 4.2. β_0 is a constant and ϵ_i is the error term, which is assumed to be i.i.d.

Y_i represents the dependent variable for a household's climate risk perception, which we measure in three ways as explained in Section 4.4.3. In Model 1, Y_i is set to the Risk Perception Index $\tilde{P}_i$, which measures respondents' perceptions of whether climate risks to crops are increasing or decreasing across six categories of hazards. In Model 2, Y_i is set to the Salience Index $\tilde{S}_i$, which measures the degree to which respondents believe long-term weather conditions are salient to their economic success, relative to other factors. Finally, Model 3 sets Y_i equal to the Composite Risk Index $\tilde{R}_i$, which is a product of $\tilde{P}_i$ and $\tilde{S}_i$ and captures the degree to which respondents perceive climate risks to be important and increasing in nature.

Results for each model are shown in Table 4.5. Broadly, demographic factors and indices of social and informational capital tend to have little explanatory power in shaping generalized farmer climate risk perceptions. Across the three models, the only consistently significant finding is that the Dalit caste identity is correlated with lower perception of climate risk compared to the baseline Brahmin-Chetri identity ($p < 0.01$), as measured by all three measures of risk perception. This is a somewhat counter-intuitive finding, as households belonging to the Dalit caste tend to have lower overall wealth and less landholdings compared to most other castes; one would therefore expect climate risks to be especially relevant for these farmers. However, it may be that Dalit households contend with other substantial economic and social pressures, and that climate-driven risks are not seen as especially relevant in this context. Another finding is that higher exposure to past climate hazards is associated with a modest, but significant increase in climate risk perceptions, as measured by the Risk Perception Index and Composite Risk Index ($p < 0.05$). Specifically, a 1 standard deviation increase in this index (i.e. 1.3 additional hazards experienced) is associated with a 4.0 basis point increase in the general perception that climate risks to crops will worsen in the coming years ($p < 0.05$), equivalent to a 9.4 percentage point increase from the mean risk perception score. The equivalent increase is also associated with a 3.0 basis point increase (13.4 percentage point increase from the mean score) in the composite risk index ($p < 0.05$), accounting for the relevant salience of climate factors in respondents' risk perceptions. While significant, this is a surprisingly small effect, given the well-documented phenomenon that recent natural disasters seem to substantially shape climate risk perceptions across a variety of geographical and cultural contexts [161, 170–172], at least over 2-4 years [173]. Perhaps even more surprisingly, neither access to information nor participation in social groups appears significantly correlated with any dimension of climate risk perception.

One potential explanation for these results is that farmers' risk perceptions may differ significantly across specific types of climate hazards. Indeed, 68.6 percent of respondents predicted the impact of at least one type of climatic hazard to worsen over the next 5 years, while also assessing at least one other type of hazard to alleviate in impact over the same time period. In Appendix C.2, we further deconstruct the dependent variable $\tilde{R}_i$ into risk perceptions of specific hazards, including droughts, floods, heat, and lack of groundwater. Here, we find that some demographic variables are significant in predicting particular risks. For example, gender is significantly correlated to risk perceptions regarding a lack of groundwater ($p < 0.05$), with women perceiving an average risk of 0.24 points higher than men (out of an overall scale of 2 points). This may be related to traditional gender roles among rural Chitwan farming households, in which women traditionaly have been responsible for household chores and may perceive issues in water supply more quickly than men [168, 174]. Respondents with at least some secondary school attainment perceive significantly lower risk of drought (-0.15 points, $p < 0.1$). This may reflect the role of at least some intermediate educational attainment in increasing adaptive capacity and/or resources to absorb shocks from natural hazards.

Perceptions of a few specific climate risks are also significantly correlated with access to social and informational capital, but in different directions. In particular, access to greater diversity of information sources (accessing 2 additional sources) is significantly correlated with a decrease in perceived risk of droughts (-0.09 points, $p < 0.05$) and a lack of groundwater (-0.07 points, $p < 0.1$). Conversely, greater participation in social groups (participating in 1.0 additional groups) is significantly associated with heightened perception of a lack of groundwater (0.1 points, $p < 0.01$) and frost (0.06 points, $p < 0.1$). For all hazards except heat and lack of groundwater, previous experience with a particular hazard was significantly and positively correlated with increased perceptions of its future risk.

While the positive correlations of specific climate risks with past exposure and (for some hazards) higher participation in social groups partially supports H1, the negative correlation of climate risks with access to information is surprising. In the context of this survey population, households with access to greater sources of information typically are ones that have communicated with professionalized services, e.g. agricultural extension officers, veterinarians, migrant recruitment agencies, and other government agencies. In theory, these information sources are more likely to be aware of general climate trends and the high likelihood that climate impacts on Nepali agriculture will worsen in the coming years. At the same time, such agencies may have confidence that they can provide solutions to help farmers cope with such impacts, perhaps explaining the neutral or negative effect of access to informational capital on climate risk perceptions. They also may have less localized information about climate risks and transmit information on average climate risks across a wider region in Nepal, which may be lower than specific risks faced by Chitwan farmers. While we do not have disaggregated data on exactly how local each information source is, in future work we can use farmers' frequency of consulting local friends vs. those living abroad as a proxy for this variable. We next turn to the salience of climate risks for overall perceptions of livelihood risks.

4.5.2 How Salient are Climate Risk Perceptions to General Perceptions of Livelihood Risks?

In the previous section, we analyzed the factors that shaped farmers' perceptions of climate risks and the salience of those factors to general economic success. In this section, we further the analysis by investigating how significant climate risk perceptions are to farmers' perceptions of overall livelihood riskiness. We also distinguish how climate risk shapes perceptions of the three livelihood strategies that survey respondents generally perceived to be most risky: farming cereal crops, migrating internationally, and working off-farm wage labor jobs (Fig. 4.5). As a check, we also test for these effects on risk perceptions regarding pension income, which was perceived to be the least risky livelihood source and likely less susceptible to climate risk.

In this analysis, the dependent variable is respondents' perception of livelihood risk, expressed on a Likert Scale ranging from 1 ("Not Risky") to 3 ("High Risky"). This variable is well-suited to an ordered logistic analysis, in which coefficients of independent variables can be transformed into the odds of moving one category higher on the Likert Scale (e.g.

Table 4.5: Factors Influencing Generalized Climate Risk Perceptions. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Variable	Risk Perception ($\tilde{P}_i$)	Salience ($\tilde{S}_i$)	Composite Risk ($\tilde{R}_i$)
Constant	0.395^{***} (0.119)	0.687^{***} (0.045)	0.298^{***} (0.078)
Gender	-0.0272 (0.042)	-0.013 (0.016)	-0.026 (0.027)
Age	0.0015 (0.002)	-0.0006 (0.001)	0.0004 (0.001)
Secondary School	-0.0077 (0.044)	-0.028^{*} (0.017)	-0.025 (0.029)
Gurung-Magar-Tamang	-0.0327 (0.058)	-0.027 (0.022)	-0.040 (0.038)
Dalit	-0.172^{***} (0.057)	-0.058^{***} (0.021)	-0.113^{***} (0.037)
Newar	-0.0177 (0.135)	-0.016 (0.050)	-0.034 (0.087)
Tharu-Darai-Kumal	-0.0048 (0.044)	-0.023 (0.017)	-0.043 (0.029)
Other	-0.0277 (0.100)	-0.0046 (0.048)	-0.0088 (0.065)
Hazard Index ($\bar{H}_i$)	0.042^{**} (0.019)	-0.0026 (0.007)	0.029^{**} (0.012)
Source Index ($\bar{S}_i$)	-0.011 (0.018)	-0.011 (0.007)	-0.0099 (0.012)
Group Index ($\bar{G}_i$)	-0.0010 (0.019)	-0.0074 (0.007)	0.0037 (0.012)

the odds of picking "Somewhat Risky" instead of "Not Risky", or "Highly Risky" instead of "Somewhat Risky"). This is formalized as:

$$Prob(Y_i \geq j) = \frac{1}{1 + exp(-\alpha_j - \beta_1 * Gender_i - \beta_2 * Age_i - \beta_3 * Secondary_i - \beta_4 * \tilde{R}_{10,i} - \beta_5 * \tilde{I}_i - \beta_6 * \tilde{G}_i)} \tag{4.6}$$

where Prob($Y_i \geq j$) is the probability of household i ranking livelihood Y's riskiness above level j (where j ∈ ["Not Risky", "Somewhat Risky"]). The other variables are the same as in Equation 5, with the exception that we multiply the composite risk index, $\tilde{R}_i$, by 10. This transformation allows for a more meaningful interpretation of the coefficient β_4, which now stands for the log odds that moving 1/10th up the risk index scale (equivalent to 0.2 points) will increase the risk perception of livelihood Y.

Table 4.6 displays the coefficients and significance levels for each of the four livelihoods assessed. We find that higher perceptions of climate risk, as measured by the transformed Composite Climate Risk index $\tilde{R}_{10}$, are indeed significantly and positively correlated with higher perceptions of livelihood risks for cereal crops, international migration, and wage labor. An increase of 0.2 points on the Climate Composite Risk scale increases the odds that a household will assign a riskier ranking these livelihoods by 1.17, 1.25, and 1.19 times, respectively ($p < 0.01$). In fact, climate risk perceptions are even more salient in driving general perceived risks of international migration and wage labor as they are to perceived risks of farming cereal crops. This suggests that rising climate threats may either be directly affecting the viability of these livelihoods, e.g. by making migration trips or outdoor labor more hazardous, and/or indirectly affecting these by reducing households' abilities to afford these options. At the same time, this coefficient does not have a significant effect on the odds of pension income being ranked riskier, which matches our intuition.

Access to greater informational and social capital have mixed effects on the perceptions of livelihood risks. On the one hand, access to more information sources is significantly correlated with a decrease in the likelihood of finding wage labor risky ($p < 0.05$), and weakly correlated with a decrease in finding pension incomes risky ($p < 0.1$). On the other hand, membership in more social groups is weakly correlated with diminished risk perceptions of farming cereal crops and engaging in international migration ($p < 0.1$). One plausible explanation for these results is that membership in groups e.g. farmer cooperatives and migrant networks help to reduce the long-term risks of these two livelihoods, while having more information about wage labor opportunities, which are likely more temporary, may be especially important in finding a suitable short-term income source.

Table 4.6: General Drivers of Livelihood Risk Perceptions. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Variable	Cereal Crops	Intl Migration	Wage Labor	Pension Income
Gender	-0.047 (0.218)	-0.388 (0.272)	0.193 (0.215)	0.344 (0.0214)
Age	0.0007 (0.009)	-0.0052 (0.011)	-0.0084 (0.009)	-0.003 (0.009)
Secondary School	0.398^{*} (0.220)	0.280 (0.269)	-0.137 (0.222)	-0.025 (0.216)
Composite Climate Risk	**0.160***** **(0.037)**	**0.227***** **(0.045)**	**0.177***** **(0.037)**	**0.0411** **(0.035)**
Information Sources	-0.104 (0.095)	-0.108 (0.111)	-0.278^{**} (0.093)	-0.188^{*} (0.097)
Social Networks	-0.162^{*} (0.094)	-0.190^{*} (0.114)	0.062 (0.096)	0.019 (0.095)

In Table 4.7, we further decompose the role of climate risks in shaping general perceived risks of livelihoods by specific hazards. Among the more notable results, we find that elevated perceptions of drought risks significantly drive higher risk perceptions of engaging international migration ($p < 0.01$) and farming cereal crops ($p < 0.05$). Perceptions of heat risk drive higher perceptions of the riskiness of wage labor ($p < 0.05$), while perceptions of hail risks significantly drive risk perceptions of both cereal crops and international migration ($p < 0.01$ for each). Not surprisingly, pest risk perceptions also driver higher perceptions of the riskiness of cereal crops ($p < 0.05$). These results provide strong evidence that farmers perceive climate risks in multifaceted ways. While several climate hazards are generally connected to higher perceived risks of farming livelihoods, some hazards are also correlated to higher perceived risks of livelihood alternatives, e.g. migration and off-farm wage labor - sometimes with even stronger effects than they have on perceived farming risk. This complex relationship suggests one understudied mechanism for why previous literature tends to find low uptake of adaptation actions among farmers: as climate change renders farming livelihoods increasingly volatile, it may be seen by farmers as making alternative livelihoods even riskier. In the next section, we turn to how risk perceptions and informational and social capital drive farmer adaptation decisions.

4.5.3 How Do Risk, Information Sources, and Social Networks Shape Adaptation Strategies?

We next assess which factors are associated with farmers' adaptation strategy choices (Table 4.8). As described in Section 4.4.4, we group the 14 individual adaptation strategies into three main groups: farming strategies, financial strategies, and livelihood strategies. The relevant hypothesis for this stage of the analysis is:

Table 4.7: Specific Climatic Drivers of Livelihood Risk Perceptions.

Variable	Cereal Crops	Intl Migration	Wage Labor	Pension Income
Gender	0.0075 (0.221)	-0.387 (0.279)	0.218 (0.216)	0.367* (0.216)
Age	-0.0003 (0.009)	-0.0039 (0.011)	-0.0077 (0.009)	-0.0008 (0.009)
Secondary School	0.313 (0.219)	0.294 (0.271)	-0.253 (0.221)	-0.0092 (0.214)
Drought Risk	0.290** (0.125)	0.592*** (0.147)	0.119 (0.125)	0.213* (0.128)
Flood Risk	0.088 (0.133)	0.044 (0.160)	0.128 (0.132)	0.292** (0.141)
Heat Risk	0.119 (0.124)	−0.138 (0.155)	0.243** (0.124)	-0.159 (0.124)
Pest Risk	0.461** (0.195)	0.053 (0.224)	0.268 (0.196)	0.214 (0.213)
Groundwater Risk	−0.091 (0.119)	−0.163 (0.150)	0.063 (0.117)	0.080 (0.118)
Hail Risk	0.328*** (0.127)	0.480*** (0.159)	0.190 (0.126)	0.051 (0.123)

- H4: *Farmers' likelihood of taking an adaptive action to a climate event (e.g. switching crops or sending a household member as a migrant) will be positively correlated with (a) perceived climate risk, (b) the diversity of information sources to which they have access, and (c) the size of their social networks.*

Again, here we assume that farmers generally receive localized information on climatic conditions from the various sources they consult, though this could be more specifically assessed in future rounds of the survey. To test this hypothesis, we estimate whether a respondent has taken at least one action in a particular category of adaptation strategies, based on their general perceived climate risk, perceived risks of various livelihood options, access to information sources, and participation in social groups. As the dependent variable (whether or not household i has taken an action in category Y) is binary, we build a simple logistic model:

$$\text{Prob}(\text{Y}_i = 1) = \frac{1}{1+exp(-\alpha_j-\beta_1*Gender_i-\beta_2*Age_i-\beta_3*Secondary_i-\beta_4*\tilde{R}_{10,i}-\beta_{5-8}\cdot\vec{L}_i^k-\beta_9*\tilde{I}_i-\beta_10*\tilde{G}_i)}$$

where $\text{Prob}(Y_i = 1)$ represents the probability that household i adopted an adaptation action in category Y, and L^k represents household i's generalized risk perceptions of farming cereal crops, farming fruits and vegetables, engaging in international migration, and engaging in off-farm wage labor.

One main finding is that access to an increased number of information sources is positively correlated with the likelihood of adopting on-farm ($p < 0.01$) and livelihood diversification ($p < 0.05$) strategies, though it is not significantly correlated with the likelihood of adopting financial strategies. A 1 standard deviation increase in the information index, $\tilde{I}$ (representing access to 2 additional information sources) increases the odds of adopting on-farm (livelihood diversification) strategies by 1.49 (1.28) times. Neither perceived climate risk nor membership in social groups were significantly associated with the likelihood of taking adaptation strategies in any of these categories. These results offer qualified support for H4. Access to diverse information sources appears to be important in promoting at least some forms of climate adaptation, which might further explain why households with greater access to information also tend to perceive lower risks for certain hazards (Section 4.5.1).

Although we did not find evidence for a significant effect of perceived climate risk on climate adaptation, this may be partially explained by households' risk perceptions of livelihood alternatives. Specifically, households are significantly less likely to pursue financial-based adaptation strategies if they perceive high risks to either fruit/vegetable farming ($p < 0.01$) or off-farm wage labor ($p < 0.05$), and are somewhat less likely to pursue on-farm adaptation or modify livelihood strategies if they perceive high risks to fruit/vegetable farming ($p < 0.1$). Building on the findings of Section 4.5.2, this suggests that climate adaptation decisions are not simply a function of perceived risks to current farming strategies. Rather, the riskiness of available alternatives may temper farmers' willingness to try new strategies, even if they are concerned about climate risks to their current livelihoods.

Surprisingly, we also find that educational attainment is negatively correlated with the adoption of on-farm management strategies; holding at least some secondary school education is associated with 0.53 times the odds of deploying such technique compared to farmers without this education ($p < 0.05$). One plausible explanation could be that more highly-educated farming households may have better access to additional non-farm sources of livelihoods to manage climate risks, but educational attainment was not significantly associated with adoption of other kinds of adaptation actions. This suggests that higher-educated households simply may have more resources to manage short-term shocks to their incomes, and are less motivated to change their farming practices in response to individual hazards. Still, this result warrants further study on the effects of education with respect to farmer climate adaptation.

Table 4.8: Propensity to Deploy Adaptation Strategies in Specified Category.

Variable	Farm Strategies	Financial Strategies	Livelihood Strategies
Gender	-0.412 (0.296)	0.078 (0.311)	0.089 (0.299)
Age	-0.011 (0.012)	-0.0042 (0.012)	-0.014 (0.012)
Secondary School	-0.647^{**} (0.302)	-0.110 (0.316)	0.099 (0.290)
Composite Climate Risk	-0.018 (0.499)	0.488 (0.530)	-0.102 (0.488)
Cereal Crop Risk	0.241 (0.218)	0.246 (0.239)	-0.036 (0.216)
Fruit/Veg Risk	-0.383^{*} (0.206)	-0.593^{***} (0.202)	-0.329^{*} (0.191)
Intl Migrate Risk	-0.019 (0.265)	-0.246 (0.255)	-0.076 (0.245)
Wage Risk	-0.118 (0.230)	-0.530^{**} (0.217)	-0.216 (0.207)
Social Networks ($\tilde{G}$)	0.089 (0.129)	0.068 (0.135)	-0.067 (0.126)
Information Sources ($\tilde{I}$)	0.398^{***} (0.146)	0.050 (0.132)	0.243^{**} (0.120)

4.5.4 What Factors Lead to Household Income Diversification?

In addition to respondents' stated adaptation strategies, we also seek to understand how household income sources are related to farmer risk perceptions, access to social and informational capital, and experience with climate shocks. Relevant hypotheses for this question come from NELM and SP/A frameworks, and include:

- H2: *The degree to which household incomes are diversified away from farming will be positively correlated with farmers' overall perception of climate risk to their livelihoods.*

- H4: *Farmers' likelihood of taking an adaptive action to a climate event (e.g. switching crops or sending a household member as a migrant) will be positively correlated with (a) perceived climate risk, (b) the diversity of information sources to which they have access, and (c) the size of their social networks.*

- H5a: *In years without a climate shock, households' livelihood choices will be negatively correlated with their perceived risk of individual livelihood options.*

- H5b: *In years with a climate shock, households' livelihood choices will be positively correlated with their perceived risk of individual livelihood options.*

To test these hypotheses, we construct two econometric models related to income diversification. First, we develop a cross-sectional model, in which the dependent variable is the proportion of each household's income that comes from farming, remittances, or off-farm labor, averaged across the seven years for which respondents reported income (2015-2021). This may serve as a proxy for households' long-term strategies with respect to their income portfolios. Here, all variables, including the dependent variable, are averaged at the household level. Then, we develop a panel model, in which we test whether annual exposure to climate events and household-level variables influence annual changes in the distribution of household incomes. In this model, the dependent variable and climate exposure are assessed at the household-year level, while all other variables are averaged at the household level.

The cross-sectional model is specified as follows:

$$Y_i^k = \beta_0 + \beta_1\text{Gender}_i + \beta_2\text{Age}_i + \beta_3\text{Secondary}_i + \beta_4\tilde{R}_i + \beta_{5-8}\cdot\vec{L}_i^k + \beta_{10}\tilde{I}_i + \beta_{11}\tilde{G}_i + \epsilon_i \quad (4.7)$$

where Y_i^k represents the proportion of household i's income coming from k source (representing farming, remittances, and off-farm labor, respectively, in the three versions of the model). Gender, Age, and Secondary represent the same demographic variables as before. $\tilde{R}_i$ represents the composite climate risk index for respondent i, and $\vec{L}_i^k$ represent respondent i's general perceived risks towards cereal crops, international migration, and wage labor. Finally, $\tilde{I}_i$ and $\tilde{G}_i$ represent the information and group index, respectively, for household i, and ϵ_i is the error term, assumed to be i.i.d.

Our results indicate that general climate risk perceptions do not seem to significantly affect long-term income portfolio strategies. The composite climate risk has a marginally significant negative effect on the proportion of long-term income coming from off-farm labor, with an increase of 1 unit in this index associated with a 12.5 percentage point decrease in the contribution of this livelihood to household incomes ($p < 0.1$). Building on findings from Section 4.5.2, this may indicate that many off-farm labor options in the Chitwan District, e.g. construction and working on other farms, are themselves subject to climatic risks, and households perceiving high climate risks generally seek to reduce their dependence on these strategies. Still, the negligible effect of climate risk perceptions on the long-term proportion of income coming from farming and migration runs counter to our hypothesis from NELM (H2). There are at least three plausible interpretations of this result: (i) because most Chitwan households already have highly diversified income portfolios, the incremental effects of climate risk may not matter; (ii) households may wish to further diversify their income sources, but do not believe they have the ability to do so; or (iii) households may believe that climatic factors also make alternative strategies riskier (Section 4.5.2), and that there is no motivation to switch strategies when risks are correlated across livelihood options.

Other factors may partially explain households' decisions to diversify their income portfolios. Membership in social groups is strongly correlated with an increase in the proportion of income coming from farming livelihoods ($p < 0.01$). Access to diverse information sources is positively correlated with deriving more income from remittances ($p < 0.05$) and less from off-farm labor ($p < 0.05$). These results provide mixed evidence for H4. Increased access to social and informational capital appear to be relevant to farmers' livelihood decisions, but at least in the case of social networks, farmer cooperatives and related groups may be giving households more confidence in their ability to secure income through farming livelihoods, and/or applying peer pressure to conform to predominant livelihood practices in their immediate surroundings. Conversely, greater access to information sources, including friends living outside of Chitwan, migrant recruitment agencies, and media, may provide households with more confidence that migration is a viable strategy to diversify their income.

General perceptions of specific livelihood risks also matter: households who view migration as a risky option tend to derive less of their income from remittances ($p < 0.1$) and more from off-farm labor ($p < 0.01$), indicating that households may view these two sources of livelihood diversification as substitutes. Surprisingly, farmers with higher generalized perceptions of cereal crop risks derive more of their income from farming livelihoods ($p < 0.05$). This may reflect some households switching to other types of crops or may indicate some degree of reverse causality, in which households that are more dependent on farming for their income also view this livelihood as riskier.

We further test our hypotheses through the panel model, in which we assess drivers of annual changes to households' income sources. This is specified as:

$$Y_{i,t}^{k} = \beta_0 + \beta_1 \text{Gender}_i + \beta_2 \text{Age}_i + \beta_3 \text{Secondary}_i + \beta_4 \tilde{R}_i + \beta_5 \tilde{I}_i + \beta_6 \tilde{G}_i + \beta_7 L_i^k + \beta_8 H_{i,t} + \beta_9 L_i^k * H_{i,t} + \delta_t + \epsilon_i \tag{4.8}$$

In this model, $Y_{i,t}^{k}$ represents the proportion of household i's income coming from livelihood k in year t. We again assess three versions of this model for income coming from farming, remittances, and off-farm labor. L_i^k denotes household i's general risk perception of livelihood k. $H_{i,t}$ denotes whether household i reported exposure to a particular hazard in time t. For this analysis, we focus especially on exposure to floods to exploit the especially high temporal variation in houses that were exposed to this hazard during the study period (Fig. 4.3). The variable $L_i^k * H_{i,t}$ represents the interaction between whether households experienced a flood and their risk perceptions of livelihood k. If the coefficient β_9 is significant and positive, this would indicate support for H5b, as households experiencing a shock would be more likely to derive revenue from a livelihood they perceived to be risky. Conversely, if β_7 is significant and negative, this would support H5a, as it would suggest that households would reduce income from risky sources when there is no shock. Finally, we add time fixed effects (δ_t) to control for any population-wide temporal trends in income sources.

Our analysis indicates partial support for both H5a and H5b. In the absence of flood exposure, households perceiving migration and wage labor to be riskier generally derive less of their income from remittances and off-farm labor. Specifically, increasing risk perceptions of international migration by one category (e.g. moving from viewing it as "not risky" to "somewhat risky") is associated with a 7 percentage point decrease in the proportion of household income coming from remittances ($p < 0.01$). A similar increase in the risk perception of wage labor is associated with a smaller, but still significant, 1 percentage point reduction in household income coming from off-farm labor ($p < 0.05$). However, an increase in risk perceptions of cereal crops is associated with an 1.5 percentage point increase in the proportion of household income coming from farming ($p < 0.01$). This could again reflect reverse causality (a greater dependence on farming engenders higher risk perceptions), or reflect limited capabilities to diversify income sources.

As expected, households experiencing a flood in a given year see an average decrease in the proportion of income coming from farming by 4.4 percentage points, all other conditions equal ($p < 0.01$). Flood exposure also decreases the proportion of income coming from off-farm labor by 9.5 percentage points ($p < 0.01$), highlighting that climate risks may be correlated across localized economic sectors. However, the interaction of livelihood risk perception and flood exposure leads to significant and positive coefficients for both farming and off-farm labor income sources, providing support for H5b. That is, when experiencing an income shock e.g. a flood, households with higher risk perceptions of cereal crops are in fact more likely to derive income from farming sources. Put another way, a household that generally views cereal crops (wage labor) as risky derives on average 3.6 (3.0) percentage points more of its income from this source in a flood year vs. a non-flood year ($p < 0.01$ for both effects). This result provides some evidence that households may actually resort to riskier strategies when facing the possibility of a loss through a climate-driven shock. However, this result may also be subject to reverse causality: if households are constrained to a limited set of livelihoods during a shock (e.g. farming and off-farm labor), they may come to see these livelihoods as particularly risky compared to other options. To test for the possibility of reverse causality, an ideal survey design would measure household risk perceptions both before and after an income shock, and assess whether these results are robust to pre-shock risk perceptions.

Table 4.9: Drivers of Long-Term Household Income Sources. In this table, the DV is operationalized as the proportion that each income source makes to a household's overall income, averaged from 2015-2021.

Variable	Farming Prop.	Remittance Prop.	Off-Farm Labor Prop.
Constant	0.123^{**} (0.061)	0.552^{***} (0.149)	0.501^{***} (0.142)
Gender	-0.015 (0.016)	0.078^{**} (0.039)	-0.081^{**} (0.037)
Age	0.0001 (0.001)	-0.0012 (0.002)	-0.005^{***} (0.001)
Secondary School	0.007 (0.016)	0.015 (0.040)	-0.117^{***} (0.038)
Composite Climate Risk	0.016 (0.027)	0.098 (0.067)	-0.125^{*} (0.064)
Social Networks ($\tilde{G}$)	0.022^{***} (0.007)	-0.005 (0.017)	-0.021 (0.016)
Information Sources ($\tilde{I}$)	0.0007 (0.007)	0.037^{**} (0.017)	-0.037^{**} (0.016)
Cereal Crop Risk	0.026^{**} (0.012)	-0.006 (0.029)	-0.044 (0.028)
Intl Migrate Risk	-0.023 (0.014)	-0.065^{*} (0.035)	0.116^{***} (0.034)
Wage Risk	-0.017 (0.012)	-0.027 (0.029)	-0.0006 (0.027)

Table 4.10: Drivers of Changes to Annual Household Income Composition. The dependent variables in these models represent the contributions of [Farming, Remittances, Off-Farm Labor] to household income in each year. DVs and the Flood Exposure variable are aggregated at the household-year scale. For each model, we interact whether a household reported exposure to floods with their perception of livelihood risk relating to the DV. For example, in the Farming Proportion model, we interact flood exposure with perceptions of Cereal Crop farming; in the Remittance Proportion model, we interact flood exposure with perceptions of international migration. The variable Year represents annual fixed effects to capture community-scale temporal trends in livelihood incomes.

Variable	Farming Prop.	Remittance Prop.	Off-Farm Labor Prop.
Constant	0.649^{**} (0.057)	1.00^{***} (0.096)	0.044 (0.094)
Gender	-0.021^{**} (0.003)	0.083^{***} (0.006)	-0.108^{***} (0.006)
Age	-0.0001 (0.000)	-0.0009^{***} (0.000)	-0.0059^{***} (0.000)
Secondary School	0.010^{***} (0.004)	0.033^{***} (0.006)	-0.140^{***} (0.006)
Composite Climate Risk	-0.016^{***} (0.006)	0.070^{***} (0.010)	-0.073^{***} (0.010)
Social Networks ($\tilde{G}$)	0.022^{***} (0.002)	-0.008^{***} (0.003)	-0.029^{***} (0.003)
Information Sources ($\tilde{I}$)	0.0080^{**} (0.002)	0.030^{***} (0.003)	-0.036^{***} (0.003)
DV Livelihood Risk	**0.015***** **(0.003)**	**-0.071***** **(0.006)**	**-0.010**** **(0.005)**
Flood Exposure	-0.044^{***} (0.015)	0.016 (0.034)	-0.095^{***} (0.027)
Livelihood Risk*Flood Exposure	**0.036***** **(0.006)**	**-0.018** **(0.012)**	**0.030***** **(0.010)**
Year	-0.007^{***} (0.001)	-0.008^{***} (0.001)	0.010^{***} (0.001)

4.6 Discussion

Increasing climate risks to agriculture in the coming decades are likely to require substantial and sometimes swift changes to subsistence livelihoods. This is especially true if regional and global ecosystem tipping points are breached [6, 175, 176], resulting in large-scale changes to water availability, soil fertility, and temperature and precipitation patterns. Farmers have had to contend with highly volatile livelihoods for decades, and in some respects are well positioned to cope with uncertainty. As this analysis has demonstrated, smallholder farmers already exhibit highly diversified income portfolios that are malleable in the face of shocks. Yet, to ensure food security and avoid maladaptive outcomes e.g. displacement, deforestation, and increased civil conflict, governments and civil society organizations have sought to connect farmers with better information about climate risks. So far, the utility of such climate information services appears mixed with respect to incentivizing systematic transitions to climate-smart agriculture.

While previous work has elaborated various factors that impact farmers' climate risk perceptions and adaptation choices, how climate change shapes farmer decisions across a portfolio of risky livelihood options is less well understood. In this analysis, we seek to disentangle the effects of perceived climate risk on how farmers evaluate a range of livelihood strategies, including farming, migration, and engaging in off-farm labor. We derive four tentative conclusions from our analysis. First, climatic conditions appear to be highly salient to farmers' overall perceptions of livelihood risks, including farming and non-farming occupations. This was assessed both by comparing respondents' ranking of various risk factors to their economic success (Section 4.4.3), and through an econometric analysis demonstrating that climate risk perceptions highly influence perceived risks of livelihoods as diverse as cereal crops, international migration, and wage labor (Section 4.5.2). In some cases, climatic hazards may actually be contributing to higher risk perceptions of non-farm livelihoods. Second, we find that access to a higher diversity of information sources and social networks does not necessarily lead to higher perceptions of climate risks (Section 4.5.1). In fact, for specific hazards e.g. droughts and lack of groundwater, access to more information may actually dampen perceived risk, perhaps reflecting local organizations' confidence in their ability to address these issues. However, access to more information appears to be a key driver of farmer adaptation, including on-farm management and diversifying livelihoods (Section 4.5.3), as well as diversifying income sources through migration (Section 4.5.4). This may reflect access to local institutions - formal (e.g. agricultural extension offices) and informal (e.g. friend and migrant networks) - that are well-suited to providing technical help to farmers, even if they are not in a position to implement large-scale strategic shifts in the agricultural sector. Finally, we find that while households are generally reluctant to invest in livelihoods they find risky, they may in fact "double down" on these livelihoods during periods of acute climate shocks (Section 4.5.4). This behavior could be driven by a strong aversion to losses, especially for households living at or near subsistence levels, and the willingness to take risks in order to avoid losses.

Our findings provide some qualified support for each of the three main theoretical frameworks that informed our hypotheses (Table 4.11). On the one hand, we find that rural households generally seek to reduce risks to their income portfolios, in line with NELM. However, in times of acute income shock, the reverse may be true - providing more support for the SP/A framework, which emphasizes the goal of meeting a basic aspiration level. Still, we find that households perceiving higher risks to cereal crops nevertheless rely more on farming for their income, even in the absence of a shock, contrary to expectations from both NELM and SP/A. We also find some support for PMT in that past experience with climate hazards appears to make climate risk a more salient threat, and that access to informational resources could enhance farmers' perceived capacity to implement an adaptive action to reduce this threat. However, increased access to information also may diminish perceptions of climate threats, perhaps because it engenders greater confidence that such threats can be successfully managed.

There are several considerations that temper the strength of our conclusions. First, our survey comprised a relatively small sample of 500 households, which especially limits our statistical power to investigate interactions between multiple factors. There is likely much more nuance to demographic and geographic factors that condition the relationships we explored in this analysis. Second, it is difficult for our research design to reject the likelihood of reverse causality. An especially relevant possibility is that households' previous adaptation and livelihood decisions influence their current climate risk perceptions. An ideal research design could disentangle the direction of causality by collecting data on farming households' risk perceptions over multiple survey waves, and track how these perceptions change in relation to changes in respondents' livelihood choices. Absent this opportunity, a potential area of future work is to develop survey vignettes and experiments that ask respondents to consider their future livelihood intentions, and test for relationships between these and current risk perceptions. Third, our survey design is subject to multiple potential sources of measurement error. In particular, we encountered several nuanced choices about how to measure risk perceptions, including whether to assess risk as a general belief about future hazards or include the salience of such hazards, and whether to combine beliefs about multiple climate risks or keep them disaggregated. A further nuance is how to assess adaptation: is a strategy that relies even more on farming, but with different seeds or crops, considered adaptation to climate change? Should engaging in risky off-farm wage labor count as adaptation, even if this is done as an option of last resort to make up for losses in income? These questions especially highlight the difficulty of assessing respondents' perceived level of agency in their decision-making, which may be a more direct indicator of whether a strategy could be considered adaptive.

Nevertheless, our findings point to avenues for future analysis and theoretical development. From an analytical perspective, it would be fruitful to integrate the data we collected from mostly close-ended survey questions with qualitative insights from in-depth interviews and focus group discussions. Questions on how farmers compare risks across different livelihood options and the type of information that is obtained from different sources would be especially relevant to this analysis. Expanding the survey area to different agro-ecological regions of Nepal, particularly farming areas in the Himalaya and mid-Hills, could also provide useful insights on how different types and degrees of climate risks are shaping farmers' livelihood choices. In this regard, the Government of Nepal's forthcoming Agricultural Census may offer valuable national-scale data on farmer climate adaptation. Finally, further exploring farming households' basic aspirations, including how farmers evaluate these during an income shock e.g. a drought or flood, may facilitate more nuanced theoretical development.

Table 4.11: Theoretical Frameworks - Application to Smallholder Farmer Climate Adaptation

Framework	Relevant Hypotheses	Supporting Evidence	Contradicting Evidence
New Economics of Labor Migration	H1; H2	Income diversification tied to risk perceptions	Households double down on risky strategies during shock
Protection Motivation Theory	H3; H4	Hazards correlated with perceived risks; Info. access correlated with adaptive action	Info. sources correlated with decreased risks
Security-Potential /Aspiration	H5a; H5b	Risk of farm alternatives generally reduces income diversification; More investment in risky strategies during shocks	Higher farm risks correlated with higher reliance on farm income

Chapter 5

Robust Climate Adaptation Policies for Subsistence Agriculture

In preparation as: N. Choquette-Levy, F. Errickson, A.B. Pokhrel M. Oppenheimer, and K. Keller. Robust climate adaptation policies for subsistence agriculture.

Abstract

Farmers make livelihood decisions in deeply uncertain environments regarding weather conditions, economic markets, and the social-political systems in which they operate. In turn, uncertainty in how farmers make such decisions challenges the ability of policymakers at multiple governance scales to achieve key objectives such as maximizing economic growth, minimizing inequality, ensuring food security, and limiting rates of outmigration. Farming households and policymakers must therefore make climate adaptation decisions under exogenous sources of deep uncertainty, e.g. unknown probability distributions of climatic and economic states of the world, and endogenous deep uncertainty resulting from misalignment or misunderstanding of objectives among key stakeholders in a system. Here, we propose an

integrated robust decision-making – agent-based model (RDM-ABM) framework to analyze how both types of deep uncertainty affect the robustness of potential climate adaptation policy interventions in the agricultural sector of Nepal. Our work expands on a previous analysis of smallholder farmer livelihood decisions under climate risk by incorporating endogenous feedbacks between policymakers at multiple levels of government, international development agencies, and farming households. We apply this framework to investigate how real-world complexities of the policymaking process – including potentially competing objectives, misalignment between scales of policymaking, and lags in policy implementation – affects the robustness of proposed climate adaptation policies for subsistence agriculture in Nepal.

5.1 Introduction

The evolving nature of climate risks highlights the importance of decision support tools for governing social-ecological systems facing "deep uncertainty". Deep uncertain describes a condition in in which the key variables of a system have unknown probability distributions, or in which stakeholders do not agree on key objectives, making it difficult to assess the effects of policy interventions [56, 175]. This is especially true for agricultural systems, in which farmers, communities, and local policymakers each make decisions in deeply uncertain environments regarding weather conditions, economic markets, and the social-political systems in which they operate. In turn, local, national, and international policymakers develop agricultural development strategies in the face of uncertainty regarding how farmers will respond to policy incentives, in addition to climatic and socioeconomic uncertainty. Stakeholders at all decision-making levels must therefore make climate adaptation decisions under exogenous sources of deep uncertainty, e.g. unknown probability distributions of climatic and economic states of the world, and endogenous deep uncertainty resulting from misalignment or misunderstanding of objectives among key stakeholders in a system.

In this paper, we create an integrated robust decision-making - agent-based model (RDM-ABM) to analyze how both types of deep uncertainty affect the robustness of evolving governance regimes in the agricultural sector of Nepal. Nepal is a particularly important case study for this topic, owing to its high exposure to multiple climate risks [32, 33, 166], high dependence on subsistence agriculture and remittances from outmigration [79, 149], and recent transition to a federal governance structure. This transition splits relevant climate adaptation decision-making responsibilities across multiple governance agencies and scales [59]. RDM is a framework to evaluate the performance of a set of strategy alternatives under multiple states of the world (SOWs), usually with the goal to minimize a decision-maker's regret in the worst-case SOWs. A related framework, Dynamic Adaptive Policy Pathways (DAPP), seeks to identify policy sequences that keep policy options open as uncertain exogenous parameters change over the timeline of an investment or decision. Previous work has typically applied RDM and DAPP frameworks to investigate "hard" infrastructure decisions under climate uncertainty [56, 58, 175, 177, 178]. More recent work evaluates the robustness of farming strategies to deep climate and economic uncertainty [179, 180] and assesses the prospects for reconciling resource tradeoffs between agriculture and other economic sectors under future climate scenarios [181, 182]. We contribute to this growing literature by analyzing (i) potential tradeoffs that emerge from differences between smallholder farmer objectives and those of policymakers at multiple scales regarding climate adaptation in Nepal's agricultural sector, (ii) the importance of different exogenous and endogenous sources of uncertainty in determining the likelihood of meeting these various objectives, and (iii) how different potential policy interventions - including investing in irrigation infrastructure, providing cash transfers, subsidizing weather-based crop insurance, and supporting migration remittances - compare in their robustness to these sources of uncertainty.

In this analysis, we apply the concept of RDM to analyze an emerging system facing both exogenous and endogenous sources of deep uncertainty: the agricultural sector in Nepal. Specifically, our research questions are:

- What implicit tradeoffs exist between the objectives of smallholder farmers, local institutions, and national ministries regarding climate adaptation in Nepal's agricultural sector?
- Which climate, socioeconomic, and governance-related sources of uncertainty are most important in determining the likelihood of meeting these objectives?
- How do potential policy interventions - including investing in irrigation infrastructure, subsidizing specific crops, providing cash transfers, subsidizing weather-based crop insurance, and supporting migration remittances - compare in their robustness to climate and socioeconomic sources of uncertainty?
- What governance principles (referred to as "collective choice rules" in the polycentricity framework) allow institutions to best manage the effects of deep uncertainty? For example, how do different policy time horizons, lags, and decision triggers affect the robustness of key system outcomes?

Our work expands on a previous analysis of smallholder farmer livelihood decisions under climate risk in Chapter 2, which used an ABM calibrated with survey data on Nepali farmers' livelihood decisions and risk preferences. This model allows us to explore how farmers who are heterogeneous in their financial resources, risk preferences, and access to information make livelihood decisions under various climatic, economic, and policy states of the world. Additionally, we incorporate endogenous feedbacks between policymakers at multiple levels of government, international development agencies, and farming households. Through this framework, we investigate how real-world complexities of the policymaking process – including potentially competing objectives, misalignment between scales of policymaking, and lags in policy implementation – affects the robustness of proposed climate adaptation policies for subsistence agriculture in Nepal.

