Socio-environmental modelling for sustainable development: Exploring the interplay of formal insurance and risk-sharing networks

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Abstract

As envisaged in the Sustainable Development Goals, eradicating poverty by 2030 is among the most important steps to achieve a better and more sustainable future. A key contribution to reach this target is to ensure that vulnerable households are effectively protected against weather-related extreme events and other economic, social and ecological shocks and disasters. Insurance products specifically designed for the needs of low-income households in developing countries are seen as an effective instrument to encompass also the poor with an affordable risk-coping mechanism and are thus highly promoted and supported by governments in recent years. However, apart from direct positive effects, the introduction of formal insurance may have unintended side effects. In particular, it might affect traditional risk-sharing arrangements where income losses are covered by an exchange of money, labour and in-kind goods between neighbours, relatives or friends. A weakening of informal safety nets may increase social inequality if poor households cannot afford formal insurance. In order to design insurance products in a sustainable way, sound understanding of their interplay with risk-sharing networks is urgently needed.

Socio-environmental modelling is a suitable approach to address the complexity of this challenge. In the first part of this thesis, an agent-based model is developed to investigate the effects of formal insurance and informal risk-sharing on the resilience of smallholders. To lay the conceptual foundation for this approach, a literature review is presented which provides an overview of how to couple agent-based modelling with social network analysis. In two subsequent modelling studies, it is analysed (i) how the introduction of insurance influences the overall welfare in a population and (ii) what determines the resilience of the poorest to shocks when income is heterogeneously distributed and not all households can afford formal insurance. The simulation results underline the importance of designing insurance policies in close alignment with established risk-coping arrangements to ensure sustainability while striving to eradicate poverty. It is shown that introducing formal insurance can have negative side effects when insured households have fewer resources to share with their uninsured peers after paying the insurance premium or when they reduce their solidarity. However, especially when many households are simultaneously affected by a shock, e.g. by droughts or floods, formal insurance is a valuable addition to informal risk-sharing. By applying a regression analysis to simulation results for an empirical network from the Philippines, it is furthermore inferred that network characteristics must be considered in addition to individual household properties to identify the most vulnerable households that neither have access to formal insurance nor are adequately protected through informal risk-sharing.

In the second part of this thesis, a broader perspective is taken on the use of models in socio-environmental systems. First, it is envisioned how models in combination with empirical studies could improve insurance design under climate change. Second, requirements for making socio-environmental modelling more useful to support policy and management and scientific results more influential on policy-making are synthesised.

Overall, this thesis offers new insights into the interplay of formal and informal risk-coping instruments that complement existing empirical research and underlines the potential of socio-environmental modelling to address sustainability and development challenges.

Contents

List of Figures

List of Tables

1 Introduction

1.1 Background: Risk management with formal and informal instruments

Floods, droughts, storms and other extreme weather events pose significant financial risks, in particular to agricultural households in developing countries. Especially when people have limited resources at hand, unexpected incidents resulting in crop failures or livestock loss can have serious implications for the standard of living. Climate change, which leads to increased frequency and severity of weather-related shocks (Sheffield & Wood, 2008; Dai, 2013; Thornton et al., 2014; Tabari, 2020) and disproportionately affects people living in poverty (Linnerooth-Bayer & Hochrainer-Stigler, 2015; Hallegatte & Rozenberg, 2017; Charles et al., 2019), could therefore threaten sustainable development. Global change processes such as demographic growth leading to a rising competition for land, water and energy (Godfray et al., 2010) or increased health threats from the spread of new diseases (Bong et al., 2020; Josephson et al., 2021) or air pollution (Kurmi et al., 2012; Gordon et al., 2014) may further increase individual risks.

To defeat poverty, as envisaged in the Sustainable Development Goals by the United Nations (UN, 2015), encompassing also the poor with appropriate and affordable risk-coping instruments is consequently a key component (GIZ, 2015). Microinsurance or inclusive insurance, i.e. insurance products specifically designed for the needs of low-income households, are seen as a promising tool to protect the most vulnerable from climate-related extreme events and other economic, social and ecological shocks and disasters, and strengthen their resilience to unforeseen losses (Schaefer & Waters, 2016; Wanczeck et al., 2017). These insurance schemes are characterized by modest premium levels that are intended to be affordable for the low-income population (Churchill, 2006). Current programs include life, accident, and funeral insurance, as well as low-cost health insurance, which mainly covers hospitalization. In addition, agricultural insurance against crop failures and livestock loss is offered (Merry, 2020). While personal insurance products are mostly indemnity-based, i.e. they cover the actual losses occurred, insurance against the impacts of natural hazards is increasingly linked to an index. In this case, payouts are triggered when an index that maps a weather-related variable exceeds a predefined threshold. The level of a drought can, for example, be inferred using the normalized difference vegetation index (NDVI) as a proxy for vegetation condition, water level indices denote the severity of flood events, and wind indices can provide an estimate of the intensity of storms (Brown et al., 2011; Benami et al., 2021). This concept bears the advantage of low operation costs compared to traditional insurance product since actual losses do not need to be controlled by the insurance company or proven by the policy holder (Alderman & Haque, 2007; Barnett & Mahul, 2007; Hazell et al., 2010). In recent years, microinsurance products have been highly promoted and supported by governments. The 'InsuResilience' initiative launched by the G7 countries in 2015, for example, promotes the development of innovative and sustainable climate risk insurance in developing and emerging countries (GIZ, 2015). The Global Index Insurance Facility managed by the World Bank Group (GIIF, 2019) and the Access to Insurance Initiative (A2ii, 2020) have similar aims.

In the absence of formal protection mechanisms, in many developing countries, social networks are an important element of risk-coping (Platteau, 1991; Dercon, 2002; Cronk et al., 2019a). To deal with the consequences of unexpected income losses, households in need borrow from neighbours, relatives or friends (Fafchamps & Lund, 2003; De Weerdt & Dercon, 2006; Kinnan & Townsend, 2012). In addition to monetary support, exchanges also include in-kind transfers, such as when households share food (Nolin, 2010; Nolin, 2012) or borrow material goods like kerosene from their neighbours (Banerjee et al., 2013). Informal support in social networks is often established on the basis of agreements among several households in a village (De Weerdt & Dercon, 2006; Caudell et al., 2015). In addition, there are also community-based arrangements with often hundreds of members. In Ethiopia, for example, such groups offer financial assistance to compensate costs for funerals, medical expenses or food shortage against the payment of a premium (Dercon et al., 2006; Aredo, 2010; Abay et al., 2018). Some of these semi-formal risk-sharing arrangements include external enforcement through courts and other adjudication processes (Barr et al., 2012). Most support networks are, however, based on unwritten rules with punishment being only implicitly included through reductions in support (Coate & Ravallion, 1993; Kranton, 1996; Fafchamps, 2011). Two main motives are assumed for people to engage in informal risk-sharing: altruism and reciprocity. In the case of altruism, contributions are driven solely by a preference for social welfare, i.e. people help either because they are concerned about the well-being of a particular person or out of a general sense of goodwill or duty (Foster & Rosenzweig, 2001; Leider et al., 2009; Ligon & Schechter, 2012). Altruism might also be driven by the existence of social norms with people contributing to transfers to avoid social sanctions (De Weerdt & Fafchamps, 2011; Fafchamps, 2011; Ligon & Schechter, 2012). On the other hand, transfers might be granted on the basis of self-interest if households assume reciprocity and expect their generosity to be returned when they are in need themselves (Coate & Ravallion, 1993; Leider et al., 2009; Fafchamps, 2011).

In general, social support arrangements have the potential to contribute to risk management. However, among the poorest, most households are exposed to strong income fluctuations and have few financial resources at their disposal (Banerjee & Duflo, 2007). In addition, certain types of risks are better insured by informal risk-coping arrangements than others. While idiosyncratic shocks that affect only particular individuals or households can be covered by private transfers, risk-sharing networks may not work for covariate shocks that hit many households simultaneously (Gautam et al., 1994; Dercon, 2002; Devereux, 2007). Because networks are often not diversified and risks are therefore spread across households that live geographically close or have similar occupations, connected households are more likely to be affected by similar shock events and often not able to support each other when in need (Banerjee & Duflo, 2007). Especially as the threat of weather-related losses due to climate change will continue to increase, the fact that informal risk-sharing arrangements do not provide adequate support for these types of losses becomes particularly concerning.

While formal insurance products are undoubtedly an important contribution to addressing the shortcomings of informal risk-sharing arrangements, assessment studies of these policies show that, apart from direct positive effects, the introduction of formal insurance may have unintended side effects (see review in Müller et al., 2017). Two potential consequences deserve particular attention: First, the availability of insurance might result in a change of land-use strategies leading to a degradation of natural resources. Insurance coverage providing financial means for supplementary fodder may, for example, prevent the need to reduce livestock following a drought (Schulze et al., 2016; Gebrekidan et al., 2019). While having a positive impact on households' livelihood in the short-term, this may result in overgrazing and pasture degradation, which increases the vulnerability to future extreme events. Similarly, the availability of insurance may create incentives to intensify production and, for instance, turn to cash crops or mono-cropping, which yield higher returns but are riskier and potentially less environmentally sustainable (Mobarak & Rosenzweig, 2012; Mobarak & Rosenzweig, 2013; Cai, 2016; Cole & Xiong, 2017; Jensen et al., 2017). Reduced diversity in agricultural production systems may also ultimately have a crucial impact on household food and nutrition security (Habtemariam et al., 2021). Second, lab-in-the-field experiments and household surveys covering different cultural contexts and insurance products have provided evidence that households covered by formal insurance may be more reluctant to help uninsured neighbours (Landmann et al., 2012; Lin et al., 2014; Geng et al., 2018; Strupat & Klohn, 2018; Anderberg & Morsink, 2020; Lenel & Steiner, 2020). This would not only have consequences for households that cannot afford formal insurance and thus may no longer have access to support, but could also have far-reaching consequences in other areas of life. Informal social networks provide social capital that goes beyond mere financial support including information sharing, access to resources or equipment, or conflict intervention (Fletcher et al., 2020). These features may get lost if social networks become less important when formal insurance is available.

When introducing insurance products, potential side effects must be taken into account. However, only few studies analyse possible long-term implications on the welfare of a population and consequences on the environment following the introduction of insurance. In particular, little is known about lasting impacts that potential behavioural changes in informal support from households with access to insurance may have on the effectiveness of formal and informal risk-coping instruments and whether this may result in unintended social side effects. In addition, insurance policies must be able to deal with changing circumstances that pose new challenges for developing the measures. In particular, increasing shock frequency and intensity due to climate change must be explicitly taken into account in the design of insurance products in order to continue to provide adequate protection against unexpected income losses. Therefore, to help policymakers shape insurance products for sustainable and effective risk management, a better understanding of these interrelated aspects is urgently needed.

1.2 Methodological background: Socio-environmental modelling

1.2.1 Using models to address sustainability and development challenges

Unintended side effects of policies can occur if a system is not considered as a whole but only particular components are taken into account. Especially in socio-environmental systems, it is important to take an integrated view on coupled natural and human components and their feedbacks to derive sustainable solutions (Reid et al., 2010; Liu et al., 2015). To deal with the complexity of sustainability and development challenges in such interlinked systems, simulation models are a suitable approach. They allow to explore dependencies between social, environmental and economic influences that need to be understood to effectively manage risks (Barbero Vignola et al., 2020). By including quantitative descriptions of the main components of a system and their relationships, models can help to disentangle cause and effect of human behaviour, environmental dynamics, and policy implications, and identify where solutions are needed and how they can be reached (Levin et al., 2013; Barbero Vignola et al., 2020). Since models of socio-environmental systems can cover different temporal and spatial scales, an additional advantage is that they can represent short- or long-term effects as well as regional or global developments, depending on the focus of the research question (Elsawah et al., 2020).

When a system of interest is composed of autonomous decision-making entities like humans, households, firms or institutions, agent-based modelling is a particularly well suited analysis tool (Parker et al., 2003; Squazzoni et al., 2014; Schulze et al., 2017). It allows including the complexity of a system as well as the diversity of its individual actors (Bonabeau, 2002; Railsback & Grimm, 2012). By accounting for agents' micro-level behaviour, capturing feedback between their current state and interactions with other agents and the environment, they enable the exploration of emergent patterns at the macro-level. Policies can only lead to a change towards sustainable management if human behaviour is appropriately considered and the instruments are aligned accordingly. When models are used to depict the effects of policy measures in socio-environmental systems, an adequate representation of human behaviour is therefore as important as a sound account of environmental components (Milner-Gulland, 2012; World Bank, 2014). A particular strength of agent-based models in this regard is that different aspects of human behaviour, such as learning, adaptation or uncertainty, can be included (Bonabeau, 2002; An, 2012). However, despite the importance of integrating human decision-making explicitly, the theoretical basis of the behavioural frameworks used in agent-based models is often still quite simplified (Groeneveld et al., 2017; Schlüter et al., 2017). Furthermore, analyses of human behaviour in socio-environmental models are demanding and often not systematic enough (Schlüter et al., 2012; Schulze et al., 2017; Schwarz et al., 2020).

Human decisions are rarely made independently of others but are often affected by personal relationships or communities. To understand complex socio-environmental processes, it is therefore essential to consider the structure and dynamics of social networks that influence individual decisions. A promising approach to address these aspects is to combine agent-based models with social network analysis, which can help to understand social phenomena by quantifying patterns of relationships among social entities using formally defined graph-theoretic methods (Emirbayer & Goodwin, 1994; Wasserman & Faust, 1994; Scott, 2011). Since the interaction of agents with one another can be mapped to the concept of nodes and links established in the field of network science, a combination of both approaches can be easily achieved. This helps to fill gaps that both methods have and opens many possibilities to study human behaviour that neither the evaluation of social networks nor agent-based models alone can provide. However, despite a wide range of applications in various disciplines of current research, the potential for combining both approaches is far from being exhausted and needs to be further pursued to adequately represent and evaluate the dynamics of human interactions in agent-based models.

1.2.2 Using models to support policy and management

Models are a critical tool to inform decision-making, as they allow to evaluate consequences of specific policies prior to their implementation (Baumgärtner et al., 2008; Holtz et al., 2015; Grimm et al., 2020). With the help of models, it can be assessed which of the intended goals can be achieved with an intervention and which undesirable side effects may occur. By means of a multi-criteria analysis that takes into account effects on different aspects of a system, models can provide concrete contributions to disentangle interdependencies between different objectives (IPBES, 2016; Barbero Vignola et al., 2020). This can help to harmonize socioeconomic and environmental goals (Allen et al., 2016). In other words, models can be used as a "virtual lab" to test the impact of different policy options and evaluate multiple scenarios (Carley et al., 2009; Seppelt et al., 2009). Scenarios are considered as possible futures of individual components of the combined human and environmental system (Swart et al., 2004; Baumgärtner et al., 2008). This includes direct and indirect drivers and their anticipated change, as well as alternative policy and management options that target these drivers (IPBES, 2016). Models can help to translate these different future scenarios into socioeconomic and environmental consequences (Holtz et al., 2015; Allen et al., 2016; IPBES, 2016).

Despite the fact that modelling can provide effective support to decision-making, dynamic process-based modelling, and agent-based modelling in particular, has so far mainly made contributions in the scientific field, but few socio-environmental models have had impact on decision support and policy-making (Schulze et al., 2017; Polhill et al., 2019; Elsawah et al., 2020). To make progress in this regard, it is important to understand the underlying reasons of the low application to date, so that socio-environmental modelling can be further advanced and eventually realize its full potential.

1.3 Objectives and structure of this thesis

The preceding sections provided the motivation for the two overarching research objectives (R1 and R2) of this thesis, each of which is composed of two subthemes (i and ii):

R1: Assessing risk management with formal and informal instruments: (i) Explore the interplay of formal insurance and risk-sharing networks and (ii) advance insurance design under climate change

R2: Advancing socio-environmental modelling: (i) Investigate the potential of social network analysis and agent-based modelling to explore dynamics of human interaction and (ii) make socio-environmental modelling more useful to support policy and management

In this thesis, these objectives are approached in several interlinked steps (Figure 1.1) which are structured in two main parts. Part I focusses on modelling the interplay of formal insurance and risk-sharing networks and comprises the core of this thesis. Part II is in close relation to Part I and takes a broader perspective on the use of models to address socio-environmental challenges in the context of risk management and beyond. In the following, the overall structure of the two parts is presented, after which a brief summary of each chapter of this thesis is given.

1.3.1 Overall structure

In **Part I**, the focus is on modelling the effects of the interplay of formal and informal risk management instruments (insurance and risk-sharing networks) on the resilience of smallholders (R1.i). This topic is presented in two studies with different problem settings and methodological emphases. To lay the conceptual foundation for these studies, an introductory literature review provides an overview on coupling agent-based models with social networks and on evaluating the integrated approach (R2.i, Chapter 2). The first modelling study analyses the social side effect on the overall welfare in a population when insured households no longer show solidarity with their uninsured peers after the introduction of formal insurance (Chapter 3). In the second modelling study, it is examined what determines the resilience of the poorest to shocks when income is heterogeneously distributed (Chapter 4).

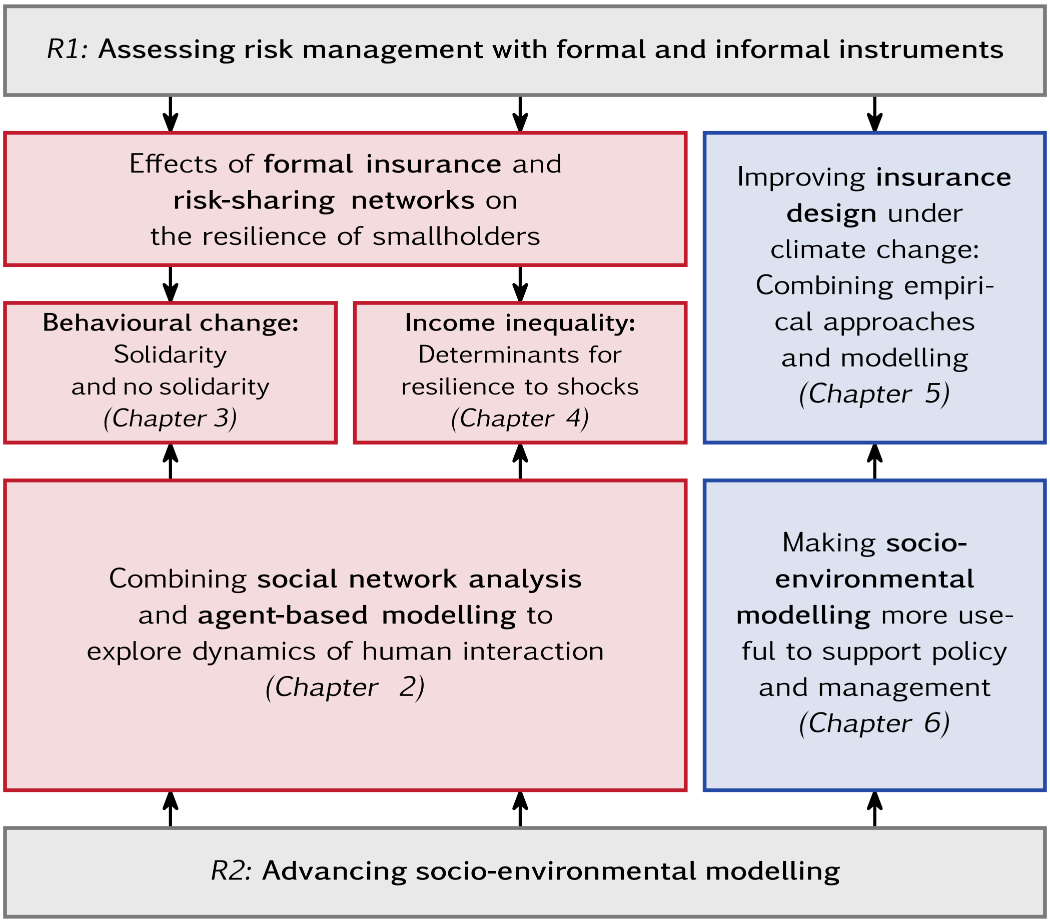

Figure 1.1: Schematic overview of the chapters in Part I (red) and Part II (blue) and their relations within the two overarching research objectives (R1 and R2) of this thesis (grey)

In this case, it is assumed that all households show solidarity, but not everyone can afford formal insurance.

Part II focuses on the importance of models to address pressing socio-environmental challenges in the context of risk management and beyond. First, it is outlined how empirical and model-based approaches should be combined to advance insurance design under climate change (R1.ii, Chapter 5). Second, the topic is addressed from a broader perspective by giving an overview on what has to be done to make socio-environmental modelling more useful to support policy and management, i.e. how scientific results such as those derived in this thesis can have an impact on actual policy-making (R2.ii, Chapter 6).

1.3.2 Chapter overview

Chapter 2: An introductory literature review provides an overview on the coupling of agent-based models with social networks and the evaluation of the integrated approach. Selected studies from three main areas of application (epidemiology, marketing and social dynamics) are classified based on three aspects covering the purpose of networks in agent-based models, the way of integrating networks in models and the type of their analysis. All of these approaches are illustrated with key examples from the reviewed literature. Current implementations are critically evaluated and recommendations on how to overcome common shortcomings are provided. The findings are synthesized in guidelines that contain the main aspects to consider when integrating social networks into agent-based models. This chapter has been published in *Socio-Environmental Systems Modelling* (Will et al., 2020).

Chapter 3: The first modelling study presents a stylized agent-based model to explore indirect effect of the introduction of formal insurance products on the resilience of those smallholders in a social network who cannot afford this financial instrument. Specifically, it is analysed whether and how economic needs of households (i.e. level of living costs) and characteristics of extreme events (i.e. frequency, intensity and type of shock) influence the ability of formal insurance and informal risk-sharing to buffer income losses. In the model, households can request money from their neighbours in a stylized small-world network when their financial resources are not sufficient to sustain themselves. To investigate which unintended side effects might arise when insured households lower their contribution to traditional informal arrangements, two types of behaviour with regard to monetary transfers are explicitly considered. First, all households are assumed to provide financial assistance whenever they are asked for support and can afford to contribute. In a second scenario, only uninsured households show solidarity and insured households do not transfer. All households have access to the same financial resources and insurance uptake is randomly distributed across the population neglecting explicit reasons behind the decision to insure. This chapter has been published in *PLOS ONE* (Will et al., 2021a).

Chapter 4: In a second study using the same modelling approach as in the previous chapter, the focus is not on transfer decisions but on the effectiveness of formal and informal risk management in communities with heterogeneous wealth. While many aspects of the model are still stylized, income distribution and network characteristics are based on a household survey that was conducted in 2012 on the Philippines (Lenel, 2017). In this study, insurance uptake is linked to the financial resources of a household. Only households that are wealthy enough to cover the costs of insurance can decide to insure. All households are assumed to show solidarity with uninsured peers. The model is used to assess the impact of heterogeneity in income and network characteristics on the effectiveness of informal risk-sharing for the poorest that cannot afford formal insurance. With the help of a logistic regression analysis of simulation outcomes, a variety of factors going beyond the individual financial resources are identified that determine the households' resilience to shocks.

Chapter 5: A broad range of methods including experimental games, household surveys, process-based crop models and agent-based models is currently used to assess the demand for and the effectiveness of insurance products. However, climate change raises specific socioeconomic as well as environmental challenges that need to be considered when designing insurance schemes. In the light of these challenges, some of the currently used methodological approaches might reach their limits when applied independently. In this chapter, it is envisioned how methodological synergies, particularly when linking empirical analyses and modelling, can make insurance products more effective in supporting the most vulnerable, especially under changing climatic conditions. This chapter is currently under review in *Climate and Development*.

Chapter 6: In this chapter, a broader view is taken on dynamic process-based modelling that is often proposed as a powerful tool to understand complex socio-environmental problems but has so far only limited impact to support policy-making. By investigating a number of good practice examples from fields where models have influenced policy and management, the main aspects that promote or impede the application of these models are identified. These insights are used to synthesise four key factors for successful modelling for policy and management support in socio-environmental systems and to give recommendations specifically to modellers, decision-makers or both to make the use of models for practice more effective. This chapter has been published in *People and Nature* (Will et al., 2021b).

Chapter 7: The last chapter of this thesis summarizes the main finding on the interplay of formal insurance and risk-sharing networks and provides methodological reflections on the value of an agent-based modelling framework with integrated social network and the general merit of models to address socio-environmental challenges. The thesis concludes with a final summary and an outlook on future studies and potential areas of application.

Part I

Modelling the interplay of formal insurance and risk-sharing networks

2 Combining social network analysis and agent-based modelling to explore dynamics of human interaction: A review

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Abstract

Agent-based modelling (ABM) and social network analysis (SNA) are both valuable tools for exploring the impact of human interactions on a broad range of social and ecological patterns. Integrating these approaches offers unique opportunities to gain insights into human behaviour that neither the evaluation of social networks nor agent-based models alone can provide. There are many intriguing examples that demonstrate this potential, for instance in epidemiology, marketing or social dynamics. Based on an extensive literature review, we provide an overview on coupling ABM with SNA and evaluating the integrated approach. Building on this, we identify current shortcomings in the combination of the two methods. The greatest room for improvement is found with regard to (i) the consideration of the concept of social integration through networks, (ii) an increased use of the co-evolutionary character of social networks and embedded agents, and (iii) a systematic and quantitative model analysis focusing on the causal relationship between the agents and the network. Furthermore, we highlight the importance of a comprehensive and clearly structured model conceptualization and documentation. We synthesize our findings in guidelines that contain the main aspects to consider when integrating social networks into agent-based models.

2.1 Introduction

Many of the challenges society is facing today are not determined by individualistic action, but by behaviour embedded in complex networks of personal relationships, communities and markets. Climate change, for example, can only be tackled if people change their everyday behaviour, which strongly depends on actions of their surroundings (Senbel et al., 2014; Kjeldahl & Hendricks, 2018). Connections in a digitalized world allow communication independent of physical distances, but also bear specific risks (Pastor-Satorras & Vespignani, 2001; Kaplan & Haenlein, 2010). Epidemics such as measles and Ebola spread more easily the more people resist proper prevention (Andre et al., 2008; Chowell & Nishiura, 2014), and global markets are largely dominated by the interaction of customers, suppliers and businesses (Gereffi, 1999; Garlaschelli & Loffredo, 2005). To understand these complex social processes of our time, it is essential that research draws attention both to human behaviour and to the structure of social networks and their dynamics. A promising approach to address these two aspects is the combination of social network analysis (SNA) and agent-based modelling (ABM).

Analysing social structure in a formalized way has attracted interest from a wide range of social and behavioural disciplines (Borgatti et al., 2009; Butts, 2009). As an approach to rigorously quantifying patterns of relations between social entities by means of formally defined graph-theoretic methods, SNA can contribute to the understanding of various social phenomena (Emirbayer & Goodwin, 1994; Wasserman & Faust, 1994; Scott, 2011). On the other hand, ABM, too, has proven to be a valuable approach to address the complex task of analysing the interplay between individuals or groups (Gilbert, 2008; Squazzoni, 2010). Agent-based models are process-based simulation tools that can capture feedbacks between the behaviour of heterogeneous agents and their surroundings. In this context, agents can be entities such as humans, households, firms or institutions (Railsback & Grimm, 2012). On a micro-level, agents act interdependently according to prescribed rules and adjust their behaviour to the current state of themselves, of other agents and of the environment (Bonabeau, 2002; Railsback & Grimm, 2012). On the macro-level, emergent patterns and dynamics arise from the aggregated individual behaviours and the interactions between the agents (Kiesling et al., 2012).

As the interaction of agents with one another can be mapped to the concept of nodes and links established in the field of network science, a combination of both approaches can be easily achieved. Embedding networks in ABM makes it possible to define the set of agents with which a focal agent interacts not exclusively via spatial relationships, as in virtually all spatial agent-based models, but via the agent's social network, i.e. a (dynamic) set of other agents (Railsback & Grimm, 2012). Since individual behaviour and network structure are largely intertwined, social systems often show nonlinear and unpredictable behaviour. Integrating social networks in computer simulations such as ABM helps to understand these processes (Bonabeau, 2002; Squazzoni et al., 2014). Furthermore, ABM can complement the sampling bias that is common in network structures mapped by empirical approaches of the social sciences (Costenbader & Valente, 2003; Stumpf et al., 2005). As complete network data is rare, a comprehensive picture of the whole node-ties landscape is often missing. Computational modelling can be used as a "virtual lab" to explore systems in space and time and to test hypotheses about causal relationships (Carley, 2009). A systematic combination of these theory-driven approaches with the empirically-driven aspects of network science thus helps to fill gaps that both approaches have and opens many possibilities to investigate human behaviour that neither the evaluation of social networks nor agent-based models alone can provide.

The potential to explore the dynamics of social networks with agent-based models has been recognized in various disciplines of contemporary research. Examples can be found, among others, in the context of epidemiology (Eubank et al., 2004; Verelst et al., 2016), marketing (Rand & Rust, 2011; Kiesling et al., 2012; Rai & Henry, 2016) or social dynamics (Macy & Willer, 2002; Castellano et al., 2009; Squazzoni et al., 2014). Despite this broad range of application, the potential to combine both approaches is far from being exhausted, as will be shown in this review.

The aim of this paper is threefold: (i) bring together different research streams, in which ABM is coupled with social networks, to enable an increased methodological cross-fertilization between disciplines, which has so far been hardly realized, (ii) detect current limitations in the combination of the two methods, and (iii) propose guidelines that provide a basis for a comprehensive and clearly structured model set-up which supports the application of a systematic and quantitative analysis of social networks in agent-based models. The guidelines take full advantage of combining both approaches to explore human interaction and are meant to serve modellers in future projects.

2.2 Methods

To reveal the diverse range of applications and identify key challenges when combining agent-based models and social networks, we provide a review of a selection of exemplary studies. We evaluated 54 publications from different fields to gain an overview of the current usage of social networks in agent-based models and to find possible gaps in their implementation and analysis. Our search was limited to agent-based and multi-agent models, a term often used as a synonym for agent-based models, where it is explicitly stated that social networks are integrated (see Appendix A.1 for details). We are aware that especially in the area of network research there are other terminologies (e.g. network model or game-theoretic model) that refer to similar concepts and do not fall under our search restrictions. However, we believe that ABM is a reasonable umbrella term for all these approaches and that most results are transferable. Furthermore, we did not aim to conduct a systematic review of all sampled models, but tried to cover the most recent and, according to the number of citations, the most established results (see Appendix A.1 for the selection criteria and Appendix A.2 for a detailed classification of the reviewed models). As an outcome of this investigation, we elaborate in the remainder of the review on the potential of linking ABM with social networks. We highlight three areas of common shortcomings and offer opportunities for improvement. First, we focus on the role of social networks in agent-based models in terms of their purposes. Second, we distinguish ways of integrating networks in agent-based models; and third, we emphasize currently used as well as potentially more beneficial approaches for model analysis. Table 2.1 summarizes all aspects on the classification for social networks in ABM that will be revealed in the course of the review. To address the observed deficiencies in terms of comprehensive and clearly structured model conceptualization and evaluation, we conclude with proposing guidelines covering all aspects that need to be considered for sound modelling and systematic analysis of social networks.

2.3 Potential of linking ABM with social networks

The unmatched potential to address the dynamics of social interaction through a coupled social network and ABM approach has been recognized in various disciplines of contemporary research. By reviewing the selected publications, we identified three main areas of application, which are not without overlaps: epidemiology, marketing and social dynamics. To reveal the full spectrum of social networks in these contexts, we illustrate different (i) purposes, (ii) ways of network integration, and (iii) types of analysis of social networks in ABM and give recommendations on how to overcome common shortcomings. For all approaches in the following sections, we include key examples from the reviewed literature to illustrate different possible realizations and their suitability.

Table 2.1: Summary of classification aspects for social networks in ABM used in this review with reference to the respective sections that address these aspects

	Levels		
Purpose (section 2.3.1)	**Diffusion:** Links between agents in a network serve as channels for transfer of material or non-material resources.	**Social integration:** Social ties represent integration of actors in a group; agent's network position provides social capital which leads to achievements, success or power.	
Network integration (section 2.3.2)	**Endogenous:** Network topology evolves during the simulation based on individual decisions of agents and further impacts through the environment.	**Exogenous:** Network topology is imposed and fixed during the simulation; focus on how social network structure affects state of the agents and system dynamics.	**Co-evolutionary:** Feedback loop between changing the states of agents through their interaction and adapting the topology of the network leads to dynamically evolving network.
Types of analysis (section 2.3.3)	**Agent-centric:** Effect of parameters not related to the network.	**Network-centric:** Effect of link properties or global network measures.	**Structurally explicit:** Causal relation between agents and network structure, effect of local network measures.

2.3.1 Purpose

Social networks in ABM have two main purposes: diffusion and social integration (Macy & Willer, 2002; Borgatti & Foster, 2003; Goldstone & Janssen, 2005; Granovetter, 2005; Klabunde & Willekens, 2016). The relevance of both is addressed separately in the following two sections.

2.3.1.1 Diffusion

If diffusion is the model purpose, the linkages between agents in a network serve as channels for transfer of material (e.g. goods) or non-material resources (e.g. information). Implementing connections between agents allows to model how new ideas, practices or diseases spread within and between communities through interpersonal contacts (Wasserman & Faust, 1994; Valente, 2005).

In epidemiology, ABM with integrated social networks is widely used to overcome the unrealistic assumptions of homogeneous mixing used in traditional models of disease spread based on differential equations (Eubank et al., 2004; Rahmandad & Sterman, 2008). As the transmission of a disease is directly influenced by the behaviour of individuals, social networks are not only included in the models to serve as a channel for the diffusion of epidemics but they allow the direct incorporation of social factors such as the propensity to vaccinate (Fu et al., 2011) or hygiene compliance (Hornbeck et al., 2012) that can influence health outcomes (El-Sayed et al., 2012; Verelst et al., 2016).

Marketing research addresses the spread of non-material processes when dealing with the diffusion of innovations (Peres et al., 2010; Kiesling et al., 2012). Agents exchange information with their peers which influences their decision towards a new product (Janssen & Jager, 2001; Janssen & Jager, 2003; Goldenberg et al., 2007; Bohlmann et al., 2010; Amini et al., 2012; Haenlein & Libai, 2013; Libai et al., 2013; Hu et al., 2018; Negahban & Smith, 2018) or technology such as sustainable mobility (Huétink et al., 2010), solar photovoltaics (Pearce & Slade, 2018; Wang et al., 2018), water conservation (Rasoulkhani et al., 2018), smart metering (Zhang & Nuttall, 2011), flood prevention measures (Erdlenbruch & Bonte, 2018) or innovations like autonomous vehicles (Talebian & Mishra, 2018).

Similar research questions are addressed with respect to social dynamics (Macy & Willer, 2002; Bianchi & Squazzoni, 2015). In this field, the main focus is on social influence on the dissemination of attitudes (e.g. regarding sustainable energy use (Moglia et al., 2018; Niamir et al., 2018) or organic farming (Kaufmann et al., 2009)), culture (Flache & Macy, 2011; Keijzer et al., 2018), language (Ke et al., 2008; Lou-Magnuson & Onnis, 2018), opinions (Lu et al., 2009; Biondo et al., 2018; Piedrahita et al., 2018), trends (Weng et al., 2012; Schlaile et al., 2018) or information (Chareunsy, 2018; Frank et al., 2018).

2.3.1.2 Social integration

Interaction between agents, however, does not necessarily involve a direct exchange. Apart from being channels for transfer, social ties also represent the social integration of actors in a group. These connections to others provide possibilities and constraints for action (Granovetter, 1985; Macy & Willer, 2002; Borgatti & Foster, 2003; Smith & Christakis, 2008; Bianchi & Squazzoni, 2015). The network structure can be seen as a form of coordination which enables collective action, self-organization and cross-scale support (Cumming, 2016; Rockenbauch &

Sakdapolrak, 2017). An agent's network position provides social capital which leads to certain achievements, success or power. Examples include the evolution of cooperation based on familiarity (Son & Rojas, 2011), similarities (Hadzibeganovic et al., 2018) or trust (Bravo et al., 2012; Growiec et al., 2018; Laifa et al., 2018). Additionally, a social environment can provide existential security (Gore et al., 2018) or can support people to promote an activity (Garcia et al., 2018).

2.3.1.3 Recommendations

We observe that ABM most often addresses the concept of networks as channels for transfers and considers social integration only rarely. We want to underline that the two different purposes of networks, however, both have their justification and want to encourage modellers to apply the concept of social integration which is one of the main thrusts of SNA in agent-based simulations.

2.3.2 Network integration

2.3.2.1 Exogenously imposed and endogenously emerging networks

The critical specification for networks in agent-based models is whether their structure is exogenously imposed or endogenously emerging (Macy & Willer, 2002; Jackson, 2010; Bruch & Atwell, 2015; Namatame & Chen, 2016). In the first case the network structure is fixed and the focus is on how social network structures affect the state of the agents and system dynamics (Figure 2.1a). The vast majority of the models assessed in this review focuses on this approach.

On the other hand, networks can also emerge based on predefined rules in the model. In this case, agents are aware of the impacts of each connection and decide whether they establish relations with other agents, depending on the gains these links provide (Figure 2.1b). In established network formation models such as random networks (Erdős & Rényi, 1959), small-world networks (Watts & Strogatz, 1998) or scale-free networks (Albert & Barabási, 2002), the formation rules are not necessarily appropriate to describe sociological questions (Flache & Snijders, 2008). Endogenously evolving networks in agent-based models of social networks enable the integration of individual decisions of agents and further impacts through the environment in the formation process and can therefore be used to investigate which structures are likely to emerge in certain contexts. Furthermore, ABM allows to analyse the effect of agents' knowledge of the network on the choice of connections. Partial or imperfect information on existing and possible connections induces agents to create, maintain or strategically invest in their ties. Examples of network formation can be found mostly in context of social dynamics and include friendship selection in secondary schools (Fetta et al., 2018), relationships based on similar attitudes (Neal & Neal, 2014) or creation of urban networks due to spatial closeness of agents' residential locations and workplaces (Zhuge et al., 2018).

2.3.2.2 Co-evolutionary networks

Models considering both endogenous network formation and a dynamic update of the state of the agents depending on the network and vice versa are often called co-evolutionary network models (Gross & Blasius, 2008) (Figure 2.1c). The incorporation of the feedback loop

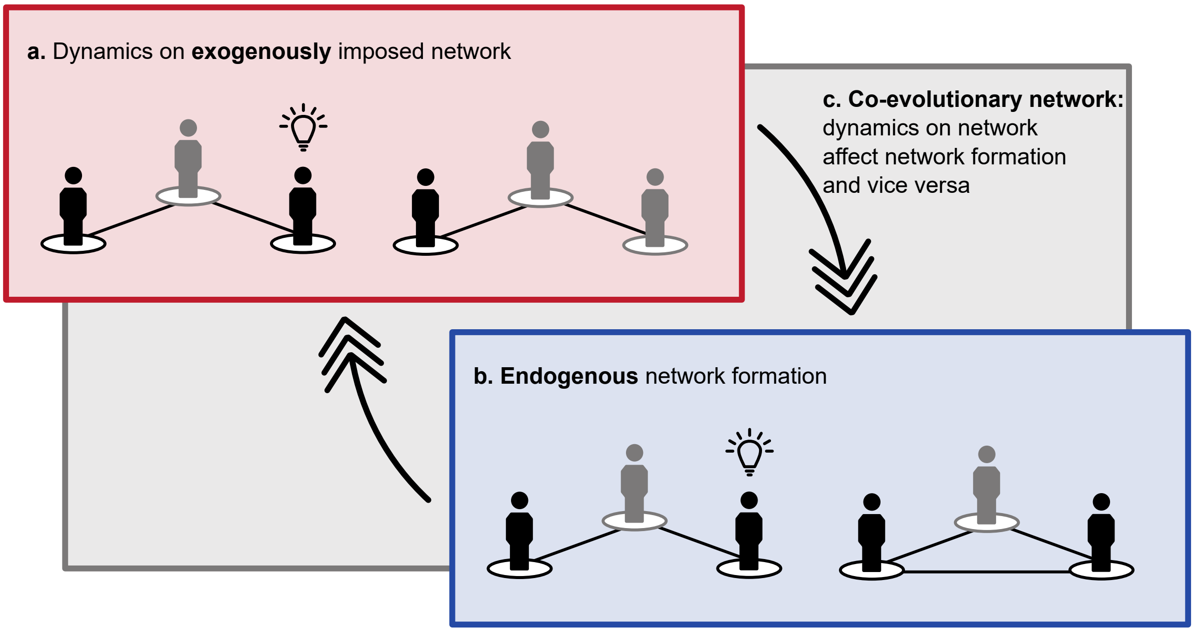


Figure 2.1: Exogenous, endogenous and co-evolutionary networks in agent-based models with social networks. **a. Exogenous network:** Social networks enable an appropriate representation of the social interaction between agents. The model dynamics are determined by the interaction of agents linked in an exogenously imposed network which is fixed during the simulation. Here, the focal agent (marked with a bulb) decides to change its state (black to grey) based on the current status of the agents it is linked to. **b. Endogenous network:** Agent-based models allow the integration of individual behaviour and environmental influences in models of network formation. Links between agents emerge and disappear, but the states of the agents do not necessarily change. Here, the focal agent decides to establish a new link to another agent. **c. Co-evolutionary network:** The combined approach of both aspects takes into account the feedback loop between state of agents and topology. Agents change their state according to their network connections and their network connections according to their state. Figure adapted from Gross & Blasius (2008).

between changing the states of agents through their interaction and adapting the topology of the network (i.e. the arrangement of nodes representing agents and links connecting them) through link formation and dissolution combines the advantages of pure network models and the modelling of human behaviour in agent-based models. We observed, however, that this has rarely been used in ABM so far. Examples for co-evolutionary networks comprise agents that add or remove links to maximize the information they can gain from their acquaintances (Frank et al., 2018; Lozano et al., 2018; Moradianzadeh et al., 2018; Phan & Godes, 2018), to establish monogamous mating relationships (Simão & Todd, 2002), to express their dissatisfaction within a cooperation (Bravo et al., 2012) or if the trust between agents has vanished due to offenses between neighbours (Laifa et al., 2018). Additionally, modified spatial configurations that emerge from the behaviour of the agents (e.g. migration decisions (Fu & Hao, 2018)) or the appearance and disappearance of additional agents due to birth and death (Hadzibeganovic et al., 2018) can lead to changes in the network structure.

2.3.2.3 Recommendations

The choice of a suitable approach for network integration depends, apart from the research question at hand and the availability of data, largely on the time scale on which the relevant processes take place (Figure 2.2). Both the network structure and the interaction of the agents

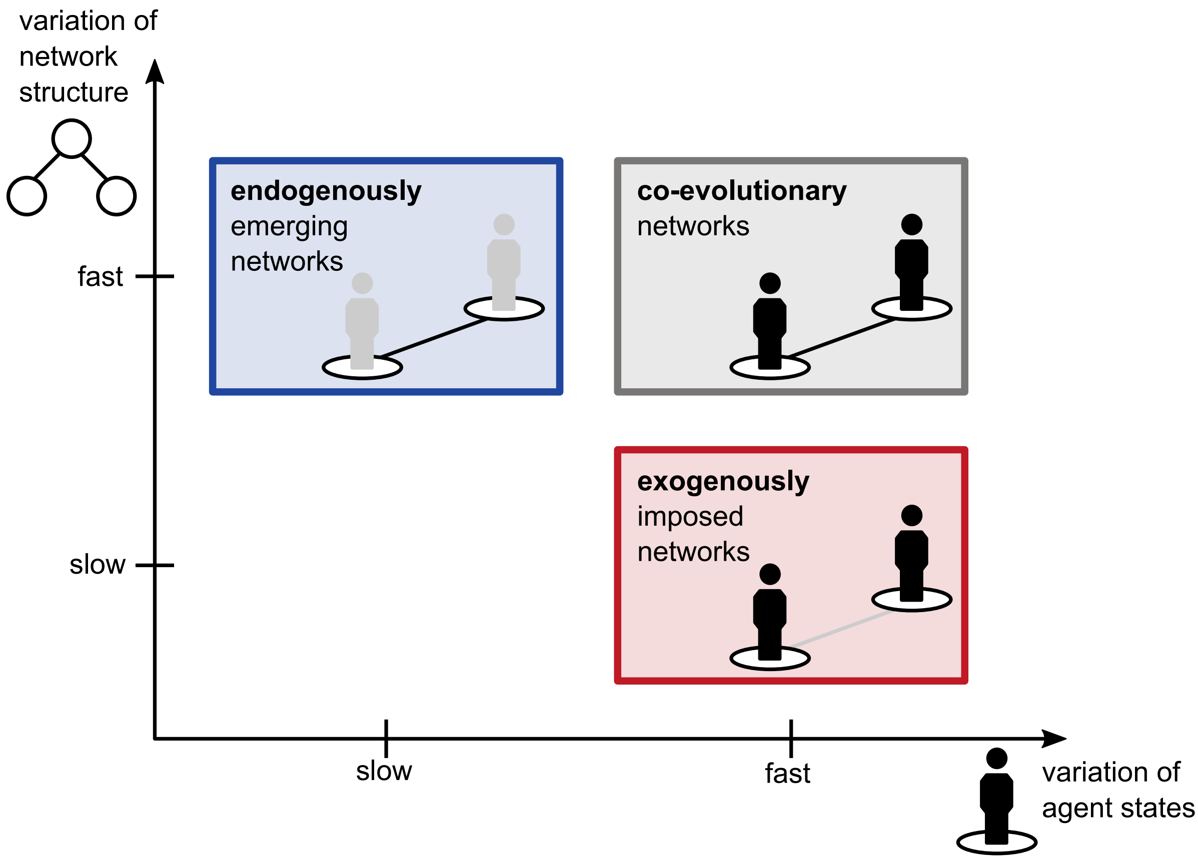


Figure 2.2: Time scales of variation of network structure and agent states and adequate ways of integrating social networks in ABM. Fixed exogenously imposed networks are suitable if the states of the agents adapt rapidly but changes on the network structure are slow. Endogenously emerging networks capture situations with fast network changes and slowly adjusting agent states. In co-evolutionary networks both processes, variation of network structure and agent states, run fast.

can change slowly or quickly (for an overview on the concept of slow and fast variables see e.g. Walker et al., 2012). A network that slowly adapts to the actions of the agents can be considered constant, i.e. it can be determined by fixed exogenously imposed structures. In cases where connections between agents change rapidly but their states adjust slowly, networks form endogenously without affecting the internal characteristics of the agents. If both processes run fast, co-evolutionary networks are the appropriate method of choice. As many social connections change over time, this allows adopting concepts of dynamic social networks observed in reality for connections in agent-based models. We strongly recommend that modellers carefully determine the relevant time scales of network and agent dynamics in the specific cases to capture cross-fertilization between network topology and agent behaviour if needed. In situations in which either only the causes or only the consequences of networks are to be investigated, however, the use of endogenously emerging or exogenously imposed structures, respectively, is equally appropriate.

2.3.3 Types of analysis

Understanding overarching patterns that emerge from assumptions and model rules at the individual level is the key challenge in interpreting the outcomes of agent-based models. We distinguish three approaches to assessing social networks in agent-based models with

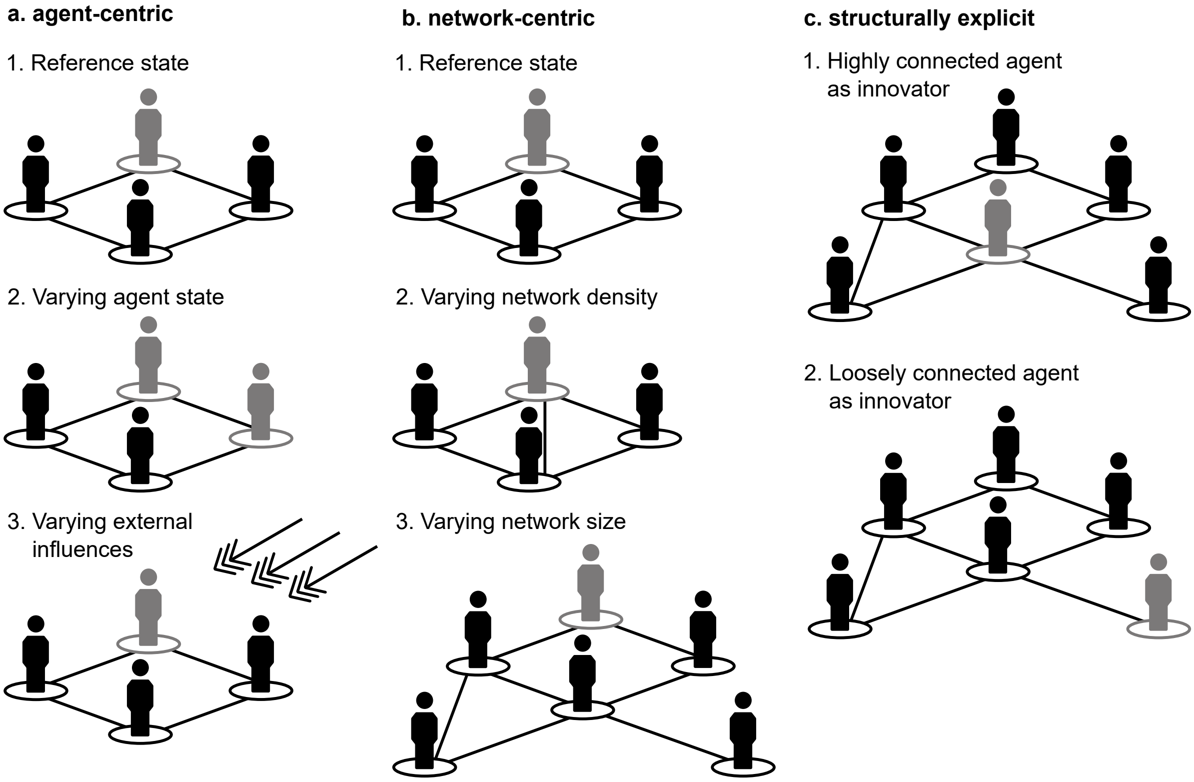


Figure 2.3: Agent-centric analysis, network-centric analysis, and structurally explicit analysis of social networks in agent-based models. **a. Agent-centric analysis:** The network plays an important role in the interaction between agents, but different model outcomes are obtained by varying input parameters that are not related to the network itself, such as agent states (1,2), which here are represented by the agent colours, or external influences such as policies (3). **b. Network-centric analysis:** Agent states are kept constant and the focus is on the impact of modifications at the network level such as varying initial network density (1, 2) or size (3). **c. Structurally explicit analysis:** Model outcomes are assessed not only based on agent or network properties but depend on the location of specific agents in the network. The example shows the initial condition for an innovation to spread (grey colour) for two different scenarios: highly connected agent as innovator (1) and loosely connected agent as innovator (2).

increasing emphasis on structural characteristics: (i) agent-centric, (ii) network-centric, and (iii) structurally explicit analysis. Figure 2.3 illustrates all three types of analysis exemplarily. These distinctions mainly apply to exogenously imposed and co-evolutionary networks, since the analysis of models dealing with endogenous network formation is always network-centric. However, driving mechanisms behind endogenous network formation can be classified similarly.

2.3.3.1 Agent-centric analysis

Topics that require agent-centric analysis cover cases where the network plays an important role in the interaction between agents, but the effect of its structure on model results does not need to be explicitly addressed. Figure 2.3a shows a stylized representation of the initial state of a diffusive system. Input parameters that are not related to the network itself, such as agent states, e.g. the number of black and grey agents, or external influences, e.g. policies, can have effects on the outcome, i.e. how many agents are of grey state at the end of the simulation. Examples from the literature include the comparison of agent properties like variable adoption thresholds (Bohlmann et al., 2010) or group identification of agents (Frank et al., 2018), or the inclusion of external influences such as policies accompanying the introduction of new products (Amini et al., 2012; Negahban & Smith, 2018), influencing risk prevention of individuals (Erdlenbruch & Bonte, 2018), mitigating influenza pandemics (Davey et al., 2008; Perlroth et al., 2010) or encouraging the transformation towards sustainable behaviour (Kaufmann et al., 2009; Zhang & Nuttall, 2011; Rasoulkhani et al., 2018; Wang et al., 2018).

2.3.3.2 Network-centric analysis

Network-centric analysis, on the other hand, is applicable for questions where agent properties can be kept constant and the focus is on the impact of modifications on the network level. This can be induced by varying link properties or global network measures (such as density or size, see stylized example in Figure 2.3b) or by a comparison of different network topologies. In contrast to modifications at the agent level, these changes affect the network as a whole. Global network measures map network properties to a single value (Araújo & Banisch, 2016), thus modifying them also changes the entire network. SNA provides several metrics at this level such as network density (Kaufmann et al., 2009; Chica et al., 2018; Growiec et al., 2018; Phan & Godes, 2018) and size (Janssen & Jager, 2001; Ke et al., 2008; Chen et al., 2012; Laifa et al., 2018) or the rewiring probability in small-world networks (Janssen & Jager, 2001; Janssen & Jager, 2003; Bohlmann et al., 2010; Baggio & Hillis, 2018). In addition, the global clustering coefficient, network diameter and average path length fall under this category. For the comparison of network topologies, model outcomes emerge based on different network structures such as scale-free, small-world or regular networks (Janssen & Jager, 2003; Ke et al., 2008; Lu et al., 2009; Bohlmann et al., 2010; Huétink et al., 2010; Fu et al., 2011; Bravo et al., 2012; Chen et al., 2012; Chica et al., 2018; Erdlenbruch & Bonte, 2018; Hadzibeganovic et al., 2018; Heinrich, 2018; Keijzer et al., 2018; Moglia et al., 2018; Negahban & Smith, 2018; Rasoulkhani et al., 2018; Schlaile et al., 2018). Changes in link properties include strength (Goldenberg et al., 2007) and direction of social interaction (Flache & Macy, 2011).

2.3.3.3 Structurally explicit analysis

Both agent- and network-centric analysis methods capture the network as a way to connect agents, but do not address its internal characteristics. The third approach, a structurally explicit analysis, allows a shift to a more causal relation between agents and network structure (Bodin et al., 2011). Here, SNA is applied at the local level to determine the association between the state of the agents and their location in the network. This approach goes beyond the mere combination of agent- and network-centric analysis. The network is not evaluated separately, but directly associated with the properties of agents. Network metrics that can be considered from this perspective are for example degree distribution, local clustering and centrality measures. These local network measures provide information about the relative position to other agents, the importance of specific agents or the existence of subgroups. The stylized example in Figure 2.3c shows the initial condition for an innovation to spread for two different scenarios with either a highly or a loosely connected agent as innovator. With insights into the correlation between network and agents, implications of the network structure on human behaviour and vice versa can be sensibly addressed. In comparison to network-centric analysis, this allows a targeted modification of both network and model rules to compare the results of different scenarios. Agents can be selected and manipulated not only according to their properties, but also depending on their position in the network.

