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Behavioural Economics of Climate Change Mitigation in Swiss Agriculture:

The role of farmers' individual characteristics and social networks

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Abstract

Global agricultural production contributes around 20% of total anthropogenic greenhouse gas (GHG) emissions. At the same time, agriculture has large potential to reduce its emissions and additionally sequester carbon. Hence, the agricultural sector has an important role to play in mitigating further climate change and achieving international and national climate policy goals. Simultaneously, agriculture must provide sufficient food for a growing world population. To tackle this challenge, numerous mitigation measures to reduce GHG emissions from livestock and crop production have been proposed, including adaptation of farm management and technological innovations. However, successful climate change mitigation under current agricultural production levels relies on farmers who are willing to change farming practices and adopt respective measures. The goal of this thesis is to provide insights into the determinants of mitigation adoption in agriculture with a focus on the role of behavioural economic factors such as farmers' individual characteristics and social interactions. A thorough understanding of farmers' decision-making in this context is key to design effective and efficient policies aiming to reduce agricultural GHG emissions.

To explore the behavioural aspects of farmers' adoption of climate change mitigation practices and assess the effect of respective agricultural policies, the thesis applies different quantitative methods including social network analysis, which build on each other and ultimately flow into an agent-based model. The analyses are based on a Swiss case study and use a combination of farm census, survey, and in-depth social network data, which were specifically collected for this purpose.

The introductory chapter provides general background information, motivates the goals of the thesis, and presents the conceptual framework and research questions. The following chapters represent the main body of the thesis and contain the original research articles. More precisely, the second chapter uses an OLS regression based on census and survey data of 105 farmers to investigate the role of non-cognitive skills, namely perceived self-efficacy and internal locus of control on the adoption of on-farm climate change mitigation measures. Farmers who are convinced of their capability to effectively reduce on-farm GHG emissions and generally believe to be in control over life's outcomes are more likely to adopt climate change mitigation measures on their farms. The underlying mechanism is farmers' innovativeness, which is positively associated with high non-cognitive skills and ultimately leads to mitigation adoption.

The third chapter of the thesis uses social network analysis based on personal interview data of 50 farmers to explore the features of social networks and their role in agricultural climate change mitigation. The regular exchange of relevant knowledge among connected peers positively affects the uptake of mitigation measures. In particular, strong social ties to others who are perceived as knowledgeable in agricultural climate change mitigation can enhance adoption. Moreover, connections to members of a local farmers' initiative for GHG reduction in agriculture ("AgroCO_2ncept Flaachtal") are found to be

associated with mitigation uptake. This indicates that local grassroot initiatives can have spillover effects on the wider region.

The fourth chapter integrates the findings of the previous chapters in an agent-based modelling approach and quantifies the effect of farmers' individual characteristics and social networks in terms of overall reduction of GHG emissions and farm-level marginal abatement cost. For the analysis, the data of a subsample of 49 dairy and beef cattle farmers is used. Knowledge exchange among socially connected farmers can substantially increase overall GHG reduction. Moreover, farmers' social networks can reduce marginal cost of agricultural climate change mitigation.

The fifth chapter compares two differently designed policy incentives (action- and results-based designs) to achieve a certain GHG reduction goal, accounting for heterogeneous cost and benefits of mitigation measures as well as farmers' individual preferences, reluctance to change and social interactions in an agent-based modelling approach. Specifically, the role of a so-called win-win measure that reduces GHG emissions and at the same time increases farm income is investigated. The analysis uses the same model parametrization based on the data of 49 Swiss dairy and beef cattle farmers as presented in the fourth chapter. Depending on whether the win-win measure is included in the policy scheme, result- or action-based designs are more efficient from a governmental perspective. Independent of that, results-based designs lead to lower marginal abatement cost on farm level. With both action- and results-based policies, behavioural factors and especially farmers' reluctance to change lead to a substantial decrease of overall GHG reduction as compared to a situation where farmers strictly optimize farm income.

The findings of the thesis reveal some relevant policy implications. When assessing policies for agricultural climate change mitigation, decision-makers should account for farmers' behavioural characteristics. Particularly, farmers' sense of self-efficacy related to successful on-farm GHG reduction should be strengthened by providing relevant knowledge and advisory service. Moreover, social learning among farmers should be fostered by supporting adequate platforms of knowledge exchange. Regarding the choice of policy designs for mitigation adoption, farmers' individual preferences, social interactions as well as cost and benefits of the considered mitigation measures should be equally considered.

Zusammenfassung

Die weltweite landwirtschaftliche Produktion ist für rund 20% der gesamten anthropogenen Treibhausgasemissionen (THG) verantwortlich. Gleichzeitig hat die Landwirtschaft ein grosses Potenzial, ihre Emissionen zu reduzieren und zusätzlich Kohlenstoff zu binden. Der Agrarsektor spielt daher eine wichtige Rolle im Kampf gegen den Klimawandel und bei der Erreichung internationaler und nationaler klimapolitischer Ziele. Gleichzeitig muss die Ernährung einer wachsenden Weltbevölkerung sichergestellt werden. Zur Bewältigung dieser Herausforderungen gibt es zahlreiche Ansätze und Massnahmen, um die THG aus Tierhaltung und Pflanzenbau zu verringern. Diese umfassen zum Beispiel Anpassungen in der Betriebsführung und beim Herdenmanagement sowie technologische Innovationen. Der Erfolg des landwirtschaftlichen Klimaschutzes hängt jedoch zentral von den Landwirtinnen und Landwirten ab. Denn sie müssen bereit sein, bisherige landwirtschaftliche Praktiken zu ändern und entsprechende Klimaschutzmassnahmen zu ergreifen. Das Ziel dieser Arbeit ist es, die Einflussfaktoren von landwirtschaftlichem Klimaschutz besser zu verstehen und Einblicke in die Entscheidungsfindung von Landwirtinnen und Landwirten in diesem Zusammenhang zu gewinnen. Dabei liegt der Schwerpunkt auf verhaltensökonomischen Faktoren wie individuellen Präferenzen, persönlichen Eigenschaften und sozialen Interaktionen. Dieses Verständnis ist Voraussetzung für die Gestaltung von effektiven und effizienten Politikinstrumenten zur Reduktion landwirtschaftlicher THG.

Zur Untersuchung verhaltensökonomischer Aspekte von landwirtschaftlichem Klimaschutz und Bewertung entsprechender Politikinstrumente werden in dieser Dissertation verschiedene quantitative Methoden einschliesslich sozialer Netzwerkanalyse angewandt. Diese Methoden bauen aufeinander auf und münden schliesslich in ein agentenbasiertes Modell. Die Analysen basieren auf einer Schweizer Fallstudie und verwenden eine Kombination aus landwirtschaftlichen Strukturdaten, Umfragedaten und sozialen Netzwerkdaten, die speziell für diesen Zweck erhoben wurden.

Das einleitende Kapitel liefert allgemeine Hintergrundinformationen, motiviert die Ziele der Arbeit und stellt den konzeptionellen Rahmen sowie die Forschungsfragen vor. Die folgenden Kapitel stellen den Hauptteil der Arbeit dar und enthalten die originalen Forschungsartikel.

Im zweiten Kapitel wird die Bedeutung sogenannter nicht-kognitiver Fähigkeiten, genauer der Selbstwirksamkeit und internen Kontrollüberzeugung für die Umsetzung von Klimaschutzmassnahmen auf dem landwirtschaftlichen Betrieb untersucht. Dafür wird eine Regressionsanalyse auf Basis von Struktur- und Umfragedaten von 105 Landwirtinnen und Landwirten in der Schweizer Region «Zürcher Weinland» durchgeführt. Die Ergebnisse der Untersuchung zeigen, dass Landwirtinnen und Landwirte, die davon überzeugt sind, dass sie THG auf ihrem Betrieb effektiv reduzieren können (hohe Selbstwirksamkeit) und glauben, ihre Lebenssituation allgemein unter Kontrolle zu haben (interne Kontrollüberzeugung), mit größerer Wahrscheinlichkeit Klimaschutzmassnahmen umsetzen. Der zugrundeliegende Mechanismus dieses Zusammenhangs ist die Innovationskraft der Landwirtinnen und Landwirte, welche mit hoher Selbstwirksamkeit und Kontrollüberzeugung korreliert.

Im dritten Kapitel der Arbeit geht es um die Bedeutung von Wissensaustausch innerhalb sozialer Netzwerke für den landwirtschaftlichen Klimaschutz. Dazu wird eine soziale Netzwerkanalyse auf Basis detaillierter Interviewdaten von 50 Landwirtinnen und Landwirten durchgeführt. Es zeigt sich, dass regelmässiger Austausch von Klimaschutzwissen unter vernetzten Kolleginnen und Kollegen die Umsetzung von Massnahmen zur THG-Reduktion auf den Betrieben fördert. Besonders positiv wirkt die Verbindung zu Personen, die als sachkundig im landwirtschaftlichen Klimaschutz wahrgenommen werden. Darüber hinaus wird festgestellt, dass Verbindungen zu Mitgliedern einer lokalen Bauerninitiative für landwirtschaftlichen Klimaschutz („AgroCO_2ncept Flaachtal") positiv mit der Umsetzung von THG-Reduktionsmassnahmen assoziiert sind. Dies weist darauf hin, dass lokale bottom-up Initiativen positive Überlaufeffekte auf die weitere Region haben können.

Das vierte Kapitel integriert die Erkenntnisse aus den vorherigen Kapiteln in einem agentenbasierten Modell. Dabei wird die Wirkung der individuellen Eigenschaften und sozialer Netzwerke von Landwirtinnen und Landwirte in Bezug auf die Gesamtreduktion der THG-Emissionen sowie der entstehenden Grenzvermeidungskosten auf Betriebsebene quantifiziert. Für die Analyse werden die Daten einer Teilstichprobe von 49 Milchkuh- und Rinderhaltern genutzt. Die Ergebnisse zeigen, dass der Wissensaustausch zwischen sozial vernetzten Landwirtinnen und Landwirten die gesamte THG-Reduktion innerhalb einer Region erheblich steigern kann. Darüber hinaus können soziale Netzwerke die Grenzkosten des landwirtschaftlichen Klimaschutzes reduzieren.

Im fünften Kapitel werden zwei unterschiedliche Politikinstrumente (massnahmen- und ergebnisorientierte Direktzahlungen) verglichen, um ein bestimmtes THG-Reduktionsziel zu erreichen. Dabei werden heterogene Kosten und Nutzen von verschiedenen Klimaschutzmassnahmen sowie individuelle Präferenzen, Abneigung gegenüber Veränderungen und soziale Interaktionen berücksichtigt. Konkret wird die Rolle einer sogenannten Win-Win-Massnahme untersucht, welche THG-Emissionen reduziert und gleichzeitig das landwirtschaftliche Einkommen erhöht. Die Analyse verwendet dasselbe agentenbasierte Modell und basiert auf den Daten derselben 49 Schweizer Milchkuh- und Rinderhaltern wie das vierte Kapitel. Abhängig davon, ob die Win-Win-Massnahme berücksichtigt wird oder nicht, sind massnahmen- oder ergebnisorientierte Politikdesigns aus staatlicher Sicht effizienter. Unabhängig davon führen ergebnisorientierte Zahlungen zu niedrigeren Grenzvermeidungskosten auf Betriebsebene. Sowohl mit massnahmen- als auch ergebnisorientierten Politikinstrumenten führen individuelle Präferenzen und insbesondere die ablehnende Haltung der Landwirtinnen und Landwirte gegenüber Veränderungen zu einer erheblichen Verringerung der gesamten THG-Reduktion im Vergleich zu einer Situation, in der das landwirtschaftliche Einkommen auf Basis rein rationaler Entscheidungen optimiert wird.

Die Ergebnisse der vorliegenden Dissertation sind in mehrerlei Hinsicht relevant für die Agrarpolitik. Bei der Bewertung von Strategien zur Förderung des Klimaschutzes in der Landwirtschaft sollten politische EntscheidungsträgerInnen individuelle Verhaltensmerkmale von Landwirtinnen und

Landwirten berücksichtigen. Insbesondere deren Selbstwirksamkeitsgefühl in Bezug auf eine erfolgreiche THG-Reduktion auf dem Betrieb sollte durch entsprechende Information und Beratungsdienstleistungen gestärkt werden. Darüber hinaus sollte soziales Lernen unter Landwirtinnen und Landwirten gefördert und geeignete Plattformen für den Wissensaustausch unterstützt werden. Bei der Wahl konkreter Politikinstrumente für die Einführung von Minderungsmassnahmen sollten die individuellen Präferenzen der Landwirtinnen und Landwirte, soziale Interaktionen sowie Kosten und Nutzen der in Betracht kommenden Klimaschutzmassnahmen berücksichtigt werden.

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Chapter 1: Introduction

Agriculture is a major contributor to global climate change. Farming activities and related land use changes make up for around 20% of overall anthropogenic greenhouse gas (GHG) emissions. Regarding single emission types, agriculture is in fact the biggest source of total non-CO_2 GHG emissions, namely methane (CH4) and nitrous oxide (N2O) (FAO, 2021; IPCC, 2019). To achieve the goals of national and international climate policies to limit global warming to well below 2°C, preferably to 1.5°C, the agricultural sector must therefore inevitably contribute to overall mitigation of GHG emissions (Leahy et al., 2020; Lynch et al., 2021). Consequently, most countries have included their agricultural sector in Nationally Determined Contributions under the Paris Agreement (Crumpler et al., 2019) and national policies have set emission reduction goals for agriculture and related land use. For example, Switzerland aims to reduce agricultural emissions by 40% until 2050 in its Long Term Climate Strategy (Swiss Federal Council, 2021). Technically, by reducing emissions from crop and livestock production, land use changes and increased carbon sequestration, the agricultural sector has the potential to become close to carbon neutral until 2030 in the most optimistic scenarios (Smith et al., 2008). However, despite ambitious goals and models of reduction pathways (IPCC, 2018), agriculture has so far not been exposed to binding carbon prices and emission trading schemes (Leahy et al., 2020). Among the barriers to include agriculture in stringent climate policy schemes are uncertainties related to cost and technical potential of mitigation measures, high transaction cost, e.g., due to large heterogeneity of actors and conditions (Ancev, 2011) as well as concerns about global food security and social equity (Frank et al., 2017; Fujimori et al., 2022). To ensure a sufficient food supply, GHG reduction in agriculture is particularly constrained by maintaining relatively stable production levels.

Policies that aim to mitigate agricultural GHG emissions thus usually base on the "beneficiary pays principle", i.e., producers are paid for their efforts to reduce emissions. For example, some countries have introduced voluntary schemes such as payments (i.e., subsidies) to incentivize the reduction of agricultural GHG emissions, compensate farmers for additional cost of mitigation and enhance voluntary carbon farming initiatives (OECD, 2019; European Commission, 2021). For these policies to be successful, farmers must adapt current farming practices and adopt respective mitigation measures. Understanding farmers' decision-making related to climate change mitigation is therefore crucial for effective policy-design. Figure 1.1 depicts the general conceptual framework of this thesis presenting an overview of key factors that affect farmers' decision-making with respect to on-farm climate change mitigation: Farmers' adoption decisions are influenced by farm structures and environmental conditions, individual farmer characteristics, the social environment as well as policies and market conditions. Farmers' decisions in turn affect overall GHG reduction as well as farm incomes. Furthermore, potential trade-offs and co-benefits of measures to mitigate agricultural GHG emissions can occur. This can for example concern positive and negative effects on animal welfare, biodiversity, or other environmental pollutants (Bustamante et al., 2014; Cohen et al., 2021). Farmers' adoption decisions and resulting changes in GHG emissions and farm incomes as well as potential side-effects in turn determine the effectiveness and efficiency of policies.

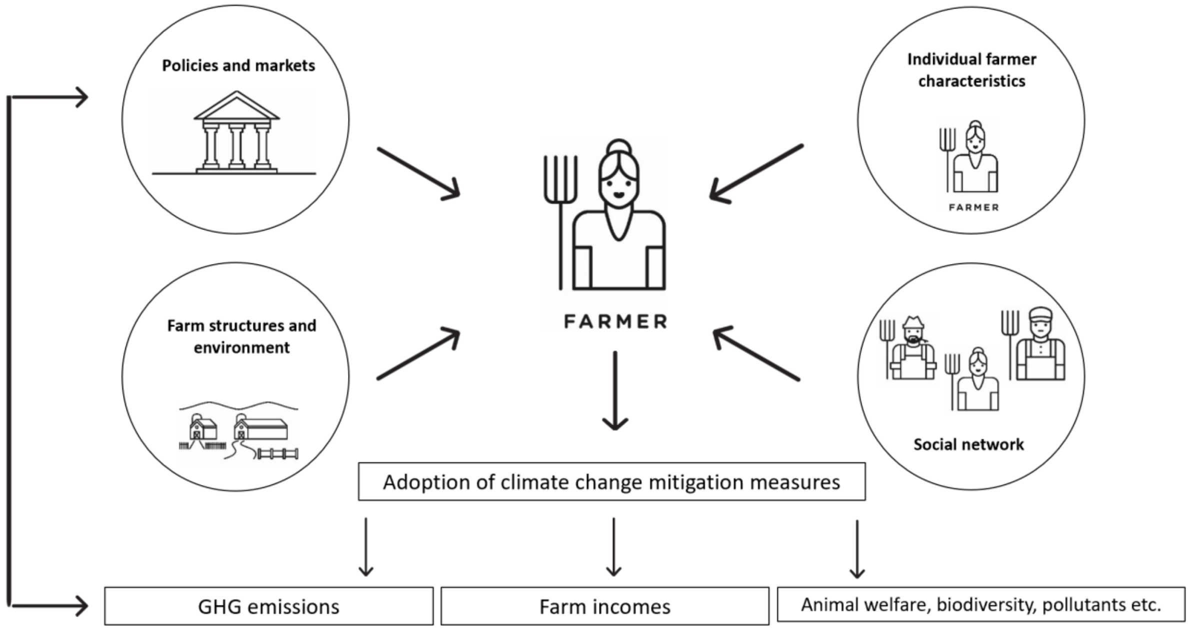

Figure 1.1: Overview conceptual framework: Factors affecting farmers' decisions to adopt climate change mitigation measures.

The overarching goal of this thesis is to provide further insights into the determinants of agricultural climate change mitigation and ultimately inform policies aiming at a reduction of agricultural GHG emissions. The focus is on the role of behavioural economic aspects such as farmers' individual preferences, non-cognitive skills, and social networks on adoption of climate change mitigation measures, achieved GHG emissions reduction and associated cost. Spanning a bridge between all parts of the thesis, the effects of farmers' individual characteristics and social networks are each investigated separately at first, and later integrated in an agent-based modelling framework combining individual, social as well as bio-economic factors and policy incentives.

The thesis is based on a regional case-study around the climate protection initiative "AgroCO_2ncept Flaachtal" located in northern Switzerland, in which farmers collaborate to reduce agricultural GHG emissions across the region. To collect data on farmers' current mitigation adoption, individual characteristics and social networks, an online survey as well as personal interviews were conducted and combined with census data on farm structures.

The thesis is structured as follows: The remainder of Chapter 1 contains background information, research questions and the main findings of each of the single research articles. After a summarizing conclusion, limitations and recommendations for further research are discussed. Chapter 1 ends with a list of abstracts and author contributions of the single articles. Chapters 2-5 present the four research articles. Finally, the appendix to this thesis contains two additional data articles presenting the collected survey and interview data.

1.1 Background

This section presents background information on the contribution of agriculture to overall GHG emissions globally and in Switzerland as well as the technical and economic potential of agricultural climate change mitigation. Moreover, it provides an overview of the influence of individual behavioural factors as well as social networks on farmers' decision-making.

1.1.1 GHG emissions from agricultural production

Global agricultural production and related land use changes account for 9.3 billion tons (t) of CO_2 equivalents (CO_2eq). Crop and livestock production alone make up for around 12% (6.2 billion t) of total anthropogenic GHG emissions (IPCC, 2019). The majority of emissions directly associated with agricultural production are non-CO_2 emissions, namely methane (CH_4) from anaerobic decomposition of organic matter in ruminants and manure as well as nitrous oxide (N_2O) from microbial transformation of nitrate in soils and manure (FAO, 2020). Figure 1.2 gives an overview of non-CO_2 emission sources from global agriculture and respective shares in total agricultural emissions.