5.2 Background: Polycentricity and Nepali Federalism

A useful theoretical framework to guide this analysis is that of polycentric governance. The concept of polycentricity was first developed by Elinor Ostrom and colleagues in the 1960s to describe regular patterns that emerged from "many centers of decision-making that are formally independent of each other" in providing public services in U.S. municipalities [183]. More recently, it has been extended to describe promising approaches for resolving public good and common-pool resource (CPR) dilemmas, including climate mitigation. Traditional economic theory would predict that absent a powerful top-down institution, CPR systems would collapse due to free-riding concerns and the lack of an external authority to enforce formal rules of CPR use, leading to a tragedy of the commons [184]. Yet, Ostrom and colleagues documented many CPRs that maintain their basic functions in the absence of a omnipotent central actor [185] through peer monitoring, social norms, and locally-derived institutions that coordinate diverse stakeholder interests. Moreover, Ostrom found that permissive institutions at higher decision-making scales were important in providing the boundary conditions that favor the establishment of more local institutions. For example, in the case of groundwater management in California, decisions made in the state court and legislature gave judges the power to allocate water rights. This subsequently motivated diverse stakeholders to collaborate on creating local water associations. These associations provided low-cost ways for system actors to monitor and sanction water use, but the ability of courts to provide more formal sanctions when needed ensured that water users had incentive to maintain their local institutions. Furthermore, as separate water associations realized that their basins were interconnected, they gradually set up multiple-agency systems to coordinate across their geographical boundaries [185].

The California water example illustrates several key benefits of polycentric governance systems to help actors navigate deep uncertainty. First, local institutions allow for tighter coupling between resource users and rule-making, providing an incentive for users to abide by formal and informal rules. Second, nesting institutions across decision-making scales (e.g. local water associations and state-level courts) provides stakeholders with relatively low-cost avenues to resolve disputes under normal conditions, while still providing an option for more formal sanctions and rule-making when substantial change is required [186, 187]. Third, polycentric governance systems allow multiple local institutions to explore different decision alternatives and to learn from each other's experience. This echoes calls for developing modular governance strategies to manage extreme events, in which local institutions can more quickly respond to system shocks, while global-scale institutions can provide the spatial and temporal averaging needed to allow more local institutions the ability to experiment with new approaches [188].

While polycentric governance arrangements seem particularly well-suited to help navigate deeply uncertain environments, polycentricity itself may introduce new sources of deep uncertainty for system actors. In particular, actors in different institutions may have conflicting objectives about the desired state of the system. In some cases, those conflicting objectives may be explicit (e.g. an Agriculture Ministry that wishes to expand production vs. an Environment Ministry that wishes to conserve forests). In several other cases, such conflicts may be implicit or hidden from some system actors. This is especially the case for actors at different governance scales, who have different capabilities to average losses (e.g. income, food production, and other important stocks) across time and space [21]. For example, a smallholder farming household is likely to be primarily concerned with avoiding a loss in a given cropping season, especially if it lacks access to formal credit and financial institutions. At the same time, a regional or local policymaker may be primarily concerned with maximizing gross domestic product over an election cycle, and may encourage farmers in their jurisdiction to take economic risks, knowing that the geographic and temporal average income will trend upwards. Furthermore, actors at different scales may have asymmetric access to information. Policymakers at higher governance scales are more likely to have access to long-term climate and economic forecasts, while smallholder farming households and community leaders may have more rapid access to short-term changes in environmental and market forces within a cropping season. The ability of polycentric governance to help system actors navigate deep uncertainty therefore depends in part on how it can resolve these endogenous forms of deep uncertainty.

The Nepali federal governance structure provides a relevant, contemporary example of an emerging polycentric system. Nepal's recent history was marked by a transition from a monarchy to democracy in the early 1990s, followed by a Maoist-led insurgency from the 1990s to 2006. Upon conclusion of hostilities, the country embarked on a decade-long political transition, leading to a new constitution in 2015. This constitution calls for a significant devolution of powers to a federal governance system, comprised of 7 provinces, 77 districts, and 753 village councils (including cities and rural municipalities) [59]. The latter two governance scales are often referred to as "local government" [189]. While competencies are still being established, there are already some important governance responsibilities at various levels regarding the agricultural sector. The national government is responsible for implementing the National Adaptation Plan of Action (NAPA), the country's 2010 submission to the United Nations Framework Convention on Climate Change. The NAPA establishes the Ministry of Forest and Environment as the agency responsible for coordinating a national approach to climate adaptation, with six thematic working groups, including one in Agricultural Development. The NAPA is also intended to streamline adaptation investments from international donors and non-governmental organizations by communicating areas of highest need for funding [167]. At the same time, the Ministry of Agriculture is implementing a national Agricultural Development Strategy (ADS) from 2015-2035, with the intention of transitioning the sector to achieve a net trade surplus by 2025, reduce poverty in rural areas from 27 percent to 10 percent by 2035, and increase annual average growth in the sector from 3 to 6 percent [190].

At the local level, several local governments have developed local adaptation plans of action (LAPAs), which communicate their own priorities regarding climate adaptation [191]. This reflects significant geographic and socioeconomic diversity across the country, resulting in exposure to different hazards and resources for adaptation. As part of the federal system, local governments receive some funding from the national government in the form of revenue transfers, though the details are still evolving. District-level governments also may play a coordinating role in developing certain adaptation strategies; for example, some districts (e.g. Kailali in the Western Terai plains) are experimenting with index insurance programs, while other districts have not yet explored these options (A. Pokhrel, personal communication, 6 June 2022). Districts also typically have committees with the mandate of ensuring food security and respond to disasters in the face of acute, local-level shocks. In addition to various levels of formal government, Nepal is also home to a rich array of local and international non-governmental organizations (NGOs). In some cases, NGOs work closely with government agencies to implement the NAPA and ADS priorities, but one common frustration among Nepali government officials is that some NGOs appear to disregard such plans (K. Ghimire, personal communication, 2 May 2022).

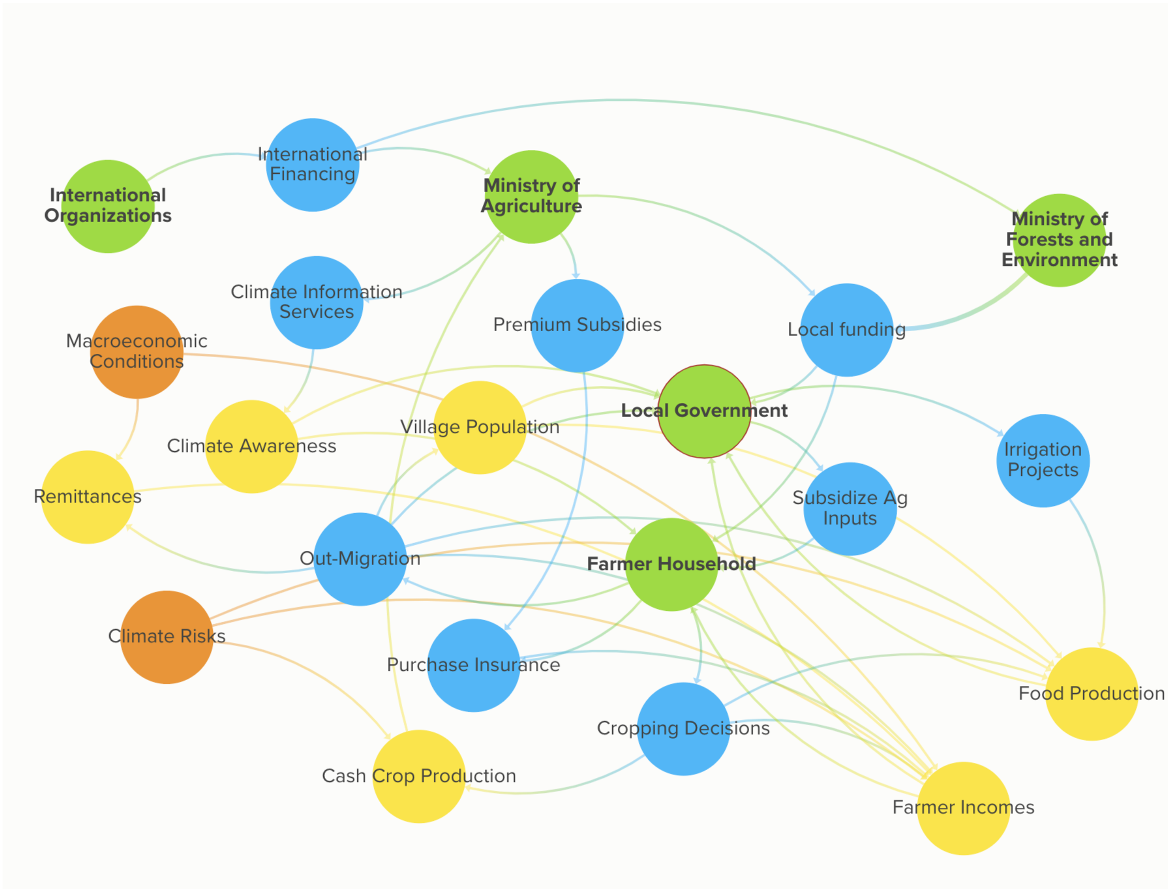


Figure 5.1: Schematic of Polycentric Governance in Nepal's Agricultural Sector. This systems map illustrates a simplified version of the key actors (green), processes and decision options (blue), stocks (yellow), and exogenous sources of deep uncertainty (orange) affecting the agricultural sector.

In sum, the Nepali agricultural sector exhibits several distinguishing features of polycentric governance. Local and provincial governments have or will have the power to determine their own adaptation priorities, supported by financial transfers and research conducted at national scales. Meanwhile, national-level government agencies set overall priorities for the agricultural sector, and have the opportunity to learn from local-level experiments on policies e.g. index insurance. Furthermore, NGOs may provide additional financial and technical support to certain regions of the country. While this polycentric system has the potential to help system actors navigate climate and socioeconomic uncertainty, it also raises potential sources of endogenous deep uncertainty. There is still uncertainty about the size and timing of revenues flowing from the national government to local institutions, and not all local institutions may have the same capacity to implement their own adaptation plans. Further, federal objectives regarding growth in the agricultural sector may implicitly conflict with local goals to ensure food security. This is particularly salient if growth requires investment in commercial agriculture in more fertile parts of the country (e.g. the Terai plains), at the expense of more marginal cropland in the Hills and Himalaya region. Additionally, NGOs may introduce their own objectives that can either support or conflict with objectives of both local and national government agencies. Figure 5.1 illustrates the key decision-makers, decision options and processes, stocks, and exogenous sources of deep uncertainty that are especially relevant to this system.

5.3 Methods

In this section, we describe a formal RDM-ABM to identify tradeoffs in the objectives of different system actors in the Nepali agricultural sector, and systematically assess how different exogenous and endogenous forms of deep uncertainty. Section 5.3.1 describes key additions and modifications to the ABM developed in Chapter 2 in order to add endogenous relationships between system actors. In Section 5.3.2, we identify existing and potential future sources of data to parameterize the model. Finally, Section 5.3.3 details an analysis plan to assess the robustness of governance pathways against exogenous and endogenous sources of deep uncertainty. Appendix D1 presents a fuller description of the model using the XLRM framework [54] to elaborate exogenous system variables (X), levers that can be taken by decision-makers (L), key relationships that map decision-maker actions to metrics (R), and metrics used to evaluate decision outcomes (M). We note that this model is still under development, and in several places distinguish between model components that have already been developed vs. those that may be developed for future work.

5.3.1 Modifications to Farmer Livelihoods ABM

Chapter 2 developed a novel ABM to track how smallholder farmer livelihood decisions evolve as a function of social relationships, changing climatic conditions, and policy interventions from a government institution that was exogenous to the model. Briefly, all model agents represented farming households with imperfect information about the costs and payoffs of three livelihood options: farming cereal crops (the Business-as-Usual strategy), farming cash crops (the Diverse strategy), and engaging in rural-urban migration through one or more household members (Migrate). Agents formed perceptions of livelihood costs, expected incomes, and income volatility through a combination of their own limited memories, observations from other households in their social networks, and incomplete access to government information. Agents deployed strategies that maximized their perceived expected incomes while minimizing perceived income volatility, balanced by a risk aversion parameter that varied across the population. Climate impacts were operationalized in two ways: gradual increases in mean annual temperature led to long-term declines in average crop yields, and also increased the probability of stochastic extreme droughts in any given cropping cycle. We explored policy scenarios in which an exogenous government institution deployed a consistent policy for the entire model timeline (2006-2050). These included a 30 USD/cycle cash transfer, an index insurance program, and a remittance bank that pooled a portion of migration remittances, smoothing out volatility across households and across time. We refer the reader back to Chapter 2 for more details on the model.

In this study, we extend the model in two main ways. First, we expand the types of agents represented in the ABM by endogenizing relationships between farming households and policymakers at local and national governance scales. We create a new local policymaker agent to represent a Nepali local government that is primarily concerned with ensuring food security and limiting out-migration from its jurisdiction. The local government agent receives a limited budget I_v from the national government (equal to 30 USD per capita per cropping cycle in the Base Case presented here) and decides how to allocate the budget to one or more of three options: subsidizing cereal crops, subsidizing cash crops, and/or investing in a public irrigation system. The council revisits its decision every λ_v cropping cycles, where λ_v denotes a typical policy window for a local government, accounting for some inertia in how often local policies are evaluated and revised (farming household agents can revisit their strategies every cropping cycle). In each decision period, the village council enters a two-step decision process:

- **Step 1: Assess whether to invest in a public irrigation system.** The local government can choose to invest its budget in an irrigation system that will improve farmer crop yields in periods of drought. The irrigation system has upfront cost $C_I >> I_v$, meaning that a government must choose to invest in it over multiple decision periods before it becomes functional. This decision is made through a benefit-cost analysis of irrigation given the government's updated knowledge of future drought risks. Specifically, it decides to invest if:

$$p_d(t) * \gamma * \sum_i \eta_i(t) * \bar{\pi}(T) > C_I - \sum_{t=0}^{t} I(t) \tag{5.1}$$

where $p_d(t)$ denotes the perceived probability of drought in time t, γ denotes the proportion of average crop yields in a non-drought cropping cycle that can be conserved in a drought year with an irrigation system, $\eta_i(t)$ represents the household-level farming productivity (which is a function of the number of working-age members left in the household in time t), and $\bar{\pi}(T)$ represents the average farming income in time t, which is itself a function of mean temperature T. The expression $\sum_{t=0}^{t} I(t)$ represents the cumulative investment made in the irrigation system up until time t. We assume that without irrigation, no farming income is earned by households during drought years. Therefore, a government will invest its budget in irrigation if it perceives the benefits of limited crop yields in drought years to be higher than the remaining investment needed to complete the system.

- **Step 2: With any remaining budget, decide whether to allocate subsidies to BAU or Diverse crops**. If the government does not invest in an irrigation system, or if the system is already built, it can decide to allocate its budget to either cereal (BAU) or cash (Diverse) crops. This decision is dependent on food security concerns. In line with Nepal's ADS, we assume that governments generally wish to ensure the self-sufficiency of their jurisdictions in terms of staple cereal crops. However, if they are satisfied with recent food security levels, they will invest subsidies in Diverse crops, which tend to be higher-income and can contribute to increased growth in the agricultural sector. Formally, local governments will switch subsidies to Diverse crops if:

$$\frac{1}{\lambda - 1} \sum_{t-\lambda t}^{t-1} P(t) > \psi P^*(N) \tag{5.2}$$

where $P(t)$ represents the total village cereal production (in tonnes) in cropping cycle t, and $P^*(N)$ represents the village-level production threshold needed to be self-sufficient in cereal grains. We use a factor of 0.378 tonnes of cereal per person per year from Lal [192], so P^* varies with N, the number of individuals living in the community at time t. Because it may not be realistic to meet 100 percent of a community's needs from its own cereal production, we include the self-sufficiency factor ψ to denote the proportion of needs that a village council wishes to meet from its own cereal production, assuming that it can procure the remainder through imports from other Nepali villages and/or international markets. The government will therefore provide cereal crop subsidies if recent production is below this threshold, and switch to cash crop subsidies if recent production has exceeded this threshold.

For the preliminary results presented in Section 4, only the second step (whether to allocate subsidies to BAU or Diverse crops) has been implemented for the local government agent. Future work includes incorporating the first step of whether to invest in an irrigation system, and also to include multiple local agents, representing localities in Nepal with different climate risks and agricultural productivity.

The second way in which we extend the ABM is to designate exogenous model parameters that are subject to deep uncertainty. Here, we target three sets of parameters: the rise in mean temperatures to 2050, Δ_T; the mean and variance of annual migration remittance income, $\mu^R(t)$ and $\sigma^R(t)$, respectively; and the mean and variance of annual market prices for crop j, $\mu_j^p(t)$ and $\sigma_j^p(t)$, respectively. For the first parameter, while climate science provides reasonable probability distributions for changes in mean annual temperatures over wide geographies [193], more localized temperature changes are still subject to high uncertainty [83]. Deep uncertainty regarding the second parameter reflects the possibility of macroeconomic shocks or border closures [85] that may suddenly alter the level of remittance incomes earned by migrants abroad. Finally, the third parameter is also subject to exogenous macroeconomic shocks in global food prices, which may impact farmer income, as well as the cost of importing enough food to meet communities' cereal crop needs. In all cases, we implement deep uncertainty by conducting a Monte Carlo analysis with 10,000 simulations, each randomly picking a value within the feasible ranges specified for each parameter. Results presented in Section 4 only examine deep uncertainty in the temperature parameter ($1.5^0C < \Delta_T < 4.5^0C$); in future work, we also plan to examine deep uncertainty in both the remittance and crop price parameters, including the simultaneous effects of deep uncertainty in multiple parameters.

5.3.2 Data Sources

As with the ABM in Chapter 2, the current version of the model is parameterized mainly with survey data obtained from previous waves of the Chitwan Valley Family Study (CVFS) [29], which provides panel data on farming household crop production, revenues, and migration remittances. Data on farming costs come from a USAID report on farming input costs for various regions in Nepal [80], and migration cost data comes from a World Bank report on Nepali migration destinations and costs [81]. Data on the distribution of household risk aversion, b_i, currently comes from a survey of Nepali tea farmers [82]. Future iterations of the model will use results from the survey presented in Chapter 4 of this dissertation to better capture variation in b_i, as well as access to formal/professional information sources, ω_i.

Food production data relevant for the village council decision-maker are aggregated from household-level CVFS data [29]. Village-level food needs are calculated from an estimate of the per capita cereal crop consumption needed for basic food security in Lal [192]. In the future, we plan to use at least two additional datasets to better parameterize village-scale metrics. First, one team member (A. Pokhrel) is in consultation with government officials from Kailali District, in the Far Western Terai plains, to obtain district-level food production data. Together with the CVFS dataset, this may provide us with the ability to model regional variation in food security metrics. Second, at the time of writing, the Nepal Central Bureau of Statistics is conducting the country's seventh national agriculture census (administered every 10 years), with data expected to be released in late 2022 or early 2023 [194]. This is also expected to provide fine-grained data on farming household cropping and livestock decisions, regional variation in crop production, and sources of farmer incomes. Data from the census will likely be useful in extending our model to incorporate multiple villages, reflecting the diversity of agricultural livelihood opportunities and climate risks in the Terai plains, Hills region, and Himalaya mountains.

5.3.3 Analytical Strategy

In Section 4, we present preliminary results to address our main research questions. This analysis was carried out in four steps:

- **Step 1: Identify tradeoffs between household and village council decision objectives**. As a first step, we run 200 simulations of the model for a Base Case scenario in which the self-sufficiency factor $\psi = 0.6$, the policy window $\lambda_l = 6$, and the mean temperature rise through 2050 $\Delta_T = 1.5^0 C$. Each simulation incorporates stochasticity in terms of the timing of droughts, the individual farming and remittance incomes earned by households in each time step, the household-level food production, and households' perceptions of livelihood payoffs and risks. We then construct scatter plots of simulation results at terminal time to compare household-level and village council-level metrics. For example, one plot constitutes the community-level cereal crop production at terminal time $P(t_{final})$ vs. the average household income volatility over the last 10 time steps in the simulation, $\bar{\sigma}_{t_{f-10,f}}$, with each point in the plot representing one simulation result. Plots are constructed such that axes increase in agents' desired goals (e.g., the x-axis is constructed in increasing village-level production, and the y-axis is constructed in decreasing household-level volatility). Thus, any potential tradeoffs in objectives can be analyzed by testing for a significant, negative slope across the scatter plot.

- **Step 2: Assess effects of different village council decision parameters on key metrics.** In a second step, we explore different values for ψ and λ_l. In the preliminary results presented below, we specifically examine food security, income, and migration metrics under two corner cases that reflect different capacities of village councils in Nepal's emerging federal framework. The first is a high-capacity council that revisits its policies over short time horizons and actively prioritizes food self-sufficiency ($\psi = 1.0$, $\lambda_l = 2$), and the second is a lower-capacity village council that is slower to update policy and does not actively prioritize self-sufficiency ($\psi = 0.2$, $\lambda = 10$). In using the terms "high capacity" and "low capacity", we do not mean to impart a normative judgment on the objectives of individual governments. Rather, we refer to capacity simply in terms of the human and administrative resources necessary to quickly develop and implement policy, which may change rapidly in the coming years as Nepal's federal structure continues to develop. In this analysis, we assess whether different capacities of local governments lead to tangibly different adaptation outcomes.

- **Step 3: Add in national policy interventions.** In a third step, we repeat Step 2 but with a national-scale policy intervention to assess whether top-down policies, combined with endogenous village-level and household-level responses, lead to tangibly different adaptation outcomes. For the results presented in Section 5.4, we analyze a national-scale crop insurance program as a test case. As described in Chapter 2 of the dissertation, in each time step households can choose whether to purchase insurance (here, premiums are subsidized by 25 percent of the actuarially-fair value), which pays farmers the expected non-drought income for their crop during a drought cycle. We compare the adaptation outcomes with this insurance program to scenarios without a top-down intervention, for both types of local government profiles described in Step 2. This leads to four discrete scenarios, as illustrated in Table 5.1.

- **Step 4 (prospective step for future work): Explore the effects of deep uncertainty in temperature change.** In a final step, we repeat Step 3, but for each scenario we run 1000 simulations, with each simulation receiving a random draw of temperature change ($1.5^0C \leq \Delta_T \leq 4.5^0C$). The purpose of this step is to compare how different combinations of top-down interventions and local government decision profiles perform in meeting household- and village-scale objectives, in a context of high climatic uncertainty.

Table 5.1: Policy Scenarios

Test	National Policy Intervention	
Local Government	**None**	**Crop Insurance**
Low Capacity	$\lambda_l = 10$ $\psi = 0.2$ No Insurance	$\lambda_l = 10$ $\psi = 0.2$ With Insurance
High Capacity	$\lambda_l = 2$ $\psi = 1.0$ No Insurance	$\lambda_l = 2$ $\psi = 1.0$ With Insurance

5.4 Results

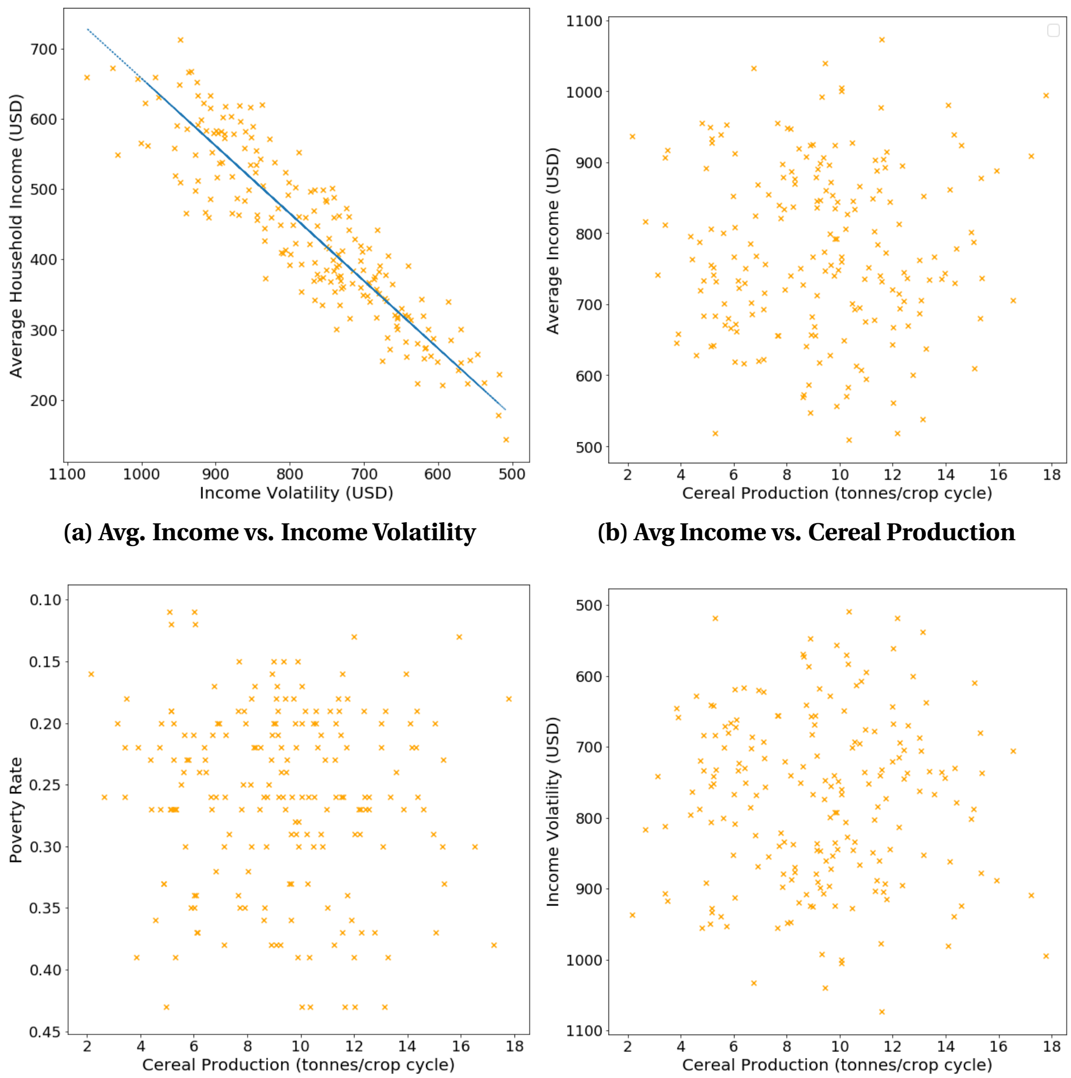
5.4.1 Do Tradeoffs Exist between Farmer and Village-Scale Objectives?

Our first set of analyses focuses on whether there are implicit tradeoffs between the decision-making objectives at the farming household and village council decision-making scales. Borrowing from survey results in Chapter 4, we conceptualize farming household objectives as three-fold: maximize income, minimize income volatility, and avoid losses that place households into poverty. Based on Nepali government documents e.g. the LAPA, NAPA, and ADS [167, 190, 191], we conceptualize village council decision-making objectives as: ensure food security, minimize poverty, and limit large outmigration flows. In Figure 5.2 each panel plots the outcomes of individual simulation runs based on two dimensions. For example, there is a clear tradeoff between maximizing average income and minimizing income volatility (Fig. 5.2a). Simulations that tend to deliver higher average incomes also tend to be associated with higher income volatility, and vice versa. This can be attributed to the limited livelihood opportunities available to smallholder farmers. Livelihoods that help farmers generate more income, e.g. switching to cash crops and/or migrating, are also subject to more volatile income streams, absent any risk transfer policies.

There are few other clear tradeoffs in decision-making objectives at these scales. For example, there is no clear correlation between local cereal production and average income, poverty rates, or income volatility (Fig. 5.2, b-d). In future work, we plan to incorporate heterogeneous communities with different village council agents, and analyze potential tradeoffs between national-scale decision-making objectives (e.g. ensuring growth in the agricultural sector), local council objectives (e.g. ensuring food security), and household-level objectives (e.g. minimizing income volatility).

5.4.2 How Do Different Local Decision Profiles Affect Adaptation Outcomes?

We now analyze how different decision-making profiles of local governments may affect climate adaptation outcomes, under a 1.5^{0}C rise in mean temperatures through 2050. As described in Section 5.3.3, we distinguish between two extreme types of council profiles to explore variation that may exist in Nepal's polycentric governance system as it transitions to federalism. These two profiles are a relatively High Capacity government, which re-evaluates investments often ($\lambda_l = 2$ cropping cycles) and maintains an ambitious goal for food security ($\psi = 1.0$ proportion of community cereal needs met by local production), and a relatively Low Capacity government, which exhibits high policy inertia ($\lambda_l = 10$ cycles) and has a low-ambition goal for food security ($\psi = 0.2$). We find that these two types of profiles may lead to significant differences in adaptation outcomes, even with farming households characterized by the same decision-making properties in each case (Fig. 5.3). First, cereal production is significantly higher under the High Capacity case ($\bar{P} = 33.0$ tonnes/cycle, $\sigma_P = 0.75$) than under the Low Capacity case ($\bar{P} = 26.9$ tonnes/cycle, $\sigma_P = 0.48$, $p < 0.05$). This is in large part because the High Capacity government maintains consistent subsidies for cereal crops throughout the model timeframe (Fig. 5.3a), which



(a) Avg. Income vs. Income Volatility

(b) Avg Income vs. Cereal Production

(c) Poverty Rate vs. Cereal Production

(d) Income Volatility vs. Cereal Production

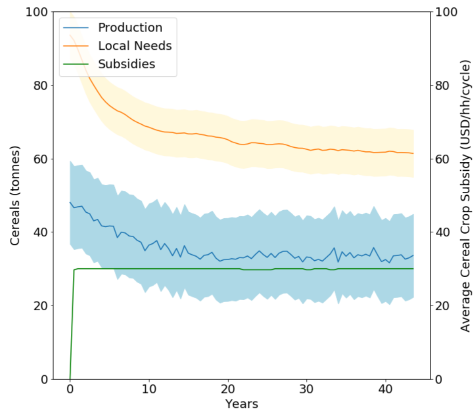
Figure 5.2: Tradeoffs between Household and Village-Scale Objectives. Results from 200 simulations are displayed for a Base Case local government policymaker, accounting for stochasticity in the timing of droughts, income draws at the household scale, and interactions between households. **a)** A strong tradeoff exists between average community income and the average volatility of household income, with higher average incomes associated with higher volatility. **b-d)** No strong relationships are discerned between average income and cereal production, poverty rate and cereal production, or income volatility and cereal production.

have a material impact on increasing the households pursuing these crops (Fig. 5.3c, green line). Furthermore, the subsidies act indirectly on food security: more farming households are able to accumulate sufficient resources to engage in migration (Fig. 5.3c, blue line). While it diminishes agricultural productivity, this outmigration also substantially reduces the food needs of the community over time (Fig. 5.3a yellow line). Still, despite active investments, the High Capacity local government is unable to close the gap between their high ambition for self-sufficiency, which would require approximately 61.7 tonnes/cycle by the end of the model timeframe, and actual community production. Nevertheless, the High Capacity government's investments lead to higher average community income (473 USD/household/cycle) and lower inequality (average GINI = 0.173, Fig. 5.3e).

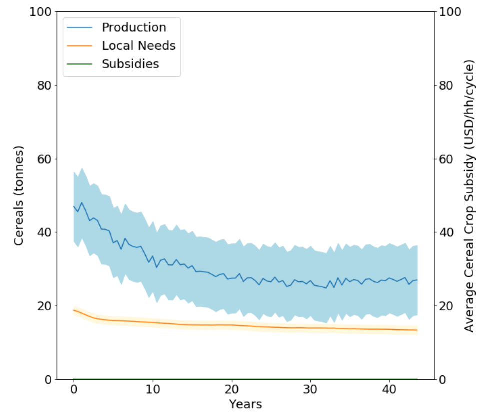
Conversely, the Low Capacity government is satisfied with importing cereal crops from other regions to meet its community food needs, and maintains its investments in cash crop subsidies. This increases the proportion of households pursuing these crops (37.1 percent vs. 20.6 percent under the High Capacity profile), but not all households have sufficient resources to take advantage of these resources. Conversely, households farming cereal crops are less likely to accumulate financial resources, limiting migration rates to 56.8 percent of households, compared to 70.0 percent of households in the High Capacity profile (Fig. 5.3c-d). Limiting outmigration and diversifying the agricultural sector may be seen as two positive outcomes of this approach; however, it comes at the cost of lower average farmer incomes (385 USD/hh/crop cycle) and higher inequality (GINI = 0.245).

5.4.3 How Do National Interventions Impact Local Investment Effectiveness?

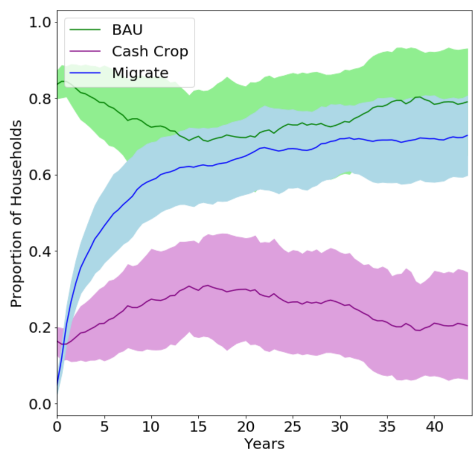
We next assess how a national-scale policy intervention impacts the ability of local-level institutions to achieve their objectives. As an example, we evaluate adaptation outcomes for High and Low Capacity governments as in Section 5.4.2, but now also compare these



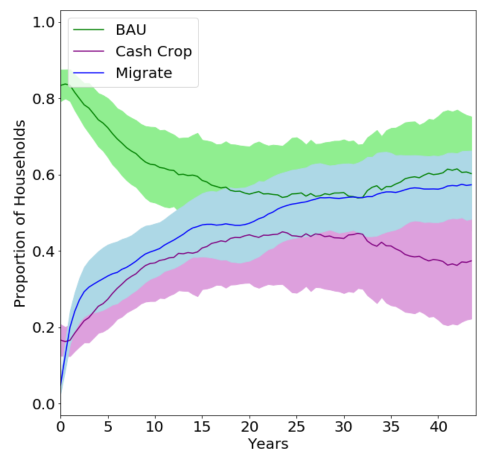
(a) High Capacity, Food Production



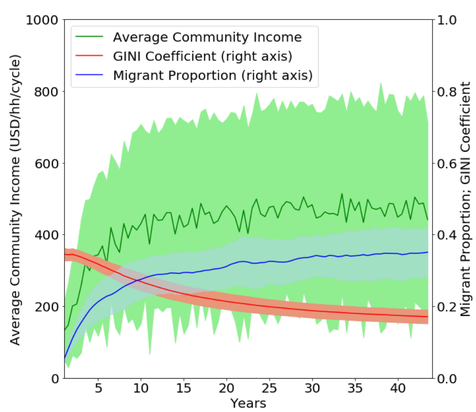
(b) Low Capacity, Food Production



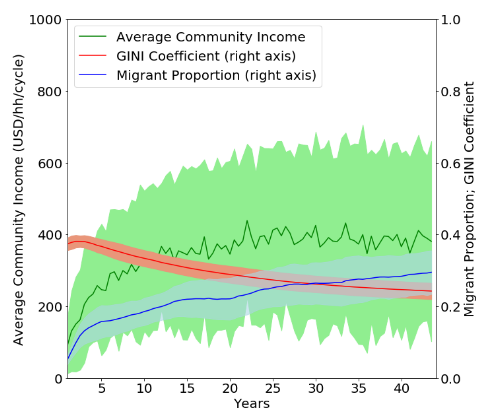
(c) Strategy Choices



(d) Strategy Choices



(e) Economic Outcomes

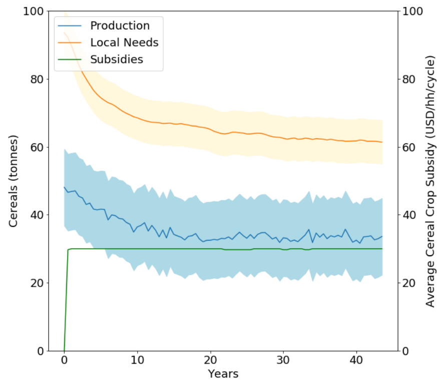


(f) Economic Outcomes

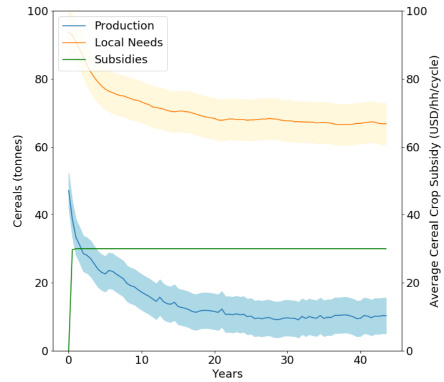
Figure 5.3: Adaptation Outcomes under Different Local Government Archetypes. Food production, farmer strategy choices, and economic outcomes are displayed for simulations under a High Capacity ($\lambda_l = 2$ crop cycles, $\psi = 1.0$ of community needs) and Low Capacity council ($\lambda_l = 10$ crop cycles, $\psi = 0.2$ of community needs).

results both with and without a national index-based crop insurance program with a 25 percent premium subsidy. An important assumption in our scenario is that the insurance program extends to both cereal crops and cash crops, providing farmers with some protection against droughts in both cases (see Section 5.3.3 for more details). We find that such an intervention may have significant and surprising effects on the ability of local village councils to shape adaptation outcomes. For High Capacity local governments, a national insurance program would substantially reduce its ability to meet its cereal crop needs (Fig. 5.4a-b). Whereas the council was able to maintain an average production of $\bar{P}$ = 33.0 tonnes/cycle without any national interventions, it now can only maintain a production of $\bar{P}$ = 9.99 tonnes/cycle with the insurance program, despite investing the same subsidies to boost production. Paradoxically, although insurance reduces the risk of cereal crops for farmers, it also reduces the risk of farming cash crops. This risk reduction is sufficient to incentivize many additional households to switch from cereal to cash crops; 51.2 percent of households now pursue this strategy, as opposed to 20.6 percent without insurance (Appendix D2.2). Although this may boost the development of the agricultural sector nationally and attenuate outmigration (Fig. 5.3f), it introduces new risks to local-level institutions seeking to maintain local food security. Furthermore, it does not significantly increase average community income ($\bar{I}$ = 453 USD/hh/cycle compared to 473 USD/hh/cycle without insurance). Essentially, the insurance policy provides households with a tradeoff between either farming cereal crops and migrating or investing more of their resources in cash crops; as the latter strategy is now less risky, more households opt for this adaptation pathway.

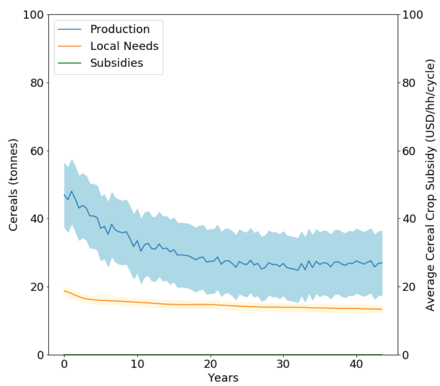
The insurance policy also has significant effects on the action of Low Capacity local governments. As the insurance policy attenuates out-migration flows, more individuals remain in the community, increasing the demand for cereal production. Furthermore, as with the High Capacity government, the insurance policy incentivizes more households to switch from cereal to cash crops. Even with the relatively low self-sufficiency ambition of this type of government, the increased demand and decreased production of cereal crops leads it to begin subsidizing this cropping strategy. Still, cereal production decreases substantially, from 26.9 tonnes/cycle without insurance, to 11.9 tonnes/cycle with insurance. Perhaps the most counterintuitive finding is that in the context of a national-level insurance program, the Low Capacity government actually retains *more* cereal crop production than the High Capacity government, despite the latter's higher ambition for self-sufficiency and more rapid policy response. This is because the latter's early investments in cereal crop subsidies allow more households to gradually accumulate financial resources, which enables them to migrate and/or switch to cash crops later in the model timeframe. This is one example of deep uncertainty wrought by conflicting objectives across multiple decision-making scales: a top-down intervention (insurance that reduces perceived risks of cash crops) combines with bottom-up objectives (wanting to maximize household income) to render a meso-scale investment counterproductive (cereal crop subsidies that facilitate switching to cash crops). This effect also substantially closes the gap between High and Low Capacity local governments in terms of economic outcomes. Whereas average community income was 18.6 percent lower under a Low Capacity relative to a High Capacity government in the absence of the insurance program, it is only 10.2 percent lower in the presence of insurance. In effect, a national-scale intervention can help reduce inequalities that might arise from differential governance capacities at the local level, but may compromise local institutions' capacities to meet ambitious goals.



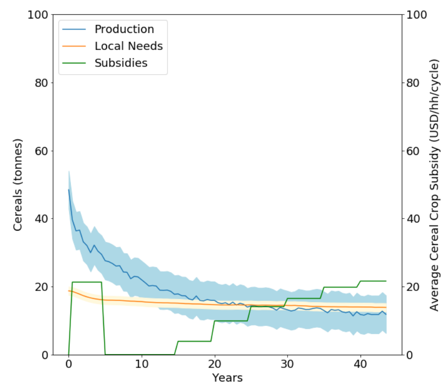
(a) High Capacity, No Intervention



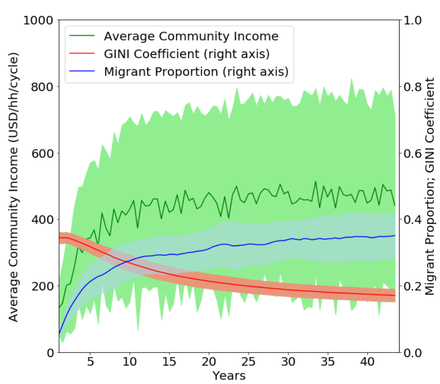
(b) High Capacity, Insurance



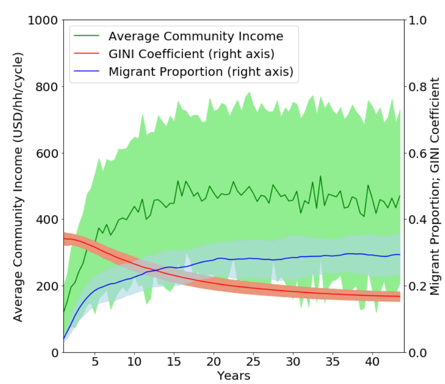
(c) Low Capacity, No Interventions



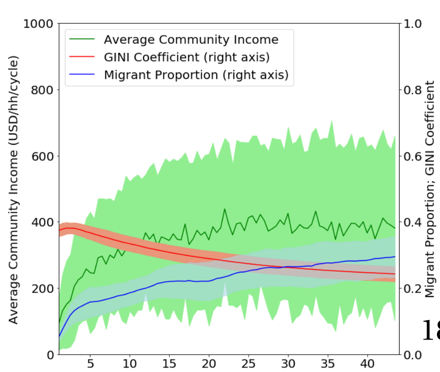
(d) Low Capacity, Insurance



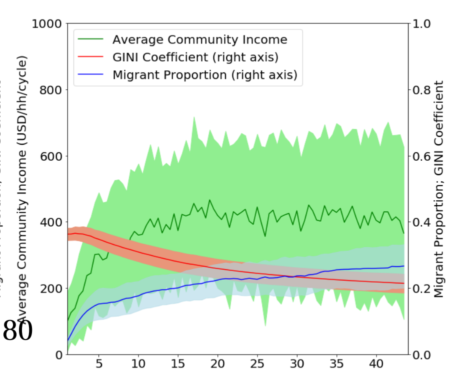
(e) High Capacity, No Intervention



(f) High Capacity, Insurance



(g) Low Capacity, No Interventions



(h) Low Capacity, Insurance

Figure 5.4

Figure 5.4: (previous page)**Effect of National Policy Intervention on Adaptation Outcomes under Different Local Government Archetypes.** Food production and economic outcomes are displayed for simulations under a High Capacity (λ_l = 2 crop cycles, ψ = 1.0 of community needs) and Low Capacity government (λ_l = 10 crop cycles, ψ = 0.2 of community needs), both without intervention and with a national-scale crop insurance program.