An example that underlines this advantage is given in the context of models dealing with diffusion in networks. The position of the seed, i.e. depending on the context the first infected or convinced agents, strongly influences model outcomes, as the number and type of contacts of the selected agents can increase or decrease the dissemination. Although there exists an extensive theoretical background on this aspect in social network sciences (Freeman, 1979; Friedkin, 1991; Borgatti, 2006), we observed that in ABM the choice of specific key players based on network properties is often undervalued. In most models the set of actors from which a diffusion starts to propagate is selected randomly or according to agent-centric properties such as personality. Table 2.2 is based on the few examples among the articles in the literature review where common network measures have been used to determine individuals selected as first adopters of an innovation or technology (Haenlein & Libai, 2013; Libai et al., 2013; Beretta et al., 2018; Hu et al., 2018; Negahban & Smith, 2018).

2.3.3.4 Recommendations

In our evaluation, we observed that the use of agent- and network-centric analysis methods is widespread. However, the application of SNA at the local level to gain insights into the relation between network structure and agent properties is the exception. Examples for specifically targeted selection of first adopters were found only in models in the context of product or technology diffusion (Table 2.2), although this issue is also relevant for the dissemination of knowledge or information in social systems or with respect to epidemic diffusion. The most common approach to assessing model outcomes is to implement various network structures and compare the results under these different assumptions. However, restricting the analysis to a limited set of network metrics that only monitor global properties of networks and omit the full range of SNA at the local level ignores a valuable aspect of the integration of social networks in agent-based models. Depending on the research problem and questions at hand, a structural analysis of the network is not a prerequisite to gain new insights. However, we would like to emphasize the additional benefits of the causal relation between network connections and agent properties and therefore encourage modellers to devote more attention to approach (iii), the structurally explicit analysis.

2.3.4 Condensed classification of models included in the review

Table 2.3 classifies all models evaluated in the review according to the types of analysis and the context of application (see Appendix A.2 for the corresponding references). It is clearly visible that most of the reviewed models focus on agent- or network centric analysis or a combination of both methods. Within the subset of studies we analysed for the review, structurally explicit analysis was found only in models in the context of marketing. Only one of the selected publications managed to combine all three methods: to evaluate the optimal combination of seeding and inventory build-up policies for new products, Negahban & Smith (2018) compared the effect of different strategies of initial dissemination, build-up periods before a product is launched and stylized network structures on adoption rates. In general, this overview provides a good starting point for a transfer of concepts between disciplines, as it facilitates seeing what has been successfully applied in one discipline and what is missing in others. We would like to stress that none of the categories is superior to the others. It is essential to consider the degree of feedback between network structure and agent states and the research questions that the model should address in order to make an informed decision about the appropriate levels of network integration and analysis.

Table 2.2: Overview of common network measures for the selection of seeding scenarios, i.e. depending on the context first infected or convinced agents, with application examples among the articles in the literature review where innovation diffusion is studied with ABM

Network measure	Description	References
Degree	Select agents based on their number of neighbours. Select agents with high degree first.	Haenlein & Libai (2013), Libai et al. (2013), Hu et al. (2018), and Negahban & Smith (2018)
Local clustering coefficient	Select agents based on the number of edges between neighbouring nodes divided by the total number of possible edges between neighbouring nodes. Select agents with low clustering as there is less overlap between the neighbours.	Negahban & Smith (2018)
Closeness centrality (average path length)	Select agents based on the average number of steps to reach any other node in the network. Select agents with the shortest average path length first.	Beretta et al. (2018) and Negahban & Smith (2018)
Betweenness centrality	Select agents based on the number of times they act as a bridge along the shortest path between two other nodes. Select agents with the highest betweenness centrality first.	Beretta et al. (2018)
Eigenvector centrality	Select agents based on the centrality of their neighbours. The eigenvector centrality is higher the more central the neighbouring agents are. Select agents with the highest eigenvector centrality first.	Beretta et al. (2018)

Table 2.3: Classification of models included in the review. The studies are distinguished according to the types of analysis (agent-centric, network-centric and structurally explicit), the network integration (endogenous, exogenous and co-evolutionary), and the context in which the model is applied (epidemiology/public health, marketing and social dynamics). Models in the context of social integration are written in italics; all other models deal with diffusion processes.

Analysis			Network integration			Context		
Agent-centric	**Network-centric**	**Structurally explicit**	**Endogenous**	**Exogenous**	**Co-evolutionary**	**Epidemiology/Public Health**	**Marketing**	**Social dynamics**
✓				✓		Davey et al. (2008), Perlroth et al. (2010), and Hornbeck et al. (2012)	Zhang & Nuttall (2011), Amini et al. (2012), Chareunsy (2018), Niamir et al. (2018), Talebian & Mishra (2018), and Wang et al. (2018)	Biondo et al. (2018), *Garcia et al. (2018)*, *Gore et al. (2018)*, Piedrahita et al. (2018)
✓					✓	Moradianzadeh et al. (2018)		Simão & Todd (2002), Frank et al. (2018), and Lozano et al. (2018), *Son & Rojas (2011)*
	✓			✓			Goldenberg et al. (2007), Huétink et al. (2010), Chen et al. (2012), Heinrich (2018), and Pearce & Slade (2018)	*Bravo et al. (2012)*, Flache & Macy (2011), *Growiec et al. (2018)*, Weng et al. (2012), Keijzer et al. (2018), and Lou-Magnuson & Onnis (2018)
	✓				✓			*Bravo et al. (2012)*, Fu & Hao (2018)
		✓		✓			Libai et al. (2013)	
✓	✓			✓		Fu et al. (2011)	Janssen & Jager (2001), Janssen & Jager (2003), Kaufmann et al. (2009), Bohlmann et al. (2010), Baggio & Hillis (2018), Erdlenbruch & Bonte (2018), Moglia et al. (2018), and Rasoulkhani et al. (2018)	Ke et al. (2008), Lu et al. (2009), Chica et al. (2018), and Schlaile et al. (2018)
✓	✓				✓		Phan & Godes (2018)	*Hadzibeganovic et al. (2018)*, *Laifa et al. (2018)*
✓		✓		✓			Hu et al. (2018)	
	✓	✓		✓			Haenlein & Libai (2013) and Beretta et al. (2018)	
✓	✓	✓		✓			Negahban & Smith (2018)	
			✓			Fetta et al. (2018)		Neal & Neal (2014) and Zhuge et al. (2018)

2.4 Conceptualization and documentation of social networks in agent-based models

When implementing social networks in agent-based models, several decisions have to be made about the structure and character of the network and the interaction of agents on it. As these choices decisively influence the model outcome, model conceptualization and documentation are crucial to make the modelling process transparent and reproducible. However, on the basis of our literature review, we observed, on the one hand, that the reasoning behind the choice of certain network topologies and network properties is often based on ad hoc assumptions, not on insights from the broad field of social network research. On the other hand, the model and in particular the network and the interactions on it are often not sufficiently documented. Similar aspects have been criticized in reviews with regard to the operationalization of decision making in agent-based models (Crooks et al., 2008; Kiesling et al., 2012; Müller et al., 2013; Flache et al., 2017; Groeneveld et al., 2017; Janssen, 2017). We build on the solutions to overcome the problems proposed in these studies and focus on (i) incorporating theoretical and empirical insights in the process of model conceptualization and (ii) guidelines as a basis for comprehensive and clearly structured model set-up and evaluation.

2.4.1 Incorporating theoretical and empirical insights

Modelling precisely how agents are linked is an essential task when integrating social networks in ABM (Amblard et al., 2015; Klabunde & Willekens, 2016). Inspired by empirical studies, a multitude of theoretical network topologies have been developed that allow an informed decision on the choice of suitable networks and their characteristics (Newman, 2003). Because of the variety of options available, the reasoning behind each choice of topology is particularly important (Cointet & Roth, 2007; Zacharias et al., 2008; Amblard et al., 2015). A thorough analysis of the impact of the underlying topology on the model outcome, which can then be tested with ABM, is required. Only when these considerations are made in advance, a meaningful conclusion can be drawn from the results. Additionally, hypotheses about the behaviour of humans in networks such as homophily (i.e. the tendency to form links with similar others), reciprocity (i.e. the number of reciprocated ties of an actor) or transitivity (i.e. friends of friends become friends), which can be drawn from empirical studies, should be integrated in the process of model design (Snijders et al., 2010). The inclusion of knowledge from empirical network research in the decision making of agents on the network is necessary to enable an adequate representation of the co-evolution of networks and behaviour.

2.4.2 Guidelines for model set-up and evaluation

Hand in hand with a sound justification of decisions made for the model conceptualization goes a precise documentation of the model (Grimm et al., 2006; Schmolke et al., 2010; Rand & Rust, 2011). The choice of a particular network model and the corresponding properties for the interaction of agents need to be substantiated in the model documentation to ensure comprehensibility, comparability and replicability of models which highly strengthens the advancement of the method and its use. We summarize the main aspects that need to be considered for agent-based models combined with social networks in guidelines which can easily be integrated in existing standards for the description of agent-based models, such as the ODD protocol (Grimm et al., 2006; Grimm et al., 2010) or its extension concerning the integration of decision making, the ODD+D protocol (Müller et al., 2013). Following the categories of these formats, networks can, for example, be listed as state variables and referred to when specifying the design concepts "Interactions" and "Collectives". Our proposed guidelines are divided into three main categories: network definition, dynamics of the network, and dynamics on the network. The first section covers different aspects of complexity concerning the set-up of nodes and links and network initialization. The two remaining sections focus on the co-evolution of networks and agents and comprise dynamics of and on the network (Gross & Blasius, 2008). Dynamics of the network cover the network itself as a dynamic system that changes according to specific rules. This section introduces the rules to be described when modifying the topology. Dynamics on the network deal with the dynamically changing state of each node, and comprise the conditions for interactions between agents, the interaction direction and the choice of interaction partners as well as the state transition of the agents and are thus only relevant for exogenously imposed and co-evolutionary networks.

The guidelines with the main principles that need to be considered for model set-up and documentation are presented in Box 2.1. Modellers intending to design a model with endogenously emerging networks need to focus specifically on the section on the dynamics of the network. For models with exogenously imposed networks, the section on the dynamics on the networks is most applicable. In models with co-evolutionary networks, all sections must be considered. Careful reflection and justification of all relevant aspects of the guidelines during the model building process provides a solid foundation for analysis. The guidelines ensure that all variables that can be investigated with an agent- or network-centric sensitivity analysis are properly introduced. In addition, it is particularly useful when local network metrics are evaluated in a structurally explicit analysis.

Box 2.1: Guidelines for improved model set-up and documentation

i. **Network definition**

a. **Nodes**

Level of aggregation: *What is represented by an agent (c.f. "Collectives" in ODD design concepts)?*
The chosen subdivision that represents interacting partners has crucial influence on the network (Levin, 1992). Subdivisions depend on the level of decision making or action and the required level of accuracy but are limited by computational power (number of interacting agents grows fast if low level of aggregation is chosen). Possible subdivisions are:

- **Individual agents:** used in situations where the personal context is relevant (e.g. epidemics, opinion formation)
- **Households:** aggregated behaviour of family members or relevant decisions made by household head (e.g. land-use context: farmers, energy consumption: data availability on household level)
- **Firms:** similar to households but no relation to family (e.g. marketing: product diffusion can be either on individual or on firm level)
- **Higher level of aggregation** possible (e.g. regions, countries)

Typology of agents: *Which entities are grouped together and treated in a similar manner?*

Within the levels of aggregation, agents are grouped according to their attributes to allow generalizations of individual actors (Arneth et al., 2014). This includes classification on the same organisational level with same (e.g. green vs. conventional farmers, early vs. late adopters) and different functions (e.g. buyers vs. sellers) or across hierarchical organisational scales (e.g. land users vs. government).

b. Links

Reciprocity: *Are the links directed or undirected?*
Some problems need reciprocal links, some can deal with both but are probably more realistic with either directed or undirected links (opinion diffusion sometimes modelled in directed networks, sometimes in undirected), some need directed links (e.g. material transfer often only in one direction).

Weight: *Do the links include weighted relationships and preferences?*
Link strength allows including weighted relationships and preferences among neighbours. Link strength can be discrete (e.g. strong/weak) or continuous (assigning relative or absolute weights to links) and can be determined by the number of common contacts or emotional intensity such as trust or similarity of opinions.

c. Initialization

Initial condition: *Which links are present as initial conditions?*
The network formation can **start from scratch** with no links between the nodes established at the beginning of the simulation or with links set up according to a **specified topology**.

Network topology: *How are initial links motivated?*
If links are set up according to a specified topology, initial network topologies can be calibrated with **empirical data** or with **idealized topologies** (e.g. random, small-world or scale-free).

ii. Dynamics of the network

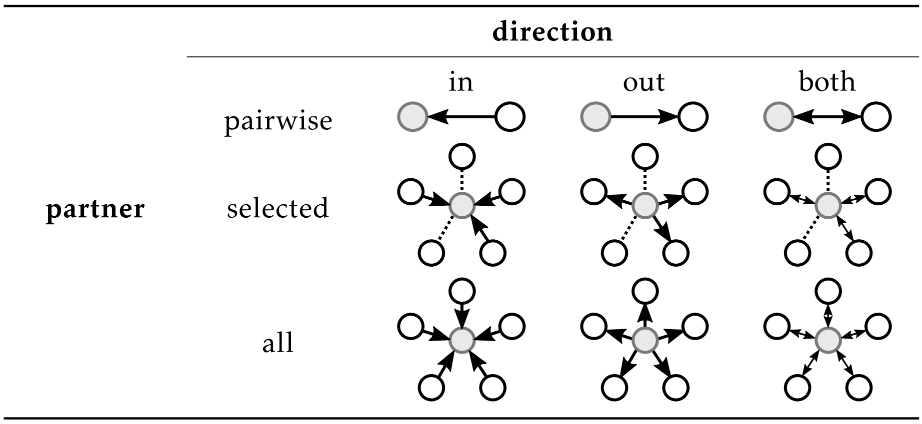
Link formation: *Why are links formed between agents?*
The formation of links between agents can be based on **agent properties** (e.g. spatial proximity or similarity), **probability**, **utility maximization**, etc.

Network size: *Does the number of nodes in the network vary during the simulation?*
Network size can be **static** if the network consists of the same nodes over the whole simulation or **dynamic** if the nodes vanish or appear during the simulation (e.g. due to extinction and reproduction processes or migration).

iii. Dynamics on the network

Condition for interaction: *When do agents interact?*
In some contexts, interaction takes place **independent of the network**. Thus, no condition on the interaction is needed (e.g. if influence of social norms is always present). Alternatively, a **threshold** (e.g. number of neighbours, fraction of neighbours, distance (spatially or between opinions), properties of neighbours etc.) has to be reached before the agents interact (Granovetter, 1978).

Interaction direction and partners: *Who do agents interact with?*
The **interaction direction** has a large effect on the dynamics on the network as it influences the direction of causality and therefore the relevance of the positions of the agents. The acting agent can either be influenced by the agents in its network ("in", unidirectional) or influence other agents it has links to ("out", unidirectional). Additionally, both agents can change their status based on the interaction ("both", bidirectional). The acting agent can either pick one ("pairwise"), several ("selected") or all other agents of its network as **interaction partners**.



Agent state transition: *How do agents change their status?*
Change of agent state is influenced by processes like e.g. **imitation or averaging** or based on **probability, distance, utility**, etc. The representation of agent state (i.e. behaviour, opinion, health condition etc.) is possible either as **continuous traits** (e.g. opinions) or **distinct nominal categories** (e.g. product adoption levels, epidemics). Change of agent state is possible either in **one way** only (e.g. adoption of an innovation: once somebody has adopted a product he will never come back to the non-adopted state; opinion dynamics: models of assimilative social influence (Flache et al., 2017)) or in **two or more ways** (e.g. opinion dynamics: models with repulsive influence, opinions can be influenced positively or negatively (Jager & Amblard, 2005; Flache et al., 2017); epidemiology: agents can get infected but also recover from a disease).

2.5 Conclusion

In this review, we analysed studies in the field of ABM and social networks with a focus on the conditions for sound implementation and evaluation. We stressed that ABM in combination with social networks is a promising approach to address the behaviour of interacting individuals. However, we also indicated that there is room for improvement and offered ways to overcome the deficits. Explicitly, we encourage modellers to improve the integration of the two methods with respect to three main aspects: (1) to not only focus on the network as channels for transfer of material or non-material resources, but also design models where the network provides social integration, such that an agent's network position allows for certain achievements, success or power; (2) to carefully determine the appropriate approach for the integration of social networks in ABM, being it endogenously emerging, exogenously imposed or co-evolutionary, according to the research question at hand, the availability of data but also the relevant time scales of network and agent dynamics; and (3) to devote attention to structurally explicit analysis of the model, i.e. to use local network metrics to gain insights into causal relations between network connections and agent properties.

In addition to these recommendations, we would like to point out that the integration of social networks in agent-based models highly benefits from interdisciplinary exchange. The core themes for the use of networks are similar in different contexts, regardless of the concrete problem they are applied to. Our cross-disciplinary review provides a starting point for this exchange, but is not intended to give a comprehensive overview of all possible realizations. Further efforts are needed to bring together the achievements in different areas and to lower disciplinary barriers that currently hinder a broader transfer of concepts. A systematic documentation of the model conceptualization, as supported by the guidelines, would facilitate this goal by allowing an efficient way of comparing models and their analyses. Additionally, as in many areas of ABM, also with regard to social networks in agent-based models the inclusion of empirical data is a crucial issue (Grimm et al., 2005; Laatabi et al., 2018). For this purpose, the approach of stochastic actor-oriented models is worth to consider. This statistical method is similar to agent-based models in the property to include local rules for actor behaviour and is an established tool for the analysis of longitudinal network data (Snijders et al., 2010; Snijders & Steglich, 2015). ABM has, however, more opportunities to include environmental constraints and heterogeneity among agents (Bruch & Atwell, 2015). Calibration of network initialization and validation of model outcomes with empirical data are therefore crucial next steps to fully exploit the potential of ABM.

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3 Informal risk-sharing between smallholders may be threatened by formal insurance: Lessons from a stylized agent-based model

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Abstract

Microinsurance is promoted as a valuable instrument for low-income households to buffer financial losses due to health or climate-related risks. However, apart from direct positive effects, such formal insurance schemes can have unintended side effects when insured households lower their contribution to traditional informal arrangements where risk is shared through private monetary support. Using a stylized agent-based model, we assess impacts of microinsurance on the resilience of those smallholders in a social network who cannot afford this financial instrument. We explicitly include the decision behavior regarding informal transfers. We find that the introduction of formal insurance can have negative side effects even if insured households are willing to contribute to informal risk arrangements. However, when many households are simultaneously affected by a shock, e.g. by droughts or floods, formal insurance is a valuable addition to informal risk-sharing. By explicitly taking into account long-term effects of short-term transfer decisions, our study allows to complement existing empirical research. The model results underline that new insurance programs have to be developed in close alignment with established risk-coping instruments. Only then can they be effective without weakening functioning aspects of informal risk management, which could lead to increased poverty.

3.1 Introduction

Within its Sustainable Development Goals, the United Nations has identified the eradication of poverty as one of the most important goals that humanity should meet by 2030 (UN, 2015). An essential contribution to achieving this target is to ensure that vulnerable households are effectively protected against extreme climate-related events and other economic, social and ecological shocks and disasters (Wanczeck et al., 2017). Traditionally, households in rural communities across the world manage to cope with such threats through informal arrangements (Platteau et al., 2017; Cronk et al., 2019a). These risk-sharing networks buffer income shocks by an exchange of money, labor or in-kind goods between households in need and those with the capacity to help. Various forms of such informal networks exist. In Ethiopia, for example, group-based support arrangements with often hundreds of members, so-called *iddirs*, offer informal insurance to compensate costs for funerals, medical expenses or food shortage against the payment of a premium (Aredo, 2010; Dercon et al., 2014; Abay et al., 2018). Similarly, in Burkina Faso, individuals linked by neighborship, religious confession or shared ethnic affiliation arrange in *tontines* and make monetary contributions to a common fund from which risk-sharing is financed (Sommerfeld et al., 2002). Among the Maasai, the bilateral gift-giving concept *osotua* is established where, based on reciprocity, households exchange livestock or other goods when in need (Cronk, 2007). However, when the whole risk-sharing network is affected by a large-scale extreme event such that many households suffer substantial losses simultaneously, private transfers can no longer provide buffering (Barrett, 2011; Wossen et al., 2016). Droughts or floods, which both are expected to increase under climate change (Sheffield & Wood, 2008; Dai, 2013; Thornton et al., 2014; Tabari, 2020), are an example of such shocks. Insurance products specifically designed for the needs of low-income households in developing countries, known as microinsurance or inclusive insurance, are seen as an effective tool to address these challenges and are therefore highly promoted and supported by governments in recent years. Current programs to help vulnerable countries, particularly in the southern hemisphere, include the G7 'InsuResilience' initiative launched in 2015 (GIZ, 2015) or the Global Index Insurance Facility managed by the World Bank Group (GIIF, 2019).

However, apart from direct positive effects, the introduction of formal insurance in communities where informal risk-coping instruments exist may have unintended side effects (Müller et al., 2017). In lab-in-the-field experiments and household surveys covering different cultural contexts and insurance products, evidence has been found that formal insurance can crowd-out informal risk-sharing arrangements (Landmann et al., 2012; Lin et al., 2014; Geng et al., 2018; Strupat & Klohn, 2018; Anderberg & Morsink, 2020; Lenel & Steiner, 2020).

It was shown that households reduce their willingness to provide informal support if they themselves do not need any other risk coverage apart from insurance. In the case of index insurance in Ethiopia, the results of household surveys suggest, conversely, that the availability of insurance could encourage informal transfers, as insured households are better able to help (Takahashi et al., 2018; Matsuda et al., 2019). Theoretical models show, on the one hand, that the introduction of insurance can lead to a decline in welfare due to reduced private transfers (Attanasio & Ríos-Rull, 2000; Boucher & Delpierre, 2014), but also that informal safety nets and microinsurance can complement each other in the presence of basis risk – the potential mismatch between actual losses and received insurance payouts (Mobarak & Rosenzweig, 2012; Dercon et al., 2014).

This broad range of studies underlines the different implications that the introduction of formal insurance can have on people's behavior towards informal transfers. However, long-term effects of these changes on the resilience of low-income households, particularly through a direct comparison of the various potential behavioral responses to private monetary support, have not yet been investigated. To address this gap, we develop an agent-based model that considers smallholders in a social network and captures dynamics between income losses, insurance payments and informal risk-sharing. We focus our analysis on smallholder farming, a predominant form of rural agriculture in developing countries that is driven by subsistence production. Households practicing this type of agriculture have limited financial means to deal with the multiple risks that affect them individually or hit an entire community. Therefore, they rely on effective mechanisms to cope with risk (Morton, 2007). By using an agent-based modelling approach, we exploit several advantages compared to empirical and theoretical methods already applied in studies on formal and informal insurance. First, insights can be gained independently of the specific local context and where empirical data is lacking (Squazzoni et al., 2014; Bruch & Atwell, 2015). In contrast to household surveys or behavioral games that cover only short time spans limited to specific regions, a model can represent conditions from several regions with different risk contexts independent of a particular case study. Second, agent-based models allow us to include complex strategies of human decision making (An, 2012; Schulze et al., 2017) that go beyond economic rationales implemented in existing theoretical models on formal and informal insurance. In particular, it is possible to integrate that households differ in their behavior as they adapt their decisions to individual characteristics and influences from their environment (Bonabeau, 2002). Third, with our model we can analyze the implications of transfer behavior of households linked to several others in a network. In most theoretical models, it is assumed that households interact only bilaterally or that all households in a community are connected. However, when households have a limited number of neighbors that they can request for help, this can give crucial information on how effective monetary transfers can be. In the context of informal risk-sharing, agent-based modelling has already helped to assess whether traditional gift-giving relationships increase the viability of pastoralists' herds (Aktipis et al., 2011; Aktipis et al., 2016) and how spatial and temporal correlations of shock events impact the resilience of households (Hao et al., 2015). Furthermore, agent-based models have been used to analyze the ecological effects of formal insurance on rangeland management and pasture conditions (Müller et al., 2011; John et al., 2019).

With our study, we contribute to that research strain by evaluating impacts of the combination of formal and informal risk-sharing mechanisms. The main objective of our model is to reveal unintended social consequences of insurance programs when households additionally help each other informally when in need. Specifically, we analyze whether and how economic needs of households (i.e. level of living costs) and characteristics of extreme events (i.e. frequency, intensity and type of shock) influence the ability of formal insurance and informal risk-sharing to buffer income losses. We assume that households are connected in a social network and can request money from their neighbors when their financial resources are not sufficient to sustain themselves. We explicitly distinguish two types of behavior with regard to monetary transfers that are based on observations from empirical studies. First, we assume that all households provide financial resources whenever they are requested and can afford to (solidarity). Second, we simulate scenarios where only uninsured households show solidarity and insured households do not transfer (no solidarity). With its stylized characterization of transfer behavior and budget dynamics, our modelling approach provides a qualitative understanding of when formal insurance complements existing risk mitigation tools and when potentially reduced support from insured households has harmful consequences for the resilience of smallholders. On the basis of a systematic analysis of external conditions and human behavior, we highlight aspects that are necessary for effective insurance design to prevent a degradation of functioning aspects of informal risk management and thus avoid an increase in poverty.

3.2 Methods

3.2.1 Model description

The model is not used to analyze a particular case study, but represents conditions from several regions with different risk contexts where informal support networks between smallholder farmers are prevalent. We simulate $N_{\mathrm{H}} = 50$ households which roughly corresponds with empirical observations of traditional support arrangements (Sommerfeld et al., 2002; Aredo, 2010; Dercon et al., 2014). Each agent H_i, $i = 1,...,N_{\mathrm{H}}$, represents a smallholder household and is characterized by its budget Y_i. Households are endowed with an initial budget Y^0. They generate a regular yearly income I and have to spend an amount C to cover annual living costs. The population is homogeneous with all households having the same initial budget, income level and annual living costs. Income shocks reduce the budget of a household by an amount S if the household is affected. We distinguish unexpected events which are either idiosyncratic, hitting the households independently (such as illness), or covariate, affecting many households at the same time (such as droughts or floods). Only one shock type is considered per simulation run. Idiosyncratic shocks occur with a probability p_s for each household. For covariate shocks, the chance of a shock at village level is p_V. If such a shock occurs, households are hit with probability p_H. Households that are not affected in this case might, for example, have a more favorable geographical location in case of floods or an agricultural management strategy more adapted to drought risks. Overall, this results in a shock probability $p_\mathrm{s} = p_\mathrm{V} \times p_\mathrm{H}$ for an individual household.

To smooth income shocks households can engage in informal safety nets. Households are connected in an undirected network on which they can request money from and donate money to other households. The network is imposed during the initialization of the model and is kept constant (i.e. static) for a simulation run. We have implemented small-world networks using the Watts-Strogatz model (Watts & Strogatz, 1998). This algorithm creates a regular ring network with each household connected to $N_\mathrm{N}/2$ neighbors on either side and each link rewired with probability p_r.

Some households have access to formal insurance schemes. Why households decide to insure is currently a highly explored topic. Next to purely economic aspects, social and cultural influences such as risk aversion and influence from peers or personal and demographic factors such as age and gender are also considered being important (Eling et al., 2014; Platteau et al., 2017). Explicitly including reasons behind the decision to insure is therefore out of the scope of this paper. Hence, we assume that a fixed proportion γ of households is informed about insurance and choose to buy it. Insurance status is then randomly assigned to households at the beginning of the simulation and is kept throughout the simulated period. Insured households insure their complete income. We model indemnity insurance that covers the actual losses a household suffers from. The payout α in case of a shock is $\alpha = S$. The yearly premium β, which insured households have to pay, is actuarially fair and thus equals the expected loss given the shock probability p_s and the shock intensity S and reads $\beta = p_\mathrm{s} \times S$.

Each household's objective is to maintain prosperity with a budget above or equal to zero. Households whose budget is below this threshold may receive transfers from households with whom they share a link in the network that are rich enough to help others, i.e. that have a budget above zero. The household randomly picks one of its neighbors and requests transfers. If the request cannot be fulfilled by one single agent, households continue requesting the missing amount from other agents in their network. We explicitly distinguish two types of transfer behavior: solidarity and no solidarity. For simplicity, in one simulation run all households decide on their transfers according to the same strategy. When households show solidarity, they transfer whenever they can afford it. This implies that households may assume that the requesting household will return the transfer in the future if they need support themselves. Since, in the simulated scenarios, insurance covers all losses, this will only occur for uninsured households. It is incorporated that donors do not put themselves at financial risk through transfers. Therefore, it is ensured that the minimum budget of a donor after a transfer is zero. On the other hand, the household in need should not get too rich through the help of others. The maximum achievable budget through support of other households is thus also zero. For the second type of transfers (no solidarity), only uninsured households show solidarity and contribute to informal risk-sharing whenever they can afford it; insured households do not transfer at all. Here, we assume that insured households refuse contribution as they are not dependent on reciprocal behavior of others.

We assume that if households do not manage to reach the poverty threshold either on their own or with the support of their neighbors, they must leave the system. This implicitly includes that households that cannot cover their living costs may migrate to other regions where they expect to strengthen their resilience to shocks through improved economic, environmental or social conditions(Black et al., 2011; Neumann & Hermans, 2017) but neglects that households may have other sources of support from outside the village that they could use to cover their losses (Adams & Page, 2005; Giuliano & Ruiz-Arranz, 2009). We condense the capacity of households to cope with income shocks in a 'survival rate' that indicates the fraction of households that manages to maintain a budget above zero over the simulated time span.

In order to make our observations comparable between scenarios with varying number of insured households, we present the results always for the same subgroup of households. When referring to uninsured households, we determined the reference group by all households that are uninsured in the case with the highest insurance rate ($N_{\mathrm{H}} = 20$, $\gamma = 60\,\%$). We ensured that these households are uninsured in every other scenario. The shock exposure, network relationships and transfer requests of this reference group is the same for each repetition of the simulation run regardless of the specific scenario. When presenting results for insured households, we refer to those households that are insured in the scenario with lowest insurance rate ($N_{\mathrm{H}} = 15$, $\gamma = 30\,\%$). These households are insured in every scenario (except $\gamma = 0\,\%$).

The model uses discrete annual time steps and a long-term perspective of $T = 50$ years is assumed. For each setting, we have carried out 100 repetitions. A detailed model description in a structured form based on the ODD+D protocol (Müller et al., 2013) can be found in Appendix B.1. The model is implemented in NetLogo and available to download at CoMSES Net (Will et al., 2021c).

3.2.2 Parameter selection

We calculate the expected value of budget change per time step to select parameter combinations for living costs C, shock probability p_{s} and shock intensity S in a range where formal and informal insurance can both be used effectively. This implies (1) that the shock intensity should be high enough to make financial protection necessary and (2) that formal insurance should be affordable. Additionally to the mathematical restrictions, we constrain the parameters with respect to ecological and economic observations. We divide all parameter ranges in equidistant steps of 0.1, which results in 52 reasonable parameter combinations that meet the constraints. A more detailed description of the selection procedure can be found in Appendix B.2.

3.3 Results

3.3.1 Effectiveness of risk-coping instruments over time

To illustrate the effectiveness of different risk-coping instruments, we present simulation runs over 50 years for one specific parameter combination of income I, living costs C, shock probability p_s and shock intensity S ($I = 1$, $C = 0.8$, $p_s = 0.3$, $S = 0.6$; I is normalized to 1, C and S are unitless and related to I). We consider idiosyncratic shocks and analyze the results for a small-world risk-sharing network with rewiring probability $p_r = 0.2$ and an average number of four neighbors ($N_N = 4$). Results for a more random network ($p_r = 0.8$) and more ($N_N = 8$) or less ($N_N = 2$) neighbors can be found in Appendix B.3. Our analysis covers different risk-coping scenarios depending on the availability of insurance and informal transfers and the transfer decision of insured households. We assume three main types of transfer behavior: (1) no informal transfer, (2) all households show solidarity and (3) only uninsured households show solidarity. Additionally, we distinguish three levels of insurance rates γ all households are uninsured ($\gamma = 0\%$), a small part ($\gamma = 30\%$) and a large part ($\gamma = 60\%$) of households is insured.

When considering the fraction of surviving households for different risk-coping instruments and insurance rates (Figure 3.1), we observe that informal transfers, independent of the transfer decision, have a positive impact on the survival rates. To disentangle the effects of insurance and decisions behind informal transfers, we have separately investigated the survival rates for uninsured households. In order to make our observations comparable between scenarios with varying number of insured households, we present the results always for the same subgroup of households. The survival rate of uninsured households is lower when insurance is available than when households cover their risks only through informal risk-sharing (Figure 3.2). For the selected external conditions, the introduction of insurance thus has negative effects for uninsured households. Even if insured households maintain showing solidarity, the introduction of insurance diminishes the survival rate of uninsured households: Shortly after the introduction the same number of uninsured households has to leave the system as if insured households refuse to contribute to informal transfers. Only in the long run, solidarity of insured households has a positive effect on uninsured households.

This can be explained by the total transfer that the selected uninsured households have given and received per time step (Figure 3.3). When more households cover their risks with formal insurance, less households need to request informal transfers. For these circumstances, our model results indicate that the transfer amount is lower when insurance rates are higher. However, the selected households receive less transfers also due to the lower contributions by insured households (Figure 3.3A). In the first time step, the transfer demand of the selected households is equal regardless of the scenario (not shown here). Each uninsured household affected by a shock needs support. However, even if insured households were in general willing to help, the total transfer was lower than in the case without insurance. From this it can be concluded that insured households did not contribute as much as uninsured households. Due to the premium payments, which lower their available budget, their ability to help through informal transfers is weakened. Especially shortly after the introduction of insurance, where insured households have not benefited much from refunded losses, this reduces the number of surviving uninsured households. Furthermore, we can see that, if insured households do not show solidarity, the side effects of the introduction of insurance is even worse. Not only do uninsured households receive less, they also have to transfer more compared to when

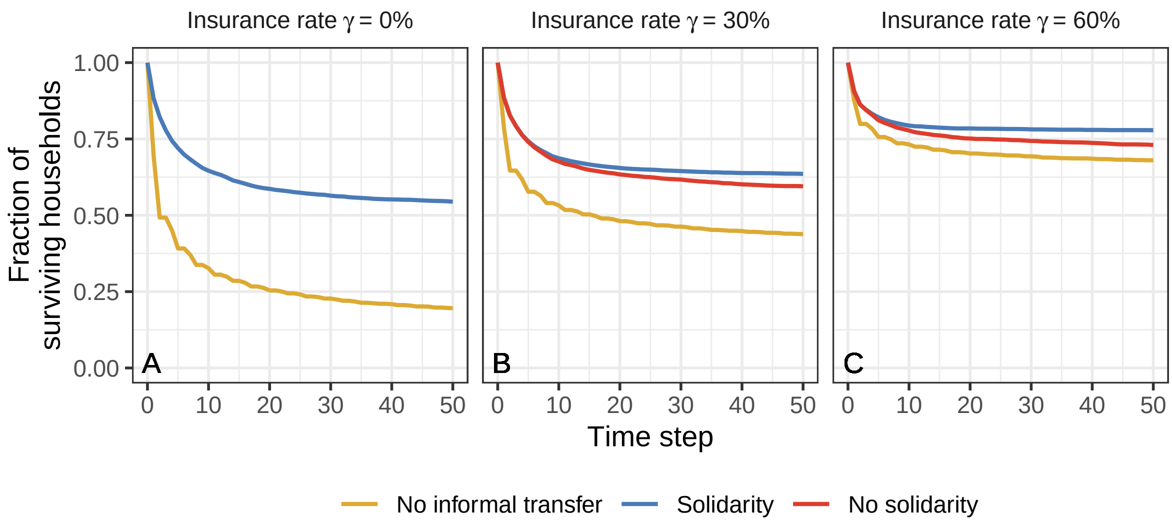

Figure 3.1: Fraction of surviving households for different risk-coping instruments and insurance rates γ (A – 0 %, B – 30 %, C – 60 %). Results show the mean over 100 repetitions for a selected parameter combination of income I, living costs C, shock probability p_s and shock intensity S ($I = 1$, $C = 0.8$, $p_s = 0.3$, $S = 0.6$).

insured households contribute as well (Figure 3.3B). This is particularly evident for high insurance rates. If transfers are only provided by households that are themselves vulnerable to transfers, this in the end lowers their own ability to cope with future losses and leads to even lower survival rates.

Resilience to shocks, i.e. the ability to recover from losses, is manifested not only in whether households survive at all but also in the amount of their financial resources. By comparing the budgets of the surviving insured and uninsured households separately (Figure 3.4), we can observe financial consequences of insurance and informal transfers. This may help to understand reasons for the empirically observed transfer decisions of insured households. Comparing the budgets of the surviving households underlines that individual uninsured households manage to obtain substantially higher budgets than insured households (Figure 3.4A). However, especially in the scenario without informal transfers, this applies only to a small fraction of households and can therefore not be seen as a sustainable strategy to ensure that budgets are resilient to shocks. Additionally, since the transfers are not repaid, these gains are at the expense of the insured households that show solidarity, which end up with a budget that is lower than what they could have received without helping households in need (Figure 3.4B).

For all outcome measures, we observe differences between the scenarios with and without solidarity of insured households. As showing no solidarity de facto reduces the links of the network that embeds the uninsured households, this indicates the importance of the number of neighbors. To investigate the relevance of the network structure more systematically, we present the same outcome measures for a small-world network with more ($N_N = 8$) or less ($N_N = 2$) neighbors in Appendix B.3. Overall, these results confirm our hypothesis and underline that a network with more interactions leads to higher resilience of uninsured households.

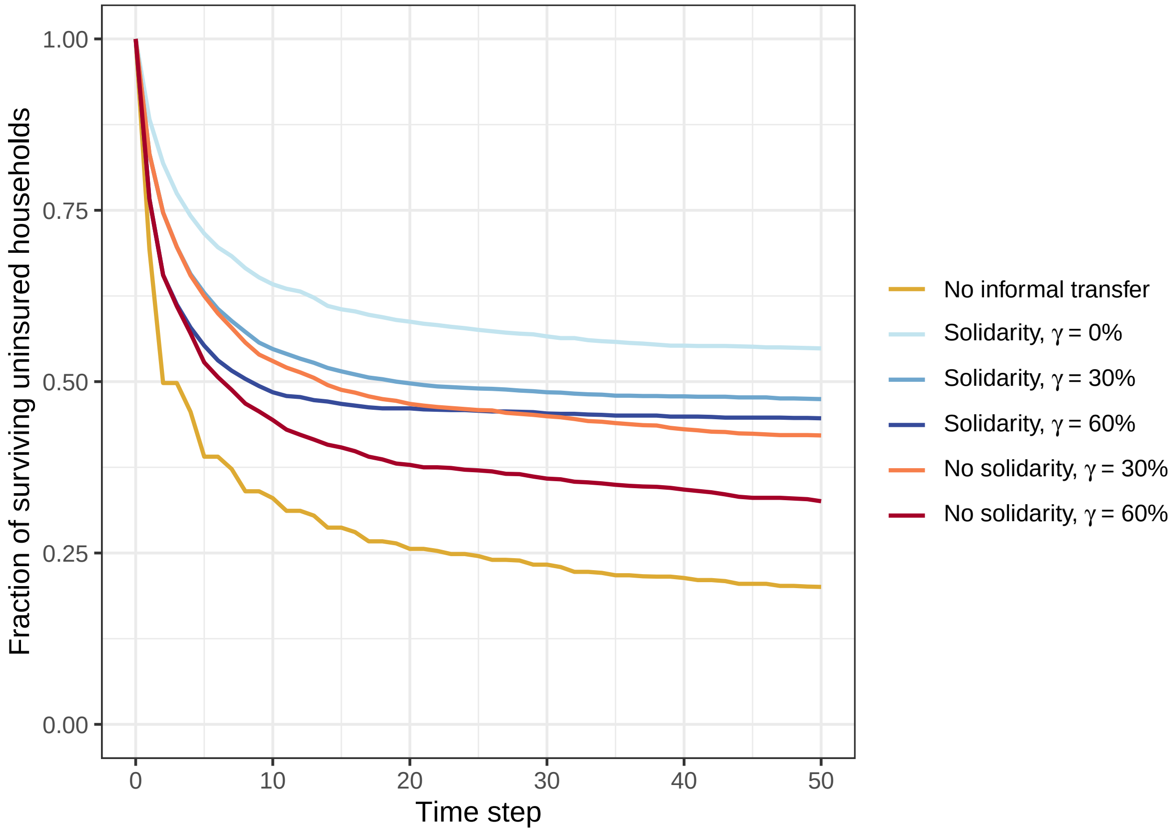

Figure 3.2: Fraction of surviving uninsured households among the 20 households that are uninsured in every scenario for different risk-coping instruments with insurance rates γ. Results show the mean over 100 repetitions for a selected parameter combination of income I, living costs C, shock probability p_s and shock intensity S ($I = 1$, $C = 0.8$, $p_s = 0.3$, $S = 0.6$). Without informal transfers the survival rates are independent of the insurance rates and the resulting curves for different insurance rates would overlap. They are therefore not represented separately.

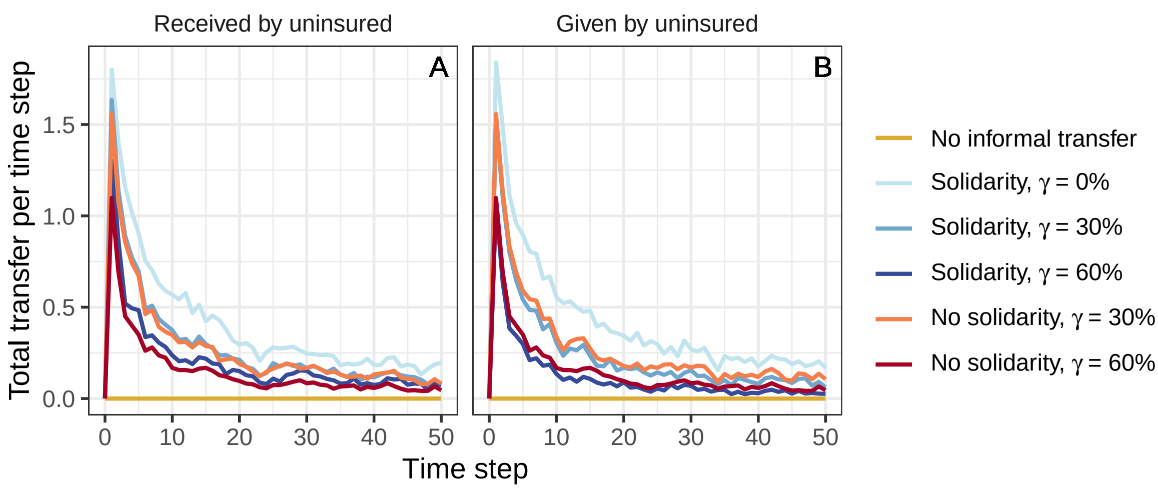

Figure 3.3: Total transfer (A) received and (B) given by all 20 households that are uninsured in every scenario per time step. Results show the mean over 100 repetitions for a selected parameter combination of income I, living costs C, shock probability p_s and shock intensity S ($I = 1$, $C = 0.8$, $p_s = 0.3$, $S = 0.6$).

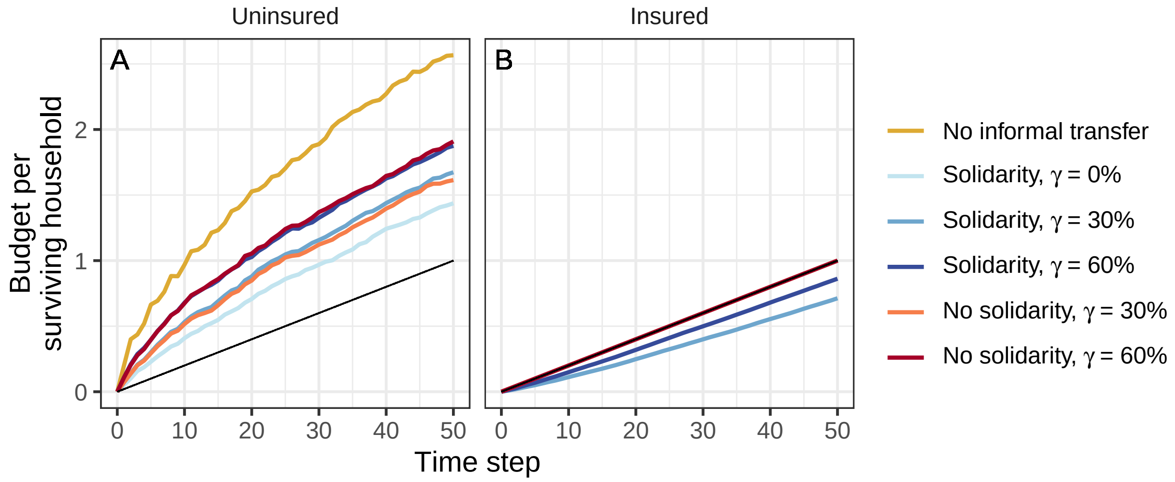

Figure 3.4: Budget per surviving household calculated based on (A) the 20 households that are uninsured in every scenario and (B) the 15 households that are insured in every scenario (except $\gamma = 0\,\%$). The straight line shows the maximum budget that an insured household can receive as reference value. Results show the mean over 100 repetitions for a selected parameter combination of income I, living costs C, shock probability p_s and shock intensity S ($I = 1$, $C = 0.8$, $p_s = 0.3$, $S = 0.6$). Without informal transfers the budget per surviving household is independent of the insurance rates and the resulting curves for different insurance rates would overlap. They are therefore not represented separately.

3.3.2 Effectiveness of risk-coping instruments for different external conditions

So far, we focused on the consideration of an exemplary scenario of external conditions. To investigate the transferability of these observations to a broader range of living costs and increased or decreased shock probability as well as intensity in a systematic way, we analyzed the behavior of the system for all parameter combinations that were found to be economically feasible (see Appendix B.2 for the selection criteria). We compared the effects of 50 years of purely informal transfers ($\gamma = 0\,\%$) on the survival rate of uninsured households to the situation 50 years after the introduction of insurance with low ($\gamma = 30\,\%$) and high ($\gamma = 60\,\%$) insurance rates, respectively. In Figure 3.5, we present the model results for a fixed income ($I = 1$) and a fixed level of living costs ($C = 0.8$). Results for higher and lower annual expenses and different network structures can be found in Appendix B.4. In general, we see that for more severe shocks, i.e. higher shock intensity, less uninsured households survive. For the same external conditions, in many cases the respective survival rate of uninsured households is lower if a fraction of households is insured, even if after the introduction of insurance all households show solidarity and contribute to informal transfers. This is due to the premium payments that lead to missing budget of insured households to help others. For few cases, there is no clear effect of the introduction of insurance with prevailing solidarity. For these external conditions, uninsured households are not harmed by the introduction of insurance but they do not benefit either. If insured households are no longer willing to help uninsured households in need, there is a clear trend that this leads to lower survival rates among uninsured households. In this case, the informal support has to be covered by a smaller subgroup of households that are willing to transfer. This lowers the available budget of these households and might bring more uninsured households to financially critical situations. In addition, especially for high insurance rates, the network of households willing to participate in transfer arrangements is thinned out. Hence, households in need may no longer be connected to households willing to help them.

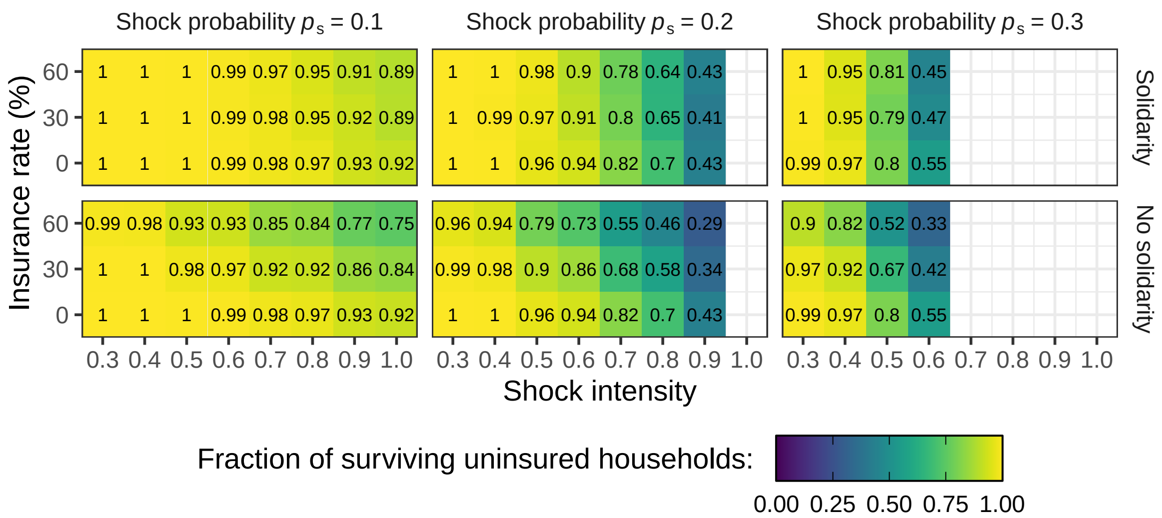

Figure 3.5: Fraction of surviving uninsured households among the 20 households that are uninsured in every scenario depending on insurance rates γ, shock probability p_s and shock intensity S for idiosyncratic shocks with fixed income ($I = 1$) and level of living costs ($C = 0.8$). Upper rows show the results for solidarity between all households, lower rows show the results for solidarity between uninsured households only. The darker the color the less households survive, numbers in each panel denote the exact fraction. If a panel is left blank, the parameter combination is economically not feasible (see Appendix B.2) and therefore not selected for the analysis. Results show the mean over 100 repetitions of the number of surviving uninsured households at the last simulation step ($t = 50$).

The overall conclusions drawn from the selected parameter combination are therefore found to be robust and valid for a broad range of external conditions with different levels of living costs, probabilities for shock occurrence and shock intensity. Households that cannot afford formal insurance do not benefit from its introduction even if their insured peers are willing to help them. In many situations, insured households might simply be not able to cover requests from the informal network in addition to their regular premium payments.

3.3.3 Effectiveness of risk-coping instruments for covariate shocks

To investigate how shocks which affect many households simultaneously stress the performance of informal risk-coping instruments, we conduct the same model analysis for covariate shocks. We again present an overview of the behavior of the system for all economically feasible parameter combinations and conduct the analysis for the subset of those households that are uninsured in every scenario to allow for best comparison. In Figure 3.6, we show the resulting survival rates of uninsured households when 80 % of the households are affected if a shock hits the village ($p_H = 0.8$). The model results for the more extreme case in which all households are affected by the shock ($p_H = 1$) can be found in Appendix B.5. Although, in total, each household suffers equally often from a shock in the idiosyncratic and the covariate cases, the survival rate of uninsured households is lower when they are exposed to covariate shocks in all external conditions which were considered. This implies that protection against this type of shock is more difficult without formal insurance. In contrast to what we observed for idiosyncratic shocks, the introduction of insurance leads to slightly higher survival rates of uninsured households if insured households are willing to contribute informal transfers. This is because, in case of idiosyncratic shocks, uninsured households were in general able

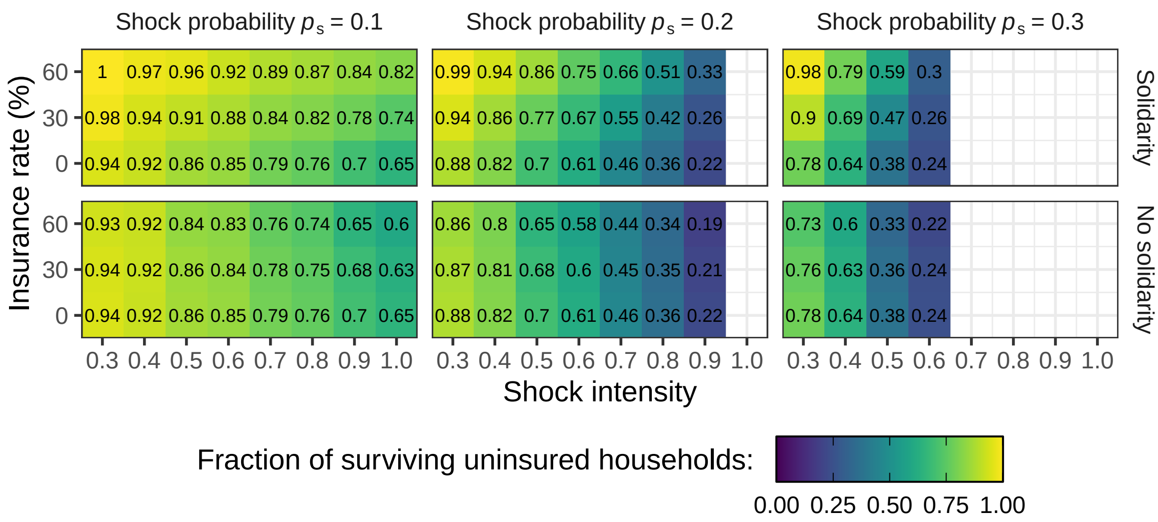

Figure 3.6: Fraction of surviving uninsured households among the 20 households that are uninsured in every scenario depending on insurance rates γ, shock probability p_s and shock intensity S for covariate shocks with fixed income ($I = 1$) and level of living costs ($C = 0.8$). In case of a shock at village level, 80 % of the households are affected ($p_H = 0.8$). Upper rows show the results for solidarity between all households, lower rows show the results for solidarity between uninsured households only. The darker the color the less households survive, numbers in each panel denote the exact fraction. If a panel is left blank, the parameter combination is economically not feasible (see Appendix B.2) and therefore not selected for the analysis. Results show the mean over 100 repetitions of the number of surviving uninsured households at the last simulation step ($t = 50$).

to make larger contributions to the transfers than insured households if not in need themselves. For covariate shocks, however, it is unlikely that an uninsured neighbor is able to make a contribution at all, as many households are in need at the same time. In this case, even the sometimes small contribution of insured households can help to ensure the survival of some uninsured households. On the other hand, if insured households are not willing to give transfer payments, this leads, as in the case of idiosyncratic shocks, to lower survival rate of uninsured households. Then, a link to an uninsured household is more valuable than that to an insured households. Uninsured households can at least provide informal transfers in the few situations where they are not affected by a shock but their neighbors are.

3.4 Discussion

To fight poverty, the poorest and most vulnerable households need opportunities to recover from financial losses that result from climate-related extreme events or other unexpected shocks. Microinsurance products are promoted as effective tools to address this challenge. With this study, we aimed to assess potential long-term consequences of introducing such formal insurance schemes to communities in which informal risk-sharing arrangements between smallholder farmers are prevalent. Since empirical studies have shown how diverse the transfer behavior of households can be after they have purchased insurance (Landmann et al., 2012; Lin et al., 2014; Strupat & Klohn, 2018; Takahashi et al., 2018; Matsuda et al., 2019; Anderberg & Morsink, 2020; Lenel & Steiner, 2020), it is important to explicitly take transfer decisions into account when assessing the effectiveness of the combination of these risk-coping instruments. To systematically distinguish situations where formal insurance complements existing risk-sharing arrangements from situations in which harmful consequences on the resilience of smallholders emerge, we developed an agent-based model with formal and informal insurance options and combined this with social network analyses. We explicitly included two behavioral implications of the availability of insurance on informal transfers: We assumed that insured households in the social network either continue to engage in informal risk-sharing arrangements or refuse transfers after taking up formal insurance.