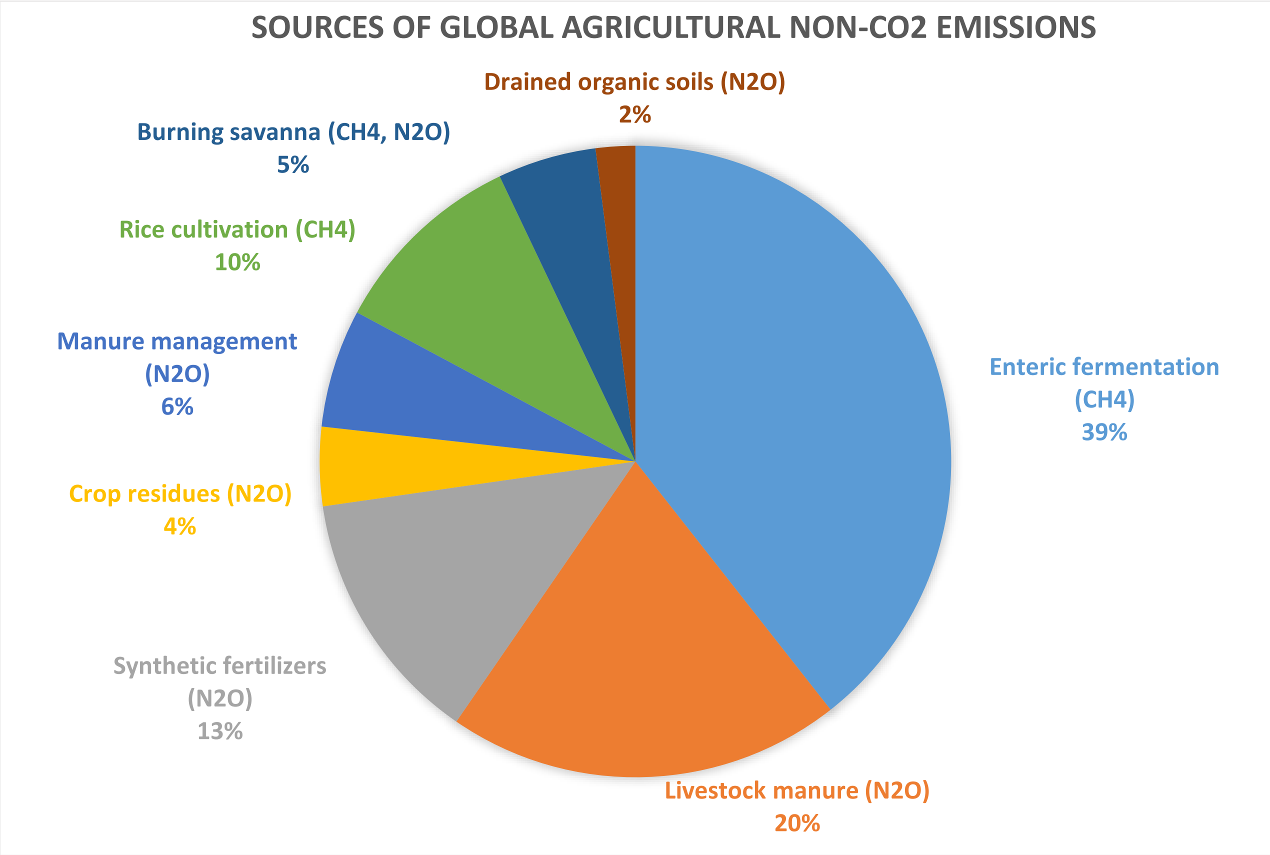

Figure 1.2: Contribution of crop and livestock activities to total non-CO2 emissions from agriculture (based on FAO, 2021).

CO_2 related to agriculture is mainly emitted by land use changes for agricultural purposes, lime and urea fertilizers as well as energy use of agricultural activities (e.g., fuel for machines) (Lynch et al., 2021).

In Switzerland, total direct emissions from agricultural production sum up to 5.75 million t of CO_2eq, which corresponds to around 13% of total GHG emissions. If production of inputs as well as land use changes and energy use of farms and machines are included, the share of emissions related to agricultural production rises to 18% of total emissions (Federal Office for the Environment FOEN, 2022). Figure 1.3 shows the distribution of emission sources in Swiss agriculture (the categorisation of emission sources slightly differs from the one based on global data by FAO presented above).

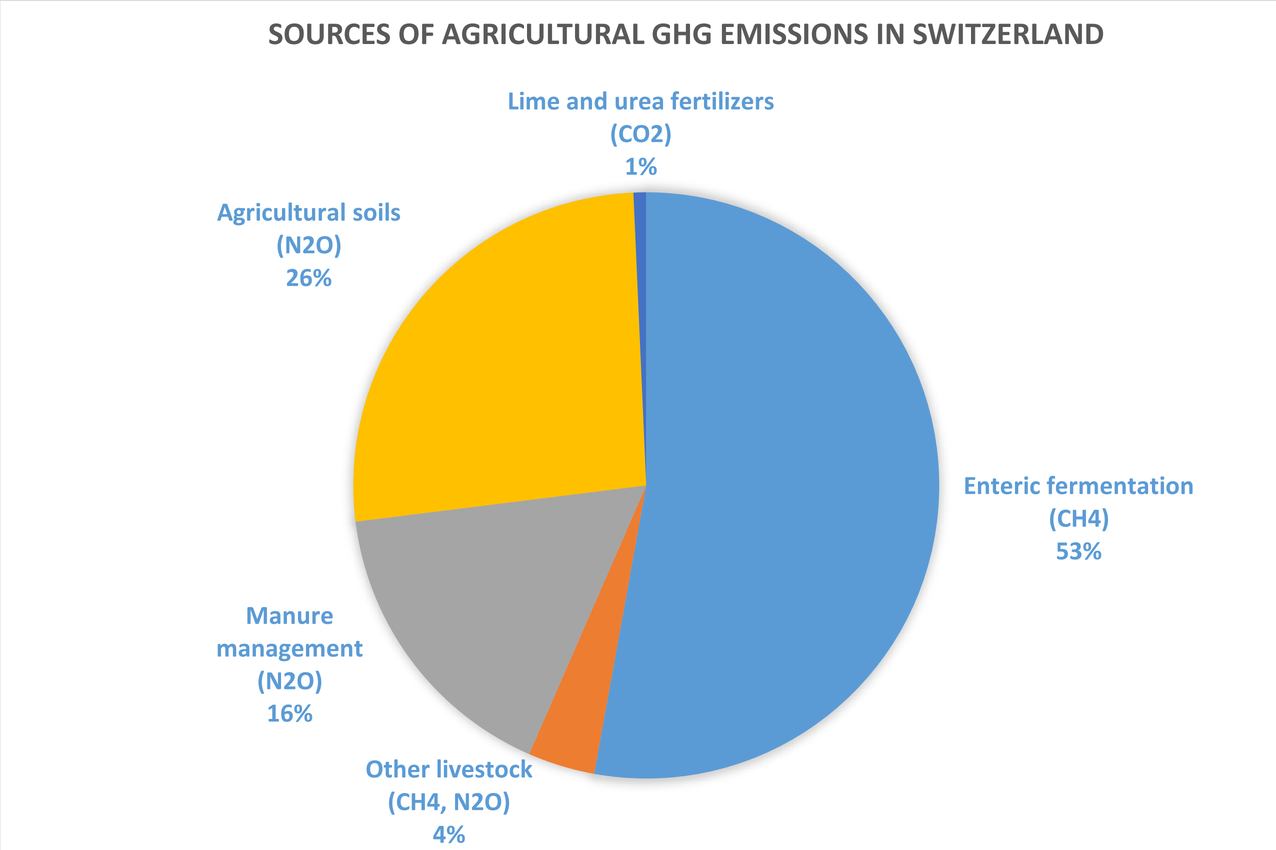

Figure 1.3: Contribution of agricultural activities to total agricultural GHG emissions in Switzerland (based on Federal Office for the Environment, 2022)

1.1.2 The potential of agricultural GHG reduction

Supply-side strategies of climate change mitigation in agriculture can be divided into three large categories: i) Reduction of direct emissions from cropland, grasslands, and livestock, ii) conservation and sequestration of organic carbon in soils or vegetation, and iii) provision of biological energy sources to substitute fossil fuels (Smith et al., 2014). The overall potential of GHG reduction in agriculture while ensuring constant production levels is subject to ongoing research. On a global scale, the biophysical or technical GHG reduction potential has been estimated to be around 5.5-6 billion t CO_2eq annually, i.e., approximately two thirds of agricultural and land use change emissions could technically be mitigated (Smith et al., 2008; Smith et al., 2007). Accordingly, studies assessing national agricultural mitigation potentials have shown that farms could substantially reduce their GHG emissions by adapting current farming practices and adopting respective mitigation measures (Martinsson and Hansson, 2021; McCarl and Schneider, 2000; Roe et al., 2021; Sánchez et al., 2016; Schader et al., 2014; Schils et al., 2005; Weiske et al., 2006).

However, actual agricultural climate change mitigation currently remains well below the technical potential. This is due to several barriers to implementation of mitigation strategies in agriculture limiting the feasible potential of on-farm GHG reduction (Wreford et al., 2017). The major obstacle discussed in the literature is the economic cost of mitigation. Studies assessing the marginal abatement cost (i.e., cost per ton of CO_2eq abated) of GHG reduction in agriculture have used supply-side micro-economic models, partial and general equilibrium models as well as engineering cost approaches (Vermont and De Cara, 2010; Mosnier et al., 2019). While marginal abatement cost vary widely across single measures, regions, and individual farms, they can be very high as compared to other sectors (MacLeod et al., 2015; MacLeod et al., 2010; Moran et al., 2011). At farm-level, some measures involve long-term investments and new technologies have potentially very high marginal abatement cost, impeding adoption by farmers (Golub et al., 2009; Morgan et al., 2015; Sánchez et al., 2016)[1]. In addition, transaction cost of knowledge acquisition, implementation and monitoring could further act as barriers of mitigation (MacLeod et al., 2015; Moran et al., 2013). At a given carbon price of 100 US$/t$CO_2$eq (which is often applied as a measure for cost-effectiveness), the overall potential of supply-side reduction of agricultural GHG emissions has been estimated to be 5-10% of current agricultural emissions (IPCC, 2014). There is however a wide range of estimates depending on the mitigation measures considered and methodologies used (OECD, 2019). For example, several studies have shown that considerable reductions of GHG emissions could be achieved at a net gain for farmers due to e.g., increased productivity or reduction of inputs (Ancev, 2011; Eory et al., 2018; MacLeod et al., 2010; Moran et al., 2013; Moran et al., 2011). This raises the question why so-called “no-regret” or win-win options are not more widely adopted (McCarl and Schneider, 2000). Part of the explanation could be that estimations of cost-effective mitigation potentials and marginal abatement cost estimations commonly lack integration of transaction cost, structural changes in the agricultural sector as well as demand-side or market feedbacks, which could lead to under- or overestimation of the actual potential (Frank et al., 2018). Particularly the reduction of animal-based foods in diets could be an enormous lever to reduce emissions from entire food systems as recent research has shown (Poore and Nemecek, 2018; Xu et al., 2021).

Apart from economic constraints, there are political barriers to the implementation of effective GHG reduction in agriculture. These are often related to potential trade-offs regarding farm incomes and food security which could potentially be negatively affected by the implementation of mitigation measures. Recent studies have however shown that well-designed and managed mitigation in agriculture and land use can in fact be cost-effective while providing additional benefits to food security and ecosystems

[1] Note that in these estimates, production levels are commonly assumed to be constant. However, some mitigation options can increase production, which would increase cost-effectiveness (Smith et al., 2014).

(Frank et al., 2017; Roe et al., 2021; Roe et al., 2019; Smith et al., 2020). The purposeful use of such synergies is also captured by the concept of climate-smart agriculture (CSA), which has gained increasing interest among scientists in the past years (Bazzana et al., 2022; Blaser et al., 2020; Gram et al., 2020; Lipper et al., 2014). Other political concerns can be related to trade-offs regarding animal welfare (Shields and Orme-Evans, 2015) or emission leakages as well as loss of competitive advantage (Leahy et al., 2020). Moreover, existing agricultural policies can act as barriers to the adoption of more climate-friendly practices (Wreford et al., 2017).

Another potential barrier of effective on-farm implementation of GHG reduction measures (even despite economic benefits) concerns the behavioural component of farmers' mitigation adoption, which is at the core of this thesis. In general, the behavioural economic perspective emphasizes the influence of farmers' individual characteristics, i.e., personal attitudes, values and perceptions, non-cognitive skills such as perceived self-efficacy as well as risk preferences and social interactions. Further background information on individual behavioural factors as well as social networks affecting farmers' adoption of climate change mitigation practices is separately presented in the following section.

1.1.3 Individual and social aspects of farmers' decision-making

In the past decades, agricultural economists have identified behavioural factors as important determinants when explaining farmers' decision-making processes, extending classical decision analysis, e.g., based on expected utility under the umbrella of behavioural economics (e.g., Dessart et al., 2019). Behavioural economic research adds subjective (non-)cognitive and psychological components to the utility functions of decision-makers, leading to potential deviations from fully rational behaviour as assumed in e.g., Expected Utility Theory developed by Von Neumann and Morgenstern (1947). For instance, perception of and attitudes towards risk differ between individuals and can even vary within a person depending on emotions, moods, experiences, cognitive abilities, and the framing of the choice problem. Prospect Theory for example states that people judge and choose relative to a reference point rather than to the final wealth (framing effect) and usually prefer the current state to a change (status-quo bias). Furthermore, people tend to overvalue objects they already own (endowment effect) and are risk averse for losses and risk seeking for gains. Thus, people care more about values of potential losses and gains than about final outcomes (Kahneman and Tversky, 1979, 1992). Other theoretical frameworks capturing the non-rational components of decision-making are for example Theory of Reasoned Action and Theory of Planned Behaviour explaining behavioural intentions and actual behaviour with personal attitudes, subjective norms and control beliefs (Ajzen, 1991; Fishbein and Ajzen, 1975). This is partly interlinked with Social Cognitive Theory and particularly, the concept of perceived self-efficacy and locus of control. These are two non-cognitive skills describing a person's confidence in their own capabilities to be successful in a certain domain and to have control over life's outcome in general (Bandura, 1977b, 1997, 2012; Wuepper and Lybbert, 2017). The development of self-efficacy in a person depends on own experiences of mastery or success, vicarious experiences of success provided by others, social persuasion through (verbal) encouragement as well as the emotional and psychological well-being of the person (Bandura, 1977b).

Such individual behavioural economic aspects have been studied in the context of farmers' participation in agri-environmental programs, conversion to organic farming, and adoption of e.g., conservation practices or animal welfare measures. For instance, farmers' perception and awareness of environmental problems can be crucial for adoption of sustainable practices (e.g., Burton et al., 1999; Espinosa-Goded et al., 2010; Gould et al., 1989; Karali et al., 2014; Lastra-Bravo et al., 2015; van Dijk et al., 2016; Wilson and Hart, 2000). Also, the attitude towards the measures at choice as well as personal values are important (Hansson and Lagerkvist, 2014; Hansson and Lagerkvist, 2015; Morris and Potter, 1995). Regarding climate change mitigation, knowledge about climate change, vulnerability towards climatic changes as well as awareness and experience of risks and respective consequences are among the drivers of mitigation uptake (Arbuckle et al., 2013, 2015; Barnes and Toma, 2012; Haden et al., 2012; Karrer, 2012). Moreover, farmers' reluctance to change and tendencies to inertia (or status-quo bias) have been found to be among the most important barriers of behavioural change and might even lead farmers to restrain from adoption of win-win measures (Burton et al., 2008; Hermann et al., 2016).

Besides individual characteristics, farmers' social networks, interactions and social norms affect adoption decisions. The theoretical framework is rooted in social psychology. For instance, the Theory of Social Influence states that social interactions lead to increasingly similar behaviour of the connected actors (Friedkin, 2006; Marsden and Friedkin, 1993). The Theory of Social Learning suggests that humans learn through observation and imitation of others (Foster and Rosenzweig, 1995; Bandura, 1977). Social networks in which farmers observe the behaviours of others and exchange knowledge are commonly found to enable social learning and thereby influence adoption decisions in various contexts, also known as spillover, neighbourhood- or peer-effects (Conley and Udry, 2010; Krishnan and Patnam, 2014; Läpple and Kelley, 2014; Mathijs, 2003; Matuschke and Qaim, 2009; Vroege et al., 2020). Moreover, the wish to belong to a social group, the fear of losing social status and resulting conformism are central determinants of behaviour (Bernheim, 1994; Thaler et al., 2008). Consequently, the role of social networks, social learning and norms has gained more and more interest in the research on farmers' decision-making.

1.2 Research Questions

The overarching goal of this thesis is to provide insights into individual and social determinants of farmers' decision-making regarding the adoption of climate change mitigation measures. Building on this, the thesis aims to provide further knowledge about cost and effectiveness of on-farm GHG reduction measures as well as related policy instruments. To this end, the main research questions guiding the thesis are:

(1) *What individual characteristics determine farmers' adoption of climate change mitigation measures?*

While most studies that deal with economic aspects of agricultural climate change mitigation have focused on cost (Eory et al., 2018; Jones et al., 2015; MacLeod et al., 2010; Moran et al., 2011), policies (Bustamante et al., 2014; Cooper et al., 2013; De Cara and Vermont, 2011) and related carbon markets (Maraseni, 2009; Pérez Domínguez et al., 2009), little is known about behavioural factors of mitigation in agriculture. Understanding the underlying mechanisms of individual farmers' adoption behaviour can contribute to better targeting of policies aiming at a reduction of agricultural GHG emissions.

(2) *How does knowledge exchange in social networks influence farmers' decisions to adopt climate change mitigation measures?*

The impact of social networks on farmers' decision-making and behavioural change has been studied in the context of e.g., innovation, diversification, and agri-environmental schemes (e.g., Bandiera and Rasul, 2006; Conley and Udry, 2010; Nyantakyi-Frimpong et al., 2019; Skaalsveen et al., 2020; Spielman et al., 2011; Vroege et al., 2020; Wossen et al., 2013). Few studies are available on the role of farmers' social interactions in agricultural climate change mitigation. Investigating how social ties of farmers support knowledge exchange and ultimately mitigation adoption contributes to understanding regional diffusion dynamics. This can constitute an important policy lever to enhance the spread of mitigation practices.

(3) *What is the impact of farmers' social networks on regional GHG reduction, associated abatement cost of farms and policy effectiveness?*

Social networks are regularly found to influence farmers' adoption of agri-environmental or conservation practices (cf. RQ (2) above). However, the impact of farmers' social interactions has rarely been quantified in terms of resulting environmental outcomes and associated cost. Estimating the effect of farmers' knowledge exchange within farmers' social networks on the overall amount of GHG reduction and farm incomes given a fixed carbon price provides important information on the effectiveness of policies to incentivize GHG reduction.

(4) *How cost-efficient are action-and results-based policy designs for agricultural climate change mitigation when accounting for farmers' behavioural characteristics and heterogeneous cost of measures?*

Results-based policy schemes paying farmers for an achieved outcome are commonly considered more cost-efficient in reaching desired goals and less prone to windfall effects than action-based policies where farmers are paid for adopting certain measures (Burton and Schwarz, 2013a; Engel, 2016; Sidemo-Holm et al., 2018; Wuepper and Huber, 2021). However, the actual efficiency gain of results-based schemes might depend on several factors, including the specific policy goal, cost and benefits of considered measures as well as individual farmer characteristics. A comparison of both payment schemes is so far lacking in the context of agricultural climate change mitigation. In particular, no study has looked at how behavioural factors such as farmers' reluctance to change, individual preferences and social networks influence cost-efficiency of results- and action-based payments.

1.3 Case study, data collection and methods

1.3.1 Case study region and AgroCO$_2$ncept Flaachtal

This thesis is based on a case study in the region of Zürcher Weinland, which belongs to the Canton of Zurich in Switzerland and consists of 24 municipalities. The region is particularly interesting for the research purposes of this thesis: First, agriculture is an important economic sector in the region and diverse farm types typical for Swiss agriculture are represented. Main products are beef, milk, grain, potatoes, sugar beets, maize as well as some vegetables and wine (BFS, 2017). Most farmers in the analysed sample keep livestock while around a third produces arable crops or specialized crops only. The mean farm size is almost 30 hectares (ha), which is larger than the Cantonal (25 ha) and the overall Swiss average (21 ha) (BFS, 2019; Canton Zurich, 2018).