5.5 Discussion

In this paper, we present a model for extending robust decision-making analysis techniques to exogenous and endogenous sources of deep uncertainty. In particular, whereas previous RDM analyses typically assume that a policymaker is exogenous to the system of interest, here we seek to endogenize relationships between decision-making agents at multiple governance scales - including farming households, local village councils, and (eventually) national-level institutions. In so doing, we build linkages between RDM methods and the theory of polycentric governance, in order to better analyze the collective choice and constitutive rules that can help system actors develop adaptation strategies that are robust to both sources of uncertainty.

This effort is especially relevant for the real-world case study of evolving federalism in the Nepali agricultural sector. As a case study, we extend the ABM presented in Chapter 2 by adding decision-making agents at two additional scales: local village councils and national institutions. In the example described in this chapter, we add endogenous relationships between one local village council and a community of farming households, and examine how decision-making characteristics of the village council (including its policy window and self-sufficiency objectives) affect adaptation outcomes at both the household and collective scales. We also design a simplified experiment to analyze how top-down interventions from national institutions may impact local institutions' capacity to achieve their main adaptation objectives.

Our initial results demonstrate that polycentricity may indeed introduce important sources of uncertainty to system actors. In the absence of national-level interventions, local governments are better able to improve local food production, raise household incomes, and reduce inequality if they can update policies over shorter time intervals and fix ambitious objectives regarding food security. However, in the context of a top-down insurance program, even high capacity local institutions are limited in their ability to achieve these objectives. In fact, a combination of top-down incentives and bottom-up household objectives may even render local interventions counterproductive, in that early subsidies for cereal crops and reduced risk of cash crops make it easier for households to transition away from cereal crop production. However, the national-level insurance program improves community income and inequality outcomes if a local government has low capacity to implement policy, indicating that such a policy may be an important way of addressing inequality in governance capabilities across Nepali regions.

This chapter represents a first attempt at developing a RDM-ABM framework to address deep uncertainty in polycentric governance systems, and points to several directions for further work. First, we plan to implement additional levers at both the local and national governance scales, reflecting real-world policies that are currently piloted by Nepali institutions. At the local level, this includes the option for governments to invest in irrigation as a long-term public good, mitigating drought risks to farmers. At the national level, we also plan to investigate other pecuniary policies, e.g. a cash transfer or remittance bank, as well as investments in climate information services that can provide local governments with more accurate projections of drought risk. Second, we plan to endogenize national institutions' decision-making in the RDM-ABM. These institutions also have limited ability to quickly respond to changing conditions and implement policy, and likely have even longer time lags than do local institutions. With this in mind, a fruitful question is which national-level policy pathways support robust adaptation outcomes. For example, should national institutions prioritize early investments in climate information services to build the capacities of local-level institutions, or direct financial incentives to farmers to promote certain farming strategies? Third, we plan to incorporate several different types of Nepali farming villages with different socioeconomic characteristics and exposure to climate risks, based on forthcoming data from the Nepal Agriculture Census. This will enable us to better investigate questions relating to the role that national institutions can play in averaging spatial and temporal variations in agricultural production, allowing local institutions to experiment with more fit-for-purpose adaptation pathways. A fourth step is to more systematically assess exogenous sources of uncertainty, including climate variables such as mean temperature rise and economic variables such as crop prices and remittance incomes. Adding this component to the model will allow us to more fully analyze which institutional decision-making rules at each scale prove most robust to the wide array of potential states of the world that await the Nepali agricultural sector.

Chapter 6

Conclusion

Climate change will apply multiple pressure points on societies around the world over the course of the 21st century. These pressures are perhaps most acutely felt by smallholder farmers, whose livelihoods, assets, and institutional arrangements are directly tied to the land and the sustenance it provides. Climate change poses long-term risks not just to farmers' harvests and direct income, but also their ability to continue coping with uncertainty by diversifying livelihoods, including through rural-urban migration. Increasingly volatile income and the potential for extreme losses may prevent farmers from amassing the capital to afford such alternatives, and threaten existing community cooperative arrangements to manage risks. Furthermore, increasing climate pressures may fundamentally re-shape farmers' perceptions of risk to their livelihoods, and even lead them to take greater risks in times of shock in the hopes of avoiding large losses. Such systemic risks pose governance challenges to local and national institutions, especially as decision-makers contend with uncertainty in climatic and macroeconomic conditions while also coordinating potential conflicting objectives.

6.1 Summary of Research Findings

This thesis has sought to identify policy principles to help decision-makers navigate some of the many challenges that climate change poses to the subsistence agriculture sector. In Chapter 2, my collaborators and I developed an agent-based model (ABM) based on agricultural and migration data from Nepal to examine farmer livelihood choices under future climate scenarios. This model shows that climate change threatens the viability of rural livelihoods directly through decreased crop yields, and indirectly by eroding farmers' resources to diversify income streams. Climate change may thus exacerbate existing poverty traps and contribute to immobility among smallholder farming households. Furthermore, with fewer neighbors pursuing livelihood alternatives e.g. migration and cash crops, farmers may perceive these options as increasingly risky. Effective policy responses to help farmers maintain viable livelihoods will therefore have to address both financial resources and the riskiness of diversification strategies.

Chapter 3 developed an evolutionary game theory (EGT) framework to further investigate the potential for risk transfer instruments, including new index-based insurance programs, to protect subsistence farmers against climate-driven losses. This chapter demonstrates that a combination of formal insurance programs and informal community revenue-sharing arrangements can best help farming communities cope with both idiosyncratic and covariate risks. Yet, as climate risks increase, strategic interactions among farmers may lead to the collapse of such combined risk management strategies, in part due to the temptation to free-ride on others' decisions to purchase expensive insurance. A combination of insurance subsidies and behavioral interventions that cultivate pro-social preferences can provide a way for subsistence communities to support the co-existence of both types of mechanisms. This will be important not just to provide farmers with the financial protection to manage climate-driven losses, but also to maintain the social and informational capital that help subsistence communities navigate fundamental changes to their livelihoods.

Chapter 4 further investigates how informational and social capital shape farmers' perceptions of climate risks and their likelihood of deploying adaptive strategies. Through a survey of 500 smallholder farmers in one of Nepal's main agricultural regions, the Chitwan District, my collaborators and I found that climatic conditions are already among the most salient factors affecting farmers' perceptions of livelihood risks. Almost all respondents reported experiencing at least one climate-linked hazard in the past seven years (including droughts, floods, and pests), and often were affected by multiple types of hazards. Additionally, most households already maintain a diversified income portfolio, with migration remittances, off-farm labor, and livestock all making substantial contributions to Chitwan household incomes. While climate risk perceptions drove higher perceptions of farming risks, they also were linked to perceptions of higher risks among livelihood alternatives, including international migration and off-farm wage labor. Access to increased social capital was generally correlated with a higher propensity to deploy intentional adaptation strategies to climate hazards. Meanwhile, access to increased information was associated with a higher propensity to diversify income sources through livelihood alternatives, suggesting that both information and social networks may provide farmers with important resources to cope with future climate risks. Paradoxically, however, farming households appear to be especially reliant on riskier strategies when experiencing acute climate shocks.

Chapter 5 developed a agent-based model-robust decision-making (ABM-RDM) framework to investigate how various decision-makers can navigate deep uncertainty in adapting the subsistence agricultural sector to climate change. Such uncertainty comes from exogenous variables such as climate and macroeconomic conditions, as well as uncertainty from potentially competing objectives among system actors. Using Nepal's ongoing transition to federalism as a case study, we begin to investigate how polycentric governance arrangements can develop robust decision rules to meet policy objectives across decision-making scales. In particular, we show one example of how a national-level insurance policy may lead local-level agricultural investments to produce unintended consequences for food security objectives. Future work includes expanding the types of policy responses that both local and national institutions can deploy to meet their objectives, and more systematically assessing their robustness to uncertain climatic and macroeconomic conditions.

6.2 Research Contributions and Recommendations

This work was informed by a rich body of literature across disciplines, and sought to integrate multiple tools to contribute new insights to climate adaptation in subsistence agriculture. Here, I summarize key contributions and recommendations from this work to advance theory, policy, and methodology on this issue.

6.2.1 Theoretical Contributions

From a theoretical perspective, much of this work was underpinned by the New Economics of Labor Migration (NELM), developed in the 1980s and 1990s to explain how rural households in emerging economies manage highly risky livelihoods. NELM states that in contexts with imperfect access to credit and financial institutions, households must diversify their income streams by pursuing a portfolio of livelihoods, including rural-urban migration. As climate change is likely to contribute even more volatility to farming revenues, a reasonable hypothesis would be that households will further diversify livelihoods and rely even more on migration remittances as a form of climate adaptation. However, an important gap in this framework is how farming households perceive risks to livelihood alternatives. Chapter 4 demonstrates that households already view migration and off-farm wage labor as riskier than farming, and that climate hazards may further increase the perceived riskiness of these strategies. A useful extension of NELM would thus be to assess how environmental, economic, and policy factors (e.g. labor regulations) also shape risks to livelihood alternatives available to farmers - including migration, wage labor, and entrepreneurship.

Furthermore, increased climate risks may lead farming households to engage in fundamentally different decision-making processes, including pursuing risky behaviors in an attempt to avoid losses during climate shocks. In this regard, a fruitful area for further theoretical development would be to synthesize contributions from NELM with those from other theories of decision-making under uncertainty, such as Security-Potential/Aspiration (SP/A). For example, farming household decision-making under climate risks could be conceptualized as taking place along two time scales. Over longer time scales and in response to slow-onset climate risks, NELM appears to provide accurate predictions: households that perceive higher climate risks to their livelihoods are generally more likely to diversify their income streams. However, when faced with acute risks and fast-onset climate hazards, households appear more likely to double down on risky strategies, including farming, in an attempt to avoid losses.

6.2.2 Policy Recommendations

This dissertation's theoretical developments regarding farmer decision-making under climate risk also lead to several policy recommendations. At the highest level, this dissertation demonstrates ways in which climate change poses truly systemic risks to rural livelihoods, affecting not just crop yields but also the viability of strategies farmers have typically deployed to manage livelihood risks. Therefore, effective interventions need to find complementarities across traditional policy spheres and bureaucratic divisions. For example, cash transfer policies can prove effective in bolstering farmer incomes and lifting households out of poverty, but will be even more effective if they are paired with other risk transfer policies, like index insurance and remittance banks, that address diversification risks (Chapter 2). Index insurance can serve as a particularly important tool to help farming communities cope with increasing covariate risks due to climate change. However, insurance companies and policymakers would do well to pair these with behavioral interventions that cue prosocial preferences, in order to address social dilemmas that may arise when insurance is introduced in communities with informal risk-sharing arrangements (Chapter 3). Such policies could include informational campaigns that promote climate risk management as a social norm, and forums through which farmers can communicate their risk management preferences in order to build trust for collective action.

This dissertation also demonstrates the potential for misaligned policies and decision-making objectives to impede the capacity of policymakers to promote adaptation goals. While still under development, the RDM-ABM framework in Chapter 5 highlights one example in which a well-intentioned national crop insurance program may hamper local policies to promote food security, in part by enabling farming households to pursue riskier livelihood alternatives. This dilemma highlights the importance of establishing policymaking forums in which decision-makers at multiple governance scales can seek complementary ways of achieving their goals. For example, a local policymaker may be willing to accept policies that reduce local production of cereal crops if they are accompanied by policies and investments that facilitate importing grains from other regions of the country.

Much of this dissertation was informed by the case study of climate adaptation and rural-urban migration among Nepali smallholder farmers. Although Nepal is exceptional in its high reliance on remittance income and subsistence agriculture, it serves as an important case study for the challenges faced by subsistence agricultural sectors in other countries, including many of its South Asian neighbors. Research from this dissertation (Chapter 4) highlights that Nepali farmers are already quite savvy about climate risks: climatic conditions are among the most salient factors for farmers' decision-making, the majority of households have implemented multiple adaptation strategies in response to climate hazards, and Nepali farmer incomes are highly diversified. Still, the country is likely to face significant challenges in finding resilient adaptation pathways to looming climate risks. Most farming households still have relatively few financial assets to facilitate livelihood transitions, and the increased frequency and severity of climate shocks threatens to contribute to physical and economic immobility among farmers. Efforts to deploy formal insurance programs in the Nepali agricultural sector are still nascent and will need to overcome the wariness that typically accompanies new top-down interventions, while finding ways to complement existing informal risk-sharing arrangements. Nepal's transition to a federal government structure offers promise to effectively cope with environmental changes through polycentricity, but will need to be accompanied by processes that facilitate the coordination of objectives from decision-makers at multiple scales.

6.2.3 Methodological Insights

From a methodological perspective, this dissertation identifies ways in which tools from multiple disciplines can be integrated to better inform decision-making in highly complex environments. Modelling frameworks such as ABMs, EGT, and RDM are useful tools to investigate feedbacks and non-linear relationships between dynamic variables. For example, formal insurance and informal revenue-sharing can co-exist even among self-interested farmers under low covariate risk, but may crowd out one other as climate risks increase. Models can also be used to create counterfactual scenarios that help quantify the impacts of future states of the world and potential policy interventions. This dissertation used such counterfactuals to demonstrate that future climate change is likely to contribute to immobility among smallholder farmers, unless a combination of financial and risk transfer policies provides them the means to continue using migration as part of their livelihood portfolios. As well, models can be useful to identify uncertain parameters that substantially influence predicted outcomes and warrant further study. In this dissertation, models in Chapters 2 and 3 identified farmers' perceptions of climate risks as a key variable affecting their livelihood and risk management strategy decisions, which motivated the survey design in Chapter 4.

Yet, models are also constrained by their assumptions regarding agents' decision-making behavior. Often, models assume that agents will make economically rational decisions under perfect information. Even if models account for common decision-making biases such as risk and loss aversion, they typically assume that agents' objectives and decision-making frameworks will stay consistent under changing environments and social networks. In this respect, empirical work on how individuals make decisions under uncertain and dynamic conditions can provide valuable insights to improve modelling tools. Chapter 4 provided support for some of the key assumptions used in developing the ABM and EGT from previous chapters, including farmers perceiving migration to be riskier than farming and generally seeking to diversify livelihoods as a function of increased climate risk perceptions. However, it also found evidence of multiple counterintuitive behaviors among farmers that were not predicted by those models. These include climate risks being even more salient in driving perceptions of migration and wage labor risks, relative to perceived farming risks, and the propensity of farmers to rely even more on riskier strategies while experiencing a climate shock. These insights were not evident *a priori* to developing the ABM and EGT models, which subsequently informed data collection for Chapter 4, and therefore were not included in the initial versions of these models. However, such insights are important to capture in future socio-ecological systems (SES) models, in order to better characterize how changing environmental conditions may shape fundamental behavioral patterns.

6.3 Paths Forward: Future Research Directions

Finally, research from this dissertation points to several concrete next steps that can continue to develop better decision-making tools for climate adaptation. First, modelling and empirical research on migration could better integrate dynamics in both origin and destination communities. Nearly all of the migration research in this dissertation has focused on how climate change interacts with other social and economic factors in origin communities to shape migration decisions. However, climate change may also lead to non-linear dynamics in common migration destinations, affecting future opportunities for potential migrants from origin communities. A particularly relevant example for the case study in this dissertation is how climate change affects health and economic outcomes in the Persian Gulf, one of the most common destinations for Nepali migrants. Extreme heat, prolonged droughts, and lack of freshwater resources may fundamentally alter future migration opportunities to this region, which will need to be reflected in long-term adaptation strategies in Nepal.

A second avenue for future work is in expanding the system actors and political factors that are included in SES models, particularly models constructed to understand migration responses to climate change. Migration flows and climate adaptation pathways are not just determined by individual decisions, but also constrained, expanded, and/or re-routed by multiple institutional actors. Chapter 5 of this dissertation presents an initial attempt to explore these institutional factors by examining how policy responses at local governance scales may change in response to top-down and bottom-up adaptation strategies. This represents one important dimension in expanding how system actors are represented in models, but there are several others. Even within a single governance scale, departments or ministries may have competing objectives (for example, an Environment Ministry prioritizing conservation vs. an Agriculture Ministry promoting economic growth), and may implement policies that can either complement or impede each other. Moreover, several non-governmental institutions, including civil society organizations, private sector companies, and labor recruitment agencies may be influential in shaping migration decisions. Like other institutions, they each seek to promote their own interests, which may or may not align with the objectives of farming households and formal governance institutions.

Third, and perhaps most importantly, future research should continue to find ways to improve the relevance of the types of tools used in this dissertation to actual decision-makers in applied settings. Models can be powerful tools to elucidate relationships, feed-backs, and potential scenarios that are not intuitively obvious to system actors. However, without regular input from applied practitioners, there is also a temptation to construct models that are theoretically pure, but miss important elements of real-world decision-making constraints. Such models may indeed be useful to clarify socially optimal strategies and outcomes, but researchers would do well to bridge the gap between "pure" models and those that can actually inform applied strategies to manage climate change - even if they lead to second- or third-best solutions. Two emerging methods for bridging this gap are participatory modelling and serious games. In participatory modelling, models are co-created with input from diverse stakeholders on research questions and key social patterns that a model should be able to replicate in order for decision-makers to trust its outputs. Serious games use simplified models and outputs to engage stakeholders in making decisions under hypothetical scenarios; information gleaned from such interactions can be used to create more realistic modelling relationships. As decision-makers navigate the complex and multifaceted challenges of climate change, SES models have an important role to play in illuminating feasible pathways for prosperous, sustainable, and just societies.

Appendix A

Risk Transfer Policies and Climate-Induced Immobility among Smallholder Farmers - SI

A.1 Further Background Material on Previous ABMs

The strengths and challenges of agent-based models (ABMs) are apparent in their previous applications to the climate-migration relationship. Kniveton et al. [71] developed one of the first such ABMs to predict future migration patterns based on changing climatic conditions, focusing on Burkina Faso as a case study. Agents are assigned migration probabilities based on statistical relationships with historical migration, demographic, and climate data. Social networks are determined by randomly assigning each agent 50 connections to other agents in the community. Hassani-Mahmooei and Parris [72] also build a predictive ABM of climate-induced migration in Bangladesh, but focus on the response to climate-induced shocks, rather than long-term climate change as in Kniveton et al. Decision agents represent blocs of 10,000 individuals of the Bangladeshi population, and evaluate migration decisions by assessing how push, pull, and intervening factors compare to a decision threshold for moving to different districts. Social networks influence these thresholds through an imitation process in which agents emulate the thresholds of agents with higher overall wealth. While these studies provide an initial framework for conceptualizing climate-migration ABMs, they focus specifically on the climate-migration relationship and do not embed the choice to migrate in the context of other potential adaptation strategies.

A more recent set of climate-migration ABMs have sought to endogenize smallholder farmer migration strategies in a broader decision-making process that includes other livelihood choices. Smith [73] explores the effects of different rainfall scenarios on internal migration in Tanzania, where the climate-migration relationship is conditional upon the agent income and food supply. There are two migration channels: a household can either pursue opportunity-based migration if it can afford the opportunity cost of lost farm labor, or it may be forced to engage in need-based migration if its resilience level drops below a minimum threshold. Entwistle et al. [74] develop future migration responses under various scenarios of rainfall shocks in rural Thailand. Their model allows households to adjust the types of crops and amount of fertilizers used as climatic and soil conditions change; young villagers between the ages of 15-29 can also migrate to the city to earn remittances. Hailegiorgis et al. [20] explore adaptation among nomadic pastoralists in Ethiopia, who decide how to allocate farm resources between crops and livestock, and whether to migrate to different agricultural regions. Agents are more motivated to migrate once their assets fall below a certain threshold, and rely on information from the past three years to estimate payoffs of farming livelihoods in different regions. In contrast, the ABM developed by Bell et al. [75] includes a wider range of livelihood strategies, including agricultural, industrial, and service sector occupations. Decision-making agents are assigned an initial geographic region and can choose to invest in local livelihoods or to migrate to other regions with different livelihood prospects.

We also note a wide literature of ABMs that explores various aspects of farmer decision-making under uncertainty, without including migration as a livelihood option. While the majority of these studies represent agent decision-making through economic optimization, several studies conceptualize decision-making using boundedly rational characteristics [67]. For example, van Duinen et al. [68] compare economically rational decision-making to a suite of behavioural heuristics in projecting Dutch farmer decisions to invest in irrigation under climate change. They find that heuristic-based approaches delay the adoption of irrigation techniques compared to economically rational decision-making, though key state variables, e.g. household income, are relatively similar over a 30-year timeframe. Wossen and Berger [69] investigate both *ex ante* and *ex post* forms of farmer adaptation to climate and price variability, focusing on ramifications for food security. Migration is introduced indirectly as one policy option to provide off-farm employment, but is not systematically part of farmers' suite of coping mechanisms.

The flood adaptation literature has also produced ABMs that seek to model similar adaptation decisions to a different kind of climate risk. For example, Haer et al. [65] develop an ABM to analyze the relationship between private household and government measures to reduce flood risk, and compare results using economically vs. boundedly rational household agents. They find that household-level measures are likely to outweigh government policies in their contribution to reducing flood disaster risk, at least in the short term, and especially for economically rational agents. de Koning and Filatova [66] develop an ABM with interactions between flood shocks, risk aversion, and market interactions between home buyers and sellers to evaluate the impact of repeated flood events on outmigration and gentrification. These studies provide further justification to embed migration in a portfolio of farmer livelihood options, and to contrast decision-making under economic and bounded rationality.

A.2 ABM Model Specification

A.2.1 Layer 1: Economic Rationality Details

Incomes derived from farming strategies are obtained from the Weibull distribution with probability density function

$$P(I) = \begin{cases} \frac{\kappa}{\mu}\left(\frac{I}{\mu}\right)^{\kappa-1} e^{-\left(\frac{I}{\mu}\right)^{\kappa}} & \text{if } I \geq 0 \\ 0 & \text{if } I < 0\,, \end{cases} \tag{A.1}$$

where μ is the scale parameter and κ is the shape parameter of the distribution. Values of μ vary by strategy k, but there is no long-term trend in the moments of the strategies. This assumption is relaxed in the Climate Impacts Layer.

The farm income $I_{ik}(x_k, t)$ with $k \in \{\text{BAU}, \text{CashCrop}\}$ is calculated using a saturating function of the number of on-farm household members x_k and the household's draw from the farming income distributions $I_{ik}(t) \sim \text{Weibull}(\mu_{I,k}, \kappa)$

$$I_{ik}(x_k, t) = \begin{cases} I_{ik}(t) & \text{if } x_k = x_{\text{hh}} \\ I_{ik}(t) \cdot \left(\frac{x_k^{l_1}}{x_k^{l_1}+1}\right) & \text{if } x_k \neq x_{\text{hh}}\,, \end{cases} \tag{A.2}$$

where l_1 represents the Hill coefficient controlling the steepness of the saturating function. This functional form is commonly used to represent saturating functions in ecological and population dynamic settings [195, 196]. Here, it ensures that the opportunity cost in terms of lost farm productivity is initially minimal for the first migrant leaving the household, but increases with subsequent migrants until there are relatively few people left on the farm, resulting in low productivity.

Incomes earned from migration remittances are obtained from the log-normal distribution with probability density function

$$P(R) = \frac{1}{R\sigma_R\sqrt{2\pi}} \cdot e^{-\frac{(\ln R-\mu_R)^2}{2\sigma_R^2}} \qquad R \geq 0\,, \tag{A.3}$$

where μ_R and σ_R the mean and standard deviation of the distribution, respectively. According to the New Economics of Labor Migration (NELM) theory, households engaging in labor migration as a risk diversification strategy prioritize sending migrants with the highest earning potential and the greatest incentive to remit. By this theory, subsequent migrants from the same household would likely exhibit lower earning potential and/or lower incentive to remit (e.g. an elderly parent). There is some empirical evidence from India that households with multiple migrants tend to exhibit decreasing per capita remittances, compared to single-migrant households [197]. We therefore adjust migration remittances as a function of the number of household migrants as follows

$$R_i(x_k, t) = R_i(t) \cdot \sum_{y=0}^{y=x_m} \left(1 - \frac{y^{l_2}}{y^{l_2}+1}\right), \tag{A.4}$$

where $x_m = x_{\text{hh}} - x_k$ represents the number of migrants from household i at time t, l_2 is the Hill coefficient for migration remittances, and $R_i(t)$ is household i's draw of remittances from the log-normal distribution with parameters defined in Table A.1. For low values of x_m (i.e., households that have not yet sent many migrants), economically rational agents will generally perceive that the net present value of expected remittances will outweigh the opportunity cost of lost farm labor. However, depending on the relative values of l_1 and l_2, at some x_m the expected returns of sending an additional migrant may be less than this opportunity cost, and the household will refrain from sending additional migrants. Such a relationship roughly approximates observed phenomena in South Asian countries that working-age males tend to form the majority of labor migration streams, while females and the elderly/young are more likely to remain in farming occupations [150].

The model is initialized by randomly assigning each household i a starting savings $S_i(0)$ drawn from an exponential distribution, and a starting strategy $k_i(0)$. The initial distribution of $k_i(0)$ can be set by a particular case study of interest. We use 2007 data from the Chitwan Valley Family Study Labour Migration, Agricultural Productivity and Food Security Survey to initialize our model. Initial distributions for BAU and Cash Crop are taken from the proportion of farmland devoted to cereal and cash crops, respectively, and the initial Migrate proportion reflects the proportion of households with at least one migrant in that year.

Table A.1 displays Base Case values for key parameters in the Economic Rationality Layer, which are used to generate results in Section 3 of the main text. The sensitivity of these results to different parameter values is explored further in Section 2.3.2 of the main dissertation and Appendix A.3.5.

Table A.1: Layer 1 (Economic Rationality) Parameters for one cropping cycle.

Parameter	Average	Std Dev	Notes
I_{BAU}	163	199	Decreases with decreasing household size
C_{BAU}	170	0	
I_{CashCrop}	822	650	Decreases with decreasing household size
C_{CashCrop}	547	0	
R	595	998	Per migrant, decreases with increasing migrants
C_{Migrate}	500	0	For first year only
l_1	2	N/A	Exponent for decreasing farm productivity
l_2	2	N/A	Exponent for decreasing remittance returns
$P(k_i(0)) = \mathrm{BAU}$	0.832	N/A	BAU initial proportion
$P(k_i(0)) = \mathrm{CashCrop}$	0.168	N/A	Cash Crop initial proportion
$P(k_i(0)) = \mathrm{Migrate}$	0.045	N/A	Migrate initial proportion

A.2.2 Layer 2: Bounded Rationality and Social Network Impact Details

A.2.2.1 Risk Aversion Details

In Layer 2, agents make risk-averse decisions based on a risk aversion parameter, b_i, reflecting the weight that household i assigns to the objective of minimizing income volatility, relative to maximizing expected income, in assessing the utility of strategy k (Equation 2.1 in Section 2.7). This conceptualization of risk aversion is drawn from modern portfolio theory, which hypothesizes that investors evaluate the utility of portfolio options as a function of their expected mean return and variance [96]. While smallholder farmers are not likely to have access to the same data and computational tools as an average investor, we believe this approach is consistent with NELM. NELM postulates that households engage in labour migration in part to increase household income relative to a reference group, while minimizing the volatility of aggregate household income [76, 77].

While not directly related to concepts of absolute and relative risk aversion, previous work has sought to correlate the risk weight used in modern portfolio theory with these more standard risk aversion models. As a general approximation, Freund [95] finds that the weight assigned to variance of a risky option is equal to 1/2 the coefficient of a decision maker's absolute risk aversion r_a such that

$$U(\mu_k, \sigma_k) = \mu_k - \frac{r_\mathrm{a}}{2} \cdot \sigma_k^2 \tag{A.5}$$

where μ_k represents the expected profit of strategy k and σ_k^2 represents its variance, which accords with empirical analysis of Norwegian farmers' risk preferences [198]. In Equation 2.1, we define b_i in relation to agent i's perception of strategy k's expected income at time t, $\mu_{ik}(t)$ and its standard deviation $\sigma_{ik}(t)$. We can thus re-write Equation 1 of the main manuscript as follows

$$U(\mu_{ik}(t), \sigma_{ik}(t)) = \mu_{ik}(t) - \frac{b_i}{\sigma_{ik}(t)} \cdot \sigma_{ik}^2(t) \tag{A.6}$$

Generalizing to any time t for notational simplicity, we find from Equations A.5 and A.6 that

$$r_{\mathrm{a},i} = 2\frac{b_i}{\sigma_{ik}} \tag{A.7}$$

Further, the coefficient of relative risk aversion, $r_{\mathrm{r},i}$, is the product of $r_{\mathrm{a},i}$ and a decision-maker's expected income, such that

$$r_{\mathrm{r},i} = 2 \cdot \mu_{ik} \cdot \frac{b_i}{\sigma_{ik}} \tag{A.8}$$

As a general approximation, the average income of a household in Layer 4 of our model is 400 USD, and the standard deviation is 400 USD. Therefore, an average household in our model with risk weight $\bar{b} = 0.5$ with these average income values would have relative risk aversion $r_{\mathrm{r},i} = 1$, which is aligned with the midpoint of r_{r} found among Nepali tea farmers [82].

A.2.2.2 Social Network Details

The social network in Layer 2 is established by randomly assigning each agent a set of connections to other agents in the model. These connections are directional (i.e., A may influence B, but B does not necessarily influence A), and the number of connections j_i established for household i is determined by randomly drawing from a power law distribution of the form

$$P(j_i) = j_i^{-\gamma}, 0 \leq j_i \leq N, \tag{A.9}$$

where γ is a parameter that controls the steepness of the distribution. Here, connections represent incoming links, in that any connections assigned to household i represent the reference group to which it will compare its wealth and derive information on strategy incomes.

Households combine information about the percentage difference $\triangledown_{ii}(t)$ between own profits at time $t-1$ and profits in the previous m years, and the percentage difference $\triangledown_{ji}(t)$ between the profit at time $t-1$ and the profit among their social connections at the same time. These quantities can be written as

$$
\begin{aligned}
\nabla_{ii}(t) &= \frac{\sum_k \pi_{ik}(t-1) - m^{-1} \cdot \sum_k \sum_{v=t-m}^{t-1} \pi_{ik}(v)}{m^{-1} \cdot \sum_k \sum_{v=t-m}^{t-1} \pi_{ik}(v)} \\
\nabla_{ji}(t) &= \frac{\sum_k \pi_{ik}(t-1) - \pi_{jk}(t-1)}{\sum_k \pi_{jk}(t-1)} \quad .
\end{aligned}
\tag{A.10}
$$

The average of the profit differentials must be lower than the status-quo threshold λ in order to motivate the household to re-evaluate its strategy. Let $\mathscr{J}_i$ be the set of social connections of household i with cardinality $|\mathscr{J}_i|$, then we can write the probability $p_{i,\mathrm{r}}(t)$ of household i to re-evaluate its strategy as

$$
p_{i,\mathrm{r}}(t) = \begin{cases} 1 & \text{if } \frac{\nabla_{ii}(t) + \sum_{j \in \mathscr{J}_i} \nabla_{ji}(t)}{|\mathscr{J}_i|+1} < \lambda \\ 0 & \text{if } \frac{\nabla_{ii}(t) + \sum_{j \in \mathscr{J}_i} \nabla_{ji}(t)}{|\mathscr{J}_i|+1} \geq \lambda \quad . \end{cases}
\tag{A.11}
$$

Note that in this layer, households are assumed to equally weigh information about changes in their own profits over time and that of each of their network connections. It is also assumed that λ and risk weight b_i remain constant for each household throughout the duration of the simulation, as empirical evidence demonstrates that risk preferences are unlikely to change significantly over one's adult lifetime [98].

Households combine information from public sources and their social network in forming perceptions about strategy incomes. For simplicity, we assume that this public information represents the true expected income and income volatility of each strategy. However, the degree to which households rely on public information is limited by poor literacy, limited access to information media through websites and newspapers, and/or limited trust in public sources. Households also rely in part on memories of their own income derived from the strategies they deployed in previous years, as well as information received from other households in their social network. We also assume that households forget older information, such that perceived incomes only reflect observations within a given memory window with memory length m. In the perception of household i, the expected income $\mu_{I,ik}(t)$ and income volatility $\sigma_{I,ik}(t)$ are a convex combination of public and social information with respective weights ω_i and $1-\omega_i$. The perception of expected income and income volatility are given by

$$\begin{aligned}\mu_{I,ik}(t) &= \omega_i \cdot \mu_{I,k}(t) + (1-\omega_i)\cdot \mu_{I,ik,\text{social}}(t)\\ \sigma_{I,ik}(t) &= \omega_i \cdot \sigma_{I,k}(t) + (1-\omega_i)\cdot \sigma_{I,ik,\text{social}}(t)\,,\end{aligned} \tag{A.12}$$

with $\mu_{I,k}(t)$ and $\mu_{I,ik,\text{social}}(t)$ the public and social information on expected income, and $\sigma_{I,k}(t)$ and $\sigma_{I,ik,\text{social}}(t)$ the public and social information on income volatility. As to the public information, $\mu_{I,k}(t)$ and $\sigma_{I,k}(t)$ are the actual mean and standard deviation of the Weibull/log-normal distributions specified for each strategy, according to parameters listed in Table A.1. By contrast, the values of $\mu_{I,ik,\text{social}}(t)$ and $\sigma_{I,ik,\text{social}}(t)$ differ for each household; they are a function of the household memories for income received over the memory window and the observations of received income over the memory window of the social connections of household i. Let $\mathscr{J}_{ik}(t)$ represent the set of social contacts of household i applying strategy k at time t with corresponding cardinality $|\mathscr{J}_{ik}(t)|$, then we can write

$$\mu_{I,ik,\text{social}}(t) = \frac{\sum_{v=t-m}^{t-1} I_{ik}(v) + \sum_{v=t-m}^{t-1} \sum_{j\in\mathscr{J}_{ik}(v)} I_{jk}(v)}{m + \sum_{v=t-m}^{t-1} |\mathscr{J}_{ik}(v)|}$$

$$\sigma_{I,ik,\text{social}}(t) = \sqrt{\frac{\sum_{v=t-m}^{t-1}(I_{ik}(v) - \mu_{I,ik,\text{social}}(v))^2 + \sum_{v=t-m}^{t-1} \sum_{j\in\mathscr{J}_{ik}(v)} (I_{jk}(v) - \mu_{I,ik,\text{social}}(v))^2}{m + \sum_{v=t-m}^{t-1} |\mathscr{J}_{ik}(v)|}}, \tag{A.13}$$

where $I_{ik}(t)$ represents the income received by household i from strategy k at time t. The perceived expected utility $U(\mu_{\pi,ik}(t), \sigma_{\pi,ik}(t))$ from strategy k becomes more accurate with a higher weighting ω_i and through increased network connections, which increase its observations of strategy incomes. In this layer, ω_i is randomly assigned to households through a normal distribution (Table A.2). In the Demographic Layer, we introduce a correlation between ω_i and the educational attainment of the head of household.

The literature on migrant networks indicates that networks of current and previous migrants provide potential future migrants with crucial information about safe and efficient ways to reach the city, an economic and social support system to facilitate the first few months in the city, and help to normalize a process that otherwise might appear daunting or even frightening [100, 101]. In this layer, the effects of social networks on migration propensity are operationalized by adjusting the cost of migration $C_{\text{Migrate}}(t)$ as a decreasing function of the fraction $f_i(t)$ of a household's social network that is currently residing in the city. This is governed by the equation

$$C_{\text{Migrate}}(t) = \begin{cases} C_{\text{Migrate},0} \cdot e^{-f_i(t)} & \text{for year } t \\ 0 & \text{for years } t+1, t+2, \ldots \end{cases} \tag{A.14}$$

Table A.2: Layer 2 (Bounded Rationality and Social Network Impact) Parameters

Parameter	Average	Std Dev	Description
λ	0.0	0.0	Status quo threshold
b_i	0.5	0.2	Risk aversion coefficient
ω_i	0.25	0.0	Weight of public information
γ	-2.5	N/A	Exponent for network connections
Avg. degree	4.5		Average number of social connections
m	10	0	Memory of agents (crop cycles)

where $C_{\text{Migrate},0}$ represents the initial migration cost without assistance from the social network. This assumes that migration requires the household to pay an initial up-front cost for travel and initial establishment in the city, and that this cost decays exponentially as a greater proportion of i's social network migrates. After the first year, the migrant from household i is assumed to be self-sufficient and returns any additional revenues earned as remittances for the household.

A.2.3 Layer 3: Demographic Stratification Details

In this layer, household agents are assigned an educational status (Primary, Secondary, and Tertiary). For this analysis, we aggregate the breakdown of the population by educational status in Nepal's Chitawan District (which includes the Chitwan Valley) in the 2011 Nepal Population and Housing Census [**?**] to approximate the proportion of households in each of these categories. Each status is correlated with three parameters: the initial savings level $S_i(0)$, the degree of risk aversion b_i, and the weight of public information sources ω_i. Table A.3 displays the proportions of households in each educational attainment category, as well as the values assigned for each of the three parameters.

Table A.3: Layer 3 (Demographic Stratification) Parameters

Educational Attainment	**Proportion of households**	**Savings $S_i(0)$ (Variance)**	**Risk Weighting b_i (Variance)**	**Public Weight ω_i (Variance)**
Primary	0.65	100 (100)	0.60 (0.2)	0.10 (0.0)
Secondary	0.30	1000 (1000)	0.30 (0.2)	0.25 (0.0)
Tertiary	0.05	2500 (2500)	0.20 (0.2)	0.50 (0.0)

A.2.4 Layer 4: Climate Stress Details

The specification for long-term impact of temperature increase on crop yields is as follows:

$$\mu_{I,k}(t) = \mu_{I,k}(t_0) \cdot (1 - \beta_{\text{yield}})(T(t) - T_0))\,, \tag{A.15}$$

with $T(t) = T_0 + \Delta_T \cdot t$. The parameter β_{yield} is the coefficient relating temperature increase to a proportional change in crop yield, and Δ_T represents the average annual rate of change in mean temperature. A main hypothesis under this scenario is that accuracy of information and the willingness to adopt new strategies becomes increasingly important for accurately perceiving climate risks and securing resilient livelihoods. Therefore, households with a higher number of social connections and low risk aversion are more likely to choose viable livelihoods; these factors are linked with higher educational attainment, which also correlates with a higher initial wealth that enables households to afford new management strategies. By contrast, households with poor social connections and/or low social thresholds are more likely to hold onto farming-based strategies even as these incomes decrease over time. Some households may decide to remain with non-optimal strategies until they can no longer financially afford to change, reflecting an emergent immobility of the population [15, 85].

The increasing frequency of droughts is calculated based on the standardized precipitation and evapotranspiration index (SPEI). The SPEI combines two key features of drought indices: it allows for droughts to be calculated on multiple timescales (e.g. measures of 3-month vs. 48-month water deficits) and explicitly includes temperature as an input for measuring potential evapotranspiration (PET). Importantly, the SPEI is more strongly correlated with measures of crop yield reductions than other drought indices for most regions in the world [117]. The SPEI 3-month index is the most relevant timescale for agricultural purposes given that most cereal crops growing seasons are between 3-4 months in most regions of the world. This has also been shown to be the most strongly correlated timescale with crop yield changes in the North China Plain [114].

In each timestep of the model, we assign the community a drought index by randomly sampling from the SPEI distribution. To account for changing climatic conditions, we adjust the mean of the SPEI distribution as a function of mean annual temperature. To estimate this relationship, we perform a regression analysis on the historical minimum 3-month SPEI value in each year from 1980-2005 for the Chitwan Valley, as a function of the mean annual temperature from the same region:

$$\mu_{\text{SPEI}}(T) = \beta_{\text{SPEI}} \cdot (T(t) - T_0) \tag{A.16}$$

The regression analysis provides a coefficient of -0.247, indicating that an increase of 1^o C in mean annual temperature is correlated with a decrease of 0.247 in the minimum

Table A.4: Layer 4 (Climate Stress) Parameters

Parameter	Average	Std Dev	Notes
ΔT	1.5^{o}C	N/A	Change in mean annual temperature over modelled horizon
β_{yield}	-0.1	0.0	Change in crop yield due to 1^{o}C warming
β_{SPEI}	-0.25	0.0	Change in historical annual minimum SPEI03 due to 1^{o}C warming
τ_{BAU}	-2.0	0.0	Threshold SPEI03 value for BAU extreme drought
τ_{CashCrop}	-1.5	0.0	Threshold SPEI03 value for Cash Crop extreme drought

3-month SPEI value in each year.