Our model results showed that the introduction of formal insurance can have serious consequences, even if insured households maintain private transfers. Informal risk-sharing is only effective with a sufficient number of strong actors. Insured households that do not contribute at all or are, due to premium payments, only able to contribute a small amount, reduce the strength of informal transfers. Similarly, in the case of covariate shocks where many households are affected simultaneously, purely informal risk-coping cannot be considered effective. In this case, the solidarity of insured households contributes to saving some uninsured households, which makes formal insurance a valuable complement to informal private transfers. As extreme weather events like droughts or floods which cause such types of shocks are expected to occur more frequently under climate change (Sheffield & Wood, 2008; Dai, 2013; Thornton et al., 2014; Tabari, 2020), formal insurance will become increasingly important in the future. In any case, the resilience of the financial resources to shocks is the highest for insured households. In general, households can financially benefit from not investing in any form of risk protection, but this is at the expense of a small number of uninsured households which can survive and is therefore the riskiest option. Taking part in informal risk-coping within social networks lowers this risk and, at the same time, still leads to individual budgets which are on average higher than those of insured households. From this perspective, it is understandable that insured households might stop their contribution to uninsured households.

The use of an agent-based model in this theoretical study enabled a systematic analysis of external conditions as well as human behavior in a social network, and allowed to disentangle effects of formal and informal insurance on the resilience of smallholders to shocks. With the particular focus on the role of monetary transfers as a risk-coping mechanism emerging from the social network and insurance as an external factor, we provided a differentiated view on drivers contributing to vulnerability and resilience in coupled human-environmental systems (Turner et al., 2003). Here, the combination of agent-based modelling with social networks was crucial (Will et al., 2020). It allowed, on the one hand, to integrate individual behavior explicitly and distinguish responses to the introduction of formal insurance depending on the insurance status of the households. On the other hand, it was possible to assess how these specific decisions affect other households given the limited the range of interaction with few neighboring households defined by the imposed network structure. Both aspects, household behavior and network characteristics, could be modified and tested separately which contributed to an improved mechanistic understanding that would not have been possible without the use of these two methods.

Still, the model results should be seen in light of our rather stylized conceptualization that entails some limitations which narrow the external validity of our conclusions to some degree. Specifically, the assumption that all households have the same initial budget, income level and annual living costs, the actuarially fair insurance design with losses being covered completely and the stylized network offer plenty of potential for further studies.

In particular, if households had different financial resources, the decision to insure and potential changes in transfer behavior could be included into the model in more detail. When limited economic means alone inhibit some households from purchasing insurance (Eling et al., 2014; Platteau et al., 2017), uninsured households would on average have lower assets at their disposal which might increase their dependence on informal support. Given the different characteristics of the shock events this could have various consequences. On the one hand, the capacity of insured households to support their peers might be substantially lowered through premium payments even though they have more financial resources available than their uninsured peers. As a result, the negative effects of introducing formal insurance might potentially be even greater than that revealed in our analyses, as poor uninsured households could be less often able to sustain themselves. On the other hand, wealthy households with insurance might still be able to make effective contributions to informal risk-sharing when the premium payments only cover a small share of their available budget. In this case, informal risk-sharing could probably increase the overall welfare and formal insurance might pay-off not only for the insured households themselves but also for their uninsured peers.

Furthermore, when it is assumed that not all households with the possibility to insure are willing to do so, a heterogeneous income distribution would allow to include changes in transfer behavior more specifically. In addition to the two extreme cases of full support, on the one hand, and complete decline of solidarity by insured households, on the other hand, as shown in our analyses, a more nuanced sharing scenario could be taken into account. One could, for example, assume that insured households help only those who cannot afford insurance but do not support households with sufficient financial resources who have deliberately chosen not to purchase insurance (Lenel & Steiner, 2020). In this case, the poorest might benefit from their insured peers being protected against income shocks and richer households that do not get any help from others might be able to cover losses from shocks through their own budget, making the lack of informal support potentially less severe.

Additional dynamics could also be observed when taking into account a discrepancy between actual losses and insurance payouts. This could be due to basis risk, i.e. when index insurance measurements do not match the suffered damages, or due to a contract with reduced insurance coverage that requires insured households to pay for parts of their losses. Similarly, when insurance is actuarially unfair, i.e. when it comprises an insurance load that covers administrative costs, moral hazard and adverse selection or allows the insurance company to make profit, households get on average less return in case of a loss compared to what they have paid as premium (Gollier, 2003; Landes, 2015). In these cases, informal support might get more important also for insured households that could profit from neighbors taking over losses not covered by insurance (Mobarak & Rosenzweig, 2012; Dercon et al., 2014; Takahashi et al., 2018; Matsuda et al., 2019).

Another step towards increased realism would be the use of empirical social networks in which households differ in their number of neighbors. Heterogeneity with respect to the network position could affect the resilience to shocks of uninsured households. If a household in need has few neighbors and is not connected to those having enough resources to share, the informal support might not be able to effectively cover its losses. Next to further alignment with context-specific details, the model could also be used to test other behavioral theories and try to replicate empirically observed practices (Schlüter et al., 2017). This could include explicit assumptions on risk-sharing motives such as tit-for tat (Axelrod & Hamilton, 1981) or indirect reciprocity (Nowak & Sigmund, 2005; Clark et al., 2020) combined with punishment to those who free-ride on the cooperation of others (Fehr & Gächter, 2002). On the other hand, the model could be extended to account for rather unexpected behavior, such as insured households increasing their informal transfers driven by guilt-aversion (Lin et al., 2020) or uninsured households sanctioning their insured peers for their privilege through reducing contributions to a public good (Cecchi et al., 2016). The latter could, for example, be analyzed by explicitly modelling a common property grazing system (Dressler et al., 2019). Incorporating these diverse aspects into the model would further allow for increased interaction between empirical and model-based studies, as results obtained from different model assumptions can also inspire additional empirical research (Chávez-Juárez, 2017).

Disentangling cause-effect relationships of empirically observed patterns of transfer behavior and exploring their long-term implications is valuable for sustainable insurance design. From our model results, we can derive that insurance products should be developed in close alignment with existing risk-coping arrangements in order to maintain these crucial structures and use their benefits effectively. If an extensive uptake of formal insurance results in crowding-out of informal networks, this bears consequences not only for households that cannot afford formal insurance. Social networks include adaptive strategies going beyond financial support such as information sharing, access to resources or equipment, or conflict intervention (Fletcher et al., 2020). Moreover, embeddedness within communities promotes forward-looking decisions that can contribute to finding ways out of impoverishment (Jachimowicz et al., 2017). Offering insurance to groups rather than individuals or families could be a suitable approach to harness formal insurance but at the same time maintain informal relationships (Dercon et al., 2006; Trærup, 2012; Müller et al., 2017; Chemin, 2018). The network would in this case pay the insurance as a whole which allows internal agreements on contributions to the premium. Thus, every household could provide a fair share to a formal contract that protects the whole group. Existing informal associations have been successfully addressed in the context of savings (Karlan et al., 2017) and microfinance (Banerjee et al., 2013). Given different group structures and power relations, group insurance is, however, not equally well applicable to all informal networks (Trærup, 2012). Furthermore, as underlined by our simulation model, idiosyncratic risks can be covered at least partially by informal risk-sharing and only when facing covariate risks households are highly dependent on formal protection. Taking this risk layering into account by including informal risk management in the design of formal insurance products could reduce insurance costs, which would allow more households to participate and decrease social inequality (Mahul & Stutley, 2010; Ahmed et al., 2016; Fisher et al., 2019).

3.5 Conclusion

Introducing formal insurance in communities with functioning informal risk-sharing arrangements can have a crucial impact on household welfare, especially for those who do not have access to formal insurance. Our simulation results show that when insured households become unwilling to help households without insurance and withdraw their contribution to informal transfers, this largely reduces the ability of households without access to insurance to cope with income losses. Uninsured households alone cannot provide the assistance that is required by households in need. We also observe that even if the solidarity of insured households remains unchanged, uninsured households may be worse off than without some of their neighbors being insured. This is because the regular premium payments that insured households have to make reduce their ability to contribute to informal transfers. However, in the case of shocks that affect many households at the same time (such as droughts or floods), formal insurance complements informal risk-sharing, since in this case uninsured households cannot do much to help their peers.

Overall, our study offers new perspectives on the interplay of formal and informal risk-coping instruments that complement existing empirical research. The combination of agent-based modelling and social networks made it possible to systematically analyze the effects of external conditions as well as human interaction on the resilience of smallholders to shocks. By embedding a broad range of theoretical and experimental findings, our results allow conclusions on potential unintended consequences that the introduction of formal insurance may have on the functioning of informal transfers in a long-term perspective. These potential feedbacks have to be kept in mind for an effective design of insurance policies as only if formal insurance and existing risk-sharing mechanisms are well aligned, they provide a good basis for achieving the goal of eradicating poverty worldwide in a sustainable manner. However, since our results are based on a theoretical simulation model, which by its nature involves a number of simplifying assumptions, the specific empirical circumstances must be taken into account in any case when evaluating an appropriate insurance design. To this end, our analyses provide an orientation on which potential side effects should be borne in mind.

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4 Determinants of household resilience in networks with formal insurance and informal risk-sharing

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Abstract

Insurance products specifically designed for the needs of low-income households in developing countries can effectively buffer financial losses from personal or weather-related risks. However, even though this type of insurance specifically addresses the poor, not all households can afford to pay the regular premiums. The resilience of these households to shocks, i.e. their ability to cope with income losses, often highly depends on traditional informal arrangements where risk is shared through private monetary support in social networks. If income is heterogeneously distributed in a network and poor households are not connected to those with enough resources and willing to share, this support might, however, not reach the households in need. With this study, we assess the impact of heterogeneity in income and network characteristics on the effectiveness of informal risk-coping for the poorest when some of their neighbours have access to formal insurance. In addition, we derive a functional relationship between the resilience of the poorest and key household and network characteristics to obtain a measure for actual vulnerability. Using a stylized agent-based model, we show that formal insurance pays off not only for the insured households themselves, but also for poor households that benefit from their neighbours being insured, especially when shocks affect many households simultaneously. By applying logistic regression to the simulated data for random networks, we infer that, in addition to one's own financial situation, the financial situation of neighbouring households and the position in the network, which is determined by a household's indegree and outdegree, are crucial for coping with income loss. We show the transferability of our findings by testing the accuracy of the regression model for an empirical risk-sharing network of a village on the Philippines. Our study highlights the potential of using model-based approaches to identify vulnerable households by assessing their financial as well as network characteristics. This can help to effectively target subsidies when informal risk-sharing is insufficient and households cannot afford formal insurance.

4.1 Introduction

Unexpected losses due to personal or weather-related shocks pose significant financial risks to the poor in developing countries (Dercon, 2002; Xu et al., 2003; Strömberg, 2007). Illness, for example, can force people to use a large share of their income to cover costs of medical care and is simultaneously often associated with reduced labour supply and a loss of income

(Gertler & Gruber, 2002). Additionally, many households in low-income countries are particularly susceptible to damages by natural disasters such as droughts or floods resulting in harvest failure or livestock loss (Barrett & Santos, 2014; Thornton et al., 2014). Due to climate change it is expected that such weather-related shock events become even more frequent and severe in the future (Sheffield & Wood, 2008; Dai, 2013; Thornton et al., 2014; Tabari, 2020). Building resilience of the most vulnerable against income loss is thus key to ending poverty as aspired by the Sustainable Development Goals (UN, 2015). Microinsurance or inclusive insurance, i.e. insurance products specifically designed for the needs of low-income households, are seen as a promising tool to encompass also the poor with an appropriate and affordable risk-coping instrument and strengthen their resilience to unforeseen losses (Wanczeck et al., 2017). Current programs include funeral insurance, health insurance as well as crop and livestock insurance (Merry, 2020).

However, even though these schemes are intentionally designed for the most vulnerable, they might not reach the poorest as for this part of the population unsubsidised premiums are often still too expensive (Biener & Eling, 2012; Eling et al., 2014; Marr et al., 2016; Platteau et al., 2017). The ability of these households to cope with income losses therefore highly depends on traditional informal arrangements where households help each other in times of need with money, labour, or in-kind goods (Platteau, 1997; Cronk et al., 2019a). Such risk-sharing networks exist in various forms and cover extended families, villages, ethnic groups, or professional relations (Dercon, 2002). It is assumed that engaging in these arrangements is driven by altruism and reciprocity, i.e. by contributions solely due to a preference for social welfare and those where later reward is expected (Leider et al., 2009; Ligon & Schechter, 2012). However, when households rely on informal support, their ability to maintain resilience to shocks depends largely on their position in these networks. If income is heterogeneously distributed and poor households are not connected to those with enough resources and willing to share, the informal support might not reach the households in need. Similarly, if many households seek financial help from the same households that are expected to be wealthy these may not be able to fulfil all requests. Yet, while several studies consider the effect of wealth differences on the formation of risk-sharing networks (Fafchamps & Gubert, 2007; Schechter & Yuskavage, 2011; Caudell et al., 2015; Lenel, 2017), little is known about how well households are protected in these arrangements, especially if some households can afford formal insurance in addition to informal risk-sharing and others cannot.

We address this gap by analysing the impact of heterogeneity in income and network characteristics on the effectiveness of informal risk-sharing for the poorest when some of their neighbours have access to formal insurance. Specifically, we assess under which conditions formal insurance complements informal risk-sharing and whether the availability of insurance can have an indirect benefit for poor, uninsured households. In addition, we derive a functional relationship between the resilience of the poorest and key household and network characteristics to obtain a measure for actual vulnerability. Using a stylized agent-based model, we simulate the resilience of individual households to income losses. By applying logistic regression to the simulated data, we reveal which household and network characteristics can strengthen a household's ability to cope with extreme events.

Agent-based modelling is a valuable approach to disentangle the complex interplay of formal and informal insurance, network characteristics, and external conditions as it allows to systematically analyse interlinked causal relationships of human and environmental processes (Schulze et al., 2017). The method already helped to understand how different degrees of inequality between nodes evolve in stylized risk-sharing networks (Chiang, 2015). In a more applied setting, agent-based models provided useful insights into how risk-sharing can stabilize herd sizes when households exchange livestock (Aktipis et al., 2011; Aktipis et al., 2016). The approach was also used to determine how the resilience of pastoralists depends on whether households in need prefer to ask the wealthiest of their partners for help (Hao et al., 2015) and whether households with the capacity to help decide to provide transfers based on the social status or the financial situation (Kayser & Armbruster, 2019).

We contribute to the literature by evaluating the interplay of formal and informal risk-coping instruments in the presence of wealth inequality. We analyse a broad range of conditions in order to provide insights on how these mechanisms might be affected by climate change resulting in more frequent extreme weather events like droughts or floods (Dai, 2013; Tabari, 2020) or by demographic changes such as urbanization that impose greater health threats especially with respect to chronic diseases (Allender et al., 2008; Vearey et al., 2019). We build on an existing model (Will et al., 2021a) and extend this model by incorporating income and network characteristics based on empirical observations of a village on the Philippines (Lenel, 2017). Through the development of a functional relationship between the resilience of the poorest and key household and network properties, our study helps to reveal which characteristics are crucial to identify those households that neither have access to formal insurance nor are adequately protected through informal risk-sharing. In cases where informal risk-sharing is insufficient and not all households have enough financial resources to cover formal insurance premiums, additional support, for example through subsidised insurance contracts, is needed to make more households resilient to shocks. Assessing financial as well as network characteristics of households allows a systematic understanding of their vulnerability that can be used to effectively target such external assistance. In combination with an improved insurance design that is attractive to a large share of the population, this can have a major impact on reducing poverty.

4.2 Methods

4.2.1 Model description and parametrization

We describe the key processes of the model with a focus on budget dynamics of individual households and their formal and informal risk-coping instruments. The main processes of the simulation model, presented in a structured form based on the ODD+D protocol (Müller et al., 2013), can be found in Appendix B.1. Details on the differences to the model version used in Chapter 3 are outlined in Appendix C.1. The model is implemented in NetLogo and the source code of the model is available at CoMSES Net (Will et al., 2021d).

To model the effectiveness of formal and informal risk-coping instruments, we simulate $N_{\mathrm{H}} = 65$ households and the dynamics of their budgets Y over a long-term perspective of 50 years with annual time steps. We consider households connected in a social network as individual agents. All households gain a regular income I and have to spend a fraction c of their income to cover living costs. Additionally, they are exposed to unexpected events that lower their budget by an amount S. These income shocks either occur independently for each household with probability p_{s} (idiosyncratic shocks) or affect several households in the village simultaneously, e.g. through extreme weather events. In case of such covariate shocks, the village is hit with probability p_{V}. The individual households are then affected with probability p_{H} which reflects that some households are resistant to income losses, e.g. due to a more favourable geographical location or better adapted agricultural strategy. To make individual shock frequencies p_s comparable to that of the idiosyncratic shocks, we assume that the probability for a specific household to be hit by a shock is $p_s = p_V \times p_H$. In each simulation run, only one shock type is considered.

When their financial resources are not sufficient to sustain their livelihood, i.e. when their budget is below zero, households can request money from other households to which they are connected in a social network. A household requests as much money as is needed to reach the poverty threshold of zero from a household randomly chosen among its links. If the selected household cannot provide the full amount, the household in need asks further neighbours for support until it obtains the desired amount or until no more households are left to ask. To investigate to which extent our results can be generalized or are conditional on specific network properties, we simulate two different types of networks in which the households are connected: Households are either linked based on an empirical network (see section 4.2.2) or in random networks with the same number of nodes and links as in the empirical case.

We assume that income is distributed heterogeneously among the households and households gain an individual income I_i. In the empirical network, the income distribution is derived from the survey data (see section 4.2.2). In the artificially created networks, the same distribution of income as in the empirical case is assumed. Here, the position of households in the network is randomly assigned and varies for each newly created network topology. Households are endowed with an initial budget Y^0 which is set to zero to facilitate comparison across different external conditions. Relations between income and consumption are not unambiguously confirmed in the literature (Howe et al., 2009). As a first approach to account for heterogeneous consumption, we assume a simplistic linear relation where households spend a fixed proportion c of their income to cover their living costs. We model a subsistence economy with low saving rates and set $c = 0.8$. The increase in consumption with income can be justified by the fact that income is not adjusted for household size and that there is potentially higher consumption of goods exceeding basic needs when more income is available than needed.

In addition to informal risk-sharing, some households have access to formal insurance schemes. Formal insurance is offered with a yearly premium that is actuarially fair, i.e. the premium β equals the expected payout determined by the shock probability p_s and shock intensity S ($\beta = p_s \times S$). Only households that have enough budget available to cover the premium after paying the living costs can decide to insure. This is in accordance with empirical studies showing a positive relationship between wealth and insurance purchase (Eling et al., 2014). We assume that not all households with enough financial resources to insure are willing to do so and distinguish three levels of insurance propensity δ, where either none ($\delta = 0$), half ($\delta = 0.5$), or all ($\delta = 1$) of the households wealthy enough to afford the premium choose to insure. This allows us to implicitly account for other non-financial factors, such as social or cultural influences, that affect the decision to insure but are not included in the model (Eling et al., 2014; Platteau et al., 2017; Panda et al., 2020). For each simulated scenario, we assume a constant insurance propensity for all households that can afford insurance.

Households that do not manage to reach the poverty threshold either on their own or with the help of others are excluded in further time steps of the model, i.e. it is assumed that these households are no longer part of the system. This assumption implicitly includes migration, as households that are not able to cover their living costs might leave the region and search for improved economic, ecological, or social conditions elsewhere (Black et al., 2011; Neumann & Hermans, 2017). However, this does not take into account that households might obtain further support from outside the village which is not included in the model (Adams & Page, 2005; Giuliano & Ruiz-Arranz, 2009). We summarize the resilience of households to shocks, i.e. their capacity to cope with income losses, in a 'survival rate' which indicates the fraction of households that manage to maintain a budget above zero over a specific time span.

For further analyses, we examine selected parameter conditions for shock intensity p_s and shock probability S for which, due to the resulting premium levels, a different proportion of the population can afford insurance. On the one hand, as microinsurance products are specifically designed for low-income households, we consider scenarios where at least 50 % of all households can afford to insure. On the other hand, as we are particularly interested in how households that do not have enough financial resources to insure cope with income losses, we focus on external conditions of shock frequency and severity where at least 25 % of the population are too poor to afford the regular premium payments. We assume a shock frequency between 10 and 30 % which is in the range of empirically observed values (see section 4.2.2 for the reported shock frequency in the case study on the Philippines). Dividing all parameters in equidistant steps of 0.1, this results in five possible parameter combinations with between 54 % and 75 % of the population having enough financial resources to insure. If not all households that can in principle afford the insurance are inclined to pay the annual premiums, the effective insurance rate in the population is reduced accordingly (see Appendix C.2 for details on the parameter selection and the resulting number of insured households for different external conditions).

4.2.2 Case study

Empirical network and income data are based on a household survey that was conducted in 2012 in small fishing villages in the provinces Antique and Iloilo in the region Western Visayas on the Philippines (Lenel, 2017). The focus of the survey was the use of financial services and the structure of support networks. One village with 65 households was surveyed completely. The survey covered socioeconomic characteristics of all household members, including access and use of formal financial services, housing characteristics, as well as detailed questions on the informal support networks within and outside the community (see Table C.2 for a summary of the household characteristics). In particular, the respondents were asked to provide a list of households that they consider as close to their household. There were no limitations on the number of names that respondents could list. For each of the mentioned households, the respondent was asked (1) "Would these people help you if you/the main income provider would turn very ill and would not be able anymore to earn income and in addition you would need to cover the medical expenses?" and (2) "Would you ask these people for help?". For these questions, respondents could respond "Immediately", "After some hesitation", "Only in extreme emergency situations", or "Never". A support link was defined as existing if a respondent answered "Immediately" for both questions. In total, 236 links were reported with on average 3.63 support links per household (see Figure C.1 for the resulting network and Figure C.2 for the degree distribution). 55 of the 65 households named at least one other household from the village as a potential source of support and 62 households were named by at least one household. One household is isolated, i.e. this household was neither naming other households nor was this household named by any other household. The resulting network characteristics resemble those of rural social networks in villages in Malawi, Uganda and India, where similar data have been collected (for an overview see Chandrasekhar, 2016).

As most of the declared income is highly irregular and income reports are not always reliable, an asset index normalized to a value between 0 and 1 was derived as a measure for wealth (Moser & Felton, 2007). The asset index includes variables that describe ownership of technical devices, agricultural tools, or livestock and housing characteristics such as roof materials, source of lighting, and general housing conditions. The asset distribution of the selected village fits well with that of a larger sample obtained in the same survey campaign with only slightly less poor households and slightly more rich households (Figure C.3) and can therefore be seen as a good proxy for the wealth distribution in the region. Although an asset index differs from income as a wealth measure (Poirier et al., 2020), it is seen as a valuable proxy to differentiate the economic status of households (Ucar, 2015). We therefore base the income distribution in the model on the empirically derived asset values and assume that households gain a regular income according to their asset index.

Among all households in the sample, 24.6 % reported a severe health shock in the year previous to the survey. This is in accordance with a study from Kenya, where households denoted to experience losses due to illness in 26.6 % of the weeks in one year (Geng et al., 2018).

4.3 Results

4.3.1 Effectiveness of informal risk-sharing

We focus our analysis of the effectiveness of informal risk-sharing on the poorest of the population, i.e. households that cannot afford formal insurance. To determine their long-term protection against income losses and their dependency on transfers from other households, we present simulation runs over 50 years with varying degrees of propensity to insure δ among those households with sufficient income to consider insurance. We show results for cases with half ($\delta = 0.5$) or all ($\delta = 1$) of these households being insured and, as reference, scenarios without formal insurance ($\delta = 0$). In a first step, we analyse one specific parameter combination of shock probability $p_s = 0.1$ and shock intensity $S = 0.6$. For this scenario, the threshold below which households cannot afford insurance is at $I_t = 0.3$ which leads to an effective insurance rate of 31 % ($\delta = 0.5$) and 62 % ($\delta = 1$) in the whole population. We first focus on the outcome for random networks that are newly generated in every repetition of the simulation. In a second step, we compare the results with those for the empirical network that does not change between simulation runs.

To analyse to which extent households that cannot afford formal insurance rely on the support of others, we present how many of them manage to cover their living expenses over the simulated time span (Figure 4.1A) and the transfer amount that these households receive during this period (Figure 4.1B). Whereas without the help of their neighbours only 8 % of these households manage to survive the entire simulated period, the fraction increases to up to 47 % when other households provided informal transfers to those in need. The most important contribution to the survival of uninsured households comes from wealthy households with enough financial resources to insure (Figure 4.1B). The positive effect of informal risk-sharing on the survival of the poorest slightly varies for different insurance levels. In the long-term, poor households benefit from many of their neighbours being insured ($\delta = 1$). Only shortly after the introduction of insurance, rich households cannot cover the requests to the same extent as they could when they were not insured ($\delta = 0$). This is due to the lower budget that insured households have available after paying the insurance premium which is especially pronounced in the early years of the contract, when insured households have not yet benefited from reduced losses due to insurance payouts (Will et al., 2021a). In the long run, however, formal insurance pays off not only for the insured households themselves but also for their uninsured peers. For households that can afford insurance but choose not to, we

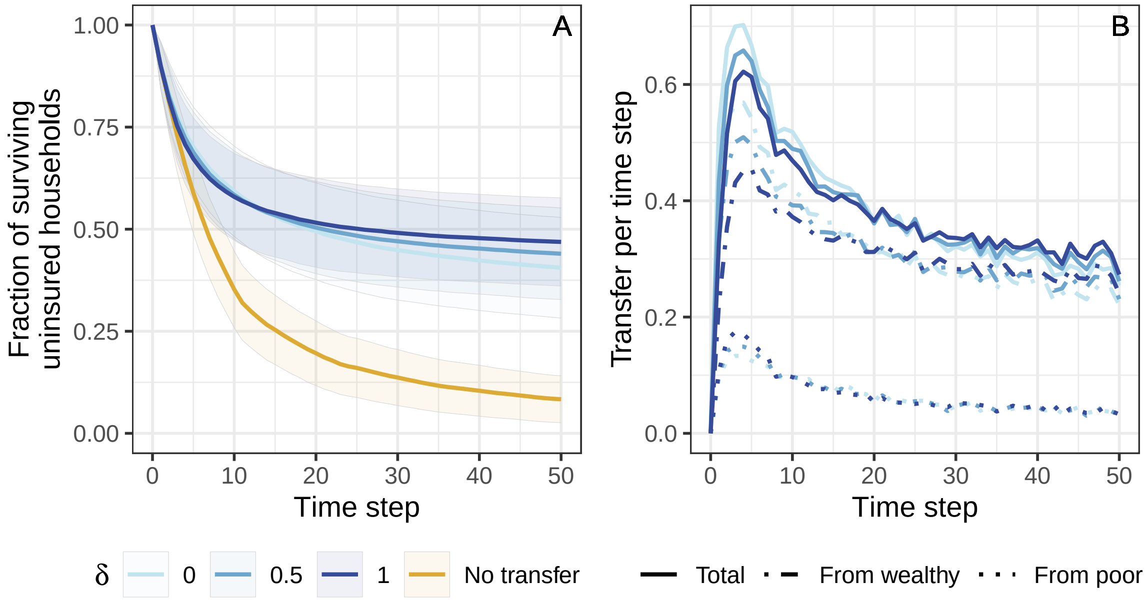

Figure 4.1: (A) Fraction of surviving uninsured households without enough financial resources to insure for three different insurance propensities δ. The scenario without informal transfer is added as reference (yellow line). As in this case the survival rates are independent of the insurance rates, results for different insurance rates overlap and are not represented separately. The shaded areas represent the 95 % confidence interval. (B) Mean transfer that households without enough financial resources to insure receive per time step. Line types distinguish the source of the transfer. For both panels, results show the mean over 1000 repetitions for a selected parameter combination of shock probability $p_s = 0.1$ and shock intensity $S = 0.6$ and households connected in a random network that is newly created in every repetition.

observe in general similar trends (Figure C.4). However, their higher income makes it easier for them to buffer income shocks which reduces their dependence on informal transfers.

Based on this analysis, it is, however, still unclear why some households survive and others do not. One reason could be the heterogeneous income distribution, which allows some to save more than others when not affected by a shock. To examine the importance of households' own financial situation, we determine the survival probability of a household with certain income for 1000 replications of the simulation (Figure 4.2). We observe that in random networks, households tend to survive more often the higher their income. Because insurance covers complete losses, survival is certain for insured households. This is reflected in the increase in survival probability for income greater than 0.3, which denotes the threshold below which households cannot afford insurance. In the empirical network described in section 4.2.2, i.e. a specific network configuration that is fixed for every repetition of the simulation, a household with the lowest income is, however, far more likely to survive than one with nearly enough financial resources to insure (similar observations can be made for a selected random network kept fixed for 1000 repetitions, see Figure C.5). Thus, income does not seem to be the only determinant for survival. In addition, network characteristics, which vary between simulation runs in the case of the random networks but remain fixed for the empirical network, might influence the survival rate.

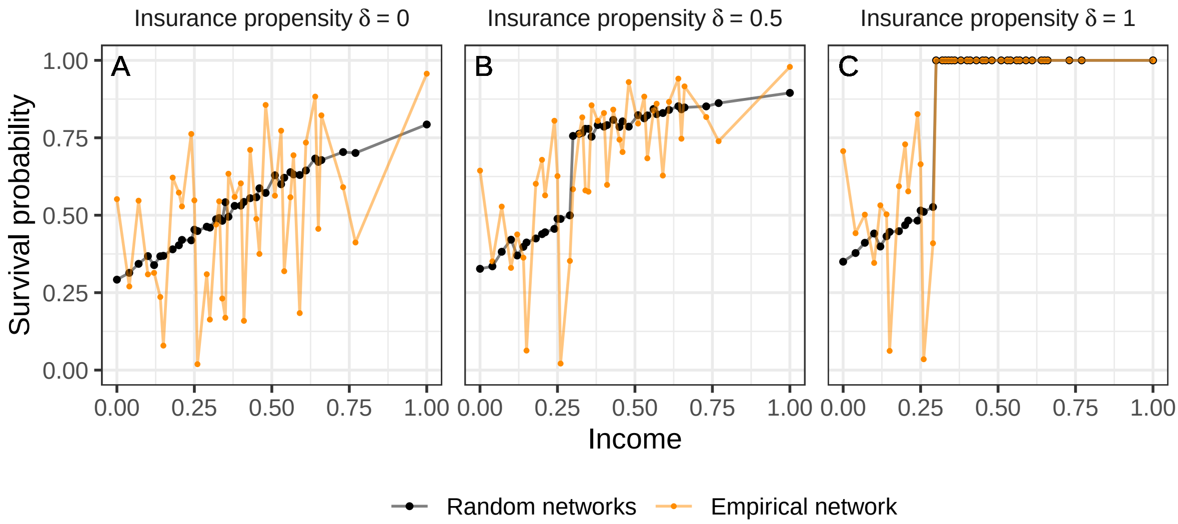

Figure 4.2: Fraction of runs out of 1000 repetitions in which a household with a given income I_i survives in random networks that are newly created in every simulation run (black) and the empirical network where a household with a certain income has always the same position in the network (orange). For each simulation run, shocks occur in random order for individual households. As some households have the same income, not all dots represent exactly one household. Results are shown for a selected parameter combination of shock probability $p_s = 0.1$ and shock intensity $S = 0.6$ (with resulting threshold below which households cannot afford insurance at $I_t = 0.3$) and different insurance propensities δ.

4.3.2 Determinants for the survival of the poorest

To reveal the functional influence of various factors on the survival probability of those households that do not have enough financial resources to pay for formal insurance, we perform a logistic regression on the simulated data of households' survival after a time span of 50 years. Specifically, we include as dependent variable the survival of the poorest households that cannot afford formal insurance (25 households). We consider three different insurance propensities δ and 1000 repetitions of the simulation which overall leads to 75000 observations that are used in the regression. The regression model contains independent variables on the financial situation of a household and its neighbours as well as information on its network position. For the financial situation, we include in particular the household's income and the disposable income of its neighbours. The latter includes the budget that all households a household is connected to can on average share, i.e. the amount that they have available after paying their living costs and the insurance premium. For uninsured households, the average expected loss from shock events is deducted instead of the premium. Households that have a negative budget after subtracting these costs do not contribute the disposable income of a household's neighbours. With respect to network characteristics, we include the number of households that can be asked for support (outdegree) and the number of households that potentially need support (indegree). Here, we only consider links from households that are not insured as insured households do not need informal support. We test the influence of insurance propensity δ by including interactions between all four predictors and the insurance levels $\delta = 0.5$ and $\delta = 1$. In particular, we estimate with a logistic regression the following specification

$$
\begin{aligned}
P(\text{active}_i = 1) = \beta_0 &+ \beta_1 I_i + \beta_2 D_i + \beta_3 \deg_{\text{out},i} + \beta_4 \deg_{\text{in},i}^{\text{unins}} + \beta_5 \delta_{0.5} + \beta_6 \delta_1 \\
&+ \beta_7 I_i \times \delta_{0.5} + \beta_8 D_i \times \delta_{0.5} + \beta_9 \deg_{\text{out},i} \times \delta_{0.5} + \beta_{10} \deg_{\text{in},i}^{\text{unins}} \times \delta_{0.5} \\
&+ \beta_{11} I_i \times \delta_1 + \beta_{12} D_i \times \delta_1 + \beta_{13} \deg_{\text{out},i} \times \delta_1 + \beta_{14} \deg_{\text{in},i}^{\text{unins}} \times \delta_1 + \varepsilon_i
\end{aligned}
\tag{4.1}
$$

i.e. the probability $P(\text{active}_i = 1)$ that household i survives the simulated time span of 50 years is explained by i's income I_i, the disposable income of i's neighbours D_i, where $D_i = \sum_{j=1}^{J} \max\{I_j(1-c) - p_s \times S, 0\}$ with $j = 1,...,J$ being those households household i can ask for support, i's outdegree $\deg_{\text{out},i}$, and i's indegree from uninsured households $\deg_{\text{in},i}^{\text{unins}}$. Furthermore, we include the prevalent insurance propensity, where the dummy variables $\delta_{0.5}$ and δ_1 denote whether the insurance propensity equals 0.5 or 1, respectively. Standard errors ε_i are clustered on household level.

Results using standardised coefficients for better interpretability are reported in Table 4.1. Unstandardised coefficients can be found in Table C.3. As already assumed, a household's survival depends less on its own financial situation than on how much potential donors can share. The number of neighbours that can be asked for support (outdegree) is also crucial whereas the number of households that might approach a household for support (indegree) plays a smaller role. Requests from other households lead to a slight decrease in a household's survival probability, since the money given to others in one year might be missing in subsequent years. With increasing insurance propensity, the importance of the donors' disposable income further increases while the number of potential donors (outdegree) becomes less important. It should be kept in mind that the higher the propensity to insure, the lower the number of households a donor's disposable income must be shared with. In addition, for uninsured households the disposable income is only an average value that results from the shock probability and shock intensity. When these households are affected by shocks, they have a smaller budget to share and may not be able to fulfil requests. Only for insured households does disposable income represent the amount actually available for transfers. This further explains why this factor becomes more important as insurance propensity increases.

When not all households with enough financial resources decide for or against insurance ($\delta = 0.5$), we can furthermore disentangle whether insured or uninsured neighbours are more important for the survival of the poorest. We therefore run an additional regression with the donors' disposable income split into two parts (Table C.4). Both predictors are of high importance with the disposable income of insured neighbours having slightly higher impact on the survival of poor uninsured households.

4.3.3 Transferability to the empirical network

To assess whether the regression results obtained for the random networks are a suitable proxy to derive survival rates of the poorest households, we test the accuracy of the regression-based predictions compared to the simulation results for the empirical support network from the Philippines. Here, we exploit the fact that for this network the replications of the simulation differ only in the occurrence of shocks but not in the household characteristics considered in the regression. We can therefore directly compare the survival probabilities for each individual household obtained through regression with the fraction of runs among the 1000 simulations where this household manages to cover the living costs over the whole simulated period. To assess how well the survival rates of these two approaches match, we

Table 4.1: Standardised regression coefficients for the selected parameter combination of shock probability $p_s = 0.1$ and shock intensity $S = 0.6$ for the data obtained from the simulation on random networks that are newly generated for each simulation run. The data contains 25 households without sufficient resources to insure for three levels of insurance propensity ($\delta = 0, 0.5, 1$) in 1000 repetitions. Coefficients are mean-centred and scaled by 1 standard deviation (Menard, 2011). Standardised estimates for interaction terms are derived by standardising the product of both predictors. Standard errors in parentheses, clustered on household level.

	Standardised
(Intercept)	-0.27^{***}
	(0.01)
income	0.26^{***}
	(0.02)
donors' disposable income	0.75^{***}
	(0.02)
outdegree	0.49^{***}
	(0.02)
indegree (unins. neighbors)	-0.10^{***}
	(0.01)
ins. propensity $\delta = 0.5$	0.09^{***}
	(0.02)
ins. propensity $\delta = 1$	0.16^{***}
	(0.03)
income × ins. propensity $\delta = 0.5$	-0.00
	(0.01)
donors' disposable income × ins. propensity $\delta = 0.5$	0.09^{***}
	(0.01)
outdegree × ins. propensity $\delta = 0.5$	-0.07^{***}
	(0.02)
indegree (unins. neighbors) × ins. propensity $\delta = 0.5$	-0.04^{**}
	(0.01)
income × ins. propensity $\delta = 1$	-0.02
	(0.02)
donors' disposable income × ins. propensity $\delta = 1$	0.14^{***}
	(0.02)
outdegree × ins. propensity $\delta = 1$	-0.15^{***}
	(0.02)
indegree (unins. neighbors) × ins. propensity $\delta = 1$	-0.03^{*}
	(0.01)
McFadden R^2	0.18
AIC	84576.73
Log Likelihood	−42273.37
Num. obs.	75000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 4.2: Goodness-of-fit statistics (R^2, RMSE and bias) for the estimation of the survival probabilities of households without enough financial resources to insure for different insurance propensities δ and predictors in the regression model. In addition to the dummy variables for insurance propensity, the following predictors are included: (#4) donors' disposable income, own income, outdegree, indegree from uninsured neighbours; (#2a) own income, outdegree; (#2b) own income, outdegree to wealthy households; (#1) own income.

	$\delta = 0$			$\delta = 0.5$			$\delta = 1$		
#	R^2	RMSE	Bias	R^2	RMSE	Bias	R^2	RMSE	Bias
4	0.806	0.150	0.098	0.878	0.113	0.070	0.906	0.089	0.045
2a	0.515	0.191	0.068	0.514	0.180	0.048	0.465	0.175	0.032
2b	0.673	0.149	0.021	0.643	0.150	−0.001	0.561	0.159	−0.015
1	0.018	0.259	−0.050	0.016	0.257	−0.070	0.010	0.247	−0.081

provide goodness-of-fit statistics including R^2, root mean square error (RMSE), and bias, i.e. the mean difference between the values predicted by the regression model and those derived by the simulation. This allows us to analyse whether the variability in the survival rates is captured accordingly (R^2), how accurate the fit is (RMSE) and whether the prediction shows some general trends (bias).

Survival rates of the poorest households in the empirical network can be adequately predicted, even without explicitly mapping the temporal dynamics of the budget but by aggregating the most important influence factors and assessing the survival rate only at the end of the simulated period (Table 4.2, see Figure C.6 for a graphical representation). However, on average, the regression model tends to slightly overestimate the survival rate of the poorest (positive bias). The better prediction quality for higher insurance propensities is due to the fact that the disposable income of the neighbours becomes more reliable as δ increases. The drawback of such an accurate regression model is the amount of information needed about the income distribution of all households as well as the network structure. Since this might not be available for all empirically observed networks, we also test the performance of models with fewer predictors. Specifically, we consider models in which, in addition to one's own financial situation, only the number of neighbours one would approach if in need (outdegree) is included, but no information about their income. In addition, we assume that households are able to estimate whether their neighbours are wealthy enough to insure.

Missing information about the financial resources available for transfers crucially lower the prediction accuracy of the regression model. Nevertheless, when the network structure, i.e. the number of households that could be asked for support, is included in the regression, the prediction is much more reliable than when only the household's own income is considered. Including information on whether a neighbour is wealthy enough to afford insurance further improves prediction accuracy. The analysis underlines the importance of network characteristics for revealing the actual vulnerability of households in situations where informal transfers are an important risk-sharing mechanism and income is not homogeneously distributed. In contrast to networks where all households have on average the same budget, including the disposable income of potential donors is essential to precisely predict the surviving chances of households that are unable to formally insure.

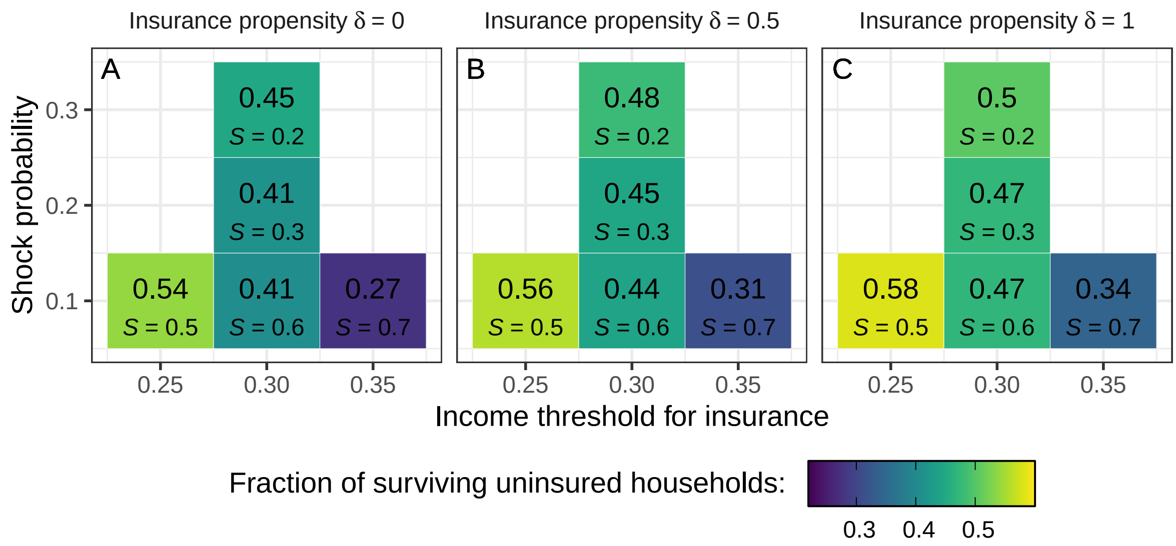

Figure 4.3: Fraction of surviving uninsured households without enough financial resources to insure for different shock probabilities p_s and income thresholds for insurance I_t (due to different shock intensities S, $I_t = p_s \times S/(1-c)$). The darker the colour, the less households survive, numbers in each panel denote the exact fraction. If a panel is left blank, the parameter combination was not selected for the analysis (see Appendix C.2 for details on the selection criteria). Results show the mean over 1000 repetitions for different insurance propensities δ at the last simulation step ($t = 50$). Tables C.5 and C.6 report Z-scores to assess whether the differences between the survival rates are statistically significant.

4.3.4 Transferability to different external conditions

So far, the results were obtained for one selected parameter combination of shock probability and intensity. To investigate the effect of other external conditions that might arise, for example, from changing climatic or demographic circumstances, we perform the same analyses on the survival rate of the poorest, the logistic regression, and the prediction accuracy in empirical networks for the remaining four of the selected parameter combinations. First, we compare scenarios with the same shock probability ($p_s = 0.1$) but lower ($S = 0.5$) or higher ($S = 0.7$) shock intensity than in the previous case. Here, 75 % and 54 % of all households have enough financial resources to insure. In addition, we analyse cases in which shocks occur more frequently but less severe ($p_s = 0.2$, $S = 0.3$ and $p_s = 0.3$, $S = 0.2$), and where the number of households with access to insurance remains the same (62 % of all households).

For all parameter combinations, the same trend as described in section 4.3.1 is prevalent: The more households decide to insure the more households without enough financial resources to formally insure survive (Figure 4.3). This overall picture underlines the importance of the contributions of insured households to informal risk-sharing for the poorest. When comparing the outcome for different external conditions, we observe a large effect of shock intensity when shocks occur equally often ($p_s = 0.1$) but with different intensities. Since less severe shocks result in lower premiums, more households can afford insurance and at the same time more budget is available for informal transfers, leading to more effective informal risk-sharing. When the same number of households are insured ($I_t = 0.3$) and the scenarios differ in the combination of shock probability p_s and intensity S, the variation in the survival rate is less pronounced. There is no significant difference between seldom shocks where households lose a large share of their income ($p_s = 0.1$, $S = 0.6$) and shocks that occur more frequently but impose lower losses ($p_s = 0.2$, $S = 0.3$). Only for shocks that hit households even more frequently and cause even smaller losses ($p_s = 0.3$, $S = 0.2$), a slight increase in survival rates can be observed. Here, low support request make it easier to help others, even when households have to cover own losses.

By applying the regression analysis to the different scenarios, the trends observed for the selected parameter combination can be confirmed for all combinations of shock probability and intensity (Tables C.7 and C.8). For each scenario, the disposable income of the neighbours is most important followed by the outdegree and the own income. The slightly negative influence of links from uninsured households is also present independent of the shock characteristics. For all scenarios, the disposable income of insured neighbours has a larger impact on the survival of the poorest than that of uninsured neighbours when these are treated separately for $\delta = 0.5$ (Tables C.9 and C.10). Overall, the main conclusions on the determinants for household survival are independent of the frequency and intensity of extreme events.

Across all scenarios, the simulated data of the empirical network can be reproduced with similar prediction accuracy with the regression model. Again, information about the financial situation of all households in combination with details on network characteristics reveals the best prediction on the survival rate of the poorest (Table C.11). For shocks that occur rarely and with low intensity ($p_s = 0.1$, $S = 0.5$), we observe that restricting the predictor that covers the outdegree of a household only to the wealthy neighbours does not lead to an increased prediction accuracy compared to considering all links. This can be explained by the fact that for low losses not only the rich but all households can contribute effectively to informal risk-sharing.

4.3.5 Transferability to covariate shocks

For some types of shocks, households are not affected independently but several households have to deal with financial losses simultaneously, e.g. if households derive their income from agriculture and extreme weather events reduce the yields. To investigate the effect of such covariate shocks, we perform the same analyses on the survival rate of the poorest, logistic regression and prediction accuracy for the empirical network when in case of a shock event 80 % of all households face losses at the same time.

Although on average each household is affected equally often by shock events for idiosyncratic and covariate shocks, we observe that less of the poorest households can cover their living costs when many households suffer from shocks simultaneously for all of the considered external conditions (Figure 4.4). However, the relative difference between surviving rates for idiosyncratic (Figure 4.3) and covariate shocks (Figure 4.4) decreases with increasing insurance rate. This indicates that insured households can cover most of the requests even if many of their peers need help simultaneously. For covariate shocks, the increase in survival with insurance level is much more pronounced than for idiosyncratic shocks, which highlights the importance of insurance in these cases. When comparing the different external conditions for shock events, we observe similar trends as for idiosyncratic shocks. Household survival is strongly affected by the intensity of the shocks with more severe shocks leading to fewer households that can cope with the losses. Again, the survival rate of the poorest does not vary significantly between frequent shocks with low intensity and seldom shocks which impose high losses.

Looking at the regression model, also for covariate shocks the disposable income of the potential donors has the largest influence on the survival of the poorest (Tables C.15 and C.16).

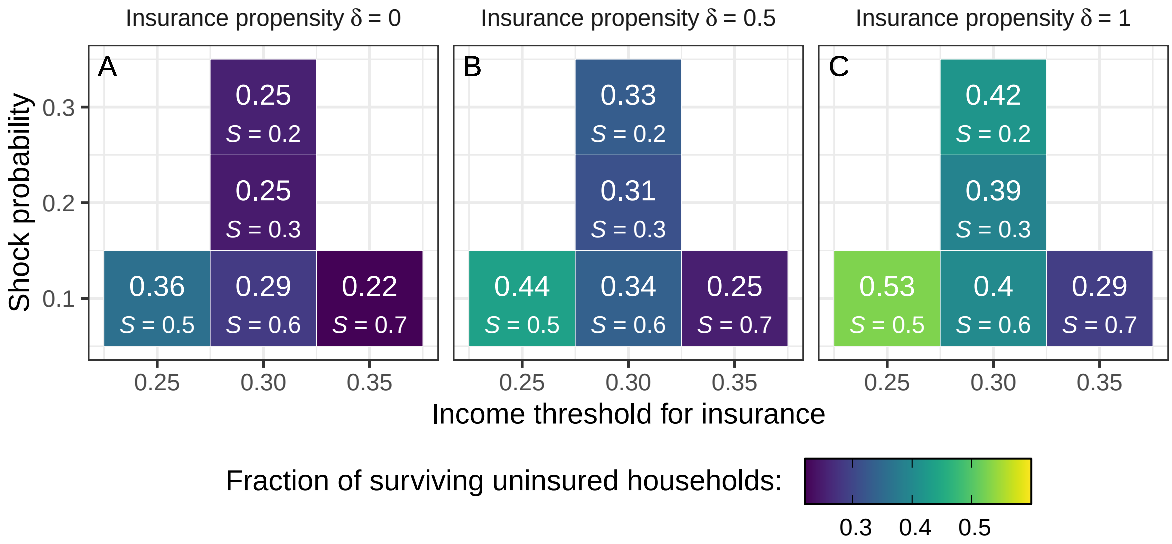

Figure 4.4: Fraction of surviving uninsured households without enough financial resources to insure for different shock probabilities p_s and income thresholds for insurance I_t (due to different shock intensities S, $I_t = p_s \times S/(1-c)$) for covariate shocks. In case of a shock at village level, 80 % of the households are affected ($p_H = 0.8$). The darker the colour, the less households survive, numbers in each panel denote the exact fraction. If a panel is left blank, the parameter combination was not selected for the analysis (see Appendix C.2 for details on the selection criteria). Results show the mean over 1000 repetitions for different insurance propensities δ at the last simulation step ($t = 50$). Tables C.12, C.13 and C.14 report Z-scores to assess whether the differences between the survival rates are statistically significant.

In contrast to idiosyncratic shocks, the number of neighbours that can be asked for transfer is, however, less important than the own income. This could be because having a large number of neighbours is of little use if many of them are affected by shocks at the same time as oneself. The number of uninsured households requesting informal transfers is insignificant for the survival of the poorest. This is plausible as only few of the poor households can contribute to informal transfers when most of them deal with the same shocks. The importance of insured neighbours becomes even more apparent when the influence of insured and uninsured donors is considered separately (Tables C.17 and C.18).

The simulated survival probabilities of the poorest households in the empirical network can be predicted with slightly lower accuracy than for idiosyncratic shocks (Table C.19). When restricting the regression to predictors that can more easily be obtained from interview data, the prediction accuracy for covariate shocks is far lower than that for idiosyncratic shocks. This indicates that for covariate shocks exact information about the financial situation of all households is even more important to effectively estimate the vulnerability of specific households.

4.4 Discussion

With this study, we gained insights into how effectively households without formal insurance can cope with income shocks by interacting in a social network. We specifically analysed whether the availability of insurance can have an indirect benefit for poor, uninsured households. To identify which households are most vulnerable, we uncovered the functional relationship between the survival probability and key household and network characteristics by combining agent-based modelling with regression analysis.

Our model results show that formal insurance does not only pay off for the insured households themselves, but also for poor households that benefit from their peers being insured. The actual effectiveness of the interplay between formal insurance and informal risk-sharing is dependent on the characteristics of the shock events: Mild losses can be well covered with private transfers and without formal insurance. For more severe shocks, such support is limited as households have fewer resources to share due to higher losses. Especially in this case, insurance significantly increases the chances of survival also of the weakest. Furthermore, the indirect positive effect of insurance is particularly strong in the case of covariate shocks that affect many households simultaneously. Since few of the uninsured households can help their peers as they also face losses, insurance plays an even more important role: When many households are insured, private transfers can be provided almost as effectively as in the case of idiosyncratic shocks.

By applying a logistic regression analysis to the outcomes of the agent-based model, we were able to show that a household's financial situation alone says little about its ability to cope with income losses. Rather, in addition to the individual budget, the disposable income of potential donors and the network position must be taken into account. We tested the prediction accuracy of the regression model on empirical network data from the Philippines. When incorporating detailed information about household and network characteristics, we were able to precisely reproduce the simulated results. Furthermore, we showed that even a simplified model can give important insights into the resilience of individual households. The regression model can therefore be considered a valuable proxy for the outcome of the structured agent-based model and a predictor of the survival probability of the poorest households. In this sense, the regression analysis can serve as an 'early-warning system' to test whether formal and informal risk-coping instruments are effectively interplaying for the benefit of a particular household or whether additional support is needed.

Given the stylized character of our model, we, however, neglected a number of factors, which needs to be taken into account when interpreting the results. First, we assumed that all households are unconditionally willing to provide informal transfers. Yet, households might decide how much to transfer and to whom, depending on their wealth differences, possible other sources of support that a household might have or the neediness of a household relative to others (Chiang, 2015). Second, the insurance status was not explicitly considered in the transfer decision. This neglects empirical observations which show that the availability of formal insurance can alter transfer behaviour (Strupat & Klohn, 2018; Takahashi et al., 2018). Insured households might, for example, no longer be willing to transfer to uninsured households, at least not to those that could have afforded to insure (Anderberg & Morsink, 2020; Lenel & Steiner, 2020). In a previous modelling study, this was shown to greatly reduce the ability of uninsured households to cope with income losses when the income distribution is homogeneous (Will et al., 2021a). If households differ in income and the poorest rely solely on informal transfers in times of need, a decline in solidarity could have an even greater impact on their resilience. Third, the network was assumed to be fixed, but connections might change over time and in response to external circumstances. To improve the external validity of the result, these aspects could be incorporated into later model versions.

Potential for further studies also exists with regard to the regression model. For simplicity, we focussed on a small subset of potential explanatory variables, namely the financial resources of a household and its neighbours as well as its network position. However, especially with regard to the disposable income of the neighbours, there are a number of further scaling options that could increase the explanatory power of the regression and the respective influence factors. We could imagine weighting the disposable income with the number of households that are requesting support from the same household and their probability of being affected by income losses. Effects of an even higher order can be considered if we would incorporate information on how many further possibilities of informal support are available to the requesting households and how effective this help is likely to be, i.e. how wealthy the other neighbours are. Moreover, in most analyses, we only considered the survival of the poorest after a given period of time but did not include the complete temporal dynamics. Especially for the regression analysis, we did not predict every single time step of the simulation but used the aggregated outcome of the complete simulated time span. However, this might overlook certain situations, such as when insured neighbours have few resources for private support immediately after the introduction of insurance because they have not yet benefited from reimbursed losses but must cover premium payments. By taking into account the temporal dynamics more explicitly, it would be possible to examine even more specifically which households can cope with shocks and for how long, and when households need external support in the form of subsidies.