Second, the region is home to the pioneer bottom-up initiative "AgroCO$_2$ncept Flaachtal" (hereafter AgroCO$_2$ncept). The project was launched in 2012 by farmers in the region of Flaachtal in the northern part of Canton Zurich in Switzerland and aims to collectively reduce at least 20% of GHG emissions on the participating farms (AgroCO$_2$ncept, 2016). In Switzerland, it is among the very first projects that aim at practical on-farm climate change mitigation. Long term, the project also aims at 20% less cost due to higher efficiency as well as 20% higher added value due to climate friendly products and improved image of the region. All types of farms are eligible to participation in AgroCO$_2$ncept. Participants agree to an up-front analysis of GHG emissions on the farm and receive in-depth advisory service on possible mitigation strategies. They can choose from a range of measures and are financially compensated for implementing them. Changes in GHG emissions are measured twice more to assess the progress made until the end of the official project period. In total, 26 farmers on 24 farms actively participate in AgroCO$_2$ncept. Since 2016, AgroCO$_2$ncept gets funding over a six-year period by the

Swiss Federal Office for Agriculture as so-called resource project (BLW, 2018). This thesis is part of the obligatory scientific research accompanying these projects.

1.3.2 Data collection

Data was collected with farmers in the case study region of Zürcher Weinland. The online survey on adoption of mitigation measures and individual characteristics was conducted in spring 2019 and sent to 389 farmers via email. To assess farmers' risk preferences, a lottery in form of a multiple price list based on Tanaka et al. (2010) was included in the survey. Farmers received 10 Swiss Francs for participating in the survey and the lottery was additionally incentivized with real payouts for wins. In total, 105 farmers completed the survey, corresponding to a response rate of 27%. The survey data was matched with official farm census data provided by the Canton of Zurich. The sample covers typical Swiss production types, namely dairy, meat and crop producers as well as vegetable, fruit, and wine growers. The mean farm size is 30 ha, which is approximately 5 ha larger than the average in Canton Zurich (Canton Zurich, 2018). 24 of the 105 farms are participating in the climate protection initiative AgroCO_2ncept. A detailed description of the data and methods used can be found in Kreft et al. (2020) (see Appendix Chapter 1 to this thesis). For the survey, 13 mitigation measures were chosen according to scientific evidence of GHG reduction potential as well as suitability to Swiss farming systems. Seven measures relate to livestock (mainly dairy and beef cattle) production, three measures to crop production and three measures to energy use on the farm. Table 1.1 lists the mitigation measures included in the survey.

Table 1.1: Mitigation measures included in the survey and associated GHG reduction mechanism

Mitigation measure	Main GHG reduction mechanism	References
Replacement of (imported) concentrate feed with domestic legumes (e.g., peas, beans, lupines)	Reduced transport and land-use-changes for soy cultivation overseas	(Hörtenhuber et al., 2011) (Baumgartner et al., 2008) (Knudsen et al., 2014b)
Reduction of concentrate content to maximum of 10% of feed ration	Reduced concentrate production (e.g., mineral fertilizer, energy use)	(Schader et al., 2014)
Increasing the number of lactations per dairy cow (min. 5)	Reduced CH_4-emissions per kg milk over entire lifespan of cows and reduced replacement rate	(Mellado et al., 2011) (Vijayakumar et al., 2017)
Use of dual-purpose cattle breed (e.g., original Swiss brown)	Reduced number of animals needed for meat and milk production (mainly CH_4)	(Schader et al., 2014) (Zehetmeier et al., 2012)
Introduction of feed additives (e.g., tannins, lipids etc.) to feed ration of cattle	Reduced enteric fermentation by partly inhibiting methanogenesis in rumen (reduced CH_4-emissions)	(Jayanegara et al., 2020) (Sinz et al., 2019) (Wang et al., 2017)
Coverage of manure storage	Reduced ammonia (NH_3-) emissions due to anaerobic conditions under coverage	(Chadwick et al., 2011)
Composting of manure	Reduced N_2O-and CH_4-emissions due to aerobic decomposition in compost	(Pattey et al., 2005) (Necpalova et al., 2018)
Manure application with drag hoses	Reduced NH_3-emissions (i.e., precursor of N_2O) from manure and slurry application	(Weiske et al., 2006) (Thomsen et al., 2010) (Wulf et al., 2002)
No-tillage	Reduced N_2O-emissions and increased soil C sequestration	(Six et al., 2004) (Mangalassery et al., 2014) (Alskaf et al., 2021)
Cover and catch crops in crop rotation	Reduced need for mineral N-fertilizer and increased soil C sequestration	(Alig et al., 2015) (Smit et al., 2019)
Solar panels for energy production	Reduced need for fossil fuels (CO_2) in heating and energy use of the farm	(Alig et al., 2015)
Fermentation of manure in biogas-plant	Reduced need for fossil fuels in electricity generation (CO_2) and manure storage (CH_4, N_2O)	(Meyer-Aurich et al., 2012) (Massé et al., 2011)
Drive tractors fuel-efficient (eco-drive mode)	Reduced fuel consumption of tractor driving (CO_2)	(Schader et al., 2014) (Stadler and Schiess, 2000)

The face-to-face interviews on farmers' social networks took place in fall 2019. The newest available version of the survey software Network Canvas (Network Canvas, 2016) was used to design and conduct the interviews using tablets. A sub-sample of 50 farmers who had previously participated in the online survey was interviewed by the author of the thesis and four trained student assistants. Half of the sample (25 farms) was participating in the climate protection initiative AgroCO_2ncept Flaachtal. The data is further described in Kreft et al. (2021) (see Appendix Chapter 2 to this thesis).

1.3.3 Methods

To answer the research questions, the thesis uses three complementary methods, which enrich and build upon each other (Figure 1.4). First, a linear regression analysis (OLS) is carried out based on the collected survey and census data to investigate the influence of farmers' individual characteristics on the adoption of mitigation measures. Second, to explore the role of knowledge exchange in social networks on farmers' mitigation behaviour, a social network analysis is conducted based on the personal interview data and using covariates derived from survey and census data. More precisely, a network autocorrelation model (Dittrich et al., 2020) is used to assess social influences within farmers' networks. Third, a bio-economic agent-based modelling approach is applied, bringing together the previous findings and data sources to estimate the effectiveness and efficiency of mitigation policies accounting for farmers' social networks as well as individual behavioural and farm structural characteristics. In the absence of an observable counterfactual situation without individual behavioural and social influences, the modelling approach allows to quantify previously found effects of such influences on resulting GHG emissions and associated cost for which empirical farm level data is lacking.

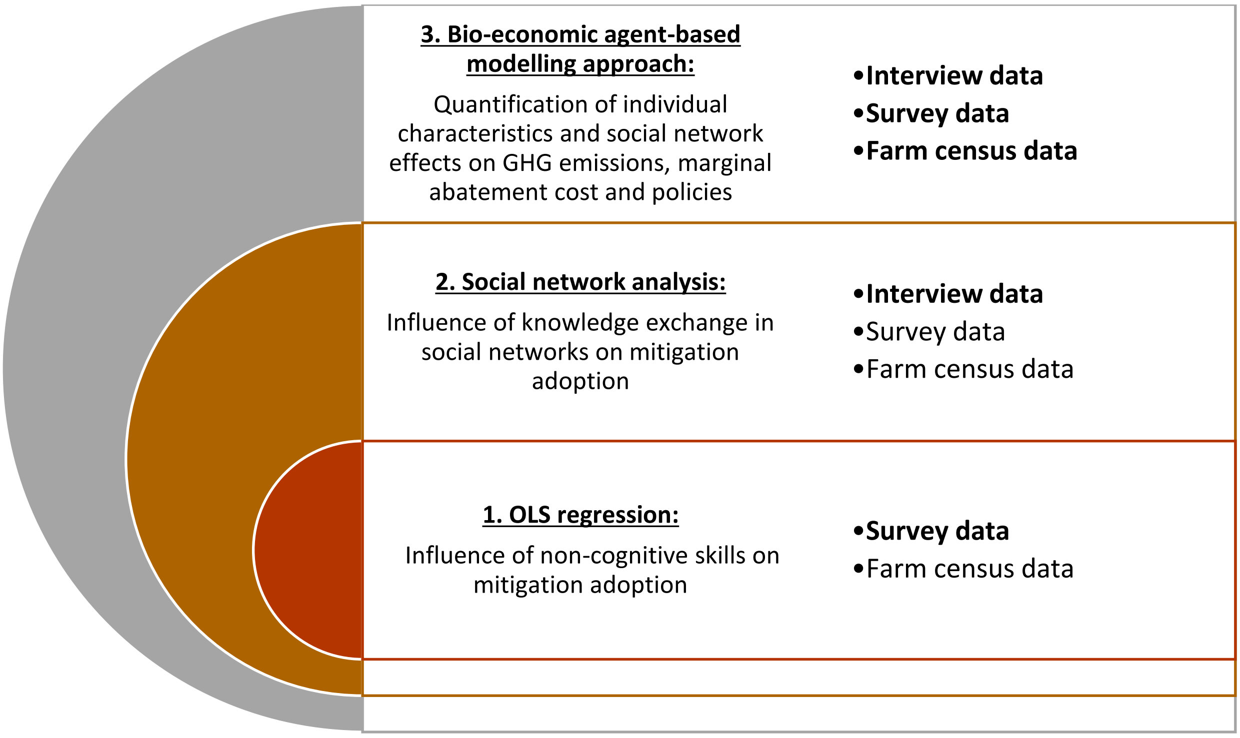

Figure 1.4: Interrelations of methods and data used in the thesis.

1.4 Structure of the thesis

The main body of the thesis is represented by Chapters 2-5, which contain the original research articles. The red threat of the entire thesis leads from the separate investigation of behavioural aspects, i.e., individual farmer characteristics and social networks in the first two chapters to a combined analysis of bio-economic and behavioural factors considering different policy instruments in the last two chapters (Figure 1.5).

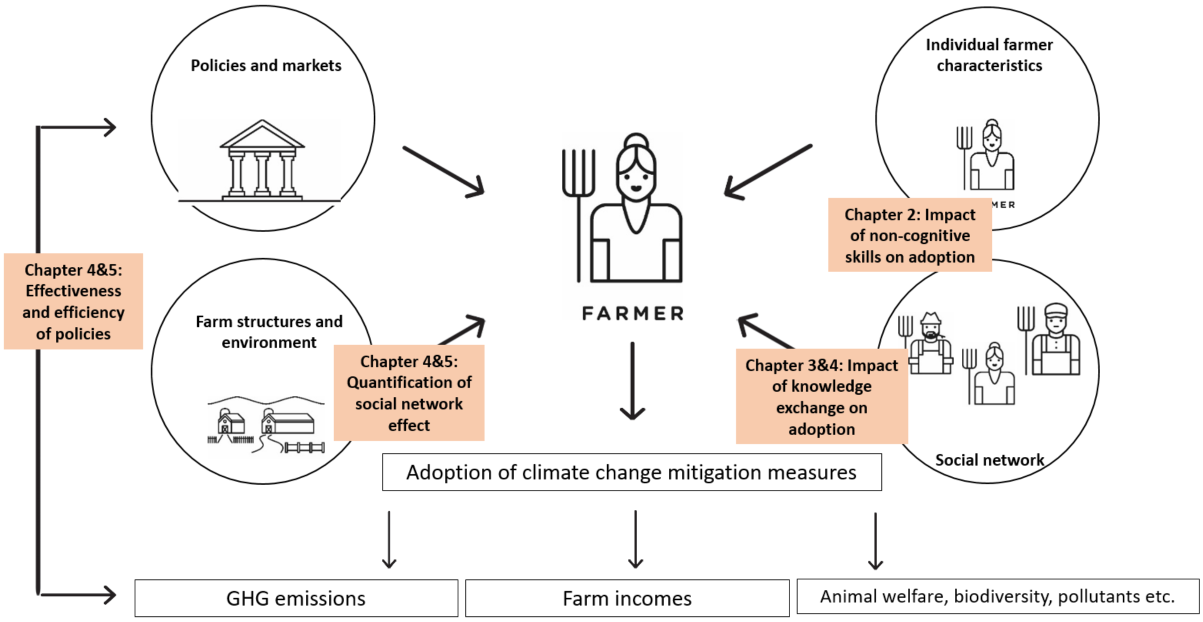

Figure 1.5: Conceptual framework of farmers' decision-making in the context of agricultural climate change mitigation and related chapters of the thesis.

Chapter 2 deals with research question (1) and investigates the influence of certain individual farmer characteristics on adoption of climate change mitigation measures. Chapter 3 answers research question (2) by investigating the effect of farmers' social networks on adoption of mitigation measures. Chapter 4 focuses on research question (3) and estimates the effect of social networks on actual GHG reduction levels and abatement cost at a given carbon price. Chapter 5 answers research question (4) by comparing the cost-efficiency of results- and action-based policy designs for agricultural climate change mitigation under consideration of individual farmer characteristics and social interactions. The appendix provides detailed information on the collected survey and interview data.

1.5 Summary and discussion of main findings

In the following sub-sections, the main findings of each of the four research articles are summarized separately. Details on the online survey and interviews as well as the resulting data are presented in the appendix.

1.5.1 The role of non-cognitive skills in farmers' adoption of climate change mitigation measures

Farmers' (non-) adoption of climate change mitigation measures remains poorly understood, which can hinder the implementation of effective policies to reduce agricultural emissions. This chapter provides further knowledge on the role of individual farmer characteristics in agricultural climate change mitigation based on survey and census data of 105 farmers in a Swiss region (Kreft et al., 2020). More precisely, it investigates how farmers' non-cognitive skills, namely perceived self-efficacy and internal locus of control, affect adoption of GHG reduction measures. Results show that both self-efficacy and locus of control are positively associated with adoption. Hence, farmers who are convinced that their actions can successfully contribute to climate change mitigation and who generally believe to have control over life's outcomes are more likely to adopt mitigation measures. This is consistent with findings from psychology and social science, e.g., suggesting that lack of self-efficacy acts as a barrier to behavioural change, particularly in the context of global environmental problems (Frantz and Mayer, 2009; Mulilis and Duval, 1995). In line with previous literature on the association of non-cognitive skills with innovative behaviour (Abay et al., 2017; Wuepper et al., 2019), the underlying mechanism is farmers' innovativeness, i.e., farmers with strong non-cognitive skills are more innovative which in turn leads to more adoption of mitigation measures. The results are robust to the inclusion of a broad range of co-variates and robustness checks against potential omitted variable bias. Strengthening farmers' self-efficacy and control beliefs regarding agricultural climate change mitigation through provision of knowledge and advisory services can thus contribute to increase adoption of GHG reduction measures.

1.5.2 Farmers' social networks and regional spillover effects in agricultural climate change mitigation

Social networks facilitate the spread of knowledge within farming communities. These often also called peer – or neighbourhood effects have been explored in various contexts (e.g., Skaalsveen et al., 2020; Vroege et al., 2020; Wood et al., 2014). The article investigates the role of social learning on farmers' adoption of on-farm mitigation practices applying a network autocorrelation model (Dittrich et al., 2020). The analysis is based on interview data of 50 farmers containing detailed information on personal network contacts combined with survey and farm census data (Kreft et al., 2021c; Kreft et al., 2020). While previous literature mainly focused on endogenous network effects (imitation of observed behaviour), this study additionally explores how a specific trait of the connected peers, here the (perceived) mitigation knowledge, influences behaviour, i.e., exogenous network effects (Manski, 1993). The results indicate that the presence of mitigation knowledge within farmers' personal networks is positively associated with adoption of mitigation measures while actual mitigation behaviour of peers is not. Hence, exchanging knowledge is arguably more important for own mitigation adoption than "silent" observation. This finding can be explained by the specific nature of agricultural climate change mitigation still being a rather unknown terrain for most farmers and thus making knowledge acquisition relatively more important. However, endogenous network effects are present when looking at social ties between two sub-groups of the sample, i.e., the behaviour of farmers participating in a climate protection initiative is positively associated with mitigation adoption of socially connected non-participants, suggesting a local spillover effect of the initiative. Providing access to knowledge about agricultural climate change mitigation and supporting social learning within farming communities as well as local initiatives can help to increase the adoption of on-farm GHG reduction measures.

1.5.3 Quantifying the impact of farmers' social networks on the effectiveness of climate change mitigation policies in agriculture

Assessments of GHG reduction potentials in agriculture, associated abatement cost and respective policy schemes currently lack consideration of behavioural factors (Lengers et al., 2014; MacLeod et al., 2010; Moran et al., 2011). This article aims to fill this research gap by quantifying the effect of farmers' social networks in terms of total GHG reduction and policy effectiveness assuming a payment per ton of GHG emissions reduced. To this end, the agent-based modelling framework FARMIND (Huber et al., 2021) integrating individual preferences and social interactions is used in combination with the bio-economic model FarmDyn (Britz et al., 2019), which allows to simulate GHG emission levels and farm incomes. Simulations are based on survey and census data of 49 dairy and beef cattle farms (i.e. producing beef from suckler cows and bull-fattening) in a region in northern Switzerland (Kreft et al., 2020). While GHG reduction potentials and abatement cost are heterogeneous across the analysed measures and farms in the sample, the results show that with a payment of 120 Swiss Francs (CHF) per ton of CO_2 equivalent (t CO_2eq) and assuming constant production levels, total GHG reduction is increased by 42% on a regional level due to social learning within farmers' networks. Without this effect, the payment would have to be increased by 76% (i.e., 500 CHF in total) to achieve the same level of GHG emissions reduction. The effectiveness of policy incentivizes for climate change mitigation in agriculture can thus be improved by supporting knowledge exchange in farmers' social networks, which would help to reduce governmental expenditures. However, despite a technical reduction potential of 38% of baseline GHG emissions, the actually achieved GHG reduction in our sample is at maximally 8% of baseline emissions when accounting for economic constraints as well as individual and social factors. This suggests that substantial reduction especially in livestock farming will likely be rather limited at current production levels.

1.5.4 Action- vs. results-based policy designs for agricultural climate change mitigation

The effectiveness and efficiency of action- and results-based policy designs have been compared, e.g., in the context of biodiversity conservation. Based on theoretical considerations (e.g., Engel, 2016), paying farmers for an achieved outcome is usually found to be more cost-efficient than compensation for adopting specific management measures since it enables flexible and innovative decision-making of farmers (Sidemo-Holm et al., 2018; Wuepper and Huber, 2021). However, the actual efficiency gain from result-orientation of payments might depend on the specific policy goal (e.g., whether the outcome is measurable), cost and benefits of the considered mitigation measures as well as on individual characteristics and social networks of decision-makers. So far, the cost-efficiency of action- and results-based payments has not been compared in the context of agricultural climate change mitigation. Moreover, previous studies comparing both policy designs have not included behavioural aspects. This article uses an agent-based bio-economic modelling approach to compare the cost-efficiency of action- and results-based payments for climate change mitigation in terms of total governmental spending and farm-level marginal abatement cost under consideration of farmers' individual behavioural characteristics. We find that total governmental expenditures associated with a policy design depend on the cost and benefits of the measures considered as well as the behavioural characteristics of farmers. When a win-win measure is included that reduces GHG emissions and increases farm profits at the same time (here: increasing the number of lactations per dairy cow) and additional incentives for adoption of such a measure are needed due to farmers' reluctance to change, governmental spending can be higher with results-based than with action-based payments. In such a situation, targeting the payment on the costs of the specific measure (i.e., an action-based design) can result in lower governmental spending than targeting it on cost-efficiency of individual farm-level by paying a uniform amount for reduction of GHG emissions (i.e., results-based design). However, without such win-win measures, results-based designs are more efficient in terms of public cost than action-based designs. Independent of inclusion of the win-win measure, farm-level marginal cost of reducing GHG emissions are lower with results-based designs. Moreover, we find that with both policy designs, farmers' individual preferences and reluctance to change substantially lower the adoption of mitigation measures and hence overall GHG reduction potential.