In drought years for crop strategy k, households deploying this strategy receive a random income draw, $I_{ik,\text{d}}$, from the bottom portion of the truncated income distribution for strategy k. Specifically, we establish an upper income threshold value for this part of the distribution based on the percentile in the initial income distribution of k that is equivalent to the initial drought probability, $p_{k,\text{d}}(t=0)$. For a BAU crop, $p_{k,\text{d}}(0) = 0.025$ (representing a 1-in-40 year drought), and this percentile in the initial BAU income distribution is 5.52 USD/cycle. For a Cash Crop, where $p_{k,\text{d}}(0) = 0.067$ (representing a 1-in-15 year drought), this threshold is 57.10 USD/cycle.

A.2.5 Policy Interventions Details

Households form perceptions about the risk of drought $p_{ik,\text{d}}(t)$ for crop k by combining public and social information sources. Similar to Section 2.2.2, social information sources combine observations from household i's network connections, as well as its own experiences over the past m years. The perception of drought risk can therefore be written as

$$p_{ik,\text{d}}(t) = \omega_i \cdot P(d_k(t)) + (1-\omega_i) \cdot \left[\frac{\sum_{v=t-m}^{t-1} d_{ik}(v) + \sum_{v=t-m}^{t-1} \sum_{j \in \mathscr{J}_{ik}(v)} d_{jk}(v)}{m + \sum_{v=t-m}^{t-1} |\mathscr{J}_{ik}(v)|} \right], \quad \text{(A.17)}$$

where the second term in the square brackets represents the social information from direct neighbours. The variable $d_{ik}(t)$ is a binary variable representing a drought event that takes the value of 1 if a household experienced a drought in year t, and 0 if not. The probability $P(d_k(t))$ represents the objective probability of an extreme drought for farming strategy k at time t. As such, households use a combination of objective forecasts on the probability of drought, as well as memories of the frequency of previous disasters for specific farming strategies as a heuristic to forecast the probability of future disasters. The perceived drought risk $p_{ik,\mathrm{d}}(t)$ is used to calculate the perceived expected income $\mu_{I,ik}(t)$ and income volatility $\sigma_{I,ik}(t)$ as follows

$$\mu_{I,ik}(t) = (1 - p_{ik,\mathrm{d}}(t)) \cdot \mu_{I,ik,\mathrm{nd}}(t) + p_{ik,\mathrm{d}}(t) \cdot \mu_{I,ik,\mathrm{d}}(t)) \tag{A.18a}$$

$$\sigma_{I,ik}(t) \approx (1 - p_{ik,\mathrm{d}}(t)) \cdot \sigma_{I,ik}(t)\,. \tag{A.18b}$$

where $\mu_{I,ik,\mathrm{nd}}(t)$ and $\mu_{I,ik,\mathrm{d}}(t)$ are the perceived expected incomes for the non-drought and drought portions of strategy k's income distributions, respectively. The right-hand side of (A.18b) is a close approximation of the standard deviation adjusted for index insurance.

The notation used throughout the paper is summarized in Table A.5.

Table A.5: Summary of notation

Notation	Description
λ	status-quo parameter
b_i	risk aversion parameter of household i
ω_i	information preference parameter of household i
E_i	education parameter
Δ_T	average annual rate of change in mean temperature
ΔT	increase in mean annual temperature between 2006 and 2050
h	time horizon in decision-making process
ρ	discount rate
$U(\mu_{\pi,ik}(t), \sigma_{\pi,ik}(t))$	utility function
$\nabla_{ii}(t)$	profit differential with respect to past profits
$\nabla_{ij}(t)$	profit differential with respect to past profits of social connections
$p_{i,\mathrm{r}}(t)$	probability to re-evaluate strategy
β_{yield}	coefficient relating temperature increase with change in crop yield
β_{SPEI}	coefficient relating temperature increase with change in mean SPEI
τ_k	drought threshold for strategy k
$S_i(t)$	household savings
$\mathcal{K}$	strategy set
$\lvert\mathcal{K}\rvert$	cardinality of set $\mathcal{K}$
$\mathcal{J}_i$	set of social contacts of household i
$\mathcal{J}_{ik}(t)$	set of social contacts of household i applying strategy k at time t
$I_{ik}(x_k, t)$	household income from farming strategy k with x_k on-farm household members
x_{hh}	total number of household members

$R_i(x_k, t)$	remittances received by household i with x_k on-farm household members
$C_{ik}(t)$	cost of strategy k
$\pi_{ik}(t)$	profit of household i employing strategy k
$\mu_{\pi,ik}(t)$	expected profit of strategy k perceived by household i
$\sigma_{\pi,ik}(t)$	profit standard deviation of strategy k perceived by household i
$\mu_{I,k}(t)$	true expected income from farming strategy I_k
$\sigma_{I,k}(t)$	true income standard deviation from farming strategy I_k
$\mu_{I,ik,\text{social}}(t)$	social information on expected income from farming strategy I_k
$\sigma_{I,ik,\text{social}}(t)$	social information on income standard deviation from farming strategy I_k
$\mu_{I,ik}(t)$	expected income from farming strategy I_k perceived by household i
$\sigma_{I,ik}(t)$	income standard deviation from farming strategy I_k perceived by household i
$\mu_{I,k,\text{nd}}(t)$	true expected income from farming strategy I_k in non-drought year
$\mu_{I,k,\text{d}}(t)$	true income standard deviation from farming strategy I_k in drought year
$\mu_{I,ik,\text{nd}}(t)$	perceived expected income from farming strategy I_k in non-drought year
$\mu_{I,ik,\text{d}}(t)$	perceived income standard deviation from farming strategy I_k in drought year
$\tilde{\mu}_{I,k}(t)$	true expected income from farming strategy I_k adjusted for index insurance
$\tilde{\sigma}_{I,k}(t)$	true income std dev from farming strategy I_k adjusted for index insurance
$\tilde{\mu}_{I,ik}(t)$	perceived expected income from farming strategy I_k adjusted for index insurance
$\tilde{\sigma}_{I,ik}(t)$	perceived income std dev from farming strategy I_k adjusted for index insurance
μ_R	true expected income of remittances
σ_R	true standard deviation of remittances
$\tilde{\mu}_R(x_i, t)$	true expected income from remittances adjusted for presence remittance bank
$\tilde{\sigma}_R(x_i, t)$	true income std dev from remittances adjusted for presence remittance bank
$L_k(t)$	expected losses in drought year for farming strategy k
I_{subs}	government subsidy
$R_{i,\text{dep}}(x_i, t)$	deposits to remittance bank by household with x_i on-farm household members

$R_{i,\mathrm{po}}(x_i, t)$	payouts by remittance bank to household with x_i on-farm household members
ρ_{rem}	fraction of remittances deposited in the remittance bank
$p_{k,\mathrm{d}}(t)$	probability of a drought for farming strategy k at time t
l_1	exponent for decreasing farm productivity
l_2	exponent for decreasing remittance returns
γ	exponent of the degree distribution for the number of social connections
R_{subs}	government subsidy for remittance bank

A.3 Further Model Results

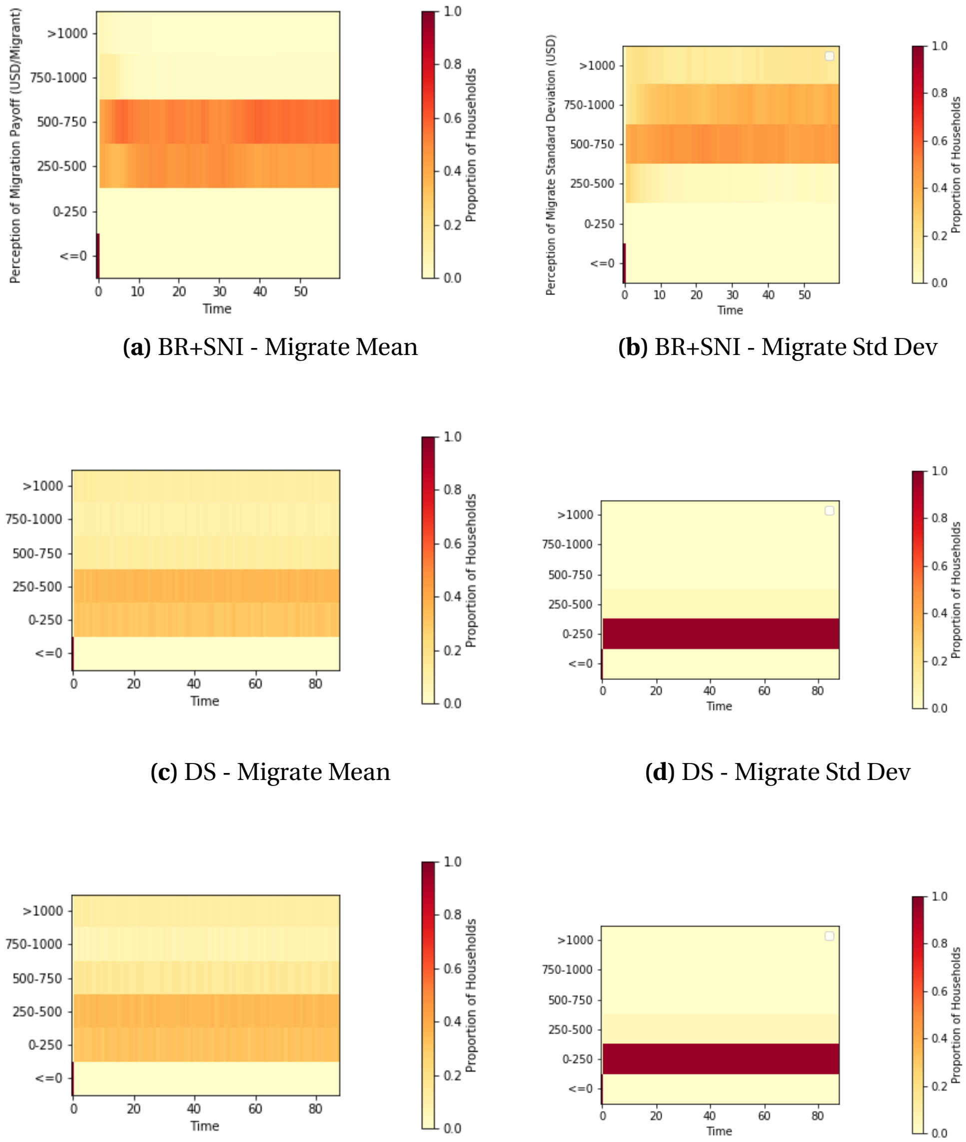
A.3.1 Household Perceptions of Cash Crop and Migrate Income

Households in the model can form different perceptions of the mean and variance of an income distribution for each strategy k. These perceptions are influenced by the observations of specific income draws for strategy k received by the social network of household i, as well as its own income draws over the memory window (Appendix A2.2.2, Equation A.13). The perception of the income distribution also depends on the weight ω_i that each household assigns to objective information (Appendix A2.2.2, Equation A.12).

Here we show by means of a spectrogram how household perceptions of the mean and variance of the Migrate (Fig. A.1) and Cash Crop (Fig. A.2) strategies are distributed through the course of the model timeframe. For both strategies, we observe that as Demographic Stratification and Climate Impacts are introduced, household perceptions of the mean and standard deviation of these income distributions diverge. This is particularly the case for the perceived standard deviation of each strategy in the Climate Impacts layer. This suggests a feedback between the diminished ability of some households to afford high-cost, high-risk, high-reward strategies as climate impacts manifest, and differential perceptions of strategy risks. As fewer households have the ability to adopt such strategies and share information within their networks, households with lower access to objective information are more likely to diverge in terms of their perceived risks.

A.3.2 Analysis of Migrants at Terminal Time

In Sections 3.2 and 3.3 of the main text, we present the results of a sensitivity analysis and policy interventions, respectively, on the proportion of community migrants by



(a) BR+SNI - Migrate Mean

(b) BR+SNI - Migrate Std Dev

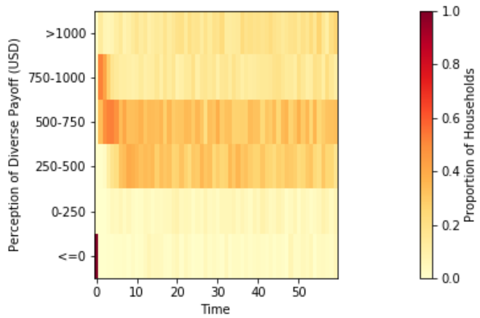
(c) DS - Migrate Mean

(d) DS - Migrate Std Dev

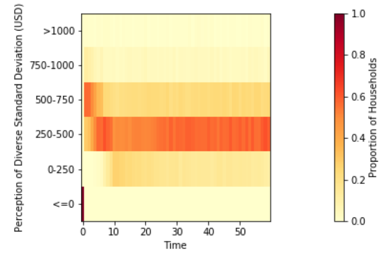
(e) CI - Migrate Mean

(f) CI - Migrate Std Dev

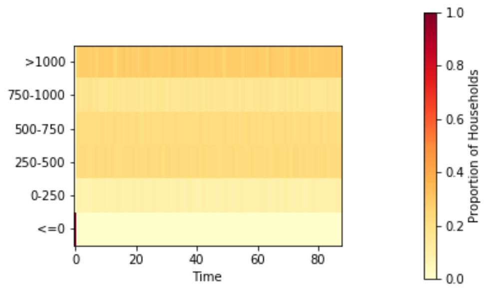
Figure A.1: Perception of mean (left) and standard deviation (right) of remittances per migrant. For each plot, ranges of the perceived mean and standard deviation are displayed on the y-axis, and the proportion of households perceiving this range of values is indicated by the color shading, with red indicating a higher proportion of households perceiving this range. Time is displayed on the x axis in units of cropping cycles. Plots are arranged progressively for three model layers (BR+SNI = Bounded Rationality + Social Network Impact; DS = Demographic Stratification; CI = Climate Impacts).



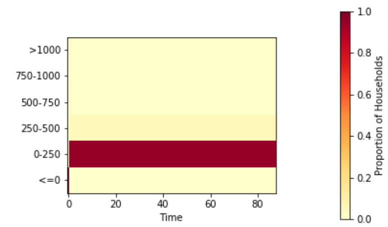
(a) BR+SNI - Cash Crop Mean



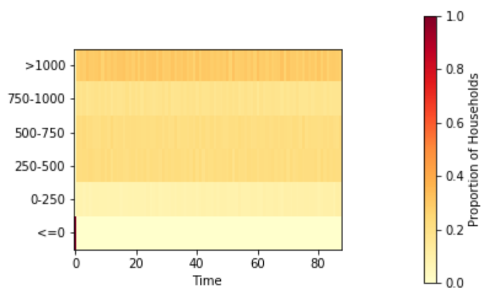
(b) BR+SNI - Cash Crop Std Dev



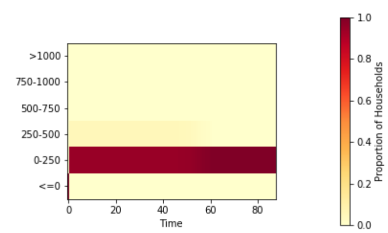
(c) DS - Cash Crop Mean



(d) DS - Cash Crop Std Dev



(e) CI - Cash Crop Mean



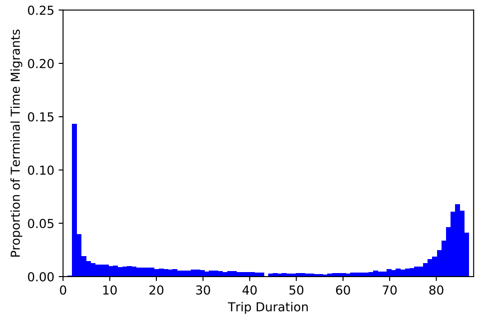
(f) CI - Cash Crop Std Dev

Figure A.2: Perception of mean (left) and standard deviation (right) of payoff for Cash Crop strategy. For each plot, ranges of the perceived mean and standard deviation are displayed on the y-axis, and the proportion of households perceiving this range of values is indicated by the color shading, with red indicating a higher proportion of households perceiving this range. Time is displayed on the x axis in units of cropping cycles. Plots are arranged progressively for three model layers (BR+SNI = Bounded Rationality + Social Network Impact; DS = Demographic Stratification; CI = Climate Impacts).

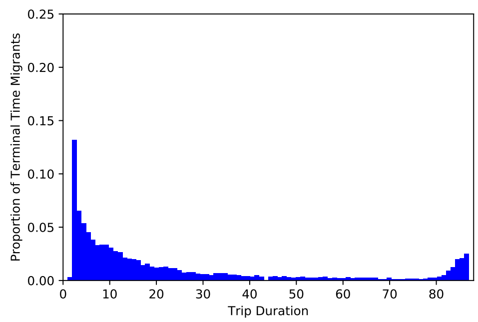
terminal time in the model. While our analysis does not make a sharp distinction between temporary and permanent migrants, we claim that the migrant proportion at terminal time can serve as an approximation for long-term migration. Here, we examine this assumption more closely.

Fig. A3 displays a histogram of the migrants at model terminal time for the three scenarios we explore in the main text, arranged by the consecutive number of years for which they have been at the destination. For example, the bar for 5 years represents the proportion of such migrants who have been at their destination for each of the 5 previous years, equivalent to 10 time steps in our model. The bar for 1 year represents migrants who have just reached the destination in the previous year, and the bar at 44 represents migrants who have been at the destination continuously since the beginning of the model time horizon.

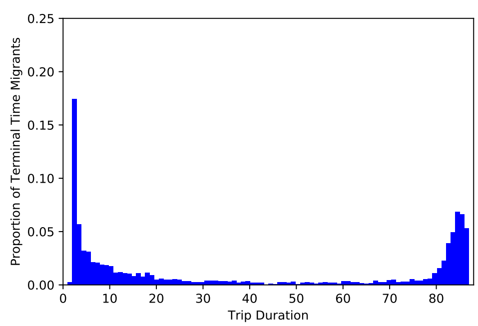
In each scenario, at least 50 percent of migrants have resided at the destination for at least the 5 previous years (73, 53, and 61 percent, respectively, for Scenarios A, B, and C). We note that in each scenario, there is a substantial proportion of migrants who have just moved in the previous year (14-18 percent, depending on the scenario), which reflects some persistent turnover in the individuals who emigrate vs. those who return to the village. We also note that in Scenario B, our Base Case, the distribution of migrants at terminal time skews more towards shorter-term migrants than the two other scenarios. This likely reflects a closer tradeoff in households' perceived utility of migration relative to the other farming strategies in this Scenario, leading to shorter trips on average. Still, even in Scenario B, the majority of migrants have been at their destination for at least 5 years by terminal time. We therefore use the proportion of migrants at terminal time as an approximation of the long-term migrant population.



(a) Scenario A: $\bar{b} = 0.25$**,** $\Delta_T = 4.5^0$**C**



(b) Scenario B: $\bar{b} = 0.5$**,** $\Delta_T = 1.5^0$**C**

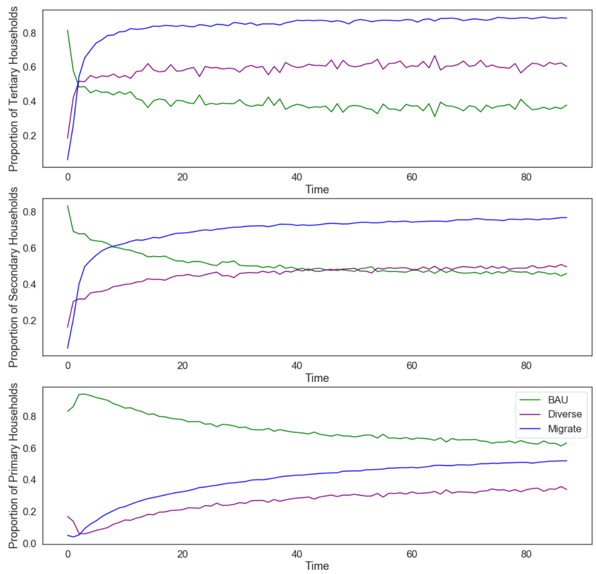


(c) Scenario C: $\bar{b} = 1.25$**,** $\Delta_T = 3.0^0$**C**

Figure A.3: Histograms of Migrants at Terminal Time, by Trip Duration. Each panel displays a histogram of terminal time migrants based on the duration of their trip, measured in the number of years for which they have been residing at the destination. Results display the aggregate distribution over 100 model simulations for **a)** Scenario A, **b)** Scenario B, and **c)** Scenario C.

A.3.3 Differential Effect of Demographic Stratification and Climate Stress

In the Demographic Stratification and Climate Impacts layers, agents are assigned an educational attainment level (Primary, Secondary, or Tertiary educational attainment). A household's educational level is correlated with three variables that affect strategy decisions: risk aversion b_i, weight given to objective information ω_i, and an initial savings level, $S_i(t = 0)$ (Appendix A.2.3). Here, we disaggregate household strategy choices by educational status under Scenario B ($\Delta T = 1.5^o C$, $\bar{b} = 0.5$) for both of these layers (Fig. A.4). Generally, households with higher educational status are more likely to pursue both Cash Crop and Migrate as livelihood strategies, whereas households with lower educational status are more likely to remain in the BAU livelihood. Climate impacts reduce the proportion of households pursuing Cash Crop in all educational categories, compared to the Demographic Stratification layer. However, the effects of climate on the use of migration is dependent on educational status: households with tertiary and secondary educational status do not display a significant drop in migration compared to the demographic stratification layer, whereas migration is reduced by 50 percent among primary educated households. This supports previous work that demonstrates the significance of educational attainment for mitigating climate risk vulnerability [103].



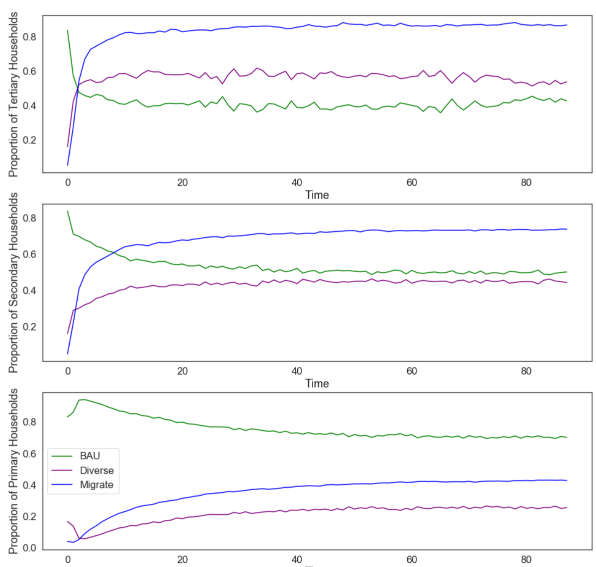


Figure A.4: Breakdown of livelihood strategy choices by household educational status for Demographic Stratification model layer (top) and Climate Impacts model layer (bottom). For each layer, the choices of tertiary-educated households are displayed in the top panels, followed by secondary-educated households in the middle panels, and households with primary educational attainment in the bottom panels.

A.3.4 Model Validation

Data collected by the CVFS allow a partial validation of the model results. The CVFS "Labour Migration, Agricultural Productivity and Food Security Survey" is a longitudinal survey of 2,255 households in the Chitwan Valley from 2006-2015, with questions regarding household farming and migration decisions, including both on-farm and remittance income earned in each survey year [29]. We initialize the agent-based model with the CVFS data on the initial distribution of households farming cereal crops vs. fruits and legumes, and the proportion of households engaging in migration. As the 2006 data only reported 2 households engaging in migration, we use the 2007 data, in which 101 households (4.5 percent of the sample) reported migration, as the starting point.

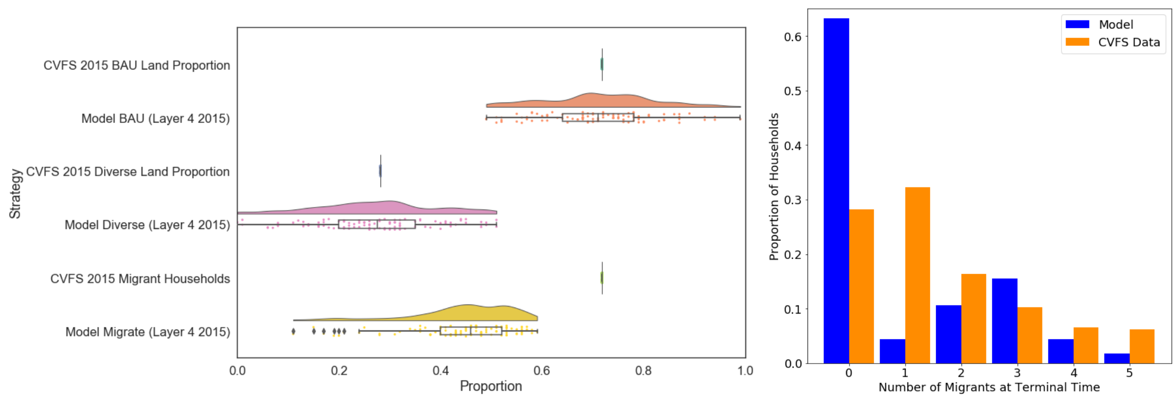
A partial validation of the ABM is conducted by comparing the predicted model outcome with survey data along two dimensions. First, we conduct 100 simulations of the full model (i.e. including all layers through Climate Impacts) to generate a distribution of the proportion of households pursuing each livelihood strategy by year 2015 (time step 17 in the model). We then compare this with data from the CVFS survey on the area of farmland devoted to farming cereal crops vs. legumes and fruits at this time (Fig. A.5a).

The distribution of model results exhibits substantial variance, reflecting several sources of stochasticity. Specifically, in each simulation, we randomize: (1) the exact structure of the social network (while keeping the average degree and power law distribution of connections constant); (2) the specific time steps in which droughts for BAU and Cash Crop crops occur ; and (3) the specific income draws, $I_{ik}(t)$ and $R_i(t)$, for each household in each time step (while keeping the true expected income $\mu_{I,k}(t)$ and standard deviation $\sigma_{I,k}(t)$ of each strategy constant). Despite these sources of stochasticity, the model predictions of the mean fraction of households pursuing BAU vs. Cash Crop strategies by 2015 (67 and 33 percent, respectively) closely match the observed CVFS data on the proportion of agricultural land dedicated to these crop types by the same time (72 and 28 percent). However, the model significantly underestimates the observed proportion of households that migrate by that time (a predicted value of 40 percent vs. an observed value of 72 percent). There are likely two reasons for this discrepancy. First, the model only accounts for migration motivated by economic reasons, whereas real-world migration may also occur for other motives (e.g. marriage). Second, some of the observed migration may reflect short-distance moves within Nepal, whereas the migration costs in our model assume longer-distance migration.

To further explore this discrepancy, we conduct validation along a second dimension: the distribution of model household members/survey respondents that migrate by the year 2015 (Fig. A.5b). In the model, this number can range from 0 to 5; the range in the CVFS data is from 0 to 17. For comparison purposes, we group all CVFS households sending 5 or more migrants in the same "5+" category. We find that our model substantially overestimates the percentage of households sending no migrants (63.2 percent in the model vs. 28.2 percent in the CVFS data), and underestimates the proportion of households sending only 1 migrant (4.4 percent in the model, vs. 32.3 percent of households in the CVFS data).

On the other hand, the model closely matches the proportion of households sending between 2 and 4 migrants (30.8 percent in the model, vs. 33.2 percent in the CVFS data). It is difficult to draw firm conclusions from this comparison without further data on household motivations for migration, but we can assume that households sending multiple migrants are more likely to be reflective of economic motivations for migration, while households that only send 1 migrant likely reflect a combination of economic and social (e.g. marriage) motivations for migration. We therefore interpret this result as further support for the model's ability to capture the dynamics of economic migration decisions, while acknowledging that other migration motivations are outside our scope.

We also note that the model underestimates the proportion of households sending 5 or more migrants (1.8 percent of households in the model send 5 migrants by this time, compared to 6.3 percent of households in CVFS data sending at least 5 migrants). This reflects the model's limitations in capturing the dynamics of livelihood decisions for large household sizes. The decision to limit household size in our model was made for reasons of modelling efficiency, but we acknowledge that larger household sizes are likely to play a small but important role in shaping agricultural adaptation pathways, and could be incorporated in future work.



(a) Household Strategies in 2015

(b) Migrants per Household in 2015

Figure A.5: (a) Comparison of model results and CVFS data for the year 2015, displayed in a raincloud format that illustrates the distribution of outcomes (including mean and interquartile range) over 100 simulations for Model Layer 4. CVFS data is represented by the single points above each strategy. Note that the data for BAU and Cash Crop represent the proportion of cropland that was dedicated to cereal and vegetable crops, respectively, as several households grew both kinds of crops. (b) Comparison of model results (blue) and CVFS data (orange) for the distribution of household members/survey respondents based on the number of migrants per household in 2015. As the CVFS data included a few households with more than 5 migrants, the right-hand orange bar represents the number of households with 5+ migrants in 2015.

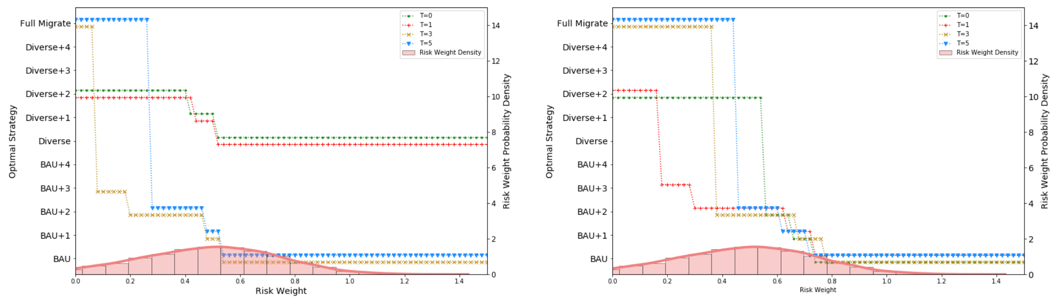
A.3.5 Sensitivity of Optimal Strategy and Adaptation Pathways to Key Parameters

To test the robustness of model results to uncertain model parameters and other sources of stochasticity, we conducted sensitivity analyses of household strategy choices to various exogenous and cognitive parameters (Figs. A.6-A.8).

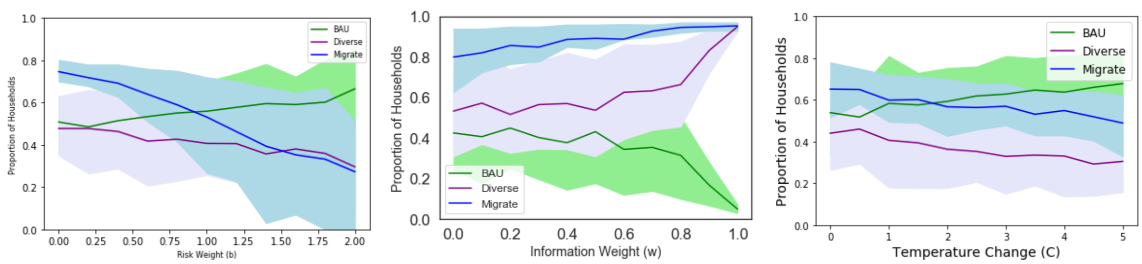
Figure A.6 displays the sensitivity of model results to three key parameters: the risk aversion parameter b_i, the information preference parameter ω_i, and the degree of temperature change ΔT during the model run. We analyze the effects of these parameters on individual decision-making and on collective outcomes. At the individual scale, different parameter combinations of risk weighting, access to information, and temperature change lead to different preferences regarding the optimal strategy option (Fig. A.6a-b). With little to no temperature change ($\Delta T = 0$ and $\Delta T = 1$), the optimal strategy under objective information and low risk weightings ($b_i <= 0.5$) is farming Cash Crops, plus sending two household migrants (Fig. A.6a). For households with higher risk weightings (e.g., $b_i > 0.75$), a full household farming Cash Crops would be the optimal strategy. However, there are discrepancies between the optimal strategy choice under objective and social information for low temperature change; for example, under a temperature increase of 1^0C and risk weightings $b_i > 0.2$, households perceive various combinations of farming BAU crops and migration to be the optimal choice (Fig. A.6b). If temperature increases become more significant (e.g., $\Delta T = 3^0C$, gold markers), the objective optimal choice for low risk weightings is to send all working-age household members as migrants, while under most risk preferences the optimal choice is for households to farm BAU crops (with some migration for moderate risk weightings). By contrast, information from households' social networks generally indicate that fully abandoning farming is the optimal strategy choice for households with risk weightings $b_i < 0.4$ and high temperatures. Under more extreme temperature increases (e.g., $\Delta T = 5^0 C$, blue markers), there is more agreement between the objective and perceived optimal strategy choices: either completely migrate if a household has low risk preference, or stay and farm BAU crops if households have high risk preferences. Discrepancies between the optimal strategy choices under objective and social information are driven by the limited information that can be obtained from social networks. As most households in our scale-free network have relatively few connections and relatively short memories (10 cycles, or 5 years), they often have only a few observations of the higher-risk, higher-cost strategies (i.e., Cash Crop and Migrate). As the income distributions for these strategies are positively-skewed, this causes some households to underestimate both the mean and variance of these strategies, which can lead to different perceived strategy choices compared to objective information.

On a community scale, strategy choices become more disperse across several options, as households make choices and exchange information reflecting different risk preferences, differential access to objective information, and differential financial abilities to afford higher-cost strategies. We assess the community-scale impacts of risk weighting, access to information, and temperature change using Model Layer 2, in which all households exhibit homogeneous bounded rationality parameter values. These are held constant at average values ($b = 0.5$ and $\omega = 0.25$), except for the parameter being varied, in order to isolate its effect on model outcomes. We also include the effect of random droughts under a stationary distribution ($\Delta T = 0^o C$), except for the temperature sensitivity. Results display the average distribution of strategy choices among households at $t = 50$ in the model, with shaded areas representing +/- 1 standard deviation in results among the 100 simulations. The main sources of stochasticity in these tests are: (1) the social network configuration for each simulation, in which households are assigned randomized social networks based on a constant power law function; (2) the random draws of income in each time step from the strategy payoff functions; and (3) randomized occurrence of extreme droughts.

Increasing the risk aversion through the parameter b_i decreases the adoption of high-risk, non-BAU strategies (Fig. A.6c), consistent with the individual-scale results above. Most of this sensitivity occurs in the range $0.5 \leq b \leq 1.0$, over which there is a sharp decrease in the proportion of households that migrate and farm Cash Crops. Consistent with results from Fig. A.6b, this is the range over which the relatively high variance of these strategies, relative to their expected incomes, are perceived to be too high by most households. As households increasingly weigh objective sources of information on strategy payoffs, relative to their social networks - owing to trust in and/or access to objective sources - their adoption of the Cash Crop strategy increases (Fig. A.6d). Again, this reflects the tendency of agents to underestimate the skewed distribution of income from each strategy under limited information. Once households have close to perfect information ($\omega > 0.8$), the proportion of households engaging in migration drops sharply; this reflects the transition point at which a full Cash Crop strategy becomes optimal under objective information, a risk weight of $b \geq 0.5$, and $\Delta T = 0^o C$ (Fig. A.6a). As temperatures increase, households increasingly switch to the lower-risk BAU farming strategy (Fig. A.6e). This is somewhat different than what is predicted by the individual-scale result, in which households with low risk preferences prefer to fully migrate. This discrepancy is due to increasing climate stress eroding farmers' financial resources; even though some households would prefer to completely migrate, they have less financial ability to do so.



(a) Opt. Strategy - Objective Information **(b)** Opt. Strategy - Social Network Information



(c) Risk Weight, b_i **(d)** Objective Information Weight, ω_i **(e)** Temperature Change, Δ_T

Figure A.6: Effects of Risk Weight(b_i), Objective Information Weight (ω_i), and Temperature Change (ΔT) on Household Strategy Choices. a-b) Comparison of optimal individual strategy options (y-axis) over a range of risk preferences (x-axis). For each risk preference value on the x-axis, markers indicate the strategy option that maximizes utility after different degrees of temperature change ΔT. Labels on the y-axis refer to individual strategy options; e.g., "Cash Crop + 2" indicates farming Cash Crop crops with 3 household members, and sending 2 household members as migrants. Vertical dashed lines are included for illustrative purposes to indicate a change in optimal strategy as a function of risk weight. Panel (a) displays these optimal strategies using completely objective information; panel (b) displays optimal strategy choices using the average information obtained from social networks. The actual distribution of households by risk preferences is indicated by the red histogram. Panels (c) - (e): Community-level sensitivities of household strategy choices to key uncertain parameters. Results reflect the proportion of households deploying each strategy after 50 time steps in the model, representing year 2032, by which time most strategy distributions are close to steady-state. Solid lines indicate average values over 100 simulations for each parameter value; shaded regions represent +/- one standard deviation.

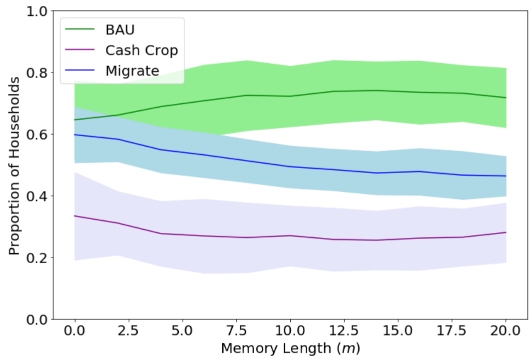
In addition to these sensitivities, we also display single-parameter sensitivities for other model parameters in Fig. A.7. The proportion of households pursuing the Migrate strategy exhibits some sensitivity to household memory length, m. All other parameters held at their Base Case values, fewer households are likely to pursue Migrate if memories are longer (Fig. A.7a). Similar to the sensitivity mentioned above to the weight of public information, ω_i, longer memory lengths provide more observations, and therefore more accurate information regarding the true expected mean and variance of the Migrate strategy. As more households accurately perceive the true expected income and volatility of Migrate, fewer households engage in this strategy, with fewer positive externalities on other would-be migrants (this is explored in more depth in Appendix A.3.8). By contrast, altering the household discount rate has a negligible effect on terminal time household strategy choices (Fig. A.7b). For the BAU and Cash Crop strategies, households project the same set of strategy costs, expected income, and income volatility for each timestep in their horizon. Therefore, a modified discount rate does not change relative preferences between these two strategies. For the Migrate strategy, households anticipate paying the upfront cost in the first time step, and then receiving remittances in future timesteps. The discount rate therefore has an impact on the utility of this strategy relative to the farming options. However, as some members of a household's network migrate, the up-front migration cost diminishes. A higher discount rate therefore diminishes the onset of outmigration, but does not have a sizeable impact on terminal time household strategies. Fig. A.8 illustrates the difference between a lower discount rate (Fig. A.8a, $\rho = 0.1$) and high discount rate (Fig. A.8b, $\rho = 0.5$).

The total number of agents in our model, N, does not exert a substantial influence on terminal time household strategies over the range of $10^1 \leq N \leq 10^4$ number of agents (Fig. A.7c). At the time of the 2011 Nepali Census, there were 130,000 total households living in the district that includes the Chitwan Valley [**?**]. Much of the region is comprised of small farming villages [29] that are likely to have the number of households in the range of $10^1 - 10^2$. Our model results do not exhibit substantial sensitivities to our assumptions around the starting household size x_{hh} (Fig. A.7d), or the initial distribution of Migrate and Cash Crop households (Fig. A.7e-f), though the use of Migrate increases slightly for higher initial proportions of households employing either Migrate or Cash Crops. We note that the sensitivity to household size is especially conditional on our assumptions regarding how strategy incomes change as a function of multiple migrants from a household (Appendix A.2.1, Equations A.2 and A.4), and on how migration costs are a function of the proportion of migrants in a household network (Appendix A.2.2.2, Equation A.14). Future work is necessary to test whether these relationships hold for a large range of household sizes.

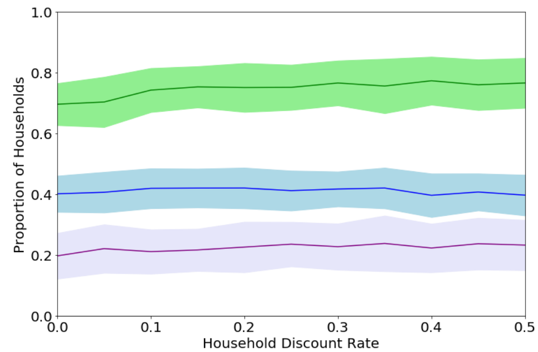
Finally, we explore sensitivities of our results to different social network structures in two ways. First, household strategy choices display a slight sensitivity to the parameter γ, which controls the degree distribution of the scale-free network (Fig. A.7g). In particular, the percentage of households pursuing Migrate by the end of the model timeframe decreases from 56.4 percent to 51.5 percent as the average network degree increases from 2.2 to 12.1. We also test this relationship for an Erdös-Rényi network, in which each agent forms social connections with constant probability for all households. With such a network, household strategy choices exhibit slightly more sensitivity: the percentage of households engaging in Migrate ranges from 56.8 percent with degree of 0, to 44.4 percent for degree of 12.5, to 42.7 percent with average degree of 20 (Fig. A.7h). In both cases, these sensitivities are in line with insights from the sensitivity to the weight of objective information, ω_i, which suggests that households engage in less migration as they receive more accurate information regarding strategy payoffs.

As a second test, we also compare the number of migrants per household under scale-free and Erdös-Rényi networks of different average degrees (Fig. A.9). For both types of networks, an increased average degree results in fewer households sending four or five migrants, in addition to a higher proportion of households that do not engage in migration. Households connected via an Erdös-Rényi network also generally have fewer households sending four or five migrants, and more households sending no migrants, compared to a scale-free network of similar degree (for example, comparing Fig. A.9a with Fig. A.9c, and Fig. A.9b with Fig. A.9d). This pattern is also consistent with the role of more accurate information on household migration choices: for a given degree, the median number of social connections in an Erdös-Rényi network will exceed that of a scale-free network (where a few households have many connections, while most households have fewer than the average number of connections). Therefore, more households in a Erdös-Rényi network are likely to have more accurate information regarding the Migrate income distribution, and thus less likely to engage in migration. Nevertheless, we note that differences in household strategy choices and the number of migrants per household are still modest between these two network structures, and between networks of different degrees, compared to the impact of other model parameters, such as risk weight, objective information weight, and temperature change.