In our study, the regression approach allowed us to aggregate the results of the agent-based model and to make general statements about the resilience of an uninsured household to income losses. However, all results are based on the same income distribution derived from empirical observations on the Philippines. A systematic comparison of different network structures and income distributions is needed to test which further insights emerge from specific household and network characteristics. For example, in networks where segregation between wealthier and less wealthy households is prevalent and households in need are not supported by wealthier peers, informal risk-sharing might not be effective. Similarly, it could have an effect whether income differences in the population are extreme, i.e. there are many rich and many poor households, or whether all households have roughly the same level of income. The structure of the network might also have an influence. For example, the effectiveness of informal transfers might be different with a homogeneous distribution of links than when there are pronounced hubs where many households ask the same few for help. To obtain a comprehensive picture and develop a reliable tool to derive implications on the resilience of the poorest, it would therefore be necessary to systematically analyse different network configurations and compare the regression results in these scenarios. The basis for the regression analysis yielding valuable results lies in the fact that household and network characteristics were explicitly considered and disentangled in the agent-based model. Such a structurally explicit approach is essential for understanding systems where humans interact with each other as well as with the environment (Will et al., 2020). Despite the simplified setting, our study already shows the potential of systematically analysing the sensitivity of resilience to structural household and network characteristics and provides far-reaching insights into the effectiveness of formal and informal risk-coping mechanisms under different external conditions. Exploiting this strategy even further by analysing the interplay of household and network characteristics more systematically will further improve the understanding of the effects of formal insurance and informal risk-sharing on the ability of the poorest to deal with extreme events. If this model-based approach was applied to other network typologies and overarching conclusions could be found, this would allow transferability to any empirical network to make predictions about the actual vulnerability of individual households without having complete information about all network characteristics, but by aggregating the relevant metrics.

While this study showed that formal insurance is a valuable complement to informal risk-sharing for households that are too poor to pay insurance premiums, a large fraction of these households still cannot cover their living costs over a long period of time when regularly affected by income shocks. This underlines how important it is that also the poorest have access to formal protection instruments in order to reduce their dependence on other households and strengthen the resilience of the entire population. One way to achieve this goal would be to make insurance more widely accessible. There are various options for doing this: First, transaction costs related to distribution and administration must be reduced in order to lower insurance premiums (Eling et al., 2014; Platteau et al., 2017). With respect to weather-related risks, index-based insurance where payouts are linked to environmental proxies rather than individual losses, is a promising approach for decreasing costs (Barnett & Mahul, 2007). Similarly, for other types of insurance, using local infrastructure to distribute the products, collect premiums and process claims might lower transaction costs (Biener & Eling, 2012). Second, insurance schemes that incorporate price differentiation, with premiums specifically tailored to the available financial resources of potential policyholders, could help make insurance accessible to a larger part of the population. By making richer households pay a higher share than poorer ones, coverage for the entire population can improve. When combined with collective insurance programs where insurance is offered to groups rather than individuals (Trærup, 2012; Santos et al., 2021), internal agreements within a social network on contributions to the premium would be possible. Third, especially for crop farmers where income is only realized at the end of the harvesting season, delaying premium payments until the end of the insured period is another option to improve accessibility to insurance (Liu & Myers, 2016). Finally, offering direct subsidies is also an effective tool to achieve affordability and promote insurance, at least for a finite period after the introduction of a new scheme (Mahul & Stutley, 2010; Biener & Eling, 2012; Hazell & Varangis, 2020). Here, the insights obtained in our studies can help to target them effectively to support the most vulnerable. In addition to insurance products, other government and non-government social assistance programs that provide asset and cash transfers can contribute to promoting resilience among the very poor (Johnson et al., 2013).

4.5 Conclusion

Even though insurance products specifically designed for the needs of low-income households are a valuable tool to buffer financial losses from personal or weather-related risks, they might not be able to strengthen the resilience of all parts of the population as premium payments can be too expensive for the poorest. Our simulation results show, however, that these households can also indirectly benefit from formal insurance when requesting informal support through their social network. Especially for covariate shocks where many household are affected by income losses simultaneously, access to insurance increases the resilience of the whole population including those that cannot afford the premiums. By aggregating our results from a structurally realistic agent-based model in a regression model, we derived that a household's own income is not the main determinant of its financial survival. Rather, it is important that its neighbours have enough disposable income and an atmosphere of solidarity is preserved. By testing the predictive accuracy of the regression model for simulated data of an empirically observed support network on the Philippines, we conclude that this aggregated model is a valuable tool for identifying those households among the poorest in a population that benefit from informal protection, but also those households that are not protected from income loss and are thus particularly vulnerable. This information can be used to effectively target subsidies to households that cannot afford formal insurance and for whom also informal support is insufficient.

The combination of agent-based modelling and social networks on the one hand and an aggregated regression analysis on the other hand made it possible to systematically test the effects of varying external conditions. While the implications for the resilience of the poorest are based on a theoretical simulation model with a range of simplifying assumptions, the presented analyses nevertheless provide helpful insights into how effective the combination of formal and informal risk-coping instruments can be and which factors have to be considered when estimating the vulnerability of specific households.

Part II

Using models to address socio-environmental challenges

5 Improving insurance design under climate change: Combining empirical approaches and modelling

This chapter is currently under review in Climate and Development as Will, M., Backes, A., Campenni, M., Cronk, L., Dressler, G., Gornott, C., Groeneveld, J., Habtemariam, L. T., Kraehnert, K., Kraus, M., Lenel, F., Osgood, D., Taye, M., & Müller, B. Improving insurance design under climate change: Combining empirical approaches and modelling.

Abstract

Extreme weather conditions in the face of climate change often disproportionately affect the weakest members of society. Agricultural insurance programs that are specifically designed for smallholders in low-income countries are seen as valuable tools that can help farmers to cope with the resulting risks. At the moment, a broad range of methods including experimental games, household surveys, process-based crop models and agent-based models is used to assess the demand for and the effectiveness of such insurance products. However, climate change raises specific socioeconomic as well as environmental challenges that need to be considered when designing insurance schemes. We argue that in light of these pressing challenges, some of the currently used methodological approaches reach their limits when applied independently. We therefore advocate for a sound combination of different methods especially by linking empirical analyses and modelling and underline the resulting potential with the help of stylized examples that address the main challenges for insurance design under extreme weather conditions. Our study highlights how methodological synergies can make insurance products more effective in supporting the most vulnerable, especially under changing climatic conditions.

5.1 Introduction

Extreme weather events resulting from climate change, such as droughts or floods, pose a particular threat to low-income households in developing countries that are engaged in agricultural activities (World Bank, 2009; Hallegatte & Rozenberg, 2017). Agricultural insurance products specifically designed for the needs of smallholder farmers, known as microinsurance or inclusive insurance, are seen as a promising tool for managing disaster risks. The International Panel on Climate Change (IPCC), for example, has stressed the need for risk-sharing and transfer mechanisms such as insurance as a climate adaptation mechanism (IPCC, 2012). Similarly, the UNFCCC has pointed out the importance of insurance for addressing effects of climate change in their Warsaw International Mechanism for Loss and Damage (UNFCCC, 2013). However, climate change poses specific socioeconomic as well as environmental challenges to effective insurance design (Table 5.1). First, to allow for an adequate combination of insurance with other risk management options such as credits, savings, and traditional informal risk-sharing arrangements, it has to be considered that an increasing number of extreme events can alter the effectiveness or increase the costs of these existing strategies (Peterson, 2012; Trærup, 2012; Linnerooth-Bayer & Hochrainer-Stigler, 2015). Second, the introduction of insurance might have environmental side effects such as degradation of natural resources (Bhattacharya & Osgood, 2014; Müller et al., 2017) as smallholders with access to insurance might, for example, be able to quickly restock their livestock herd size after an extreme event (Bertram-Huemmer & Kraehnert, 2018), giving the pasture hardly any time to regenerate. Changing climatic conditions that lead to an increased risk of droughts and other extreme weather events further weaken the state of the natural resource. Third, a particular challenge for agricultural index insurance, where payouts depend on exceeding or falling short of a threshold derived from rainfall or vegetation data (Brown et al., 2011; Benami et al., 2021), is the accurate assessment of crop yields especially when extreme events occur on a local scale. A mismatch between actual losses from a weather shock and received insurance payouts, commonly defined as spatial basis risk, could lead to low acceptance rates of the insurance (Clement et al., 2018).

With experimental games, household surveys, process-based crop models or agent-based models, a wide range of methods is currently used to assess the demand for and impact of agricultural insurance and to identify its shortcomings and unintended side effects. However, with respect to the pressing questions arising due to climate change, some of the methods reach their limits. Experimental games, for example, are a valuable tool to assess specific behaviour, but they usually include only a small number of individuals and, unless the same experimental design is replicated in different contexts, the results are difficult to generalize. The econometric analysis of household surveys allows researchers to draw inferences from large samples representative of the population. However, such surveys, and household panel surveys in particular, from which conclusions can be drawn about the impacts of potentially changing external conditions, are time and cost intensive. Modelling approaches allow researchers to overcome these time and space constraints: Process-based crop models that cover biophysical aspects of crop yield dynamics and agronomic management information, however, do not include human behaviour explicitly. Agent-based models, on the other hand, where human decision-making can be implemented in detail, depend heavily on the availability of data to validate model assumptions.

From our point of view, the potential of each of these methods to contribute to a better understanding of insurance could be considerably enhanced by combining them. We believe that this could lead to a more appropriate and sustainable insurance design given the current challenges of climate change. Mixed-method approaches that link quantitative and qualitative techniques have already been advocated in the context of microinsurance (White, 2014). We reinforce this demand by proposing a combination of modelling and empirical analyses. We address this aim by (a) exploring strengths and limitations of current approaches to assess and improve the impact of insurance; (b) illustrating how a more holistic approach can be beneficial to advance an appropriate and sustainable insurance design; and (c) underlining the potential of combining different methods with three stylized examples that address challenges for insurance design under climate change.

Table 5.1: Challenges for insurance design under climate change

Research theme	Challenges
Risk management options	How can insurance products be adequately combined with other risk mitigation strategies especially when an increasing number of shocks occurs? How can insurance be used to overcome shortcomings of other risk mitigation strategies?
Environmental effects	Which (indirect) effects does insurance have on natural resource use? How can insurance design mitigate unintended consequences?
Index design	How to accurately assess crop yields and yield losses remotely to minimize basis risk? How to distinguish between climate-related and non-climate-related yield loss?

5.2 Strengths and limitations of current methods to evaluate insurance design

Below, we provide brief descriptions of several methods that illustrate the range of approaches currently used to assess insurance demand and the impact of insurance payouts, identify unintended social and environmental side effects, and develop appropriate insurance indices. We focus on experimental games, the econometric analysis of household surveys, process-based crop models and agent-based models, as these are the methods we propose to combine to tackle current challenges. For each of these approaches, we describe the technique in general, highlight their strengths and limitations, and present problems that have been addressed in the context of insurance. Importantly, the methods discussed are not exclusive; analytical models, Bayesian Belief Networks, or qualitative research, for example, may be similarly useful in examining the impact of microinsurance and improving its design.

5.2.1 Experimental games

Experimental games are used to learn what choices people make in specific, well-defined situations and which factors drive these choices. Games can contribute to understanding individuals and groups by mimicking the actual environments where policy interventions will take place (Hernandez-Aguilera et al., 2020a). In most experimental games, the experimenter first endows participants with a fixed amount of money or another easily shared resource such as small packages of food and then gives them one or more decisions to make about what to do with the resource. Because experimental games can be conducted in laboratory and field settings located in any society in the world, they can yield useful insights not only into behaviour but also into local cultural models (Henrich et al., 2004). One weakness of the game method is that a researcher's choice of a game and its usefulness for addressing the research question at hand depends on the researcher's understanding of the local cultural context; in turn, researchers' design choices can interact with the cultural contexts that subjects bring to an experimental game. Indeed, small variations in the game design have been shown to affect results considerably (DellaVigna & Pope, 2019; Landy et al., 2020). Another drawback is that it can be difficult at many field sites to obtain large sample sizes, particularly if the game takes a long time to play or requires participants to play simultaneously. Furthermore, although games aim to map realistic situations, participants might not behave as they do in their everyday life, but rather as they think they should (Zizzo, 2010; de Quidt et al., 2018). In the context of insurance, experimental games have been used primarily to study whether formal insurance crowds out grassroots risk pooling. Such experiments have been conducted in laboratory settings (Lin et al., 2014), and at field sites in the Philippines (Landmann et al., 2012), Ethiopia (Anderberg & Morsink, 2020), and Cambodia (Lenel & Steiner, 2020). Similarly, Cecchi et al. (2016) studied at a field site in Uganda whether formal insurance crowds out social capital, operationalized as donations to a public goods game. Norton et al. (2014) assessed demand for index insurance among farmers in Ethiopia by using a game in which people could allocate money across different risk management options. Agricultural insurance is furthermore beginning to adopt game approaches known as "gamification" (Hernandez-Aguilera et al., 2020b), which is the use of game design elements in non-game contexts (Seaborn & Fels, 2015).

5.2.2 Econometric analysis of household surveys

Household surveys are an essential source of information on the well-being and behaviour of individuals. The sample of households surveyed is ideally representative of subgroups and geographical areas of the population of interest, and is usually based on census or administrative data. Household surveys may address different objectives, ranging from documenting the living conditions of a target population to estimating the impact of development programs and policies on households' well-being (Grosh & Glewwe, 2000). Cross-sectional surveys that are implemented with similar questionnaire design in several years, allow monitoring how living standards change over time. A special case particularly informative to policy design are household panel surveys, in which the same households are traced over time. When analysed with econometric methods, household surveys are a key source to establish a cause and effect relationship between policy-relevant variables and household-level outcomes.

Despite these major advantages, household surveys are also subject to limitations. Depending on the level of representativeness and, in turn, the sample size, implementing household surveys – and especially panel surveys – can be expensive. Furthermore, the amount of information that can be recorded in household surveys is constrained by the time respondents readily devote to a survey interview. Also, there is a limit to the level of detail that respondents can be asked to recall. While major events in life are usually remembered well, individuals typically face more difficulties to recall income streams retrospectively (Wooldridge, 2012). Moreover, some information can hardly be recorded at all, such as inherent ability, skills, or work attitude. Finally, specific mechanisms that drive behavioural changes are difficult to detect with pure survey data. In the context of agricultural insurance, the econometric analysis of household surveys was used to study drivers of the demand for insurance among farmers in India (Mobarak & Rosenzweig, 2012; Cole et al., 2013; Mobarak & Rosenzweig, 2013), Ethiopia (Dercon et al., 2014), and Ghana (Karlan et al., 2014). In addition, the impacts of agricultural insurance *ex ante*, i.e. before an extreme weather event occurred, on the investment decisions of farm households were quantified using household survey data (Hill & Viceisza, 2012; Cai, 2016; Cole et al., 2017; Hill et al., 2019). A related field of research assesses whether indemnity payments from index insurance help farmers to recover from losses. Studies quantifying these *ex post* effects of agricultural insurance based on survey data have focused on Kenya (Jensen et al., 2017; Janzen & Carter, 2019), Mongolia (Bertram-Huemmer & Kraehnert, 2018), and Bangladesh (Hill et al., 2019).

5.2.3 Process-based crop models

Process-based crop models include biophysical plant and soil processes such as the growth of above- and below-ground biomass as well as water and nutrient flows in the plant and the soil to calculate interactions between environment and crop development (White et al., 2011; Boote et al., 2013). Due to their plant physiological algorithm, the models can capture effects like extreme temperatures, dry spells or shifts in the growing season which have not been observed in the past. Hence, these models can be used for quantifying yield and environmental effects of adaptation measures and for projections of future periods or other environments which is particularly interesting in the face of changing climatic conditions (Wallach et al., 2016; Lobell & Asseng, 2017; Rötter et al., 2018). Since process-based crop models can provide information on yield losses immediately after the harvest, they can be used for risk assessments and adaptation planning (Challinor et al., 2018; Webber et al., 2020). This is highly relevant for insurance indices, in particular in developing countries, where crop yield information is not available and/or too expensive to collect because of remotely located fields. Furthermore, the process-based organization of the model allows to distinguish between weather and management attributable influences on crop yield which is crucial for the design of insurance indices, as only weather-induced losses should be covered by the insurance product (Arumugam et al., 2020).

To feed process-based models, weather, soil and management information are needed. Weather information is available on a global scale informed by weather stations, satellite observations and weather models. Soil data are also widely accessible from global or regional soil maps. However, there is often little information about management practices and underlying drivers of management decisions (Asseng et al., 2013; Folberth et al., 2019; Wang et al., 2019). In particular, responses of farmers to changing environmental and economic conditions are not reflected. This lowers the ability of process-based crop models to capture and reproduce accurate crop yields, especially in developing countries where the range of management practices differs highly across space, time, and farmer groups. So far, mainly weather indexes (Dalhaus & Finger, 2016), remote sensing satellite vegetation indexes (Enenkel et al., 2019), and statistical models (Conradt et al., 2015) have been used to quantify crop yield losses. However, there is a growing interest among governments and insurance companies in process-based model assessments, for instance in India (Arumugam et al., 2020).

5.2.4 Agent-based models

Agent-based models (ABMs) are simulation tools that focus on individual actors such as humans, households, firms or institutions. The interaction of these agents with each other and the environment is explicitly considered in behavioural rules (Bonabeau, 2002; Railsback & Grimm, 2012). Agents can differ in their characteristics, i.e. they can be heterogeneous in their attributes and decision rules. Based on the prescribed rules and micro-level properties, emergent temporal dynamics such as the spread of an innovation or collective behaviour can be observed on a macro-level. ABMs can be used to systematically disentangle several influence factors by including and excluding environmental features or aspects that impact the individual decision-making. Furthermore, they have few time and space constraints: Results can be obtained for large regions, which would require high financial resources if empirical methods were used. In addition, ABMs can simulate long-term effects of new policies or altered climatic conditions on a time scale beyond what can be detected with empirical observations. Apart from such explorative analyses, ABMs can also take a backward perspective and help to uncover relations that cannot be fully explained empirically. This so-called pattern-oriented modelling can be used to test assumptions about human behaviour, which can then be compared to observed results (Grimm et al., 2005).

As every other modelling approach, ABMs are only a simplified version of reality which has to be taken into account when drawing general conclusions. Furthermore, ABMs can easily become complex when many influencing factors are included, which can make it impossible to derive cause and effect relations of certain aspects. Besides this, model outcomes crucially depend on assumptions that require careful calibration with data that is often not available. Moreover, although the explicit integration of human behaviour is one of the strengths of ABMs, the theoretical basis of the decision-making frameworks used in such models is often quite simplified (Groeneveld et al., 2017; Schlüter et al., 2017).

ABMs have been used to analyse potential long-term effects of index insurance on sustainability of rangeland management (Müller et al., 2011) and resulting pasture conditions (John et al., 2019). In other studies, the effectiveness of insurance through informal risk-sharing (Aktipis et al., 2011; Hao et al., 2015; Aktipis et al., 2016) and impacts of combining formal and informal insurance (Will et al., 2021a) were investigated.

5.3 Synergies between different approaches to improve insurance design

To overcome some of the individual limitations of the different methods, a holistic approach that couples several approaches could be beneficial. We use three examples that focus on (1) combining different risk management options, (2) evaluating environmental effects of insurance uptake, and (3) appropriately designing insurance indices to show how this can be used to address pressing challenges of insurance design under climate change. We suggest approaching these challenges by linking empirical analyses that provide grounding in reality and models that reduce this complex reality to a limited number of key variables and processes. We use the first two examples to elaborate on combining household surveys, experimental games and ABMs, mediated by the use of econometric methods; with the third example, we show the potential of integrating empirically parameterized ABMs into process-based crop models.

5.3.1 Interplay between empirical data and ABMs

The general insights from household surveys and specific hypotheses tested using experimental games provide an excellent basis for specifying ABMs. While econometric analyses of household surveys can be used to parameterize individual household characteristics such as income, social relationships, insurance status, and environmental conditions (Smajgl et al., 2011), decision-making in ABMs can be based on inferences drawn from small-scale experimental games with the same decision space (Smith & Rand, 2018). The outcome of ABMs can, in return, help to refine experimental research. If this results in new observations, these can again be implemented in ABMs (Chávez-Juárez, 2017). There exist successful examples

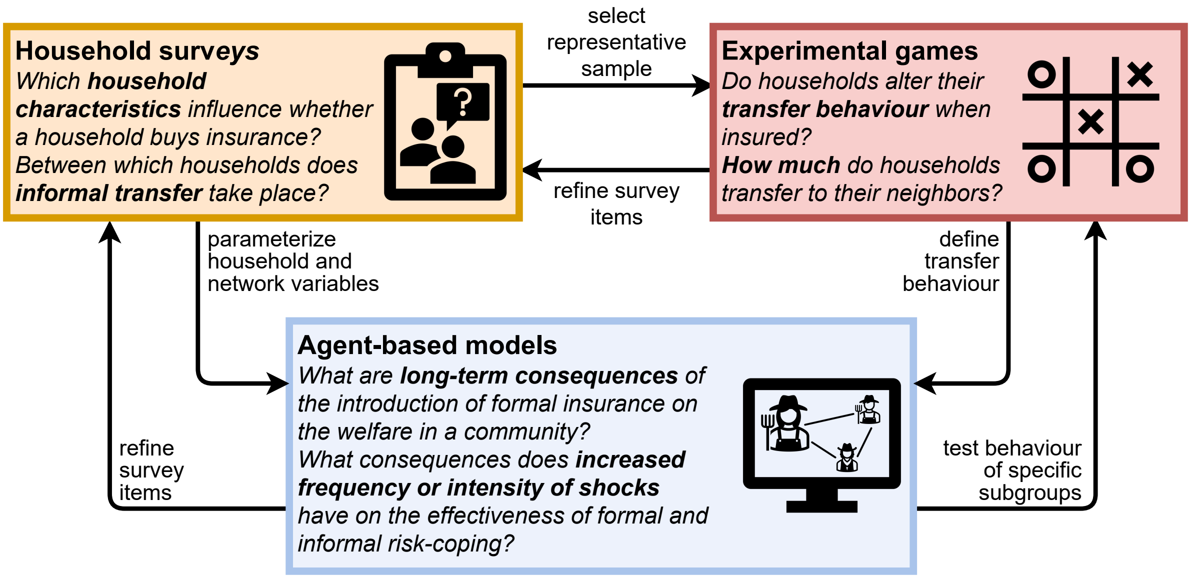

Figure 5.1: Schematic representation of the interplay between empirical data and ABMs to determine the effectiveness of formal and informal risk-coping instruments under climate change

of such back-and-forth approaches. Cronk et al. (2019b), for instance, designed a two-player game to study risk pooling in a laboratory based on earlier ABMs of risk pooling in dyads (Aktipis et al., 2011; Aktipis et al., 2016). The results from the game and ABMs were then used to inform the design of additional experimental games (Claessens et al., 2021).

In the context of insurance, we suggest that a combination of methods could help to determine the effectiveness of formal and informal risk-coping instruments under climate change (Figure 5.1). An increasing number of covariate shocks may threaten existing risk-sharing instruments, such as when an entire community is affected by an extreme event and informal safety nets can no longer absorb the losses (Wossen et al., 2016). At the same time, the introduction of insurance may lead to rising social inequality if insured households no longer contribute to traditional risk-sharing arrangements (Anderberg & Morsink, 2020; Lenel & Steiner, 2020). The behaviour of insured households can be tested in experimental games where participants are randomly matched. In reality, however, the structure of risk-sharing networks determines their effectiveness. Informal protection varies depending on whether, for example, particularly poor households are linked to rich households or whether there is income segregation. Network structures can be revealed with the help of survey campaigns. Integrating information on household behaviour observed during the games as well as network structures of specific villages in ABMs allows researchers to draw precise conclusions on the long-term welfare effects of potentially altered solidarity norms in a society.

A combination of methods is also promising for investigating the potentially negative side effects of insurance uptake on the environment (Figure 5.2). In pastoralist communities, insurance coverage may prevent the need to reduce livestock following a drought (Gebrekidan et al., 2019). While having a positive impact on households' livelihood in the short-term, this may result in overgrazing and pasture degradation, which increases the vulnerability to future extreme events. In agricultural communities, insurance coverage may create incentives to intensify production and, for instance, turn to cash crops or mono-cropping, which yield higher returns but are riskier (Mobarak & Rosenzweig, 2012; Mobarak & Rosenzweig, 2013; Cai, 2016; Cole et al., 2017; Jensen et al., 2017). To grasp the long-term effects of insur-

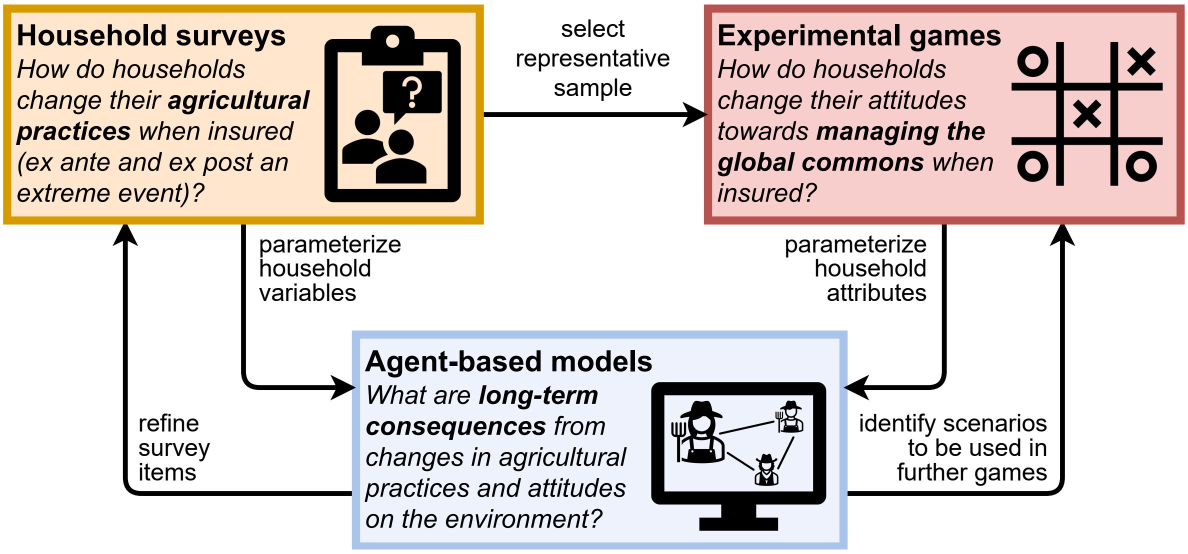

Figure 5.2: Schematic representation of the interplay between empirical data and ABMs to quantify the side effects of insurance coverage on rural communities

ance uptake on the environment, econometric methods may be used to infer from surveys, how households adapt their agricultural practices in response to purchasing insurance. Here, behavioural changes before a payment-inducing extreme event (*ex ante*) as well as once payments from insurance are made (*ex post*) are of interest. Complementary experimental games, conducted in the same empirical context, may reveal more explicitly how the introduction of agricultural insurance changes households' attitudes towards managing the global commons, e.g. to what extent households shift priorities between maximizing their own utility and communal welfare. Agent-based models may be used to extrapolate from the behaviour observed at the micro-level and derive macro-level trends in natural resource use under different scenarios of insurance design and uptake.

5.3.2 Interplay between ABMs and process-based crop models

In order for insurance products to be effective not only under the given conditions but also in the long term, their design must take into account changes in climate but also adjustments in agricultural practices (Siebert, 2016; Surminski et al., 2016). Whereas several long-term climate projections exist and can be used in agricultural modelling (Asseng et al., 2013; Jones & Thornton, 2013; Folberth et al., 2019), future management decisions are much more difficult to predict. Agricultural practices are highly dependent on a farmer's individual psychological and socioeconomic characteristics such as risk aversion, habits or openness to innovations. Furthermore, there is a feedback between farming strategies and global change processes. Farmers might adjust their crop portfolios or invest in irrigation to avoid losses due to altered climatic conditions (Collier et al., 2009). In addition, there might be indirect adaptations of farming decisions when insurance uptake incentivizes different management strategies (cf. section 5.3.1) and insurance uptake is largely determined by farmers' satisfaction with the product (Shirsath et al., 2019).

The exchange of in- and output between process-based crop models and ABMs can help to disentangle the complex interplay between human and environmental processes. ABMs are suggested to be a powerful tool to investigate land use decisions (Parker et al., 2003;

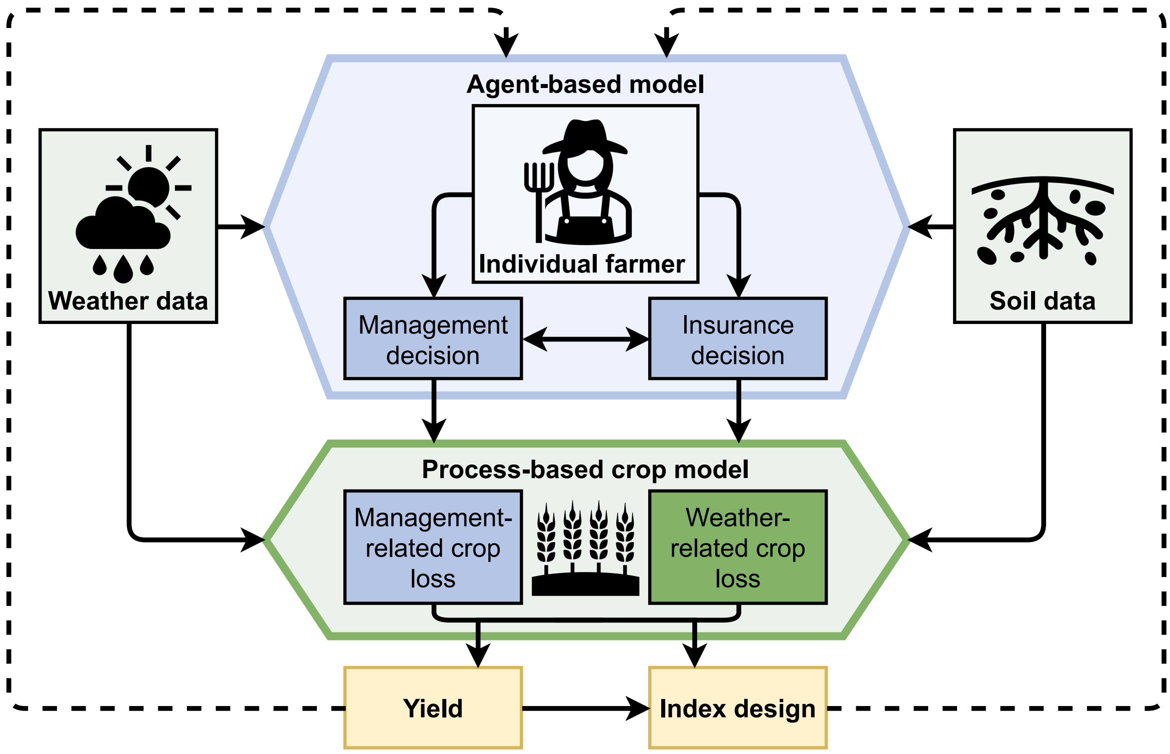

Figure 5.3: Schematic representation of the interplay between ABMs and process-based crop models to improve index design

Matthews et al., 2007; Rounsevell et al., 2014), especially when empirically parameterized (Robinson et al., 2007). Furthermore, insurance uptake can be explicitly modelled as adoption of innovations (Kiesling et al., 2012). Here, the influence of other farmers and additional factors that affect the insurance decision could be taken into account (Jones et al., 2017). Explicitly considering how farmers incorporate various influence factors into their management and insurance decisions and providing these results as input to the process-based crop model would therefore allow for a more holistic picture of the system and improve the accuracy of insurance indices (Figure 5.3). The outcome of the process-based model could then again be used as input for the ABM to further refine long-term projections.

5.4 Conclusions

In this study, we compiled how combining several methodological approaches could help to tackle challenges associated with insurance product design under climate change. We specifically addressed the potential of coupling empirical and model-based approaches to overcome limitations that arise when applying these methods separately. The combination of empirical research and agent-based models can help to understand the interplay between different risk management options as household surveys identify potential income sources, experimental games clarify in which situation households rely on which financial instrument and ABMs extrapolate the findings to a larger spatial and temporal extent. Furthermore, this combined approach can reveal the impact of insurance on natural resource use. How households change their management of global commons after having access to insurance can be assessed using household surveys and experimental games. ABMs allow estimates of resulting long-term consequences on the environment. The challenge of adequately defining insurance indices can be mitigated by established process-based crop models. Combining this approach with ABMs helps to further improve the insurance design as it allows incorporating feedback loops between humans and the environment by explicitly including local environmental constraints and potential effects on farmers' behaviour.

To successfully combine different methods, it is important to clearly indicate which contribution can be achieved with which methods while keeping the limits of each approach in mind (White, 2014; Jones et al., 2017; Kline et al., 2017). An issue that needs to be addressed in the context of microinsurance is, for example, choosing the most representative time to obtain information on insurance uptake or land use. While this is also crucial for stand-alone empirical studies, it is especially important in combination with models, since model rules based on these observations are used to make statements about broad temporal and spatial scales. Furthermore, it must be clearly communicated how much data is needed for the simulations and uncertainties in the empirical observations must be accounted for in the model (Cheong et al., 2012). Additional challenges that arise for interdisciplinary research, such as establishing a common language for exchange and allowing sufficient time for iterative cycles of reflection across all phases of the research process, should also be considered (Kelly et al., 2019).

In this study, we did not focus on the integration of qualitative research which can add further relevant perspectives (Paluck, 2010; White, 2014; Millington & Wainwright, 2017). Since understanding the local cultural process is crucial to framing specific research questions, the use of quantitative methods should ideally be combined with qualitative ethnographic approaches obtained through interviews and participant observation. For example, Cronk (2007) used trust games to study a Maasai risk pooling system. He selected the game based on what he learned during a first round of interviews and conducted a second round of interviews in light of the results of the game. In the context of microinsurance, qualitative methods could be used to assess risk exposure, risk perceptions, and risk management strategies to gain an overall understanding of vulnerability particularly under climate change (Turner et al., 2003).

Overall, we believe that the use of complementary methods to evaluate the effectiveness of insurance and to elucidate potential (unintended) side effects as presented in our study may improve insurance design and make this instrument more powerful in supporting the most vulnerable in a sustainable manner. Future research projects should strive for such methodological synergies to tackle the pressing issue of effectively protecting the poorest against extreme events that will be even more pronounced under climate change.

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6 How to make socio-environmental modelling more useful to support policy and management?

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Abstract

Dynamic process-based modelling is often proposed as a powerful tool to understand complex socio-environmental problems and to provide sustainable solutions as it allows disentangling cause and effect of human behaviour and environmental dynamics. However, the impact of such models in decision-making and to support policy-making has so far been very limited. In this paper, we want to take a critical look at the reasons behind this situation and propose steps that need to be taken to change it. We investigate a number of good practice examples from fields where models have influenced policy-making and management to identify the main aspects that promote or impede the application of these models. Specifically, we compare examples that differ in their extent to how explicitly they represent human behaviour as part of the model, ranging from purely environmental systems (including models for river management, honeybee colonies and animal diseases), where modelling techniques have long been established, to coupled socio-environmental systems (including models for land use, fishery management and sustainable water use). We use these examples to synthesise four key factors for successful modelling for policy and management support in socio-environmental systems. They cover (a) the specific requirements caused by modelling the human dimension, (b) the importance of data availability and accessibility, (c) essential elements of the partnership between modellers and decision-makers and (d) insights related to characteristics of the decision process. For each of these aspects, we give recommendations specifically to modellers, decision-makers or both to make the use of models for practice more effective. We argue that if all parties involved in the modelling and decision-making process take into account these suggestions during their collaboration, the full potential that socio-environmental modelling bears can increasingly unfold.

6.1 Introduction

Socio-environmental systems (SES) are characterised by a tight coupling of human and environmental dynamics (Berkes & Folke, 1998; Folke et al., 2010; Schulze et al., 2017). Both aspects need to be understood to support sustainable management of these systems (Carpenter et al., 2009; Ostrom, 2009; Chapin et al., 2010). Dynamic process-based modelling, and in particular agent-based or individual-based modelling, is often proposed as an effective approach to address such interlinked dynamics and provide solutions to pressing challenges, as it allows disentangling cause and effect of human and environmental processes (Levin et al., 2013).

Socio-environmental modelling has made many contributions in the scientific realm answering environmental issues on the sustainable management of natural resources focusing on land use/land cover change (Parker et al., 2003), agriculture (Huber et al., 2018), fishery management (Lindkvist et al., 2020) or biodiversity conservation (Drechsler, 2020). However, few SES models have had impact on decision support and policy-making (Schulze et al., 2017; Polhill et al., 2019; Elsawah et al., 2020). In contrast, models from other areas such as transportation planning, epidemiology or pesticide risk assessment have been routinely integrated into policy-making processes. Literature reviews evaluate the usefulness of models for specific fields such as conservation management (Addison et al., 2013), marine systems (Gregr & Chan, 2015), agriculture (Primdahl et al., 2010; Reidsma et al., 2018) or environmental health (Currie et al., 2018), but this work does not address how to foster the integration of socio-environmental modelling into practice.

With this paper, we aim to explore models across disciplines and topics that have already influenced policy-making and management. We look at seven good practice examples ranging from those tackling purely environmental problems that do not explicitly represent a human component as part of the model, such as the management of rivers for both fish and amphibian populations or control of animal diseases, to coupled SES models such as sustainable fisheries in Australia and water management in Jordan. Based on the evaluation of these models, we explore factors that enabled or impeded the transfer of management-oriented model results into practice. The examples have in common that they did deliver scientifically innovative insights and had an impact on policy or management decisions. Impact can range from stimulating a discussion process (e.g. raising awareness for so far neglected issues), influencing debates around a decision (e.g. laying out certain options or scenarios), to policy or management decisions being directly based on model results (see van Daalen et al. (2002) for different roles of computer models in the environmental policy cycle). Impact does not state whether the outcome of the decision was positive or negative from a given perspective. In the context of modelling for decision support and policy-making, participatory approaches for involving non-scientists in the modelling process have been suggested as an effective tool to incorporate expert knowledge not only to validate model assumptions but also to tailor policies to relevant local practices (Castella et al., 2014). Stakeholders' expertise is required in different stages of the project, ranging from defining a problem to solving conflict situations after the implementation of a measure (Pahl-Wostl, 2002). Several methods of citizen engagement have proven to be effective including interviews, focus groups, scenario workshops, citizen science and digital participation (Šucha & Sienkiewicz, 2020). In the context of modelling, various studies show the demand for stakeholder participation with a focus on participatory modelling (Voinov & Bousquet, 2010; Voinov et al., 2016) where different approaches have been reviewed (Voinov et al., 2018; Sterling et al., 2019), classified (Barreteau et al., 2017) and standardised (Seidl, 2015; Gray et al., 2018).

While we acknowledge both the benefits and the challenges of such transdisciplinary stakeholder engagement, this is not the focus of this paper. Instead, we concentrate specifically on the potential science–policy interface between (academic) modellers and (administrative) decision-makers. When referring to stakeholders, we therefore primarily address decision-makers who work in policy and management. Better integration of models in policy-making has been suggested with a focus on modelling for public policy (Gilbert et al., 2018), model acceptance in policy-making (Kolkman et al., 2016) and models used as decision support tools (McIntosh et al., 2007; van Delden et al., 2011; Zasada et al., 2017). Our paper contributes to this strand of literature targeting the special requirements that SES modelling bears.

The paper is structured as follows: in the next section, we present how the good practice examples were evaluated, and list the criteria used to classify them. We introduce background information about the seven models in section 6.3. In section 6.4, we present key principles of success or failure that we derive from the evaluation. We conclude our paper with recommendations to make modelling more relevant in policy-making and management.

6.2 Methods

6.2.1 Interview framework

Based on an initial literature review and the authors' experience, we drafted a list of analytical categories which we suspected to be relevant to our problem regarding the practical impact of SES models. We arranged them according to the 'Four Ps' framework developed by Gray et al. (2018) which focuses on the purpose of the modelling endeavour, the processes of exchange between modellers and managers, details on these partnerships, and the products that emerge from this exchange, that is, the range and type of application of the model outcome in practice. This results in the following grouping of the categories:

1. Purpose: background information, relevance of outcome, driving motivation
2. Processes: group size, actors involved, data availability and accessibility
3. Partnerships: previous relationship and experience, organisation of modelling process
4. Products: building confidence and transparency, learning processes, difficulties in the project, usability of the model.

We formulated these categories as questions to compose a questionnaire for semi-structured interviews (see Appendix D).

6.2.2 Interviews

Based on the questionnaire, we conducted semi-structured interviews with seven researchers who were currently or had previously been part of modelling projects in a policy or management context. The selection was by referral through colleagues and collaboration partners and reflects a wide spectrum of models with impact in policy or management, ranging from purely environmental models that do not explicitly involve a human component to socio-environmental models coupling human and environmental processes. All interviews were digitally recorded. Prior to the interviews, informed verbal consent to be included in this research was obtained from the participants. As the study only includes expert interviews and the participants were informed about the research objectives, it does not require ethical approval according to the criteria of the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG). We assessed the respondents' narratives against our categories. This process helped us identify missing aspects as well as emerging common themes, which we added and condensed in subsequent iterations, loosely inspired by 'grounded theory' approaches (Strauss & Corbin, 1997). This led, in the end, to a set of 14 gradients that include most of our questionnaire items but also go beyond them and thus reflect a conceptual learning process by which we amended our initial assumptions.

6.2.3 Gradients to describe good practice examples

The 14 gradients are again grouped according to the 'Four Ps' framework (Purpose, Processes, Partnerships, Products; Gray et al., 2018) and listed with their definitions in Table 6.1. For each gradient, the seven case studies are categorised as 'low', 'medium' or 'high'. The interviewees reviewed our evaluation afterwards (and sometimes suggested modifications). In the following, we present details on the classification according to the gradients.

6.2.3.1 Purpose

The first three gradients (system complexity, model complexity and demand-drivenness) address the background of the modelling example and ask by whom the modelling process was initiated. **System complexity**, on the one hand, refers to the real-world system under study in terms of the number of actors involved or the diversity of processes and interactions that are important in that system. Depending on the research question, the identification of a 'system' already involves some degree of abstraction, as in most SES it is difficult to clearly delineate what elements and links to include and which ones to leave out. On the other hand, **model complexity** indicates to what level of detail elements and mechanisms of the real-world system are represented in the model, that is, whether they are included in detail, appear in strongly simplified form or are ignored altogether. **Demand-drivenness** reflects how far the initiation of the modelling process was driven by demand from the decision-makers' side.

6.2.3.2 Processes

The five gradients in this section (persons involved, decision-maker involvement, academic fields, data availability and data accessibility) relate to the organisation of the modelling process. This includes the number of **persons involved** (ranging from a single-person project to a high number of participants involved), the number of **academic fields** or backgrounds involved (from a single discipline to a highly interdisciplinary project) or the **involvement of decision-makers** in the conceptualisation and development of the model. The latter relates both to the number of decision-makers involved and to the extent of their participation in the process. **Availability of data** refers to the general abundance of qualitative and quantitative data needed to build the model. Here, the situation can be mixed, with, for example, biological data readily available and socio-economic data hard to come by. **Data accessibility** reflects that even when sufficient data bases exist, for example, within a public institution, accessibility may be low if it is difficult for modellers to obtain access to them.

6.2.3.3 Partnerships

Gradients of partnerships (familiarity, modelling experience, exchange frequency and continued support) address the relations and interactions between the different project partners, especially between modellers and decision-makers. **Familiarity** indicates how well project partners already knew each other at the beginning of the modelling process. **Modelling experience** summarises how experienced decision-makers were with modelling approaches

Table 6.1: The 14 gradients used to classify the good practice examples. All gradients range from low to high.

Dimension	Definition/Guiding question
Purpose	
System complexity	Number of actors, processes, interactions; range of observed real-world behaviour
Model complexity	Number of variables, processes, interactions; range of emergent model behaviour
Demand-drivenness	How important was demand by decision-makers in initiating the modelling process?
Processes	
Persons involved	Number of people involved in the modelling process
Decision-maker involvement	How far were decision-makers involved in the conceptualisation and development of the model? How participatory was the process?
Academic fields	Number of academic fields/backgrounds involved
Data availability	Availability of qualitative and quantitative data to build the model
Data accessibility	Accessibility of qualitative and quantitative data to build the model
Partnerships	
Familiarity	How familiar were project partners with one another?
Modelling experience	How experienced with/open to modelling were decision-makers?
Exchange frequency	How frequently did project partners communicate?
Continued support	How willing were modellers to continually support the model users?
Products	
Practical application	How tangible were the project outcomes (e.g. actual decision-making or even legislation vs. improving understanding and stimulating discussion)?
Ease of use	How easy was it for end users to use the model themselves

before the project. **Exchange frequency** indicates how often the project partners met or communicated during the project. This may in practice be restricted by project funding timelines, staff turnover or changing situations on the ground that make models obsolete. **Continued support** reflects the modellers' willingness and ability to provide ongoing support for model users, including beyond the official project duration.

6.2.3.4 Products

The last two gradients (practical application and ease of use) relate to the end product of the modelling project: **practical application** reflects whether outcomes of the model have been relevant for decision-making or to initiate legislative changes ('high' practical application), versus stimulating discussion and generating understanding ('low' practical application). **Ease of use** reflects the complexity of the final model and how intuitive it is for the end users to utilise the model by themselves. This depends, for example, on the availability of a graphical user interface, compared to just a command line tool.

6.3 Good practice examples

The seven case studies we selected represent a wide range of influential modelling projects. They span different regional scales: some deal with concrete environmental questions while others attempt to understand complex socio-environmental or hydro-economic systems in their entirety. In the following paragraphs, we briefly introduce the seven projects. Additional background information is presented in Table 6.2.

- **FYFAM:** The Foothill Yellow-legged Frog Assessment Model (FYFAM) shows how river management affects frog breeding. It was designed to address the potential for conflicts between river management for salmon and frogs: if we provide certain conditions for the benefit of salmon, what are the impacts to frogs? Certain parts of the model (the river habitat) were borrowed from a fish model. The FYFAM model has been used to support the decision-making for river management at several sites.
- **BEEHAVE** simulates the development of a honeybee colony and its nectar and pollen foraging behaviour in different landscapes. The goal is to understand how honeybee colonies respond to multiple stressors (disease, extreme weather, beekeeping practice, insufficient forage supply and pesticides), to identify stress levels and stressor combinations that put honeybees at risk, to support risk assessment and devise mitigation measures. The model has been used by different authorities and industries to explore the effects of multiple stressors and suitable management options.
- **FarmNet-BVD** is an epidemic model. It evaluates the effectiveness of two different strategies to identify virus infections among cattle. The policy question was whether a switch to a new testing strategy would be beneficial to farmers in terms of the costs involved. This was linked to the goal of completely eradicating a cattle-related virus from the Irish cattle population. The model provided a quantitative basis for strategy comparison and influenced the decision taken by managers on a new legislation for specific testing strategies in Ireland.

- **Ecopay:** This ecological-economic model is able to simulate 15 endangered bird species, 15 endangered butterfly species and 7 rare grassland habitat types in combination with several hundred grassland conservation measures (such as different mowing and grazing regimes) in different regions in Germany and Belgium. Its objective was to identify both ecologically effective and cost-efficient payment schemes for land use measures that contribute to the conservation of endangered species and habitats in agricultural landscapes. The model systematically presents the range of alternatives, but no concrete measures were taken based on the outcomes of the model.
- **Atlantis-SE** is a fishery model representing Australia's southeast regional marine ecosystem. It covers 3 million km^2 of Australia's fisheries. The model evaluates different alternative management strategies for a complex multispecies fishery. Outcomes from the model provided information that supported change in a fishery law.
- **ALUAM-AB** is a land use model. It studies agro-pastoral systems and ecosystem services in the Swiss Alps under socio-economic and climate change. The research interest was how to make payments for ecosystem services more effective, based on biophysical factors and taking into account cooperation between land users rather than a uniform distribution scheme. Moreover, ALUAM-AB was applied to better understand which actor types and which type of collaboration are necessary to foster resilience to climate and socio-economic changes. These results were incorporated in a new agrarian policy for Switzerland.
- **JWP:** The Jordan Water Project is a coupled hydro-economic multi-agent model of the entire Jordanian water sector, allowing for an integrated analysis of short- and long-term sustainability challenges in this sector. More generally, the aim was to develop an integrated framework for the evaluation of water policy interventions in water-stressed countries, using Jordan as an example. The systematic representation of important influence factors regarding the water sector improved the awareness for socially accepted and sustainable use of water among relevant authorities in Jordan.

Table 6.2: Overview of the seven good practice examples that were evaluated. The models are arranged by how explicitly they represent human behaviour as part of the model, ranging from purely environmental to socio-environmental models.

	FYFAM	BEEHAVE	FarmNet-BVD	Ecopay	Atlantis-SE	ALUAM-AB	JWP
Degree of explicitly representing human behaviour	Environmental						Socio-environmental
Case study setting	River management model for one frog species	Development of honeybee colonies, foraging behaviour	Identification of virus infections among animals	Grassland species and conservation measures	Marine ecosystems and fishing	Mountain agro-pastoral systems and ecosystem services	Hydro-economic model of the Jordanian water sector
Location and spatial scale	Managed rivers of northern California; the model typically represents ≈1 km length of river	England, Hertfordshire, 5 km × 5 km (can be applied to any region of same scale)	Ireland, resolution depending on geographical coordinates and cadastral maps	Saxony and Lower Saxony (Germany) and Flanders (Belgium), resolution 250 m × 250 m	SE Australia (3 million km^2)	Swiss Alps, smallest landscape unit 100 m × 100 m	Representation of whole country (Jordan)
Research question	How does frog breeding success depend on river flows, temperatures, and channel characteristics?	How do honeybee colonies respond to multiple stressors? What mitigation measures will reduce risk?	Will the introduction of a new virus monitoring approach pay off?	What land use measures are effective to conserve endangered species and grassland habitats?	Which management strategies best achieve ecosystem-based fisheries management goals?	How to manage land to foster ecosystem services supply and increase resilience to climate and socio-economic changes?	How will water policy interventions affect water-stressed countries?

Project duration	2014–2018	Since 2008, ongoing	2015–2017	2008–2018 (in several projects)	2003–2007 (ongoing, use for new questions)	2008–2020	Since 2014, ongoing
Model type	ABM	ABM + simulated age-structured model	Spatially explicit, stochastic, pseudo individual-based	Ecological-economic modelling, optimisation	ODE (ordinary differential equation) model; complex hybrid approach: 58 ecological components modelled; 26 fisheries represented	ABM	ABM
People involved	Modeller, river engineer (for modelling hydraulics) and biologists	Modellers, bee ecologists, industry	Authorities (ministry); official veterinarians; private veterinarians; subject matter scientists; modelling team; farmers' organisations	Scientists (mostly modellers), nature conservation foundation, ministry of agriculture (Saxony)	Scientists, industry representatives, managers, policymakers and economists	Empirical scientists, modellers, (local) authorities, engineers, experts from different field (land use, hydrology, natural hazards, forest, rural development)	Scientists, Jordan Ministry of Water
Key reference	Railsback et al. (2016)	Becher et al. (2014)	Thulke et al. (2018)	Mewes et al. (2017)	Fulton et al. (2014)	Grêt-Regamey et al. (2019)	Klassert et al. (2015)

6.4 Results: Observed patterns in good practice examples

Reviewing the interviews, we evaluated the good practice modelling studies along the gradients explained in section 6.2. The results are graphically represented in Figure 6.1. As the positions on these gradients are not necessarily stable over the course of a project, we marked the dominant position.

By definition, all of the selected examples had some kind of impact with policy-making or management. However, the type of **practical application** differs, ranging from models as tools for discussion (JWP) or a systematic representation of alternatives (Ecopay) to direct influence on the decision-making of legislative or management authorities (ALUAM-AB, Atlantis-SE).

According to the answers obtained from our interviews, few factors are truly indispensable for models that have successfully been used for policy-making or management. **Exchange frequency, continued support** and **data availability** stand out as the factors with consistently high or high and medium ratings for all models. The majority of the aspects were mentioned as being important only in some cases and not in others. In the following, we discuss the observed patterns of all dimensions of the modelling endeavour separately to extract important factors and correlations.

In our sample, systems with a focus on environmental processes are in general less complex than systems explicitly involving a social component. These systems are also characterised by lower **model complexity**. In our good practices examples, model complexity always matches system complexity. We decided to keep both gradients in our framework because complexity mismatch may easily occur in other case studies. Similarly, the complexity of models with a social and an environmental component tends to require higher numbers of **persons involved** in the process. Due to the diverse aspects addressed, those people also have a broader range of **academic backgrounds**.

Many models were used for policy-making after modellers themselves had advocated them. Some processes were initiated on a joint proposal by decision-makers and modellers, but the case that the **demand** came solely from decision-makers was rare. In our case, only the development of FarmNet-BVD was initiated by policymakers. However, the source of original interest in the collaboration does not influence the effectiveness of the process: models initiated by modellers can also be successful in policy-making. Independently of who initiated the process, **decision-makers were involved** in model conceptualisation and development to varying degrees. Some of the projects under consideration were developed in a participatory way with considerable influence of decision-makers on the model implementation (FYFAM, Atlantis-SE and FarmNet-BVD), others were developed from an academic perspective and later applied to concrete policy-making settings (BEEHAVE, JWP). Project partners were not necessarily **familiar** with one another beforehand. Similarly, not all decision-makers were **experienced with modelling** in advance.