1.5.5 Data articles

The two data articles in the appendix of this thesis present the types and scopes of data collected as well as the methodology of data collection. The first article (Kreft et al., 2020) presents the online survey data collected in 2019 with 105 farmers in the Swiss region of Zürcher Weinland. The questionnaire sent to farmers as link via email contained questions on perceptions and concerns about climate change, non-cognitive skills, current adoption and rating of 13 selected mitigation measures, personal farming preferences, and goals as well as income satisfaction and social networks. Moreover, famers' individual risk preferences, loss aversion and probability weighting were elicited with an incentivized multiple price list based on Tanaka et al. (2010). The original survey, resulting raw data and a codebook describing the variables are available on the ETH research collection: http://hdl.handle.net/20.500.11850/383116. The second data article (Kreft et al., 2021c) presents the social network data collected in face-to-face interviews with 50 farmers in 2019. Interviews were conducted with 25 farmers participating in the regional climate protection initiative AgroCO$_2$ncept as well as 25 non-participating farmers. Social contacts of farmers based on regular exchange related to agricultural climate change mitigation were assessed with a roster (list of names to choose from) as well as a free name generator. Moreover, several name interpreter questions were included to receive information on the characteristics of connected peers. The interview questionnaires, datasets, and codebooks to describe the variables are also stored on the ETH research collection: http://hdl.handle.net/20.500.11850/458053.

1.6 Conclusion, policy implications and recommendations for future research

The following key points related to agricultural climate change mitigation can be drawn from the findings of this thesis:

First, farmers' heterogeneous adoption rates regarding GHG mitigation practices can be explained to some extent by differences in individual behavioural characteristics. In particular, high self-efficacy and locus of control are strongly associated with farmers' innovativeness and ultimately adoption of mitigation measures. Even though these personality traits are shaped in childhood, they can still be changed to some extent later in life, especially with respect to specific new domains. Policymakers should hence account for the importance of farmers' non-cognitive skills when designing policies that aim at a reduction of agricultural GHG emissions. Information campaigns, provision of practical know-how in farmer trainings as well as specific advisory services on individual farm level are potential instruments to strengthen farmers' sense of self-efficacy related to agricultural climate change mitigation. Moreover, agriculture's critical role as part of the solution to tackle climate change should be integrated in official curricula of agricultural colleges.

Second, farmers' social networks can facilitate adoption and diffusion of agricultural mitigation measures through social learning. Especially, regular exchange of information with peers who are perceived to be knowledgeable in agricultural climate change mitigation is associated with adoption of GHG mitigation measures. Moreover, local farmer initiatives for climate protection can exert spillover effects on other farmers in the region.

Third, while on-farm mitigation measures could technically achieve considerable reductions of GHG emissions, the actual realisation of this potential given current production levels is limited by economic and behavioural constraints. However, farmers' social networks can increase overall reduction of on-farm GHG emissions across a region and improve the effectiveness and efficiency of respective policy payments. Moreover, social networks can lead farmers to take more efficient adoption decisions, hence lowering average marginal cost of mitigation. Policies should consequently encourage farmers to share information and experiences with climate-friendly farming practices. This can be done by supporting the establishment of local farmer networks and bottom-up action groups as well as organizing opportunities for farmers to exchange knowledge and expertise within and beyond regions.

Fourth, to achieve a certain desired reduction level of agricultural GHG emissions, results-based policy designs can lead to higher governmental spending as compared to action-based designs when farmers are reluctant to change and need additional incentives to adopt so-called win-win measures, which reduce GHG emissions while increasing farm profits. However, if such win-win measures are not included in the policy scheme, results-based payments are superior regarding cost-efficiency from a governmental perspective. Moreover, results-based payment schemes are more efficient on farm-level in terms of lower marginal abatement cost. With both policy designs, behavioural characteristics of farmers, especially individual preferences for certain farming practices and reluctance to change lower overall GHG reduction as compared to a situation where all farmers strictly maximise incomes. This indicates that a combined consideration of behavioural characteristics and cost of the considered mitigation measures is key to assess the real efficiency gain from differently designed policy incentives in agricultural climate change mitigation.

Based on the results of this thesis, future research investigating the economics of agricultural climate change mitigation must more regularly account for behavioural characteristics of farmers and their social surroundings. In particular, some of the limitations of this thesis offer potentially interesting starting points for future studies: While the regional focus is appropriate to the case-study based approach of the thesis, the small sample size does not allow for broader generalization of results. The investigation of behavioural aspects of agricultural climate change mitigation should thus be extended to further case studies in other regions and at larger scales. Future studies should also include more and different mitigation measures and could explicitly consider the role of carbon sequestration. Along these lines, an important yet lacking tool for policymakers in Switzerland would be a comprehensive marginal abatement cost curve comparing cost and GHG reduction potentials of the relevant agricultural mitigation measures. An ambitious undertaking would be to include behavioural components into such a curve and thereby better approximate real potentials. Moreover, extending the findings related to farmers' social networks, the role of collective action and cooperation among farms and resulting economic benefits in the context of climate change mitigation constitutes another interesting field for further exploration. To account for effects on other policy areas and sectors of the economy, an analysis of potential trade-offs and co-benefits of agricultural climate change mitigation should be integrated in future research projects. Lastly, while this thesis is solely focused on supply-side mitigation, there is need for an integrated approach including also demand-side effects and market feedbacks.

In conclusion, behavioural factors are key determinants of successful agricultural climate change mitigation. Policies aiming at a reduction of on-farm GHG emissions should especially account for farmers' non-cognitive skills and the potential of knowledge exchange between socially connected farmers. This can improve both farmers' acceptance and cost-efficiency of policies. However, the results of this thesis also suggest that overall potential of reducing agricultural GHG emissions is limited if current production levels are to be held constant, especially in the dairy and beef sector. Moreover, climate change mitigation in agriculture is subject to several uncertainties related to GHG reduction of measures, associated cost, and benefits as well as potential trade-offs with other policy goals. Future studies and extensions, e.g., to other regions and farm types are needed to generalize the findings and implications of this thesis. There is furthermore need for research on cohesive climate policies across sectors and including market response to efficiently coordinate different policy goals.

1.7 Chapter abstracts and author contributions

CHAPTER 2: The role of non-cognitive skills in farmers' adoption of climate change mitigation measures

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Abstract

Farmers' adoption of climate change mitigation measures is key to successfully reduce agricultural greenhouse gas emissions. This article investigates the role of non-cognitive skills, namely self-efficacy and locus of control, in farmers' uptake of mitigation measures. The study is based on a combination of survey and census data from 105 farmers in Switzerland. Almost all farmers in our sample already adopt some of the considered measures to reduce greenhouse gases on their farm. On average, 37% of the mitigation measures available to the specific farm type are adopted. We find that a one standard deviation increase in non-cognitive skills is associated with a 20 to 40% higher share of adopted mitigation measures. This relationship is robust to the inclusion of a comprehensive vector of controls, inspired both from the agricultural economics and the psychology literature. Additionally, we find that omitted variable bias would need to be implausibly large to refute our findings. Finally, we explore potential mechanisms. The suggested pathway through which non-cognitive skills are associated with the adoption of climate change mitigation measures is the innovativeness of the farmers. Fostering farmers' non-cognitive skills could be an effective policy lever to accelerate the diffusion of climate change mitigation measures.

Author contributions

All authors conceptualized the study. CK cleaned and prepared the data, carried out the statistical analyses and prepared the figures and tables. CK wrote the original draft of the manuscript. All authors reviewed and commented on various versions of the manuscript. All authors read and approved the final manuscript.

CHAPTER 3: Farmers' social networks and regional spillover effects in agricultural climate change mitigation

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Abstract

Climate change poses a severe threat to global agricultural production and rural livelihoods, and since agriculture itself is a significant source of greenhouse gas (GHG) emissions, it can also play an important role in climate change mitigation. This article investigates how farmers' social networks influence the adoption of on-farm mitigation strategies. More precisely, we use a network autocorrelation model to explore the relationship between a farmer's own mitigation behavior and the mitigation behavior and knowledge of his fellow farmers. The analysis is based on a regional case study in Switzerland and uses data obtained from personal network interviews combined with survey and census data of 50 farmers. Half of them are members of a local collective action initiative for agricultural climate change mitigation while the others do not participate in the initiative. We find that, on average, farmers with a larger network adopt more mitigation measures and furthermore mitigation adoption is linked with the level of knowledge within farmers' networks. Indeed, the likelihood that non-members will adopt mitigation measures increases if they are closely associated with members of the collective action, suggesting a local spillover effect. It follows that strengthening knowledge exchange amongst farmers and supporting local farmers' initiatives can potentially contribute to the diffusion of agricultural climate change mitigation practices.

Author contributions

All authors conceptualized the study. CK cleaned and prepared the data, MA carried out the formal analysis and prepared the figures. CK wrote the original draft of the manuscript, MA wrote the chapter on methods. All authors reviewed and commented on various versions of the manuscript. All authors read and approved the final manuscript.

CHAPTER 4: Quantifying the impact of farmers' social networks on the effectiveness of climate change mitigation policies in agriculture

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Abstract

The mitigation of agricultural greenhouse gas (GHG) emissions is indispensable to achieve the overall temperature-goals of global and national climate policies. Farmers' adoption of measures to reduce on-farm emissions can be incentivized by respective policies. We investigate how knowledge exchange within farmers' social networks affects the effectiveness of a payment per ton of GHG emissions reduced. We base on census, survey and interview data of 49 Swiss dairy and beef cattle farms to simulate the effect of social networks on overall GHG reduction and marginal abatement cost using an agent-based modelling approach. We find that social networks increase overall reduction of GHG emissions by 42% at a given payment of 120 Swiss Francs per ton of GHG emissions. Moreover, marginal abatement cost of farms to mitigate emissions are lower due to farmers' social networks. The effectiveness of policy incentives aiming at agricultural climate change mitigation can hence be improved by simultaneously supporting knowledge exchange and opportunities of social learning in farming communities.

Author contributions

All authors conceptualized the study. CK cleaned and prepared the data, carried out the simulations with FarmDyn and FARMIND and did the statistical analysis. CK prepared all tables and figures. DS adapted the FarmDyn model to the Swiss context and integrated data and algorithms related to the simulated mitigation measures. RH carried out the parametrization and sensitivity analysis of the FARMIND model. CK wrote the original draft of the manuscript, RH wrote the chapter on methods as well the attached ODD+D protocol. All authors reviewed and commented on various versions of the manuscript. All authors read and approved the final manuscript.

CHAPTER 5: Action- vs. results-based policy designs for agricultural climate change mitigation

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Abstract

Reducing agricultural greenhouse gas (GHG) emissions is key to achieve overall climate policy goals. Effective and efficient policy instruments are needed to incentivize farmers' adoption of on-farm climate change mitigation practices. We compare action- and results-based policy designs for GHG reduction in agriculture and account for farmers' heterogeneous behavioural characteristics such as individual farming preferences, reluctance to change and social interactions. An agent-based bio-economic modelling approach is used to simulate total GHG reduction, overall governmental spending and farm-level marginal abatement cost of Swiss dairy and beef cattle farms under both action- and results-based policy designs. We find that total governmental spending associated with the compared policy designs depends on the cost and benefits of the considered measures as well as behavioural characteristics of farmers. More precisely, if farmers are reluctant to change, additional incentives are needed to increase adoption of a win-win measure. In such a case, targeting the payment on the cost of that particular measure (action-based design) instead of paying a uniform amount for abated emissions (results-based design) can lower governmental spending for agricultural climate change mitigation. Farm-level marginal cost of reducing GHG emissions are lower with results-based payments independent of the cost of measures. Moreover, we find that farmers' individual preferences and reluctance to change substantially lower the adoption of mitigation measures and hence overall GHG reduction potential of farms.

Author contributions

All authors conceptualized the study. CK prepared the data, carried out the simulations with FarmDyn and FARMIND and did the statistical analysis. CK prepared all tables and figures. RH carried out the parametrization and sensitivity analysis of the FARMIND model. CK wrote the original draft of the manuscript. All authors reviewed and commented on various versions of the manuscript. All authors read and approved the final manuscript.

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Chapter 2: The role of non-cognitive skills in farmers' adoption of climate change mitigation measures[2]

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Abstract

Farmers' adoption of climate change mitigation measures is key to successfully reduce agricultural greenhouse gas emissions. This article investigates the role of non-cognitive skills, namely self-efficacy and locus of control, in farmers' uptake of mitigation measures. The study is based on a combination of survey and census data from 105 farmers in Switzerland. Almost all farmers in our sample already adopt some of the considered measures to reduce greenhouse gases on their farm. On average, 37 % of the mitigation measures available to the specific farm type are adopted. We find that a one standard deviation increase in non-cognitive skills is associated with a 20 to 40 % higher share of adopted mitigation measures. This relationship is robust to the inclusion of a comprehensive vector of controls, inspired both from the agricultural economics and the psychology literature. Additionally, we find that omitted variable bias would need to be implausibly large to refute our findings. Finally, we explore potential mechanisms. The suggested pathway through which non-cognitive skills are associated with the adoption of climate change mitigation measures is the innovativeness of the farmers. Fostering farmers' non-cognitive skills could be an effective policy lever to accelerate the diffusion of climate change mitigation measures.

Keywords

Self-efficacy, locus of control, green innovativeness, agriculture, climate change, mitigation

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2.1 Introduction

Agricultural production substantially contributes to global anthropogenic greenhouse gas (GHG) emissions (IPCC, 2019). Consequently, the agricultural sector has also an important role in mitigating GHG emissions (Lipper et al., 2014; Ripple et al., 2013). Main sources of agricultural GHG are methane from enteric fermentation of cattle, nitrous oxide from fertilizer use and land use changes as well as carbon dioxide from fuel and energy use (IPCC, 2014). The level of these emissions varies widely between farms, depending on production type, region and individual management decisions (Henriksson et al., 2011; Olesen et al., 2006). Hence, farmers' individual production decisions are key for effective mitigation of agricultural GHG emissions. Understanding the personal characteristics driving farmers' adoption of climate change mitigation is thus of crucial importance for effective climate policy in the food and agricultural sector (OECD, 2012; Wreford et al., 2017). Apart from traditionally investigated factors such as structural farm and farmer characteristics as well as economic preferences, the role of behavioural factors in farmers' adoption of sustainable practices has gained increasing interest over the past decades (Dessart et al., 2019). Among these are so-called non-cognitive skills such as, for example, perceived control, which has been linked to actual adoption behaviour of farmers (Defrancesco et al., 2008; Läpple and Kelley, 2015).

In this article, we contribute to deepen the understanding of farmers' decision-making by examining the empirical association of non-cognitive skills and farmers' adoption of climate change mitigation measures. Here, non-cognitive skills are defined based on two concepts from Social Cognitive Theory: perceived self-efficacy and locus of control. While perceived self-efficacy refers to the confidence in one's own abilities in a given domain (e.g., Bandura, 1977), internal locus of control describes the more general belief that one has control over life's outcomes (e.g., Rotter, 1966). Based on a combination of survey and census data from 105 Swiss farmers, we investigate the association between non-cognitive skills and climate change mitigation choices. Moreover, we explore the mechanism how non-cognitive skills and farmers' innovativeness relate to these choices.

Literature shows that there is a broad range of potential on-farm mitigation strategies. Mitigation is feasible by increasing productivity and efficiency, introducing specific technology options or adapting farm management (Bryngelsson et al., 2016; Lybbert and Sumner, 2012). In this article, mitigation is measured by 13 measures suitable in the Swiss context and related to three broad categories, namely energy use (e.g., solar panels), crop production (e.g., conservation tillage) as well as livestock and herd management (e.g., increased number of lactations per cow).

Recent economic research on mitigation in agriculture has mostly focused on abatement and transaction cost (Ancev, 2011; Höglund-Isaksson et al., 2012; Moran et al., 2011; O'Brien et al., 2014; Van Kooten et al., 2002; Vermont and De Cara, 2010), policy design (Cooper et al., 2013; Pérez Domínguez et al., 2009) as well as related carbon markets (Grosjean et al., 2018; Schneider and McCarl, 2003; Smith et al., 2008). Fewer studies have addressed behavioural aspects such as the influence of farmers' climate change beliefs and perceptions on attitudes towards adaptation and mitigation (Arbuckle et al., 2013, 2015; Barnes et al., 2013; Barnes and Toma, 2012) as well as on intentions to adapt or mitigate (Haden et al., 2012). So far, however, little is known about the role of farmers' psychological traits on actual mitigation behaviour (Niles et al., 2016).

In the psychology literature and different other research areas, lack of self-efficacy and an external locus of control have been found to act as barriers to individual mitigation intentions and actual behaviours (Gifford, 2011; Hunter and Röös, 2016; Roser-Renouf and Nisbet, 2008). For example, self-efficacy explains actions against climate change of civilians (Broomell et al., 2015; Heath and Gifford, 2006). In the agricultural sector, a positive effect of self-efficacy and internal locus of control has been found on the adoption of innovations and agri-environmental measures (Abay et al., 2017; Lybbert et al., 2018; Malacarne, 2019; Marshall et al., 2016; McNairn and Mitchell, 1992; Taffesse and Tadesse, 2017; Wuepper and Lybbert, 2017; Wuepper and Sauer, 2016; Wuepper et al., 2019). With respect to agricultural climate change mitigation, Niles et al. (2016) found a positive effect of New Zealand farmers' perceived capacity to change behaviour on intended and actual mitigation behaviour.

We build on these findings and further investigate the role of non-cognitive skills in the adoption of climate change mitigation in agriculture by ruling out potential confounding effects. Moreover, we explore the mechanism mediating non-cognitive skills applying the approach of Acharya et al. (2016). Drawing from psychology, economics and management literature associating non-cognitive skills with entrepreneurship (Chen et al., 1998; Mueller and Thomas, 2001; Newman et al., 2019), we investigate innovativeness as a mediator. In this context, farmers' adoption of climate change mitigation measures can be seen as a form of "green" innovation. To the best of our knowledge, this study is the first to explore the role of innovativeness as a mechanism through which non-cognitive skills are connected to agricultural climate change mitigation.

Since our empirical analysis is based on non-experimental survey data, the distribution of non-cognitive skills in the sample is not random and could be in some way systematic, e.g., some non-observed adoption determinants such as marketing structures could potentially also affect farmers' non-cognitive skills, causing omitted variable bias. We account for this in two ways: First, we control for a broad range of various potentially confounding variables. These include farm characteristics such as size and production type, demographics such as education and age as well as individual farmer characteristics, e.g., risk preferences, loss aversion and probability weighting, social networks, climate change perceptions and concerns as well as, importantly, the perceived effectivity of the available mitigation measures.

Second, to test robustness of our findings, particularly against the risk of omitted variable bias, we use the approach of Oster (2019). This approach is based on the idea that we can quantify the stability of our estimated parameters, which informs us about selection on observables. This in turn can be used to learn about the potential role of omitted variable bias. Specifically, we can estimate the degree of omitted variable bias necessary to substantially change our main results as well as how our main results change under the assumption of equal selection on observables and non-observables.

We find that almost all of the farmers in our sample adopt some of the considered mitigation measures. On average, farmers adopt 37% of the mitigation measures included in the survey and suitable to their farm type. We find a strong, positive and robust association between non-cognitive skills and adoption of agricultural mitigation measures. Moreover, we find that innovativeness is the suggested mechanism.

The remainder of this paper is structured as follows: Section 2 presents our conceptual framework and provides some background on the influences of non-cognitive skills, green innovativeness and farm and farmer characteristics in the context of climate change mitigation choices. Section 3 introduces the econometric analysis for the assessment of the association between non-cognitive skills and mitigation behaviour as well as the mediation mechanism between non-cognitive skills and innovativeness. We introduce the case study, as well as the survey and the data in section 4. Next, we present the empirical results in section 5, followed by a discussion in section 6. We conclude with implications for policy and further research in section 7.

2.2 Conceptual framework and theoretical background

To develop our conceptual framework on farmers' climate change mitigation, we mainly built on behavioural theories: the Social Cognitive Theory by Bandura focusing on self-efficacy, locus of control, and social influences; the Theory of Planned Behaviour by Ajzen containing attitudes and subjective norms as well as Prospect Theory by Kahnemann and Tversky including risk preferences, probability weighting and loss aversion. In addition, we draw from the broad range of existing literature and empirical findings on economic and behavioural factors influencing farmers' adoption of sustainable practices (Ahnström et al., 2009; Beedell and Rehman, 1996; Beedell and Rehman, 2000; Defrancesco et al., 2008; Dessart et al., 2019; Gould et al., 1989; Knowler and Bradshaw, 2007; Lastra-Bravo et al., 2015; Sattler and Nagel, 2010; Siebert et al., 2006; Vanslembrouck et al., 2002; Willock et al., 1999; Wilson, 1996; Wynne-Jones, 2013).