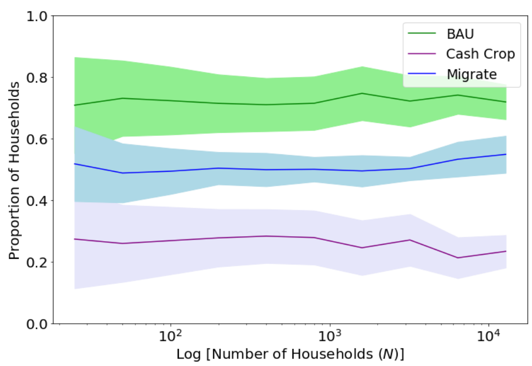
In sum, our model sensitivities indicate that in situations where farming households view migration and other adaptation strategies with a high degree of uncertainty, risk aversion and access to objective information both serve to mediate the climate-migration relationship. These two characteristics can differ across geographical and cultural contexts [199], as well as across time as societies evolve, pointing to the importance of evaluating potential policy interventions under broad ranges of these parameters.



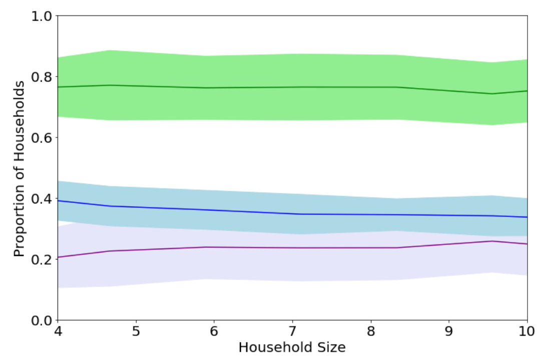
(a) Memory Length m



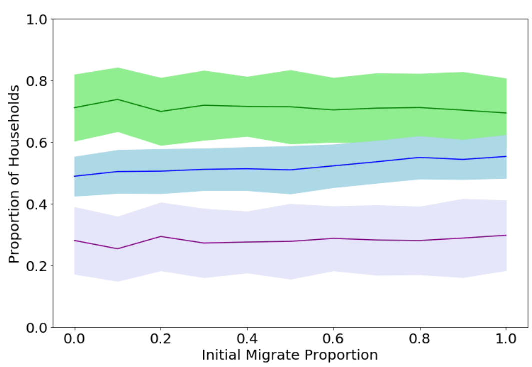
(b) Household Discount Rate



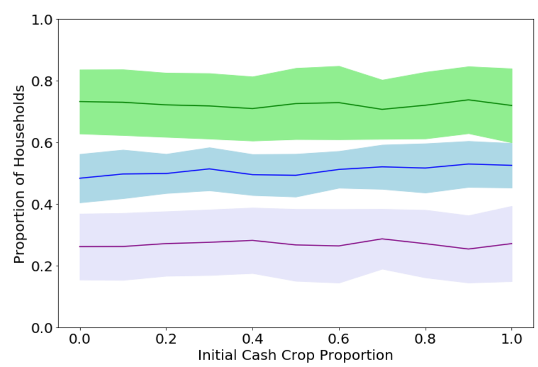
(c) Number of Households N



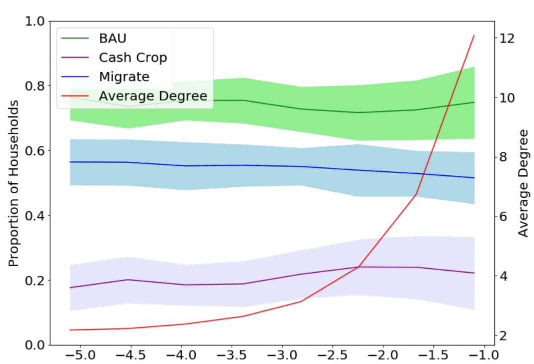
(d) Household Size x_{hh}



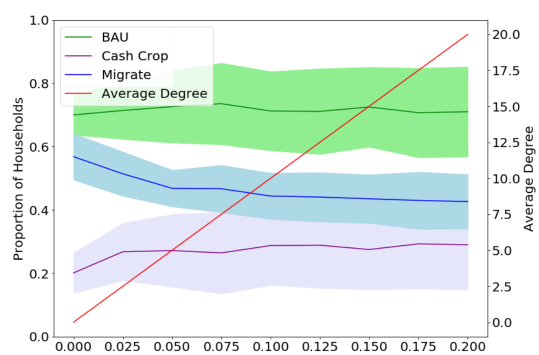
(e) Initial Migrate Distribution



(f) Initial Cash Crop Distribution

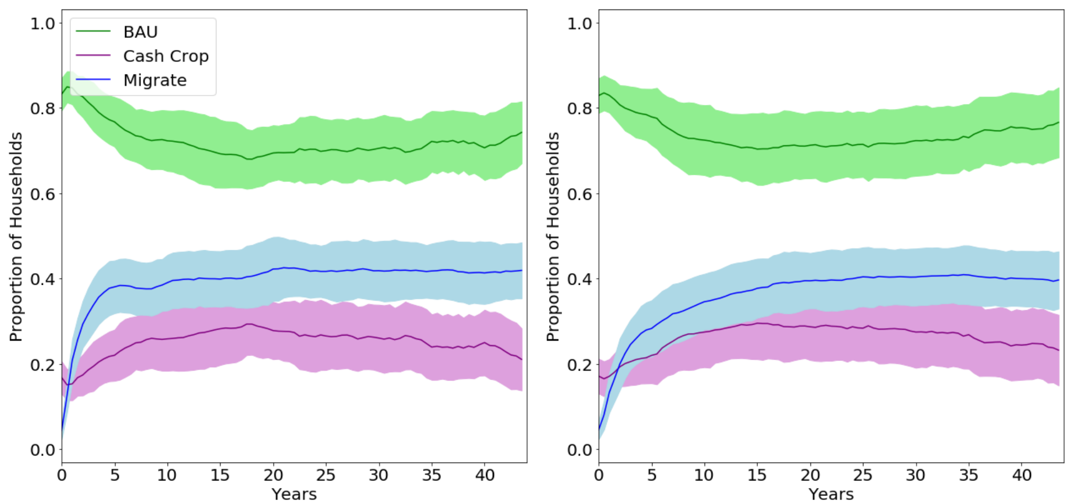


(g) Average Degree - Scale-Free Network



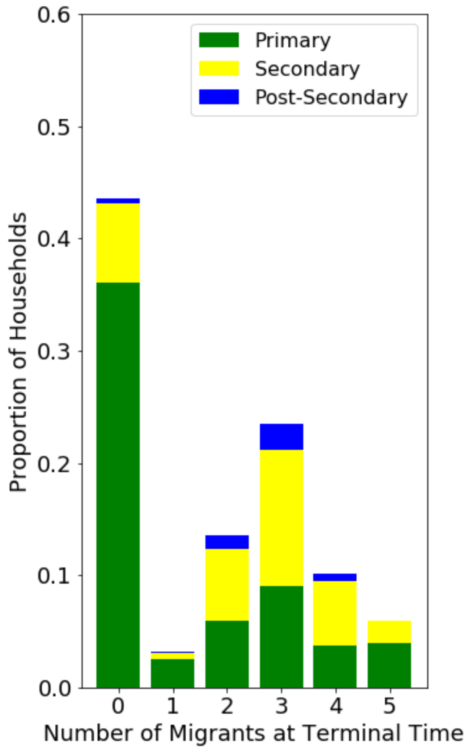
(h) Average Degree - Erdos-Renyi Network

Figure A.7: Additional sensitivities of model results to individual parameters.

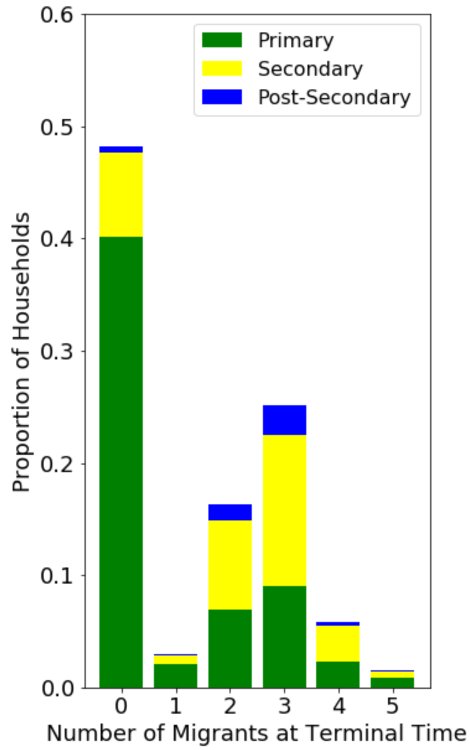


(a) $\rho = 0.1$ **(b)** $\rho = 0.5$

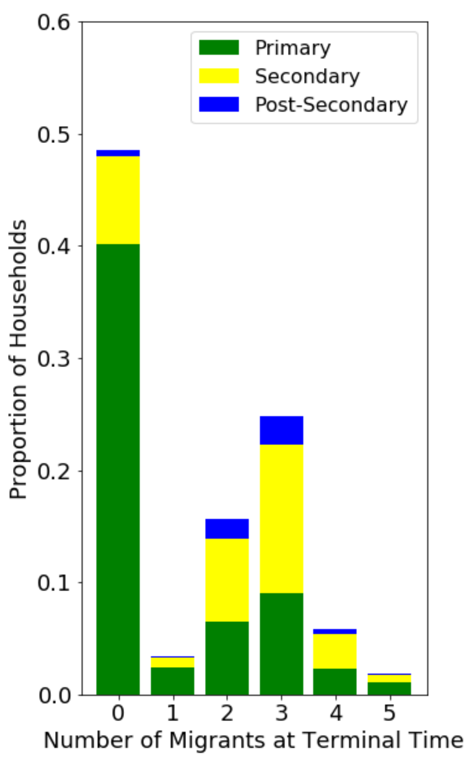
Figure A.8: Household strategy choices under different discount rates. The mean (solid lines) and standard deviation (shaded regions) of household strategy choices over 100 simulations are shown for a scenario with lower discount rate ($\rho = 0.1$, left) and higher discount rate ($\rho = 0.5$, right).



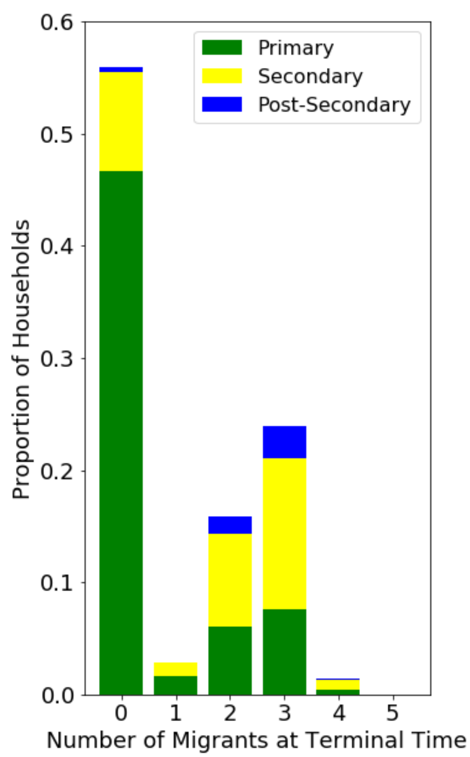
(a) Scale-Free, Gamma = -5.1
(Avg Degree = 2.2)



(b) Scale-Free, Gamma = -1.1
(Avg Degree = 12.1)



(c) Erdos-Renyi, Degree = 2.5



(d) Erdos-Renyi, Degree = 12.5

Figure A.9: Distribution of households by number of migrants at terminal time under different social networks. Results are shown for scale-free networks with average degrees 2.2(a) and 12.1(b); and Erdos-Renyi networks with average degrees 2.5 (c) and 12.5 (d).

A.3.6 Effects of Model Layers on Key Outcomes

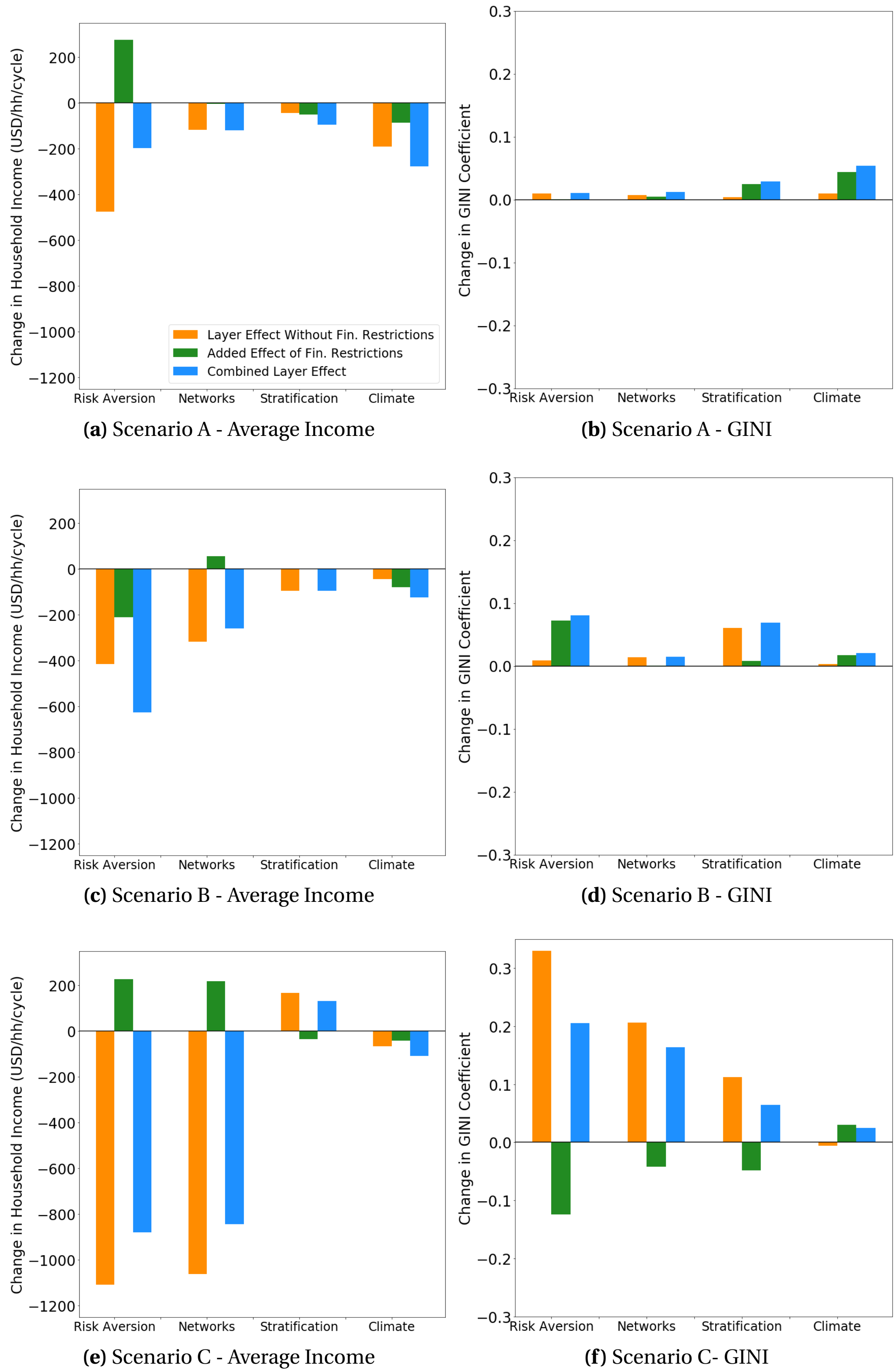
As a complement to Fig. 2.3 in the main text, in this section we display the effects of specific model factors on two additional model outcomes: average community income and GINI coefficient (Fig. A.10). Similar to Fig. 2.3, we conduct these analyses for the three illustrative scenarios: Scenario A ($\bar{b} = 0.25$, $\Delta T = 4.5^0 C$), Scenario B ($\bar{b} = 0.5$, $\Delta T = 1.5^o C$), and Scenario C ($\bar{b} = 1.25$, $\Delta T = 3.0^o C$).

We note a few robust findings that are consistent across all scenarios. First, climate impacts lower average income and increase inequality, as measured by the GINI coefficient. In all cases, each of these effects is accentuated by financial restrictions (i.e., the combination of financial restrictions and climate impacts further decreases average income, and the combination of financial restrictions and climate impacts further increases inequality).

Second, risk aversion in all cases reduces average income and increases inequality. Interestingly, financial restrictions dampen the impact of risk aversion on income; that is, risk aversion would lead to an even higher decrease in income in the absence of financial restrictions. This is because financial restrictions already prevent some households from choosing high-risk, costly strategies (Cash Crop and Migrate); therefore, risk aversion in the presence of financial restrictions has slightly less of an impact on lowering incomes than it would have if households had perfect access to credit. However, financial restrictions enhance the effect of risk aversion on increasing inequality; both of these mechanisms combine to prevent many households from pursuing the high-risk, high-reward strategies, while a few households have both the financial resources and risk appetite to adopt these strategies, thereby increasing inequality.

Third, the presence of social networks increases community incomes, but this effect is dampened by financial restrictions. In the absence of such restrictions, households that earn more income will motivate their neighbors to pursue similar strategies through the sharing of information. Migrant networks also lower the cost of migration for each subsequent migrant in a network. However, financial restrictions may prevent some households from changing strategies, even if they are motivated to do so.

Finally, demographic stratification predictably increases inequality and lowers average income. Correlating risk aversion, access to accurate information, and financial resources results in a small segment of the population (notably, those with secondary and post-secondary education) that have the information, risk appetite, and financial resources to pursue higher-risk, higher-reward strategies. Meanwhile, a larger segment of the population (those with primary educational attainment) either perceives the lower-risk, lower-reward strategy to be optimal, and/or does not have the financial resources to switch strategies.



(a) Scenario A - Average Income

(b) Scenario A - GINI

(c) Scenario B - Average Income

(d) Scenario B - GINI

(e) Scenario C - Average Income

(f) Scenario C- GINI

Figure A.10: Effect of each model layer on average community income (left) and GINI coefficient (right) across three illustrative scenarios. Orange bars represent the effect of the specified layer without financial restrictions, green bars represent the added effect of financial restrictions on the layer, and blue bars represent the combined effect of financial restrictions and the layer.

A.3.7 Additional Results Regarding Policy Effects

In addition to examining policy effects on average community income, the community GINI coefficient, and the proportion of households below a mobility threshold (main dissertation, 2.3.3), we also track the effects of these policies on the proportion of the community that migrates (Fig. A.11). As with other outcome metrics, we note that the relative effects of each individual policy vary across our three illustrative scenarios. For example, in Scenario A, the Remittance Bank is the least effective individual policy in increasing migration, because the main obstacles to further migration in this layer have to do with financial restrictions, not the perceived risk of this strategy. Both the Cash Transfer and Index Insurance provide households with more resources to overcome these restrictions than the Remittance Bank. Conversely, the Remittance Bank is the most effective policy in increasing migration in Scenario C. Here, the high average risk aversion ($\bar{b} = 1.25$) is the most significant barrier to accelerating migration in the face of climate risk, and the Remittance Bank helps lower the perceived risk of this strategy. Generally, a combination of All 3 strategies is consistent in increasing migration rates across all scenarios, which is one channel through which these policies increase average incomes and decrease inequality (Main dissertation, 2.3.3).

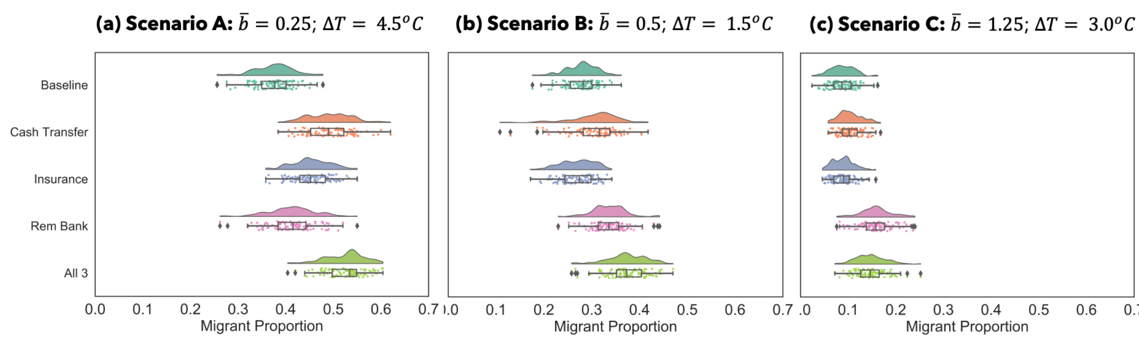


Figure A.11: Effects of policy interventions on the proportion of community that migrates for three scenarios. For each panel, individual rows represent the effect of the policy specified on the y-axis. Dots indicate individual simulation outcomes, with the smoothed data distribution for 100 simulations indicated above these dots; boxplots indicate the mean of the distribution and the interquartile range.

A.3.8 Information Policies

Besides financial incentives and risk transfer mechanisms, information policies represent an additional potential intervention for policymakers to promote climate adaptation. In particular, improving the quality and accessibility of climate forecasts for farmers has been the focus of much international development financing in recent years [200]. With better access to high-quality climate forecasts, farmers may presumably make more accurate decisions regarding the types of crops to plant, when to begin and end cropping seasons, and even whether to deploy household members as migrants (for example, if drought risks are expected to increase). Comparing the effects of financial and informational interventions, and their combination, could therefore prove fruitful to assess the cost-effectiveness of various policies to promote climate adaptation in the agricultural sector.

The model presented here provides one way to begin assessing the impact of information policies, through the parameter ω. This parameter controls the degree to which agents in the model rely on objective information regarding strategy income distributions and drought risks, relative to their reliance on information from their social networks. Increased values of ω therefore represent an increased reliance on objective information sources, reflective of improved access to and/or increased trust in such sources. In this section, we introduce a conceptual information policy in an initial attempt to simulate policies that improve information quality available to farmers. We acknowledge that there are several more nuanced information policies that could be explored, and comment on these at the end of the section.

In our information policy case, ω is increased steadily over time, reflecting a policy of continued government investments in improving the accessibility of informational services. The weight any agent i assigns to objective information at time t, $\omega_i(t)$, can thus be expressed as

$$\omega_i(t) = \min\left\{\omega_i(0) + \delta_\omega \cdot t,\, 1\right\}$$

where δ_ω represents the incremental increase in reliance on information quality due to government investment in each successive cropping cycle. For simplicity, we fix δ_ω as a constant across time and across agents, such that improvements in information quality occur homogeneously for agents across educational classes and throughout the model timeframe. More nuanced scenarios could explore different rates of δ_ω for different educational classes, and/or rates that change dynamically through the model timeframe.

As an initial estimate for δ_ω, we refer to a calculated annual increase in trust in climate forecasts according to a model presented in [52]. The model calculates farmers' trust in climate forecasts as a function of time, the probability that the forecast is accurate, and an intrinsic openness to integrate climate forecasts in one's planning. Based on field studies, the model predicts that if a forecast is accurate 60 percent of the time, it would take a farmer approximately 30 years to go from no trust to full trust in the forecast. For the Info policy in our analysis, we assume double the rate of increase in ω, reflecting persistent government policy to improve the quality and accessibility of information. This leads to a value of $\delta_\omega = 1/30\text{cycles} = 0.033$.

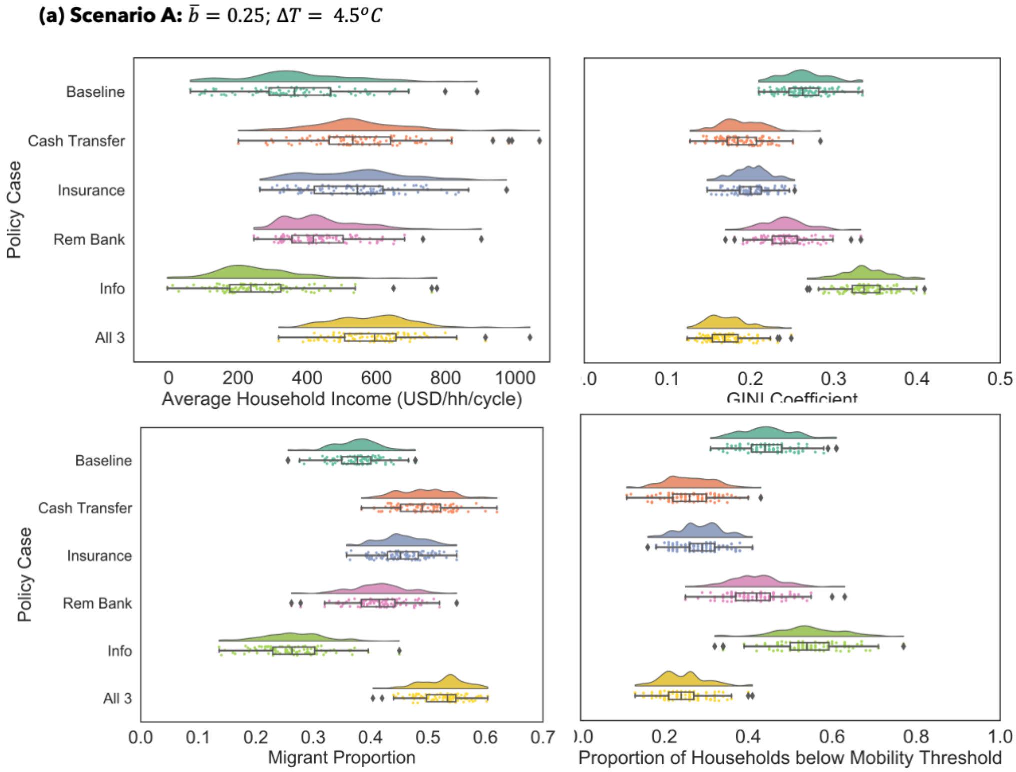
Similar to Section 2.3.3 in the main dissertation, we display the results of this policy on the terminal time distribution of four key metrics: average household income, the GINI coefficient, the migration rate, and the proportion of households below a mobility threshold (Fig. A.12). We test this policy across the same three scenarios of temperature change and risk aversion that are displayed in the main text. Perhaps surprisingly, the Info policy worsens most metrics across all three scenarios. Relative to a no-policy baseline, the Info policy decreases average household incomes, increases the GINI coefficient, and decreases the proportion of households below the mobility threshold. (One exception is Scenario C, characterized by high risk aversion and medium exposure to climate risk, in which the Info policy reduces the GINI coefficient and the proportion of households below the mobility threshold, relative to the baseline.)

One driver of these results seems to be that an increase in ω_i reduces the use of migration as a livelihood strategy across all three scenarios (Fig. A.13). This also echoes the single-parameter sensitivity to ω_i in Fig. A.6d, in which homogeneous values of $\omega_i > 0.8$ lead to a precipitous drop in the use of migration, relative to lower values of ω_i for the Base Case parameter combinations. Further analysis demonstrates that completely objective information regarding the distribution for remittance payoffs accentuates the relatively high volatility associated with this strategy, whereas under conditions of limited information, there are substantial proportions of households that underestimate and overestimate this riskiness throughout the modelled time horizon (Fig. A.15c-d).

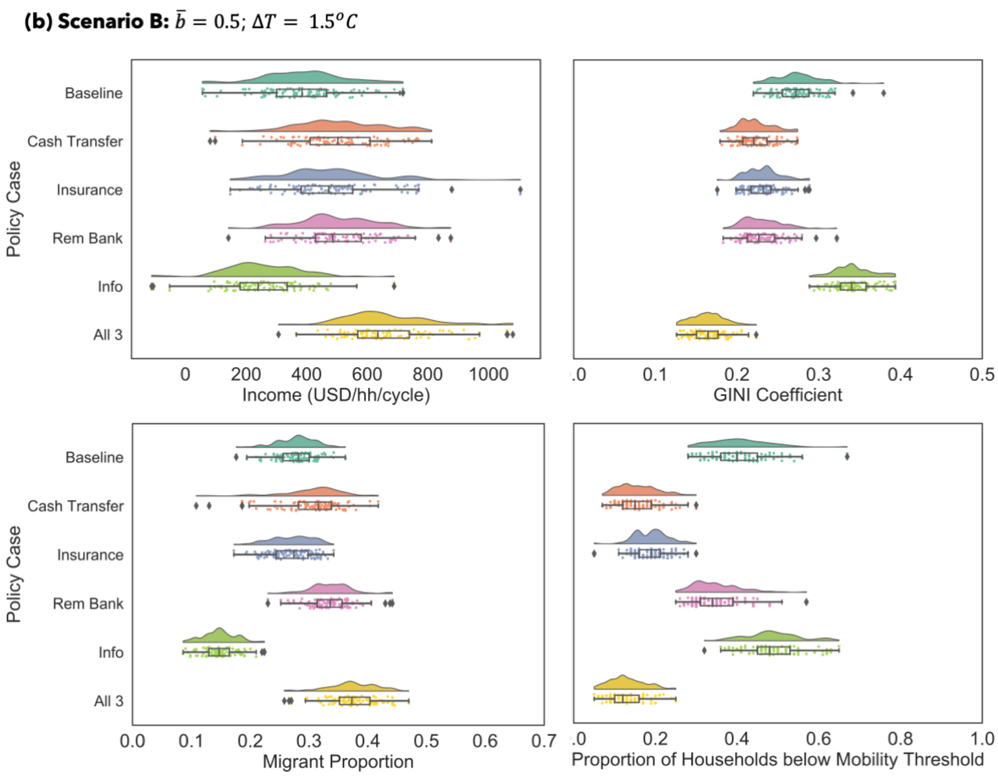
Households underestimating this volatility are more likely to choose migration as a livelihood strategy, and because of the network effects of migration, this lowers the costs for other households in their network to migrate. Thus, households acting on imperfect information (specifically, those households that underestimate migration volatility) nevertheless contribute to improving the objective payoffs to migration (Fig. A.16, c-d). This leads to a continued positive feedback effect for migration under imperfect information; conversely, the Information Policy truncates this feedback effect as agents develop more accurate understanding of the strategy's volatility. Under this policy, the proportion of households engaging in migration reaches a plateau within the first five years (Fig. A.16a-b). By contrast, in the No Policy baseline, the proportion of households engaging in migration continues to gradually increase throughout the time frame. This remains a viable option even as climate impacts worsen in the latter years of the model timeframe, leading to a higher proportion of households engaging in an alternative to BAU in the No Policy baseline, relative to the Information Policy.

The effect of improved information quality on household farming choices is more mixed. In Scenario B, improved information initially contributes to more uptake of Cash Crops (Fig. A.15b), especially as more households appreciate the relatively high expected income of this strategy (Fig. A.13b). However, improved information also leads to more households abandoning Cash Crops in the latter years of the model as they anticipate lower expected income and higher volatility due to climate impacts. For Scenario A, characterized by higher climate risk, improved information quality essentially eliminates any possibility that households pursue Cash Crops by the end of the model timeframe (Fig. A.13a). Improved information quality could therefore incentivize more households to take a chance on cash crops, until drought risks become sufficiently high as to render the strategy economically unattractive.

This initial analysis highlights the complex ways in which information policies could affect smallholder farmer climate adaptation decisions. While improving information quality in theory improves the capacity of farmers to make better adaptation decisions, it may not fully capture the implications of those decisions, such as the positive externality of migration to reduce costs for others in a household's network. While not captured in this model, similar externalities could exist for cropping decisions; for example, as the proportion of households pursuing Cash Crops increases, economies of scale could help lower input costs for this strategy. Here, we make simplifying assumptions that any government investments in information quality provide equal improvements in the perception of payoffs across all three strategies, while not accounting for potential externalities of future household decisions. In practice, a government may prioritize improving climate forecasts, which might give more objective information for the BAU and Cash Crop strategies, but leave perceptions of the Migrate strategy unaffected. Conversely, a government may wish to improve information about migration costs and opportunities at various destinations. This would affect the perceptions of the Migrate strategy, while leaving perceptions of the BAU and Cash Crop strategies relatively unchanged. Future work could explore more targeted information strategies, especially given the positive externalities of household strategy choices on others in their networks.

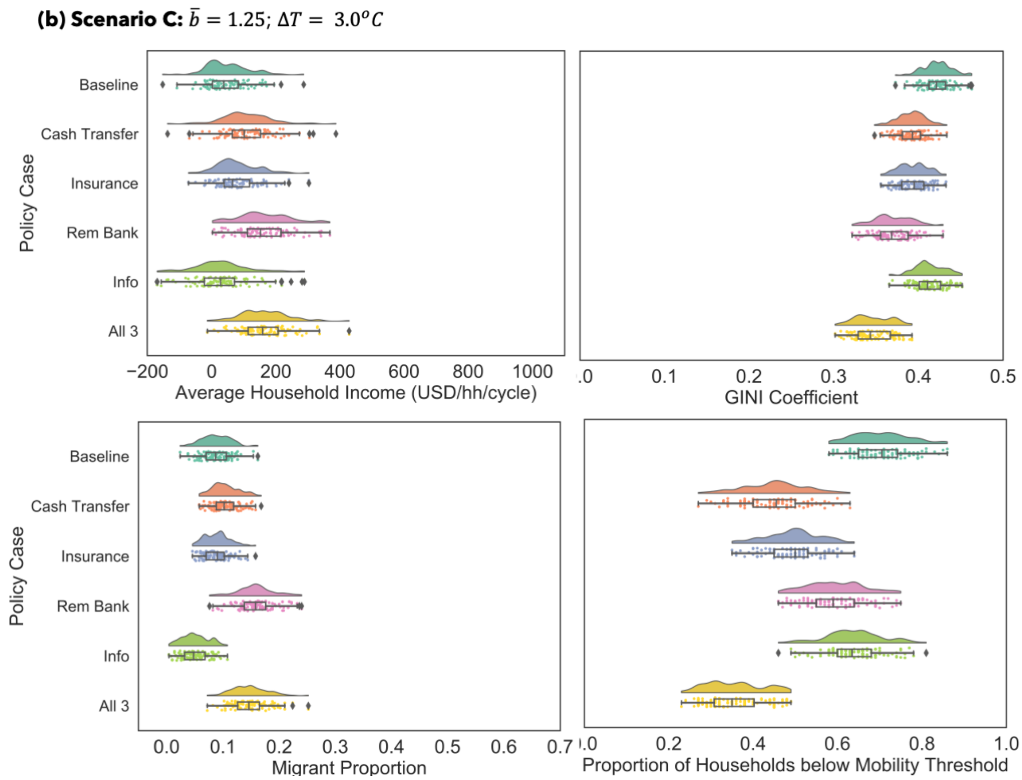


(a) Scenario A



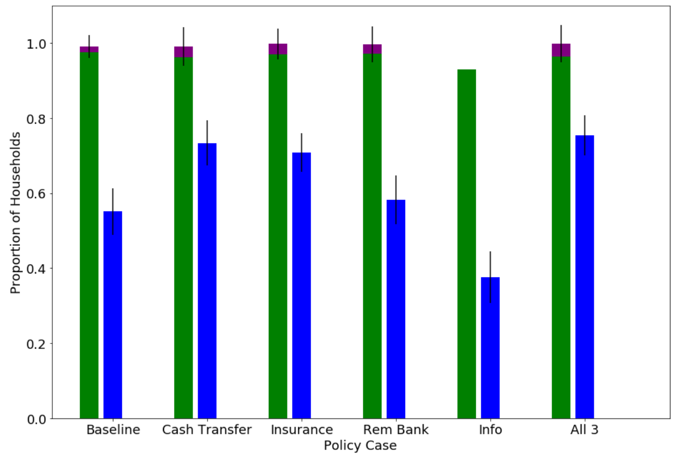
(b) Scenario B

Figure A.12

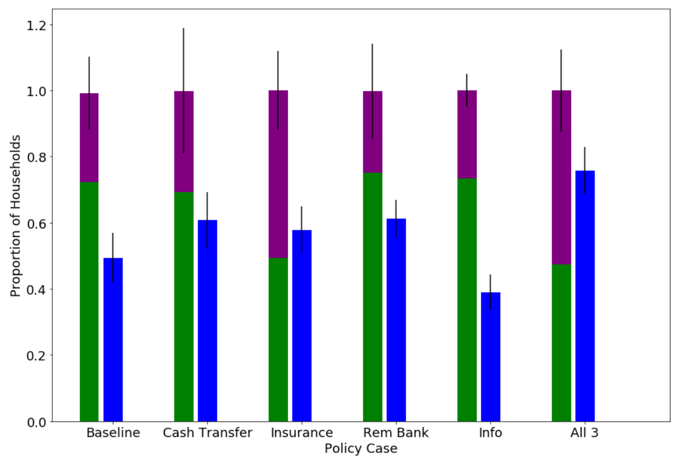


(a) Scenario C

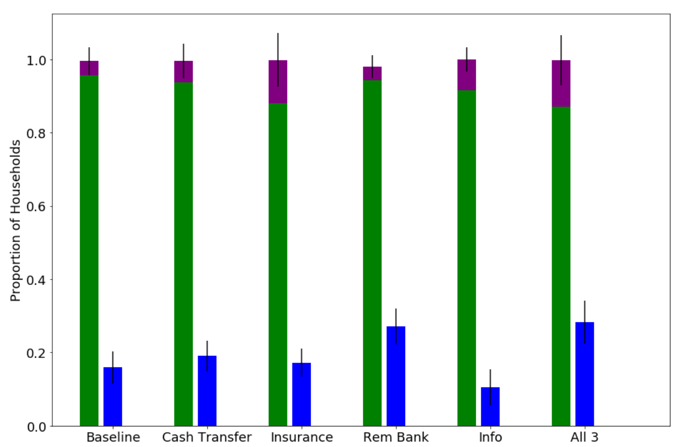
Figure A.12: (Continued from previous page.) Comparison of information policy effects with risk transfer mechanisms across three scenarios and four metrics.



(a) Scenario A $\Delta_T = 4.5C$, $\bar{b} = 0.25$

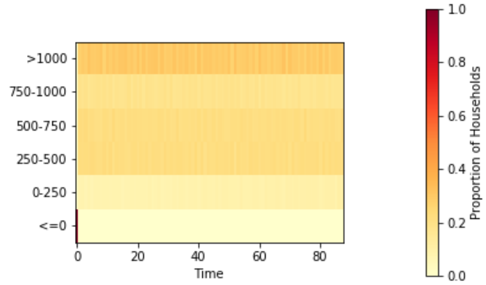


(b) Scenario B $\Delta_T = 1.5C$, $\bar{b} = 0.5$

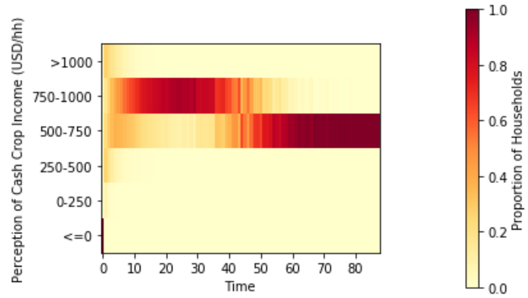


(c) Scenario C $\Delta_T = 3.0C$, $\bar{b} = 1.25$

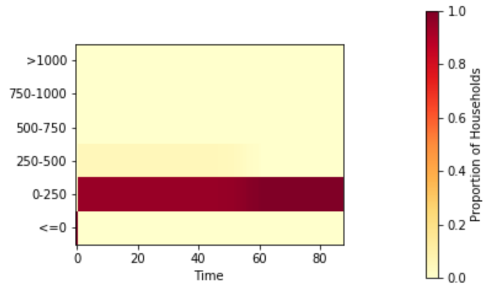
Figure A.13: Distribution of households by terminal time strategy choices under risk transfer and information policies, across three scenarios.



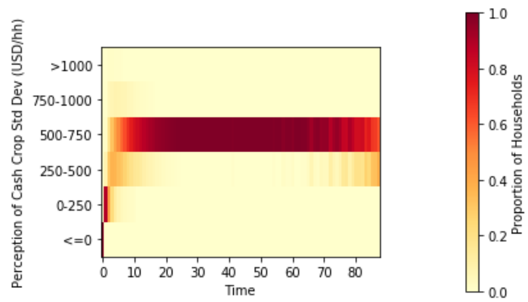
(a) No Policy - Cash Crop Mean



(b) Info Policy - Cash Crop Mean

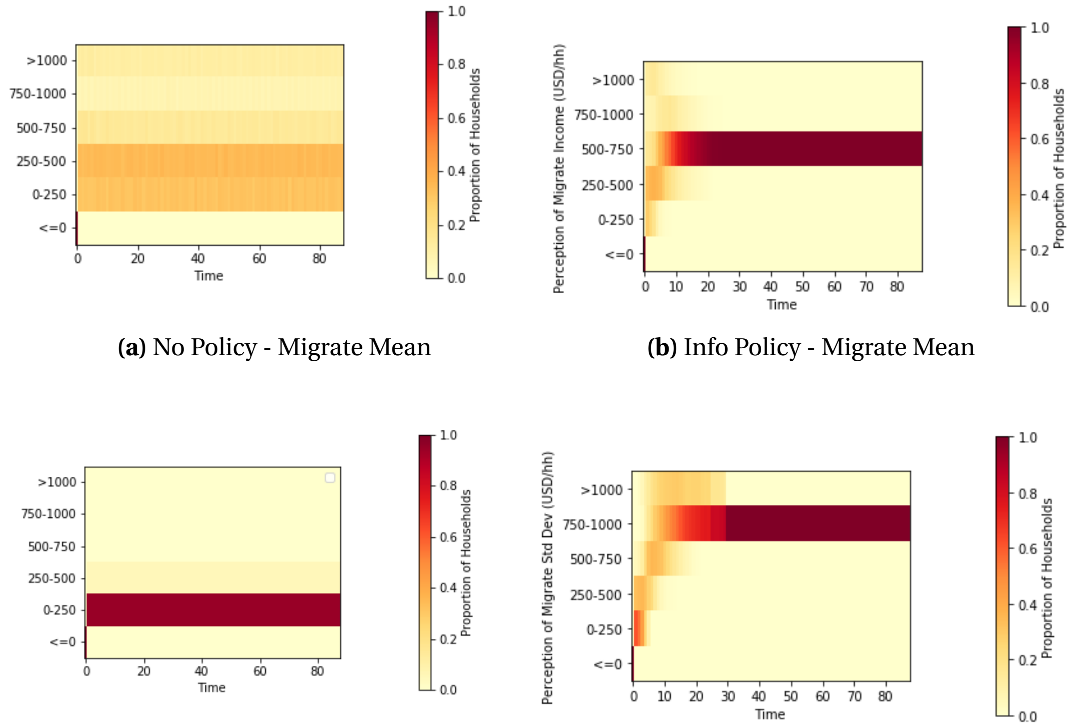


(c) No Policy - Cash Crop Std Dev



(d) Info Policy - Cash Crop Std Dev

Figure A.14: Effects of Information Policy on perceptions of Cash Crop strategy under Scenario B ($\Delta_T = 1.5^0 C$**,** $\bar{b} = 0.5$)**.** The distribution of household perceptions of the Cash Crop expected income (top) and standard deviation (bottom) are shown for the No Policy baseline (left) and the Information Policy (right). The colour plots display the proportion of households perceiving the expected income or standard deviation for the financial increment specified on the y-axis at the time specified on the x-axis, across 100 simulations. In general, the effect of the Information Policy is to remove heterogeneity in perceptions by approximately 30 time steps (equivalent to 15 years), when all agents have perfect information. The small variations that are visible for the Information Policy plots towards the end of the time horizon reflect variation in how the random occurrences of droughts affect objective Cash Crop payoffs in different simulations; by this point, agents are homogeneous in their perception of the strategy within any given simulation. Note that the No Policy plots are the same as those shown in SI Fig. 2e-f, and are re-shown here for ease of comparison.