Our interviews suggest the **exchange frequency** as the most critical aspect during the whole process. Meeting on a regular basis to discuss model results and project development ensures a stable ground for project impact. For all our examples, it was furthermore guaranteed that the model developers **continued the support** at the end of the project duration such that some of the models could be adapted to new situations with similar research questions (Ecopay, FarmNet-BVD). Besides reusing the same model in follow-up projects, continuing the application of models in policy-making can also be facilitated when decision-makers can

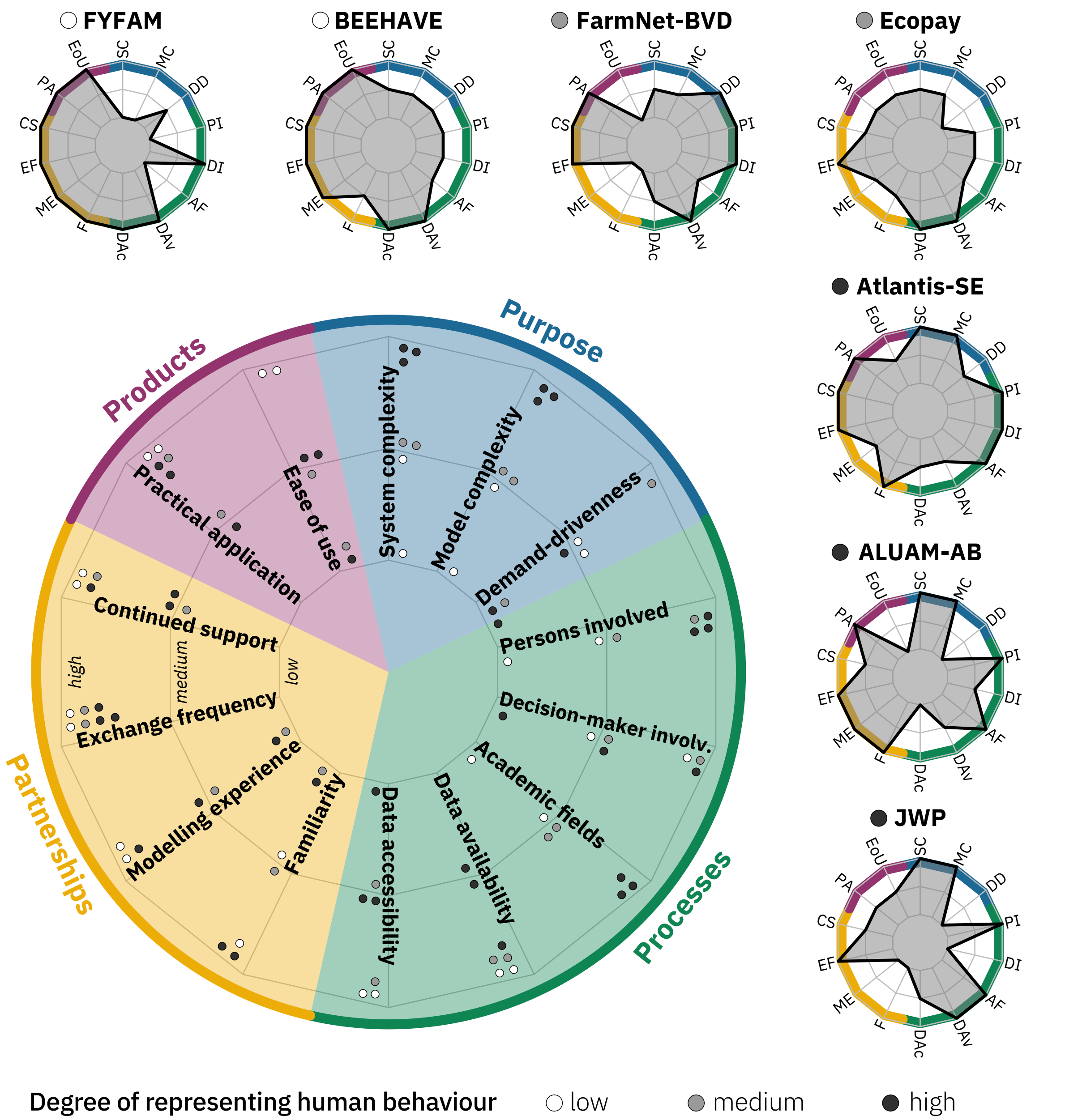

Figure 6.1: Classification of the good practice examples along the 14 gradients. The large panel shows the number of studies classified as low, medium or high for each gradient. The outer radar charts show the classification of the individual models. Abbreviations correspond to the gradient named at the respective circular position on the large panel. The outer charts are arranged according to their degree of explicitly representing human behaviour as part of the model, ranging from purely environmental to socio-environmental models. For better visualisation in the larger panel, we divided this continuous gradient in three distinct groups with similar degree of human behaviour and use different colours in the large panel to represent the classification of the models with low (white), medium (grey) and high (black) level of human behaviour.

apply the models to specific questions, potentially also different to the original one, independent of the modellers. Only two models in our sample (FYFAM, BEEHAVE) are designed in a way that policymakers can use them completely on their own. In other models, policymakers design new scenarios or evaluation options in direct collaboration with modellers (Ecopay, ALUAM-AB, JWP). One factor that simplifies the **ease of use of models** by non-modellers is the creation of an intuitively designed graphical interface. Furthermore, training provided by modellers can encourage decision-makers to work with the models on their own. Here, the application of a programming language with low complexity (e.g. NetLogo) might be beneficial.

Another key aspect across all selected studies which allowed them to be good practice examples is the **availability and accessibility** of data. Calibrating and validating models to existing data at the required resolution is essential to make policy or management decisions drawn from the models as precise and reliable as possible. Although all interview partners confirmed that their models had excellent or appropriate data available, two also mentioned that data accessibility can be an issue, for example, due to European data sharing regulations (FarmNet-BVD, ALUAM-AB).

6.5 Discussion: Specific recommendations for SES Modelling

From the seven interviews and our general experience in the field, which also includes modelling endeavours that were not seen as having achieved an impact in the sense used here, we conclude that there are four key factors for ‘successful’ models. These factors refer to what was mentioned as important by all our interviewees (data availability, exchange frequency and continued support) but also go beyond that. Once more structured around the ‘Four Ps’ framework, we discuss the importance of modelling the human dimension (purpose); data availability and accessibility (processes); collaboration, trust and acceptance (partnerships); and decision processes (products). We give recommendations for each of these factors on how to overcome difficulties that arise when modelling for policy and management support. Some parts of the discussion are transferable to other domains, but as most of the aspects are more difficult to address for socio-environmental models compared to models with a focus on environmental processes, the four key factors may explain why models have found comparatively little use in policy or management advice in this field in particular.

6.5.1 Purpose: Human dimension

The **human dimension**, the ‘socio-’ in socio-environmental systems, adds levels of complexity as humans, more vehemently than other species, continually innovate and adapt their practices while negotiating their interests. This sometimes leads to what has been called ‘wicked problems’ (Churchman, 1967; Davis et al., 2018)—problems that involve a host of stakeholders with conflicting interests, and for which no simple or optimal solutions exist. Such a situation occurred, for example, when discussing effects of strategies to prevent new infections during the coronavirus pandemic (Squazzoni et al., 2020). Here, models can be particularly useful in providing a forum for discussion by revealing the interests and assumptions of the different parties involved, creating a space to take new perspectives and, thus, have the potential to stimulate a change in lines of thinking. With respect to our good practice examples, such an approach was employed in the JWP example that aimed at a long-term sustainability perspective—a view the involved ministry had not taken before.

However, as structures and dynamics that involve humans are difficult to formalise in model terms (Schlüter et al., 2017), their inclusion in a model may drastically increase the complexity of model dynamics as well as the uncertainty around model results (Squazzoni et al., 2014).

Recommendations: We encourage the use of models as discussion tools to bring different perspectives of stakeholders together—a process that is also referred to as social learning (Edmonds et al., 2019; Schlüter et al., 2019). Furthermore, we recommend that modellers and decision-makers acknowledge that the understanding of complex socio-environmental systems depends to a large extent on a sound representation of human decision-making. The need for rapid answers must therefore not lead to models being overly simplified (Squazzoni et al., 2020). The trade-off between the expectation of quick responses and precise projections of the future, which can only be achieved by a detailed implementation of human behaviour, should rather be resolved by clearly communicating the purpose of a model (Grimm et al., 2020).

6.5.2 Processes: Data availability and accessibility

The seemingly obvious assumption that it is generally more difficult to obtain reliable **data** on socio-environmental problems compared to purely environmental ones, once again due to the complexity added by the human factor, was not fully confirmed by our good practice examples. In the cases of JWP and Atlantis-SE, socio-environmental data were relatively abundant and accessible. In contrast, accessing existing databases was an issue in two of our examples, as mentioned above. Since these difficulties arose in both the socio-economic and the ecological context, this factor appears to be context-specific rather than systematic. In the case of the BEEHAVE model, the interview partner indicated that industry partners had easier access to data; however, most of these data were subject to company confidentiality regulations and would therefore not be available for other projects to use.

Recommendations: As we have observed for our good practice examples that data availability was a key aspect for impactful models, we highly encourage coordinated and harmonised data collection not only of ecological but also of socio-economic data. Examples for this are endeavours such as Long-Term Socio-Ecological Research (LTSER) platforms, where socio-ecological data collection is organised across the world (Dick et al., 2018). These systematic efforts come along with transparent rules for data accessibility which are crucial for impactful modelling projects.

6.5.3 Partnerships: Collaboration, trust and acceptance

With exchange frequency and continued support, two aspects of the partnership between modellers and decision-makers stood out as being important in all our case studies. This suggests that the **collaborative process** is critical to an impactful modelling endeavour. Strong exchange can help to prevent false expectations of decision-makers concerning the power of models (Kolkman et al., 2016). In the Ecopay project, there were diverging expectations between scientists on the one hand (long-term project, transferable models) and decision-makers on the other (concrete measures). Providing enough time to understand the perspectives of other disciplines and to find a common language was seen as crucial. In the JWP project, for example, a series of four 2-week workshops was organised to foster understanding of the model. However, a large heterogeneity in the group of stakeholders and disciplines involved made it difficult to find the appropriate speed for workshop discussions. Continuous communication ensures the understanding of decision-makers concerning limitations and uncertainty of models and prevents turning models into black boxes (Gilbert et al., 2018). Due to a broader range of backgrounds of people involved in the process, all these factors seem to be more pronounced in socio-environmental than in purely environmental contexts (see Kline et al. (2017) for their experience in a project investigating forest wildfires, Squazzoni et al. (2020) for the importance of interdisciplinary research on the coronavirus pandemic).

When the involved parties are not familiar with one another in advance, project partners need to be aware that creating **trust** between collaborators needs time, which has to be included in planning the process (see also Briggs (2006) for the difficulties of integrating science and policy on natural resources in general). The establishment of mutual reliance in the project team was often, but not always, related to a specific 'eye-opener' or breakthrough moment which advanced the shared understanding of different stakeholder groups, led to bonding between them, and created strong confidence in the project's usefulness. In our case studies, methods that induced breakthrough moments included the use of graphical representations, games and simulation runs based on past conditions showing that the model was able to represent the recent past correctly (Atlantis-SE). During workshops in the FarmNet-BVD project, it proved helpful to explore contradictions in the assumptions of decision-makers to open up the debate about alternatives. Conventional methods of trust-building are equally important in successful projects; these can consist in benchmarking with existing models, or having an independent peer review of project-related documents and models (Atlantis-SE, BEEHAVE). In the case of BEEHAVE, such a peer review of the formerly used model of the EFSA (European Food Safety Authority) and the BEEHAVE model assured the quality of the model and finally led to the replacement of the original model with BEEHAVE. The establishment of such instances of quality control may also foster the acceptance of models in policy-making and management support. These can range from simple model code review (e.g. as offered by CoMSES Net) to the examination of complete modelling assessments (e.g. as done by the Regulatory Scrutiny Board of the European Commission).

It is not essential that decision-makers are experienced with modelling in advance. However, openness for such an approach and knowledge of similar methods such as statistical models simplifies communication and collaboration. In general, standard economic models appear to be more broadly **accepted** in policy and management support than SES models, which is partly a matter of traditions that have been established for longer, but also of many policymakers having a background in economics rather than the interdisciplinary training that is often helpful for SES analysis. We generally observe that the acceptance and use of SES modelling has actually been steadily spreading, from research to industry and on to public authorities—but it takes time. Mixed institutions that involve industry, researchers and policymakers might facilitate this process.

Recommendations: First, with respect to collaboration, we highly encourage all parties involved to make their expectations explicit at the beginning, especially concerning the outcomes of the policy-making process. To achieve successful exchange, we furthermore underline that finding a common language is crucial to combine expertise from a wide range of disciplines.

Second, to foster the understanding of models and facilitate trust in them, we encourage modellers to promote the emergence of 'eye-opener' moments using various tools of visualisation. Additionally, modellers can contribute to confidence in model results through benchmarking, independent peer review or by including quality control in the project structure

(Houweling et al., 2015). Transparent handling of model code through open-source development and sharing of models on public repositories (GitHub, CoMSES Net, etc.) helps to foster this.

Third, as in the quote famously attributed to Henry Ford that states that if one had asked people what they wanted, they would have said faster horses but not cars, decision-makers may simply not be aware of the benefits and feasibility of state-of-the-art modelling approaches. To reach acceptance of models, modellers should therefore disseminate information to decision-makers, promote exchange between modellers and decision-makers, be ready to teach modelling skills, and engage in the organisation of workshops that attract both sides. Large institutions and authorities can contribute to this exchange by employing modelling experts for consulting, evaluation and assistance.

6.5.4 Products: Decision process

Research objects in SES models tend to be more contested than those mapped by purely environmental models since they touch the interests of a broader set of stakeholders who may have diverging opinions. In contrast, resource management decisions such as in the FYFAM model—frogs versus salmon—are often less politically debated. Favouring one species over the other cannot easily be characterised as ‘progressive’ or ‘conservative’ political positions, for instance. Gotts et al. (2019) accordingly speak of SES as ‘contested systems’. Furthermore, a chain of institutions with diverging time horizons are involved in the policy cycle. To ensure that an SES model can have true impact, it is hence important (and at the same time challenging) to include those decision-makers who actually have the power and legitimacy to implement model findings. In the FarmNet-BVD model, for example, having both the ministry and farmers on board facilitated the uptake of model outcomes in new legislation in Ireland as the two implementing forces were able to discuss details during the model development phase. In ALUAM-AB, one of the key researchers later on became an influential person in the policy sector. On the other hand, for Atlantis-SE, it was reported that the absence of a competent ‘policy champion’ that modellers could turn to slowed down the policy-making process.

In general, only if model assumptions and rules are well-grounded and fitting to purpose and context, their outcomes will be able to support wise policy-making and management and should be included in the decision-making process. This can be especially harmful when models are not properly adapted to a context different to the one they were originally developed for (Squazzoni et al., 2020) or when they are still widely used in consultancy but not updated to standard practices (Railsback, 2016). One of the rare documented examples of negative impact of models can be found in the context of the 2001 outbreak of foot-and-mouth disease in the United Kingdom where misguided interpretation of mathematical model results led to the slaughtering of a large number of animals, which was later considered to have been unnecessary (Kitching et al., 2006). The modelling endeavour may, moreover, be captured by decision-makers to one-sidedly support their previously held convictions and shut down rather than open up discussions of policy or management alternatives (Squazzoni et al., 2020). Modellers thereby inevitably have to take on the role of translators for the model results, as only this allows a sound understanding by decision-makers which needs to be the basis to use the model in any decision process (Gilbert et al., 2018). Explicitly communicating assumptions in the model conceptualisation and uncertainties in the model output is particularly important for an effective incorporation of the results in the decision-making process

(Brugnach et al., 2007; Gregr & Chan, 2015; Davis et al., 2018). But even if the cooperation process is carefully framed, modellers need to be aware that policy advice is simply not always desired (Squazzoni et al., 2020) as for some problems there is only a small 'window of opportunity' (Kingdon, 1984) where policymakers are open to tackle a problem and need advice that could then be provided by models.

Recommendations: We underline that model users (including from the decision-makers' side) should have a profound understanding of the model and only apply it in cases where model assumptions are suitable. In the end, the consequences of decisions may reach well beyond the original scope of any single research question and model. In this regard, due to higher complexity, modellers are even more obliged to apply good modelling practices (Schmolke et al., 2010; Schulze et al., 2017) to SES models. Furthermore, policymakers are highly encouraged to provide a 'policy champion' or 'knowledge broker' as interface person to modellers. Ideally, this should be someone open to modelling approaches and at an influential position in the decision-making process who is able to mediate between both parties.

6.6 Conclusion

By evaluating seven good practice examples, we show that leverage points for increasing the impact of socio-environmental models in policy-making or management are manifold. While our paper focuses on the transfer of knowledge generated by models to the actual decision-making process and therefore mainly refers to the community of modellers and to decision-makers, many of the aspects we highlight, especially those referring to model development, will also apply to situations where a broader range of stakeholders is involved, such as during participatory modelling (Castella et al., 2014; Reid et al., 2016).

We conclude that the main reason currently inhibiting a wider use of socio-environmental models in policy-making or management is their higher complexity compared to purely environmental models that arises from explicitly incorporating the human dimension. Adding levels of behaviour results in more difficult models. These additional aspects also impede simple solutions for policy-making and management. This is reinforced by the fact that addressing both the social and the environmental dimension adequately in models requires involvement of people from different backgrounds. Their potentially contested positions make consensus building and thus decision-making for policies more challenging. In contrast to other problems, where decision-makers rely on the judgement of experts to assess the importance of influencing factors that should be integrated into models, human behaviour is more tangible for many of the actors involved so that more concrete expectations are placed on the representation of processes in models. This can easily threaten the acceptance of models when not all of the desired factors can be addressed. Furthermore, data accessibility, a crucial aspect of impactful modelling projects, is more difficult due to privacy issues.

All these factors pinpoint the importance of using models for SES problems on the one hand to provide a common ground for exchange and on the other hand to allow disentangling cause and effect of human and environmental processes. The same factors, however, urge to respect fundamental aspects of science–practice interactions, such as clear communication of expectations and results or building trust. Even though any model can depict only a part of reality, this issue is, more than in other disciplines, pertinent to the inclusion of human behaviour, as some patterns will never be reproducible in model rules due to the inherent complexity of decision-making. Nevertheless, modellers and decision-makers should continue to embark on common projects and learn from successful examples to increasingly unfold the full potential that socio-environmental modelling bears. We have synthesised recommendations for dealing with common difficulties that may arise during the process of modelling for policy or management support, which are addressed to modellers, decision-makers or both. If all parties involved in the modelling and decision-making process take into account our suggestions during their collaboration, socio-environmental modelling will hopefully no longer be largely limited to contributions to the scientific debate, but will be able to be effectively integrated into supporting decisions for policy-making and management.

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Authors' contributions

M.W., G.D., D.K. and B.M. conceived the ideas and designed the interview questionnaire; M.W., G.D. and B.M. conducted the interviews; H.-H.T. and A.G.-R. were part of the interviewed group of experts; M.W., G.D., D.K. and B.M. analysed the interviews; G.D. created the figure; M.W. led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

7 Synthesis, discussion and outlook

7.1 Summary of main results: Effects of formal and informal risk management on the resilience of low-income households

The aim of the first part of this thesis was to contribute to the understanding of the impact of risk management with formal and informal instruments on the resilience of low-income households in developing countries (research objective R1.i). A main focus was on potential unintended social side effects of microinsurance as novel policy instruments when households additionally help each other in informal risk-sharing networks in times of need. These objectives were addressed using socio-environmental modelling in two studies that were based on the same agent-based modelling framework, but differed in certain aspects (see Table 7.1 for a summary of the differences between the studies). As the degree of realism was gradually increased between the studies, it was possible to gain a generic understanding of the system behaviour before explaining outcomes from more complex interactions of the components (Schlüter et al., 2019). Deliberately omitting income and network heterogeneity in the first study (Chapter 3) provided the opportunity to uncover and understand possible side effects of the introduction of formal insurance in general. The specific effects on particularly poor households could then be examined separately in the second study (Chapter 4).

In Chapter 3, it was shown that the introduction of formal insurance in communities with existing informal risk-sharing arrangements can have crucial impacts on household welfare. On the one hand, insurance in the model provided full protection against income losses for households that signed an insurance contract and thus made an important contribution to the resilience of these households. On the other hand, when insured households in the model became unwilling to help households without insurance and withdrew their contribution to informal transfers, this largely reduced the ability of uninsured households to cope with income losses. In the model, uninsured households alone could not provide the assistance which households in need required from their network. Even more critical, however, was the finding that even if insured households remained willing to help their uninsured neighbours, these were less effectively protected against income losses with some of their potential donors being insured. This was largely driven by the fact that insured households had less money available to support others after paying the regular insurance premium. Especially in the years following the introduction of formal insurance instruments, this had a large impact on the volume of informal transfers in traditional risk-sharing networks. However, when shock events such as droughts or floods affected many households simultaneously, formal insurance complemented informal risk-sharing in our model setting to a large extent. These model outcomes underline the increasing importance of formal insurance instruments, especially since weather-related extreme events are expected to occur more frequently under climate change (Sheffield & Wood, 2008; Dai, 2013; Thornton et al., 2014; Tabari, 2020).

In the case of heterogeneity in income and network links investigated in Chapter 4, it was shown that formal insurance can pay off not only for the insured households themselves,

Table 7.1: Differences of the two agent-based modelling studies in this thesis regarding the network implementation, household characteristics including income distribution and insurance uptake, and transfer behaviour

	Behavioural change (*Chapter 3*)	**Income inequality** (*Chapter 4*)
Network	Stylized small-world network (undirected links)	Empirical network of a village on the Philippines and stylized random networks based on characteristics of the Philippine network (directed links)
Income distribution	Homogeneous	Heterogeneous, based on empirical data
Insurance uptake	Random	Based on available financial resources
Transfer behaviour	"Solidarity" shown by all households vs. "Solidarity" shown by uninsured households and "No solidarity" shown by insured households	"Solidarity" shown by all households

but also for poor households that may benefit from many of their peers being insured. In the model, this effect was found to be particularly strong for severe shocks where uninsured households had fewer resources to share. Similar to what was observed in Chapter 3, the positive impact of insurance for uninsured households turned out to be especially pronounced for shocks that affected many households simultaneously. However, it must be taken into account that these results only cover cases with insured households showing solidarity with their uninsured peers. Since, in the case of a heterogeneous income distribution, a large share of informal transfers was contributed by wealthy households who could afford insurance, the withdrawal of solidarity from insured households would likely have a particularly strong impact on the resilience of uninsured households (Anderberg & Morsink, 2020; Lenel & Steiner, 2020). It was also shown that in addition to the individual budget, the disposable income of potential donors and the number of neighbours that can be asked for help must be taken into account to derive insights into how well a household can cope with income losses. How many households might ask the household for help also played a role, as household may need the money they distribute to others in years without shocks in subsequent years themselves. These results highlight the importance of considering both individual household characteristics and network position to identify vulnerable households that can neither afford formal insurance nor are effectively protected in informal risk-sharing networks. The resulting regression model can be seen as a decision support tool, as it aggregates all effects relevant to the resilience of households and allows the same conclusions to be drawn based on the specified attributes as with the full simulation model.

The results obtained in the two modelling studies offer new perspectives on the interplay of formal and informal risk-coping instruments that complement existing empirical research. They uncover potential long-term implications and feedbacks that need to be considered to design insurance products in an effective way such that they provide a good basis for achieving the goal of eradicating poverty worldwide in a sustainable manner (UN, 2015). While it was shown that formal insurance is often a valuable complement to informal risk-sharing, it was also revealed that, under certain conditions, insurance can have negative consequences for households that do not have sufficient financial resources to insure (Chapter 4) or choose not to purchase insurance due to other reasons (Chapter 3). To strengthen the resilience of the entire population, it is therefore necessary to develop insurance products in close alignment with existing risk-coping arrangements. This might help to maintain these important structures and use their benefits effectively.

Several aspects that have been found to positively affect insurance uptake can be addressed by actively involving the existing social network. Among others, economic factors regarding the affordability of insurance and social factors including trust in the product have a crucial influence on the decision to insure (Patt et al., 2009; Eling et al., 2014; Dror et al., 2016; Platteau et al., 2017). When insurance is offered to groups rather than to individuals, the network could pay the premium as a whole which would allow internal agreements on financial contributions making insurance affordable also to the poorest of the population (Dercon et al., 2006; Trærup, 2012; Sibiko et al., 2018). Similar approaches have been taken with respect to savings (Karlan et al., 2017) and microfinance (Banerjee et al., 2013). However, if households are facing different risks (Barrett et al., 2001), group-level insurance might in turn trigger inequalities, when some in the group benefit more from payouts than others. Here, price differentiations with every household providing a fair share to a formal contract according to its available resources and risk exposure could help to insure a larger part of the population while at the same time avoiding conflicts. Additionally, losses from idiosyncratic shocks that can be well covered by the informal network could be excluded from formal insurance. Explicitly involving the informal network as part of the risk management could reduce insurance costs, which would allow more households to participate and decrease social inequality (Mahul & Stutley, 2010; Ahmed et al., 2016; Fisher et al., 2019). Furthermore, the network could also play a significant role in increasing trust in insurance products and the institution that sells and manages them (Trærup, 2012; Sibiko et al., 2018). It was shown that people are more likely to purchase insurance when advised by a trusted farmer or village leader (Giné et al., 2008). Involving the social network in the insurance decision could therefore help to establish confidence in the product.

7.2 Methodological reflections

7.2.1 Value of an agent-based modelling framework with integrated social network

The literature review on agent-based modelling and social network analysis presented in Chapter 2 highlighted how essential the explicit inclusion of network structures and household properties is for understanding coupled human–natural systems (R2.i). This potential was addressed in the two agent-based modelling studies of this thesis to understand the impact of formal insurance and informal risk-sharing on the resilience of smallholders. In this regard, the concepts identified through the literature review provided a basis for addressing various content-related research questions. At the same time, the wide range of possibilities for integrating social networks in agent-based models and analysing the combined approach identified in the review also shows where there is room for further model-based studies that address formal and informal risk-coping instruments. In order to highlight how the concepts from the review have been implemented in the modelling studies and what advantage each

Table 7.2: Classification of how the aspects for social networks in agent-based models defined in Chapter 2 were used in the two modelling studies (Chapters 3 and 4) of this thesis

	Levels		
Purpose	**Diffusion:** Links as channels for monetary transfers between households		**Social integration:** Network providing social capital through risk-sharing
Network integration	**Endogenous:** *Not considered within this thesis*	**Exogenous:** Small-world network (*Chapter 3*), empirical network and empirical-based random network (*Chapter 4*)	**Co-evolutionary:** *Not considered within this thesis*
Types of analysis	**Agent-centric:** Variation of economic needs of households and external influences through different characteristics of extreme events (*Chapter 3*)	**Network-centric:** Variation of rewiring probability and number of neighbours in small-world network (*Chapter 3*)	**Structurally explicit:** Functional relationship between resilience and income situation as well as network position (*Chapter 4*)

approach has brought for the understanding of the effectiveness of different insurance instruments, the classification of the two studies according to three main aspects covered in the review (purpose, network integration, type of analysis) is discussed hereafter (see Table 7.2 for a summary of this overview).

The primary **purpose** of the network in both studies was ‘diffusion’ as the links in the network served as channels for monetary transfers between households with the capacity to help and those in need. ‘Social integration’ with the network position providing social capital was implicitly also considered as the main focus of both studies was to assess consequence of solidarity for risk management.

With respect to the **network integration**, the focus of both studies was on an exogenous network, i.e. the network topology was defined at the beginning of the simulation and kept fixed during the model run. The network topologies differed between the two studies with a stylized approach in Chapter 3 (small-world network) and an empirically-based approach in Chapter 4 where a network of a village on the Philippines built the basis for the analysis. Networks that evolve during the simulation based on individual decisions of agents and further impacts through the environment (endogenous networks) or feedback loops between the states of agents and the topology of the network (co-evolutionary networks) were not considered within this thesis.

From a methodological point of view, the main difference between the two modelling studies was with respect to their **type of analysis**, i.e. the way in which the social network in the agent-based model was evaluated. In the first model study (Chapter 3), agent-centric aspects were addressed by considering the effect of the economic needs of households (i.e. their level of living costs) and external influences through different characteristics of extreme events (i.e. frequency, intensity and type of shock). A network-centric analysis was included in Chapter 3 by varying the properties of the stylized small-world network in which the households were connected. Specifically, the effect of different numbers of neighbours and the rewiring probability indicating the randomness of the network were systematically analysed. A structurally explicit analysis was applied in the second model study (Chapter 4) with the aim to uncover the functional dependence of the simulated resilience of households without access to formal insurance on both network characteristics such as the number of potential donors (outdegree) and the number of households that might ask for support (indegree), as well as household attributes such as the income of each household and the disposable income of its neighbours.

The two modelling studies underlined how important the integration of social networks in agent-based models is when addressing effects of formal and informal insurance. First, it allowed to explicitly consider the transfer behaviour between the individual households. The underlying network provided a way to map potential unintended side effects of introducing formal insurance on uninsured households. Without the explicit consideration of network links, it would still be possible to test the interplay of formal and informal insurance assuming a common risk-sharing pool (see e.g. Santos et al., 2021), however, the limited range of interaction with particular other households as described in several empirical studies (Fafchamps & Lund, 2003; De Weerdt & Dercon, 2006; Kinnan & Townsend, 2012) is only possible when considering an underlying network structure. Second, by explicitly representing the network structure, it was possible to address and systematically test the effects of different household and network characteristics separately. Analysing system responses to the resilience of households revealed detailed insights into the effectiveness of formal and informal risk-coping mechanisms under different external conditions (e.g. shock frequency and intensity) and support characteristics (e.g. the number of neighbours). Third, the combination of the two methods provided the basis to test, especially in Chapter 4, the relative importance of household attributes and network characteristics for the effectiveness of different risk-coping instruments. If these two main sources of influence had not been explicitly considered in the agent-based model, a generalization of these factors which makes it possible to detect vulnerable households could not have been realized.

Further insights into the effectiveness of formal and informal risk-coping instruments could be gained if the entire range of the review framework outlined in Chapter 2 was exhausted. This is particularly applicable to the network integration, which was assumed to be static (exogenous) in both modelling studies. However, connections might change over time and in response to external circumstances, so it would be worth considering a co-evolutionary approach (for an example in this direction, see Bramoullé & Kranton, 2007). This could include, for example, agents abandoning connections to households when they realize that an exchange is not reciprocal as the other household is not willing or wealthy enough to make a transfer. In addition, when shock frequency increases or more covariate shocks occur, connections to insured households are particularly helpful. This might be reflected in network dynamics through newly emerging links.

7.2.2 Using models to address socio-environmental challenges

For the research questions addressed in this thesis, the use of an agent-based model had several advantages which can also be beneficially to solve other socio-environmental challenges.

First, the modelling approach provided a detailed system understanding which helped to disentangle how the effectiveness of different risk-coping instruments depends on household characteristics and the surrounding network structure. Second, the approach was not limited to time and space constraints that many empirical approaches face. For the specific case addressed in this thesis, this advantage was exploited to combine empirical knowledge obtained in laboratory settings (Lin et al., 2014) and at field sites in Cambodia (Lenel & Steiner, 2020), the Philippines (Landmann et al., 2012), and Ethiopia (Anderberg & Morsink, 2020). Using the stylized modelling approach, it was possible to draw overarching conclusions on the effectiveness of formal insurance and informal risk-sharing when insured households change their transfer behaviour (Chapter 3) or some households do not have enough financial resources to insure (Chapter 4). In addition, agent-based models can simulate long-term effects of new policies or altered climatic conditions on a time scale beyond what can be detected with empirical observations. In this thesis, the modelling approach allowed to identify risk areas that might potentially emerge in the future due to rising living costs or climate change resulting in an increased frequency or intensity of extreme weather events.

To exploit the full potential of socio-environmental modelling, it should be used in combination with several other methodological approaches. While this is true for several contexts (Janssen et al., 2006; Robinson et al., 2007; Bruch & Atwell, 2015), in this thesis, the particular advantage of a synthesis of several methods was highlighted with respect to insurance design under climate change (R1.ii). In Chapter 5, it was envisioned that experimental games, household surveys, process-based crop models, and agent-based models could be effectively combined to contribute to better insights into insurance. Such an improved understanding is needed to effectively address the challenge of strengthening the resilience of the most vulnerable, especially under climate change.

As every theoretical simulation model, also the model framework used in this thesis involves a number of simplifying assumptions that need to be taken into account when interpreting the results and evaluating an appropriate insurance design. While the stylized modelling approach of the two studies has the potential to reveal qualitative trends, it cannot provide quantitative predictions. By clearly communicating the model purpose (in this case 'theoretical exposition' following the classification in Edmonds et al. (2019) or 'demonstration' following the classification in Grimm et al. (2020)), such models can nevertheless be helpful for decision support (Schlüter et al., 2019; Grimm et al., 2020). In Chapter 6, it was outlined how socio-environmental modelling can be effectively integrated into policy-making and management (R2.ii). It was argued that models are a powerful tool to address the complexity added to a system by the human dimension when used as a discussion tool to bring different perspectives of stakeholders together. Furthermore, the importance of data availability and accessibility for a successful use of models for policy-making was highlighted. With respect to the partnership between modellers and decision-makers, three elements were found to be essential for an impactful modelling endeavour: (i) the collaborative process including frequent exchange, (ii) building trust in model outcomes by including quality control in the project structure, and (iii) increasing the acceptance of models by promoting the exchange between modellers and decision-makers. While the modelling framework used in this study was not created with the intention of directly guiding policy and therefore does not meet some of the key aspects raised in Chapter 6, it has in general the potential to be used for exchange with policymakers. The model allows clearly structured conclusions that highlight fundamental problem areas, point to possible side effects and call for caution. The broad range of different scenarios, for example with regard to shock frequency and intensity, but also to household and network characteristics, allows policymakers to understand the impact of policy measures under different assumptions. While the model remained stylized within the scope of this thesis, it could be extended to incorporate empirical data in a more concrete way. For example, specific shock events or economic conditions could be included such that the results could be targeted to local insurance products which could then be directly improved.

7.3 Final conclusion and outlook

In order to achieve the target to eradicate poverty by 2030 set by the United Nations within the Sustainable Development Goals (UN, 2015), protection of the most vulnerable against extreme climate-related events and other economic, social and ecological shocks and disasters is a key component (GIZ, 2015). This work contributes to addressing these sustainability and development challenges in two ways. First, insurance products that are seen as an effective tool to strengthen the resilience of low-income households to unforeseen losses are investigated in three studies (Chapters 3, 4 and 5) to improve the effectiveness of these risk-coping instruments (R1). Second, the advancement of socio-environmental modelling (R2) – an approach that is particularly helpful to tackle coupled human–natural challenges – is addressed in two studies with a focus on adequately representing the dynamics of human interaction in agent-based models (Chapter 2) and successful modelling for policy and management support (Chapter 6).

Beyond the results shown in this thesis, socio-environmental models have further potential to provide insights into the effectiveness of insurance products and reveal potential side effects. The focus of the two modelling studies in this thesis was strongly on social aspects. However, it has been shown that a potentially harmful impact of insurance on the environment should also be considered, for example, when insurance uptake leads to a change in land use strategies (Bhattacharya & Osgood, 2014; Bulte & Haagsma, 2021). Models have already been used to study the long-term effects of these change processes (Müller et al., 2011; John et al., 2019). By combining the model developed in this thesis with these models, a comprehensive picture of potential side effects of insurance and a holistic view on the human–environment system could be obtained. This could provide further helpful knowledge for the design of effective and sustainable insurance products. In addition, to increase the impact of the findings of this thesis, a more intensive exchange with policymakers is desirable. Discussing potential implications of the introduction of insurance observed in the model could broaden policymakers' awareness of potential side effects that need to be considered when designing insurance products. On the other hand, researchers would also benefit from increased collaboration with decision-makers to gain a deeper understanding of current challenges with respect to insurance products. When these further insights are incorporated into the modelling framework, it would provide a more holistic view on the system. Overall, this mutual exchange would help to ensure that insurance products serve their purpose and contribute to strengthening the resilience of the poorest.

Appendices

A Appendix of Chapter 2

A.1 Selection criteria for review articles

We conducted a Web of Science Topic Search (TS) using the search term TS = ("agent based model*" OR "agent based simulation" OR "multi-agent model*" OR "multi-agent simulation") AND "social network*". We restricted our search to publications published until the end of 2018 in English which yielded 518 results. We are aware that especially in the area of network research there are other terminologies (e.g. network model or game-theoretic model) that refer to similar concepts and do not fall under our search restrictions. However, we believe that agent-based modelling is a reasonable umbrella term for all these approaches and that most results are transferable.

Due to the broad range of agent-based models coupled with social networks we did not aim to provide a systematic comparison of all publications in the field. We narrowed the focus to two main aspects: awareness and recentness. We thus pre-selected the most-cited publications (publications with 30 or more citations (66), 4 January 2019) and the newest articles (those published in 2018 (70)). Of course, this selection is not intended to be exhaustive but it provides an overview of the diverse ways of integrating and evaluating social networks in agent-based models.

From this redefined data set, we selected 54 publications to be included in the review (23 with 30 or more citations and 31 published in 2018) in the following way: We excluded articles if the methods used did not fit with the focus of our examination. This was the case if no agent-based model was presented in the paper, or if no social network was explicitly integrated in the model, or if the agent-based model has not been used to study social networks or the network did not play a significant role in the model description or evaluation. Additionally, we excluded models without an explicit connection between the agents (covering e.g. location based networks where the agents move around and visit the same spaces but do not directly link to each other) and models relying only on lattice networks or fully connected graphs as these structures limit the range of methods for evaluation that we suggest as being advantageous for agent-based models with integrated social networks. We furthermore focused on social networks where the connections are set up between human beings and thus removed articles targeting at ecology and animal related questions. As we concentrate on applications of agent-based models, we also did not include reviews.

A.2 Classification of the reviewed models

The following table provides the classification of the reviewed agent-based models. It is structured according to the three main areas of application: Epidemiology/public health (6 publications), marketing (25 publications) and social dynamics (23 publications). The description of the studies includes a summary of the research interest and key findings as well as a characterization of the main aspects concerning agent behaviour and network properties.

In particular, this covers information on the decision making of the agents, the interaction topology (exogenously imposed, endogenously emerging or co-evolutionary), the relevance of the network to the model (network effect) and aspects considered in the analysis of the model (agent-centric, network-centric or structurally explicit for exogenous or co-evolutionary networks and evaluation quantity for endogenous network formation). Furthermore, models where the purpose of the network is social integration are marked (in section research focus); all other models deal with diffusion processes. We do not provide information on network properties such as link reciprocity and link weight as this information is not clearly stated in all reviewed studies.

Epidemiology/Public Health

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Davey et al. (2008)	Examine interventions and strategy combinations for pandemic influenza mitigation.	The spread of influenza in a person-to-person transmission event should be reduced by network- and case-based interventions. Agents cannot actively make decisions.	*Exogenous network:* Groups of given sizes within which individuals of specified ages (kids, teens, adults, seniors) interact and average number of individuals with which a person has contact within the group is specified; basis for fully connected, random or ring networks for each group; contact network exhibits "small-world" character and multiply-overlapping quality of structured community; demographics of the population within this model conform to the 2000 U.S. Census Detail	Person-to-person transmission event within contact network; simulation instigated with 10 adults chosen at random	*Agent-centric:* Effect of network-based (school closure, child and teen social distancing, adult and senior social distancing) and case-based (quarantine, antiviral treatment, household antiviral prophylaxis, extended contact prophylaxis) interventions on percentage of population infected, average adult days at home and population antiviral coverage	Best strategy combines network-based and case-based interventions and is robust to a wide range of uncertainty.
Fetta et al. (2018)	Explore the effect of individual friendship selection decisions and the impact they may have on the overall evolution of a social network. Compare the resulting network with existing data from a smoking cessation program in secondary schools.	Agents decide whether to form links based on six different approaches: random, Adamic/Adar, Katz, Stochastic Actor Based, PageRank and a newly developed algorithm PageRank-Max (based on the optimisation of an individuals' eigencentrality).	*Endogenous network formation*	Agents iterate through the links changes offered by the selected link prediction method finding their maximum personal objective function.	*Evaluation quantity:* Precision of network formation algorithms to replicate existing school network data	The proposed PageRank-Max methods is the most successful in predicting the evolution of adolescent friendships, in terms of both precision and network structure.

Reference	**Research focus**	**Agent decision-making**	**Interaction topology**	**Network effect**	**Model analysis**	**Key findings**
Fu et al. (2011)	Explore the roles of individual imitation behaviour and population structure in vaccination.	Agents decide whether to change their vaccination uptake strategy depending on their own current payoff and that of one randomly chosen other agent.	*Exogenous networks:* Lattice (von Neumann), random, scale-free	Spread of disease (SIR Model) and vaccination behaviour (probability for adoption given by Fermi function)	*Agent-centric/Network-centric:* Effect of population structure (structured vs. well-mixed case) on vaccination level and final epidemic size Parameter variation: Cost of vaccination, sensitivity to observed payoffs	Vaccination uptake depends on agent's sensitivity to observed payoffs and costs. As agents become more adept at imitating successful strategies, the equilibrium level of vaccination falls below the rational individual optimum. In structured populations, vaccination is widespread over a range of low vaccination costs, but coverage plummets after cost exceeds a critical threshold.
Hornbeck et al. (2012)	Determine the impact of hand hygiene noncompliance among peripatetic healthcare works compared with less-connected workers.	Agents are assigned a level of hand hygiene noncompliance which influences the spread of pathogens.	*Exogenous network:* Empirical data recording contacts among healthcare workers and patients	Infection is passed with fixed probability in case of contact between infected and uninfected individual, additional infection by environment possible.	*Agent-centric:* Parameter variation: Probability of transmission, hand hygiene baseline compliance, hand hygiene efficacy, environmental contamination transmission rate Scenarios: Impact of hand hygiene compliance based on connectedness of healthcare workers	The average number of infected patients is higher when the most connected healthcare worker not practice hand hygiene and lower when the least connected healthcare workers are noncompliant.
Moradianzadeh et al. (2018)	Optimize the palliative care system where agents search the networks to find a proper team of care provider agents to fulfil their missing capabilities with the lowest overall cost.	Patients need help to fulfil their goal and send requests to care providers which can also spread this request to other care providers in their own network. Patients choose the team with minimal operational and geographical distance costs.	*Co-evolutionary network:* Initial network structure generated by an algorithm that is following the power-law distribution; links are added between care provider and patient if care provider forwards request to its network and patient makes use of the offer it is not linked to so far	Care provider linked to patients in the network offer their help to support them in achieving their goals.	*Agent-centric:* Comparison of synthetic networks with various distributions of patients and care providers against simulations with Brute Force model (patients can search among all care providers) and random selection model (patient request is sent to a set of care provider agents which are chosen randomly)	The proposed approach is capable of finding the proper team of care providers with the highest satisfaction rates in a shorter time (compared to other models taken into account).

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Perlroth et al. (2010)	Evaluate health outcomes, costs and cost-effectiveness of antiviral and social distancing strategies (combinations of adult social distancing, child social distancing, school closure, household quarantine, antiviral treatment and antiviral household prophylaxis) during an influenza pandemic.	The spread of influenza in a person-to-person transmission event should be reduced by network- and case-based interventions. Agents cannot actively make decisions.	*Exogenous network:* Same network structure as in Davey et al. (2008)	Same transmission as in Davey et al. (2008)	*Agent-centric:* Effect of mitigation strategies on health outcomes and costs and cost-effectiveness Parameter variation: Infectivity, case fatality rate, level of population compliance and antiviral effectiveness	Preferred mitigation response to a pandemic depends on its severity. Influenza pandemic with moderate severity, the most cost-effective strategy involves a combination of adult and child social distancing, school closure and antiviral treatment and prophylaxis, if available. For mild pandemics, a multi-layered strategy of adult and child social distancing and antiviral treatment and prophylaxis is effective and cost-effective but that the addition of school closure is relatively expensive.

Marketing

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Amini et al. (2012)	Compare the impact of three supply chain production-sales policies and negative word-of-mouth on the supply restricted diffusion process of a new generic product and the net product value of profit generated by this product.	The probability that agents adopt a new product depends on positive word-of-mouth, advertising, and/or negative word-of-mouth.	*Exogenous network:* Random	Adoption of new product with probabilities based on number of satisfied/dissatisfied adopters, rejecters and lost consumers	*Agent-centric:* Performance characteristics of three production-sales policies based on the net present value of profit generated over the diffusion process	Build-up policy with delayed marketing is the preferred policy. It is critical to consider the impact of negative word-of-mouth in choosing production-sales policies.
Baggio & Hillis (2018)	Examine the simultaneous diffusion of ecological disturbances and management strategies across a multiplex, social-ecological network. Address the relationship between learning, social-ecological structural properties and the adoption of treatment strategies that counter ecological disturbances.	Each social agent is able to exclusively manage one patch. Agents are able to adopt a treatment at a specific cost. Agents make their adoption based on their payoff, the type of learning they employ (individual or social), the feedback from the ecological path they are managing, and the information they acquire from their social network. Feedbacks between the social and ecological systems occur in form of general utility that a social agent receives from the ecological path they are managing.	*Exogenous networks:* Ecological: Spatial; Social: Spatial (matching ecological network), random, small-world with rewiring probability 0.2 and 0.3, scale-free with low or high preferential attachment	When agents employ social learning, they are either conformists (adopt strategy adopted by the majority of their social neighbours) or success-biased imitators (adopt strategy of the individual neighbour that is doing best).	*Agent-centric/Network-centric:* Effect of learning types and network structural properties on the expected disturbance	Managers who imitate other successful managers and have access to accurate information are most effective at controlling disturbances. The structural properties of the social-ecological network also play an important role: An increase in inter-layer assortativity and average multiplex degree reduce the expected disturbance prevalence, while an increase in local clustering increases it.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Beretta et al. (2018)	Investigate the effect of cultural dissimilarity of the adopters and their degree of assortativity on technology diffusion using the example of the diffusion of fertilizers in five Ethiopian villages.	Households decide to adopt the technology if their randomly chosen level of adoption exceeds a threshold. The threshold depends on their cultural group status and the number of neighbours and adopters per group.	*Exogenous networks:* Small-world (low and high clustering), scale-free (low and high clustering)	Threshold value depends on the cumulative group-wise counts of neighbours who have adopted (minority, majority), the number of neighbours per group and an assortativity factor.	*Network-centric/ Structurally explicit:* Effect of network type, seeding strategy and assortativity levels for majority and minority on technology adoption Comparison of model results with observed data from Ethiopian villages	Diffusion evolves the fastest in small-world settings. Scenarios with first adopters in a marginal network position and, in general, the scale-free network with low clustering displays a slower pace of adoption. For the scale-free network with high clustering, betweenness and eigenvector seeding differ only marginally and display almost congruent shapes for the other network structures. To minimize the differences between the observed and simulated data, similar social network structures but a different position of the first adopter in the network and different levels off the average assortativity are suggested.
Bohlmann et al. (2010)	Examine the effects of various network structures (network topology and the strength of communication links between innovator and follower market segments) and relational heterogeneity on innovation diffusion within market networks.	Agents decide on adoption based on the behaviour of their neighbours (probabilistic threshold).	*Exogenous networks:* Lattice, random, small-world with rewiring probability 0,1 and 0,2, scale-free	Agents decide on adoption based on the behaviour of their neighbours (probabilistic threshold); link weight implicitly included in two-segment model where agents weigh interaction in their own segment more heavily than those in the other segment	*Agent-centric/Network-centric:* Parameter variation: Level of adoption threshold, segment sizes Comparison of network structures	Network structure can impact diffusion in terms of peak adoption and the likelihood of saturated diffusion. Individual locations within a network and communication influences for new product diffusion are important.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Chareunsy (2018)	Simulate the diffusion of three development initiatives (encourage school attendance, introduce safe water handling practices, feeder road to facilitate engagement with markets) that differ in their approaches to reaching targeted groups in a southern Lao community.	The decision to adopt a change in behaviour is based on the relative influence of adopters and non-adopters within a household's network. Agent will choose to adopt a practice if the window of influence of adoption (determined by the weighted sum of agents across common network activities) is greater that the window of influence for non-adoption. At the beginning, an outsider recruits selected agents to change their behaviour.	*Exogenous network:* Connection to all agents with common activities	Agents' decision to adopt is based on relative influence of adoptees vs. non-adoptees in the network.	*Agent-centric:* Comparison of the dynamics of the three development initiatives for a synthetic population of 58 agents equipped with properties from household survey data	The Water initiative is the most successful both for the community as a whole and in reaching the lowest tier of society. The Education initiative fails to transmit a behaviour change, such that ultimately even the educators (the chosen agents) give up. The Market initiative succeeds in reaching all community members but the gains accrue disproportionately to the well-off who are best positioned to absorb the initial impetus.
Chen et al. (2012)	Examine the influence between network structure (size, degree, weight) and energy-saving behaviour.	Agents decide whether to increase or decrease their energy consumption based on the norm imposed by the energy use of their peers.	*Exogenous networks:* Random (varying number of nodes, degree and link weight)	Agents change their energy consumption behaviour based on the behaviour of their network neighbours.	*Network-centric:* Comparison of network structure	Network energy consumption does not decrease or increase with the expansion of the random network, if newly added vertices have a similar level of energy consumption. Connection degree and strength of the relationship between residents each has a positive impact on residents' energy saving.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Erdlenbruch & Bonte (2018)	Simulate the adoption of individual adaptation measures to floods and evaluate the efficiency of different communication policies in a model parameterized with data from a survey conducted in France.	The decision model of the agents is based on the psychological protection motivation theory (PMT) that decomposes the individual adaptation motivation into variables relating to threat appraisal and coping appraisal. A logistic regression of an individual's intention to implement non-permanent adaptation measures on the household's attributes is run.	*Exogenous networks:* Spatial, small-world (spatially explicit), random (varying degree)	The higher the proportion of neighbours in the household's network who have adapted, the higher its attribute level for the social network variable.	*Agent-centric/Network-centric:* Comparison of adaptation levels with and without network influence Comparison of network structures	Policies which contain information on both the risk of flooding and how to cope with it perform better than policies which only deal with risk. People centred policies on risk and coping perform the best in all scenarios. The absence of the small-world network decreases the absolute value of adaptation levels. The network types and degrees have no impact on the simulation results.
Goldenberg et al. (2007)	Understand how the interplay between positive and negative information, as well as weak and strong ties, affects the growth of new products and the consequent economic results.	The probability that agents adopt a new product depends on positive word-of-mouth, advertising, and/or negative word-of-mouth.	*Exogenous network with dynamic properties:* "dynamic small-world" with strong-tie structure inside each social system being fixed and weak-tie structure randomly reassigned in each period	Spread of information on new product with probabilities based on number of satisfied/dissatisfied adopters and rejecters	*Network-centric:* Linear regression with dependent variable of Net Present Value to analyse the effects of dissatisfaction, strength of the weak ties, advertising and interaction effects (level of weak and strong ties)	The effect of negative word-of-mouth on the Net Present Value of the firm is substantial. Weak ties help to spread harmful information through networks and can become a negative force for the product's spread.
Haenlein & Libai (2013)	Compare the effectiveness of revenue leader seeding with opinion leader seeding and random seeding on the spread of a new product.	The probability that agents adopt a new product depends on positive word-of-mouth, advertising, and/or negative word-of-mouth.	*Exogenous network:* Algorithm reproducing link formation in actual social networks (relatively small average distance between pairs of nodes, clustering coefficient larger than in random networks, approximately scale-free degree distribution)	Adoption of new product with probabilities based on number of satisfied/dissatisfied adopters, rejecters and lost consumers	*Network-centric/ Structurally explicit:* Parameter variation: Network clustering coefficient, standard deviation of the customer lifetime value, customer lifetime value assortativity and seed size	Both revenue leader seeding and opinion leader seeding can create greater value compared with random customer seeding. The distribution of customer lifetime value in the population and the seed size play a major role in determining which seeding approach is preferable.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Heinrich (2018)	Apply a catastrophe theory model to the problem of network industries. Compare the equation-based implementation to an agent-based model with a simple decision heuristic for several network structures.	Every agent is either an adopter of the new technology or not. Agents decide whether or not to adopt based on their expected utility from using the better technology.	*Exogenous networks:* Fully connected, ring, scale-free, scale-free with triadic closure	The adoption of the new technology by current non-adopters and the disbandment of the newer technology by current adopters follow a probabilistic function which is a cubic function of the number of adopters in the agent's network.	*Network-centric:* Effect of number of initial adopters Comparison of network structures Comparison of equation-based and agent-based model	The general behaviour of the findings of the equation-based model is preserved in the agent-based model. The behaviour of the model changes locally depending on the network structure, especially if networks with features that resemble social networks (low diameter, high clustering, and power law distributed node degree) are considered.
Hu et al. (2018)	Examine promotional strategies for new product diffusion based on different target (influential, susceptibles, or unsusceptibles), size and intensity of the seeding incentive.	Consumers decide whether to adopt the product using a threshold model where each agent has a unique threshold to map the heterogeneity between the agents. If the peer effect, which is determined by the fraction of adopted peers in the local network of the consumer, exceeds this threshold, the consumer adopts.	*Exogenous network:* Small-world (spatially explicit in social space)	The proportion of adopted peers in the local network determines the peer effect which has to exceed the individual threshold of the consumer to induce adoption.	*Agent-centric/Structurally explicit:* Effect of target types (influential, susceptibles, unsusceptibles, and random), target sizes and promotion intensity on product diffusion	Where a budget is limited, the best approach is to target as many susceptibles as possible with a weak promotion. Targeting unsusceptibles with free products should be the first choice, where the budget is large. In other cases, the best approach is to target as many influential as possible with a moderate promotion.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Huétink et al. (2010)	Study the development of the market for hydrogen vehicles taking into account different strategies for hydrogen infrastructure development and user behaviour.	Consumers: The decision of the consumers to adopt a hydrogen vehicle depends on their level of innovativeness, their reservation price and on the perceived attributes of hydrogen vehicle technology determined by technological learning, social learning processes and fuel availability. Refuelling station: The refuelling station considers the percentage of consumers within its customer base that have adopted a hydrogen vehicle. When this percentage of adopters exceeds a threshold value, the station adds hydrogen to its product range.	*Exogenous networks:* Fully connected, lattice (Moore), small-world	Consumers evaluate the fraction of adopters in their network and adopt the innovation if the adoption rate exceeds their personal threshold determined by the adopter group they are assigned to.	*Network-centric:* Effect of infrastructure strategies (station placement, size of initial fuel infrastructure) on number of adopters Parameter variation: Number of initial adopters Comparison of network structures	Maximum geographical coverage with initial stations is more effective as a deployment strategy than focusing on densely populated areas. The structure of the social network among consumers does influence the resulting diffusion patterns; a small world social network is most favourable to fast diffusion.
Janssen & Jager (2001)	Explore the dynamics of markets where artificial consumers have to choose each period between similar products from a psychological perspective. Explore the consequences of changing preferences and the size of social networks.	Depending on uncertainty and satisfaction of social needs, agents apply different mechanisms to choose a product: Repetition, deliberation, imitation or social comparison ("consumat" approach).	*Exogenous networks:* Small-world with rewiring probability 0, 0.01 and 0.1	For imitation and social comparison, agents evaluate the product which is consumed the most in its social network.	*Agent-centric/Network-centric:* Effect of minimum level of need satisfaction and uncertainty tolerance on market share of products Comparison of network topology and size	Behavioural rules that dominate the artificial consumer's decision making determine the resulting market dynamics. Psychological variables like social networks, preferences and the need for identity are important to explain the dynamics of markets. If social processes dominate a market, an increase in the size of the network causes the market to be dominated by a few products.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Janssen & Jager (2003)	Investigate the effects of different network structures on market dynamics.	Depending on uncertainty and satisfaction of social needs, agents apply different mechanisms to choose a product: Repetition, deliberation, imitation or social comparison ("consumat" approach).	*Exogenous networks:* Small-world with rewiring probability 0, 0.1 and 1, scale-free, scale-free with 1 % inactive links	For imitation and social comparison, agents evaluate the product which is consumed the most in its social network.	*Agent-centric/Network-centric:* Extension of Janssen & Jager (2001) Comparison of network topology and network parameters	Market dynamics is a self-organized property depending on the interaction between the agents' decision-making process, the product characteristics, and the structure of interactions between agents (size of network and hubs in a social network).
Kaufmann et al. (2009)	Study the diffusion of organic practices through farming populations in Latvia and Estonia and evaluate the effectiveness of policies (effect of social influence, introduction of a higher subsidy, increased support by organic farm advisors) to promote them.	Based on Theory of Planned Behaviour, farm agents exchange opinions, update subjective norm estimates, and adopt organic farming practices if intention exceeds an empirically derived threshold.	*Exogenous network:* Small-world and scale-free properties (network parameter derived from survey)	Subjective norm as one factor characterizing intention towards adoption is influenced by one selected neighbour using the relative agreement model.	*Agent-centric/Network-centric:* Effects of social influence, introduction of a higher subsidy and of increased support by organic farm advisors on the diffusion of organic farming practices Parameter variation: Network density, preferential attachment and small-world property, type of agents on the hubs (not shown)	Social influence alone makes little difference; introduction of a subsidy is more influential. The combined adoption rate from social and economic influences is higher than the sum of the proportion of adopters resulting from just social influence and from just subsidies.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Libai et al. (2013)	Explore how acceleration and market expansion combine to generate value in a word-of-mouth seeding program for two competing products.	The probability that agents adopt one of the competing products depends on external and internal factors.	*Exogenous networks:* 12 empirical networks	Adoption of new product with probabilities based on number of consumers in network who have already adopted	*Structurally explicit:* Comparison of social value of word-of-mouth programs for different seeding strategies affected by competition, program targeting, profit decline, and retention	Market expansion dominates the social value of word-of-mouth programs. Relative to random programs, acceleration drives a greater proportion of influential programs' social value. The stronger a brand is relative to its competitor, the more acceleration drives its seeding program's social value, and the lower the program's social value is overall. The lower the future value of customers, the higher the acceleration ratio and the higher the relative social value of a program. A shorter horizon of analysis on the program's effect leads to a higher overestimation bias of the seeding program's social value. The higher the disadoption rate, the lower the acceleration ratio.
Moglia et al. (2018)	Describe the uptake of low carbon and energy efficient technologies and practices by households and under different interventions (non-financial and social network).	Households decide whether to buy a new product if the old product has reached the end of its life or the agent has been approached by a sales agent. The decision which product to buy depends on the level of needs satisfaction and uncertainty and results in repetition, imitation or optimisation or inquiry (based on the "consumat" approach).	*Exogenous networks:* Small-world, scale-free, spatial, random	For imitation, agents copy the behaviour of a satisfied household in their social network.	*Agent-centric/Network-centric:* Comparison of interventions on adoption rates Comparison of network structures	Focus of the model on questions whether it is more effective to incentivise sales agents to promote energy efficient technologies, whether it is more effective to provide a subsidy directly to households, or whether it is better to work with plumbers so that they can promote these systems. Effect of social networks on adoption is only marginally discussed.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Negahban & Smith (2018)	Evaluate the optimal combination of seeding and inventory build-up policies for new products.	Consumers adopt or reject with probabilities depending on number of satisfied consumers or dissatisfied adopters, rejecters and lost customers that did not receive the product due to supply shortages, respectively.	*Exogenous networks:* Lattice (26 neighbours), random, small-world (based on lattice network), scale-free	Adoption of new product with probabilities based on number of satisfied and dissatisfied adopters, rejecters and lost customers (customers that did not receive the product due to supply shortages)	*Agent-centric/Network-centric/Structurally explicit:* Effect of seeding strategy (number of neighbours, number of nodes reachable within two steps, shortest average path length, lowest clustering coefficient, random), seeding fraction and build-up period (time before product is launched) on product adoption Comparison of network structures	The seeding strategy that maximizes the adoption rate is not necessarily optimal in the presence of supply constraints. Random seeding can maximize the expected net product value of profit for a scale-free network. However, random seeding increases the uncertainty in the diffusion dynamics.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Niamir et al. (2018)	Track impacts of behavioural changes in individual energy use behaviour concerning (1) investments to save or produce energy, (2) conservation of energy by changing consumption patterns and habits, and (3) switching to another energy source.	Based on Norm Activation Theory, households assess a four step procedure to pursue an economic decision: (1) If households feel guilty as their awareness (based on survey data) exceeds a threshold they (2) check their personal and subjective norms to calculate their motivation for each of the three actions. For those actions for which the motivation exceeds a threshold, the households feel responsible and go into (3) the consideration step where their perceived behavioural control is assessed to measure their intention. If a household has high intentions to undertake any of the three actions for making an energy decision, its expected utility based on its current energy sources and its budget constraints is calculated. To maximize their utility and make their energy decisions, households analyse their utility expectations and compare it with their current utility.	*Exogenous network:* Spatial	Households compare values of their own behavioural factors (awareness and motivation) with those of their 8 closest neighbours and adjust their value to become the mean of the 9 compared values.	*Agent-centric:* Effect of social learning in knowledge activation or in knowledge activation and motivation on the behavioural changes in individual energy use	Exchange in knowledge about energy and climate leads to a significantly higher total count of the three types of household actions, while there is more intentions for investments that for the two other actions. Introducing additionally opinion dynamics regarding household motivation to act leads to a further increase in the diffusion of all three actions.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Pearce & Slade (2018)	Simulate the adoption of small-scale solar photovoltaic systems (PV) in Great Britain by considering decision-making of individual households based on household income, social network, total capital cost of the PV system, and the payback period of the investment.	Agents calculate the total utility of adoption and adapt if the utility exceeds a threshold. The total utility is made up of a weighted sum of partial utilities depending on household income, the social environment of the agent, economic attractiveness of the investment, and the capital cost of the investment.	*Exogenous network:* Random	Social utility of an agent depends on the number of adopters and agent is connected to and increases if an agent they are connected to adopts.	*Network-centric:* Effect of number of links to adopters on social utility (Social influence is not analysed in more detail)	Focus of the model is on the effect of feed-in tariffs. Effect of social networks on adoption is only marginally discussed.
Phan & Godes (2018)	Analyse the dynamics of the diffusion of several ideas for two types of individuals (independents with exogenous information and imitators) with endogenous link formation.	Independents are influenced with a fixed probability. Imitators adopt if the proportion of neighbours who have adopted exceeds a threshold. Between the diffusion of two ideas, agents may drop and add links while maintaining the same in-degree. Communication can be influenced by noise and time discounting.	*Co-evolutionary network:* Initially random; links deleted based on adoption status, new links formed randomly	Agents adopt if the proportion of neighbours who have adopted exceeds a threshold.	*Agent-centric/Network-centric:* Effect of penetration rate for variation in network density, probability that independents receive information, probability that independents listen to others in a period and probability that independent listen to other independents in a period for fixed network density on diffusion of ideas Scenarios with and without noise and with and without time discounting	In the baseline study (no noise, no time discounting) penetration is increasing with network density. Independents with good exogenous information have fewer followers than the average imitator. When independents listen to other agents, they gain more influence by producing access to better information. Less noise allows agents to be further away from the original source.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Rasoulkhani et al. (2018)	Identify the effects of demographic and household characteristics, social network influence, and external factors such as water price and rebate policy on residential water conservation technology adoption.	Households are in one of the three states: non-adopter, potential adopter or adopter of the technology. The transition between non-adopter and potential adopter and between potential adopter and adopter is reached if the adoption utility and the affordability index exceed a utility and affordability threshold, respectively. If the utility threshold for the transition between non-adopter and potential adopter status is not reached, an agent can additionally be positively influenced by the network which also induces a transition.	*Exogenous networks:* Random, ring, small-world, scale-free	Given a user-defined likelihood of influence, if the non-adopter agent is connected to an adopter agent, there is a chance that the non-adopter will transition into the potential adopter state.	*Agent-centric/Network-centric:* Effect of water price and rebate scenarios on technology adoption Comparison of network structures	The adoption percentage fluctuates across all five social networking schemes under each scenario of water price and rebate status. The distance based network reached equilibrium in a shorter period. The peer effect through neighbouring social connections can speed up technology adoption potential more than other social networks.
Talebian & Mishra (2018)	Forecast long-term adoption of connected autonomous vehicles (CAVs) and show the applicability of the approach is using survey data.	Individuals decide to adopt when (1) there is a need for a new vehicle, (2) their willingness-to-pay (WTP) is greater than the CAV price, and (3) their overall impression about CAVs reaches a cut-off value. Agents update their perception about CAVs based on advertisement and peer-to-peer communication.	*Exogenous network:* 8-dimensional distance minimization in social space	The influence depends on the number of binary interaction between the two agents and the weight of the social tie. Depending of the opponent being satisfied or dissatisfied the influence is positive or negative. Similarly, the WTP is updated.	*Agent-centric:* Effect of annual rate of CAV price reduction, (pre-introduction) advertisement, peer-to-peer communication on WTP and probability of becoming a dissatisfied adopter on CAV adoption	The automobile fleet will be near homogeneous in about 2050 only if CAV prices decrease at an annual rate of 15 % or 20 %. A 6-month pre-introduction marketing campaign may have no significant impact on adoption trend. Marketing will ignite CAV diffusion but its effect is capped. CAV market share grows with the effect of peer-to-peer communication of WTP.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Wang et al. (2018)	Assess households' decision-making process towards the adoption of residential photovoltaic (PV) under different scenarios about policies that concern both the economic benefits and the information diffusion on social networks.	Agents are either adopters or non-adopters of residential photovoltaic and have a positive or negative attitude towards the technology. The decision to adopt residential PV is made at each time-step if the utility to the household outweighs the adoption barriers. The utility is a combination of economic factors, social effect and personal preference. Before the decision-making process agents assess the revenue and quality information of PV and can change their attitude accordingly.	*Exogenous network:* Scale-free	The social effect is the average of the attitude of the adjacent nodes. Revenue information includes the expected revenue according to the experience of their friends. Quality information includes the risk probability according to the performance of friends' residential PV.	*Agent-centric:* Effect of policy scenarios (with parameter variation) on adoption of residential PV	Providing free insurance for damage of residential PV to adopters can improve the adoption rate. The intervention of information campaigns is effective and necessary to promote the diffusion of residential PV. Information screening intervention which blocks rumours and deliberately discrediting for residential PV can only work when the policy strength is high enough. The enhancement in communications (increase of social networks' mean degree) can become new barriers to the residential PV adoption.
Zhang & Nuttall (2011)	Study the impact of policy options on the dynamics of smart metering diffusion in retail electricity markets and suggest policy implications.	Based on Theory of Planned Behaviour, consumer agents exchange opinions with other consumers and electric supplier agent and adopt the energy supplier towards which their intention is maximal.	*Exogenous network:* Small-world (based on lattice network (parameter defining radius of interaction))	Subjective norm towards choosing an option is calculated as the sum of weighted influences from residential electricity consumer agents in the neighbourhood.	*Agent-centric:* Effect of different policy options on the patterns of diffusion	"S-curve" pattern of technology adoption is reproduced for all policy scenarios. The most successful scenario is the government financed competitive roll-out. A stable market share of electricity supplier agents appears. Residential electricity consumer agents switch electricity supplier agents dynamically.