Against this theoretical and empirical background, we assume that farmers' decision-making with respect to the adoption of climate change mitigation measures, comparable to other agri-environmental measures, is determined by farm structural and farmers' individual characteristics. More specifically, we distinguish three main factors (Figure 2.1): (i) characteristics of the farm, (ii) non-cognitive skills, and (iii) other individual characteristics such as demographics, attitudes and risk preferences.

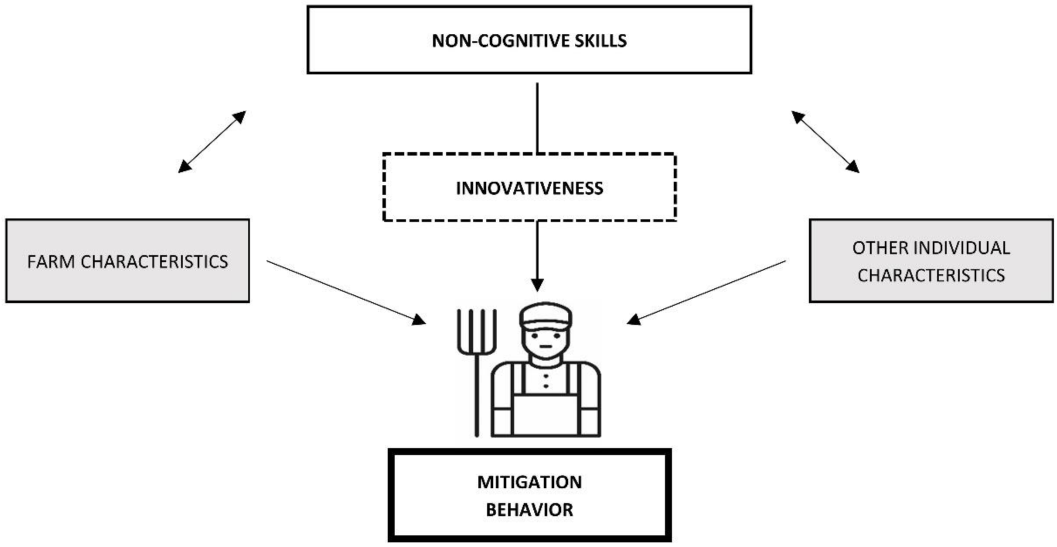

Figure 2.1: Conceptual framework of farmers' decision-making with respect to climate change mitigation. Farm and individual farmer characteristics serve as control variables, while the focus is on non-cognitive skills. The latter are mediated through innovativeness. Potentially confounding effects of farm and individual characteristics are indicated with double arrows.

The focus here is on the role of non-cognitive skills, namely self-efficacy and locus of control, in farmers' decision-making with respect to climate change mitigation and the potential role of green innovativeness in the mediation between non-cognitive skills and mitigation behaviour[3]. We have introduced innovativeness in our framework since Social Cognitive Theory predicts it as important mediator between non-cognitive skills and actual behaviour (Bandura, 1997). This has also been shown empirically, for example in the context of entrepreneurship or contract farming (Newman et al., 2019; Wuepper et al., 2019).

In the following sub-sections, we present the concepts of non-cognitive skills and green innovativeness in more detail and introduce the most relevant farm and individual farmer characteristics.

2.2.1 Non-cognitive skills

The literature generally refers to non-cognitive skills as the part of human capital that is not captured by common IQ and achievement tests (Kautz et al., 2014; Lundberg, 2017) but rather represents "patterns of thought, feelings and behaviours" (Borghans et al., 2008). The role of non-cognitive skills in individual decision-making processes has recently gained increasing interest among economists (Abay et al., 2017; Lybbert et al., 2018; Wuepper and Lybbert, 2017; Wuepper and Sauer, 2016; Wuepper et

[3] Regarding *adaptation* to climate change impacts, Grothmann and Patt (2005) have included perceived self-efficacy in their Model of Proactive Private Adaptation to Climate Change (MPPACC). There, self-efficacy is part of the so-called overall 'adaptation appraisal', i.e. the individual's perception of the ability to avert negative climate change impacts (Grothmann and Patt, 2005).

al., 2019). They are for example seen as a source of heterogeneity in innovation adoption (Feder et al., 1985; Stoneman and Ireland, 1986; Sunding and Zilberman, 2001).

We here focus on farmers' perceived self-efficacy and locus of control, which are arguably among the most important non-cognitive skills for behavioural change and success (Bowles et al., 2001; Chiteji, 2010; Wuepper and Lybbert, 2017; Wuepper et al., 2019). Self-efficacy and locus of control can be seen as part of the broader concept of perceived behavioural control which was introduced by Ajzen in his Theory of Planned Behaviour and defined as "the perception of the ease or difficulty of performing the behaviour of interest" (Ajzen, 1991, 2002).

Self-efficacy is defined as a person's belief in her or his own capability to solve a particular task in a certain domain (Bandura, 1977, 1997, 2012). It is the central concept in Social Cognitive Theory (Bandura, 1986). It is for example shaped by a persons' own mastery experiences, e.g., success can increase perceived self-efficacy, failure can decrease it. Vicarious experiences such as observing one's peers succeed can increase perceived self-efficacy, while observing them fail can decrease it. Moreover, social persuasion impacts self-efficacy - one can be convinced by others to have high or low domain specific abilities. Also, the emotional and physiological state plays an important role, i.e., depression or tiredness can decrease one's sense of self-efficacy, being healthy and happy can increase it. Individuals with high perceived self-efficacy typically see problems as a challenge they are willing and able to rise to. On the contrary, low perceived self-efficacy lets people perceive a problem as insurmountable and they are more likely to resign (Eker et al., 2019; Newman et al., 2019; van Valkengoed and Steg, 2019).

The concept of individuals' locus of control (Rotter, 1966, 1975; Rotter et al., 1972) captures how much people believe that their abilities and efforts matter for outcomes (internal locus of control) and how much they belief that outcomes rather depend on forces outside of one's control (external locus of control). This belief, too, has a range of important economic implications (Abay et al., 2017; Almlund et al., 2011; Cobb-Clark, 2015; Cobb-Clark et al., 2014; Wuepper, 2019; Wuepper et al., 2019). Locus of control is highly complementary to perceived self-efficacy (Bandura, 1997; Lopez and Snyder, 2009; Rotter, 1966). To motivate investments (e.g., money or efforts), individuals need to believe that their actions are actually important determinants of outcomes (internal locus of control) and that they have all the necessary abilities to achieve the required performance for a positive outcome (perceived self-efficacy). Differences in locus of control and perceived self-efficacy can both explain why otherwise similar individuals in the same context behave differently, see Lopez and Snyder (2009) for more discussion of the psychological literature, and Carter (2016) as well as Lybbert and Wydick (2018) on the integration of positive psychology and economics. A testable prediction of the literature is that perceived self-efficacy and internal locus of control increase individual's propensity to innovate (Bandura, 1997; Eker et al., 2019; Newman et al., 2019; Wang et al., 2016; Wuepper and Lybbert, 2017).

2.2.2 Green innovativeness

Green innovations are defined as technologies, managerial as well as organizational changes that “have the potential to enhance […] environmental sustainability” of a production activity (Lioutas and Charatsari, 2018). In recent years, green innovations have gained importance within the disciplines of business administration and innovation management (Schiederig et al., 2012). Unlike in other sectors of the economy, green innovations and related green innovativeness have only attracted little attention in the agricultural domain and only few research explicitly focuses on the role of farmers’ green innovativeness. For example, Lioutas and Charatsari (2018) investigated determinants of farmers’ green innovativeness and found that expected economic benefits, convenience of the measures at stake, environmental concern and the internal need for change had an influence. Moreover, Mann (2018) found that Swiss farmers who adopt innovative conservation measures such as banding technologies and drift-reducing spreaders for fertilizer application were more dedicated to innovation in general (Mann, 2018). We here refer to climate change mitigation measures as a form of green innovation.

2.2.3 Farm and farmer characteristics

Among the standard measures in the analysis of technology or innovation adoption are structural farm characteristics such as size and type as well as demographic characteristics of the farmer, namely education and age (Defrancesco et al., 2008; Knowler and Bradshaw, 2007; Lastra-Bravo et al., 2015; Prokopy et al., 2008). However, the literature reveals diverging results – from positive to insignificant and negative correlations (Knowler and Bradshaw, 2007; Lastra-Bravo et al., 2015).

In addition, we control for various individual farmer characteristics, which, according to the relevant literature, are among the most important drivers of adoption, i.e., knowledge and beliefs about climate change, climate vulnerability, the experience of direct consequences such as decreased rainfall and the expected efficacy of the mitigation strategy are likely to affect agricultural mitigation (Arbuckle et al., 2013; Barnes et al., 2013; Haden et al., 2012). Moreover, social networks have been found to influence farmers’ attitudes towards climate change (Barnes et al., 2013; Dang et al., 2014; Tang et al., 2013).

An important aspect in adoption decisions are farmers’ attitudes and perceptions of risks and potential losses (Bocquého et al., 2014; De Pinto et al., 2013; Fischer and Wollni, 2018; Ghadim et al., 2005; Kallas et al., 2010; Liu, 2013; Meraner and Finger, 2019). In our analysis we control for risk and loss aversion as well as probability weighting based on the theoretical foundation of Cumulative Prospect Theory (Kahneman and Tversky, 1992; Tanaka et al., 2010).

2.3 Econometric analysis

The first objective of our study is to investigate the association between farmers’ non-cognitive skills and adoption of agricultural climate change mitigation measures on the farm. The latter is measured as a share [0-100%] of implemented mitigation measures, which are suitable to the specific farm type ($Mitigation_i$). We start our analysis by testing for an empirical relationship between non-cognitive skills and adoption of mitigation measures. The baseline OLS regression model is without any control variables. We estimate:

$$Mitigation_i = \beta_0 + \beta_1 noncog + \varepsilon_i \tag{1}$$

Similarly, we want to investigate the single effect of innovativeness on mitigation and thus estimate a second baseline model:

$$Mitigation_i = \beta_0 + \beta_1 innovativeness + \varepsilon_i \tag{2}$$

Next, we include a vector of control variables ($\beta_i X_{1i}$) as discussed above, comprising farm structural variables (e.g., farm size, farm type) and farmers' demographics (e.g., age, education) as well as other farmer characteristics (e.g., climate change concern, risk and loss aversion, size of social network). See Table 2.2 in section 2.4 for a complete overview of control variables.

$$Mitigation_i = \beta_0 + \beta_1 noncog + \beta_i X_{1i} + \varepsilon_i \tag{3}$$

Note that innovativeness is not included in the vector of control variables as we aim to explore the mechanism between non-cognitive skills and innovativeness with a separate approach presented in the following step. In general, mechanisms describe a potential pathway through which a certain variable of interest affects the outcome via a mediating factor (Imai et al., 2011). We here explore the pathway or mechanism through which non-cognitive skills impact mitigation. To avoid omitted variable bias and rule out potential other drivers, we use the approach of Acharya et al., 2016 and calculate the direct association of non-cognitive skills, i.e., the association net the mediator innovativeness. The latter refers to the mechanism or the variable that lies on the pathway between the variable of interest and the outcome (Del Prete et al., 2019). The method is also known as sequential g-estimation (Joffe and Greene, 2009; Vansteelandt, 2009).

Technically, sequential g-estimation is a two-step procedure: First, the effect of the mediator (innovativeness) is removed from the dependent variable by fixing it at a certain level (usually to zero). The outcome is transformed in the following way:

$$\widehat{Mitigation}_i = Mitigation - \beta_2 innovativeness \tag{4}$$

Second, we estimate the association of the variable of interest (non-cognitive skills) with the transformed outcome:

$$\widehat{Mitigation}_i = \beta_0 + \beta_1 noncog + \beta_i X_i + \varepsilon_i \tag{5}$$

If in (5) the null hypothesis H_0 cannot be rejected ($\widehat{\beta_1} = 0$), we can show that innovativeness is the only pathway through which non-cognitive skills impact mitigation. To get correct standard errors, we use a consistent variance estimator developed by Acharya et al., 2016. The results are comparable with bootstrapped standard errors (Acharya et al., 2016). Commonly, mechanisms are explored by simply including potential mediator variables in the regression to test whether the coefficient of interest changes (Cockx et al., 2018). As elaborated by Acharya et al., 2016, this approach might lead to omitted variable bias. For a comparison, we here perform both types of analysis.

We account for potentially confounding factors in the model by testing several different specifications. For example, perceived effectivity of mitigation technologies is likely to be correlated with the belief in one's own abilities to effectively reduce emissions. Moreover, almost 23 percent of the farmers participate in a regional climate initiative ("AgroCO_2ncept") with the aim of a collaborative reduction of agricultural greenhouse gas emissions (more details are provided in Appendix A2.1). The participating farmers may potentially bias results since they might have particularly high scores in non-cognitive skills and innovativeness. Also, social capital and social networks are often found to play an important role in adoption decisions. Finally, organic farmers in our sample on average adopt a slightly higher share of mitigation measures (Table 2.1), which might influence the results. Therefore, we test sensitivity by excluding i) perceived effectivity of mitigation measures, ii) participation in AgroCO_2ncept, iii) size of the social network and iv) organic farming. Moreover, we test our model for the subsample of livestock farmers only. These build the vast majority in our sample and play a crucial role for effective climate change mitigation in agriculture since they have a greater reduction potential as well as more opportunities to reduce emissions compared to arable farms.

As we are working with non-experimental data, we carefully evaluate sensitivity to omitted variables. To this end, we use the Oster bound approach (Oster, 2019). The method allows to assess the relative degree of an omitted variable bias necessary to fully eradicate the established statistical significance of a specific variable. Unlike former approaches, Oster also accounts for different weights of control variables in terms of improving the R^2. Technically, a specification with only baseline controls is compared against a specification with the full vector of controls, resulting in the following ratio:

$$\hat{\beta}_{1,F} \,/ (\hat{\beta}_{1,R} - \hat{\beta}_{1,F})$$

$\hat{\beta}_{1,F}$ is the coefficient of the specification with baseline controls and $\hat{\beta}_{1,R}$ is the coefficient of the specification with all controls. This ratio tells us how high the risk of selecting on non-observables is: The smaller it gets, the higher the risk of omitted variable bias. On the contrary, the higher the ratio, the less likely is selection on non-observables. For example, if the ratio is two, the effect of an unobserved variable would have to be twice as large as the originally estimated coefficient (Oster, 2019).

2.4 Case study and data

To elicit farmers' individual characteristics, attitudes and preferences, we conducted an online survey, which was sent to the 389 farmers registered in the case study region (more information on the region is provided in Appendix A2.1). The survey took place from March until May 2019 and was announced via Email together with a supporting letter of the Cantonal Farmers Union. Participation was incentivized by a payment of CHF 10 and the opportunity to win up to 190 CHF in a lottery task to elicit risk preferences (see below). The full survey[4], the dataset and the codebook describing the variables are available in Kreft et al. (2020) as well as freely accessible on the ETH Zürich Research Collection: http://hdl.handle.net/20.500.11850/383116. Farmers were reminded twice, leading to 105 complete responses[5], i.e., a response rate of 27%. Table 1 provides summary statistics of the total sample and subsamples.

Table 2.1: Summary statistics

Variable	**Total**	**Missing**	**Mean non-cognitive skills (1: low, 5: high)**	**SD**	**Mean share of mitigation adoption (0-100%)**	**SD**
Total number of respondents	105		3.02	0.88	0.37	0.18
Organic farmers	11%	4	3.87	0.57	0.54	0.15
Farmers participating in AgroCO_2ncept Flaachtal	23%		3.74	0.74	0.43	0.19
Distribution of farm types		3				
Arable Farming (no livestock)	22.6%		2.95	0.83	0.4	0.22
Livestock	59.8%		3.0	0.97	0.38	0.16
Specialized crops	8.8%		2.93	0.69	0.23	0.2
Others	8.8%		3.33	0.72	0.35	0.16
Mean farm size (ha)	29.4	3				

We carefully designed the questionnaire based on two rounds of pre-tests. First, we tested general wording, understanding and user-friendliness with six students of agricultural sciences. In a next step, we got more content-related feedback from ten farmers at the farming school of the Canton of Zurich.

The questionnaire containing 26 questions was structured as follows: (i) climate change perceptions and expected consequences, (ii) current implementation and expected efficacy of mitigation measures, (iii) perceived self-efficacy and locus of control, (iv) personal values and innovativeness, (v) income and satisfaction, (vi) personal social networks and social comparison, (vii) risk preferences. Except for the question on social network, where participants had to insert names of persons, all questions were closed questions on Likert scales or multiple-choice format. Questions consisting of several items were later summarized by means of a factor analysis (see Appendix A2.2 for detailed results of the factor analyses). Non-cognitive skills were merged from three questions measuring self-efficacy and two questions measuring locus of control. To elicit risk and loss aversion as well as probability weighting, we used an incentivized multiple price list following the approach of Tanaka et al. (2010). Farmers could indicate to receive the gained money from the lottery and get aggregated information on the whole sample. From

[4] Please also find the full survey in the supplementary material to Appendix Chapter 1 of this thesis
[5] Given the strong expected association between non-cognitive skills and entrepreneurial behaviour, a power calculation suggests that for a statistical power of 0.9 and a statistical significance level of 0.05, we require at least a sample of 42-69 for our empirical analysis, depending on the model specification (Cohen, 2013).

the survey data, we derive 13 variables to include in our analysis. Additionally, we use farm census data (BLW, 2019), containing amongst others information on farm size, organic farming, production type and age of the farmer (Table 2.2).

The 13 mitigation measures included in the survey were chosen according to mitigation potential as well as actual relevance and suitability for Swiss farms (Alig et al., 2015; Schader et al., 2014). We included three energy measures (solar panels, biogas plant, eco-drive mode for tractors), three crop management measures (emissions reducing fertilizer application, cover or catch crops, conservation tillage) and seven livestock related measures (domestic legumes instead of imported concentrates, reduction of concentrates to max. 10 % of ration, at least 5 lactations per cow, double-purpose cattle breed, feed additives, coverage of manure storage, composting of manure). Depending on the farm type, some measures were not relevant, e.g., increasing the number of lactations is only relevant for dairy farms. Hence, the total number of relevant mitigation measures varies between farm types. We account for this by calculating the share of adopted mitigation measures out of all suitable measures for the respective farm type.

Table 2.2: Overview of variables included in the regression

Variable name	*Variable specification*	*Method*
Dependent variable		
Share of adopted mitigation measures suitable to the specific farm type	Share (0-100%)	
Farmer's behavioural characteristics		
Non-cognitive skills	5-point Likert scale (1=low; 5= high)	Factor Analysis summarizing 5 questions (Cronbach alpha : 0.8)
Innovativeness	5-point (1=low; 5= high)	Factor Analysis summarizing 5 questions (Cronbach alpha: 0.66)
Climate change perception	3-point Likert scale (1=no change, 2= decrease/increase, 3= strong decrease/increase)	Factor Analysis summarizing 6 questions (Cronbach alpha : 0.63)
Climate change concerns	5-point (1= very negative; 5= very positive)	Mean of expected consequences for own farm and total AG sector
Perceived effectivity of measures	6-point Likert scale (1=not effective at all, 5=very effective, 6= don't know)	Mean of effectivity expected of single measures
Network size	Number of persons listed (max. 10)	
Social comparison	5-point(1=low; 5= high)	Factor Analysis summarizing 5 questions (comparison, superiority, importance of others' opinions) (Cronbach alpha : 0.66)
Loss aversion	Parameter lambda	Multiple price list following Tanaka et al. (2010)
Risk aversion	Parameter sigma	Multiple price list following Tanaka et al. (2010)
Probability weighting	Parameter alpha	Multiple price list following Tanaka et al. (2010)
Farmer's demographic characteristics		
AgroCO_2ncept	Participation (0,1)	
Education	Categorical variable (5 levels: Agricultural School, Agricultural Mastership, Agricultural technician, University or University of Applied Sciences)	
Age	Age of farmer in 2019	
Farm characteristics		
Farm size	Total agricultural land (in hectares)	
Farm type	Categorical variable (4 types: Livestock, Arable, Specialized, Others)	
Organic farming	Organic farming (0,1)	
Share of agricultural income in total income	Categorical variable (4 levels: 0-25%, 26-50%, 51-75%, 76-100%)	

2.5 Results

Almost all farmers in our sample adopt at least two of the proposed measures. The average farmer adopts 37% of the mitigation measures included in the survey and suitable to his or her farm type (Table 2.1). The share of adopted climate change mitigation measures ('Mitigation share') is most strongly correlated with farmers' non-cognitive skills, their self-assessed innovativeness, and their reported perceptions of the effectivity of the available mitigation measures (Figure 2.2). In contrast, the standard explanations for adoption decisions such as farm size, age, and education are uncorrelated with farmers' share of adopted mitigation measures.