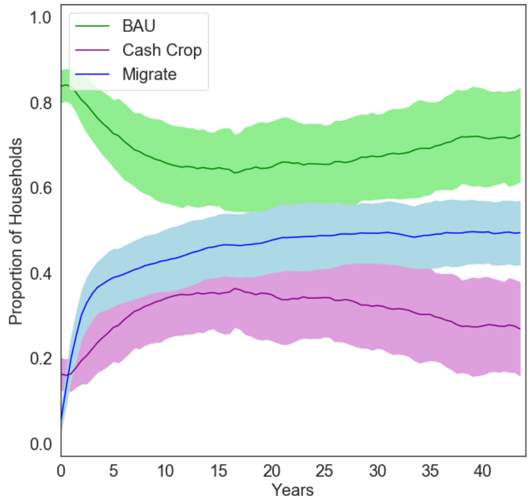
(a) No Policy - Migrate Mean

(b) Info Policy - Migrate Mean

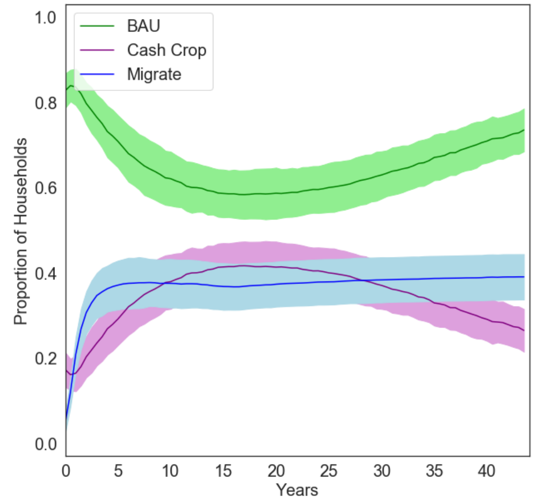
(c) No Policy - Migrate Std Dev

(d) Info Policy - Migrate Std Dev

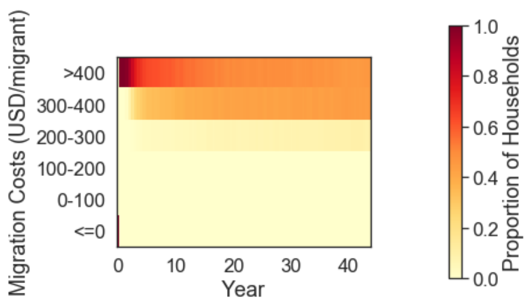
Figure A.15: Effects of Information Policy on perceptions of Migrate strategy, Scenario B. The distribution of household perceptions of the Migrate expected income (top) and standard deviation (bottom) are shown for the No Policy baseline (left) and the Information Policy (right) under Scenario B ($\Delta_T = 1.5^0 C$, $\bar{b} = 0.5$). The colour plots display the proportion of households perceiving the expected income or standard deviation for the financial increment specified on the y-axis at the time specified on the x-axis, across 100 simulations. Here, the Information Policy completely removes heterogeneity in perceptions by approximately 30 time steps (equivalent to 15 years), when all agents have perfect information. Note that the No Policy plots are the same as those shown in SI Fig. 3e-f, and are re-shown here for ease of comparison.



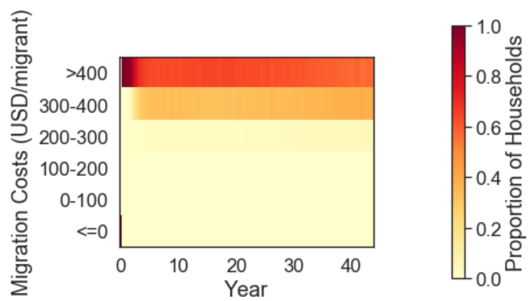
(a) No Policy - Household Strategy Choices



(b) Info Policy - Household Strategy Choices



(c) No Policy - Migration Costs



(d) Info Policy - Migration Costs

Figure A.16: Household Strategy Choices and Migration Costs over Time, Scenario B. The dynamics of household strategy choices (top) and migration costs (bottom) for Scenario B ($\Delta_T = 1.5^0 C$, $\bar{b} = 0.5$ are displayed for the No Policy baseline (left) and Information Policy (right). In the top row, the proportion of households deploying each strategy for a given year are displayed for 100 simulations, with solid lines indicating the mean value and shaded regions indicating +/- 1 standard deviation for each time step. While there is an initial spike in migration under both conditions, the proportion of households deploying this strategy plateaus within the first 5 years under the Information Policy. By contrast, this proportion gradually increases throughout the model timeframe in the No Policy Baseline. In the bottom row, the distribution of households by their migration costs is shown as a colour map, with darker shades of red indicating a higher proportion of households with migration costs in the increment specified on the y-axis. Under the Information Policy, almost all households have migration costs of 300 USD/migrant or higher, with a significant majority of households facing a cost of 400 USD/migrant or higher. By contrast, in the No Policy baseline, there are roughly equal proportions of households in both increments, and some households with costs between 200-300 USD/migrant by the end of the model timeframe.

Appendix B

Pro-Social Preferences Improve Climate Risk Management in Subsistence Farming Communities - SI

B.1 Modelling Framework

B.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 [132]. Similar to traditional game theory from economics, EGs are typically used to identify one or more best-response strategies that are superior to any other strategy when played against other individuals acting strategically. However, EGs differ from traditional economic game theory in several important respects that are relevant to our research questions. Whereas traditional economic 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 traditional 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 equlibria, 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 population-level distribution of risk management strategies at equilibrium.

While EGs were initially developed for ecological applications, they have more recently been applied to the study of human populations. Such applications require a few adaptations of typical EG concepts. For example, whereas ecological EGs typically consider games between two traits (e.g. whether an individual escalates or de-escalates conflict when encountering another individual), in our EG, agents can choose between eight discrete strategy options. Furthermore, 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; this thus leads us to develop a simulated EG. Further, ecological EGs often have a clear interpretation of which strategies are deemed cooperative, vs. which strategies are deemed as defection. 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.

Finally, our simulation differs from agent-based models (ABMs) in several ways. First, in an ABM, an agents may not consider others' actions in calculating the utilities of various strategy options, whereas in an EG, a central concern of agents is how others' strategies will affect their utility. Second, whereas agents in an ABM typically consider multiple strategy options in a given timestep, in our 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. On the other hand, whereas agents in an ABM may have imperfect information about strategy options and rely on their limited memories and communication to form perceptions of strategy payoffs, in this EG, we assume agents have perfect information about the strategy option they are considering at any given time. Finally, whereas agents in an ABM may all update their strategy choices simultaneously, in our EG, 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.

B.1.2 Moments of the income distributions for different strategies

Based on (3.1), the elements of expected strategy payoffs $\pi_i(, t)$ are displayed in Table B.1 for each strategy i. Table B.2 displays the variances of each strategy, σ_i^2.

B.1.3 Loss Aversion Re-Scaling

To conserve the core feature of loss aversion, we calculate the loss aversion parameter under 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 CPT, given a

Table B.1: Expected payoff of strategy options

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

loss aversion parameter γ. Formally, this is calculated as

$$\lambda \frac{U^{\text{MVT}}(I^{\text{d}})}{U^{\text{MVT}}(I^{\text{nd}})} = \frac{U^{\text{CPT}}(I^{\text{d}})}{U^{\text{CPT}}(I^{nd})} \tag{B.1}$$

or in terms of model parameters

$$\lambda \frac{(I^{\text{d}} - C_{\text{f}}) - b \cdot \sigma_{I^{\text{d}}}}{(I^{\text{nd}} - C_{\text{f}}) - b \cdot \sigma_{I^{\text{nd}}}} = -\gamma \frac{[-(I^{\text{d}} - C_f)]^{\alpha_{\text{CPT}}}}{(I^{\text{nd}} - C_{\text{f}})^{\alpha_{\text{CPT}}}} \tag{B.2}$$

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 [152], 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 $C_f = 221$, $I^{\text{nd}} = 280$, $\sigma_{I^{\text{nd}}} = 247$, $I^{\text{d}} = 26$, and $\sigma_{I^{\text{d}}} = 235$, we calculate the rescaled loss aversion factor $\lambda = 1.33$.

B.1.4 Estimation of Parameters

Model parameters listed in Table B.3 are calibrated with empirical data from two relevant contexts: crop farming in the Chitwan Valley of Nepal, and a combination of crop farming

Table B.2: Variance of strategy options under idiosyncratic risk. To shorten notation, σ^2_{IFI} and σ^2_{IM} represent the variance for the farming + formal insurance and the farming + migration strategies, respectively. Similarly, σ^2_{IMFI} represents the variance for the farming + migration + formal insurance strategy. I_{II} and σ^2_{II} represent the income and variance, respectively, for the farming + informal revenue-sharing strategy.

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

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 [86] and was introduced in Ethiopia's Borena region starting in 2012 [201]; and (5) both case studies come with high-frequency data, collected over several years, on farmers' livelihood choices and incomes [29, 151].

Additionally, there are several important differences between the two contexts that can help to generalize of 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 (Appendix B.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 [29]. 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 [151]. 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.

B.1.4.1 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 economic 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

Table B.3: List of Model Parameters

Symbol	Parameter Name	Base Case	Source	Sensitivity	Robustness
N	Number of Households	100	Assumed	N	Y
T	Time Steps	20,000	Assumed	N	Y
I	Avg. Farm Income/Cycle	163 USD	[29]	N	Y
σ_I	Farm Income Std Dev.	199 USD	[29]	N	Y
C_f	Farming Costs/Cycle	170 USD	[80]	N	Y
η	Migrant Farm Productivity Adjustment	0.9	Assumed	N	Y
R	Avg. Remittance/Cycle	595 USD	[29]	N	Y
σ_R	Remittance Std Dev	998 USD	[29]	N	Y
C_m	Up-front Migration Cost	500 USD	[81]	N	Y
β	Proportion of Income Shared in Pool	0.2	Assumed	N	Y
ρ_{cov}	Correlation between Household Incomes	0.35	[29]	Y	N
ρ_{mig}	Corr. between Farming and Migration	0.0	Assumed	N	N
p	Drought Probability	0.35	[117]	Y	N
r	Discount Rate	0.1	Assumed	Y	N
h	Time Horizon (crop cycles)	10	Assumed	N	Y
b	Risk Weight	0.5	[82]	Y	N
α	Altruism Factor	0.0	Assumed	Y	N
κ	Solidarity Factor	0.0	Assumed	Y	N
γ	Re-scaled Loss Aversion	1.33	[152]	N	Y
S	Premium Subsidy Factor	0.0	Assumed	Y	N
ω	Selection Strength	27.7	Calculated	N	Y
μ	Mutation Rate	0.01	Calculated	N	Y
τ	Consumption Threshold	84.43 USD	[29]	N	Y

key economic parameters for the Base Case, including the mean and standard deviation of farming incomes (I and σ_I, respectively); mean and standard deviation of migration remittances (R and σ_R, respectively); and the correlation between farming incomes (ρ_{cov}, Appendix B.1.5.2).

While the CVFS data does not explicitly include income earned from agricultural activities, we convert observed data on crop production to revenues using 2010 crop prices for Nepal from Food and Agricultural Organization data [202]. 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

$$TFR_{it} = \frac{\sum_k A_{itk} \cdot Y_{itk} \cdot w_k}{\bar{A}} \tag{B.3}$$

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. Note that 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 the mean and variance of the remittance income distribution (R and σ_R, respectively), we analogously standardize remittances reported by household i in year t to the number of migrants from that household in the same year, M_{it}. While the majority of households in the CVFS data either have 0 or 1 migrants, a substantial proportion (0.43) reported at least 2 migrants living outside of the household by 2017. As remittance income is aggregated at the household*year scale, we make an assumption that each household migrant sends roughly the same amount of remittances

$$R_{it} = \frac{\tilde{R}_{it}}{M_{it}} \tag{B.4}$$

where $\tilde{R}_{it}$ is the aggregate remittance income reported by household i for year t. We then take the mean and variance of these values to calculate R and σ_R^2.

B.1.4.2 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_{cov}. 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 scenario represents the lower bound for the two covariate risk parameters that are currently observed in the Chitwan Valley and Borena region ($p = 0.25$ and $\rho = 0.05$). Climate risks are likely to only increase over the remainder of the century [33], and it is unlikely that farming incomes will become less correlated than the already low value we observe. The Medium risk scenario roughly represents an upper bound for covariate risk currently faced by such communities ($p = 0.35$, $\rho = 0.35$), 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 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 [117]. 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 2006-2020, and calculate the number of months with drought or flood conditions during this time period. Specifically, if the minimum 3-month SPEI in any given year is below -1.0, we classify this as an extreme drought occurrence; conversely, we characterize an extreme flood as a 3-month SPEI value greater than 1.0 during the wet seasons. This is in line with the standard used by IBLI, which compensates policyholders if a vegetation index is below 1 standard deviation of a historical baseline [151]. The drought risk, p, is thus calculated as the number of extreme events (droughts + floods) occurrences divided by the total number of seasons.

For the years 2000-2018, the Chitwan Valley was characterized by a high number of both droughts (with a minimum 3-month SPEI < -1.0 in 14 out of 19 seasons) and floods (12 out of 19 wet seasons with maximum 3-month SPEI > 1.0). This leads to a total of 22 extreme events out of 38 seasons, or a probability $p = 0.58$. In Borena, 7 out of 19 years were characterized by drought, and 3 out of 19 years were characterized by floods, leading to a total of $p = 0.26$.

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 B.3. 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, this yields up to 4 years per household. To best capture temporal correlation of incomes, 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 95 percent confidence interval (-0.26, 0.54). For the Borena dataset, this results in a mean correlation of 0.08, with the 95 percent confidence interval (-0.018, 0.24).

B.1.5 Decomposition of utility functions

We present in this section how utility functions including altruism and solidarity can be decomposed according to expected income, losses, and risk.

Altruism:

$$
\begin{aligned}
v_i^{\mathrm{F}}(, t) &= (1-\alpha)\cdot u_i(, t) + \alpha \cdot \frac{1}{N} \cdot \sum_j x_j \cdot u_j(, t) \\
&= (1-\alpha)\,\lambda_i \cdot \big(I_i(t) + S_i(, t)\big) + \alpha \cdot \frac{1}{N} \sum_j \cdot \lambda_j x_j \big(I_j(t) + S_j(, t)\big) \\
&\quad - \left((1-\alpha)\lambda_i + \alpha \cdot \frac{1}{N} \sum_j \lambda_j x_j\right) C_{\mathrm{f}} \\
&\quad - b \cdot \left((1-\alpha)\,\lambda_i \sigma_{I,i}(, t) + \alpha \cdot \frac{1}{N} \sum_j \lambda_j x_j \sigma_{I,j}(, t)\,,\right)
\end{aligned} \tag{B.5}
$$

where the loss aversion parameter λ_i takes different values depending on the difference between farming income and farming costs.

Solidarity:

$$
\begin{aligned}
w_i^{\mathrm{F}}(, t) &= \mathbb{E}\left[u_i^{\mathrm{F}}(, t)\right] \\
&\approx \lambda_i \cdot \Big(I_i(t) + S_i(\mathbb{E}[], t) - C_{\mathrm{f}} - b \cdot \sigma_{I,i}(\mathbb{E}[], t)\Big)
\end{aligned} \tag{B.6}
$$

Combination of altruism and solidarity:

$$
\begin{aligned}
z_i^{\mathrm{F}}(, t) &= \mathbb{E}_{\tilde{}}\left[(1-\alpha)\cdot u_i(\tilde{}, t) + \alpha \cdot \frac{1}{N} \cdot \sum_j x_j \cdot u_j(\tilde{}, t)\right] \\
&\approx (1-\alpha)\,\lambda_i \cdot \big(I_i(t) + S_i(\tilde{}, t)\big) + \alpha \cdot \frac{1}{N} \sum_j \cdot \lambda_j \tilde{x}_j \big(I_j(t) + S_j(\tilde{}, t)\big) \\
&\quad - \left((1-\alpha)\lambda_i + \alpha \cdot \frac{1}{N} \sum_j \lambda_j \tilde{x}_j\right) C_{\mathrm{f}} \\
&\quad - b \cdot \left((1-\alpha)\,\lambda_i \sigma_{I,i}(\tilde{}, t) + \alpha \cdot \frac{1}{N} \sum_j \lambda_j \tilde{x}_j \sigma_{I,j}(\tilde{}, t)\,,\right)
\end{aligned} \tag{B.7}
$$

B.1.6 Transition Probability and Selection Strength

In the simulation results, the probability of transition between two strategies, $T_{k \to l}$, depends on the selection strength parameter β, as well as the relative difference in the utilities of the two strategies, f_l and f_k (see [8]). Here, we display $T_{k \to l}$ 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 $\beta = 10$ leads to a probability of transition, $T = 0.8$. For a selection strength $\beta = 50$, this probability approximates 1.0.

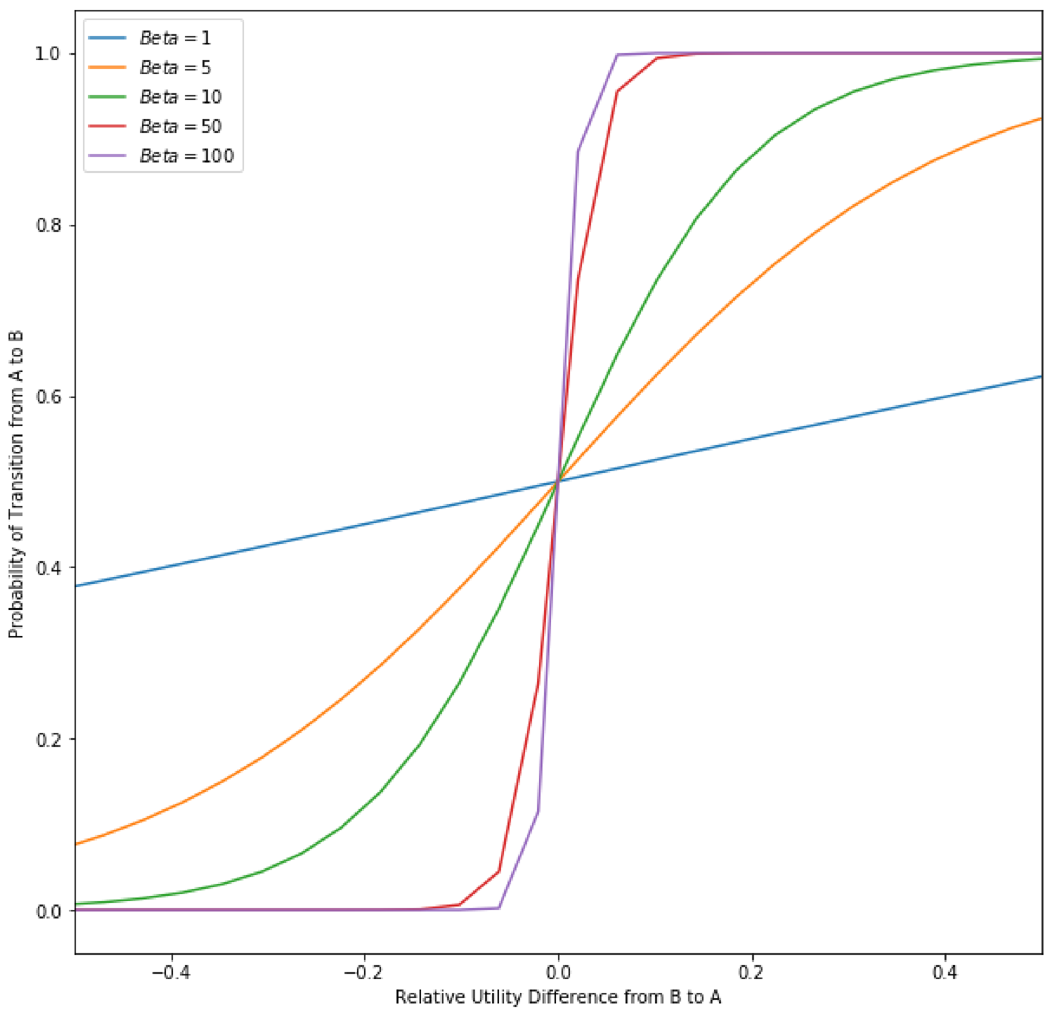
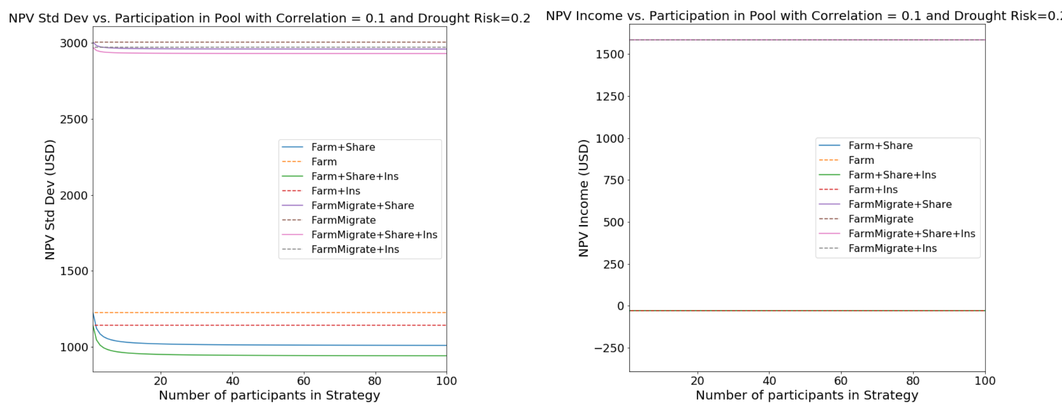


Figure B.1: Transition probabilities between two strategies as a function of the relative difference in utility (x-axis) and selection strength parameter, β (represented by different lines).

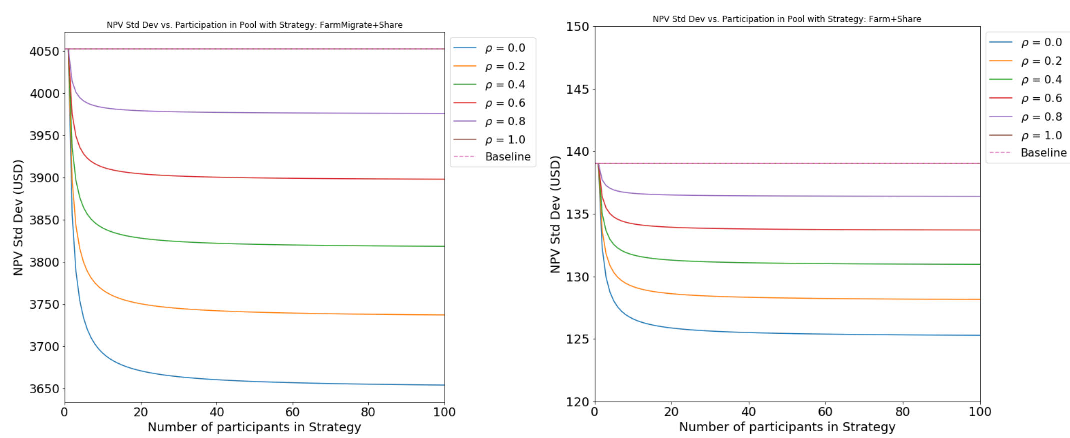
B.2 Supporting Results and Sensitivities

B.2.1 Income Variance and Informal Risk Pool



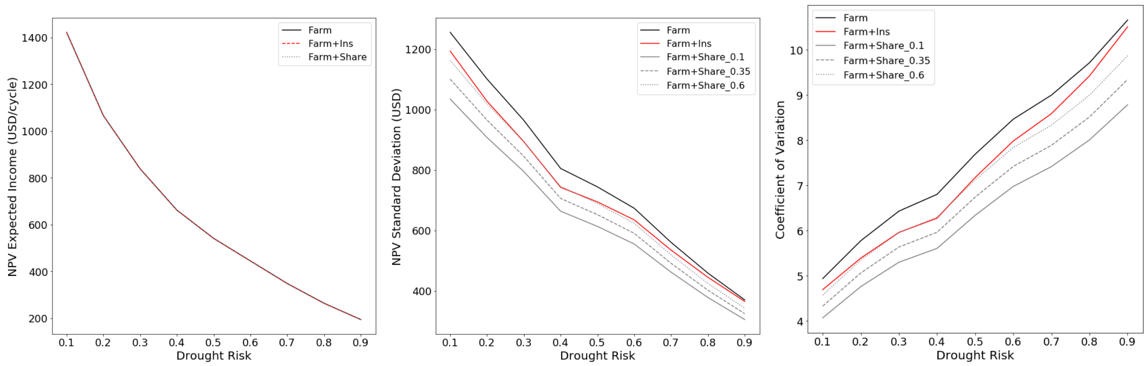
(a) Std Dev **(b)** Expected Income

Figure B.2: Standard Deviation (left, y-axis) and Expected Income (right, y-axis) as a function of number of households playing the same strategy (x-axis). Here, we assume a covariance between household incomes of $\rho = 0.5$.



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

Figure B.3: 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.



(a) Expected Income **(b)** Standard Deviation **(c)** CoVA

Figure B.4: Effect of Drought Risk on Strategy Incomes, Variance, and Coefficient of Variation. The net present value of the (a) expected income, (b) standard deviation, and (c) coefficient of variation for the Farm, Farm+Insurance, and Farm+Share strategies are shown for increasing drought risk (x-axis). For the Farm+Share strategies, the standard deviation is shown for $\rho = 0.1, 0.35, 0.6$.

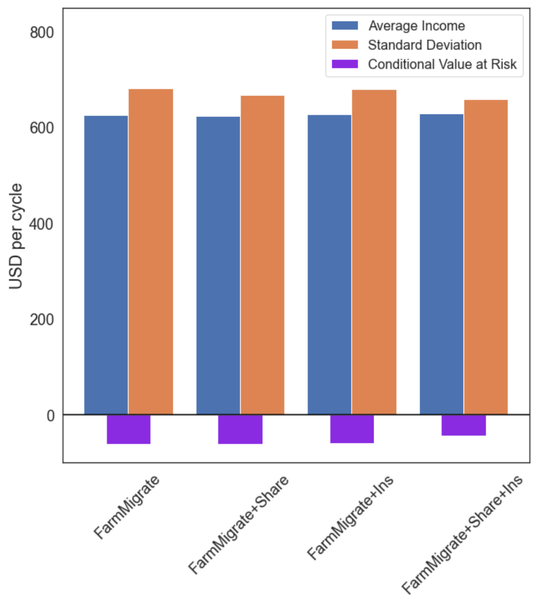
B.2.2 Utility Components for Low and High Risk Scenarios

B.2.3 Comparison of Strategy Utilities

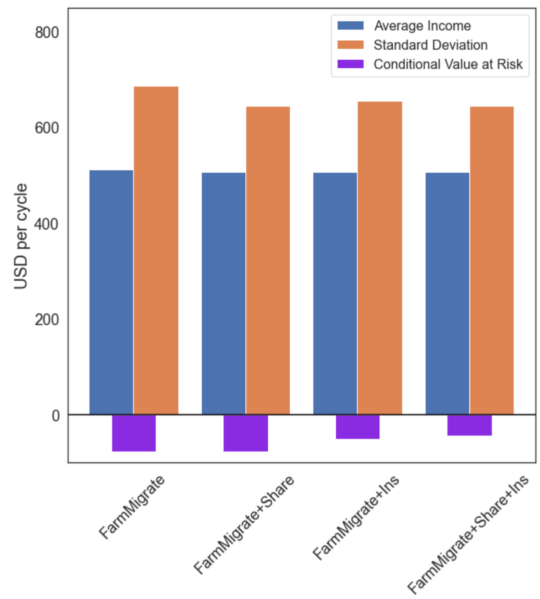
This section details how the utilities of some risk management strategies in our model change as a function of the number of other households who also adopt the same strategy. We also compare utilities of the different risk management strategies under different scenarios to illustrate how different equilibria strategies are reached under different drought risk (p) and income correlation (ρ) conditions.

B.2.4 Comparison of Collective Outcomes for Non-Migration Strategies

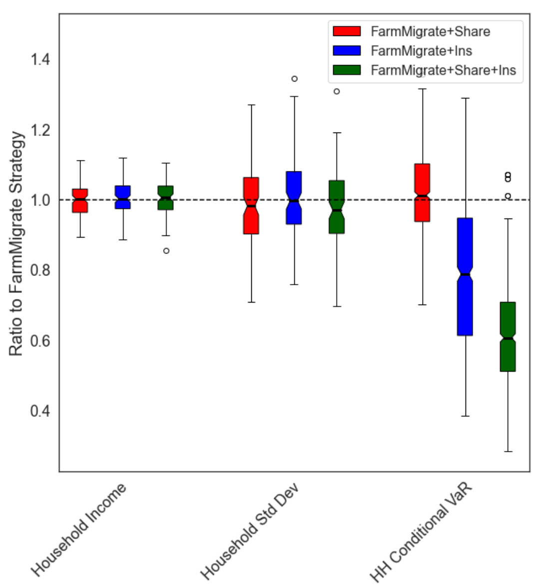
As a companion to Figure 3.1 in the main dissertation, Section 3.3.1, here we present collective outcomes (Average Community Income, GINI Coefficient, and Poverty Rate) of monomorphic strategies without migration. There are two main differences between outcomes under these strategies compared to those presented for strategies with migration.



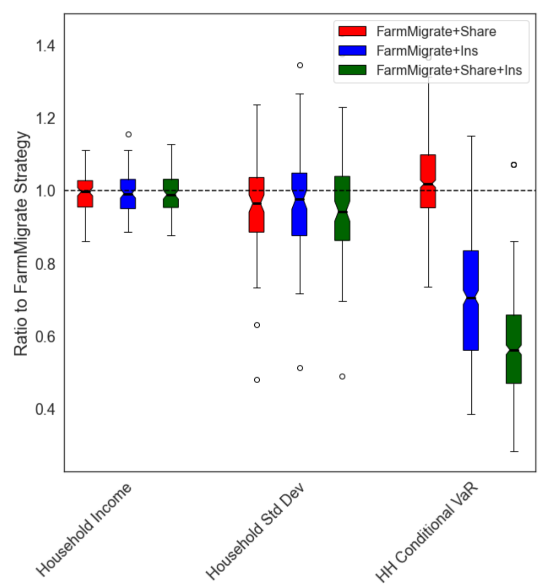
(a) Low Risk, Payoffs



(b) High Risk, Payoffs



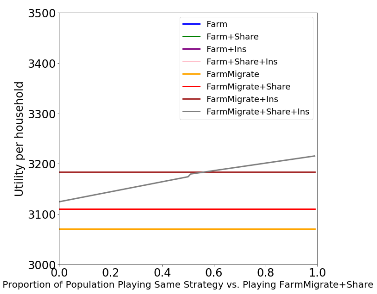
(c) Low Risk, Ratio



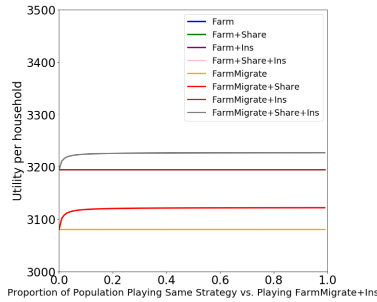
(d) High Risk, Ratio

Figure B.5: Disaggregation of farmer utility components. a-b) The disaggregated elements shaping farmer utilities - average incomes, standard deviation, and losses (expressed as conditional value at risk) are shown for the Low (left) and High (right) risk scenarios. **c-d)** The ratios of each of these are shown with respect to the FarmMigrate strategy.

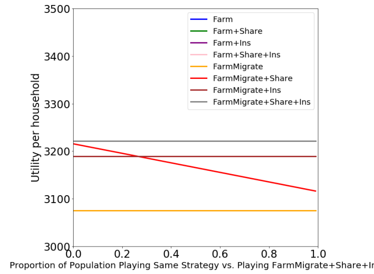
First, outcomes for average income and poverty are uniformly worse for strategies without migration compared to those that include migration as a livelihood diversification strategy.



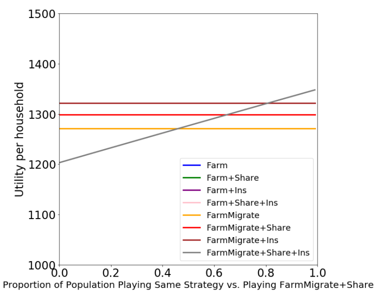
(a) Low Risk; Sharing



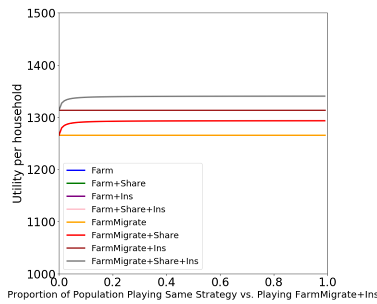
(b) Low Risk, Insurance



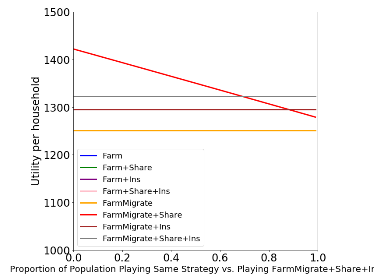
(c) Low Risk; Both



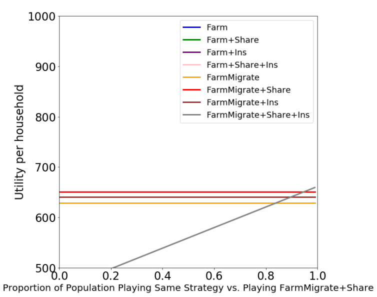
(d) Medium Risk; Sharing



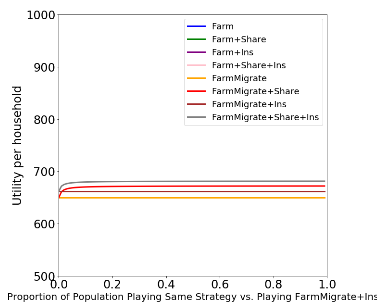
(e) Medium Risk, Insurance



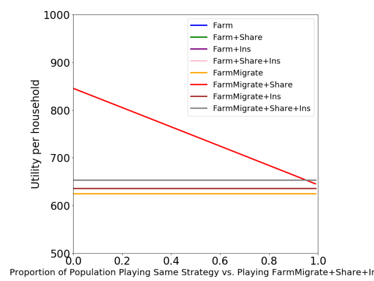
(f) Medium Risk; Both



(g) High Risk; Sharing



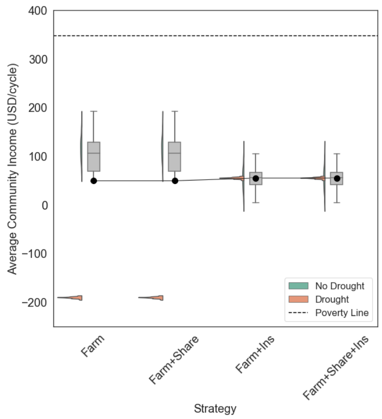
(h) High Risk, Insurance



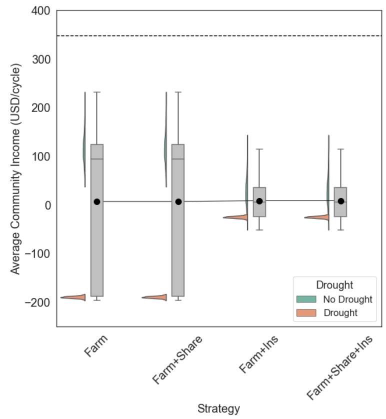
(i) High Risk; Both

Figure B.6: Utilities of Risk Management Strategies as a Function of Participants, Relative to FarmMigrate+Share Baseline. Each panel displays the utility to an individual household of playing each of the eight risk management strategies as a function of the proportion of other households playing that strategy, assuming all remaining households play FarmMigrate+Share (red line, the dominant strategy before insurance options are introduced). For example, at $x = 0.5$, each line indicates the utility of half of the population playing the strategy indicated by the line's color, and half of the population playing FarmMigrate+Share. As with Figure 1, the panels reflect: **a)** Low Risk ($p = 0.2$) and low farming income correlation ($\rho = 0.1$); **b)** Medium Risk ($p = 0.35$; $\rho = 0.35$); **c)** High Risk ($p = 0.5$, $\rho = 0.6$). In all cases, the combination of FarmMigrate+Share+Insurance (gray line) eventually leads to a higher utility than informal revenue-sharing alone, if a sufficient number of households also play this strategy. This coordination threshold is indicated by the dotted blue line.

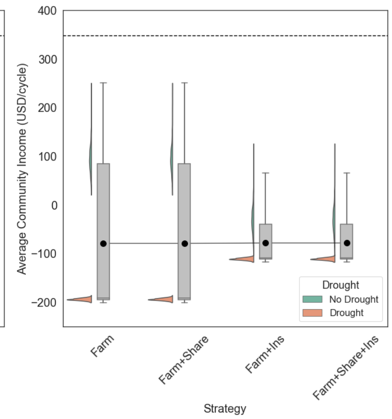
Without remittance income, households earning potential through farming strategies alone is quite limited and leaves many households at or near the poverty line, even in cases of Low covariate risk ($p = 0.2$, $\rho = 0.1$). If covariate risks increase to Medium ($p = 0.35$, $\rho = 0.35$) or High ($p = 0.6$, $\rho = 0.5$) 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.



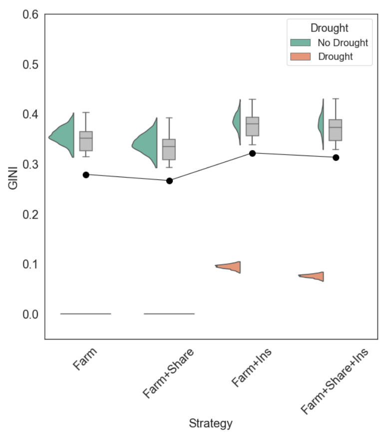
(a) Low Risk; Income



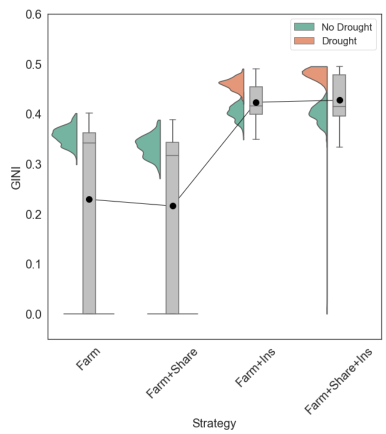
(b) Med Risk; Income



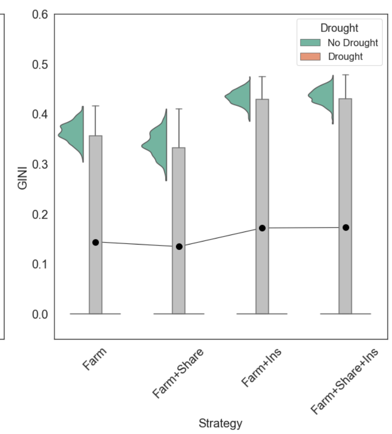
(c) High Risk; Income



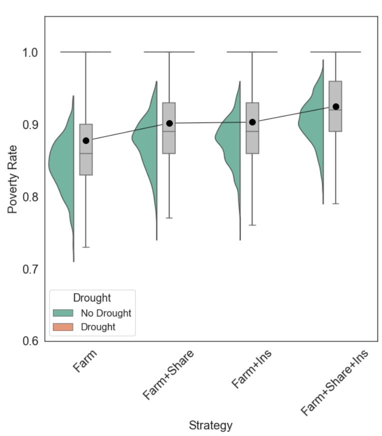
(d) Low Risk; GINI



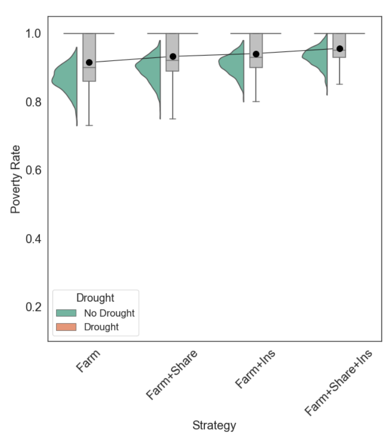
(e) Medium Risk; GINI



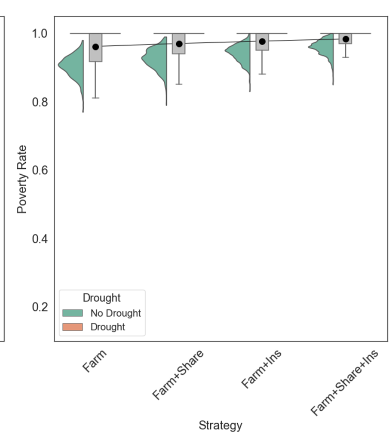
(f) High Risk; GINI



(g) Low Risk; Poverty Rate



(h) Med Risk; Poverty Rate

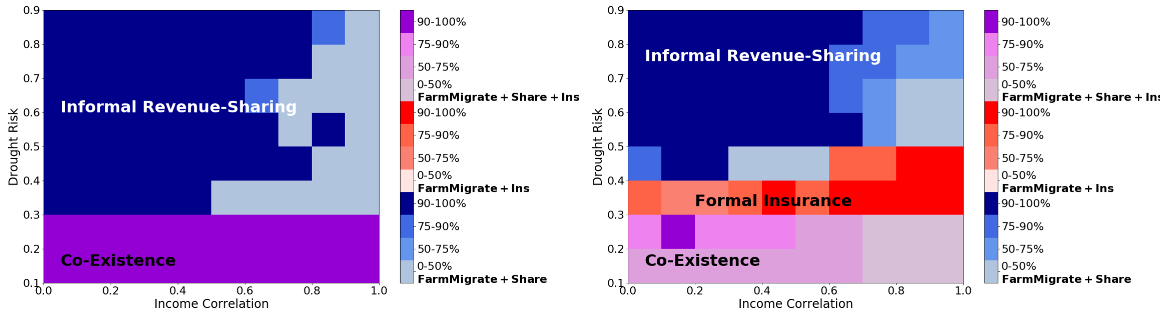


(i) High Risk; Poverty Rate

Figure B.7

Figure B.7: (Previous page.) **Community Outcomes for Monomorphic Risk Management Strategies without Migration.** 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, $p = 0.2$, $\rho = 0.1$; Medium, $p = 0.35$, $\rho = 0.35$; High, $p = 0.6$, $\rho = 0.5$). 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 the results from one simulation, averaged over the 100 households. Distributions are shown separately for outcomes in drought years (green) and non-drought years (orange), with boxplots summarizing the total distribution (drought and non-drought years). Black dots connected by the line plot indicate mean values for each strategy.