Social dynamics

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Biondo et al. (2018)	Study the impact of news media and public surveys on the electoral campaigns for political competitions.	Agents favour one of two political parties (or are undecided). Their preference is influenced by a randomly chosen opinion of one of their neighbours. Additionally, their opinion is influenced by survey results.	*Exogenous network:* Small-world (based on lattice network (von Neumann))	Agent's opinion is influenced by one randomly chosen agent in their network. The value, corresponding to the party the chosen neighbour favours, is changed by a given amount.	*Agent-centric:* Effects of survey on electoral campaigns	Surveys accentuate the spontaneous clustering of voting intentions emerging among people due to the opinions dynamics. Surveys can change the final electoral result and let the party, that otherwise would lose, to win the electoral competition.
Bravo et al. (2012)	Investigate the importance of the endogenous selection of partners for trust and cooperation in market exchange situations, where there is information asymmetry between investors and trustees. *(social integration)*	Agents decide on the amount to invest and return based on the amounts invested and received in the previous period and coefficients estimated from experimental data.	*Exogenous and co-evolutionary networks* *Exogenous networks:* Experimental data as input with variation of characteristics: Random coupling with one and two way interaction, fixed couples (maintaining initial couples), fully connected, small-world, scale-free *Co-evolutionary networks:* Initially random coupling, fully connected network or regular network; unsatisfied agents can break the link, new links are included either for both of the formerly linked agents or only for isolated agents	Agents exchange money being either in the role of the investor or the role of the trustee.	*Network-centric:* Comparison of network structures (especially distinguishing exogenous and co-evolutionary networks)	Dynamic networks lead to more cooperation when agents can create more links and reduce exploitation opportunities by free riders. The endogenous network formation is more important for cooperation than the type of network.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Chica et al. (2018)	Investigate the dynamics of the N-player evolutionary trust game consisting of three types of players: (1) an investor, (2) a trustee who is trustworthy, and (3) a trustee who is untrustworthy.	Each player makes the decision (1) whether or not to be trustworthy and (2) whether to be an investor or a trustee. An investor pays to the trustee. Trustworthy trustees return the received fund multiplied by a factor. Untrustworthy trustees return nothing but keep for themselves the received funds multiplied by a factor. Agents decide on which strategies to choose based on the wealth of a randomly chosen neighbour.	*Exogenous networks:* Scale-free (varying density), lattice (von Neumann), random	An agent decides whether to imitate or not a randomly chosen direct neighbour's strategy based on the payoff of its strategy. If the wealth of the opponent in the previous time step is higher than that of the agent if will adopt the strategy of its opponent with a probability that depends on the difference between their payoffs.	*Agent-centric/Network-centric:* Parameter variation: Temptation defect ratio, trustworthiness Comparison of network structures	Trust can be promoted with the model for low and medium temptation to defect, for high level of temptation to defect trust is only promoted when no untrustworthy players are present in the initial population. Without a network structure, even one untrustworthy player can fully eliminate investors and lead to zero global net wealth. Network densities have high importance for promoting trust and global net wealth.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Flache & Macy (2011)	Show the effects of positive and negative valences of interaction and short- and long-range ties on polarization or consensus in disconnected and connected networks.	All agents execute influence based on the weighted difference between positions.	*Exogenous networks:* Disconnected/connected caveman graph with short- and long-range ties added at different time points of the simulation	Agents are influenced by aggregated opinions of all neighbours in network.	*Network-centric:* Effect of cave size, number of cultural issues, negative valence of interaction and additional short- and long-range ties on polarization	With only positive influence and selection, long-range ties promote greater cultural integration and assimilation. When both positive and negative valences of interaction are assumed, long range ties become conduits for the spread of locally developed polarization and the effect is reversed. In connected networks, when only positive influence and selection are assumed, consensus is the inevitable outcome. Neither long-range nor short-range ties have an effect on the level of consensus. When both positive and negative influence and selection are allowed, long-range ties increase polarization sharply, but short-range ties do not.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Frank et al. (2018)	Attend how an external agent's message (policy-aligned or balanced) interacts with intra-organizational network dynamics to affect the distribution of practices and network structure within an organization.	If actors receive new information from their network connections, actors adjust their behaviours based on information and norm. Actors decide whether to maintain current network connections and if actors decide to dissolve a current connection, they from new connections.	*Co-evolutionary network:* Initially random network with higher connection probability within the two subgroups than between; links deleted based on how many consecutive times an actor is exposed to redundant information from the network connection, links formed based on utility to connect with every other actor in the organization while keeping the out-degree constant	Each member of an actor's network randomly provides one piece of information in their possession to the actor. If the information is new to the actor, the actor will add this piece of information to its own information list. Actors choose their behaviour according to their previous behaviour, new information they receive and the mean behaviour of their network members. Depending on the strength of organizational identification, more or less weight is given to the influence of the network or on own information. Another parameter determines the strength of normative influence relative to that of selection.	*Agent-centric:* Parameter variation: Organizational identification for two levels of influence Comparison of policy-aligned and balanced messages with baseline case (no external message)	When organizational identification is high, those predisposed to a policy-aligned message will engage the message and one another, becoming more extreme in their behaviours. Others not predisposed to the message will divert away from the message. This produces a divergence of behaviour based on predisposition and little overall change. Divergence does not occur even when organizational identification is high for a balanced message, which provides opportunities for actors to integrate. The trade-off is that the balanced message does not generate as large changes in average behaviour as does the policy-aligned message when organizational identification is low. Thus, when organizational identification is low, a balanced message may be a missed opportunity to shape behaviour.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Fu & Hao (2018)	Explain migration perpetuation and social network structural changes in China. Investigate the effects of the endogenous social network on the accelerating migrant stock during the 1995-2000 period.	Agents are classified in three migratory propensity groups according to their demographic attributes. The migratory propensity updates according to the migration-promoting influence and the influence of arable land. Migration-promoting influence varies with the level of impact of the network in different stages of the model (no network, implicit social network using the migration prevalence of the origin, explicit social network structure). If the migratory propensity is greater that the migratory threshold the agent decides to migrate out of the origin.	*Co-evolutionary network:* Four layered network: (1) fully connected network for observed family ties from the 2000 census micro data, probability for connecting to other families (2) within village, (3) between villages and (4) between migrants in the same destination with probability for adding further ties to create complete graph for selected connection Social network co-evolves with migration decision.	In the case of network impact, the migration-promoting influence depends on the geodesic distance from a migrant of the same origin in the agent's network.	*Network-centric:* Comparison of outcomes of different levels of network impact and aggregate data from the census Effect of social network structure on migration acceleration	Network structural changes are essential for explaining migration acceleration observed in China during the 1995-2000 period.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Garcia et al. (2018)	Explore how the interactions between psychological attributes and built and social environments may lead to the emergence and evolution of leisure-time physical activity (LTPA) patterns among adults. *(social integration)*	Agents decide whether they will practice LTPA during the current week, based on the level of intention and conditional to the perceived built environment. Persons and LTPA-places are placed randomly over patches of a grid. Person's intention to practice LTPA depends on the behaviour of those in the proximal network and perceived community, the person's behaviour in the previous week, current level of intention and the highest perceived utility amongst the LTPA sites in the person's perception radius.	*Exogenous networks:* Proximal network: Spatial, each link can be randomly exchanged for a link with any other person outside the initial proximal network Perceived community: Spatial (perception radius)	Person's intention is increased or reduced due to the average behaviour of all agents in the proximal network/perceived community times a function of the conditional likelihood that people in the proximal network/perceived community will practice LTPA if it is the best option.	*Agent-centric:* Parameter variation: Level of intention Individual and global sensitivity analysis	Time trends of LTPA practice and population distribution of levels of intention are similar those reported in literature. Influence of the person's behaviour in the previous week over his current intention, the size of the person's perception radius, and the proportion of patches in the grid that are LTPA sites significantly influence the temporal trends in the model.
Gore et al. (2018)	Forecast changes in religiosity and existential security among a collective of individuals over time. *(social integration)*	Agents update their religiosity based on social network interactions. Additionally, agents interact with the environment by checking if their value for existential insecurity is below the existential security value of the environment.	*Exogenous network:* Algorithm reproducing social networks observed in the wild	The extent to which the variable is influenced is determined by a time-dependent weighed average.	*Agent-centric:* Comparison of the accuracy of predictions from competing approaches (baseline based entirely on historical data, Linear Regression, ABM) for countries on which models where trained/not trained	For a given country and a given time period, the ABM provides a more accurate forecast of changes in the existential security and the religiosity than the two alternative approaches for a specific time period for specific country.

Reference	**Research focus**	**Agent decision-making**	**Interaction topology**	**Network effect**	**Model analysis**	**Key findings**
Growiec et al. (2018)	Identify the key mechanism allowing the social network structure to affect individuals' social trust, willingness to cooperate, economic performance and social utility, and trace how these individual-level outcomes aggregate up to the society level. *(social integration)*	Agents are matched in pairs and engage in economic interaction. The matching is random but the probability of a match depends on the degree of mutual trust between the two agents, implying that agents who are generally more trustful are also relatively more likely to engage in economic interaction.	*Exogenous network:* Small-world (varying density)	Probability that agent will choose to cooperate is negatively related to the distance to the opposing agent in the social network and positively related to the decision maker's bridging social capital.	*Network-centric:* Effect of network density, inverted probability of local cliques, and the inverted share of local cliques that are family-based on average economic performance in the society	Societies that are better connected, exhibit a lower frequency of local cliques, or have a smaller share of family-based cliques, record relatively better aggregate economic performance. As long as family ties are sufficiently valuable, there is a trade-off between aggregate social utility and economic performance, and small world networks are then socially optimal. In dense networks and trustful societies, there is a trade-off between individual social utility and economic performance; otherwise both outcomes are positively correlated in the cross section.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Hadzibeganovic et al. (2018)	Study the effects of phenotypic diversity, network structure, and rewards on cooperative behaviour in a population of reproducing artificial decision makers playing tag-mediated evolutionary games. *(social integration)*	Depending upon the tag colour of the neighbouring opponents, agents decide whether to cooperate or defect in Prisoner's Dilemma-like pairwise interactions. Ethnocentric agents will cooperate only with neighbours who share the same tag colour, cosmopolitans will provide help only to others displaying a different tag colour, altruists will always cooperate, and egoists will always defect. Each cooperation act is related to a reduction of the reproductive potential of the donator and an increase of the reproductive potential of the receiver.	*Co-evolutionary networks:* Lattice (von Neumann), small-world (based on lattice network) Networks change due to reproduction and death	Agents chose one of their neighbours to play pairwise Prisoner's Dilemma and decide whether to cooperate and defect based on their attitude which influences the reproduction rate of the receiver and themselves.	*Agent-centric/Network-centric:* Parameter variation: Number of tag colours, length of reward frame Comparison of behavioural strategies Comparison of network structures	Small reward frames promote unconditional cooperation in populations with both low and high diversity. When the reward frame is large, there is a strong difference between the frequencies of conditional co-operators populating rewired versus non-rewired networks. In a less diverse population, the total number of defections is comparable across different network topologies; in more diverse environments defections become more frequent in a regularly structured than in a rewired, small-world network of contacts.
Ke et al. (2008)	Simulate language change as a process of innovation diffusion. Examine the effect of four different network types, different types of learners and the network size on the diffusion.	Agents decide which language (unchanged or innovative) to use based on the frequencies of users of the two variants in their network and the functional values of the languages.	*Exogenous networks:* Ring, random, small-world, scale-free	Agents evaluate the frequencies of users of the two variants of the language in their networks.	*Agent-centric/Network-centric:* Effect of different types of learners and network size on the diffusion Comparison of network structures	Innovations always diffuse to the whole population as long as the advantage of the innovation over the unchanged form is high enough. The success rates and the speed of the diffusion vary across the different network structures. The presence of statistical learners who can learn and use both linguistic variants increases the probability for linguistic innovations. Population size has an influence on the diffusion only in regular networks.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Keijzer et al. (2018)	Analyse the implications of one-to-many communication (as present e.g. in online social networks) on the population using Axelrod's model of cultural dissemination as an example.	The social influence component of Axelrod's model of cultural dissemination is adapted to a one-to-many communication: Randomly selected agents from the population communicate one of their features on which they differ with at least one neighbour.	*Exogenous networks:* Lattice (Moore), spatial, ring (rewired following an algorithm which decreases network transitivity while preserving the degree distribution)	Neighbours adopt the feature with a probability equal to the proportion of traits that they share with the communicating agent.	*Network-centric:* Comparison of the one-to-one and the one-to-many communication regime for different scenarios in different network structures	One-to-many communication fosters the isolation in bigger populations. Network transitivity fosters the emergence of isolated individuals and cultural clusters. These findings hold for network topologies that mimic the structure of real social networks.
Laifa et al. (2018)	Study the consequences of different trust dynamics with forgiving and unforgiving strategies after an offence. *(social integration)*	Offences occur between two connected agents. Agents can react on these offences with two different strategies: Either the network is updated by deleting the affected relationships considering neither relationships characteristics nor forgiveness or the trust value is reduced.	*Co-evolutionary network:* Initially random (size 10^2 and 10^3 and connection probability 0.05 and 0.1); links are weighted by trust which is influenced by offences that occur in the network, links are deleted if trust value falls below a threshold	Between connected agents a specific number of randomly assigned offences occur. Agents react on these defences and thereby modify the network structure.	*Agent-centric/Network-centric:* Effects of network structure on average degree, average betweenness centrality and density of the networks after revaluating trust with both forgiving and unforgiving strategies	The average degree decreases for all the networks and with both strategies. When the number of links in a network decreases, the density of the network declines as well. The network density lessens more for the first strategy, where networks became very sparse, compared to the resulting networks from the second strategy in which they were relatively dense. For betweenness centrality, oscillating curves can be observed for all the networks and with both strategies.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Lou-Magnuson & Onnis (2018)	Simulate how human languages may change over time across a social network of speakers.	Speakers select a signal from their active repertoire and present it to their partner (hearer). The Partners use their passive repertoire to see if they know that signal or search the passive repertoire for a significantly close signal of the same meaning. If a signal in an agent's passive repertoire can be found such that the signal being shared with it is intelligible, the agent adds it to the passive repertoire if not already present. If a signal cannot be found in the passive repertoire, the speaker will try and repair the communication by using any other active signals it possesses with the same meaning. After a set number of communication events, each agent undergoes a replacement process that simulates intergenerational transfer.	*Exogenous networks:* Fully connected, random (different connection probabilities), hierarchical, scale-free	Agents exchange linguistic signals in agent-agent communication.	*Network-centric:* Effect of transitivity (different connection probabilities in random networks) and network topology (complete, hierarchical, scale-free, random network) and network size on linguistic reanalysis	Transitivity is critical for the evolution of compositional structure. The hierarchical patterning of scale-free distributions is inhibitory.

Reference	**Research focus**	**Agent decision-making**	**Interaction topology**	**Network effect**	**Model analysis**	**Key findings**
Lozano et al. (2018)	Simulate Prisoner's Dilemma (PD) games where reputation can be faked and compare the results to experimental work. Simulate much larger population sizes over longer times and test other model parameters to see whether the observed behaviour generalizes in those conditions that cannot easily be conducted in experiments.	Agents receive a random sequence of past actions to determine their initial cooperation index. Agents receive information on the cooperation index of their current neighbours and select cooperation or defection as action for all PD games with their neighbours with probability proportional to the average cooperation index of their neighbours. In selected simulation runs, cheater are introduced that defect with fixed probability.	*Co-evolutionary network:* Random regular graph; links deleted based on how many times the agent cooperated, new link created randomly	Agents play PD games with all their neighbours and select cooperation or defection based on the average cooperation index of their neighbours.	*Agent-centric:* Comparison of simulated and empirical results for real and faked reputation Parameter variation: Number of participants, time frame	Comparison between numerical simulation results and laboratory experiment leads to good qualitative fit. Larger populations essentially behave in the same qualitative manner as the small one, except that all results have smaller fluctuations.
Lu et al. (2009)	Study how the community structure of the underlying graphs affects the emergence of meta-stable or long-living opinion clusters. Investigate how choosing committing agents and external influence facilitate convergence to global consensus.	Speakers transmit a word from their lists to listeners who add it to their list if they do not know the transmitted word or both players delete all other words and agree on transmitted word if listeners know it.	*Exogenous networks:* Empirical data (high-school friendship network), small-world with same number of nodes, average degree and clustering coefficient	Speaker transmit words to randomly chosen listeners from network.	*Agent-centric/Network-centric:* Effect of different selection methods for committed agents and strength of external influence on community structure Comparison of network structures	Networks with strong community structure hinder the system from reaching global agreement; the evolution of the Naming Game in these networks maintains clusters of coexisting opinions indefinitely. Small number of committing agents is sufficient to facilitate an exponential decay toward global consensus of the selected opinion. Global external influence leads to an increasing rate of convergence.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Neal & Neal (2014)	Explore whether in network formation respect for diversity and sense of community can both be achieved following the principles of homophily and proximity.	Agents form links with each other based on a logistic selection function depending on their similarity and physical distance weighted by the direction and strength of the tendency towards homophily and proximity.	*Endogenous network formation*	Agents establish links based on their similarity and physical distance and their tendency towards homophily and proximity.	*Evaluation quantity:* Relationship between diversity and sense of community depending on the weight given to the direction and strength of the tendency towards homophily and proximity	It is not possible to simultaneously promote respect for diversity and sense of community in a world where relationship formation is driven by homophily and proximity.
Piedrahita et al. (2018)	Analyse the contagion dynamics that emerge in networks when repeated action is allowed, that is, when actors can engage recurrently in a collective effort. Investigate how the structure of interdependence, the variance in individual propensities to activate and the strength of social influence affect contagion and the emergence of large-scale coordination.	Agents' propensity to participate in collective events depends on their intrinsic motivation (how quickly they reach the activation limit (and on their social influence (strength of signals received from other agents). When nodes activate, they shift the state of their neighbours and reset their own state back to the beginning phase. If an actor is activated, connected actors' activation increases by a fixed amount.	*Exogenous networks:* Random, ring, small-world, scale-free	Agents influence their neighbours when activated towards a higher level of activation.	*Agent-centric:* Effect of intrinsic motivation and social influence for homogeneous and heterogeneous distribution of the intrinsic motivation on time to coordinate	Homogeneous networks (degree distribution not significantly skewed) are more conducive to coordination. There is a critical value for social influence for all topologies and levels of intrinsic motivation below which actors do not achieve coordination.

Reference	Research focus	Agent decision-making	Interaction topology	Network effect	Model analysis	Key findings
Schlaile et al. (2018)	Illuminate the influence of particular social network characteristics on the ALS Ice Bucket Challenge's (IBC) diffusion.	The simulation is initially seeded by five randomly chosen initiators who already performed the IBC. Each agent who accepted the challenge nominates three of its neighbours who have not previously accepted the IBC. Agents are resistant against the challenge with a factor drawn from a random distribution in a fixed interval. Each time an agent is nominated, its resistance value is reduced by another value, determined as the effect of nomination. If an agent's resistance is reduced to zero or lower, the agent will accept the challenge.	*Exogenous networks:* Scale-free, small-world, random	Agents nominate three neighbours from their network to participate at the challenge. The nomination reduces their resistance against the challenge.	*Agent-centric/Network-centric:* Parameter variation: Mean resistance against the challenge Comparison of network structures Effect of average degree and celebrities	The model can qualitatively reproduce central elements of the empirically observed IBC's diffusion pattern. The IBC has to reach a critical mass of carriers in order to stall prematurely. Networks with a high average clustering coefficient as well as a moderate average degree are beneficial for the IBC meme's diffusion performance. The assumption that hubs have a higher influence on others leads to a faster and more wide-ranging diffusion of the IBC in networks exhibiting a highly skewed degree distribution.
Simão & Todd (2002)	Study mate choice in monogamous mating systems and evaluate performance and robustness of different agent strategies.	Agents decide on whether to initiate relationship or switch partner based on (1) the age and quality of the potential and current partner and the focal agent and (2) their aspiration level.	*Co-evolutionary network:* Pairs of male and female meet at certain stochastic rate, agents switch between single and courting state based on the quality of the partner and their aspiration level	Agents try to find optimal partner based on the properties of the other agents and their aspiration level.	*Agent-centric:* Comparison of the efficiency of the different mating strategies Comparison of the predictions of the model with theories from social sciences	Being able to switch partners during a courtship period is superior to courtship without partner switching.

Reference	**Research focus**	**Agent decision-making**	**Interaction topology**	**Network effect**	**Model analysis**	**Key findings**
Son & Rojas (2011)	Understand how team networks evolve over time and affect performance. *(social integration)*	Agents participate in social interactions with a probability determined by their familiarity towards the other agent. Agents choose whether to cooperate or to defect from a newly met agent based on comparison of the current payoff that they are attaining from a combination of existing partners and the potential payoff that they could achieve by forming a new relationship with the candidate partners and severing the least efficient relationships.	*Co-evolutionary network:* Social interactions with probability depending on familiarity, links created and deleted based on expected payoff, maximum number of connections limited	Agents get payoff from relationships with other agents which they try to maximize. Agents' behavioural dynamics and overall network dynamics co-evolve during interaction. When two agents meet, their familiarity with one another increases.	*Agent-centric:* Effects of costs for relationships with other agents from same or different group and for familiarity	The fewer individuals are familiar with others in the network, the more time it takes for networks to reach stable states. The tendency of cohesion increased as the effort to form relationships with outside partners rose. The more effort needed to from relationships with those from other organizations, the less efficient the networks were.
Weng et al. (2012)	Study whether competition among ideas may affect the popularity of different memes, the diversity of information we are exposed to, and the fading of our collective interests for specific topics.	Agents spread information with fixed probability. The information is either chosen from the memory of the agents (records posted memes) or from the screen (records received memes).	*Exogenous networks:* Random, sampled graph from Twitter follower network, empirical data with only retweets	Spread of information between connected agents with probabilities depending on the source of the information	*Network-centric:* Effect of network structures and meme competition (length of time window until meme is removed) on meme lifetime, meme popularity, user activity and breadth of user attention	The massive heterogeneity in the popularity and persistence of memes can be explained as deriving from a combination of the competition for our limited attention and the structure of the social network, without the need to assume different intrinsic values among ideas.
Zhuge et al. (2018)	Generate both close and somewhat close social networks separately for a synthetic population containing individuals and their attributes and locations and compare the networks to survey data from Beijing, China.	Agents built and resolve friendships based on a utility function which incorporates the similarity between a pairs of agents and the spatial closeness of their residential locations and workplaces.	*Endogenous network formation*	A social network is generated by fitting the degree distribution and the transitivity distribution considering a utility function of the similarity between the agents.	*Evaluation quantity:* Generation of close and somewhat close social networks	Close and somewhat close social networks generated for Beijing exhibit a good ability to match target and generated distributions of network degree and transitivity.

B Appendix of Chapter 3

B.1 Model documentation

In the following, we describe the main processes of the simulation model in a structured form based on the ODD+D protocol (Müller et al., 2013). A conceptual diagram of the model entities and their relationships is shown in Figure B.1.

I Overview
I.i Purpose
I.i.a What is the purpose of the study?

The purpose of the study is to assess the impact of microinsurance and informal safety nets on the resilience of smallholders. We systematically compare the effectiveness of formal insurance and informal risk-sharing to buffer income shocks given different economic needs and characteristics of extreme events. We explicitly distinguish two types of behavior of insured households with regard to private monetary transfers.

I.i.b For whom is the model designed?

Due to the stylized character of the model, it is primarily designed for the scientific community to understand impacts of the combination of formal and informal insurance. However, with adaptation to specific regions, it could be also valuable to increase understanding of political decision-makers and insurance providers.

I.ii Entities, state variables, and scales
I.ii.a What kinds of entities are in the model?

There is a single type of agents representing smallholder households. Each household is linked to other households in an undirected small-world network (Watts & Strogatz, 1998) with given number of neighbors and rewiring probability.

I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?

- **Budget:** Current budget of a household determined by its initial budget, regular earnings, regular expenses, budget loss due to shocks, insurance premium payment, insurance payout in case of a shock and private monetary transfers to or from other households
- **Insurance:** Status of a household whether insured or not
- **Shock affection:** Status of a household whether affected income shocks or not
- **Donation willingness:** Status of household whether willing to transfer or not (see III.iv.a for details)
- **Transfer-behavior:** Type of behavior that the household follows when asked for transfers (see III.iv.a for details)

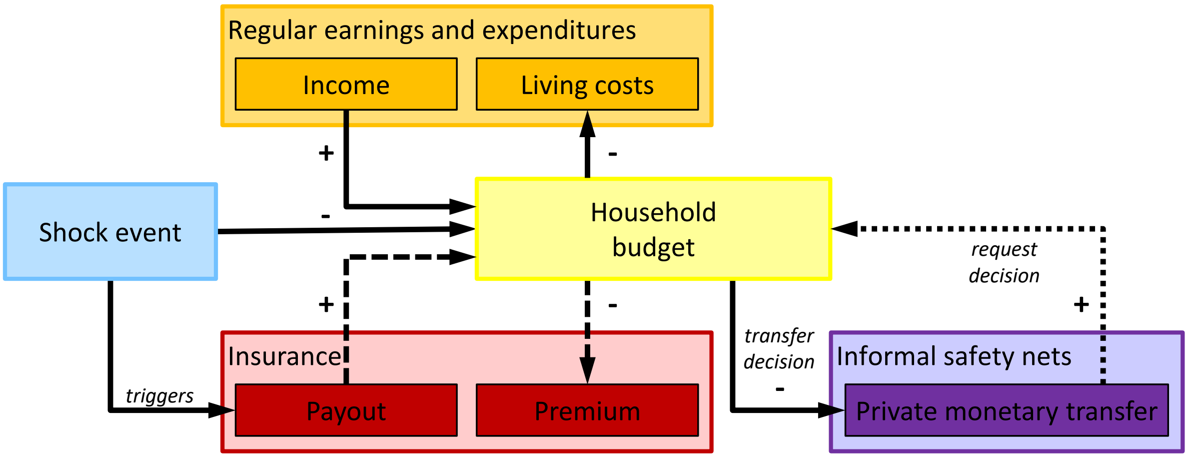

Figure B.1: Conceptual diagram of the model showing the household budget, its main drivers and their relationships. Long-dashed relations are only important for insured households, short-dashed relations only for uninsured households.

- **Links:** Households are connected to other households via undirected links

I.ii.c What are the exogenous factors/drivers of the model?

Households are exposed to income shocks whose occurrence is determined stochastically.

I.ii.d If applicable, how is space included in the model?

Space is not explicitly included in the model. However, the small-world network algorithm allows to create networks with varying levels of heterogeneity which can be seen as roughly representing different spatial clustering in villages. Low rewiring probabilities lead to highly clustered regular networks whereas high rewiring probabilities create poorly clustered random networks.

I.ii.e What are the temporal and spatial resolutions and extents of the model?

The model uses discrete time steps. One time step (tick) represents one year. The time horizon of the model is 50 years. Space is not explicitly included.

I.iii Process overview and scheduling
I.iii.a What entity does what, and in what order?

1. **Initialization:** Set up of households (initial budget, insurance status, donation willingness) and small-world network
2. In every tick:
   - All households (synchronous):
     - Budget increases by **income** and decreases by **annual living costs**
     - Insured households: Pay insurance **premium**
     - Shock affected households: Budget decreases by **shock intensity**
     - Insured households affected by shock: Receive **payout**
   - All households (random order):

- Households in need **request transfers** from randomly chosen households they are connected to in the network
- Requested households **transfer money** to requesting households according to transfer behavior

• **Check for surviving households:** If household's budget is below zero, household has to leave the system.

II Design Concepts
II.i Theoretical and Empirical Background
II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?

- We assume that households have access to formal insurance and traditional informal safety nets to secure themselves against income shocks. These shocks can be idiosyncratic shocks, hitting the households independently (such as health shocks), or covariate shocks, affecting many households at the same time (such as drought shocks).
- Complexity results from the feedback between the dynamics of the budget of individual households and monetary transfers between households in networks.
- By explicitly including two types of behavior of insured households with regard to private monetary transfers, the model contributes to the debate of unintended side effects of formal insurance schemes and helps to identify long-term effects and structural peculiarities that influence the outcome.

II.i.b On what assumptions is/are the agents' decision model(s) based?

The decision models for transfer provision are based on observations from case studies and reflect behavior with and without solidarity of insured households.

II.i.c Why is a/are certain decision model(s) chosen?

Empirical observations show mixed results with respect to the transfer behavior of insured households. Therefore, we have chosen two strategies of transfer decisions which reflect behavior with and without solidarity towards uninsured households. In one simulation run, all households decide on their transfers according to the same strategy. For the first strategy, all households show solidarity, i.e. they transfer whenever they can afford it. In a second strategy, we assume that only uninsured households show solidarity and contribute to informal risk-sharing whenever they can afford it; insured households do not transfer at all. We have implemented the two decision rules to compare the effects of both behaviors on the resilience of smallholders.

II.i.d If the model/a submodel (e.g. the decision model) is based on empirical data, where does the data come from?

Most parts of the model are not directly based on empirical data. The values of household characteristics are chosen in a range derived from literature on microinsurance and informal transfer networks in different countries (for specific references see III.iv.b). Furthermore, the combined parameter space for income, living costs, shock probability and shock intensity is reduced based on economic constraints (for details see III.iv.c).

II.i.e At which level of aggregation were the data available?

Not applicable.

II.ii Individual Decision-Making

II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision-making included?

There is one **level of decision-making**, the household level. Households are the **subject** of decision-making. The monetary transfer provision from wealthy households to households in need in the network is the **object**.

II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?

- **Transfer request:** Each household's objective is to maintain prosperity with a budget above or equal to zero. Households with a budget below zero request help from other agents with a budget above zero in their network.
- **Transfer provision:**
  - **Solidarity:** Households transfer whenever they can afford it (i.e. have a budget above zero). This implies that households may assume that the requesting household will return the transfer in the future if they need support themselves. Since, in the simulated scenarios, insurance covers all losses, this will only occur for uninsured households.
  - **No solidarity:** Only uninsured households show solidarity and contribute to informal risk-sharing whenever they can afford it (i.e. have a budget above zero); insured households do not transfer at all. This implicitly includes that they are (1) not dependent on reciprocal behavior of other households because shocks are fully covered by the insurance and (2) not willing to transfer as they have more costs due to the insurance that uninsured households avoided.

II.ii.c How do agents make their decisions?

Agents' decision rules are implemented as if-then rules.

- **Transfer request:** Households in need randomly pick one of the households in their network with budget above zero. If the request cannot be fulfilled by one single agent, households continue requesting the missing amount from other agents in their network.
- **Transfer provision:** Households that have been requested for a transfer decide how much to transfer based on one of two decision rules:
  - **Solidarity:** The transfer amount is determined by the request and their own budget. The minimum budget of a donating household after the transfer is zero.
  - **No solidarity:** Insured households do not transfer at all; uninsured households show solidarity. In this case, the transfer amount is determined according to the same rules as for solidarity.

II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?

Yes. Households adapt the transfer amount to the requested amount and their own budget. It is incorporated that donors do not put themselves at financial risk through transfers. Therefore, the minimum budget of a donor after a transfer is zero. On the other hand, the household in need should not get too rich through the help of others. The maximum budget that can be achieved through transfers is thus also zero.

II.ii.e Do social norms or cultural values play a role in the decision-making process?

Transfer behavior with solidarity is implicitly based on expected reciprocity.

II.ii.f Do spatial aspects play a role in the decision process?

No, space is not explicitly included in the model.

II.ii.g Do temporal aspects play a role in the decision process?

Households make decisions based only on the current state of the system.

II.ii.h To which extent and how is uncertainty included in the agents' decision rules?

Uncertainty is not included in the decision-making.

II.iii Learning
II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?

No, learning is not included.

II.iii.b Is collective learning implemented in the model?

No.

II.iv Individual Sensing
II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?

Households adapt their decision-making to variables of households they are linked to in the network (see II.iv.b).

II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?

Requested households sense the amount asked for by the household in need. The sensing is not erroneous, i.e. the households always perceive the true requested amount. Households in need do not know the insurance status of their neighbors.

II.iv.c What is the spatial scale of sensing?

Not applicable directly as space is not explicitly included in the model. Concerning sensing in the network, households include their direct neighbors in the network only.

II.iv.d Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?

Agents are assumed to know the values of the sensed variables.

II.iv.e Are costs for cognition and costs for gathering information included in the model?

No.

II.v Individual Prediction

II.v.a Which data uses the agent to predict future conditions?

Households do not predict future conditions.

II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?

Not applicable.

II.v.c Might agents be erroneous in the prediction process, and how is it implemented?

Not applicable.

II.vi Interaction

II.vi.a Are interactions among agents and entities assumed as direct or indirect?

Interactions between households are direct. Households in need request money from households they are linked to in the network which then decide how much to transfer.

II.vi.b On what do the interactions depend?

Interactions depend on the budget of the household in need and the requested household as well as the transfer decision and insurance status of the requested household.

II.vi.c If the interactions involve communication, how are such communications represented?

Communication is represented by transfer request and provision. The transferred amount is reduced from the budget of the giving household and added to the budget of the household in need.

II.vi.d If a coordination network exists, how does it affect the agent behavior? Is the structure of the network imposed or emergent?

The network does not directly influence the behavior, but requests for transfers are only possible between directly linked households. The network structure is imposed during the initialization of the model and is kept constant (i.e. static) for a simulation run.

II.vii Collectives

II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeler or do they emerge during the simulation?

Households are connected in a network that influences their interaction range for monetary transfers. The network is imposed during the initialization of the model and is kept constant (i.e. static) during the simulation run. The network is based on a stylized small-world network.

II.vii.b How are collectives represented?

Collectives are represented as a network.

II.viii Heterogeneity

II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

All agents have the same set of state variables and processes. A fixed proportion of the households is insured, the rest is uninsured. The population is homogeneous with all households having the same initial budget, income level and annual living costs.

II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?

Households take the same decisions on whom to ask for transfers and how much to transfer. However, based on their insurance status, households' choices on transfer provision can be heterogeneous (see II.ii.b or III.iv.a).

II.ix Stochasticity
II.ix.a What processes (including initialization) are modeled by assuming they are random or partly random?

- Insurance status is assigned randomly.
- Income shocks occur randomly (different for idiosyncratic and covariate shocks, see III.iv.a).
- Households in need request transfers from households randomly chosen among the households they are linked to in the network.

II.x Observation
II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?

For **parameter variations** conducted with the R-package nlrx (Salecker et al., 2019), we collect for every time step the states of (NetLogo variable names are given in brackets):

- **Resilience:** Fraction of surviving households (*fraction–active*) and surviving uninsured households (*fraction–active–uninsured*)
- **Budget:** Total budget of all (*total–budget*), insured (*total–budget–insured*) and uninsured households (*total–budget–uninsured*) and mean budget of all (*mean–budget*), insured (*mean–budget–insured*) and uninsured households (*mean–budget–uninsured*)
- **Transfer requests:** Number of households that need help per time step (*requesting–households*), the amount of money they need per time step (*total–money–needed*) and the total amount of money needed up to that time step (*cum–money–needed*)
- **Transfer provision:** Total transfer given up to that time step by all (*total–transfer*), active (*total–transfer–active*), insured (*total–transfer–given–insured*), uninsured (*total–transfer–given–uninsured*) and uninsured active households (*total–transfer–given–uninsured–active*) and transfer received by uninsured active households (*total–transfer–received–uninsured–active*)
- **Inequality:** GINI coefficient of all (*get–gini*), insured (*get–gini–insured*) and uninsured households (*get–gini–uninsured*)

For each **household**, we collect for every time step:

- **Budget:** The total budget of a household (*budget*) and if a households' budget is above or equal to zero (*active*)

- **Transfer:** If a household is willing to provide transfers (donation–willingness), the total amount of money received by (*received*) and transferred to (*given*) other households, the total number of transfers (*total–donates*) and transfers per time step (*current–donates*) and the total number of requests (*total–requests*) and requests per time step (*current–requests*)
- **Shock:** Whether a household is affected by a shock in that time step (*shock–affected*) and how often a household was affected by a shock (*shock–affected–sum*)

For each **link**, we collect for every time step:

- **Transfer:** The total amount of money (*total–flow*) and the amount per time step (*current–flow*) transferred between the two households in the direction of the link and the number of transfers on that link (*number–flows*)
- **Resilience:** If a link is active, i.e. if both connected households have a budget above zero (*active–link*)

In the **graphical user interface**, we plot the values of the following variables for each time step:

- **Resilience:** Fraction of surviving households (*fraction–active*) and surviving uninsured households (*fraction–active–uninsured*)
- **Budget:** Mean budget of all (*mean–budget*), insured (*mean–budget–insured*) and uninsured households (*mean–budget–uninsured*)
- **Transfer provision:** Current transfer per time step given by all, insured and uninsured households
- **Inequality:** GINI coefficient of all (*get–gini*), insured (*get–gini–insured*) and uninsured households (*get–gini–uninsured*)

II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)

We can observe the effectiveness of formal and informal insurance given different economic needs (income, living costs), characteristics of extreme events (shock probability, shock intensity, type of shock), transfer behavior (solidarity, no solidarity) and network properties (average degree, rewiring probability) on the resilience of the households, i.e. the fraction of surviving households, and their budget.

III Details
III.i Implementation Details
III.i.a How has the model been implemented?

The model has been implemented in NetLogo 6.1.1.

III.i.b Is the model accessible and if so where?

The model is available at CoMSES Net (Will et al., 2021c).

III.ii Initialization
III.ii.a What is the initial state of the model world, i.e. at time $t = 0$ of a simulation run?

At the beginning of each simulation, households are initialized with initial budget and insurance status. Shock type and households' transfer behavior is defined according to the chosen scenarios (see III.iv).

III.ii.b Is initialization always the same, or is it allowed to vary among simulations?

Initialization varies between different scenarios (for details of the implementation of the scenarios see III.iv.a).

III.ii.c Are the initial values chosen arbitrarily or based on data?

Initial values are arbitrarily chosen.

III.iii Input Data
III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?

The model does not use input data to represent time-varying processes.

III.iv Submodels
III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?

1. **Setup processes**
   Function name: setup

   a) **Household setup**
   Function name: setup–households
   N_{H} households are created and initialized with an initial budget Y^0. Initial budget and income level is the same for all households. A shock series is determined for the simulated time span T. The calculation of the shock series is different for idiosyncratic shocks hitting the households independently and covariate shocks affecting many households at the same time:

   - **Idiosyncratic shocks:** For each household, the shock series is determined individually. Shocks occur with probability p_{s}.
   - **Covariate shocks:** A shock series is determined for the whole village. Shocks occur with probability $p_{\mathrm{V}} = p_{\mathrm{s}}/p_{\mathrm{H}}$. In time steps where the village is affected by a shock, individual households are affected with probability p_{H}. This results in an overall shock probability $p_{\mathrm{s}} = p_{\mathrm{V}} \times p_{\mathrm{H}}$ for an individual household. We distinguish between cases in which all households without exception are affected by the shock ($p_{\mathrm{H}} = 1$) and cases in which some households are exempted ($p_{\mathrm{H}} = 0.8$), for example by a more favorable geographical location in case of floods or an agricultural management strategy more adapted to drought risks.

   To make the strategies comparable, in one repetition the shock series of one specific household is the same for every risk-coping instrument.

   b) **Network setup**
   Function name: create–small–world–network
   A small-world network is generated using the generate–watts–strogatz primitive in the NetLogo Nw Extension which is based on the Watts-Strogatz model (Watts & Strogatz, 1998). Essentially, the algorithm creates a ring of households with each node connected to N_{N} nodes on either side. Each link is rewired with rewiring probability p_{r}. To allow for the control of the transfers in both directions of a link separately, the algorithm is slightly modified so that directed links to $N_{\mathrm{N}}/2$ households are created on one side of the agent. After rewiring, a link in the opposite direction is established for each existing link. This leads to an undirected

small-world network with average degree N_N. Based on data from Ethiopia, a household is on average willing to transfer to 3.8 households (Takahashi et al., 2018). Therefore, we have chosen an average neighborhood size of $N_N = 4$. To consider the effects of more or less neighbors, we additionally present the results for $N_N = 8$ and $N_N = 2$. We compare two types of spatial clustering with low ($p_r = 0.2$) and high ($p_r = 0.8$) rewiring probability.

c) **Insurance targeting**
Function name: insurance–take–up
An insurance take-up rate γ is given. Among all households $\gamma \times N_H$ (rounded down if necessary) are randomly selected to be insured. Insured households insure their complete income.

d) **Donation willingness**
Function name: set–donation–willingness
If transfers between households are considered, households' willingness to provide transfers is set to 1 for uninsured households and insured households showing solidarity and 0 for insured household not showing solidarity. For the reference case where no transfers are considered, households' willingness to provide transfers is set to 0 for all households.

2. **Processes in every time step**
Function name: go
Every time step is divided into two phases. In the first phase, households execute processes without interaction in the network. The processes run sequentially and in the following order: regular earning, regular expenses, insurance premium payment, budget loss due to shocks, and insurance payout. In the second phase, after all households have completed the first one, households are selected in random order to execute transfer requests if necessary. Since the insurance covers all losses, only uninsured households may get into the situation of having to request transfers from the neighbors with whom they have social ties. Budgets of households in need and households providing transfers are updated after each transfer according to the amount received and provided. At the end of each time step, households whose budget is less than zero have to leave the system.

Phase I:

a) **Regular earnings**
Function name: annual–income
Households add a fixed amount I to their budget as annual income.

b) **Regular expenses**
Function name: annual–consumption
Households consume a fixed amount C of their budget to cover their annual living costs.

c) **Budget loss due to shocks**
Function name: shock–loss
Shocks occur with intensity S. If according to its individual shock series a household is affected by a shock, the budget of that household is reduced by this amount.

d) **Insurance premium and payout**
Insured households insure their complete income.

- **Payout**
  Function name: insurance–payout
  The insurance covers the actual losses a household suffers from. The payout α in case of a shock is $\alpha = S$.

- **Premium**
  Function name: insurance–premium
  The insurance is actuarially fair. Insured households have to pay a yearly premium β equal to the expected payout: $\beta = p_s \times S$.

Phase II: Informal monetary transfers
Function name: informal–transfers

a) **Transfer request**
Function name: transfer–request
Households request monetary transfers from households they are linked to in the network if their budget is below zero. A requesting household i requests a transfer amount $T_{i,\text{req}}$ that covers its debts Y_i: $T_{i,\text{req}} = |Y_i|$. A household in need can ask households in its network for help which have a budget above zero. The household randomly picks one of the possible households. The budgets are updated after every transfer. Households continue to ask until they obtain the requested amount or until no more households are able to support them.

b) **Transfer provision**
Function name: transfer–money, transfer–amount
Households are potential donors if their budget Y_j is above zero. Depending on the scenario, all households show solidarity or only uninsured households show solidarity and insured households do not transfer. Households in need do not know the insurance status of their neighbors.

   - **Solidarity:** All potential donors are willing to transfer if requested. If the requested amount is smaller than their own budget, the amount transferred $T_{i,j}$ equals the requested amount $T_{i,\text{req}}$, otherwise they transfer their complete budget Y_j: $T_{i,j} = \min\{Y_j; T_{i,\text{req}}\}$
   - **No solidarity:** Potential donors that are uninsured behave as in the solidarity case. Insured households do not transfer.

c) **Household budget equation**
All processes sum up to the following equation for the budget $Y_i(t)$ of household i at time step t:

$$Y_i(t) = \begin{cases} Y_i(t-1) + I - C - \beta - S_i + \alpha_i + \sum\limits_{j \in N_i} T_{ij}(t) & \text{for insured HH} \\ Y_i(t-1) + I - C - S_i + \sum\limits_{j \in N_i} T_{ij}(t) & \text{for uninsured HH} \end{cases}$$

with income I, annual living costs C and premium β. The shock intensity S_i equals S if a household is affected by a shock and is zero otherwise. The same holds true for the insurance payout α_i. For $t = 1$ the budget of the previous time step $t-1$ is given by the initial budget Y^0.
N_i denotes all households that share a link with household i and $T_{i,j}(t)$ is the transfer between households i and j at time step t. Transfers can be positive, negative or zero for uninsured households (receiving and providing transfers) and negative or zero for insured households (only providing transfers).

d) **Check for surviving households**
If a household's budget is below zero at the end of a time step, the household has to leave the system.

III.iv.b What are the model parameters, their dimensions and reference values?