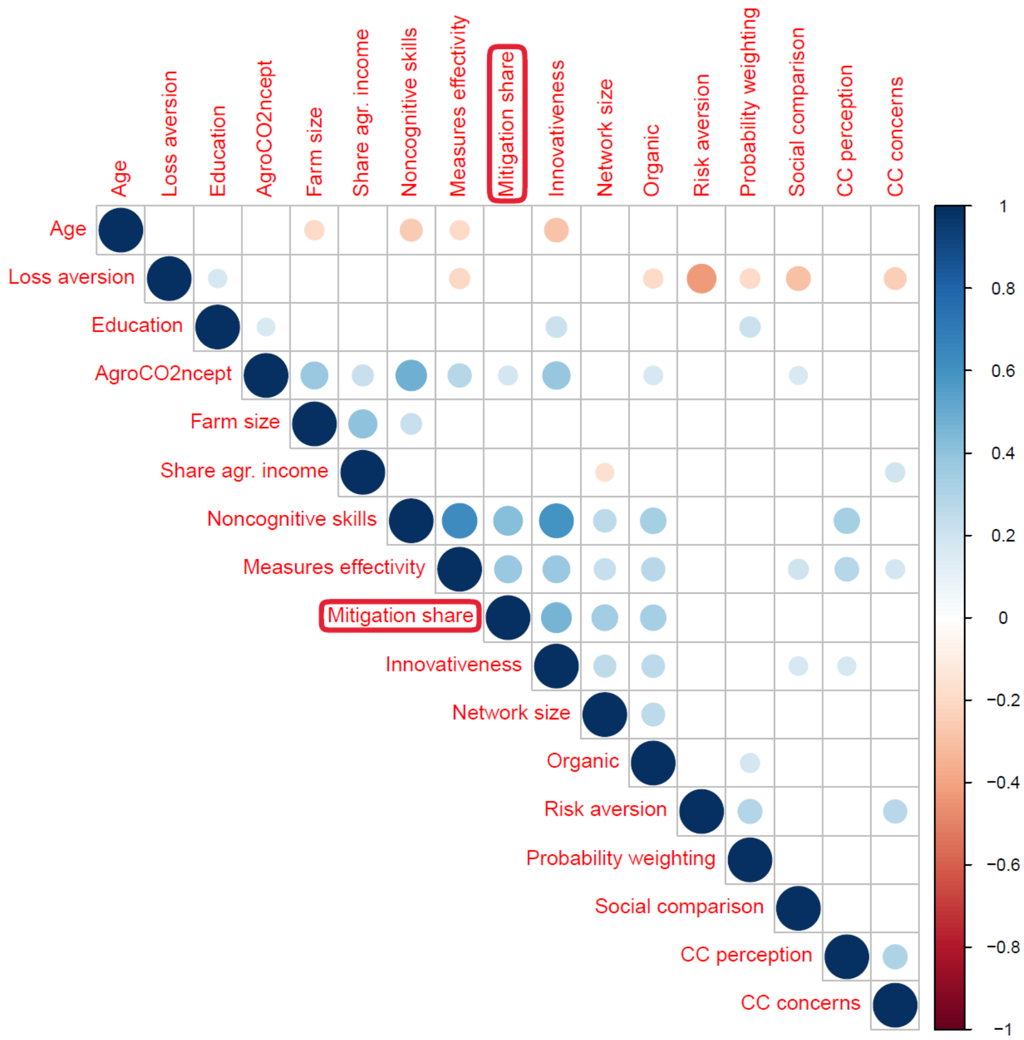

Figure 2.2: Correlation matrix: Blue and red dots signify positive and negative correlations, respectively. Size of the dots and intensity of the colour are proportional to the correlation coefficients.

The graphical overview of correlations is further explored in seven regression model specifications (Figure 2.3). In the first and second specification, we estimate the association of mitigation and non-cognitive skills without additional covariates (specification 1, Figure 2.3) and the association of mitigation and farmers' innovativeness (specification 2), respectively. In both cases, the relationship is positive and statistically highly significant. Adding a large vector of control variables to the association of mitigation and non-cognitive skills in a third and fourth specification changes the respective point estimate of non-cognitive skills and innovativeness only slightly and it remains highly significant (specifications (3) and (4)). In the fifth specification (5), we estimate the direct association of non-cognitive skills when controlling for farmers' innovativeness using the Acharya et al. (2016) approach.

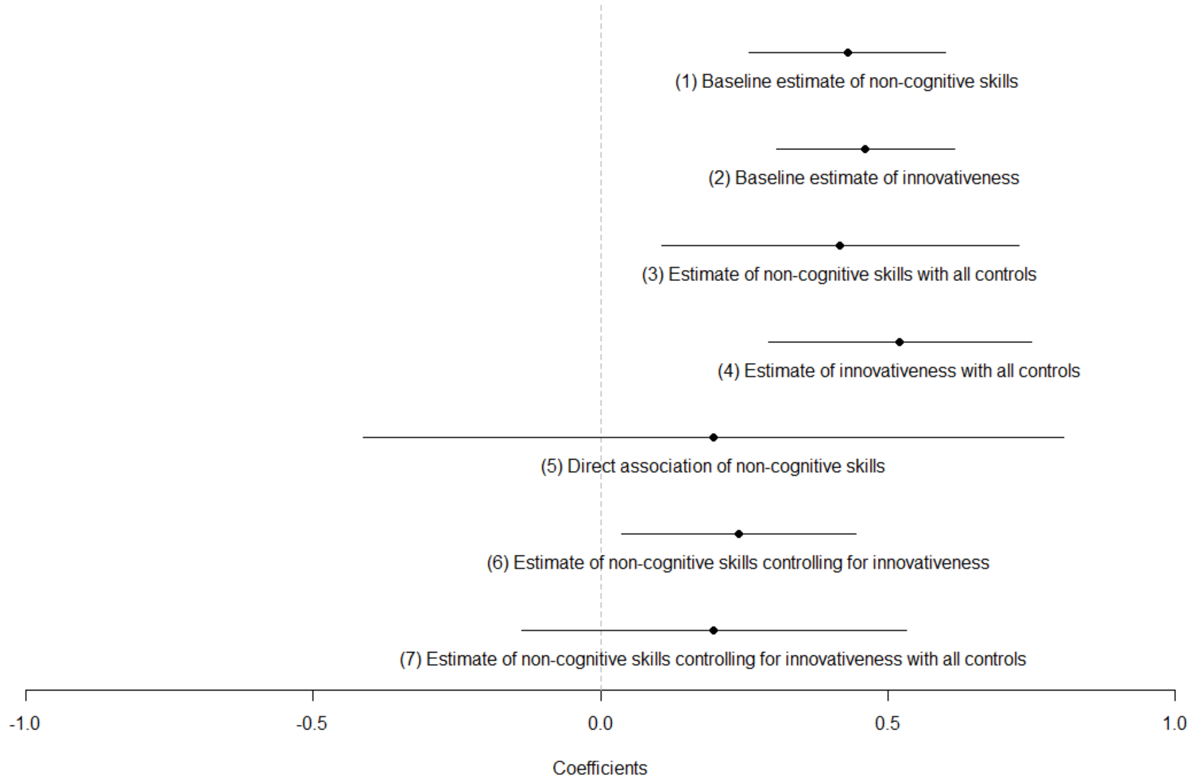

Figure 2.3: Estimated association of non-cognitive skills, innovativeness, and adoption of climate change mitigation measures. Points represent estimates, horizontal spikes the 95% confidence interval. Specifications 1, 2, 3, 4, 6 and 7 are from OLS regression, specification 5 is based on sequential g-estimation. In the baseline scenarios (1) and (2), the relationship is positive and significant. This remains the case when introducing various control variables in (3) and (4). However, when the Acharya method is applied and innovativeness is removed, the direct association between non-cognitive skills and mitigation adoption becomes insignificant (5), suggesting innovativeness as main mechanism through which non-cognitive skills are associated with mitigation uptake. When not using the Acharya method and simply adding innovativeness as another covariate in the regression (6), the association remains significant if only non-cognitive skills are considered but becomes insignificant when controlling for all covariates (7).

The association between mitigation and non-cognitive skills is no longer significant if the pathway of farmers' innovativeness is removed. This suggests that innovativeness is the main, or even sole, mechanism why farmers with higher non-cognitive skills adopt a larger share of climate change mitigation measures. For comparison, we also show the standard approach of simply including innovativeness as another covariate in the regression of mitigation on non-cognitive skills (specifications (6) and (7)) (for detailed results of the regression analyses, see Appendix A2.3).

With regard to other covariates, we see that farmers with a larger social network tend to mitigate more than those who only named few persons with whom they exchange knowledge on agricultural practices and climate change. Other personal characteristics of farmers such as climate change perceptions or concerns as well as risk preferences do not play any significant role in our specifications. The same is found for other commonly investigated factors such as farm size, farm type, education and age of the farmer. One exception is the production of specialized crops, for which we find a slightly negative association with mitigation (see Appendix A2.3).

Our results stay robust when perceived effectivity of measures (specification 8, Figure 4), participation in AgroCO$_2$ncept (specification 9), size of the social network (specification 10) or organic farming (specification 11) are excluded from the regression. The estimate of non-cognitive skills remain significant in all specifications. When we look at the subsample of livestock farmers only (specification 12), the controlled direct association of non-cognitive skills is still insignificant when innovativeness is fixed to zero, suggesting that the hypothesized mechanism is still valid when plant producers are excluded from the sample. Detailed results of the robustness tests are provided in Appendix A2.4.

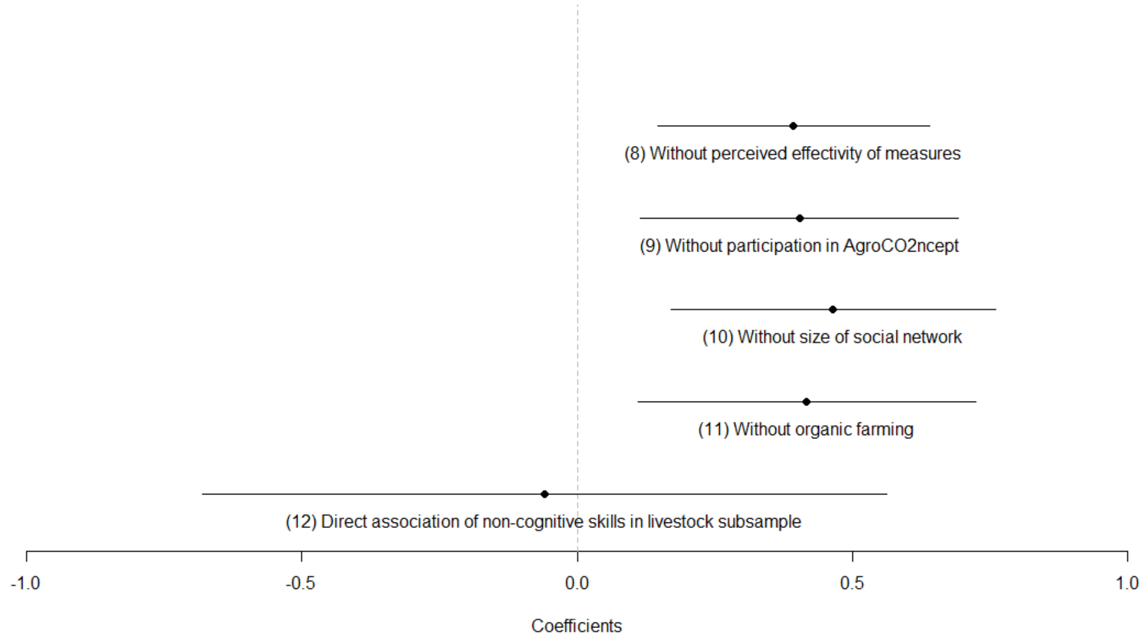

Figure 2.4: Estimated association of non-cognitive skills on adoption of climate change mitigation measures for different specifications. Points represent estimates, horizontal spikes the 95% confidence interval. Specifications 8 – 11 are from OLS regression, specification 12 is based on sequential g-estimation.

To test sensitivity towards omitted variable bias, we use the Oster bounds approach for non-cognitive skills and innovativeness (Table 2.3). We find that potentially omitted variables would need to be three times as important as the effect of our currently included covariates (Oster selection) to change our interpretation of the role of farmers' non-cognitive skills and their innovativeness. The existence of such a large omitted factor seems unlikely given our set of controls including farm and farmers' characteristics. Moreover, if we assume that selection on non-observables is equal to selection on observables (Oster estimate), we still estimate statistical associations that are quite close to our original results. In conclusion, we find that our results are highly robust to omitted variable bias, consistent with the strength of the raw correlations shown in Figure 2.2 and the coefficient stability indicated in Figure 2.4.

Table 2.3: Oster bounds

Share of mitigation measures	Innovativeness		Non-cognitive skills	
	A	B	A	B
Oster estimate	0.52	0	0.42	0
Oster selection	1	2.82	1	2.98
R^2 max	0.45	0.45	0.38	0.38

Notes: Oster estimate here refers to the estimate of the variable under the assumption that selection on non-observables is equal to selection on observables. Oster selection here refers to the maximal omitted variable bias while still resulting in the same estimate. It is expressed in relation to selection of observables.

2.6 Discussion

In this article, we provide a comprehensive empirical analysis to thoroughly test and elaborate the suggestion that farmers' non-cognitive skills affect adoption of agricultural climate change mitigation measures. We find that self-efficacy and an internal locus of control are positively associated with mitigation adoption. This adds to previous research, which has shown positive effects of non-cognitive skills on decision-making of farmers in various contexts (Abay et al., 2017; Lybbert et al., 2018; Malacarne, 2019; Marshall et al., 2016; McNairn and Mitchell, 1992; Taffesse and Tadesse, 2017; Wuepper and Lybbert, 2017; Wuepper and Sauer, 2016; Wuepper et al., 2019).

Since non-cognitive skills are difficult to measure, we used several indicator questions and a factor analysis to extract the latent construct of non-cognitive skills to counteract measurement errors from self-declaration. In addition, we developed a conceptual framework allowing us to control for the most important, potentially confounding factors such as attitudes, perceptions, and risk preferences, and quantified the likelihood that our findings are driven by omitted variable bias from factors that we did not control for (Oster, 2019). We estimate that additional variables would need to be approximately three times as important as our included control variables, i.e., farm and farmers' characteristics. Thus, our results imply that the influence of non-cognitive skills remains robust when derived from multiple dimensions and controlled by a large set of farm and farmers' characteristics.

In a broader context, our research also extends studies on pro-environmental behaviour. One factor often investigated is the role of knowledge and environmental awareness (Hines et al., 1987). However, as with many environmental challenges, there is a gap between awareness, knowledge and actual behaviour (Kollmuss and Agyeman, 2002). Our results confirm the existence of that gap, as we do not find significant effects of farmers' perception of climatic changes and climate change concerns on mitigation uptake. The confidence in one's own abilities in contributing to climate change mitigation and the general belief that one has control over one's life seem to be more important for behavioural choices than knowledge and awareness of climate change.

Findings from psychology and social science show that lack of self-efficacy and an external locus of control are important barriers to behavioural change (Mulilis and Duval, 1995). Particularly in cases of global environmental challenges, problems can seem so overwhelmingly large and complex that people tend to resign, thinking that their individual contribution is meaningless for the whole outcome. In turn, this leads to rejection of personal responsibility and is sometimes also reflected in attitudes towards mitigation (Frantz and Mayer, 2009). Against the background of climate change, high self-efficacy and strong internal locus of control beliefs are thus of even greater importance for the uptake of mitigation measures.

We also explored how non-cognitive skills are actually associated with mitigation behaviour, using an approach that avoids omitted variable bias (Acharya et al., 2016). We find that self-efficacy and locus of control are mediated by farmers' innovativeness, which is consistent with earlier literature showing a positive effect of non-cognitive skills on innovation adoption (Abay et al., 2017; Wuepper et al., 2019). As innovation here refers to the adoption of climate change mitigation measures, we see our study as a contribution to the relatively recent research on green innovativeness (Schiederig et al., 2012), which has only scarcely been investigated in the agricultural domain (Lioutas and Charatsari, 2018).

While the approach of Acharya et al. (2016) avoids omitted variable bias, innovativeness is still based on self-assessments. To some extent, self-assessed non-cognitive skills and self-assessed innovativeness could potentially be alternative measurements of the same latent construct, instead of being part of a mechanism. This clearly constitutes a limitation of our analysis. However, Social Cognitive Theory suggests that innovativeness is a mediator for non-cognitive skills and subsequent behavioural change (Bandura, 1997) which justifies our interpretation of the regression results. In addition, farmers who adopted more mitigation measures may think of themselves as more capable to effectively mitigate after their adoption choice. In our context, it is unlikely that a socio-psychological state such as the degree of non-cognitive skills is increased merely by the adoption of the mitigation measures examined here. Rather, self-efficacy and locus of control are known to be a function of long term influences such as family, social relations, culture, education and more general socio-economic context (Bandura, 1997; Cobb-Clark and Schurer, 2013; Elkins et al., 2017; Wuepper and Lybbert, 2017).

2.7 Conclusion

In this paper, we analysed survey data of 105 farmers in a region of Switzerland and investigated the relationship between non-cognitive skills and climate change mitigation. Our results suggest a strong and positive association of self-efficacy and locus of control with farmers' uptake of mitigation measures, possibly explained by differences in their innovativeness. These findings provide evidence that non-cognitive skills are important parameters to improve the understanding of farmers' decision-making processes. This is particularly important as the success of policies aiming at a reduction of agricultural GHG emissions depends on the acceptance and response of the targeted farmers.

Based on our findings, policymakers should take into account that the “innovators” among farmers are especially characterized by high non-cognitive skills, namely self-efficacy and internal locus of control. These are the farmers, who are potentially the most effective disseminators of new information about climate change mitigation measures. Moreover, our results show that also the heterogeneity of non-cognitive skills within the farm population explains heterogeneous climate change mitigation responses to policy incentives.

Particularly in an agricultural setting such as the one in this study, there is an important role for (especially young) farmers’ education and the local extension services. Given the strong association between farmers’ non-cognitive skills and their decision-making, it should be a primary aim for farming schools and extension agents to encourage farmers’ perceived self-efficacy and locus of control regarding the reduction of agricultural GHG emissions. Specific consultancy by local extension services as well as information campaigns can furthermore serve to increase the perceived effectiveness of mitigation measures (Niles et al., 2016; Wuepper and Sauer, 2016). It should be noted, however, that the largest lever to increase individuals’ non-cognitive skills is during childhood, and especially in schools (Cunha and Heckman, 2007; Cunha and Heckman, 2008).

The finding that non-cognitive skills are more important for the explanation of farmers’ behaviour than generally used factors such as age, education and farm size imply that they should be more regularly included in surveys and analyses trying to explain (non-) adoption of sustainable agricultural practices. To deepen knowledge of farmers’ adoption decisions, future research could investigate the reasons for heterogeneity in farmers’ non-cognitive skills. Moreover, testing the role of innovativeness as mediator for non-cognitive skills using panel data or even randomized control trials could add valuable insights to the existing literature. A stronger sense of internal locus of control and even self-efficacy is also enhanced by communities. Acting together with others to reach a common goal can make people feel stronger, more confident and thus less prone to denial of responsibility (Lazarus and Folkman, 1984). Even though not in the focus of this paper, we found a positive association between the size of the social network and farmers’ uptake of mitigation measures. In light of the literature on the role of community and social capital for personal responsibility assumption and behavioural change, investigating the influence of social networks on mitigation behaviour of farmers constitutes another interesting topic for future research.

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2.10 Appendix A2

A2.1: Case study background

a. Sample and regional characteristics

Our empirical research is located in a region in the northern part of the Swiss Canton of Zurich (region of Zürcher Weinland). Two main reasons make the region particularly interesting for our research purposes: First, diverse farm types are represented, covering main agricultural production in Switzerland, namely dairy and meat production as well as pure arable farming and specialized crops such as viticulture, fruits and vegetables. The majority of farmers in our sample keeps livestock while roughly 30 percent produce arable crops or specialized crops only. Around nine percent do not fit into these categories and produce other products. 11 percent produce according to the standards of the Swiss organic regulation, which is less than the regional (13 percent) and the Swiss average (14 percent) (BFS, 2019). Mean farm size is 29.4 hectares (ha), which corresponds to the regional average (29.1 ha) but is larger than the overall Swiss average (21 ha) (BFS, 2019).