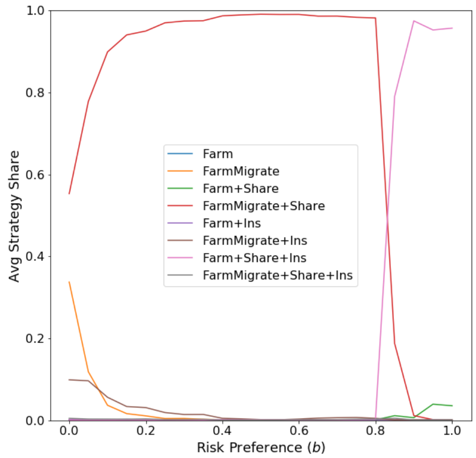
B.2.5 Effect of Migration Type on Equilibria Strategies



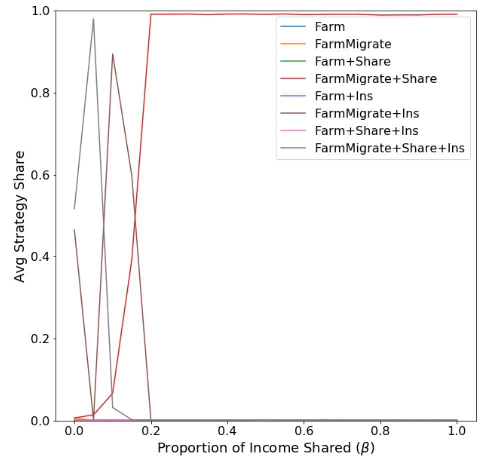
(a) Local Migration **(b)** International Migration

Figure B.8: 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.

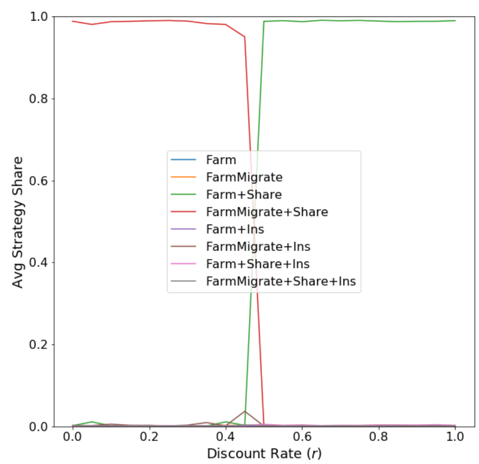
B.2.6 Sensitivities



(a) Self-Interested - Risk

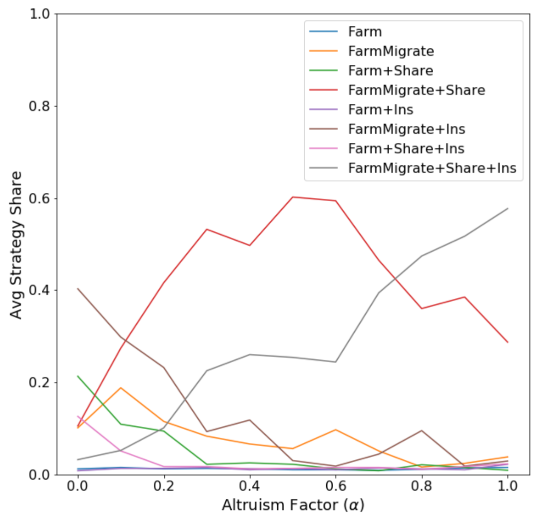


(b) Self-Interested - β

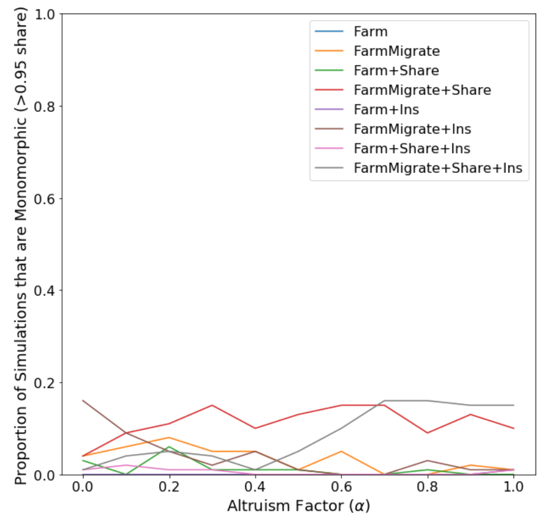


(c) Self-Interested - Discount Rate

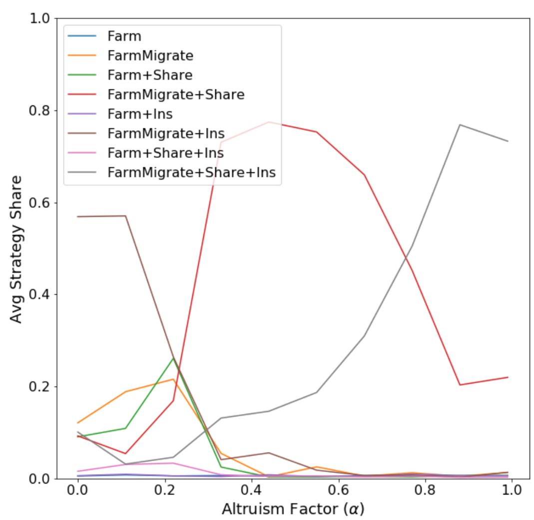
Figure B.9: Sensitivities to Decision-Making Parameters for Self-Interested Worldview. Each panel displays the sensitivity of risk management strategies to parameters for **a)** Risk Preference, **b)** Proportion of Farm Income Shared, and **c)** Discount Rate. Each panel displays the average terminal time distribution of risk management strategies in the agricultural community after 20,000 time steps. Results are averages over 100 simulations, in increments of 0.05 of the parameter value, while keeping all other parameters at their Base Case values.



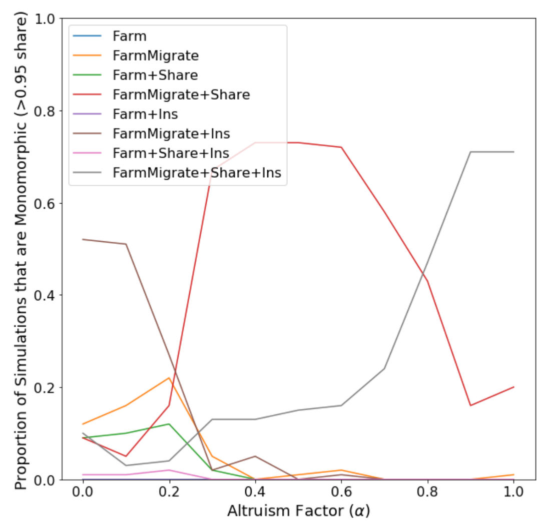
(a) $N = 10$



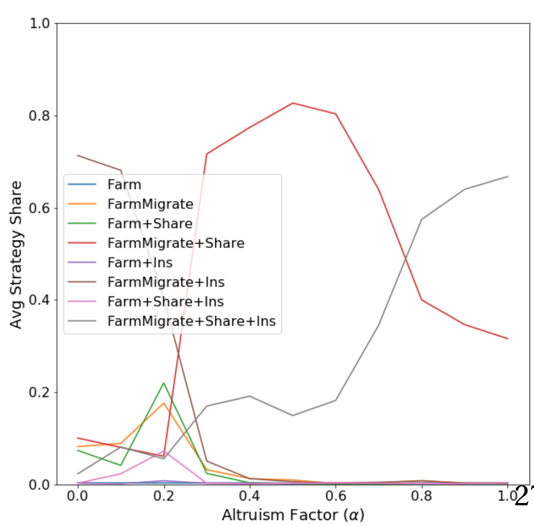
(b) Monomorphic



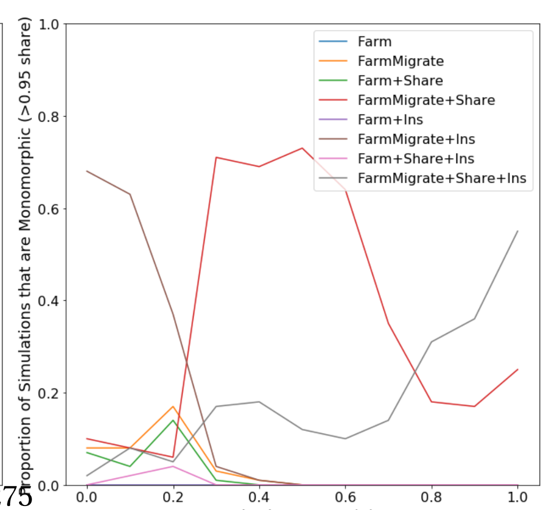
(c) $N = 25$



(d) Monomorphic

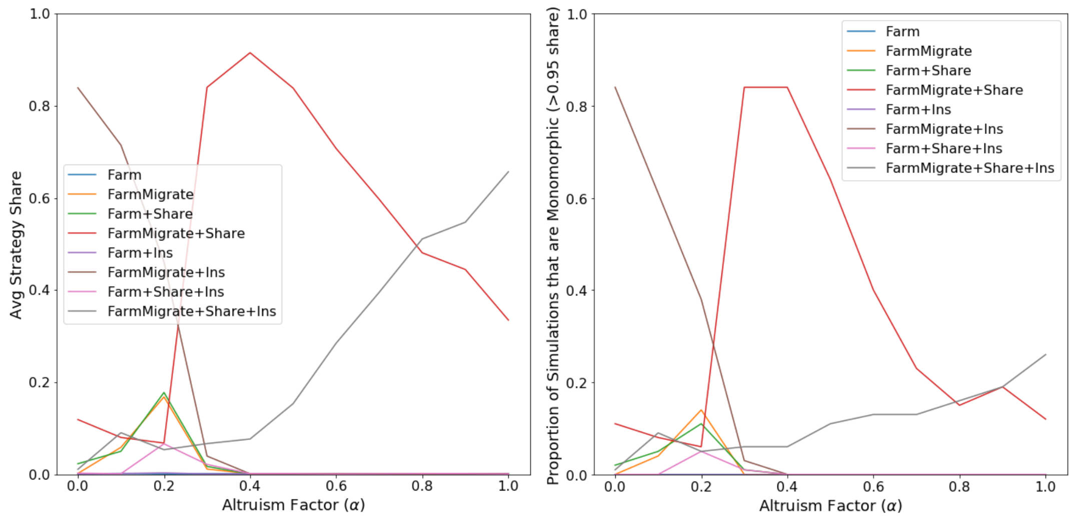


(e) $N = 50$



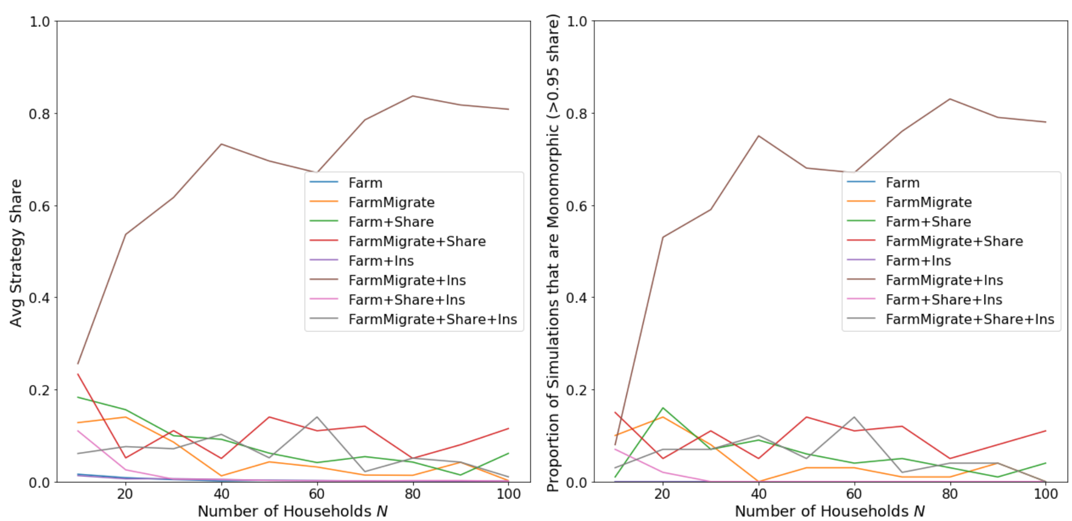
(f) Monomorphic

Figure B.10



(a) $N = 100$ **(b)** $N = 100$

Figure B.10: (continued from previous page) Sensitivity of terminal time strategy distributions to the altruism factor, α, for different community household sizes, N. Left-hand panels display the average values of strategy shares at terminal time. Right-hand panels display the proportion of simulations for which a given strategy is in a monomorphic state. Results reflect averages over 100 simulations.

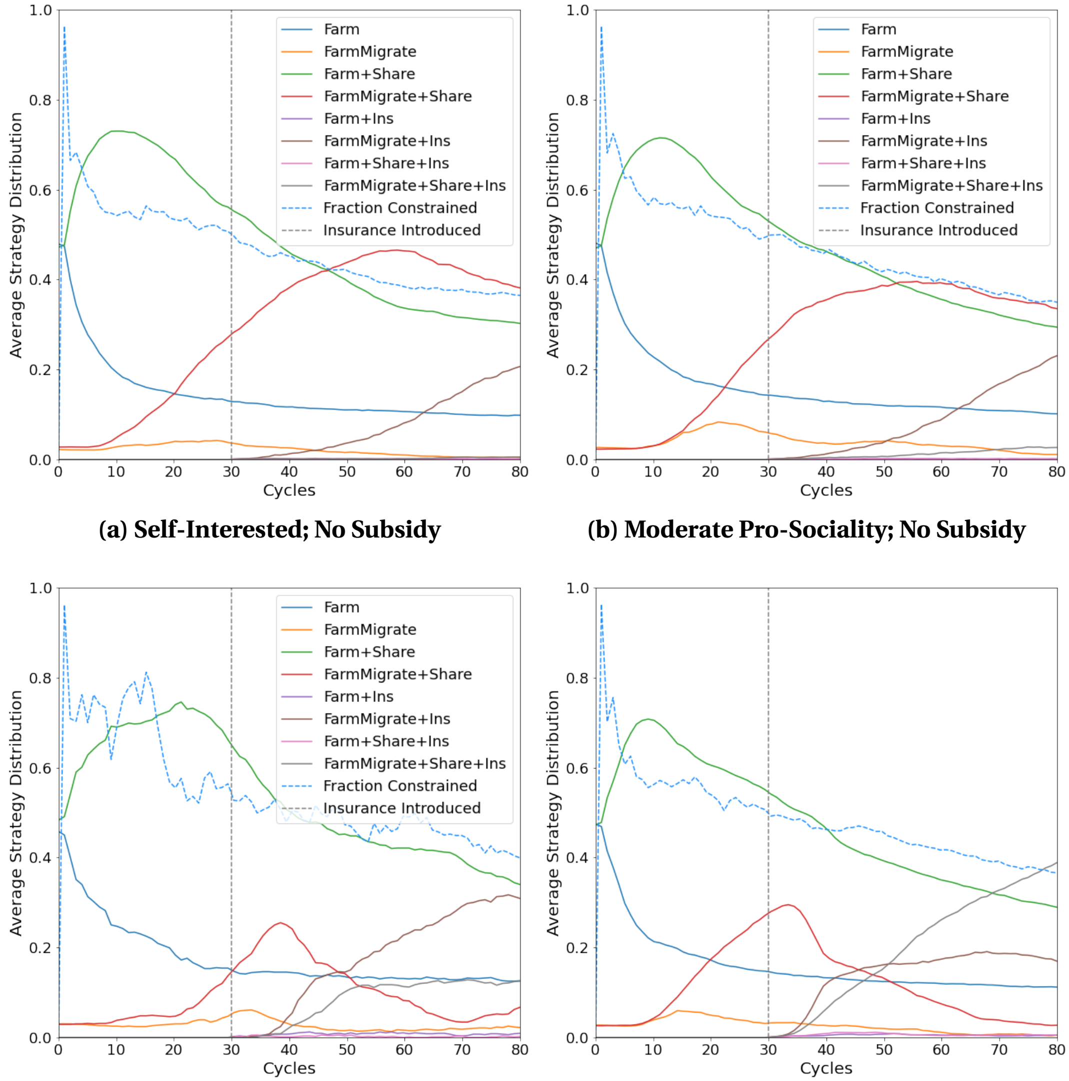


(a) Avg Proportion **(b)** Proportion Monomorphic

Figure B.11: Sensitivity of terminal time strategy distributions to community household size, N, while fixing $\alpha = \frac{1}{N}$. The left-hand panel illustrates average strategy shares, the right-hand panel illustrates the proportion of simulations in which a strategy reaches a monomorphic stage (>0.95 share). Results reflect averages over 100 simulations.

B.2.7 Policy Effectiveness under Financial Constraints

Plots below illustrate the dynamics of risk management strategy choices in a subsistence farming community in which households are constrained by the costs of various risk management strategies. In particular, 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 [29]). We assume that households with incomes above this level spend approximately 80 percent of their income on consumption, based on data from IBLI [151], 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

Figure B.12: Effect of Financial Restrictions and Social Preferences on Strategy Choices. Financial restrictions slows 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.

Appendix C

How Does Heterogeneity in Social and Informational Capital Affect Nepali Farmer Climate Risk Management? - SI

C.1 Additional Details on Survey Instrument

Below are lists of key survey questions and response options for gauging respondents' informational and social capital.

C.1.1 List of Informational Sources

How often do you typically receive information from [Source] that is relevant to your livelihood decisions, including farming, migration, and non-farm jobs?

- Radio
- Television

- Newspaper
- Agricultural Office
- Veterinarian Office
- Migrant Labour Agency
- Other Government Source
- Relative or Friend in Village
- Relative or Friend Outside of Village
- Religious Authority
- Scientist
- Social Media, e.g. Facebook, Messenger, WhatsApp
- Other

C.1.2 List of Social Groups

In the past year, how many times did you or your household members particiapte in ...

- Women's Group
- Youth Group
- Farming Cooperative
- Group Related to Livestock
- Group of Migrants from the Chitwan Valley
- Community Forest User Group
- Caste or Jati-Based Lending Group
- Other

C.2 Factors Influencing Perceptions of Specific Hazards

DV=Drought	coef	std err	t	P>|t|	[0.025	0.975]
const	0.5331	0.229	2.329	0.020	0.083	0.983
Gender	-0.0466	0.081	-0.577	0.564	-0.205	0.112
Age	-0.0004	0.003	-0.115	0.909	-0.007	0.006
Secondary	-0.1489	0.085	-1.751	0.081	-0.316	0.018
Gurung-Magar-Tamang	0.0107	0.112	0.095	0.924	-0.209	0.230
Dalit	-0.1211	0.108	-1.117	0.265	-0.334	0.092
Newar	-0.2476	0.257	-0.963	0.336	-0.753	0.257
Tharu-Darai-Kumal	-0.0305	0.087	-0.352	0.725	-0.201	0.140
Other	0.0783	0.191	0.410	0.682	-0.297	0.454
DroughtExp	0.0288	0.014	2.123	0.034	0.002	0.056
SourceIndex	-0.0873	0.035	-2.464	0.014	-0.157	-0.018
GroupIndex	-0.0220	0.036	-0.618	0.537	-0.092	0.048

DV = Floods	coef	std err	t	P>|t|	[0.025	0.975]
const	0.5858	0.217	2.705	0.007	0.160	1.011
Gender	-0.0497	0.076	-0.651	0.515	-0.200	0.100
Age	-0.0013	0.003	-0.420	0.675	-0.008	0.005
Secondary	-0.0542	0.080	-0.674	0.501	-0.212	0.104
Gurung-Magar-Tamang	-0.0675	0.105	-0.640	0.523	-0.275	0.140
Dalit	-0.1578	0.102	-1.540	0.124	-0.359	0.044
Newar	-0.2378	0.243	-0.979	0.328	-0.715	0.239
Tharu-Darai-Kumal	0.0824	0.084	0.979	0.328	-0.083	0.248
Other	-0.0599	0.181	-0.331	0.740	-0.415	0.295
FloodExp	0.0607	0.019	3.272	0.001	0.024	0.097
SourceIndex	-0.0495	0.034	-1.467	0.143	-0.116	0.017
GroupIndex	-0.0444	0.034	-1.323	0.186	-0.110	0.022

DV = Pests	coef	std err	t	P>|t|	[0.025	0.975]
const	0.6490	0.145	4.491	0.000	0.365	0.933
Gender	-0.0591	0.051	-1.163	0.245	-0.159	0.041
Age	0.0005	0.002	0.217	0.828	-0.004	0.005
Secondary	-0.0173	0.054	-0.322	0.748	-0.123	0.088
Gurung-Magar-Tamang	0.0305	0.070	0.437	0.662	-0.107	0.168
Dalit	-0.0585	0.068	-0.859	0.391	-0.192	0.075
Newar	0.0324	0.161	0.202	0.840	-0.284	0.349
Tharu-Darai-Kumal	-0.0488	0.054	-0.912	0.362	-0.154	0.056
Other	-0.4546	0.120	-3.791	0.000	-0.690	-0.219
PestsExp	0.0458	0.008	5.621	0.000	0.030	0.062
SourceIndex	0.0197	0.022	0.893	0.373	-0.024	0.063
GroupIndex	-0.0188	0.022	-0.842	0.400	-0.063	0.025

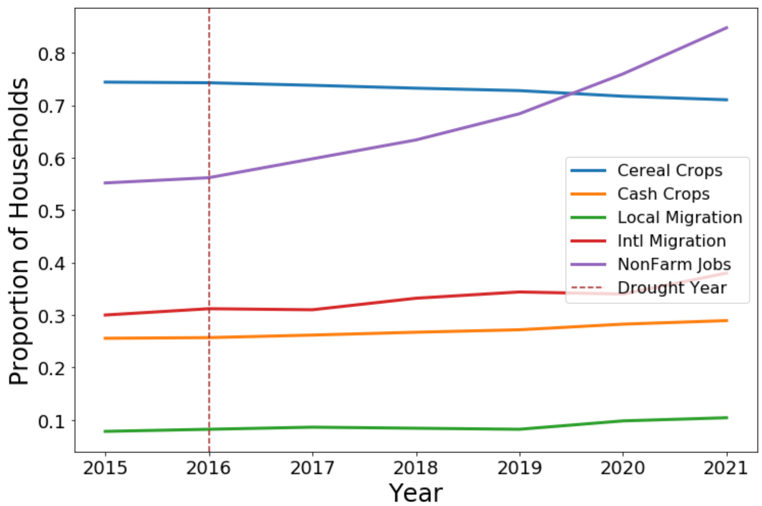
DV=Heat	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1974	0.244	0.808	0.419	-0.282	0.677
Gender	-0.0755	0.086	-0.880	0.380	-0.244	0.093
Age	0.0036	0.004	0.991	0.322	-0.004	0.011
Secondary	0.1193	0.091	1.314	0.190	-0.059	0.298
Gurung-Magar-Tamang	-0.1833	0.119	-1.541	0.124	-0.417	0.050
Dalit	-0.2483	0.116	-2.148	0.032	-0.475	-0.021
Newar	0.1154	0.274	0.422	0.674	-0.423	0.653
Tharu-Darai-Kumal	-0.2456	0.092	-2.657	0.008	-0.427	-0.064
Other	0.1845	0.204	0.906	0.365	-0.216	0.585
HeatExp	0.0258	0.018	1.406	0.160	-0.010	0.062
SourceIndex	0.0433	0.038	1.153	0.250	-0.031	0.117
GroupIndex	-0.0091	0.038	-0.241	0.809	-0.084	0.065

DV=Frost	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1981	0.222	0.892	0.373	-0.238	0.635
Gender	0.0986	0.078	1.271	0.204	-0.054	0.251
Age	0.0021	0.003	0.657	0.512	-0.004	0.009
Secondary	0.0561	0.082	0.684	0.494	-0.105	0.217
Gurung-Magar-Tamang	-0.0761	0.108	-0.708	0.479	-0.287	0.135
Dalit	-0.1975	0.106	-1.869	0.062	-0.405	0.010
Newar	0.1156	0.247	0.467	0.641	-0.371	0.602
Tharu-Darai-Kumal	-0.0006	0.082	-0.008	0.994	-0.162	0.161
Other	0.0189	0.187	0.101	0.919	-0.348	0.385
FrostExp	0.0437	0.011	4.089	0.000	0.023	0.065
SourceIndex	-0.0423	0.034	-1.234	0.218	-0.110	0.025
GroupIndex	0.0576	0.034	1.681	0.093	-0.010	0.125

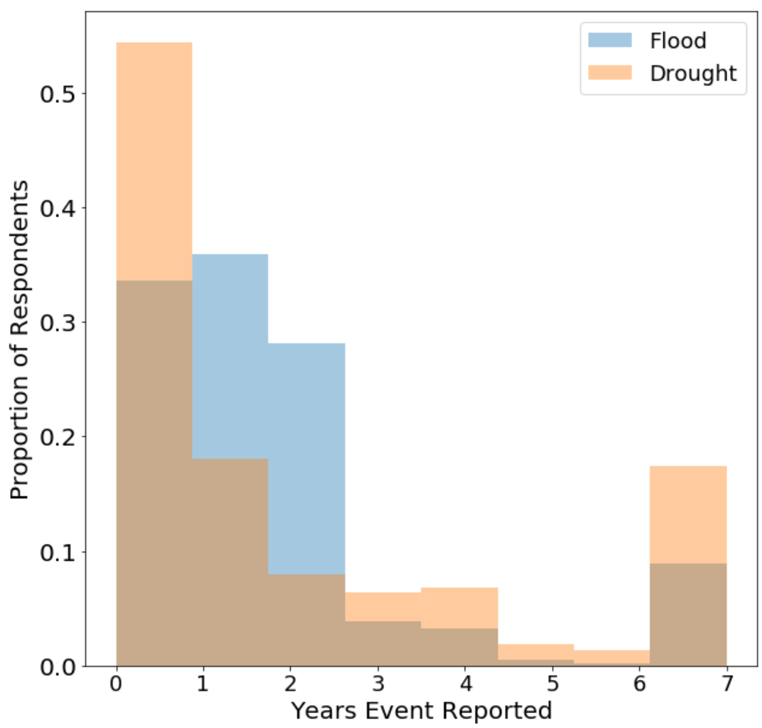
DV=Groundwater	coef	std err	t	P>|t|	[0.025	0.975]
const	0.2390	0.244	0.979	0.328	-0.241	0.718
Gender	0.1956	0.086	2.278	0.023	0.027	0.364
Age	-0.0055	0.004	-1.527	0.127	-0.013	0.002
Secondary	-0.0151	0.091	-0.167	0.867	-0.193	0.163
Gurung-Magar-Tamang	0.0460	0.119	0.386	0.699	-0.188	0.280
Dalit	0.0606	0.116	0.524	0.601	-0.167	0.288
Newar	-0.3360	0.274	-1.226	0.221	-0.874	0.202
Tharu-Darai-Kumal	0.1379	0.091	1.519	0.129	-0.040	0.316
Other	0.1538	0.204	0.756	0.450	-0.246	0.554
GroundwaterExp	0.0294	0.020	1.445	0.149	-0.011	0.069
SourceIndex	-0.0684	0.038	-1.820	0.069	-0.142	0.005
GroupIndex	0.1000	0.038	2.638	0.009	0.026	0.174

DV=Hail	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0522	0.234	-0.223	0.824	-0.512	0.407
Gender	-0.1155	0.082	-1.404	0.161	-0.277	0.046
Age	0.0005	0.003	0.153	0.878	-0.006	0.007
Secondary	-0.0519	0.087	-0.597	0.551	-0.223	0.119
Gurung-Magar-Tamang	0.0440	0.114	0.386	0.700	-0.180	0.268
Dalit	-0.1498	0.111	-1.352	0.177	-0.368	0.068
Newar	0.1028	0.263	0.391	0.696	-0.413	0.619
Tharu-Darai-Kumal	0.0296	0.088	0.337	0.736	-0.143	0.202
Other	0.2459	0.195	1.259	0.209	-0.138	0.630
HailExp	0.1071	0.056	1.898	0.058	-0.004	0.218
SourceIndex	-0.0222	0.036	-0.619	0.536	-0.093	0.048
GroupIndex	0.0343	0.036	0.940	0.348	-0.037	0.106

C.3 Additional Descriptive Statistics

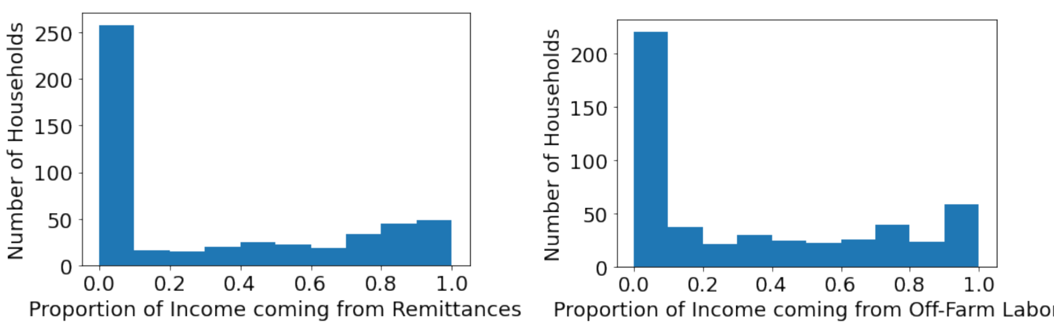


(a) Livelihood Choices



(b) Climate Exposure

Figure C.1: Aggregated Survey Calendar data detailing **a)** proportion of households deploying various livelihood strategies in each year from 2015-2021, and **b)** Distribution of households by number of years exposed to flood (blue bars) and drought (orange bars).



(a) Remittances **(b) Off-Farm Labor**

Figure C.2: Distribution of households by proportion of income coming from **a)** remittances and **b)** off-farm labor income.

Appendix D

Robust Climate Adaptation Policies for Subsistence Agriculture - SI

D.1 Model Framework

Following the XLRM framework to describe systems under deep uncertainty [54], we describe the following key elements of our model.

D.1.0.1 X - Exogenous system variables that may be uncertain

Key system uncertainties include:

- Mean growing season temperature in year t, $T(t)$, measured in ^0C;
- Mean and standard deviation of annual market price of crop j in year t, $\mu_j^p(t)$ and $\sigma_j^p(t)$, respectively, measured in USD/kg;
- Mean and standard deviation of annual migration remittance $\mu^R(t)$ and $\sigma^R(t)$, respectively, measured in USD/person*month.

Note that individual incomes earned from crops and migration, $\pi_{i,j}^{p}(t)$ and $\pi_{i}^{R}(t)$, respectively, will be drawn from a Weibull/Lognormal distribution fitted to the annual mean and variance variables.

D.1.0.2 L - Levers or actions that can be taken by decision-makers

In our expanded model, actions can be taken by decision-makers on three scales: livelihood strategies deployed by farming households, local investments from village councils, and policy interventions implemented at a national scale. Specifically, household livelihood strategies are revisited every cropping cycle and include:

- Farm subsistence crops, e.g. rice, maize, and wheat, which are generally characterized by low-risk, low-reward income distributions.
- Farm cash crops, e.g. vegetables, mustard seed, and fruits, which are generally characterized by high-risk, high-reward income distributions.
- Send one or more members of a household as a migrant to an urban location to earn remittances. These remittances are generally characterized by medium-risk, medium-reward income distributions.

Village councils can decide how to allocate I_v in annual budgets, and can revisit these decisions every λ_I cropping cycles. Their investment options include:

- Invest in an irrigation system with cost C_I, which will mitigate crop yield losses during drought years (not currently in model).
- Subsidize cereal crops to promote more grain production in the village.

- Subsidize cash crops to promote more economic development in the agricultural sector.

In the current version of the model, a national governance institution is exogenous and may deploy one or more of the following policy interventions for the entire duration of the model run. In future work, decisions this governance scale may also be endogenized to respond to changing national-level stocks of household incomes, agricultural production, and migrants, as well as updated perceptions of climate risks. In this case, national governance institutions would revisit policies every λ_n cropping cycles, where $\lambda_n > \lambda_l > 1$, reflecting increasing lags in policymaking at higher governance scales. For now, policy interventions include:

- Cash transfers, in which every household in a district is paid a fixed amount, π^C, per time step.
- Weather-based crop insurance, in which households may decide to purchase insurance against climate-driven crop losses that yield a pre-specified payout, π_j^I, based on the expected income for crop j.
- Support for migration remittances, in which a government matches remittances sent by migrants back to their households up to a certain limit per time step, $\pi^M(t)$.

In the current version of the model, national governance institutions are also assumed to provide village councils with revenue transfers of I_v proportional to the number of households N in a village. In future work, we plan to explore scenarios in which national governments can revise these transfers higher or lower in light of other investment options, introducing a new source of uncertainty for village council agents.

D.1.0.3 R - Relationships that map decision-maker actions to metrics

Key model relationships mapping farming household actions to metrics include:

- In each time step, households decide on a portfolio of livelihood strategies that maximizes their utility, subject to savings constraints. Household incomes are a function of such livelihood strategy decisions.
- Households connected through a social network also share information about the livelihood strategies they have deployed in the past m years, and the income they have earned from such strategies. Such information is factored into households' livelihood income and risk expectations, which influence their livelihood decisions.
- Household migration costs are a decreasing function of the proportion of the number of individuals in a household's network that have already migrated. Migration costs are incorporated in household evaluations of the utility of livelihood options.

Model relationships connecting village council investments to metrics include:

- Every λ_l time steps, village councils decide how to allocate a budget of I_v to a portfolio of investment options. The decision to invest in an irrigation system depends on the perceived drought risk at time t, $p_d(t)$, the average non-drought farming income at time t, $\bar{\mu}(t)$, the proportion of crop harvests that can be conserved through irrigation, γ, and the cost of irrigation $I(t)$. This means that a village council will decline to invest in irrigation if (i) it perceives drought risk to be too low to justify the investment cost, (ii) if it perceives the benefits of irrigation in drought years to not be worth the cost, and/or (iii) if it perceives average non-drought crop yields to be so low that even an effective irrigation system would not justify the cost.

- If the village council does not invest in irrigation at time $\lambda_l t$, it may invest in either cereal crop or cash crop subsidies. This decision is related to the average village-level cereal production, $P(t)$, over the previous policy window ($[t-\lambda_l t,\ t-1]$) as well as the council's threshold objective for self-sufficiency, $\psi P^*(t)$. $P^*(t)$ depends on the size of the community N at time t, so if there is a net migration outflow (inflow) during the previous policy window, the village council will perceive lesser (higher) production to achieve self-sufficiency.

D.1.0.4 M - Metrics or objectives that are relevant to the decision

This model framework assumes that decision-makers at different scales will use different metrics to evaluate the success of climate adaptation outcomes. Specifically, farming households will evaluate outcomes based on the following metrics:

- Individual annual incomes, $I_i(t)$;
- Volatility of annual incomes, $\sigma_i^I(t)$, measured over the past m years, where m represents household memory length.
- Overall savings level $S_i(t)$, which is the net cumulative sum of household of household i's incomes from time $t=0$ to time t.

Village councils evaluate the success of climate adaptation outcomes using the following community-scale variables:

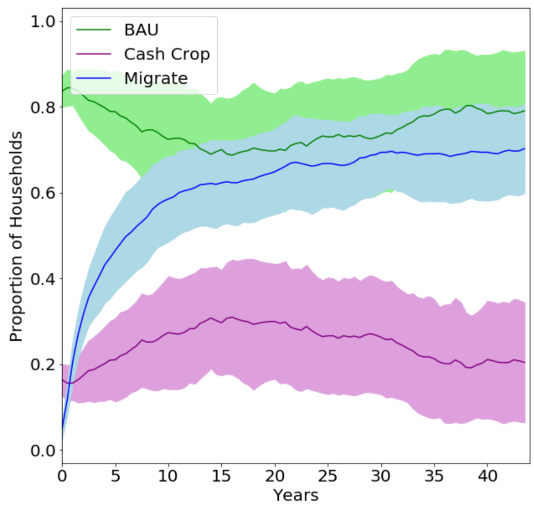
- The food security gap $\phi(t)$, which reflects the difference between average cereal production $\bar{P}(t)$ and community needs $P^*(t)$ at time t;
- Average annual income over the entire district, $\bar{I}(t)$;

- Inequality in annual incomes for a given year as measured by the GINI Coefficient, $G(t)$;
- Proportion of households whose savings fall below a poverty threshold, $V(t)$;
- Overall community migration rate, $M(t)$.

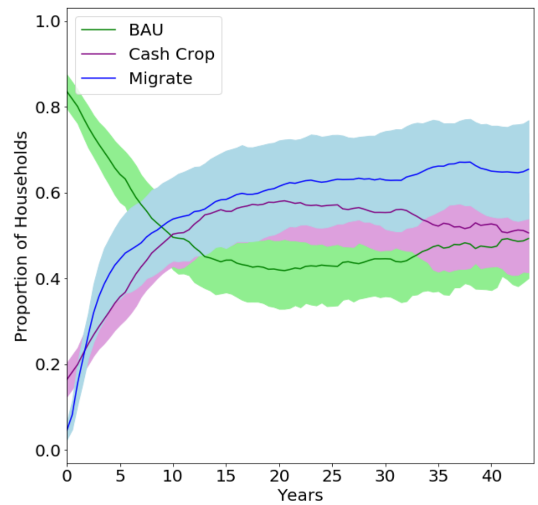
Metrics relevant to national governance institution decisions will be incorporated in a future version of the model, but may include: annual growth in agricultural economic activity, the national-scale food security gap, inequality between different Nepali regions, national-scale poverty rate, and national-scale migration rate.

D.2 Additional Results

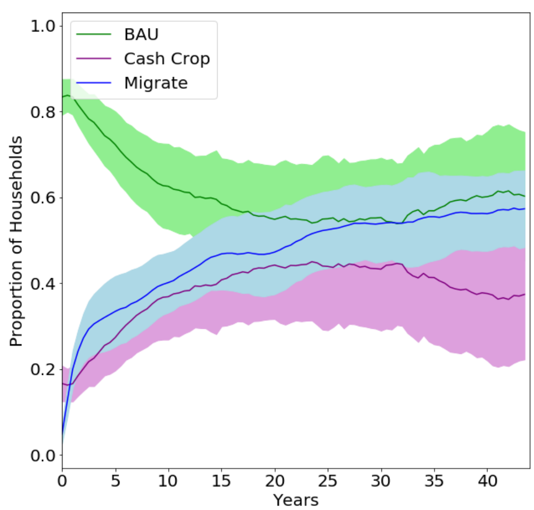
D.2.1 Effects of National Insurance Program on Strategy Choices



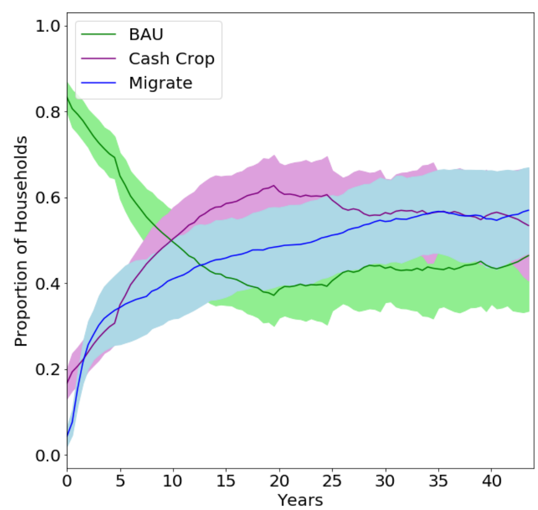
(a) High Capacity, No Intervention



(b) High Capacity, Insurance



(c) Low Capacity, No Interventions



(d) Low Capacity, Insurance

Figure D.1: Household strategy choices for High Capacity (top) and Low Capacity (bottom) village councils, without (left) and with (right) a national insurance program.