Parameter	Description	NetLogo name	Unit	Standard value/ range	Reference
T	Number of ticks that the model runs	timesteps	Years	50	–
N_H	Number of households in the system	number–households	Unitless	50	–
N_N	Neighborhood size (small-world network)	neighbor-hood–size	Unitless	2, 4, 8	Takahashi et al. (2018)
p_r	Rewiring probability (small-world network)	rewire–prob	Unitless (rate)	0.2, 0.8	–
I	Annual household income	income–lvl	Normalized to 1	1	–
Y^0	Initial budget	budget–init	Unitless, related to I	0	–
γ	Insurance take-up rate	insurance–take–up–rate	Unitless (rate)	0, 0.3, 0.6	Takahashi et al. (2018)
C	Annual living costs	consump-tion–lvl	Unitless, related to I	0.7 – 0.9	Takahashi et al. (2016) and Matsuda et al. (2019)
p_s	Probability for shock occurrence	shock–prob	Unitless (rate)	0.1 – 0.3	Geng et al. (2018) and Anderberg & Morsink (2020)
p_V	Probability for shock occurrence at village level (covariate shock)	covariate–shock–prob–vlg	Unitless (rate)	$p_V = p_s/p_H$	–
p_H	Probability that individual households are affected by a shock if the village is affected (covariate shock)	covariate–shock–prob–hh	Unitless (rate)	0.8, 1	–
S	Shock intensity, i.e. budget loss due to shock	shock–intensity	Unitless, related to I	0.2 – 1	–

III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?

The different decision submodels were chosen to build a "virtual lab" to test how transfer decisions influence overall welfare of the population and if different behavioral models lead to different outcomes. The parameter range for the network model has been adapted to literature values (see III.iv.b). The combined parameter ranges for income I, living costs C, shock probability p_s and shock intensity S need to meet two constraints: (1) Shock intensity must be high enough to make financial protection necessary and (2) formal insurance must be affordable. The resulting reduced parameter space has been adapted to economic constraints from literature values (for resulting parameter ranges see III.iv.b).

B.2 Parameter selection

To assess the impact of formal and informal insurance on the resilience of smallholders, the model should depict conditions in which both instruments are important and can be used effectively. This implies (1) that the shock intensity should be high enough to make financial protection necessary and (2) that formal insurance should be affordable. To select parameter combinations for living costs C, shock probability p_s and shock intensity S that fulfill these constraints, we calculate the budget change of a household per time step depending on its insurance state and the occurrence of a shock (see Table B.1). Based on the probability p_s with which each of these cases occur, the expected value of budget change without informal transfers equals $E[\Delta Y] = I - C - \beta$ for an insured household and $E[\Delta Y] = I - C - p_s \times S$ for an uninsured households. As the insurance is assumed to be fair ($\beta = p_s \times S$), the expected value $E[\Delta Y]$ is the same for insured and uninsured households. Based on the expected value we can select cases that are suitable for the analysis. We exclude parameter combinations with $E[\Delta Y] < 0$, as in this situations insured households lose money in every time step which would contradict the intention of insurance to protect household from monetary losses. We furthermore exclude combinations for which uninsured households do not have a negative budget change in case of a loss, i.e. we exclude cases with $E[\Delta Y] > 0$ and $I - C - S > 0$. In these cases, risk-coping instruments are not needed. Figure B.2 graphically shows the resulting parameter space. For the simulation, we use values with spacing of 0.1 for the three dimensions living costs C, shock probability p_s and shock intensity S.

Table B.1: Budget change of a household per time step depending on its insurance state and the occurrence of a shock. Budget change is calculated based on the annual income I, living costs C, shock intensity S, premium β and payout α.

	Shock	No shock
Insured	$I - C - S + \alpha - \beta$	$I - C - \beta$
Not insured	$I - C - S$	$I - C$

Additionally to the mathematical restrictions, we constrain the parameters with respect to ecological and economic observations. We assume subsistence farmers that need consume a large proportion of their income to cover their living costs. Studies for livestock farmers in Ethiopia show, for example, that households consume between 69 % (322 Ethiopian Birr

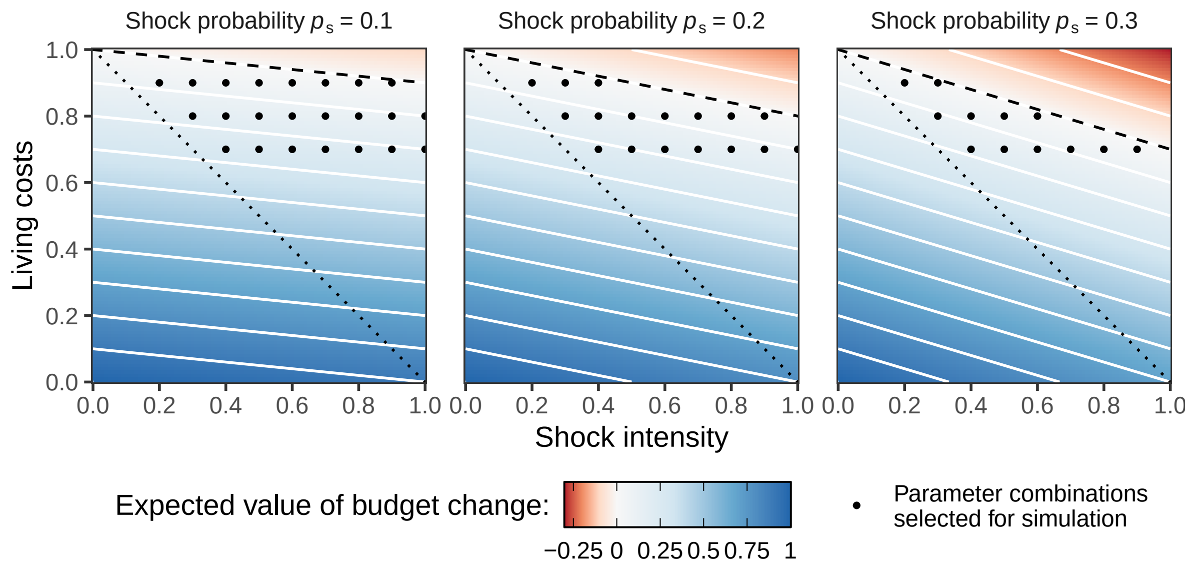

Figure B.2: Representation of the parameter space that results from assumptions for reasonable budget changes of a household per time step. White lines connect parameter combinations with equal expected value of budget change $E[\Delta Y]$. The parameter space is divided in three main zones: For parameter combinations below the dotted line $E[\Delta Y] > 0$ and $I - C - S > 0$ applies; for parameter combinations above the dashed line $E[\Delta Y] < 0$ applies. Parameter combinations in between those two zones are suitable for the analysis. Dots represent parameter combinations that fulfill the additional ecological and economic constraints ($0.1 \leq p_s \leq 0.3, 0.7 \leq C < 1$). These parameter combinations are selected for the simulation.

mean monthly per capita consumption with 467 Ethiopian Birr mean monthly per capita income (Takahashi et al., 2016)) and 81 % (mean annual household consumption 21,482 Ethiopian Birr with annual household income 26,631 Ethiopian Birr (Matsuda et al., 2019)) of their income. We therefore restrict the parameter for living costs to $0.7 \leq C < 1$. We furthermore assume shock probabilities in a range of $0.1 \leq p_s \leq 0.3$ which relate to empirically observed income losses. According to a study in Ethiopia, for example, the probability to lose 25-50 % of the crop yield was on average 21 % (Anderberg & Morsink, 2020). The rate of health shocks is similarly high. In a survey conducted in Kenya, households denoted to experience a health shock in 26.6 % of the weeks in one year (Geng et al., 2018). We do not include any further restrictions for shock intensity S to cover a broad range of possible outcomes. Based on suitable expected values, values for shock probabilities p_s and levels of annual living costs C, shock intensity S is within $0.2 \leq S \leq 1$. We divide all parameter ranges in equidistant steps of 0.1, which results in 52 reasonable parameter combinations that meet the constraints.

B.3 Additional results for idiosyncratic shocks (selected parameter combination)

We present additional results for idiosyncratic shocks, i.e. shocks that occur for all households independently with shock probability p_s. To make the different risk-coping instruments comparable, for each household the order of shocks is determined at the beginning of each simulation run. This individual shock series is equal for the same parameter combination and random seed independent of the network characteristics and risk-coping instruments that are analyzed. We present simulation runs over 50 years for one specific parameter combination of income I, living costs C, shock probability p_s and shock intensity S ($I = 1$, $C = 0.8$, $p_s = 0.3$, $S = 0.6$). All results show the mean over 100 repetitions. The outcomes can be compared to the observations shown in the main text where results for a small-world network with rewiring probability $p_r = 0.2$ and an average number of four neighbors ($N_N = 4$) are shown. Here, we analyze the fraction of surviving households (Figure B.3), the fraction of surviving uninsured households (Figure B.4), the total transfer (Figure B.5) and the budget per surviving household (Figure B.6) for (a) higher rewiring probability, (b) smaller and (c) larger average degrees.

B.3.1 Fraction of surviving households

We observe that rewiring probability (Figure B.3A) has almost no effect on the survival rates n. Only when all households show solidarity and 60 % of the households are insured slightly more households survive than for a low rewiring probability. In the 60 % insurance scenario, the survival rate is slightly lower when only uninsured households show solidarity. As even with higher rewiring probability, the average number of neighbors remains at $N_N = 4$, the similar survival rates show that, in most cases, households can rely on the same number of helping households. Only if a large number of households is insured, some households benefit from a higher number of neighbors, which can result from a high rewiring probability. With a higher number of neighbors, the small contributions of insured households can more easily sum up to effective contributions. This suggests that the average number of neighbors could play an important role. We have therefore investigated which effects a smaller (Figure B.3B) and larger (Figure B.3C) average degree than that presented in the main text ($N_N = 4$) has on the survival rate. As expected, a low number of neighbors ($N_N = 2$) clearly lowers the number of households that manage to stay in the system whereas a larger number of neighbors ($N_N = 8$) helps more households to survive. This is reasonable, since when a household in need is connected to more households, the chance that enough neighbors can and are willing to help is higher. Furthermore, the chance that even small contributions sum up to helpful transfers increases with more neighbors.

B.3.2 Fraction of surviving uninsured households

When focusing the analysis on the fraction of surviving uninsured households among the 20 households that are uninsured in every scenario, we again observe that a higher rewiring probability (Figure B.4A) has only small effects. When changing the average degree (Figure B.4B, Figure B.4C), we observe that this influences, on the one hand, the fraction of surviving uninsured households as already observable for the fraction of surviving households and, on the other hand, the effect of solidarity from insured households. The higher the average number of neighbors, the larger is the difference between uninsured households surviving with solidarity of insured households and without. This is due to the fact that when a household in need is connected to more other households, contributions of insured households that are potentially smaller than those of uninsured households more easily sum up to effective contributions.

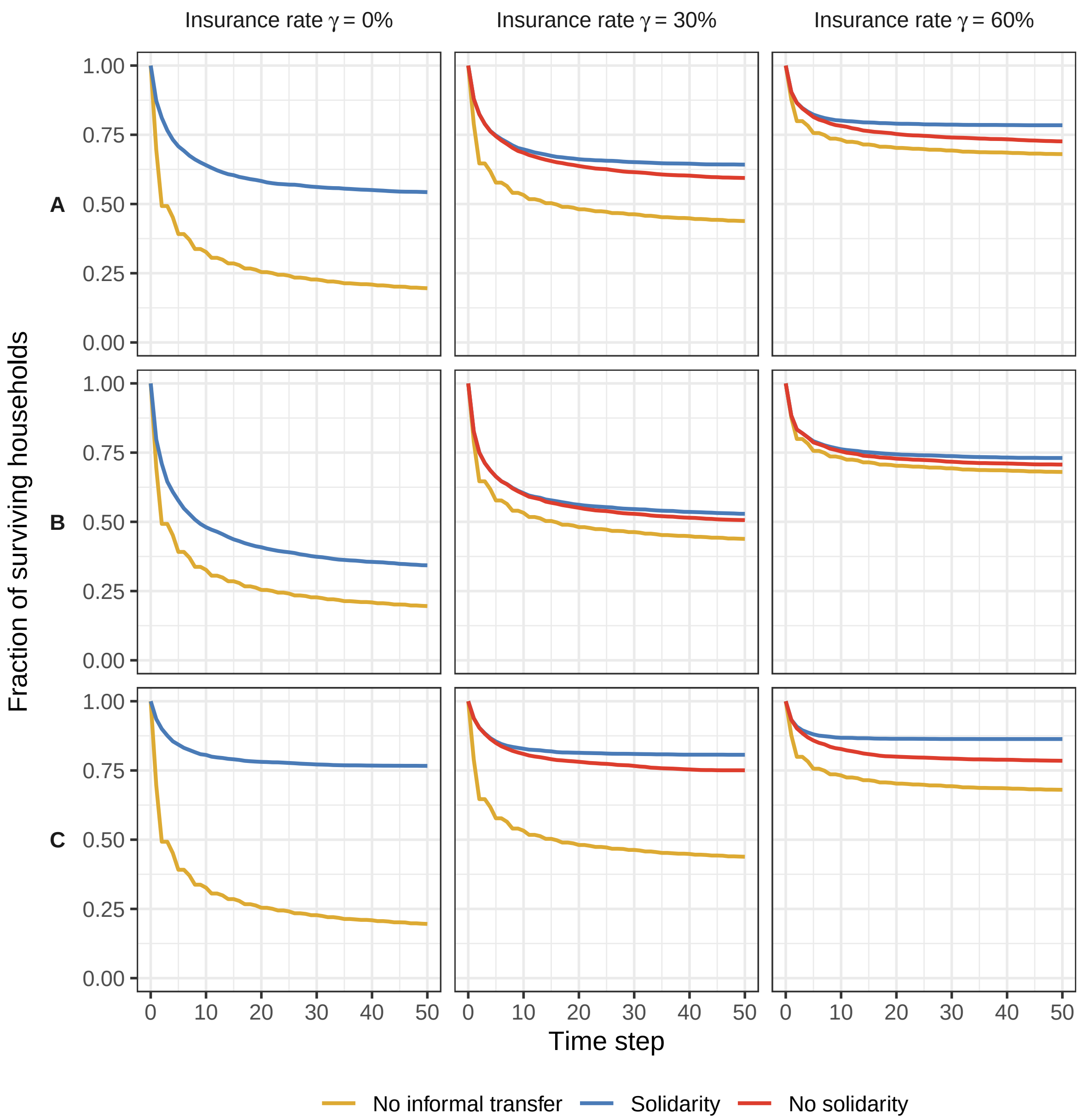

Figure B.3: Fraction of surviving households for different risk-coping instruments and insurance rates ($\gamma = 0\,\%$, $\gamma = 30\,\%$, $\gamma = 60\,\%$) with (A) high rewiring probability ($N_\mathrm{N} = 4$, $p_\mathrm{r} = 0.8$), (B) small average degree ($N_\mathrm{N} = 2$, $p_\mathrm{r} = 0.2$) and (C) large average degree ($N_\mathrm{N} = 8$, $p_\mathrm{r} = 0.2$).

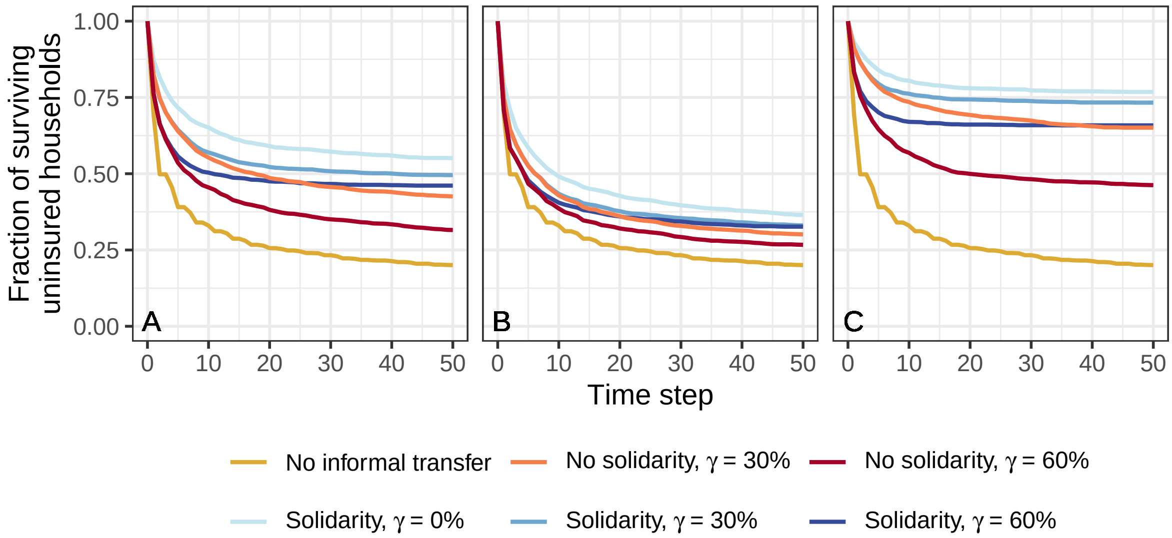

Figure B.4: Fraction of surviving uninsured households among the 20 households that are uninsured in every scenario for different risk-coping instruments with insurance rates γ and (A) high rewiring probability ($N_N = 4$, $p_r = 0.8$), (B) small average degree ($N_N = 2$, $p_r = 0.2$) and (C) large average degree ($N_N = 8$, $p_r = 0.2$).

B.3.3 Total transfer

The total transfer received and given by the 20 households that are uninsured in every scenario per time step underlines the observations for the survival rates of uninsured households for different network conditions. The transfers in a network with high rewiring probability (Figure B.5A) are, as expected from the similar survival rates, in the same range than those provided in a network with small rewiring probability. For a smaller average degree (Figure B.5B) than that presented in the main text, we observe less transfers given and received by uninsured households, for a larger average degree (Figure B.5C) correspondingly more. The trends that were observed for the baseline case presented in the main text hold, however, true for all additional network scenarios. The fact that households have to provide lower transfers when insured households show solidarity is even more pronounced with many neighbors. This is due to the fact that in this case the transfers tend to be spread over several shoulders and even small contributions can be effective.

B.3.4 Budget per surviving household

The observations for the total transfer that uninsured households receive and give for the different scenarios are directly related to the budget per surviving household. We compare the budget based on the 20 households that are uninsured in every scenario and the 15 households that are insured in every scenarios (except $\gamma = 0\%$). The straight line shows the maximum budget that an insured household can receive as reference value. As the case with no informal transfers is independent of the network characteristics, the budget per surviving household is in this case not affected by changes of rewiring probability or neighborhood size. As in all other output measures, budget as well is not affected by a larger rewiring probability (Figure B.6A). However, smaller (Figure B.6B) and larger (Figure B.6C) neighborhood sizes have effects on the budgets of uninsured and insured households. We observe that the

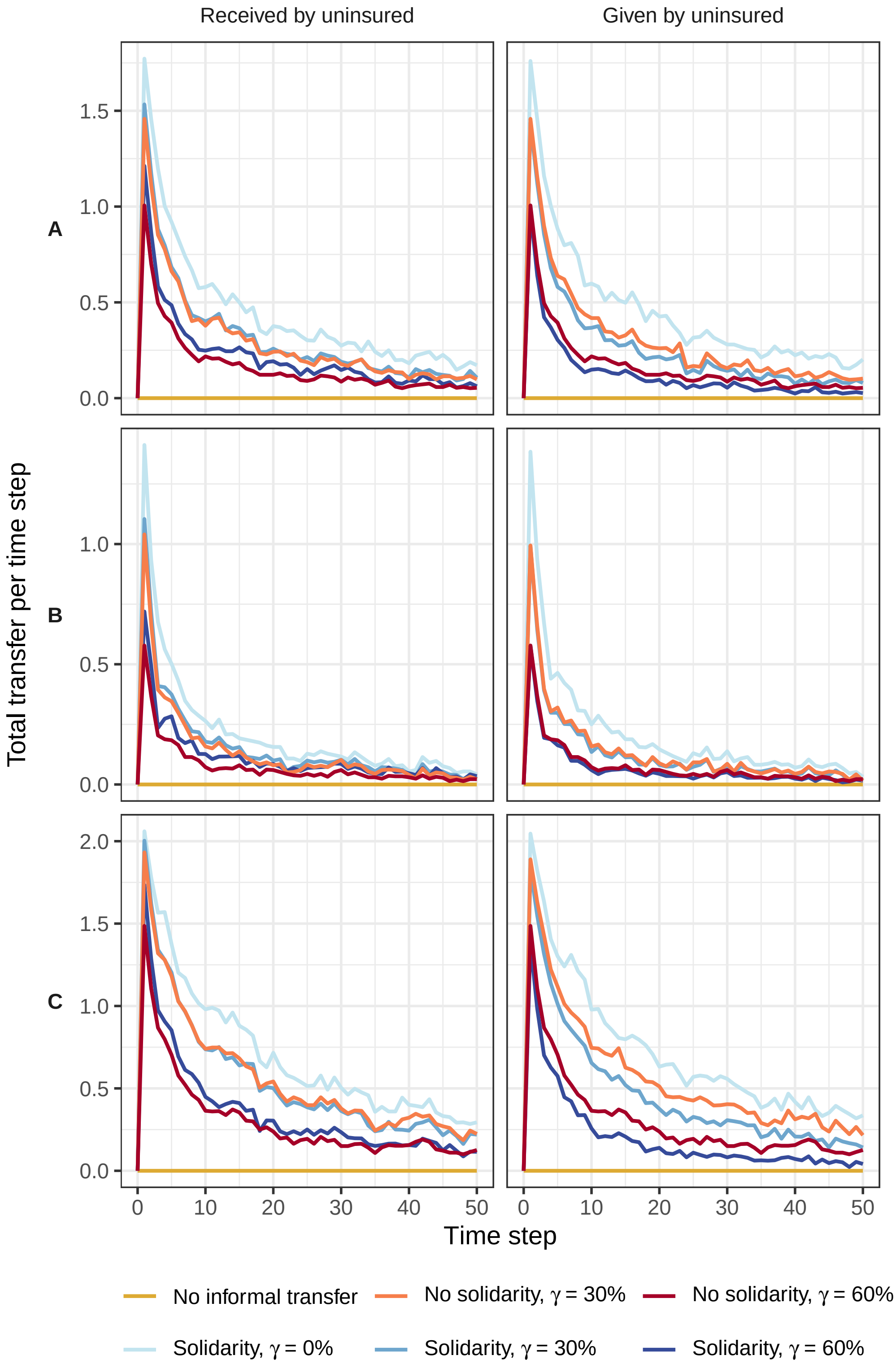

Figure B.5: Total transfer received and given by all 20 households that are uninsured in every scenario per time step. Results show (A) high rewiring probability ($N_N = 4$, $p_r = 0.8$), (B) small average degree ($N_N = 2$, $p_r = 0.2$) and (C) large average degree ($N_N = 8$, $p_r = 0.2$).

budget level of uninsured households increases with fewer number of neighbors. However, as for the case without informal transfers this only shows that some households suffer shocks in an order which makes it possible to accumulate a large budget. Since in this case only a few uninsured households survive, this still has an overall negative impact on resilience of uninsured households. Furthermore, we observed in the scenario presented in the main text with $N_N = 4$ that the budget of uninsured households is only slightly affected by the solidarity of insured households. More neighbors lead to an increased budget of uninsured households in the case of solidarity compared to the case where insured households do not contribute. A larger risk-sharing group has therefore positive effects not only on the survival rate of uninsured households but also helps them to secure their financial resources. However, as this effect is largely dominated by the contributions of insured households this comes at the cost of lower budget in this subgroup. As transfers are not paid back, insured households will end up with budgets far lower than that of uninsured households which might affect their willingness to contribute to informal risk-sharing arrangements.

B.4 Additional results for idiosyncratic shocks (all parameter combinations)

To investigate the transferability of these observations to different external conditions, i.e. other levels of living costs and increased or decreased shock probability and intensity, we evaluated the status of the system for all 52 parameter combinations that were found to be economically feasible. We compared the effects of 50 years of informal transfers ($\gamma = 0\,\%$) on the survival rate of uninsured households to the situation 50 years after the introduction of insurance with low ($\gamma = 30\,\%$) and high ($\gamma = 60\,\%$) insurance rates, respectively. In the main text, we presented the results for a fixed income ($I = 1$) level of living costs ($C = 0.8$). Here, we show the results for lower (Figure B.7) and higher (Figure B.9) annual expenses. Additionally, we present the survival rates of uninsured households for a higher rewiring probability and a smaller or larger average network degree for low (Figure B.7), medium (Figure B.8) and high (Figure B.9) level of living costs. To allow the best possible comparison between the different risk-coping instruments and insurance rates, we have again limited the analysis to the 20 households that are uninsured in the scenarios with highest insurance rate. If a panel is left blank, the parameter combination is not included in this set and therefore not selected for the analysis. Results show the mean over 100 repetitions of the number of surviving uninsured households at the last simulation step ($t = 50$).

The trends which we observed in the analysis for the selected parameter combination remains. A higher rewiring probability has also for other parameter combinations only slight effects on the survival rates of uninsured households. A smaller number of neighbors leads to lower survival rates of uninsured households, with a larger number of neighbors more uninsured households survive.

B.5 Additional results for covariate shocks

We present additional results for covariate shocks, i.e. shock events that affect many households in a village. To make the different risk-coping instruments comparable, the order of shocks is determined at the beginning of each simulation run. Therefore, a shock series with shock probability $p_V = p_s/p_H$ is created for the whole village. In time steps where the village

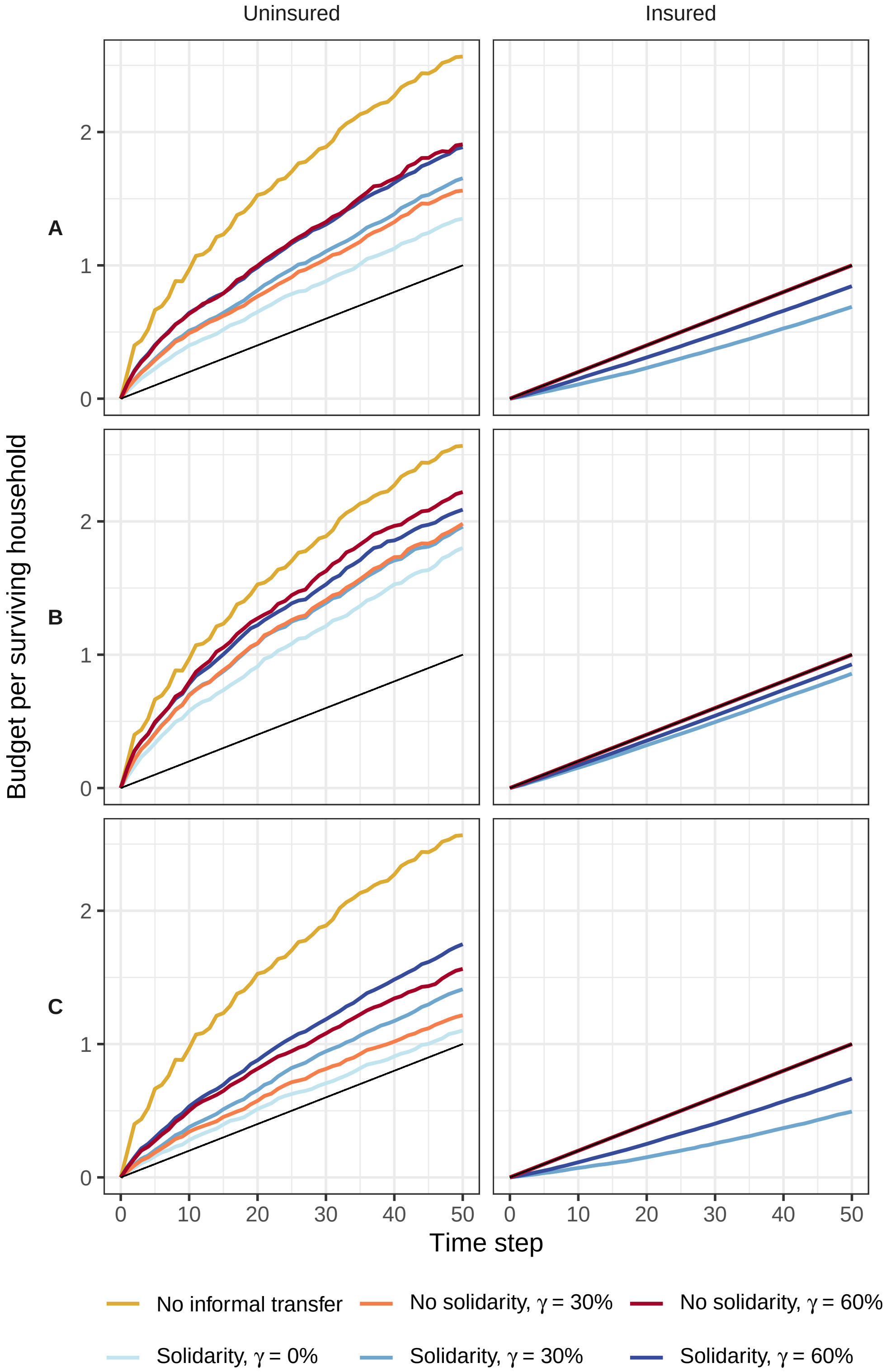

Figure B.6: Budget per surviving household calculated based on the 20 households that are uninsured in every scenario and the 15 households that are insured in every investigated scenario (except $\gamma = 0\,\%$). The straight line shows the maximum budget that an insured household can receive as reference value. Results show (A) high rewiring probability ($N_N = 4$, $p_r = 0.8$), (B) small average degree ($N_N = 2$, $p_r = 0.2$) and (C) large average degree ($N_N = 8$, $p_r = 0.2$).

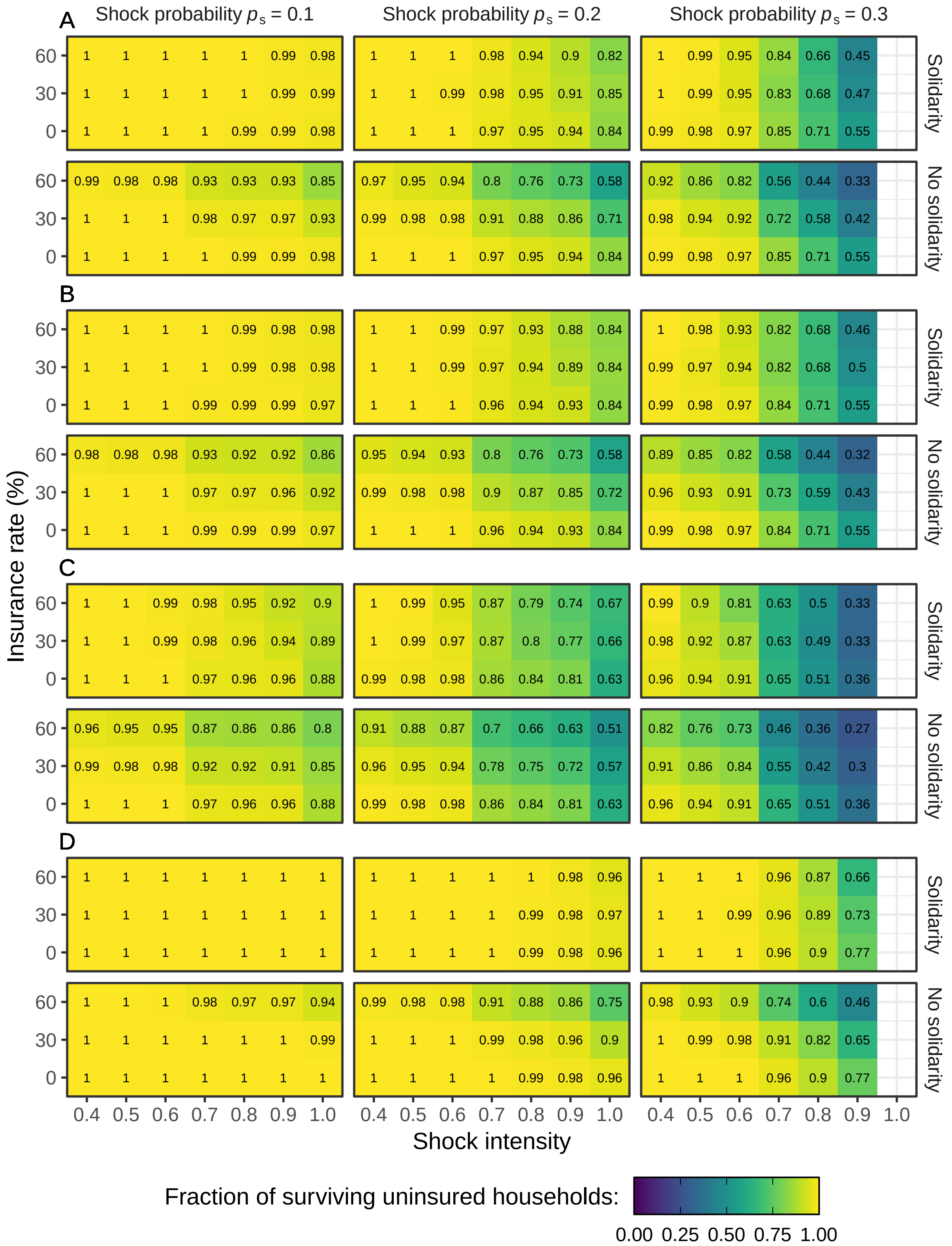

Figure B.7: Fraction of surviving uninsured households among the 20 households that are uninsured in every scenario for idiosyncratic shocks and low level of living costs ($C = 0.7$) for (A) average degree and rewiring probability as in main text ($N_N = 4$, $p_r = 0.2$), (B) high rewiring probability ($N_N = 4$, $p_r = 0.8$), (C) small average degree ($N_N = 2$, $p_r = 0.2$) and (D) large average degree ($N_N = 8$, $p_r = 0.2$).

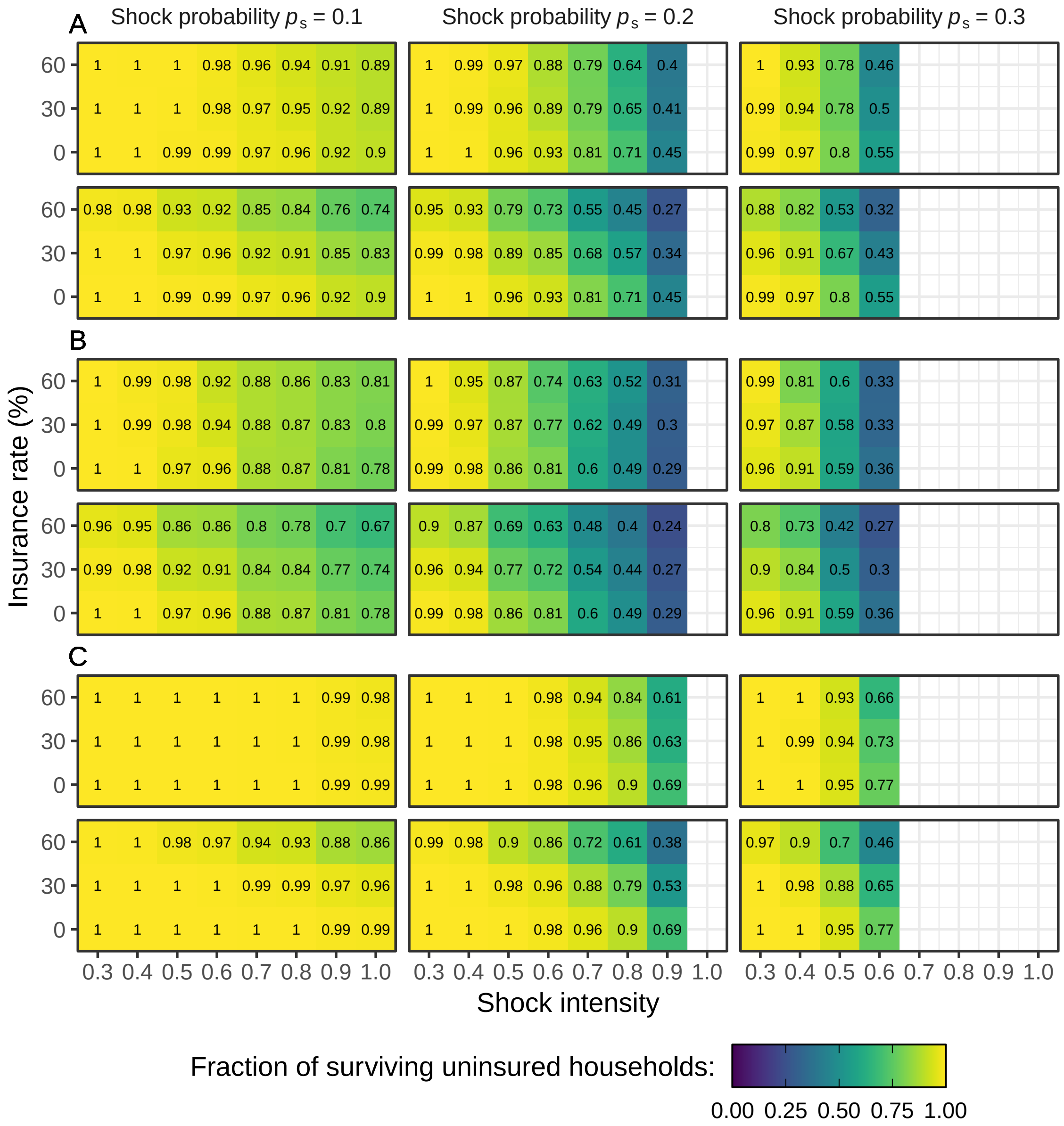

Figure B.8: Fraction of surviving uninsured households among the 20 households that are uninsured in every scenario for idiosyncratic shocks and medium level of living costs (C = 0.8) for (A) high rewiring probability (N_N = 4, p_r = 0.8), (B) small average degree (N_N = 2, p_r = 0.2) and (C) large average degree (N_N = 8, p_r = 0.2).

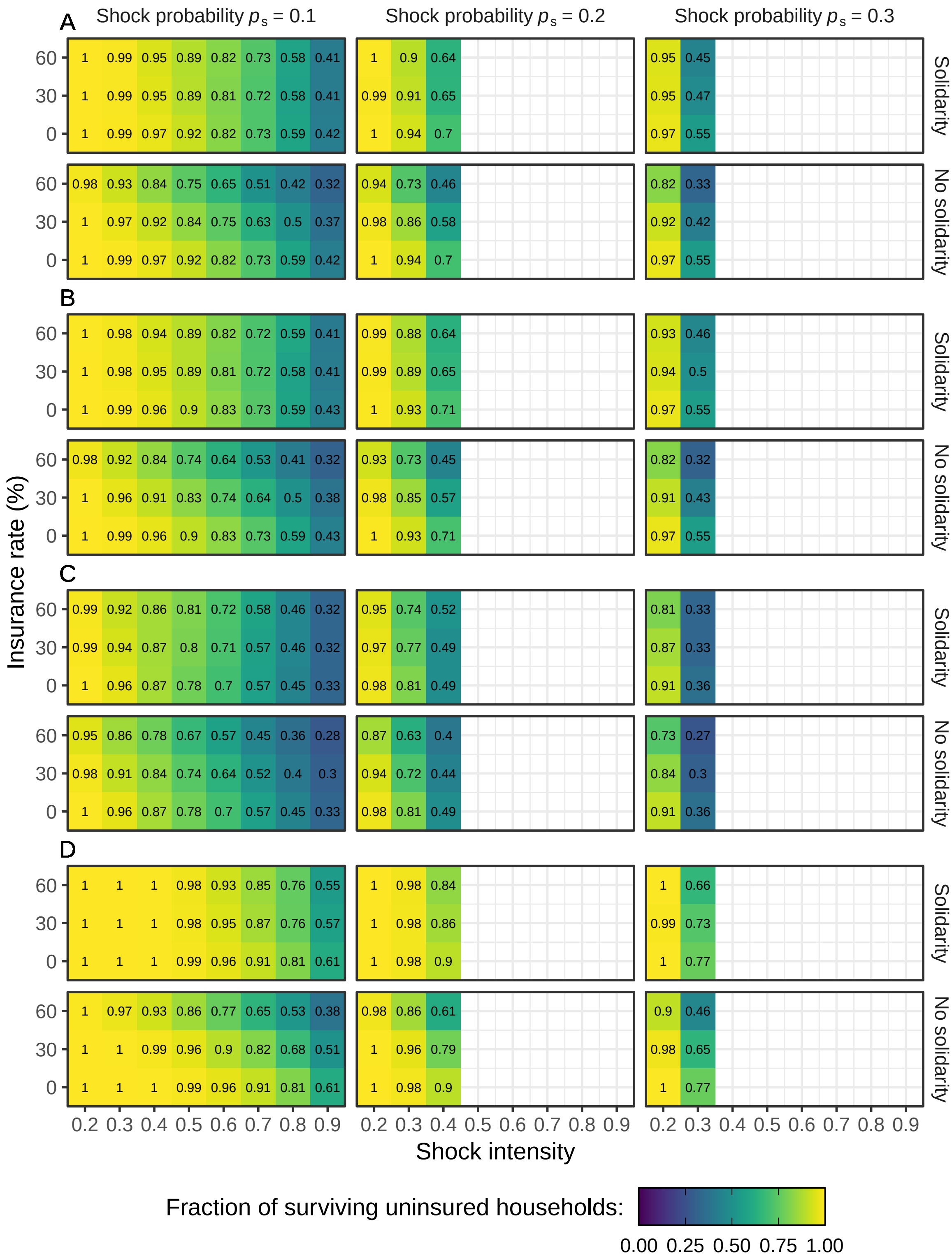

Figure B.9: Fraction of surviving uninsured households among the 20 households that are uninsured in every scenario for idiosyncratic shocks and high level of living costs ($C = 0.9$) for (A) average degree and rewiring probability as in main text ($N_N = 4$, $p_r = 0.2$), (B) high rewiring probability ($N_N = 4$, $p_r = 0.8$), (C) small average degree ($N_N = 2$, $p_r = 0.2$) and (D) large average degree ($N_N = 8$, $p_r = 0.2$).

is affected by a shock, individual households are affected with probability p_{H}. This individual shock series is equal for the same parameter combination and random seed independent of the network characteristics and risk-coping instruments that are analyzed.

In the main text, we have shown the survival rate of uninsured households for networks with average number of neighbors $N_{\mathrm{N}} = 4$ and rewiring probability $p_{\mathrm{r}} = 0.2$. Among the 52 parameter combinations that were found to be economically feasible we selected the results for a medium level of living costs ($C = 0.8$). We have presented the results for within-village shock probability $p_{\mathrm{H}} = 0.8$. In this case an individual household is affected by a shock with 80 % probability if a shock event occurs at village level. Here, we additionally include the result for the more extreme case of $p_{\mathrm{H}} = 1$ where all households are affected simultaneously if a shock occurs.

We present the full parameter set divided according to the level of living costs C with $C = 0.7$ (Figure B.10), $C = 0.8$ (Figure B.11) and $C = 0.9$ (Figure B.12). If a panel is left blank, the parameter combination is not selected for the analysis. Results show the mean over 100 repetitions of the number of surviving uninsured households at the last simulation step ($t = 50$).

We observe that, as expected, a higher within-village shock probability leads to lower survival rates of uninsured household. In this case, informal risk-coping is only possible by transfers from insured households which is not as effective as if at least some uninsured households can contribute, too. When all households are affected by shocks simultaneously and insured households do not show solidarity, the fraction of insured households has obviously no influence on the survival rate of uninsured households (lower rows in panels for $p_{\mathrm{H}} = 1$).

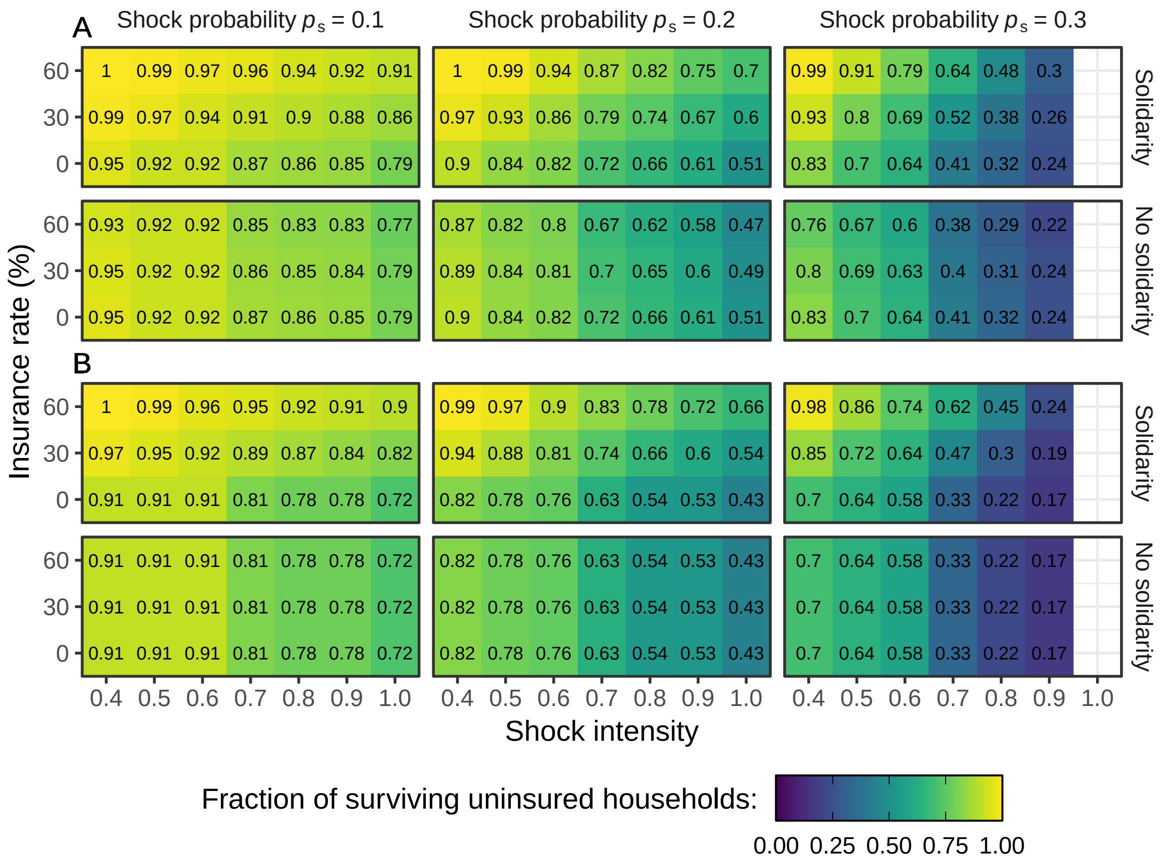

Figure B.10: Fraction of surviving uninsured households among the 20 households that are uninsured in every scenario for covariate shocks ($N_N = 4$, $p_r = 0.2$) and low level of living costs ($C = 0.7$). Upper rows show the results for solidarity between all households, lower rows show the results for solidarity between uninsured households only when (A) 80 % of the households ($p_H = 0.8$) and (B) all households are affected by a shock at village level ($p_H = 1$).

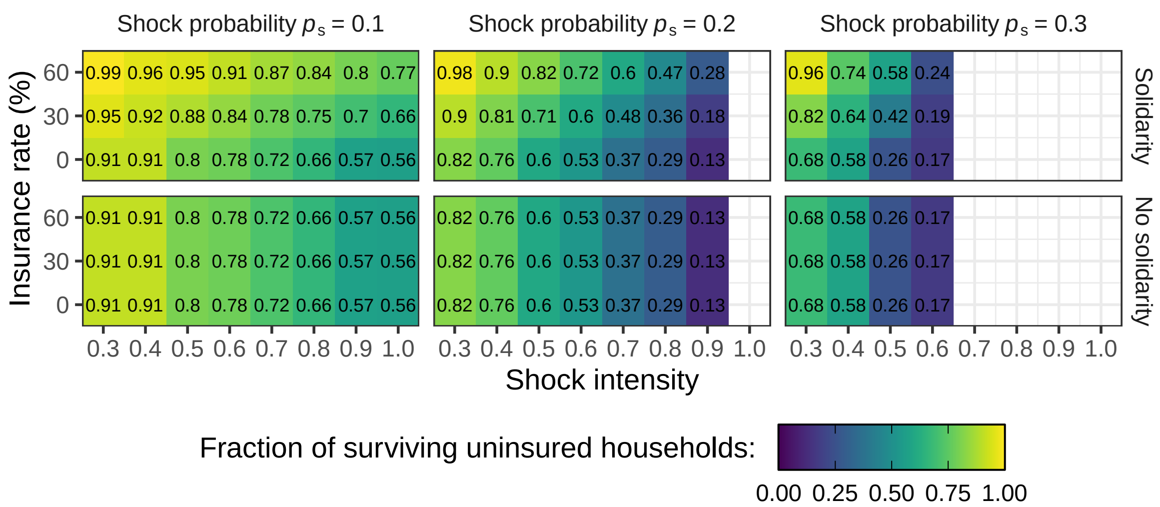

Figure B.11: Fraction of surviving uninsured households among the 20 households that are uninsured in every scenario for covariate shocks ($N_N = 4$, $p_r = 0.2$) and medium level of living costs ($C = 0.8$) when all households are affected by a shock at village level ($p_H = 1$).

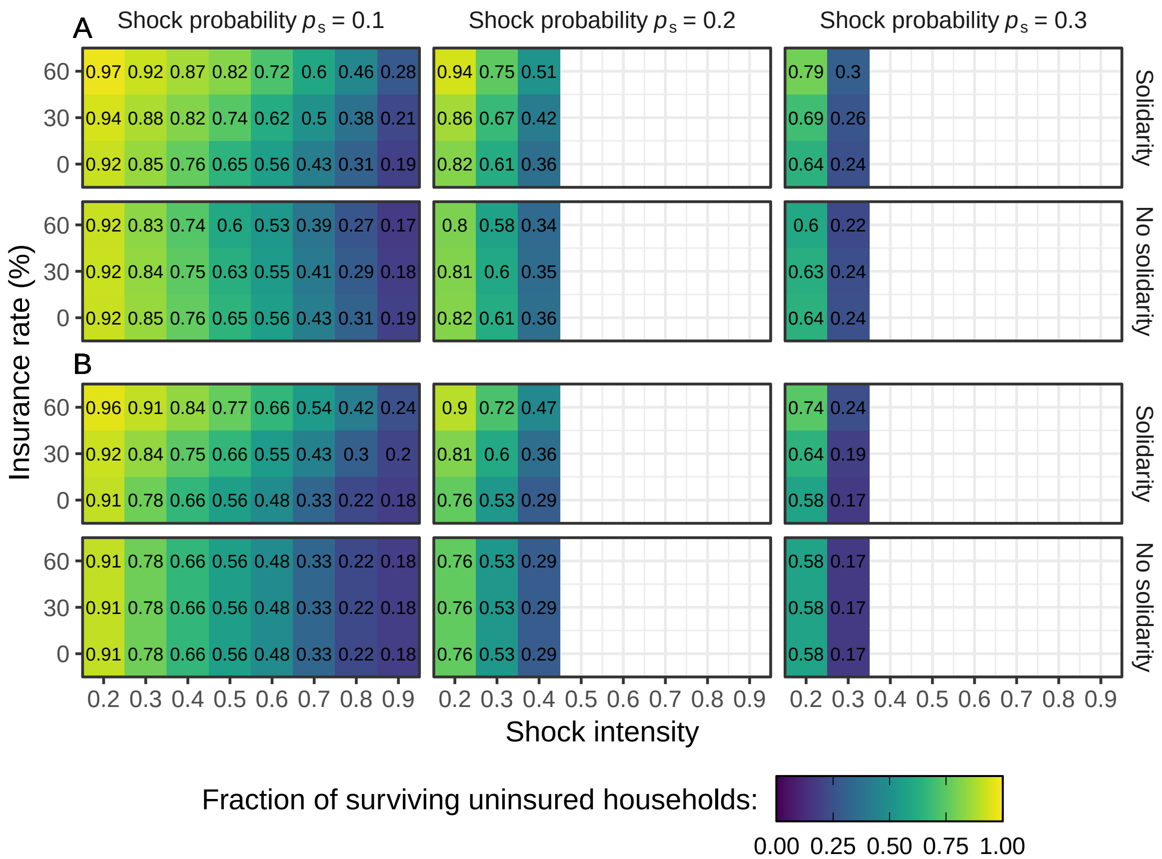

Figure B.12: Fraction of surviving uninsured households among the 20 households that are uninsured in every scenario for covariate shocks ($N_N = 4$, $p_r = 0.2$) and high level of living costs ($C = 0.9$) when (A) 80 % of the households ($p_H = 0.8$) and (B) all households are affected by a shock at village level ($p_H = 1$).

C Appendix of Chapter 4

C.1 Model documentation

The main processes of the simulation model described in a structured form based on the ODD+D protocol (Müller et al., 2013) can be found in Appendix B.1. Here, we present the differences to the model version used in Chapter 3 and outline additional processes.

The focus of this study is not on transfer decisions but on the effectiveness of formal and informal risk-coping in communities with heterogeneous income distribution. Therefore, the model only covers some aspects of empirically observed transfer behaviour (altruism and expected reciprocity) but does not include that households might withdraw their solidarity with uninsured households when being insured. While many aspects of the model are still stylized, income distribution and network characteristics are based on a household survey that was conducted in 2012 in small fishing villages in the provinces Antique and Iloilo in the region Western Visayas on the Philippines (Lenel, 2017).

For the social network in which the households are connected, we distinguish two scenarios: Either it is based on empirical data from the Philippines (Lenel, 2017) or on random networks with the same number of nodes and links as in the empirical case. In both cases, directed links (instead of undirected links in the previous model version) between the households are created.

In the previous model, all households were endowed with the same income I per time step. Here, we assume an income distribution based on empirically derived asset values from the Philippines. The asset index includes variables that describe ownership of technical devices, agricultural tools or livestock and housing characteristics such as roof materials, source of lighting and general housing conditions. We assume that households gain a regular income I_i equal to their asset index which is normalized to a value between 0 and 1. In the artificially created random networks, the same distribution of income as in the empirical case is assumed. Heterogeneity between households is also reflected in the consumption. Instead of spending a fixed amount C per time step, household use a proportion c of their income to cover their living costs. For a fixed income as in the previous model version, both implementations lead to the same outcome. However, to avoid confusion, we state this difference explicitly. All households have the same initial budget Y^0. All processes sum up to the following equation for the budget $Y_i(t)$ of household i at time step t:

$$Y_i(t) = \begin{cases} Y_i(t-1) + I_i(1-c) - \beta - S_i + \alpha_i + \sum\limits_{j \in N_i} T_{ij}(t) & \text{for insured HH} \\ Y_i(t-1) + I_i(1-c) - S_i + \sum\limits_{j \in N_i} T_{ij}(t) & \text{for uninsured HH} \end{cases}$$

with individual income I_i of household i, the fraction c of their income that households have to spend to cover their annual living costs and the premium β that insured households have to pay. The shock intensity S_i equals S if a household is affected by a shock and is zero otherwise. The same holds true for the insurance payout α_i. For $t = 1$ the budget of the previous time step $t-1$ is given by the initial budget Y^0.