A second reason for the choice of case study region is the fact that the first farmers' initiative to actively mitigate agricultural GHG emissions in Switzerland is located here. Within the state-funded resource project "AgroCO_2ncept Flaachtal", farmers collaborate to collectively reduce emissions on farm and regional level (AgroCO_2ncept, 2016). In our sample, almost 23 percent of farmers participate in the climate initiative AgroCO_2ncept Flaachtal.

b. Climate change and agriculture in Switzerland

In Switzerland, agricultural production is responsible for approximately 10 - 14 % of total GHG emissions. Main sources are methane from enteric fermentation of cattle, nitrous oxide from fertilizer, land use changes and carbon dioxide from fuel and energy use (BAFU, 2017; IPCC, 2014). Part of the Swiss national climate policy, which aims to reduce its net carbon emissions to zero by 2050 (BR, 2019), the "Climate Strategy for Agriculture" aims at a reduction of agricultural GHG emissions compared to the level of 1990 by at least 30 percent until 2050 (BLW, 2011). Thus, effective mitigation strategies are needed for a sustainable agricultural production.

While only little experience has been gained in practical GHG reduction in Swiss agriculture, farmers in Switzerland get direct payments for specific measures to reduce emissions. However, these are often only indirectly targeted at climate change mitigation. As an example, payments for emissions reducing application techniques were mainly introduced to reduce ammoniac emissions from agriculture (DZV, 2019). Moreover, farmers can apply for so-called resource projects by which e.g., the reduction of GHG emissions by a group of farmers or in a specific region can get support from the Swiss Federal Office for Agriculture (BLW, 2018).

A2.2: Factor analyses

We conducted factor analyses to create variables consisting of several items. Based on a correlation matrix, we calculate one factor and use the Bartlett method to estimate factor score coefficients. The uniqueness of each item describes its unique variance, which is not shared with the other items. The eigenvalue is the amount of variance explained by the factor. Cronbach's alpha is a measure of reliability of the factor.

Non-cognitive skills

The factor analysis of non-cognitive skills combines two questions on self-efficacy and three questions on locus of control.

Item	**Factor score non-cognitive skills**	**Uniqueness**
I can do something against climate change by reducing GHG emissions on my farm.	0.88	0.23
My behaviour as a farmer influences climate change.	0.67	0.55
How successful I can reduce GHG emissions on my farm depends primarily on my farming skills.	0.50	0.75
I am confident that I can reduce GHG emissions and at the same time produce successfully.	0.71	0.50
Climate change is a problem I cannot do anything about.	0.60	0.65
Eigenvalue	2.78	
Cronbach's Alpha	0.80	

Innovativeness

The factor analysis of innovativeness combines five questions on how innovative the farmer sees him- or herself.

Item	**Factor score innovativeness**	**Uniqueness**
I consider myself a pioneer in climate protection and adopt mitigation measures even under economic risks.	0.61	0.63
I am willing to implement mitigation measures earlier than other farmers in my region.	0.88	0.23
I am open towards climate mitigation but I want to think through all aspects before. I draw on the experience of other farmers.	0.28	0.92
I will only adopt mitigation measures if they have been tested by other farmers before.	0.29	0.92
I rely on my well-tried experiences. Implementing mitigation measures is economically too risky to me.	0.66	0.57
Eigenvalue	2.22	
Cronbach's Alpha	0.66	

Social comparison

The factor analysis of social comparison combines six questions on superiority need of farmers, comparison with others and the importance placed on others' opinions.

Item	**Factor score social comparison**	**Uniqueness**
It is important to me to impress other farmers with my work.	0.73	0.46
I feel affirmed when my income is higher than that of other farmers.	0.53	0.72
I want to produce more climate- and ecofriendly than other farmers in the region.	0.22	0.95
It bothers me if other farmers generate a higher income than I do.	0.26	0.93
If other farmers adopt mitigation measures, I want to implement them, too.	0.38	0.86
How important is to you what others think of your professional success and your farming skills?	0.72	0.49
Eigenvalue	2.32	
Cronbach's Alpha	0.66	

Climate change perception

The factor analysis of climate change perception combines six questions on experiences of different weather extremes over the past ten years.

Item	**Factor score climate change perception**	**Uniqueness**
How often have you experienced extreme weather events over the past 10 years (hail)?	0.44	0.81
How often have you experienced extreme weather events over the past 10 years (heat waves)?	0.75	0.44
How often have you experienced extreme weather events over the past 10 years (heavy rain)?	0.41	0.83
How often have you experienced extreme weather events over the past 10 years (long rainy periods)?	0.25	0.94
How often have you experienced extreme weather events over the past 10 years (frost in spring or autumn)?	0.32	0.90
How often have you experienced extreme weather events over the past 10 years (droughts)?	0.72	0.49
Eigenvalue	2.15	
Cronbach's Alpha	0.63	

A2.3: Detailed results of regression analysis

	(1) Baseline model non-cognitive skills	(2) Baseline model innovativeness	(3) Model with all controls except innovativeness	(4) Model with all controls except for non-cognitive skills	(5) Direct association of non-cognitive skills	(6) Baseline model non-cognitive skills controlling for innovativeness	(7) Model with all controls including innovativeness
Non-cognitive skills	0.43 ***		0.42 ***		0.20	0.24 **	0.20
	(0.09)		(0.16)		(0.31)	(0.10)	(0.17)
Innovativeness		0.46 ***		0.52 ***		0.32 ***	0.44 ***
		(0.08)		(0.11)		(0.09)	(0.13)
CC perception			-0.17	-0.14	-0.17		-0.17
			(0.11)	(0.10)	(0.10)		(0.10)
CC concerns			0.18	0.26 **	0.25		0.25 **
			(0.11)	(0.10)	(0.10)		(0.10)
Perceived effectivity of measures			-0.04	0.00	-0.07		-0.07
			(0.13)	(0.12)	(0.13)		(0.13)
Network size			0.23 **	0.22 **	0.21 *		0.21 *
			(0.11)	(0.11)	(0.11)		(0.11)
Social comparison			0.11	0.04	0.06		0.06
			(0.12)	(0.11)	(0.11)		(0.11)
Loss aversion			0.19	0.11	0.12		0.12
			(0.12)	(0.13)	(0.13)		(0.12)
Risk aversion			-0.01	-0.19 *	-0.16		-0.16
			(0.11)	(0.11)	(0.10)		(0.11)
Probability weighting			0.09	0.17 *	0.16		0.16
			(0.11)	(0.10)	(0.10)		(0.10)
Participation AgroCO_2ncept			-0.09	-0.23	-0.29		-0.29
			(0.26)	(0.27)	(0.27)		(0.27)
Organic farming			0.28	0.04	0.02		0.02
			(0.41)	(0.42)	(0.43)		(0.43)
Education			0.02	-0.08	-0.06		-0.06
			(0.11)	(0.11)	(0.10)		(0.11)
Age			-0.07	0.00	0.00		0.00
			(0.09)	(0.09)	(0.09)		(0.10)
Farm size			-0.08	0.09	0.05		0.05
			(0.09)	(0.08)	(0.09)		(0.09)
Type Livestock			-0.17	-0.16	-0.17		-0.17
			(0.30)	(0.27)	(0.26)		(0.26)
Type Others			-0.70	-0.90 **	-0.93 **		-0.93 **
			(0.49)	(0.41)	(0.41)		(0.42)
Type Specialized Crops			-1.05 ***	-1.31 ***	-1.28 ***		-1.28 ***
			(0.36)	(0.38)	(0.34)		(0.36)
Share agr. income			0.08	0.03	0.04 ***		0.04
			(0.12)	(0.11)	(0.11)		(0.10)
N	105	105	82	82	82	105	82
Adjusted R^2	0.18	0.21	0.37	0.45	0.31	0.25	0.46

All continuous predictors are mean-centered and scaled by 1 standard deviation. Standard errors are heteroskedasticity robust. In model (5), standard errors are manually adapted according to variance estimator by Acharya et al., 2016. The number of observations (N) changes due to missing data in certain census data.
*** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$.

A2.4: Robustness checks for various specifications

	(8) Model without effectivity of measures	(9) Model without participation in AgroCO2ncept	(10) Model without size of social network	(11) Model without organic farming	(12) Direct association of non-cognitive skills for livestock subsample
Non-cognitive skills	0.39 ***	0.40 ***	0.46 ***	0.42 ***	-0.11
	(0.12)	(0.14)	(0.15)	(0.15)	(0.40)
CC perception	-0.17	-0.17	-0.19	-0.17	-0.09
	(0.11)	(0.11)	(0.12)	(0.11)	(0.13)
CC concerns	0.17	0.17	0.14	0.16	0.09
	(0.11)	(0.11)	(0.12)	(0.11)	(0.14)
Perceived effectivity of measures		-0.04	0.00	-0.03	0.13
		(0.13)	(0.14)	(0.13)	(0.18)
Network size	0.22 **	0.23 **		0.24 **	0.23
	(0.11)	(0.11)		(0.11)	(0.11)
Social comparison	0.10	0.11	0.15	0.11	-0.10
	(0.11)	(0.12)	(0.12)	(0.12)	(0.15)
Loss aversion	0.19	0.19	0.23	0.17	0.05
	(0.12)	(0.12)	(0.14)	(0.12)	(0.15)
Risk aversion	0.00	-0.01	0.06	0.00	-0.08
	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)
Probability weighting	0.09	0.10	0.08	0.10	0.24
	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)
Participation AgroCO2ncept	-0.09		-0.12	-0.09	0.03
	(0.26)		(0.29)	(0.26)	(0.31)
Organic farming	0.27	0.28	0.36		0.13
	(0.40)	(0.41)	(0.42)		(0.35)
Education	0.01	0.01	0.01	0.00	-0.03
	(0.11)	(0.11)	(0.13)	(0.11)	(0.12)
Age	-0.07	-0.07	-0.08	-0.08	-0.07
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Farm size	-0.07	-0.09	-0.09	-0.10	0.04
	(0.09)	(0.09)	(0.10)	(0.09)	(0.29)
Type Livestock	-0.15	-0.16	-0.07	-0.11	
	(0.29)	(0.30)	(0.31)	(0.29)	
Type Others	-0.68	-0.69	-0.61	-0.69	
	(0.48)	(0.48)	(0.46)	(0.49)	
Type Specialized crops	-1.04 ***	-1.05 ***	-1.00 **	-0.90 ***	
	(0.33)	(0.36)	(0.40)	(0.34)	
Share agr. income	0.08	0.08	0.03	0.08	0.18
	(0.12)	(0.12)	(0.11)	(0.12)	(0.15)
N	83	101	101		70
Adjusted R2	0.37	0.36	0.31		0.22

All continuous predictors are mean-centered and scaled by 1 standard deviation. Standard errors are heteroskedasticity robust. In model (12), standard errors are adapted according to variance estimator by Acharya et al., 2016.
*** p < 0.01; ** p < 0.05; *p < 0.1

A2.5 References

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Chapter 3: Farmers' social networks and regional spillover effects in agricultural climate change mitigation[6]

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Abstract

Climate change poses a severe threat to global agricultural production and rural livelihoods, and since agriculture itself is a significant source of greenhouse gas (GHG) emissions, it can also play an important role in climate change mitigation. This article investigates how farmers' social networks influence the adoption of on-farm mitigation strategies. More precisely, we use a network autocorrelation model to explore the relationship between a farmer's own mitigation behavior and the mitigation behavior and knowledge of his fellow farmers. The analysis is based on a regional case study in Switzerland and uses data obtained from personal network interviews combined with survey and census data of 50 farmers. Half of them are members of a local collective action initiative for agricultural climate change mitigation while the others do not participate in the initiative. We find that, on average, farmers with a larger network adopt more mitigation measures and furthermore mitigation adoption is linked with the level of knowledge within farmers' networks. Indeed, the likelihood that non-members will adopt mitigation measures increases if they are closely associated with members of the collective action, suggesting a local spillover effect. It follows that strengthening knowledge exchange amongst farmers and supporting local farmers' initiatives can potentially contribute to the diffusion of agricultural climate change mitigation practices.

Keywords

Climate change, mitigation, agriculture, social networks, knowledge exchange, network autocorrelation models

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3.1 Introduction

Global agricultural production is a major source of anthropogenic greenhouse gas (GHG) emissions (IPCC 2019). Consequently, since successful climate change mitigation depends primarily on the reduction of these emissions, it has become a major concern for policymakers and scientists (OECD 2013). Many countries have introduced emission reduction targets for their agricultural sector under the UN Framework Convention on Climate Change (Fellmann et al. 2018; Richards et al. 2016). However, successful GHG mitigation means that farmers must actively change and adapt their practices, for example, by adopting climate friendly practices in the on-farm management of livestock, crops, or energy utilization (Smith et al. 2008). Thus, a broad-based understanding of farmers' decision-making processes is crucial for effective mitigation and appropriate policy design.

In this article, we seek to enhance this understanding by focusing on the impact of social networks on farmers' decision-making regarding the adoption of on-farm mitigation practices. More precisely, we use a Swiss case study to investigate the link between the mitigation behavior and knowledge of socially well-connected farmers and the individuals' adoption of respective practices.

Previous research has shown that social networks influence farmers' decisions in various fields. The key assumption is that new technologies or practices spread through social learning, i.e., knowledge based on observation and interaction with peers and neighbors (e.g., Šūmane et al. 2018), also referred to as spillover or neighborhood effect (e.g., Vroege et al. 2020). For example, social relations influence the occurrence of farmers' entrepreneurship (Fitz-Koch et al. 2018) and affect decisions relating to multiple land use, innovation, and technology (e.g., Bandiera and Rasul 2006; Krishnan and Patnam 2014; Matuschke and Qaim 2009;). Several scholars found that social networks impact the adoption of agri-environmental measures (e.g., Riley et al. 2018; Skaalsveen et al. 2020; van Dijk et al. 2015, 2016) and conversion to organic agriculture (e.g., Läpple and Kelley 2015; Wollni and Andersson 2014). The existing literature has focused mainly on so-called endogenous network effects (Bandiera and Rasul 2006; Manski 2000), i.e., how farmers learn from observing the experiences of others and base their decisions on the behavior of their peers. Since data is limited, very few studies have investigated exogenous network effects, namely the impact of certain peer attributes, e.g., age, education, etc., on farmers' behavior (Keil et al. 2017; Matuschke and Qaim 2009; Murendo et al. 2018).

Recently, evidence has been found indicating positive peer influence on farmers' uptake of climate change adaptation measures (Di Falco et al. 2020). However, the role of farmers' social networks in the adoption of climate change mitigation remains largely unexplored. In particular, no study has yet investigated exogenous network effects in the context of mitigation. This constitutes an important research gap since GHG reduction practices are still relatively new to most farmers, thus making knowledge sharing and social learning particularly important, also from a policy angle. Furthermore, social networks are of great relevance for agricultural mitigation practices as they can help to promote cooperation between farmers (IPCC 2014; OECD 2012). This is essential since collaboration between farmers can reduce marginal costs of mitigation, which are usually high in the agricultural sector. For instance, economies of scale facilitate investment decisions (Bouamra-Mechemache and Zago 2015; Hodge and McNally 2000), and social learning can reduce the costs of knowledge acquisition. The coordination of land use and field operations potentially leads to efficient mechanisms for mitigation. In fact, farmers' collective action and "grassroots" innovationsFootnote1 can serve as an example to others and spread to a wider region. Up until now, the spillover effects of collective action for sustainable development have been viewed from a rather general viewpoint or in different contexts, such as local low-impact housing, renewable energy production, or car-sharing (e.g., Ornetzeder and Rohracher 2013; Smith and Seyfang 2013), and research on the spillover effects of collective action in agriculture is very limited (Vaiknoras et al. 2020).

Our research contributes to this literature by exploring the characteristics of farmers' personal networks with regard to exchange of knowledge related to agricultural climate change mitigation and their association with the actual uptake of mitigation measures. Our research aims to assess the role of farmers' cooperation and collective action in the context of agricultural climate change mitigation, which constitutes a key challenge facing the agricultural sector. We apply a network autocorrelation model to study potential network influence processes and local spillover effects of a farmers' climate protection initiative. We thereby account for the strength and type of relationships, as well as specific, relevant characteristics of network members. More specifically, we use a Bayesian approach which allows us to model multiple influence processes and compare them simultaneously (Dittrich et al. 2020). Control variables such as age, education, farm type, or perceived self-efficacy are used at the individual farmer level to account for possible correlated effects which do not reflect social interactions (Kreft et al. 2021a, 2021b; Wuepper et al. 2019). Our analysis is based on a combination of census, survey, and detailed network data. The latter was obtained through tablet-based face-to-face interviews with 50 farmers in a Swiss region.

Our main contributions are threefold: Firstly, we investigate how social learning among connected farmers influences the adoption of on-farm climate change mitigation measures. Secondly, we assess how the presence of climate change mitigation knowledge within farmers' personal social networks affects their adoption decisions. Thirdly, we explore how the spillover of a local farmers' collective climate protection action group influences the adoption of mitigation measures in the wider region. Our results help to deepen the understanding of farmers' adoption decisions in the context of agricultural climate change mitigation and highlight the role of social networks. This can help to inform policymakers when deciding upon effective and efficient policy instruments to incentivize climate friendly agriculture.

The remainder of this article is as follows: Section 2 provides the theoretical background on farmers' social networks and adoption of agricultural climate change mitigation as well as the hypotheses tested in this article. Section 3 introduces the autocorrelation model used for assessing the associations between certain network characteristics and mitigation adoption. Section 4 describes the case study followed by Section 5, which presents data and data collection. Section 6 contains descriptive and estimation results and is followed by a discussion in Section 7 and conclusions in Section 8.

3.2 Theoretical background and conceptual framework

Our conceptual framework is based on the social network theory (Borgatti and Ofem 2010) and the concept of social learning (Foster and Rosenzweig 1995) whereby it is assumed that individual behavior is influenced by interaction with peers, also referred to as herd behavior, spillover, neighborhood, or peer effect (e.g., Granovetter 1978). Three possible network effects can be identified: endogenous effects (impact of network members' behavior), exogenous effects (impact of network members' characteristics), and correlated effects (resemblance between individual's behavior and that of their network due to similar environment, e.g., access to the same extension service) (Keil et al. 2017; Manski 2000). The first two effects can, to some extent, be explained by social learning, essentially defined as learning by observing others and interacting with them.

3.2.1 The role of social networks in farmers' adoption behavior

The analysis of farmers' social networks and social learning has emerged as a key tool for understanding adoption decisions. In general, close ties to other farmers facilitate knowledge spillovers and information flow related to new agricultural technologies, such as improved seeds and varieties (e.g., Conley and Udry, 2010; Krishnan and Patnam, 2014) or knowledge intensive practices such as no-tillage farming (e.g., Ingram, 2010; Skaalsveen et al., 2020).

However, whether and how social learning actually occurs, depends on many factors such as the complexity of the technology (Wuepper et al., 2017), heterogeneity of farming conditions (Munshi, 2004), number of adopters (Bandiera and Rasul, 2006), or structure of the network. For example, centralized networks and links to key actors are found to facilitate the rapid diffusion of information (Peres, 2014). Since most farmers prefer to seek advice from key network members rather than from less connected colleagues, core-periphery network structures are often observed, i.e., farmers who are less connected most frequently approach a small group of socially well-connected key farmers when seeking advice (Isaac et al., 2007). Generally, a dense, widely connected network promotes successful collaboration (Bodin and Crona, 2009). At the same time, relations to disparate groups might provide novel information and thus encourage innovation (Levy and Lubell, 2017).

To date, there are few studies which focus on both endogenous network effects and the potential exogenous effects of farmers' social networks (Matuschke and Qaim, 2009; Murendo et al., 2018). Only one study found evidence that network members' characteristics (namely education level) influence individual farming behavior (adoption of no-till practices) (Keil et al., 2017). However, the influence of exogenous effects on adoption decisions might depend on the specific situation and technologies.