Bibliography

[1] Intergovernmental Panel on Climate Change. Climate change 2022: Impacts, adaptation, and vulnerability - summary for policymakers. Technical report, Cambridge University Press, 2022.

[2] Cynthia Rosenzweig, Joshua Elliot, Delphine Deryng, Alex C. Ruane, Christoph Muller, Almut Ameth, Kenneth J. Boote, Christian Folberth, Michael Glotter, Nikolay Khabarov, Kathleen Neumann, Franziska Piontek, Thomas A.M. Pugh, Erwin Schmid, Elke Stehfest, Hong Yang, and James W. Jones. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *PNAS*, 111(9):3268–2373, 2014.

[3] Frances C. Moore, Uris Baldos, Thomas Hertel, and Delavane Diaz. New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications*, 8, 2017.

[4] David B. Lobell, Wolfram Schlenker, and Justin Costa-Roberts. Climate trends and global crop production since 1980. *Science*, (333), 2011.

[5] S. Mark Howden, Jean-Francois Soussana, Francesco N. Tubiello, Netra Chhetri, Michael Dunlop, and Holger Meinke. Adapting agriculture to climate change. *PNAS*, 104(50):19691–19696, 2007.

[6] John F. Morton. The impact of climate change on smallholder and subsistence agriculture. *PNAS*, 104(50):19680–19695, 2007.

[7] Radley M. Horton, Alex de Sherbinin, David Wrathall, and Michael Oppenheimer. Assessing human habitability and migration. *Science*, 372(6548):1279–1283, 2021.

[8] Kanta Kumari Rigaud, Alex de Sherbinin, Bryan Jones, Jonas Bergmann, Viviane Clement, Kayly Ober, Jacob Schewe, Susana Adamo, Brent McCusker, Silke Heuser, and Amelia Midgley. Groundswell: Preparing for internal climate migration. Technical report, World Bank, 2018.

[9] Frank Ellis. Household strategies and rural livelihood diversification. *The Journal of Development Studies*, 35(1):1–38, 1998.

[10] Stefan Dercon. Income risks, coping strategies, and safety nets. *The World Bank Research Observer*, 17(2):141–166, 2002.

[11] J. Edward Taylor and Philip L. Martin. Human capital: Migration and rural population change. In B. Gardner and G. Rausser, editors, *Handbook of Agricultural Economics*, volume 1, pages 458–503. 2001.

[12] Robert E.B. Lucas and Oded Stark. Motivations to remit: Evidence from Botswana. *Journal of Political Economy*, (93), 1985.

[13] Dean Yang and HwaJung Choi. Are remittances insurance? evidence from rainfall shocks in the Philippines. *The World Bank Economic Review*, (21), 2007.

[14] R. McLeman and B. Smit. Migration as an adaptation to climate change. *Climatic Change*, (76), 2006.

[15] Foresight. Migration and global environmental change: Challenges and opportunities, 2011.

[16] Helene Benveniste, Michael Oppenheimer, and Marc Fleurbaey. Climate change increases resource-constrained international immobility. *Nature Climate Change*, 12:634–641, 2022.

[17] Richard Black, Neil Adger, Nigel Arnell, Stefan Dercon, Andrew Geddes, and David Thomas. Migration, immobility and displacement outcomes following extreme events. *Environmental Science Policy*, (275), 2013.

[18] Georgina Cundill, Chandni Singh, William Neil Adger, Ricardo Safra de Campos, Katharine Vincent, Mark Tebboth, and Amina Maharjan. Toward a climate mobilities research agenda: Intersectionality, immobility, and policy responses. *Global Environmental Change*, (69), 2021.

[19] Raphael J. Nawrotzki, Fernando Riosmena, Lori M. Hunter, and Daniel M. Runfola. Amplification or suppression: Social networks and the climate change-migration association in rural Mexico. *J Econ Interact Coord*, (9), 2014.

[20] Atesmachdew Hailegiorgis, Andrew Crooks, and Claudio Cioffi-Revilla. An agent-based model of rural households' adaptation to climate change. *Journal of Artificial Societies and Social Simulation*, (21), 2018.

[21] W. Neil Adger, Nigel W. Arnell, and Emma L. Tompkins. Successful adaptation to climate change across scales. *Global Environmental Change*, 15:77–86, 2005.

[22] Lea Berrang-Ford, James D. Ford, and Jaclyn Paterson. Are we adapting to climate change. *Global Environmental Change*, 21:25–33, 2011.

[23] W.P. Pauw, R.J.T. Klein, P. Vellinga, and F. Biermann. Private finance for adaptation: Do private realities meet public ambitions? *Climatic Change*, 134:489–503, 2016.

[24] Joel B. Smith, Jason M. Vogel, and John E. Cromwell III. An architecture for government action on adaptation to climate change. an editorial comment. *Climatic Change*, 95:53–61, 2009.

[25] Joanne Linnerooth-Bayer and Stefan Hochrainer-Stigler. Financial instruments for disaster risk management and climate change adaptation. *Climatic Change*, (133), 2015.

[26] Koko Warner, Nicola Ranger, Swenja Surminski, Margaret Arnold, JoAnne Linnerooth-Bayer, Erwann Michel-Kerjan, Paul Kovacs, and Celine Herweijer. Adaptation to climate change: Linking disaster risk reduction and insurance, 2009.

[27] R.M. Wise, I. Fazey, M. Stafford Smith, S.E. Park, H.C. Eakin, E.R.M. Archer Van Garderen, and B. Campbell. Reconceptualising adaptation to climate change as part of pathways of change and response. *Global Environmental Change*, 28:325–336, 2014.

[28] Jeetendra Prakash Aryal, Tek B. Sapkota, Ritika Khurana, Arun Kathri-Chhetri, Dil Bahadur Rahut, and M.L. Jat. Climate change and agriculture in South Asia: Adaptation options in smallholder production systems. *Environment, Development and Sustainability*, (22), 2020.

[29] Dirgha J. Ghimire, William G. Axinn, Prem B. Bhandari, Humnath Bhandari, and Rebecca Thornton. Chitwan Valley Family Study: Labour Outmigration, Agricultural Productivity and Food Security, Nepal, 2015-2017, 2019.

[30] World Development Indicators. Technical report, World Bank Group, 2021.

[31] ILOSTAT. Technical report, International Labour Organization, 2022.

[32] Rahul Karki and Anup Gurung. An overview of climate change and its impact on agriculture: A review from Least Developing Country, Nepal. *International Journal of Ecosystem*, 2(2):19–24, 2012.

[33] Ministry of Forests and Environment, Government of Nepal. Climate change scenarios for Nepal. Technical report, 2019.

[34] Sondoss Elsawah, Tatiana Filatova, Anthony J. Jakeman, Albert J. Kettner, Moira L. Zellner, Ioannis N. Athanasiadis, Serena H. Hamilton, Robert L. Axtell, Daniel G. Brown, Jonathan M. Gilligan, Marco A. Janssen, Derek T. Robinson, Julie Rozenberg, Isaac I.T. Ullah, and Steve J. Lade. Eight grand challenges in socio-environmental systems modeling. *Socio-Environmental Systems Modelling*, 2, 2020.

[35] Jule Thober, Nina Schwarz, and Kathleen Hermans. Agent-based modeling of environment-migration linkages: A review. *Ecology and Society*, 23, 2018.

[36] Roman Hoffmann, Anna Dimitrova, Raya Muttarak, Jesus Crespo Cuaresma, and Jonas Peisker. A meta-analysis of country-level studies on environmental change and migration. *Nature Climate Change*, (10):904–912, 2020.

[37] Clark L. Gray and Valerie Mueller. Natural disasters and population mobility in Bangladesh. *PNAS*, 109(16):6000–6005, 2012.

[38] Pratikshya Bohra-Mishra, Michael Oppenheimer, and Solomon Hsiang. Nonlinear permanent migration response to climatic variations but minimal response to disasters. *PNAS*, (111), 2014.

[39] Andrew R. Tilman, Avinash K. Dixit, and Simon A. Levin. Localized prosocial preferences, public goods, and common-pool resources. *PNAS*, (116):5305–5310, 2018.

[40] Alessandro Tavoni, Maja Schlüter, and Simon Levin. The survival of the conformist: Social pressure and renewable resource management. *Journal of Theoretical Biology*, (299):152–161, 2012.

[41] Fernando P. Santos, Jorge M. Pacheco, Francisco C. Santos, and Simon A. Levin. Dynamics of informal risk sharing in collective index insurance. *Nature Sustainability*, (4):426–432, 2021.

[42] Vitor V. Vasconcelos, Phillip M. Hannam, Simon A. Levin, and Jorge M. Pacheco. Coalition-structured governance improves cooperation to provide public goods. *Scientific Reports*, (10), 2020.

[43] Laura Schaefer and Eleanor Waters. Climate risk insurance for the poor & vulnerable: How to effectively implement the pro-poor focus of InsuResilience. Technical report, Munich Climate Insurance Initiative, 2016.

[44] Helen Greatrex, James Hansen, Samantha Garvin, Rahel Diro, Margot Le Guen, Sari Blakeley, Kolli Rao, and Dan Osgood. Scaling up index insurance for smallholder farmers: Recent evidence and insights. Technical Report CCFAS Report No. 14, CGIAR Research Programme on Climate Change, 2015.

[45] Lena Weingärtner, Alice Caravani, and Pablo Suarez. The role of multilateral climate funds in supporting resilience and adaptation through insurance initiatives. Technical report, Overseas Development Institute, 2018.

[46] Erlend Berg, Michael Blake, and Karlijn Morsink. Risk sharing and the demand for insurance: Theory and experimental evidence from Ethiopia. *Journal of Economic Behavior and Organization*, 195:236–256, 2022.

[47] Stefan Dercon, Ruth Vargas Hill, Daniel Clarke, Ingo Outes-Leon, and Alemayehu Seyoum Taffesse. Offering rainfall insurance to informal insurance groups: Evidence from a field experiment in Ethiopia. *Journal of Development Economics*, (106):132–143, 2014.

[48] Kazushi Takahashi, Christopher B. Barrett, and Munenobu Ikegami. Does index insurance crowd in or crowd out informal risk sharing? evidence from rural Ethiopia. *American Journal of Agricultural Economics*, (101):672–691, 2018.

[49] Ahmed Mushfiq Mobarak and Mark R. Rosenzweig. Informal risk sharing, index insurance and risk-taking in developing countries. *American Economic Review*, 103:375–380, 2013.

[50] Meike Will, Jurgen Groeneveld, Karin Frank, and Birgit Muller. Informal risk-sharing between smallholders may be threatened by formal insurance: Lessons from a stylized agent-based model. *PL0S ONE*, 16(3), 2021.

[51] Kieran Findalter, Sophie Webber, Milind Kandlikar, and Simon Donner. Climate services promise better decisions but mainly focus on better data. *Nature Climate Change*, 11:731–737, 2021.

[52] Gina Ziervogel. Targeting seasonal climate forecasts for integration into household level decisions: The case of smallholder farmers in Lesotho. *The Geographical Journal*, 170(1):6–21, 2004.

[53] J. Gordon Arbuckle Jr., Lois Wright Morton, and Jon Hobbs. Understanding farmer perspectives on climate change adaptation and mitigation: The roles of trust in sources of climate information, climate change beliefs, and perceived risk. *Environment and Behavior*, 47(2):205–234, 2015.

[54] Gregory G. Garner and Klaus Keller. Using direct policy search to identify robust strategies in adapting to uncertain sea-level rise and storm surge. *Environmental Modelling* & *Software*, 107:96–104, 2018.

[55] Jan H. Kwakkel, Warren E. Walker, and Marjolijn Haasnoot. Coping with the wickedness of public policy problems: Approaches for decision making under deep uncertainty. *Journal of Water Resource Planning Management*, 142(3), 2016.

[56] David G. Groves and Robert J. Lempert. A new analytic method for finding policy-relevant scenarios. *Global Environmental Change*, 17:73–85, 2007.

[57] Nicolas Ranger, Tim Reeder, and Jason Lowe. Addressing 'deep' uncertainty over long-term climate in major infrastructure projects: Four innovations of the Thames Estuary 2100 Project. *EURO Journal on Decision Processes*, 1:233–262, 2013.

[58] Marjolijn Haasnoot, Jan. H. Kwakkel, Warren E. Walker, and Judith ter Maat. Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. *Global Environmental Change*, 23:485–498, 2013.

[59] World Bank Group. Nepal system country diagnostic: A new approach for a federal Nepal. Technical report, World Bank, 2018.

[60] Jianping Huang, Haipeng Yu, Xiaodan Guan, Guoyin Wang, and Ruixia Guo. Accelerated dryland expansion under climate change. *Nature Climate Change*, (6), 2015.

[61] Swenja Surminski, Laurens M. Bouwer, and Joanne Linnerooth-Bayer. How insurance can support climate resilience. *Nature Climate Change*, (6), 2016.

[62] Jochem Marotzke, Dirk Semmann, and Manfred Milinski. The economic interaction between climate change mitigation, climate migration, and poverty. *Nature Climate Change*, (10), 2020.

[63] Jonathan Gray, Jason Hilton, and Jakub Bijak. Choosing the choice: Reflections on modelling decisions and behavior in demographic agent-based models. *Population Studies*, (71), 2017.

[64] Anna Klabunde and Frans Willekens. Decision-making in agent-based models of migration: State of the art and challenges. *European Journal of Population*, (32), 2016.

[65] Toon Haer, WJ Wouter Botzen, and CJH Aerts Jeroen. Advancing disaster policies by integrating dynamic adaptive behaviour in risk assessments using an agent-based modelling approach. *Environmental Research Letters*, 14, 2019.

[66] Koen de Koning and Tatiana Filatova. Repetitive floods intensify outmigration and climate gentrification in coastal cities. *Environmental Research Letters*, 15, 2020.

[67] Dimitris Kremmydas, Ioannis N. Athanasiadis, and Stelios Rozakis. A review of agent based modeling for agricultural policy evaluation. *Agricultural Systems*, (164):95–106, 2018.

[68] Riane van Duinen, Tatiana Filatova, Wander Jager, and Anne van der Veen. Going beyond perfect rationality: Drought risk, economic choices and the influence of social networks. *Ann. Reg. Sci.*, 57:335–369, 2016.

[69] Tesfamicheal Wossen and Thomas Berger. Climate variability, food security and poverty: Agent-based assessment of policy options for farm households in Northern Ghana. *Environmental Science & Policy*, 47:95–107, 2015.

[70] J. Groenveld, B. Muller, C.M. Buchmann, G. Dressler, C. Guo, N. Hase, F. Hoffmann, F. John, C. Klassert, V. Liebelt, H. Nolzen, N. Panncike, J. Schulze, H. Weise, and N. Schwarz. Theoretical foundations of human decision-making in agent-based land use models - a review. *Environmental Modelling & Software*, (87):39–48, 2017.

[71] Dominic R. Kniveton, Christopher D. Smith, and Richard Black. Emerging migration flows in a changing climate in dryland Africa. *Nature Climate Change*, (2), 2012.

[72] Behrooz Hassani-Mahmooei and Brett W. Parris. Climate change and internal migration patterns in Bangladesh: An agent-based model. *Environment and Development Economics*, (17), 2012.

[73] Christopher D. Smith. Modelling migration futures: Development and testing of the Rainfalls Agent-Based Migration Model - Tanzania. *Climate and Development*, (6), 2014.

[74] Barbara Entwistle, Nathalie E. Williams, Ashton M. Verdery, Ronald R. Rindfuss, Stephen J. Walsh, George P. Malanson, Peter J. Mucha, Brian G. Frizelle, Philip M. McDaniel, Xiaozheng Yao, Benjamin W. Heumann, Pramote Prasartkul, Yothin Sawangdee, and Aree Jampaklay. Climate shocks and migration: An agent-based modeling approach. *Population and Environment*, (38), 2016.

[75] Andrew Bell, Carlos Calvo, and Michael Oppenheimer. Migration, intensification, and diversification as adaptive strategies. *Socio-Environmental Systems Modeling*, (1), 2019.

[76] Douglas S. Massey, Joaquin Arango, Graeme Hugo, Ali Kouaouci, Adela Pellegrino, and J. Edward Taylor. Theories of international migration: A review and appraisal. *Population and Development Review*, 19(3):431–466, 1993.

[77] J. Edward Taylor. The New Economics of Labour Migration and the role of remittances in the migration process. *International Migration*, (37):63–86, 1999.

[78] Volker Grimm, Eloy Revilla, Uta Berger, Florian Jeltsch, Wolf M. Mooij, Steven F. Railsback, Hans-Hermann Thulke, Jacob Weiner, Thorsten Wiegand, and Donald L. DeAngelis. Pattern-oriented modeling of agent-based complex systems: Lessons from ecology. *Science*, (310), 2005.

[79] Central Bureau of Statistics. National Population and Housing Census 2011. Technical report, National Planning Commission Secretariat, Government of Nepal.

[80] Erik Katovich and Asin Sharma. Costs and returns of grain and vegetable crop production in Nepal's Mid-Western Development Region. Technical report, US Agency for International Development, 2014.

[81] Maheshwor Shrestha. Push and pull: A study of international migration from Nepal. Technical report, World Bank, 2017.

[82] Sarah Mohan. Risk aversion and certification: Evidence from the Nepali tea fields. *World Development*, (129), 2020.

[83] Mansour Almazroul, Sajjad Saeed, Fahad Saeed, M. Nazrul Islam, and Muhammad Ismail. Projections of precipitation and temperature over the South Asian countries in CMIP6. *Earth Systems and Environment*, (4), 2020.

[84] Tomomi Tanaka, Colin F. Camerer, and Quang Nguyen. Risk and time preferences: Linking experimental and household survey data from Vietnam. *American Economic Association*, (100):557–571, 2010.

[85] Hélène Benveniste, Michael Oppenheimer, and Marc Fleurbaey. Effect of border policy on exposure and vulnerability to climate change. *Proceedings of the National Academy of Sciences*, (117), 2020.

[86] Nanda Kaji Budhathoki, Jonatan A. Lassa, Sirish Pun, and Kerstin K. Zander. Farmers' interest and willingness-to-pay for index-based crop insurance in the lowlands of Nepal. *Land Use Policy*, (85), 2019.

[87] Rebecca Holmes and Shizu Uphadya. The role of cash transfers in post-conflict Nepal. Technical report, Overseas Development Institute, 2009.

[88] Ruth Vargas Hill, Neha Kumar, Nicholas Magnan, Simrin Makhija, Francesca de Nicola, David J. Spielman, and Patrick S. Ward. Ex ante and ex post effects of hybrid index insurance in Bangladesh. *Journal of Development Economics*, 136:1–17, 2019.

[89] Ervin Prifti, Silvio Daidone, Noemi Pace, and Benjamin Davis. Heterogeneous impacts of cash transfers on farm profitability. evidence from a randomised study in Lesotho. *European Review of Agricultural Economics*, (47):1531–1558, 2020.

[90] Partha Dasgupta. The economics of poverty in poor countries. *Scandinavian Journal of Economics*, 100(1):41–68, 1998.

[91] Marcel Fafchamps and Flore Gubert. The formation of risk-sharing networks. *The Journal of Development Economics*, 83:326–350, 2007.

[92] Bhawana KC and Digby Race. Outmigration and land-use change: A case study from the Middle Hills of Nepal. *Land*, (9), 2020.

[93] Brian Beckage, Louis J. Gross, Katherine Lacasse, Eric Carr, Sara S. Metcalf, Jonathan M. Winter, Peter D. Howe, Nina Fefferman, Travis Franck, Asim Zia, Ann Kinzig, and Forrest M. Hoffmann. Linking models of human behaviour and climate alters projected climate change. *Nature Climate Change*, 8:79–84, 2018.

[94] Brian C. O'Neill, Elmar Kriegler, Kristie L. Ebi, Eric Kemp-Benedict, Keywan Riahi, Dale S. Rothman, Bas J. van Ruijven, Detlef P. van Vuuren, Joern Birkmann, Kasper Kok, Marc Levy, and William Solecki. The roads ahead: Narratives for Shared Socioeconomic Pathways describing world futures in the 21st century. *Global Environmental Change*, 42:169–180, 2017.

[95] Rudolf J. Freund. The introduction of risk into a programming model. *Econometrica*, 24(3), 1956.

[96] Harry M. Markowitz. Foundations of portfolio theory. *Journal of Finance*, (46):469–477, 1991.

[97] Herbert A. Simon. Theories of bounded rationality. In C.B. McGuire and Roy Radner, editors, *Decision and Organization*, pages 161–176. 1972.

[98] Elke U. Weber and Eric J. Johnson. *Neuroeconomics: Decision Making and The Brain*, chapter Decisions under Uncertainty: Psychological, Economic, and Neuroeconomic Explanations of Risk Preference. Academic Press, 2009.

[99] Albert-Laszlo Barabasi and Reka Albert. Emergence of scaling in random networks. *Science*, 286.

[100] Douglas S. Massey and Felipe Garcia Espana. The social process of international migration. *Science*, (237), 1987.

[101] Adriana Carolina Silva and Douglas S. Massey. Violence, networks, and international migration from Colombia. *International Migration*, (53), 2014.

[102] Wolfgang Lutz and Raya Muttarak. Forecasting societies' adaptive capacities through a demographic metabolism model. *Nature Climate Change*, (7), 2017.

[103] Erich Striessnig, Wolfgang Lutz, and Anthony G. Patt. Effects of educational attainment on climate vulnerability. *Ecology and Society*, (18), 2013.

[104] Samir KC, Marcus Wurzer, Markus Speringer, and Wolfgang Lutz. Future population and human capital in heterogeneous India. *PNAS*, (115), 2018.

[105] Jagath C. Edirisinghe. Smallholder farmers' wealth and livelihood choices in developing countries: A Sri Lankan case study. *Economic Analysis and Policy*, (45), 2015.

[106] Thea Nielsen, Alwin Keil, and Manfred Zeller. Assessing farmers' risk preferences and their determinants in a marginal upland area of Vietnam: A comparison of multiple elicitation techniques. *Agricultural Economics*, (44), 2013.

[107] Aniseh S. Bro. Climate change adaptation, food security, and attitudes toward risk among smallholder coffee farmers in nicaragua. *Sustainability*, (12), 2020.

[108] Chalmers Mulwa, Paswel Marenya, Dil Bahadur Rahut, and Menale Kassie. Responses to climate risks among smallholder farmers in Malawi: A multivariate probit assessment of the role of information, household demographics, and farm characteristics. *Climate Risk Management*, (16), 2017.

[109] Shuai Chen, Xiaoguang Chen, and Jintao Xu. Impacts of climate change on agriculture: Evidence from China. *Journal of Environmental Economics and Management*, (76), 2016.

[110] Shuaizhang Feng, ALan B. Krueger, and Michael Oppenheimer. Linkages among climate change, crop yields, and Mexico-US cross-border migration. *Proceedings of the National Academy of Sciences*, (107), 2010.

[111] David B. Lobell and Christopher B. Field. Global scale climate-crop yield relationships and the impacts of recent warming. *Environmental Research Letters*, (2), 2007.

[112] M. Zampieri, A. Ceglar, F. Dentener, and A. Toreti. Wheat yield loss attributable to heat waves, drought, and water excess at the global, national, and subnational scales. *Environmental Research Letters*, (12), 2017.

[113] Yinpeng Li, Wei Ye, Meng Wang, and Xiaodong Yan. Climate change and drought: A risk assessment of crop-yield impacts. *Climate Research*, (39), 2009.

[114] Bo Ming, Yin-qiao Guo, Hong-bin Tao, Guang-zhou Liu, Shao-kun Li, and Pu Wang. SPEIpm-based research on drought impact on maize yield in North China Plain. *Journal of Integrative Agriculture*, (14), 2014.

[115] IPCC. Climate Change 2014 Synthesis Report: Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Technical report, Intergovernmental Panel on Climate Change, 2014.

[116] IPCC. Managing the risks of extreme events and disasters to advance climate change adaptation. Technical report, Intergovernmental Panel on Climate Change, 2012.

[117] Sergio M. Vicente-Serrano, Santiago Begueria, Jorge Lorenzo-Lacruz, Jesus Julio Camarero, Juan I. Lopez-Moreno, Cesar Azorin-Molina, Jesus Revuelto, Enrique Moran-Tejeda, and Arturo Sanchez-Loreno. Performance of drought indices for ecological, agricultural, and hydrological applications. *Earth Interactions*, (16), 2012.

[118] Naomi M. Saville, Bhim P. Shrestha, Sarah Style, Helen Harris-Fry, B. James Beard, Aman Sengupta, Sonali Jha, Anjana Rai, Vikas Paudel, Anni-Maria Pulkki-Brannstrom, Andrew Copas, Jolene Skordis-Worrall, and Bishnu Bhandari. Impact on birth weight and child growth of participatory learning and action women's groups with and without transfers of food or cash during pregnancy: Findings of the Low Birth Weight South Asia Cluster-Randomised Controlled Trial (LBWSAT) in Nepal. *PLoS ONE*, (13), 2018.

[119] Nanda Kaji Budhathoki, Jonatan A. Lassa, Sirish Pun, and Kerstin K. Zander. Farmers' interest and willingness-to-pay for index-based crop insurance in the lowlands of Nepal. *Land Use Policy*, (85), 2019.

[120] Peter Hazell, Rachel Sberro-Kessler, and Panos Varangis. When and how should agricultural insurance be subsidized? issues and good practices. Technical report, International Labour Organization and International Finance Corporation, 2017.

[121] Oded Stark and David E. Bloom. The New Economics of Labor Migration. *The American Economic Review*, (75), 1985.

[122] Sara LM Trærup. Informal networks and resilience to climate change impacts: A collective approach to index insurance. *Global Environmental Change*, 22(1):255–267, 2012.

[123] Williams Ali, Awudu Abdulai, and Ashok K. Mishra. Recent advances in the analyses of demand for agricultural insurance in developing and emerging countries. *Annual Review of Resource Economics*, 12:411–430, 2020.

[124] Robert Axelrod and William D. Hamilton. The evolution of cooperation. *Science*, 211(4489):1390–1396, 1981.

[125] Simon A. Levin. Public goods in relation to competition, cooperation, and spite. *PNAS*, (111):10838–10845, 2014.

[126] Ernst Fehr and Ivo Schurtenberger. Normative foundations of human cooperation. *Nature Human Behaviour*, 2:458–468, 2018.

[127] Ingela Alger and Jörgen W Weibull. Homo moralis—preference evolution under incomplete information and assortative matching. *Econometrica*, 81(6):2269–2302, 2013.

[128] Ingela Alger and Jörgen W Weibull. Evolution and Kantian morality. *Games and Economic Behavior*, 98:56–67, 2016.

[129] Andrew D. Foster and Mark R. Rosenzweig. Imperfect commitment, altruism, and the family: Evidence from transfer behavior in low-income rural areas. *The Review of Economics and Statistics*, 83(3):389–407, 2001.

[130] Wanchuan Lin, Yiming Liu, and Juanjuan Meng. The crowding-out effect of formal insurance on informal risk sharing: An experimental study. *Games and Economic Behavior*, 86:184–211, 2014.

[131] Kurt B. Waldman, Peter M. Todd, Shahera Omar, Jordan P. Blekking, Stacey A. Giroux, Shahzeen Z. Attari, Kathy Baylis, and Tom P. Evans. Agricultural decision making and climate uncertainty in developing countries. *Environmental Research Letters*, 15, 2020.

[132] J. Maynard Smith. The theory of games and the evolution of animal conflicts. *Journal of Theoretical Biology*, 47:209–221, 1974.

[133] Immanuel Lampe and Daniel Wurtenberger. Loss aversion and the demand for index insurance. *Journal of Economic Behavior and Organization*, 180:678–693, 2020.

[134] Frederik Sagemuller and Oliver Musshoff. Effects of household shocks on risk preferences and loss aversion: Evidence from upland smallholders of South East Asia. *The Journal of Development Studies*, 56(11):2061–2078, 2020.

[135] Lola L. Lopes and Gregg C. Olden. The role of aspiration level in risky choice: A comparison of Cumulative Prospect Theory and SP/A Theory. *Journal of Mathematical Psychology*, 43:286–313, 1999.

[136] Dale T. Miller and Deborah A. Prentice. Changing norms to change behavior. *Annual Review of Psychology*, 67:339–361, 2016.

[137] John Beshears, James J. Choi, David Laibson, Brigitte C. Madrian, and Katherine L. Milkman. The effect of providing peer information on retirement savings decisions. *The Journal of Finance*, 70(3):1161–1201, 2015.

[138] Ghazala Aziz. Fiscal federalism in India: An analysis of fiscal transfers to states. Technical report, SSRN Electronic Journal, 2010.

[139] Fernando P. Santos, Simon A. Levin, and Vitor V. Vasconcelos. Biased perceptions explain collective action deadlocks and suggest new mechanisms to prompt cooperation. *iScience*, (24), 2021.

[140] Joseph Henrich, Robert Boyd, Samule Bowles, Colin Camerer, Ernst Fehr, Herbert Gintis, Richard McElreaath, Michael Alvard, Abigail Barr, Jean Ensminger, Natalie Smith Hnerich, Kim Hill, Francisco Gil-White, Michael Gurvey, Frank W. Marlowe, John Q. Patton, and David Tracer. "Economic Man" in cross-cultural perspective: Behavioral experiments in 15 small-scale societies. *Behavioral and Brain Sciences*, 28(6):795–815, 2005.

[141] World Values Survey, Wave 7, 2017-2021. Technical report, World Values Survey Association, 2021.

[142] Rajalakshmi Nirmal and Suresh Chandra Babu. When implementation goes wrong: Lessons from crop insurance in India. Technical Report IFPRI Discussion Paper 02012, International Food Policy Research Institute, 2021.

[143] Sönke Ehret, Sara M. Constantino, Elke U. Weber, Charles Efferson, and Sonja Vogt. Group identities can undermine social tipping after intervention. *Nature Human Behaviour*, 2022.

[144] Sara M. Constantino, Gregg Sparkman, Gordon T. Kraft-Todd, Cristina Bicchieri, Damon Centola, Bettina Shell-Duncan, Sonja Vogt, and Elke U. Weber. Scaling up change: A critical review and practical guide to harnessing social norms for climate action. *Psychological Science in the Public Interest*, 23(2):50–97, 2022.

[145] Jorge M. Pacheco, Francisco C. Santos, and Simon A. Levin. Evolutionary dynamics of collective index insurance. *Journal of Mathematical Biology*, 72:997–1010, 2016.

[146] Birgit Muller, Leigh Johnson, and David Kreuer. Maladaptive outcomes of climate insurance in agriculture. *Global Environmental Change*, (46):23–33, 2017.

[147] Avinash Dixit and Simon Levin. *The Theory of Externalities and Public Goods*, chapter Social Creation of Pro-Social Preferences for Public Action. Springer, 2017.

[148] Jon M. Jachimowicz, Salah Chafik, Sabeth Munrat, Jaideep C. Prabhu, and Elke U. Weber. Community trust reduces myopic decisions of low-income individuals. *PNAS*, 114(21):5401–5406, 2017.

[149] Dirgha J. Ghimire, William B. Axinn, and Prem Bhandari. Social change, out-migration, and exit from farming in Nepal. *Population and Environment*, 42:302–324, 2021.

[150] Siegfried Maharjan, Amina Bauer and Beatrice Knerr. International migration, remittances, and subsistence farming. *International Migration*, 51(S1):e249–e263, 2013.

[151] Munenobu Ikegami and Megan Sheahan. Index Based Livestock Insurance (IBLI) Borena Household Survey. Technical report, International Livestock Research Institute, 2014.

[152] Amos Tversky and Daniel Kahneman. Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics*, 106(4):1039–1061, 1991.

[153] Sarah K. Lowder, Jakob Skoet, and Terri Raney. The number, size, and distribution of farms, smallholder farms, and family farms worldwide. *World Development*, 87:16–29, 2016.

[154] Intergovernmental Panel on Climate Change. Managing the risks of extreme events and disasters to advance climate change adaptation. Technical report, Cambridge University Press, 2012.

[155] Hoa Dang, Elton Li, and Johan Bruwer. Understanding climate change adaptive behaviour of farmers: An integrated conceptual framework. *The International Journal of Climate Change: Impacts and Responses*, 3(2):255–272, 2012.

[156] Chandni Singh, Peter Dorward, and Henry Osbahr. Developing a holistic approach to the analysis of farmer decision-making: Implications for adaptation policy and practice in developing countries. *Land Use Policy*, 59:329–343, 2016.

[157] Sujata Manandhar, Diterich Schmidt Vogt, Sylvain R. Perret, and Futaba Kazama. Adapting cropping systems to climate change in Nepal: A cross-regional study of farmers' perception and practices. *Reg Environ Change*, (11):335–348, 2011.

[158] Michael Glotter, Joshua Elliott, David McInerney, Neil Best, Ian Foster, and Elisabeth J. Moyer. Evaluating the utility of dynamical downscaling in agricultural impacts projections. *PNAS*, 111(24):8776–8781, 2014.

[159] Heather Barnes Truelove, Amanda R. Carrico, and Lanka Thabrew. A socio-psychological model for analyzing climate change adaptation: A case study of Sri Lankan paddy farmers. *Global Environmental Change*, 31:85–97, 2015.

[160] Torsten Grothmann and Anthony Patt. Adaptive capacity and human cognition: The process of individual adaptation to climate change. *Global Environmental Change*, (15):199–213, 2005.

[161] Hoa Le Dang, Elton Li, Ian Nuberg, and Johan Bruwer. Farmers' perceived risks of climate change and influencing factors: A study in the Mekong Delta, Vietnam. *Environmental Management*, (54), 2014.

[162] Yibekal Abebe Tessema, Jonas Jorein, and Anthony Patt. Factors affecting smallholder farmers' adaptation to climate change through non-technological adjustments. *Environmental Development*, 25:33–42, 2018.

[163] Bridget Bwalya Umar. A critical review and re-assessment of theories of smallholder decision-making. *Renewable Agriculture and Food Systems*, 29(3):277–290, 2014.

[164] RW Rogers and S Prentice-Dunn. *Handbook of Health Behavior Research 1: Personal and Social Determinants*, chapter Protection Motivation Theory, pages 113–132. Plenum Press, 1997.

[165] Icek Ajzen. The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50:179–211, 1991.

[166] Ministry of Agriculture, Land Management, and Cooperatives. Impact of climate finance in agriculture on the poor. Technical report, Government of Nepal, 2018.

[167] Government of Nepal, Ministry of Environment. National Adaptation Programme of Action (NAPA) to Climate Change. Technical report, 2010.

[168] Douglas S. Massey, William G. Axinn, and Dirgha J. Ghimire. Environmental change and out-migration: Evidence from Nepal. *Population and Environment*, 32:109–136, 2010.

[169] William G. Axinn, Lisa D. Pearce, and Dirgha Ghimire. Innovations in life history calendar applications. *Social Science Research*, (28):243–264, 1999.

[170] Maya K. Buchanan, Michael Oppenheimer, and Adam Parris. Values, bias, and stressors affect intentions to adapt to caostal flood risk: A case study from New York City. *Weather, Climate, and Society*, 12:809–821, 2019.

[171] Kerstin K. Zander and Stephen Garnett. Risk and experience drive the importance of natural hazards for people's mobility decisions. *Climatic Change*, 162:1639–1654, 2020.

[172] Elke U. Weber. What shapes perceptions of climate change? *WIREs Climate Change*, 1:332–342, 2010.

[173] Frances C. Moore, Nick Obradovich, Flavio Lehner, and Patrick Baylis. Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change. *PNAS*, 116(11):4905–4910, 2019.

[174] Sarah Brauner-Otto, Sarah Baird, and Dirgha Ghimire. Women's employment and children's education: Longitudinal evidence from Nepal. *Social Science Research*, 103, 2022.

[175] Klaus Keller, Gary Yohe, and Michael Schlesinger. Managing the risks of climate thresholds: Uncertainties and information needs. *Climatic Change*, 91:5–10, 2008.

[176] Johan Rockstrom, Will Steffen, Kevin Noone, Asa Persson, F. Stuart III Chapin, Eric Labmin, Timonty M. Lenton, Marten Scheffer, Carl Folke, Hans Joachim Schellnhuber, Bjorn Nykvist, Cynthia A. de Wit, Terry Hughes, Sander van der Leeuw, Henning Rodhe, Sorlin Sverker, Peter K. Snyder, Robert Costanza, Uno Svedin, Malin Falkenmark, Louise Karlberg, Robert W. Corell, Victoria J. Fabry, James Hansen, Brian Walker, Diana Liverman, Katherine Richardson, Paul Crutzen, and Jonathan Foley. Planetary boundaries: Exploring the safe operating space for humanity. *Ecology and Society*, 14(2), 2009.

[177] Stéphane Hallegatte, Ankur Shah, Robert Lempert, Casey Brown, and stuart Gill. Investment decision making under deep uncertainty: Application to climate change. Technical Report 6193, World Bank Group, 2012.

[178] Jan H. Kwakkel, Marjolijn Haasnoot, and Warren E. Walker. Developing dynamic adaptive policy pathways: A computer-assisted approach for developing adaptive strategies for a deeply uncertain world. *Climatic Change*, 132:373–386, 2015.

[179] Xavier Ignacio González, Federico Bert, and Guillermo Podestá. Many objective robust decision-making model for agriculture decisions MORDMAgro. *International Transaction in Operational Research*, 0:1–30, 2020.

[180] Bramka Arga Jafino, Jan H. Kwakkel, Frans Klijn, Nguyen Viet Dung, Hedwig van Delden, Marjolijn Haasnoot, and Edwin H. Sutanjudjaja. Accounting for multisectoral dynamics in supporting equitable adaptation planning: A case study on the rice agriculture in the Vietnam Mekong Delta. *Earth's Future*, 9, 2021.

[181] J.W. Knox, D. Haro-Monteagudo, T.M. Hess, and J. Morris. Identifying trade-offs and reconciling competing demands for water: Integrating agriculture into a robust decision-making framework. *Earth's Future*, 6:1457–1470, 2018.

[182] Jim Yoon, Christian Klassert, Philip Selby, Thibault Lachaut, Stephen Knox, Nicolas Avisse, Julien Harou, Amaury Tilmant, Bernd Klauer, Daanish Mustafa, Katja Sigel,

Samer Talozl, Erik Gawel, Medellin-Azuara Josue, Bushra Bataineh, Hua Zhang, and Steven M. Gorelick. A coupled human-natural system analysis of freshwater security under climate and population change. *PNAS*, 118(14), 2021.

[183] Elinor Ostrom. Polycentric systems for coping with collective action and global environmental change. *Global Environmental Change*, 20:550–557, 2010.

[184] Garrett Hardin. The tragedy of the commons. *Science*, 162:1243–1248, 1968.

[185] Elinor Ostrom. *Governing The Commons*. Cambridge University Press, 1990.

[186] Elinor Ostrom. Beyond markets and states: Polycentric governance of complex economic systems. *Transnational Corporations Review*, 2.

[187] Johanna Koehler, Steve Rayner, Jacob Katuva, Patrick Thomson, and Rob Hope. A cultural theory of drinking water risks, values and institutional change. *Global Environmental Change*, 50:268–277, 2018.

[188] Simon A. Levin, John M. Anderies, Neil Adger, Scott Barrett, Elena M. Bennett, Juan Camilo Cardenas, Stephen R. Carpenter, Anne-Sophie Crépin, Paul Ehrlich, Joern Fischer, Carl Folke, Nils Kautsky, Catherine Kling, Karine Nyborg, Stephen Polasky, Marten Scheffer, Kathleen Segerson, Jason Shogren, Jeroen van den Bergh, Brian Walker, Elke U. Weber, and James Wilen. Governance in the face of extreme events: Lessons from evolutionary processes for structuring interventions, and the need to go beyond. *Ecosystems*, 25:697–711, 2022.

[189] Dil Kumari Rawal Thapa and Ram Guragain. Nepal's Constitution and Federalism: Vision and Implementation. Technical report, National Forum of Parliamentarians on Population and Development, Nepal, 2020.

[190] Government of Nepal, Ministry of Agricultural Development. Agriculture Development Strategy (ADS). Technical report, 2015.

[191] Tribeni Rural Municipality Ward Number: 2, Rukum (West). Local Adaptation Plan for Action LAPA. Technical report, 2019.

[192] Rattan Lal. Feeding 11 billion on 0.5 billion hectare of area under cereal crops. *Food and Energy Security*, 5(4):239–251, 2016.

[193] Intergovernmental Panel on Climate Change. Climate change 2021: The physical science basis. Technical report, Cambridge University Press, 2021.

[194] Privthi Man Shrestha. Agriculture census to record impact of climate change. *The Kathmandu Post*, 2022.

[195] Benjamin Rosenbaum and Bjorn C. Rall. Fitting functional responses: Direct parameter estimation by simulating differential equations. *Methods in Ecology and Evolution*, (9), 2018.

[196] Laura Sidhom and Tobias Galla. Ecological communities from random generalized Lotka-Volterra dynamics with nonlinear feedback. *American Physical Review*, (E101), 2020.

[197] Navita Pal and Rama Pal. Motives behind remittances: A comparative analysis of single- and multiple-migrant households in India. *International Journal of Social Economics*, (46), 2019.

[198] Gudbrand Lien. Non-parametric estimation of decision makers' risk aversion. *Agricultural Economics*, (27):75–83, 2002.

[199] Elke U. Weber and Christopher K. Hsee. Models and mosaics: Investigating cross-cultural differences in risk perception and risk preference. *Psychonomic Bulletin & Review*, (6):611–617, 1999.

[200] Bonizella Biagini, Rosina Bierbaum, Missy Stults, Saliha Dobardzic, and Shannon M. McNeeley. A typology of adaptation actions: A global look at climate adaptation actions financed through the Global Environment Facility. *Global Environmental Change*, (25):97–108, 2014.

[201] Abayineh Amare, Belay Simane, Julius Nyangaga, Akalu Defisa, Dereje Hamza, and Biriki Gurmessa. Index-based livestock insurance to manage climate risks in Borena zone of southern Oromia, Ethiopia. *Climate Risk Management*, 25, 2019.

[202] FAOSTAT. Technical report, Food and Agriculture Organization of the United Nations, 2022.