Insurance uptake was randomly distributed across the population in the previous model version. Here, it is linked to the financial resources of a household. Only households that have enough budget left to cover the premium after paying their living costs can decide to insure. An insurance threshold I_t is calculated based on the shock characteristics (frequency p_s and intensity S) and the consumption level c, $I_t = p_s \times S/(1-c)$. Households with an income below this threshold cannot insure as the premium payments would on average exceed their available budget. Among all households with $I \geq I_t$, a fraction δ (rounded up if necessary) of households is randomly selected to be insured. Insured households insure their complete income.

The model is implemented in NetLogo and the source code of the model is available at CoMSES Net (Will et al., 2021d).

C.2 Parameter selection

To assess the impact of formal and informal insurance on the resilience of the households, the model should depict conditions in which a reasonable fraction of the population has access to both instruments. Households can only afford the insurance when they can cover the premium $\beta = p_s \times S$ as well as their regular expenses which are given as fraction c of their income I_i, i.e. households can insure when $I_i(1-c) - p_s \times S \geq 0$ holds. As described in the main text, we assume a subsistence economy where households spend 80 % of their endowments to cover living costs ($c = 0.8$). The income distribution is empirically observed and not affected by the parameter selection. The remaining parameters that have to be explicitly defined are shock probability p_s and shock intensity S.

We assume shock probabilities in a range of $0.1 \leq p_s \leq 0.3$ which corresponds with empirically observed values. For the empirical data from the Philippines, for example, 16 out of 65 households (24.6 %) reported a serious illness/accident of a household member in the year before the survey (Lenel, 2017). Similar frequencies were observed in other studies. In a survey conducted in Kenya, for example, households reported experiencing a health shock in 26.6 % of the weeks in one year (Geng et al., 2018). Values for shock intensity S are not further restricted to cover a broad range of possible outcomes.

We divide all parameter ranges in equidistant steps of 0.1 and, based on these assumptions, derive for all combinations of shock intensity and probability the threshold value for I_t that denotes the minimum income that is needed to be able to afford insurance, i.e. $I_t(1-c) - p_s \times S = 0$. As the income I is bound to 0 and 1, we exclude cases with $I_t > 1$ which would result in no households being insured in our sample. We restrict the analysis to cases where at least 50 % of all households can afford insurance which is a reasonable fraction given that microinsurance products are specifically designed for low-income people. To ensure this condition, we exclude all parameter combinations that result in an income threshold I_t larger than the average income $\bar{I}$ ($\bar{I} = 0.39$ for the empirical income distribution used in the simulations, see asset wealth in Table C.2). Furthermore, as we are in particular interested in how the availability of formal insurance affects the resilience of households that do not have enough financial resources to insure, we assume a minimum income $I_{\min}$ that households need to have to be able to insure which intentionally excludes the poorest households from insurance. We set $I_{\min} = 0.25$, which results in approximately one quartile of the households (16 households) never having enough financial resources to insure, regardless of external conditions.

Table C.1: Selected parameter combinations of shock intensity S and shock probability p_s with resulting insurance threshold I_t. Effective insurance rates γ and the resulting number of insured households are calculated for the empirically observed asset distribution for insurance propensities $\delta = 1$ and $\delta = 0.5$.

			$\delta = 1$		$\delta = 0.5$	
p_s	S	I_t	γ	# insured households	γ	# insured households
0.1	0.5	0.25	75 %	49	38 %	25
0.1	0.6	0.3	62 %	40	31 %	20
0.2	0.3	0.3	62 %	40	31 %	20
0.3	0.2	0.3	62 %	40	31 %	20
0.1	0.7	0.35	54 %	35	28 %	18

The five resulting parameter combinations of shock intensity S and shock probability p_s with the respective insurance threshold I_t are shown in Table C.1. Additionally, the resulting number of insured households and the effective insurance rate γ (rounded to whole numbers) are given for the empirically observed asset distribution assuming insurance propensities $\delta = 1$ and $\delta = 0.5$.

C.3 Characteristics of the empirical support network

Table C.2: Household characteristics of the village Maramig. Surveyed 65 households, covering 225 household members; hh - households; PHP - Philippine Pesos. Income from last month includes salary, proceeds from self-employment, remittances, loans, public assistance, pensions, payouts from savings and other income (such as gambling).

	mean	sd	min	max	median	count
Household size	3.46	1.71	1	8	3	65
Female head	0.35	0.48	0	1	0	65
Head has no basic education	0.28	0.45	0	1	0	65
Head completed high school	0.40	0.49	0	1	0	65
No. of family hh within village	9.46	6.51	0	25	10	65
No. of family hh outside village	3.17	2.83	0	15	3	65
% of adults working	0.57	0.35	0	1	.5	65
% of adults working outside village	0.10	0.24	0	1	0	65
Covered by social security	0.20	0.40	0	1	0	65
Fishing as main income source	0.22	0.42	0	1	0	54
Farming as main income source	0.41	0.50	0	1	0	54
Household income last month (PHP)	14,919	43,671	160	330,975	4,000	65
Asset Wealth	0.39	0.20	.0041	1	.36	65
OFW exists	0.12	0.33	0	1	0	65
Remittances recipient	0.57	0.50	0	1	1	65
Amount remittances last year (PHP)	34,388	60,007	2,000	312,000	18,000	37
Coop member	0.34	0.48	0	1	0	65
Bank account	0.05	0.21	0	1	0	65
MFI Member	0.03	0.17	0	1	0	65
Health insurance	0.62	0.49	0	1	1	65
Informal borrowing and lending	0.66	0.48	0	1	1	65
Observations	65					

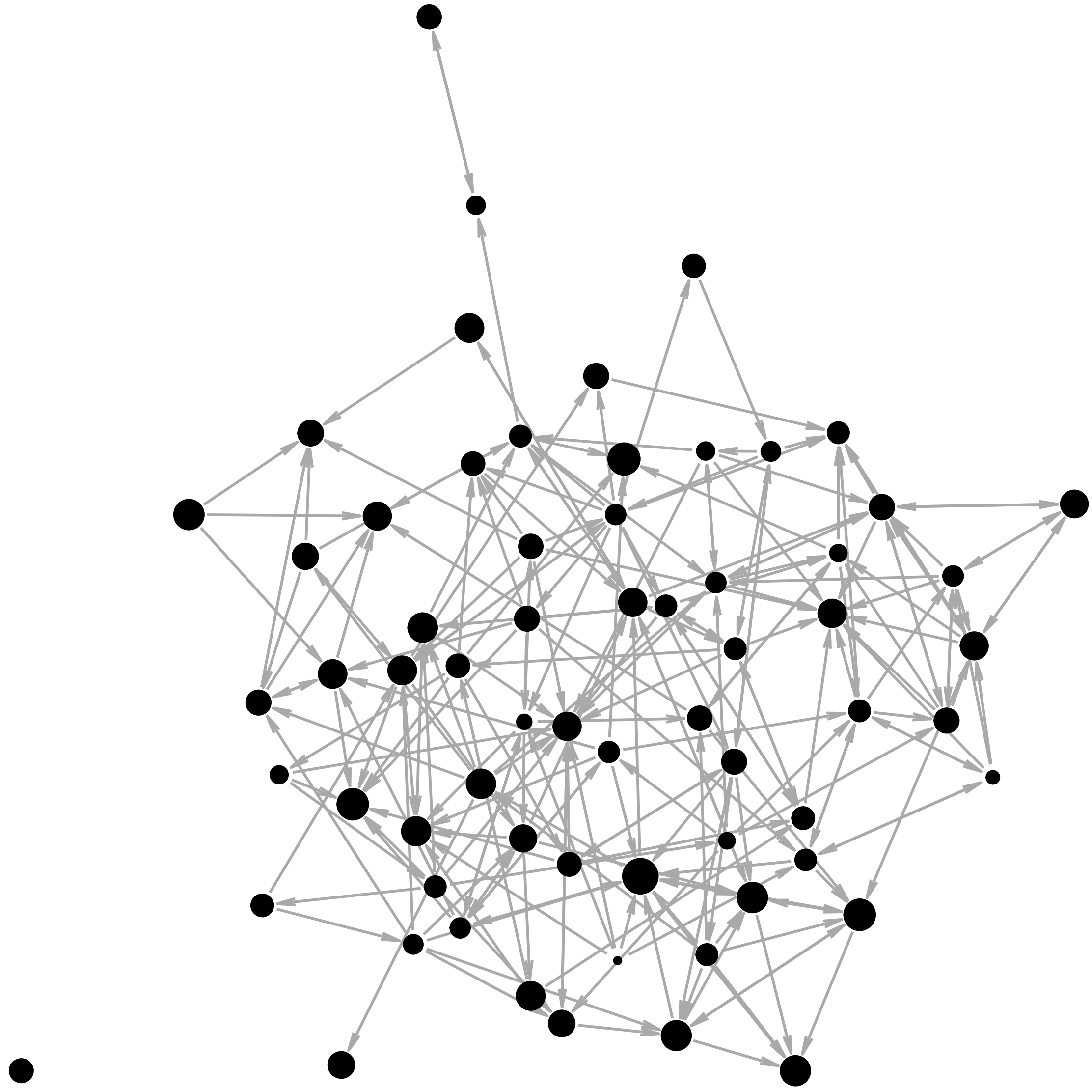

Figure C.1: Network of the reported support links within the village Maramig. The network consists of 65 households (nodes) and 236 directed links. On average a household is connected with 3.63 other households with an outdegree between 0 and 10 and an indegree between 0 and 12. Of the 4160 (65×64) possible links 5.7 % are identified as support links (network density), of these 26.3 % are reciprocated. The size of the nodes scales with the available assets.

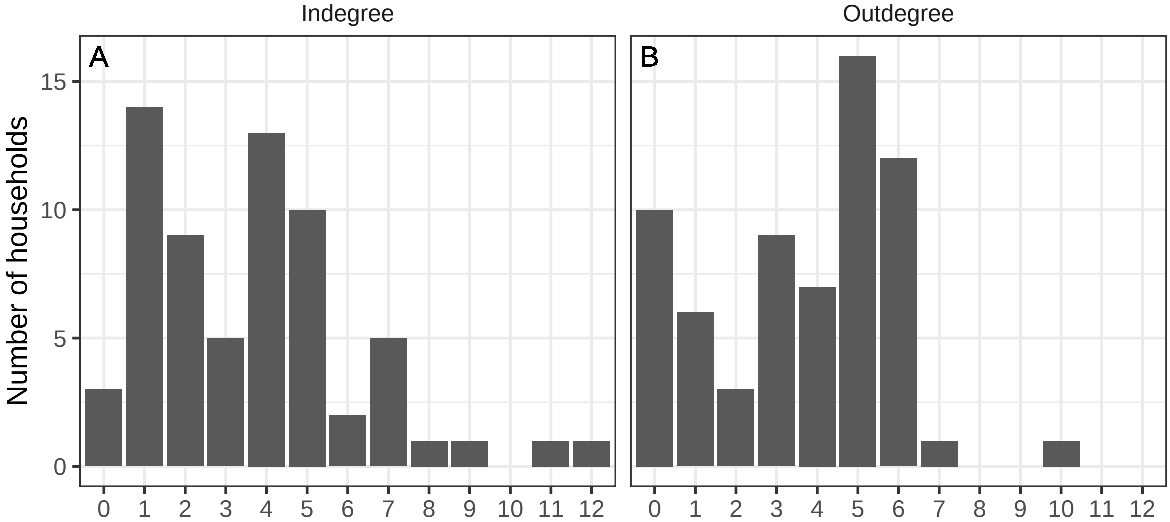

Figure C.2: Distribution of the indegree (A) and outdegree (B) in the empirically observed network.

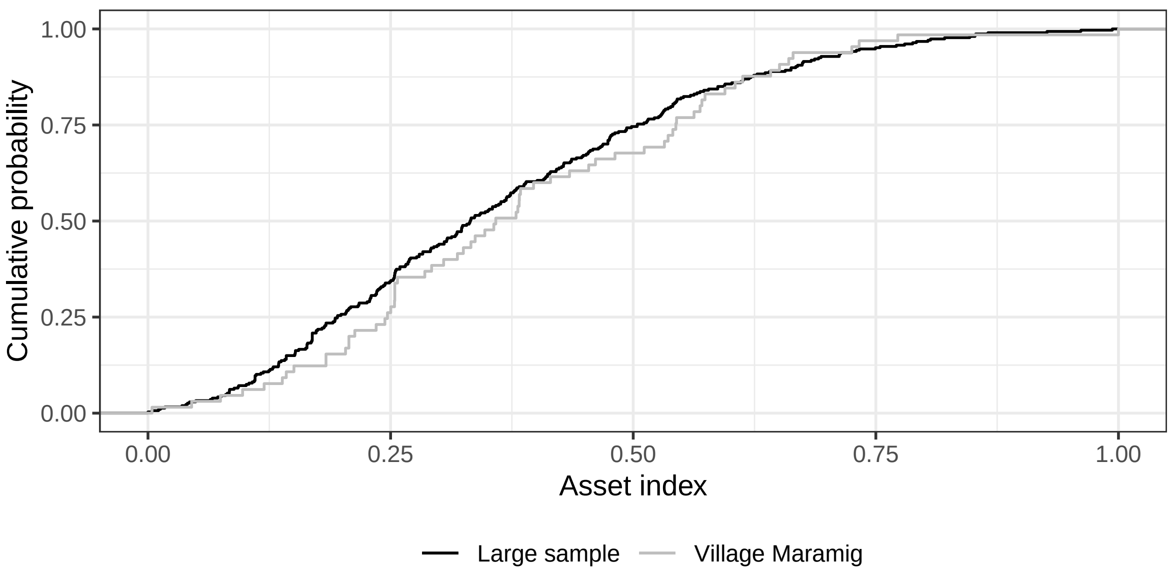

Figure C.3: Asset distribution in the village Maramig (grey) that is used in the simulations and in a larger sample (black) that was obtained in the same survey campaign. The larger sample comprises a subset of 14 households in 22 villages covering around 15 % of each village's population (including 14 randomly selected households of the village which was completely surveyed).

C.4 Additional results for selected parameter combination

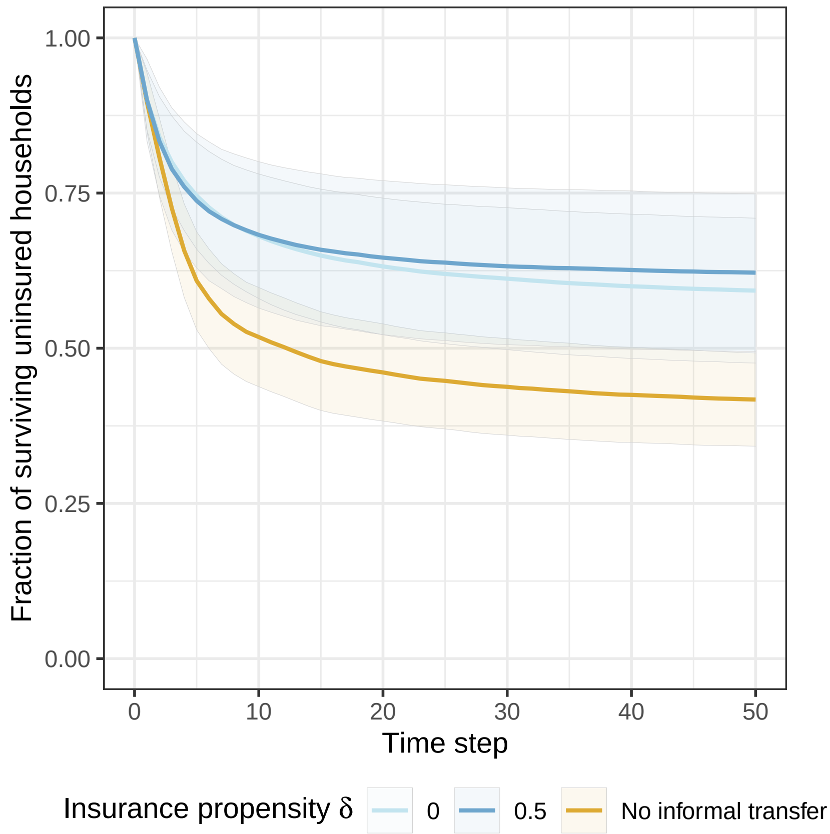

Figure C.4: Fraction of surviving uninsured households with enough financial resources to insure for three different insurance propensities δ. The scenario without informal transfer is added as reference (yellow line). The shaded areas represent the 95 % confidence interval. Results show the mean over 1000 repetitions for a selected parameter combination of shock probability $p_s = 0.1$ and shock intensity $S = 0.6$ and households connected on a random network that is newly created in every repetition.

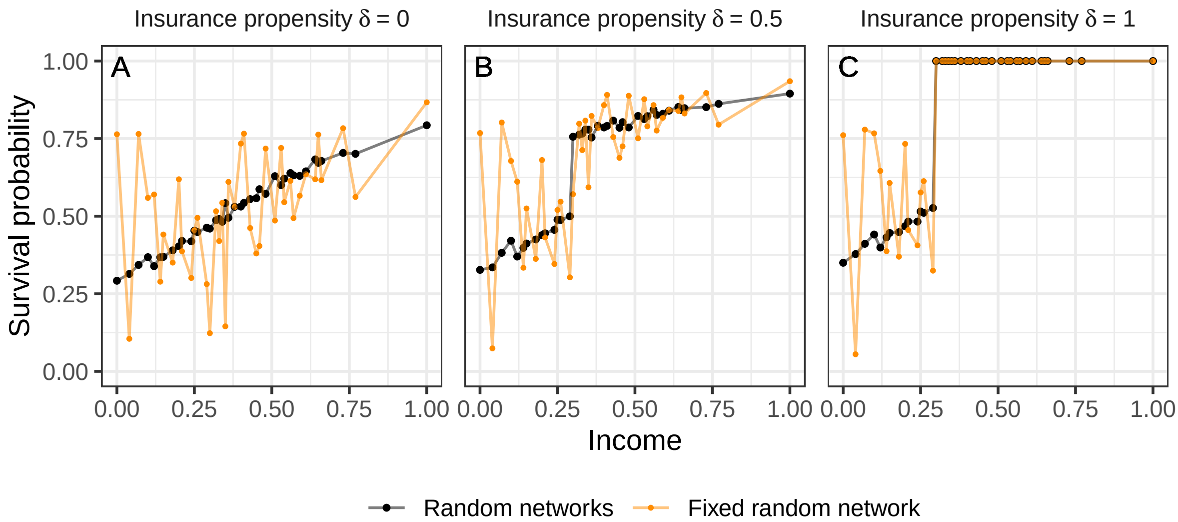

Figure C.5: Fraction of runs out of 1000 repetitions in which a household with a given income I_i survives in random networks that are newly created in every simulation run (black) and a selected random network that is kept fixed for the 1000 repetitions where a household with a certain income has always the same position in the network (orange). For each simulation run, shocks occur in random order for individual households. As some households have the same income, not all dots represent exactly one household. Results are shown for a selected parameter combination of shock probability $p_s = 0.1$ and shock intensity $S = 0.6$ (with resulting threshold below which households cannot afford insurance at $I_t = 0.3$) and different insurance propensities δ.

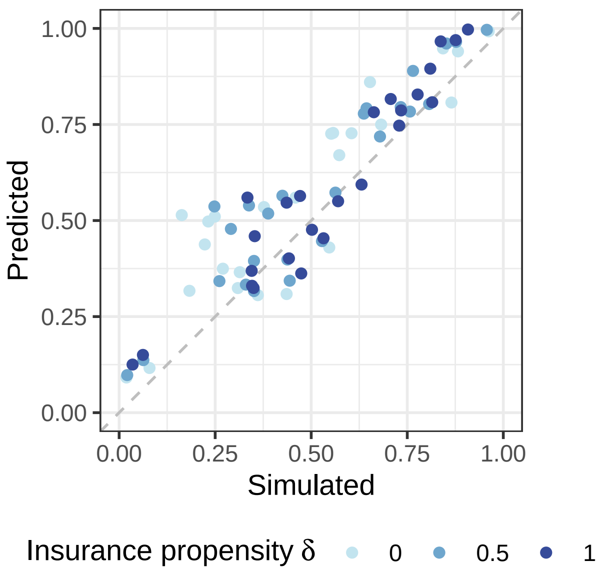

Figure C.6: Graphical representation of the goodness-of-fit between simulated and predicted survival probabilities obtained in the empirical network for the selected parameter combination of shock probability $p_s = 0.1$ and shock intensity $S = 0.6$.

Table C.3: Unstandardised regression coefficients for the selected parameter combination of shock probability $p_s = 0.1$ and shock intensity $S = 0.6$ as in the main text. Standard errors in parentheses, clustered on household level.

	Unstandardised
(Intercept)	-2.78^{***}
	(0.06)
income	3.34^{***}
	(0.20)
donors' disposable income	9.94^{***}
	(0.23)
outdegree	0.26^{***}
	(0.01)
indegree (unins. neighbors)	-0.05^{***}
	(0.01)
ins. propensity $\delta = 0.5$	0.18^{***}
	(0.05)
ins. propensity $\delta = 1$	0.35^{***}
	(0.06)
income × ins. propensity $\delta = 0.5$	-0.01
	(0.15)
donors' disposable income × ins. propensity $\delta = 0.5$	1.47^{***}
	(0.23)
outdegree × ins. propensity $\delta = 0.5$	-0.04^{***}
	(0.01)
indegree (unins. neighbors) × ins. propensity $\delta = 0.5$	-0.03^{**}
	(0.01)
income × ins. propensity $\delta = 1$	-0.16
	(0.18)
donors' disposable income × ins. propensity $\delta = 1$	2.22^{***}
	(0.28)
outdegree × ins. propensity $\delta = 1$	-0.08^{***}
	(0.01)
indegree (unins. neighbors) × ins. propensity $\delta = 1$	-0.03^{*}
	(0.01)
McFadden R^2	0.18
AIC	84576.73
Log Likelihood	-42273.37
Num. obs.	75000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table C.4: Regression coefficients (unstandardised and standardised) for the selected parameter combination of shock probability $p_s = 0.1$ and shock intensity $S = 0.6$ as in the main text with the disposable income of insured neighbours and uninsured neighbours considered separately for insurance propensity $\delta = 0.5$. Standardised coefficients are mean-centred and scaled by 1 standard deviation (Menard, 2011). Standardised estimates for interaction terms are derived by standardising the product of the predictors. Standard errors in parentheses, clustered on household level.

	Unstandardised	Standardised
(Intercept)	-2.60^{***}	-0.26^{***}
	(0.05)	(0.01)
income	3.33^{***}	0.25^{***}
	(0.19)	(0.01)
unins. donors' disposable income	10.76^{***}	0.58^{***}
	(0.29)	(0.02)
ins. donors' disposable income	12.07^{***}	0.65^{***}
	(0.32)	(0.02)
outdegree	0.23^{***}	0.42^{***}
	(0.01)	(0.02)
indegree (unins. neighbors)	-0.08^{***}	-0.12^{***}
	(0.01)	(0.02)
McFadden R^2	0.18	0.18
AIC	28110.39	28110.39
Log Likelihood	−14049.20	−14049.20
Num. obs.	25000	25000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

C.5 Additional results for idiosyncratic shocks

Table C.5: Z-scores from a two-sample z-test for the change in mean fraction of surviving uninsured households without enough financial resources to insure at the last simulated time step ($t = 50$) between different combinations of shock probability and shock intensity (p_{s1}, S_1 and p_{s2}, S_2) in case of idiosyncratic shocks.

p_{s1}	S_1	p_{s2}	S_2	$z_{\delta=0}$	$z_{\delta=0.5}$	$z_{\delta=1}$
0.1	0.5	0.1	0.6	23.03***	21.80***	21.13***
0.1	0.5	0.1	0.7	48.51***	46.90***	47.32***
0.1	0.6	0.2	0.3	1.55	1.09	0.31
0.1	0.6	0.3	0.2	7.72***	7.79***	7.65***
0.2	0.3	0.3	0.2	6.36***	6.87***	7.54***

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table C.6: Z-scores from a two-sample z-test for the change in mean fraction of surviving uninsured households without enough financial resources to insure at the last simulated time step ($t = 50$) between different insurance propensities δ in case of idiosyncratic shocks.

p_s	S	$z_{\delta=0\to\delta=0.5}$	$z_{\delta=0.5\to\delta=1}$	$z_{\delta=0\to\delta=1}$
0.1	0.5	3.07***	3.89***	6.88***
0.1	0.6	6.53***	5.89***	12.24***
0.2	0.3	6.33***	5.39***	11.60***
0.3	0.2	6.54***	5.82***	12.32***
0.1	0.7	7.88***	6.49***	14.59***

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table C.7: Unstandardised regression coefficients for the model described in the main text for different scenarios of external conditions for idiosyncratic shocks denoted by the shock probability p_s and shock intensity S (Scenario 1: $p_s = 0.1$, $S = 0.5$; Scenario 2: $p_s = 0.1$, $S = 0.6$; Scenario 3: $p_s = 0.2$, $S = 0.3$; Scenario 4: $p_s = 0.3$, $S = 0.2$; Scenario 5: $p_s = 0.1$, $S = 0.7$). Standard errors in parentheses, clustered on household level.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
(Intercept)	-2.34^{***}	-2.78^{***}	-3.43^{***}	-3.81^{***}	-3.29^{***}
	(0.08)	(0.06)	(0.07)	(0.07)	(0.05)
income	3.35^{***}	3.34^{***}	4.32^{***}	5.06^{***}	3.40^{***}
	(0.27)	(0.20)	(0.19)	(0.21)	(0.15)
donors' disposable income	10.05^{***}	9.94^{***}	14.57^{***}	17.43^{***}	9.37^{***}
	(0.38)	(0.23)	(0.28)	(0.38)	(0.24)
outdegree	0.29^{***}	0.26^{***}	0.27^{***}	0.30^{***}	0.27^{***}
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
indegree (unins. neighbors)	-0.04^{***}	-0.05^{***}	-0.05^{***}	-0.04^{***}	-0.07^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ins. propensity $\delta = 0.5$	0.22^{***}	0.18^{***}	0.06	0.03	0.16^{***}
	(0.07)	(0.05)	(0.05)	(0.06)	(0.04)
ins. propensity $\delta = 1$	0.35^{***}	0.35^{***}	0.34^{***}	−0.04	0.27^{***}
	(0.08)	(0.06)	(0.07)	(0.07)	(0.05)
income × ins. propensity $\delta = 0.5$	−0.29	−0.01	0.16	0.04	0.13
	(0.22)	(0.15)	(0.18)	(0.18)	(0.14)
donors' disposable income × ins. propensity $\delta = 0.5$	1.61^{***}	1.47^{***}	1.51^{***}	2.36^{***}	1.94^{***}
	(0.29)	(0.23)	(0.24)	(0.35)	(0.22)
outdegree × ins. propensity $\delta = 0.5$	-0.09^{***}	-0.04^{***}	−0.02	−0.02	-0.05^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
indegree (unins. neighbors) × ins. propensity $\delta = 0.5$	−0.01	-0.03^{**}	−0.02	−0.01	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
income × ins. propensity $\delta = 1$	−0.11	−0.16	−0.08	0.57^{*}	0.16
	(0.28)	(0.18)	(0.24)	(0.25)	(0.14)
donors' disposable income × ins. propensity $\delta = 1$	2.66^{***}	2.22^{***}	2.05^{***}	4.83^{***}	3.74^{***}
	(0.37)	(0.28)	(0.36)	(0.43)	(0.29)
outdegree × ins. propensity $\delta = 1$	-0.14^{***}	-0.08^{***}	-0.06^{***}	-0.03^{**}	-0.08^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
indegree (unins. neighbors) × ins. propensity $\delta = 1$	−0.02	-0.03^{*}	-0.05^{**}	-0.05^{**}	-0.03^{**}
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
McFadden R^2	0.20	0.18	0.16	0.25	0.32
AIC	53011.19	84576.73	76969.34	70927.46	93399.71
Log Likelihood	−26490.59	−42273.37	−38469.67	−35448.73	−46684.85
Num. obs.	48000	75000	75000	75000	90000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table C.8: Standardised regression coefficients for the model described in the main text for different scenarios of external conditions for idiosyncratic shocks denoted by the shock probability p_s and shock intensity S (Scenario 1: $p_s = 0.1$, $S = 0.5$; Scenario 2: $p_s = 0.1$, $S = 0.6$; Scenario 3: $p_s = 0.2$, $S = 0.3$; Scenario 4: $p_s = 0.3$, $S = 0.2$; Scenario 5: $p_s = 0.1$, $S = 0.7$). Coefficients are mean-centred and scaled by 1 standard deviation (Menard, 2011). Standardised estimates for interaction terms are derived by standardising the product of the predictors. Standard errors in parentheses, clustered on household level.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
(Intercept)	0.38^{***}	-0.27^{***}	-0.23^{***}	-0.00	-0.96^{***}
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
income	0.23^{***}	0.26^{***}	0.33^{***}	0.39^{***}	0.29^{***}
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
donors' disposable income	0.88^{***}	0.75^{***}	1.10^{***}	1.32^{***}	0.60^{***}
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
outdegree	0.54^{***}	0.49^{***}	0.50^{***}	0.56^{***}	0.50^{***}
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
indegree (unins. neighbors)	-0.08^{***}	-0.10^{***}	-0.08^{***}	-0.06^{***}	-0.12^{***}
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
ins. propensity $\delta = 0.5$	0.10^{***}	0.09^{***}	0.03	0.01	0.07^{***}
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
ins. propensity $\delta = 1$	0.16^{***}	0.16^{***}	0.16^{***}	-0.02	0.13^{***}
	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)
income × ins. propensity $\delta = 0.5$	-0.02	-0.00	0.02	0.00	0.01
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
donors' disposable income × ins. propensity $\delta = 0.5$	0.12^{***}	0.09^{***}	0.09^{***}	0.15^{***}	0.10^{***}
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
outdegree × ins. propensity $\delta = 0.5$	-0.17^{***}	-0.07^{***}	-0.03	-0.04	-0.10^{***}
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
indegree (unins. neighbors) × ins. propensity $\delta = 0.5$	-0.01	-0.04^{**}	-0.02	-0.01	-0.01
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
income × ins. propensity $\delta = 1$	-0.01	-0.02	-0.01	0.06^{*}	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
donors' disposable income × ins. propensity $\delta = 1$	0.20^{***}	0.14^{***}	0.13^{***}	0.30^{***}	0.19^{***}
	(0.03)	(0.02)	(0.02)	(0.03)	(0.01)
outdegree × ins. propensity $\delta = 1$	-0.29^{***}	-0.15^{***}	-0.12^{***}	-0.07^{**}	-0.17^{***}
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
indegree (unins. neighbors) × ins. propensity $\delta = 1$	-0.01	-0.03^{*}	-0.04^{**}	-0.05^{**}	-0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
McFadden R^2	0.20	0.18	0.16	0.25	0.32
AIC	53011.19	84576.73	76969.34	70927.46	93399.71
Log Likelihood	−26490.59	−42273.37	−38469.67	−35448.73	−46684.85
Num. obs.	48000	75000	75000	75000	90000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table C.9: Unstandardised regression coefficients for the model described in the main text with the disposable income of insured neighbours and uninsured neighbours considered separately for insurance propensity $\delta = 0.5$ for different scenarios of external conditions for idiosyncratic shocks denoted by the shock probability p_s and shock intensity S (Scenario 1: $p_s = 0.1$, $S = 0.5$; Scenario 2: $p_s = 0.1$, $S = 0.6$; Scenario 3: $p_s = 0.2$, $S = 0.3$; Scenario 4: $p_s = 0.3$, $S = 0.2$; Scenario 5: $p_s = 0.1$, $S = 0.7$). Standard errors in parentheses, clustered on household level.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
(Intercept)	-2.11^{***}	-2.60^{***}	-3.36^{***}	-3.78^{***}	-3.13^{***}
	(0.07)	(0.05)	(0.07)	(0.07)	(0.05)
income	3.06^{***}	3.33^{***}	4.48^{***}	5.10^{***}	3.54^{***}
	(0.27)	(0.19)	(0.18)	(0.23)	(0.19)
unins. donors' disposable income	10.96^{***}	10.76^{***}	15.43^{***}	19.01^{***}	10.36^{***}
	(0.48)	(0.29)	(0.41)	(0.48)	(0.31)
ins. donors' disposable income	12.36^{***}	12.07^{***}	16.75^{***}	20.60^{***}	12.21^{***}
	(0.43)	(0.32)	(0.34)	(0.42)	(0.31)
outdegree	0.21^{***}	0.23^{***}	0.25^{***}	0.28^{***}	0.22^{***}
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
indegree (unins. neighbors)	-0.05^{***}	-0.08^{***}	-0.06^{***}	-0.04^{***}	-0.07^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
McFadden R^2	0.20	0.18	0.16	0.26	0.31
AIC	17690.50	28110.39	25452.82	23720.96	31358.59
Log Likelihood	−8839.25	−14049.20	−12720.41	−11854.48	−15673.30
Num. obs.	16000	25000	25000	25000	30000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table C.10: Standardised regression coefficients for the model described in the main text with the disposable income of insured neighbours and uninsured neighbours considered separately for insurance propensity $\delta = 0.5$ with different scenarios of external conditions for idiosyncratic shocks denoted by the shock probability p_s and shock intensity S (Scenario 1: $p_s = 0.1$, $S = 0.5$; Scenario 2: $p_s = 0.1$, $S = 0.6$; Scenario 3: $p_s = 0.2$, $S = 0.3$; Scenario 4: $p_s = 0.3$, $S = 0.2$; Scenario 5: $p_s = 0.1$, $S = 0.7$). Coefficients are mean-centred and scaled by 1 standard deviation (Menard, 2011). Standardised estimates for interaction terms are derived by standardising the product of the predictors. Standard errors in parentheses, clustered on household level.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
(Intercept)	0.37***	−0.26***	−0.22***	0.00	−0.94***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
income	0.21***	0.25***	0.34***	0.39***	0.30***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
unins. donors' disposable income	0.68***	0.58***	0.83***	1.02***	0.46***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.01)
ins. donors' disposable income	0.77***	0.65***	0.90***	1.11***	0.56***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
outdegree	0.39***	0.42***	0.47***	0.52***	0.41***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
indegree (unins. neighbors)	−0.07***	−0.12***	−0.10***	−0.06***	−0.11***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
McFadden R^2	0.20	0.18	0.16	0.26	0.31
AIC	17690.50	28110.39	25452.82	23720.96	31358.59
Log Likelihood	−8839.25	−14049.20	−12720.41	−11854.48	−15673.30
Num. obs.	16000	25000	25000	25000	30000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table C.11: Goodness-of-fit statistics (R^2, RMSE and bias) for the estimation of the survival probabilities of households without enough financial resources to insure for different insurance propensities δ and predictors in the regression model. In addition to the dummy variables for insurance propensity, the following predictors are included: (#4) donors' disposable income, own income, outdegree, indegree from uninsured neighbours; (#2a) own income, outdegree; (#2b) own income, outdegree to wealthy households; (#1) own income. Subsections show different external conditions for idiosyncratic shocks denoted by the shock probability p_s and shock intensity S (Scenario 1: $p_s = 0.1$, $S = 0.5$; Scenario 2: $p_s = 0.1$, $S = 0.6$; Scenario 3: $p_s = 0.2$, $S = 0.3$; Scenario 4: $p_s = 0.3$, $S = 0.2$; Scenario 5: $p_s = 0.1$, $S = 0.7$).

		$\delta = 0$			$\delta = 0.5$			$\delta = 1$		
	#	R^2	RMSE	Bias	R^2	RMSE	Bias	R^2	RMSE	Bias
Scenario 1	4	0.743	0.134	0.072	0.827	0.098	0.042	0.891	0.078	0.029
	2a	0.635	0.140	0.047	0.625	0.120	0.020	0.486	0.132	0.013
	2b	0.598	0.142	0.025	0.593	0.124	−0.001	0.451	0.138	−0.008
	1	0.075	0.238	−0.109	0.058	0.225	−0.126	0.024	0.216	−0.123
Scenario 2	4	0.806	0.150	0.098	0.878	0.113	0.070	0.906	0.089	0.045
	2a	0.515	0.191	0.068	0.514	0.180	0.048	0.465	0.175	0.032
	2b	0.673	0.149	0.021	0.643	0.150	−0.001	0.561	0.159	−0.015
	1	0.018	0.259	−0.050	0.016	0.257	−0.070	0.010	0.247	−0.081
Scenario 3	4	0.767	0.196	0.129	0.841	0.145	0.085	0.900	0.099	0.044
	2a	0.441	0.248	0.102	0.443	0.228	0.065	0.417	0.215	0.035
	2b	0.624	0.192	0.046	0.609	0.185	0.005	0.564	0.185	−0.023
	1	0.020	0.301	−0.032	0.017	0.299	−0.071	0.010	0.291	−0.095
Scenario 4	4	0.718	0.233	0.156	0.801	0.172	0.100	0.872	0.121	0.051
	2a	0.369	0.291	0.133	0.400	0.257	0.083	0.398	0.241	0.044
	2b	0.563	0.227	0.067	0.579	0.204	0.014	0.549	0.207	−0.026
	1	0.016	0.323	−0.013	0.013	0.317	−0.065	0.014	0.319	−0.104
Scenario 5	4	0.848	0.128	0.086	0.923	0.104	0.076	0.936	0.092	0.062
	2a	0.510	0.164	0.041	0.511	0.169	0.031	0.458	0.185	0.027
	2b	0.701	0.130	0.037	0.660	0.141	0.026	0.578	0.163	0.020
	1	0.007	0.229	−0.019	0.014	0.238	−0.030	0.017	0.250	−0.035

C.6 Additional results for covariate shocks

Table C.12: Z-scores from a two-sample z-test for the change in mean fraction of surviving uninsured households without enough financial resources to insure between idiosyncratic and covariate shocks for the three insurance propensities δ at the last simulated time step ($t = 50$).

p_s	S	$z_{\delta=0}$	$z_{\delta=0.5}$	$z_{\delta=1}$
0.1	0.5	14.55***	10.57***	5.03***
0.1	0.6	10.33***	9.50***	6.67***
0.2	0.3	16.21***	13.51***	8.84***
0.3	0.2	19.72***	16.33***	10.48***
0.1	0.7	5.11***	6.01***	5.55***

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table C.13: Z-scores from a two-sample z-test for the change in mean fraction of surviving uninsured households without enough financial resources to insure at the last simulated time step ($t = 50$) between different combinations of shock probability and shock intensity (p_{s1}, S_1 and p_{s2}, S_2) in case of covariate shocks.

p_{s1}	S_1	p_{s2}	S_2	$z_{\delta=0}$	$z_{\delta=0.5}$	$z_{\delta=1}$
0.1	0.5	0.1	0.6	4.60***	6.65***	9.17***
0.1	0.5	0.1	0.7	8.99***	12.78***	17.91***
0.1	0.6	0.2	0.3	2.69***	1.62	0.79
0.1	0.6	0.3	0.2	2.24**	0.45	1.50
0.2	0.3	0.3	0.2	0.55	1.31	2.52**

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table C.14: Z-scores from a two-sample z-test for the change in mean fraction of surviving uninsured households without enough financial resources to insure at the last simulated time step ($t = 50$) between different insurance propensities δ in case of covariate shocks.

p_s	S	$z_{\delta=0\to\delta=0.5}$	$z_{\delta=0.5\to\delta=1}$	$z_{\delta=0\to\delta=1}$
0.1	0.5	4.81***	6.25***	11.02***
0.1	0.6	3.32***	4.56***	7.87***
0.2	0.3	5.04***	6.17***	11.21***
0.3	0.2	6.12***	7.89***	13.98***
0.1	0.7	2.16**	2.81***	4.97***

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table C.15: Unstandardised regression coefficients for the model described in the main text for different scenarios of external conditions for covariate shocks denoted by the shock probability p_s and shock intensity S (Scenario 1: $p_s = 0.1$, $S = 0.5$; Scenario 2: $p_s = 0.1$, $S = 0.6$; Scenario 3: $p_s = 0.2$, $S = 0.3$; Scenario 4: $p_s = 0.3$, $S = 0.2$; Scenario 5: $p_s = 0.1$, $S = 0.7$). Standard errors in parentheses, clustered on household level.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
(Intercept)	-1.66^{***}	-1.97^{***}	-2.47^{***}	-2.69^{***}	-2.31^{***}
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
income	1.99^{***}	1.94^{***}	2.47^{***}	2.62^{***}	2.08^{***}
	(0.26)	(0.20)	(0.20)	(0.21)	(0.18)
donors' disposable income	5.17^{***}	5.01^{***}	7.15^{***}	8.70^{***}	5.50^{***}
	(0.27)	(0.23)	(0.19)	(0.27)	(0.25)
outdegree	0.04^{***}	0.05^{***}	0.03^{***}	0.04^{***}	0.05^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
indegree (unins. neighbors)	−0.00	−0.00	−0.00	0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ins. propensity $\delta = 0.5$	−0.03	-0.08^{*}	−0.08	-0.10^{*}	-0.13^{***}
	(0.04)	(0.04)	(0.05)	(0.05)	(0.03)
ins. propensity $\delta = 1$	-0.17^{**}	-0.25^{***}	-0.17^{**}	-0.35^{***}	-0.29^{***}
	(0.06)	(0.05)	(0.06)	(0.07)	(0.04)
income × ins. propensity $\delta = 0.5$	0.38^{*}	0.25^{*}	0.33^{*}	0.58^{***}	0.40^{***}
	(0.16)	(0.12)	(0.14)	(0.16)	(0.09)
donors' disposable income × ins. propensity $\delta = 0.5$	2.10^{***}	2.33^{***}	2.70^{***}	3.05^{***}	2.36^{***}
	(0.20)	(0.15)	(0.18)	(0.20)	(0.16)
outdegree × ins. propensity $\delta = 0.5$	0.02^{*}	0.01	0.02^{**}	0.02^{**}	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
indegree (unins. neighbors) × ins. propensity $\delta = 0.5$	−0.00	0.00	−0.00	−0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
income × ins. propensity $\delta = 1$	1.07^{***}	0.81^{***}	0.71^{***}	1.42^{***}	0.90^{***}
	(0.22)	(0.14)	(0.19)	(0.20)	(0.14)
donors' disposable income × ins. propensity $\delta = 1$	5.99^{***}	5.34^{***}	6.64^{***}	8.35^{***}	5.41^{***}
	(0.31)	(0.21)	(0.25)	(0.29)	(0.19)
outdegree × ins. propensity $\delta = 1$	0.02	0.02^{**}	0.03^{***}	0.04^{***}	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
indegree (unins. neighbors) × ins. propensity $\delta = 1$	−0.01	0.01	−0.01	−0.02	0.00
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
McFadden R^2	0.10	0.08	0.07	0.13	0.17
AIC	58982.64	88246.51	81579.75	79350.32	94863.56
Log Likelihood	−29476.32	−44108.26	−40774.87	−39660.16	−47416.78
Num. obs.	48000	75000	75000	75000	90000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table C.16: Standardised regression coefficients for the model described in the main text for different scenarios of external conditions for covariate shocks denoted by the shock probability p_s and shock intensity S (Scenario 1: $p_s = 0.1$, $S = 0.5$; Scenario 2: $p_s = 0.1$, $S = 0.6$; Scenario 3: $p_s = 0.2$, $S = 0.3$; Scenario 4: $p_s = 0.3$, $S = 0.2$; Scenario 5: $p_s = 0.1$, $S = 0.7$). Coefficients are mean-centred and scaled by 1 standard deviation (Menard, 2011). Standardised estimates for interaction terms are derived by standardising the product of the predictors. Standard errors in parentheses, clustered on household level.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
(Intercept)	-0.23^{***}	-0.71^{***}	-0.86^{***}	-0.79^{***}	-1.16^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
income	0.14^{***}	0.15^{***}	0.19^{***}	0.20^{***}	0.18^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
donors' disposable income	0.45^{***}	0.38^{***}	0.54^{***}	0.66^{***}	0.35^{***}
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
outdegree	0.08^{***}	0.09^{***}	0.06^{***}	0.07^{***}	0.09^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
indegree (unins. neighbors)	-0.01	-0.01	-0.01	0.02	-0.02
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
ins. propensity $\delta = 0.5$	-0.01	-0.04^{*}	-0.04	-0.05^{*}	-0.06^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
ins. propensity $\delta = 1$	-0.08^{**}	-0.12^{***}	-0.08^{**}	-0.16^{***}	-0.14^{***}
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
income × ins. propensity $\delta = 0.5$	0.03^{*}	0.03^{*}	0.03^{*}	0.06^{***}	0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
donors' disposable income × ins. propensity $\delta = 0.5$	0.16^{***}	0.15^{***}	0.17^{***}	0.19^{***}	0.12^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
outdegree × ins. propensity $\delta = 0.5$	0.04^{*}	0.01	0.05^{**}	0.04^{**}	-0.00
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
indegree (unins. neighbors) × ins. propensity $\delta = 0.5$	-0.01	0.00	-0.00	-0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
income × ins. propensity $\delta = 1$	0.09^{***}	0.08^{***}	0.07^{***}	0.14^{***}	0.10^{***}
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
donors' disposable income × ins. propensity $\delta = 1$	0.45^{***}	0.33^{***}	0.42^{***}	0.52^{***}	0.27^{***}
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
outdegree × ins. propensity $\delta = 1$	0.05	0.04^{**}	0.06^{***}	0.09^{***}	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
indegree (unins. neighbors) × ins. propensity $\delta = 1$	-0.01	0.01	-0.01	-0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
McFadden R^2	0.10	0.08	0.07	0.13	0.17
AIC	58982.64	88246.51	81579.75	79350.32	94863.56
Log Likelihood	-29476.32	-44108.26	-40774.87	-39660.16	-47416.78
Num. obs.	48000	75000	75000	75000	90000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table C.17: Unstandardised regression coefficients for the model described in the main text with the disposable income of insured neighbours and uninsured neighbours considered separately for insurance propensity $\delta = 0.5$ for different scenarios of external conditions for covariate shocks denoted by the shock probability p_s and shock intensity S (Scenario 1: $p_s = 0.1$, $S = 0.5$; Scenario 2: $p_s = 0.1$, $S = 0.6$; Scenario 3: $p_s = 0.2$, $S = 0.3$; Scenario 4: $p_s = 0.3$, $S = 0.2$; Scenario 5: $p_s = 0.1$, $S = 0.7$). Standard errors in parentheses, clustered on household level.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
(Intercept)	-1.70^{***}	-2.06^{***}	-2.56^{***}	-2.80^{***}	-2.46^{***}
	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)
income	2.40^{***}	2.21^{***}	2.84^{***}	3.23^{***}	2.51^{***}
	(0.27)	(0.20)	(0.20)	(0.23)	(0.17)
unins. donors' disposable income	5.03^{***}	5.18^{***}	7.32^{***}	9.31^{***}	5.86^{***}
	(0.29)	(0.30)	(0.28)	(0.36)	(0.34)
ins. donors' disposable income	9.69^{***}	9.53^{***}	12.50^{***}	14.36^{***}	9.91^{***}
	(0.38)	(0.28)	(0.34)	(0.33)	(0.30)
outdegree	0.06^{***}	0.06^{***}	0.06^{***}	0.06^{***}	0.05^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
indegree (unins. neighbors)	−0.01	−0.00	−0.01	0.01	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
McFadden R^2	0.09	0.07	0.06	0.12	0.15
AIC	19978.99	29568.24	27486.47	27025.10	31682.68
Log Likelihood	−9983.50	−14778.12	−13737.24	−13506.55	−15835.34
Num. obs.	16000	25000	25000	25000	30000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table C.18: Standardised regression coefficients for the model described in the main text with the disposable income of insured neighbours and uninsured neighbours considered separately for insurance propensity $\delta = 0.5$ with different scenarios of external conditions for covariate shocks denoted by the shock probability p_s and shock intensity S (Scenario 1: $p_s = 0.1$, $S = 0.5$; Scenario 2: $p_s = 0.1$, $S = 0.6$; Scenario 3: $p_s = 0.2$, $S = 0.3$; Scenario 4: $p_s = 0.3$, $S = 0.2$; Scenario 5: $p_s = 0.1$, $S = 0.7$). Coefficients are mean-centred and scaled by 1 standard deviation (Menard, 2011). Standardised estimates for interaction terms are derived by standardising the product of the predictors. Standard errors in parentheses, clustered on household level.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
(Intercept)	-0.27^{***}	-0.74^{***}	-0.88^{***}	-0.82^{***}	-1.17^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
income	0.17^{***}	0.17^{***}	0.22^{***}	0.25^{***}	0.21^{***}
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
unins. donors' disposable income	0.31^{***}	0.28^{***}	0.39^{***}	0.50^{***}	0.27^{***}
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
ins. donors' disposable income	0.61^{***}	0.51^{***}	0.68^{***}	0.78^{***}	0.45^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
outdegree	0.11^{***}	0.10^{***}	0.11^{***}	0.11^{***}	0.09^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
indegree (unins. neighbors)	-0.01	-0.00	-0.01	0.01	-0.01
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
McFadden R^2	0.09	0.07	0.06	0.12	0.15
AIC	19978.99	29568.24	27486.47	27025.10	31682.68
Log Likelihood	-9983.50	-14778.12	-13737.24	-13506.55	-15835.34
Num. obs.	16000	25000	25000	25000	30000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table C.19: Goodness-of-fit statistics (R^2, RMSE and bias) for the estimation of the survival probabilities of households without enough financial resources to insure for different insurance propensities δ and predictors in the regression model. In addition to the dummy variables for insurance propensity, the following predictors are included: (#4) donors' disposable income, own income, outdegree, indegree from uninsured neighbours; (#2a) own income, outdegree; (#2b) own income, outdegree to wealthy households; (#1) own income. Subsections show different external conditions for covariate shocks denoted by the shock probability p_s and shock intensity S (Scenario 1: $p_s = 0.1$, $S = 0.5$; Scenario 2: $p_s = 0.1$, $S = 0.6$; Scenario 3: $p_s = 0.2$, $S = 0.3$; Scenario 4: $p_s = 0.3$, $S = 0.2$; Scenario 5: $p_s = 0.1$, $S = 0.7$).

		$\delta = 0$			$\delta = 0.5$			$\delta = 1$		
	#	R^2	RMSE	Bias	R^2	RMSE	Bias	R^2	RMSE	Bias
Scenario 1	4	0.785	0.087	0.050	0.837	0.097	0.058	0.877	0.102	0.065
	2a	0.234	0.107	0.030	0.313	0.131	0.035	0.327	0.155	0.043
	2b	0.311	0.110	0.029	0.430	0.124	0.031	0.449	0.141	0.035
	1	0.097	0.105	−0.035	0.098	0.147	−0.054	0.078	0.182	−0.071
Scenario 2	4	0.820	0.085	0.051	0.848	0.102	0.064	0.859	0.115	0.076
	2a	0.332	0.091	0.025	0.314	0.131	0.034	0.328	0.174	0.046
	2b	0.540	0.078	0.016	0.536	0.109	0.019	0.529	0.145	0.022
	1	0.028	0.105	−0.017	0.029	0.149	−0.027	0.030	0.203	−0.036
Scenario 3	4	0.789	0.101	0.049	0.838	0.116	0.066	0.857	0.124	0.074
	2a	0.258	0.121	0.016	0.304	0.163	0.033	0.309	0.212	0.046
	2b	0.470	0.105	0.007	0.527	0.137	0.016	0.524	0.175	0.018
	1	0.023	0.139	−0.032	0.026	0.191	−0.039	0.023	0.249	−0.049
Scenario 4	4	0.802	0.112	0.060	0.844	0.128	0.081	0.847	0.145	0.091
	2a	0.227	0.155	0.025	0.292	0.194	0.047	0.289	0.250	0.067
	2b	0.446	0.132	0.014	0.509	0.162	0.027	0.498	0.206	0.029
	1	0.019	0.173	−0.032	0.028	0.220	−0.035	0.026	0.283	−0.043
Scenario 5	4	0.802	0.076	0.039	0.870	0.089	0.052	0.886	0.105	0.067
	2a	0.330	0.073	0.011	0.301	0.110	0.016	0.289	0.153	0.024
	2b	0.599	0.060	0.015	0.630	0.083	0.022	0.599	0.117	0.030
	1	0.014	0.088	−0.008	0.017	0.130	−0.011	0.022	0.177	−0.013

D Appendix of Chapter 6

D.1 Questionnaire for the semi-structured interviews

Purpose

1. Please describe the modelling endeavour and give relevant background information on the topic, the research question(s), the method(s) used, the institutions or individuals involved, the source of data, why a policy decision was necessary, how urgent the decision was etc.
2. How concrete and practically relevant was the outcome?
3. Who had the idea/was the driving factor at the beginning to use models: Practitioners or modellers? What motivated each side to contribute to the project?

Processes and Partnerships

1. Was it already a long-lasting relationship between both sides? Did the practitioners have any previous experience with modelling?
2. How was the modelling process organised?
   a. Information on total project duration, number of meetings, number of people involved at different stages, were always the same people involved?
   b. Was the model developed in a participatory way or rather independently by the modeller(s)?
3. Did the modellers come from a modelling department? How large was the group of modellers in their department?
4. Were other types of actors such as media, local population, businesses, or other scholars involved?
5. How many disciplines were involved?
6. How available and accessible was the data needed for the model?
7. Was there a "breakthrough moment" regarding the understanding of the models by the practitioners?

Products

1. What was your “recipe” that the practitioners got confidence in the model/the modellers? Did they understand the (main) functioning of the model or did they blindly trust the modellers, since the model was too complex and it was okay for them to have a black box?
2. Did you have the impression that the model was used to support the pre-set opinion/ target of the practitioners involved? Or in contrary: Was the opinion of the practitioners changed?
3. Where did you encounter difficulties during the course of the project?
4. (How) was the model usable for practitioners?

General final questions

1. What were the reasons that other modelling endeavours have failed to have an impact?
2. What were the most important factors for success in your endeavour?
3. Open question at the end: Is there anything you would like to add?

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Erklärung über die Eigenständigkeit der erbrachten wissenschaftlichen Leistung

Ich erkläre hiermit, dass ich die vorliegende Arbeit ohne unzulässige Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet.

Bei der Auswahl und Auswertung folgenden Materials haben mir die nachstehend aufgeführten Personen in der jeweils beschriebenen Weise unentgeltlich geholfen.

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Weitere Personen waren an der inhaltlichen materiellen Erstellung der vorliegenden Arbeit nicht beteiligt. Insbesondere habe ich hierfür nicht die entgeltliche Hilfe von Vermittlungs- bzw. Beratungsdiensten (Promotionsberater oder andere Personen) in Anspruch genommen. Niemand hat von mir unmittelbar oder mittelbar geldwerte Leistungen für Arbeiten erhalten, die im Zusammenhang mit dem Inhalt der vorgelegten Dissertation stehen.

Die Arbeit wurde bisher weder im In- noch im Ausland in gleicher oder ähnlicher Form einer anderen Prüfungsbehörde vorgelegt.

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