3.2.2 *Agricultural climate change mitigation and farmers' collective action*

Farmers' collective action is increasingly recognized as an important approach to the management of agri-environmental problems (Bamière et al., 2013; Dupraz et al., 2009; Mills et al., 2011; Prager, 2012; 2015; Vanni, 2013). Similarly, it could also enhance effective strategies for agricultural climate change mitigation. Firstly, a single farmer's efforts are simply not enough to reduce GHG emissions to any significant extent (OECD, 2012, 2013). Secondly, GHG reduction is assessed as a classic collective action problem including challenges, such as freeriding, which can be overcome by farmers' collaboration (Agarwal and Dorin, 2017; Ostrom, 1990; Stallman, 2011). Given that climate change mitigation often involves new and unfamiliar measures, the role of knowledge exchange within farmers' networks is particularly important and can potentially shape perceptions on costs, risks and benefits of mitigation. Moreover, this learning and knowledge sharing can spread beyond the scope of the collective action scheme through ties between members and non-members (Bernard and Spielman, 2009; Ornetzeder, 2001).

3.2.3 *Hypotheses: Network effect, knowledge diffusion and collective action spillover*

Based on the theory outlined above and findings from previous empirical research, we derive three hypotheses (Appendix A3.1):

1. **Endogenous network effect hypothesis (H1):** Farmers' adoption of mitigation strategies is positively associated with strong social ties to other farmers who have adopted mitigation practices.

2. **Knowledge diffusion hypothesis – exogenous effect (H2):** Farmers' adoption of mitigation strategies is positively associated with strong social ties to farmers they deem to be knowledgeable about agricultural climate change mitigation.

3. **Collective action spillover hypothesis (H3):** Farmers' adoption of mitigation strategies is positively associated with ties to farmers participating in a collective action scheme to reduce agricultural GHG emissions.

3.3 Methods

All of our hypotheses describe social influence processes linking network structure (exchange relations of farmers) with individual level traits (adoption of mitigation strategies). An inherent feature of analyzing social influence processes in networks is that it cannot be assumed that the traits of interest (the dependent variable, here farmers' adoption of mitigation strategies) are independent from each other. In fact, we explicitly want to study how the expression of a dependent variable y_i of an actor i is associated with its expressions y_j, y_k in an actor's network contacts j and k. Therefore, we test our hypotheses using a network autocorrelation model (Dittrich et al., 2020).

Network autocorrelation models are an extension of normal regression models, which integrate one or more network autocorrelation parameter capturing the processes through which we assume network influence to occur. The network autocorrelation is estimated by specifying one or multiple weight matrices W to capture our theoretical models of influence relations. These weight matrices are used to add a weighted sum of attributes for an actor's network neighbors to the linear predictor of the regression model for each actor. For a single influence process acting through W, with g actors in a network, the model can be written as:

$$y = \rho W y + X\beta + \epsilon, \epsilon \sim N(0g, \sigma 2Ig) \quad (1)$$

where ρ is the network autocorrelation parameter capturing the strength of the network influence process. X is a covariate matrix as in a standard linear regression (capturing other, actor-level covariates that the model adjusts for) with associated regression coefficients in the β vector. The error terms are assumed to be independent and identically distributed[7].

We use a recently proposed, new Bayesian implementation of the network autocorrelation framework (Dittrich et al., 2020) that allows us to test our hypotheses by simultaneously estimating parameters relating to the strength of different autocorrelation processes occurring within four sub-networks of the overall network. Testing our hypotheses within this framework implies the use of four different model specifications.

The first model, corresponding to equation (1) (simple network influence), is a first-order network autocorrelation model containing a single network weight matrix to estimate network autocorrelation understood as a single process acting uniformly throughout the whole network. If we choose a weight matrix W to measure relations among farmers and the strength of these relations, an initial test of H1 can be carried out based on the resulting posterior distribution of ρ.

The second model, corresponding to equation (2), adds the coefficient $\beta_{net\_knowledge}$ estimating the association between the aggregated knowledge of network contacts about climate change mitigation and farmers' mitigation behavior. The model still uses the form described in (1) and the coefficient is estimated based on a variable in the covariate matrix X. The posterior distribution of $\beta_{net\_knowledge}$ allows for a test of H2.

$$y = \rho W y + X\beta \ + x\beta_{net_{knowledge}} * \beta_{net_{knowledge}} + \epsilon, \epsilon \sim N(0g, \sigma 2Ig) \quad (2)$$

The third model is a fourth-order network autocorrelation model (3), which assumes different strengths of network autocorrelation within and between collective action participants and non-participants. To this end, the adjacency matrix W is rearranged into four weight matrices $W_{aa}, W_{ab}, W_{bb}, W_{ba}$, which only contain entries on their respective process of interest and are separately row-standardized (Dittrich

[7] Note that there is an alternative variant of the model in which autocorrelation is modelled by specifying autocorrelation in the error terms and which has a slightly different interpretation (see e.g., Leenders (2002)).

et al., 2020). W_{aa} denotes the sub-network of relations among participants, W_{bb} among non-participants, W_{ab} and W_{ba} indicate an exchange between groups.

With the collective action participants as a network subgroup a and non-participants as subgroup b, the model takes the form:

$$y = \begin{bmatrix} y_a \\ y_b \end{bmatrix} = \begin{bmatrix} \rho_{aa}W_{aa} & \rho_{ab}W_{ab} \\ \rho_{ba}W_{ba} & \rho_{bb}W_{bb} \end{bmatrix} \begin{bmatrix} y_a \\ y_b \end{bmatrix} + X\beta + \varepsilon$$

$$= \left(\rho_{aa} \begin{bmatrix} W_{aa} & 0 \\ 0 & 0 \end{bmatrix} + \rho_{bb} \begin{bmatrix} 0 & 0 \\ 0 & W_{bb} \end{bmatrix} + \rho_{ab} \begin{bmatrix} 0 & W_{ab} \\ 0 & 0 \end{bmatrix} + \rho_{ba} \begin{bmatrix} 0 & 0 \\ W_{ba} & 0 \end{bmatrix} \right) \begin{bmatrix} y_a \\ y_b \end{bmatrix} + X\beta + \varepsilon \, , \tag{3}$$

where y_a and y_b contain values of the dependent variable (adoption of mitigation practices) for participants and non-participants, respectively. The associated network autocorrelation ρ_{aa}, ρ_{bb}, ρ_{ab}, ρ_{ba} are measures for the strength of autocorrelation within and between these sub-networks. When combined, they constitute a more differentiated test of H1, relaxing the assumption of a homogeneous network influence process. Further, ρ_{ba} is a measure for the strength of autocorrelation acting on values y_b of non-participants based on their relations to collective action participants. The posterior distribution of ρ_{ba}thus tests for H3, the collective action spillover hypothesis.

The fourth model includes $\beta_{net\_knowledge}$ to assess the extent to which the collective spillover effect might be due to unevenly distributed knowledge throughout the sub-networks and vice versa. This can be tentatively assessed in the change in ρ_{ba} after adjusting for $\beta_{net\_knowledge}$. The adjusted model takes the following form:

$$y = \begin{bmatrix} y_a \\ y_b \end{bmatrix} = \begin{bmatrix} \rho_{aa}W_{aa} & \rho_{ab}W_{ab} \\ \rho_{ba}W_{ba} & \rho_{bb}W_{bb} \end{bmatrix} \begin{bmatrix} y_a \\ y_b \end{bmatrix} + X\beta + x\beta_{net_{knowledge}} * \beta_{net_{knowledge}} + \varepsilon$$

$$= \left(\rho_{aa} \begin{bmatrix} W_{aa} & 0 \\ 0 & 0 \end{bmatrix} + \rho_{bb} \begin{bmatrix} 0 & 0 \\ 0 & W_{bb} \end{bmatrix} + \rho_{ab} \begin{bmatrix} 0 & W_{ab} \\ 0 & 0 \end{bmatrix} + \rho_{ba} \begin{bmatrix} 0 & 0 \\ W_{ba} & 0 \end{bmatrix} \right) \begin{bmatrix} y_a \\ y_b \end{bmatrix} + X\beta + x\beta_{net_{knowledge}} * \beta_{net_{knowledge}} + \varepsilon \tag{4}$$

All models were fit using the code provided in Dittrich (2020), which implements a Metropolis-Hastings algorithm to obtain the posterior distribution of model parameters in the statistical programing environment R (R Core Team, 2021). We used a recommended (multivariate) normal prior distribution with a mean of 0.1 and standard deviation of 1 for the network autocorrelation parameters and uninformative priors for all other parameters. We evaluated the model based on 5000 draws from the posterior (with a burn-in of 100 for the Metropolis-Hastings algorithm). All code and anonymized data needed to replicate the analysis, as well as additional sensitivity checks, can be accessed in a public, open repository under https://doi.org/10.5281/zenodo.7401318.

3.4 Case study

Our case study is located in the northern part of Canton Zurich in Switzerland. Agricultural production is quite diverse and ranges from dairy and meat production to arable crops, viticulture, fruit, and vegetables (Kreft et al. 2021a). The region is home to the farmers' initiative AgroCO2ncept Flaachtal, which aims to collectively reduce agricultural GHG emissions.Footnote3 It is currently one of very few examples of collective climate change mitigation in agriculture. The project was founded in 2011 in a bottom-up process on the initiative of a single farmer, who was able to convince some colleagues to collaboratively reduce agricultural GHG emissions. Strategies for on-farm climate change mitigation were elaborated with the help of agricultural experts and extension services. In spring 2012, the project was opened for the participation of more farms. Since 2016, the Swiss Federal Office for Agriculture supports AgroCO2ncept, guaranteeing financial support during 6 years for a maximum of 30 participating farms (BLW 2018). Participation is independent of farm type, farming system, or current emission level. At present, 25 farmers on 23 farms (two farms have multiple owners/managers) participate actively in AgroCO2ncept.Footnote4 The declared goal of AgroCO2ncept is to achieve a 20% reduction in the aggregated overall GHG emissions from participating farms by 2022 as compared to 2016. This refers to an amount of 4500 t of CO2-equivalents mitigated by the end of the 6-year project period. The project comprises a focus on 39 measures in different fields, i.e., crop production (14 measures), livestock farming (12), and energy use (13) (Kreft et al. 2020). When a farm joins the project, its current emission levels are assessed (status-quo assessment), and the farmer then receives extensive advisory service to choose the mitigation measures best suited to the farm's specific structures and needs. The farmer receives a compensatory payment for each mitigation measure implemented. This procedure is designed to ensure mitigation efficiency tailored to the individual farm as no measures are stipulated and farmers can choose those most appropriate for their farm.

AgroCO2ncept aims to prove that practical on-farm climate change mitigation has large potential for an effective reduction of GHG emissions in the agricultural sector. The initiative seeks to set an example for other farmers in the region and beyond. The central idea is that mitigation in agriculture cannot be achieved by single measures implemented by individual farmers but demands collective action and aggregated reduction targets beyond the single farm level. At the same time, mitigation should not result in productivity or income losses (AgroCO2ncept 2016). AgroCO2ncept embodies the characteristics of a local collective action scheme based on social ties among farmers and is perfectly suited as a case study for the hypotheses we want to test in this article.

3.5 Data collection and variables

3.5.1 Data collection

We interviewed 50 farmers, 25 of whom participate in the AgroCO2ncept initiative and 25 non-participants located in the same region. The 25 non-participating farmers were chosen based on their proximity to the region of Flaachtal, where most of the AgroCO2nept farmers are located[8].

Interviews were structured and conducted based on a questionnaire. The interviews took place in November and December 2019. They lasted between 20 and 40 minutes and were carried out on site by four trained interviewers. The questions were asked and simultaneously shown to the respondents on a tablet. Answers were directly entered via touch screen by the respondent or the interviewer.

We created the interview protocol using the newly developed digital network survey tool Network Canvas (https://networkcanvas.com). It is a free and open-source software designed to collect network data in a partly participatory way through intuitive and appealing visualizations and touch screen applications (Complex Data Collective 2016). This can help to make interviews less tedious and also reduces respondent burden (e.g., Eddens et al. 2017). Moreover, as the interviewees could enter certain answers themselves, particularly those related to potentially sensitive network information, it was possible to reduce the effects of social desirability and satisficing, which can lead to data inaccuracy (Perry et al. 2018). Structure, user-friendliness, and understanding of the interview questionnaire were pre-tested with three social network experts and six students of agricultural sciences.

The questionnaire contained 29 questions for AgroCO2ncept participants and 25 questions for non-participants and included the following sections: (i) personal characteristics of the respondent, (ii) agricultural climate change mitigation on the respondent's farm, (iii) rosterFootnote6 and name generator questions to identify other farmers (alters) with whom the respondent communicates on agricultural climate change mitigation, including frequency of these exchanges, (iv) attributes of named alters (name interpreter), (v) relations among the named alters (alter-alter relations), and (vi) influential alters, based on the respondent's perception. An additional roster containing the names of all AgroCO2ncept members was presented to non-participants to assess the contact between non-participants and participants.

The complete questionnaires, all resulting data sets plus the codebooks explaining the variables, are available in Kreft et al. (2021b) and freely accessible on the ETH Research Collection: https://www.research-collection.ethz.ch/handle/20.500.11850/458053.

We supplemented the tablet-based interview data by incorporating data from previous work. We were able to match the data of 46 of the 50 interviewees with existing data from a larger survey on farmers' adoption of climate change mitigation measures and behavioral characteristics such as climate change

[8] Appendix A3.2 shows a map with the spatial location of the interviewed farms.

concerns and non-cognitive skills, as well as census data on farm structures and demographics (Kreft et al. 2020).

3.5.2 Variables

Table 3.1 gives an overview of the variables used in our analysis as well as their summary statistics within our sample. More precisely, it shows the dependent variable of mitigation adoption, the relevant network variables as well as all additional covariates, i.e., farmers' behavioural characteristics, demographics and farm structural characteristics. Details relating to the covariates included are presented in Appendix A3.4.

Table 3.1: Overview and summary statistics of variables included in the model

Variable	Variable specification	Total sample	Farmers participating in AgroCO$_2$ncept	Farmers not participating in AgroCO$_2$ncept
Number respondents (n)		50	25	25
Dependent variable				
Mitigation adoption	Share (0-100%) of mitigation measures adopted from all potential measures suitable for the specific farm type (mean and (SD))	0.41 (0.19)	0.43 (0.19)	0.39 (0.19)
Network variables				
Frequency of contact (realised)	Ordinal variable: 1= once per year; 5= every day	1.71 (1.23)	2.32 (0.92)	1.31 (1.24)
Network knowledge	Climate change mitigation knowledge of network contacts Ordinal variable: 1= knows nothing; 5= knows a lot	3.98 (0.72)	3.97 (0.70)	4 (0.77)
Farmers' behavioural characteristics				
Non-cognitive skills (self-efficacy and locus of control beliefs)	Ordinal variable: 1= very low; 5= very high (mean and (SD)) (for modelling, a factor variable is created)	3.35 (0.88)	3.74 (0.73)	2.96 (0.85)
Climate change concerns; Swiss agriculture	Assessment of climate change consequences for future of Swiss agriculture as a whole Ordinal variable: 1= very negative; 5= very positive (mean and (SD))	4.06 (0.77)	4.2 (0.65)	3.92 (0.86)
Climate change concerns: farm	Assessment of climate change consequences for future of own farm Ordinal variable: 1= very negative; 5= very positive (mean and (SD))	3.6 (0.83)	3.68 (0.75)	3.52 (0.92)
Farmers' demographic characteristics				
Age	Age of the farmer in 2019 (mean and (SD))	52 (6.33)	48 (7.39)	55 (6.6)
Education levels	Categorical variable			
Ag. apprenticeship		24	9	15
Ag. master certificate		14	10	4
Agri-technician		3	2	1
Technical college, university		5	3	2
Missing		4	1	3
Farm structural characteristics				
AgroCO$_2$ncept	Participation (0,1)	25	25	0
Farm type	Categorical variable (in model: Arable Farming and Livestock, all others as baseline)			
Arable Farming		9	5	4
Livestock		29	16	14
Special crops		4	3	1
Others		4	1	3
Missing		4		3
Farm size	Total agricultural land in ha (mean and (SD)) (for modeling, the log is used)	34.70 (27.37)	44.26 (33.92)	24.73 (13.86)

The dependent variable of interest is defined as the share of mitigation measures adopted out of all those measures which are suitable for the farm type. In a previous survey, 13 mitigation measures were chosen based on GHG reduction potential, relevance and suitability for Swiss agriculture (Kreft et al., 2020).[9] We use the frequency of exchanges regarding agricultural climate change mitigation as the basis for testing the Endogenous Network Effect Hypothesis (H1) which implies an association between strong social ties and the adoption of mitigation strategies. Frequency of exchange is assessed by an ordinal variable with five levels[10]. We conceptualize exchange as an inherently reciprocal concept and thus calculate the presence and strength of an undirected dyadic exchange relation $E_{u_{ij}}$ between any two survey respondents i and j, as the mean of their respective answers regarding the strength of their exchange E_d, thus $E_{u_{ij}} = E_{u_{ji}} = \frac{E_{d_{ji}}+E_{d_{ij}}}{2}$. A value of 0 indicates the absence of exchange. We row-standardized the undirected, weighted network adjacency matrix capturing the network of exchange relations among farmers (Leenders, 2002) to construct the 50×50 (given that n=50) weight matrix W.

We rely on the aggregate assessment of a farmer's mitigation knowledge, as rated by others, to test the Knowledge Diffusion Hypothesis (H2) which suggests an association between the mitigation knowledge of network contacts and adoption of mitigation strategies. Respondents were asked to evaluate their exchange partners' knowledge about agricultural climate change mitigation on a five-point ordinal variable (from knows nothing to very knowledgeable). Since each farmer was rated on the basis of the mean score assigned to them by their various exchange partners, the score is a crowd-sourced assessment of farmers' knowledge, as evaluated by their peers. Finally, we calculated the sum of the knowledge scores of all peers to assess the combined knowledge of a farmer's network contacts, the main point of interest for H2. This approach helps to corroborate farmers' individual assessment of their peers' knowledge and to obtain a more realistic estimate.

A binary variable was created for each farmer indicating participation (1) and non-participation (0) in the collective action scheme AgroCO$_2$ncept to test the Collective Action Spillover Hypothesis (H3) relating to its potential impact on adoption of mitigation strategies over the wider network. Based on the network of exchange relations among farmers, this allows us to effectively divide the network into four components. One component describes the network of exchange relations among participants, a second component relates to networking among non-participants and a third and fourth component cover networks (and hypothesized influence pathways) from participants to non-participants and vice versa. Accordingly, the adjacency matrix W is rearranged into four weight matrices, which are separately row-standardized (Dittrich et al., 2020, p. 175).

[9] For further information on mitigation measures please refer to the Appendix A3 (table A 3.1).
[10] 1 = Once per year; 2= Every few months; 3 = Once per month; 4 = Once per week; 5= Every day

3.6 Results

3.6.1 Descriptive network statistics

Table 3.2 summarizes the descriptive statistics of the total network as well as the two sub-networks of AgroCO$_2$ncept participants and non-participants.

Table 3.2: Statistics of farmers' networks

	Total network	**Network of AgroCO$_2$ncept participants**	**Network of non-participants**
Number of nodes	50	25	25
Number of edges	133	74	6
Mean tie-strength	1.3	1.6	1.3

Each sub-network comprises 25 nodes (farmers). There are 133 edges (based on exchanges about climate change mitigation) between all farmers in the whole network, whereby the network of AgroCO2ncept participants is much denser (74 ties) than that of non-participants (6 ties). This is partly due to the different approaches of data collection for the two groups of participants (roster vs. free name-generator). There are 53 ties between the two sub-networks. The majority of ties are workmates, club colleagues and friends, while some of these also overlap (see Appendix A3.5 for more information on tie distribution and overlap). On average, ties are slightly stronger in the AgroCO2ncept network (1.6), i.e., exchanges are more frequent than in the overall network (1.3).

The degree of centrality (between 0 and 1) depicts just how centralized a network is. A maximally centralized network is star-shaped with only one central actor connected to everyone else (Freeman, 1979). The AgroCO2ncept network is much more centralized (0.7) than the total network (0.4). This is mainly due to the fact that the initiative was originally set up and formed by one to three central actors (see Appendix A3.4 for additional information on the distribution of degree centrality).

Figure 3.1 gives a visual impression of the networks. Black dots represent AgroCO2ncept participants, grey dots refer to non-participants. The ties connecting the farmers capture regular exchange about climate change mitigation and are weighted by frequency of contact. Larger nodes depict higher shares of adopted mitigation measures. As mentioned before, some ties exist between the two sub-groups, indicating a strong integration of AgroCO2ncept members within the region.

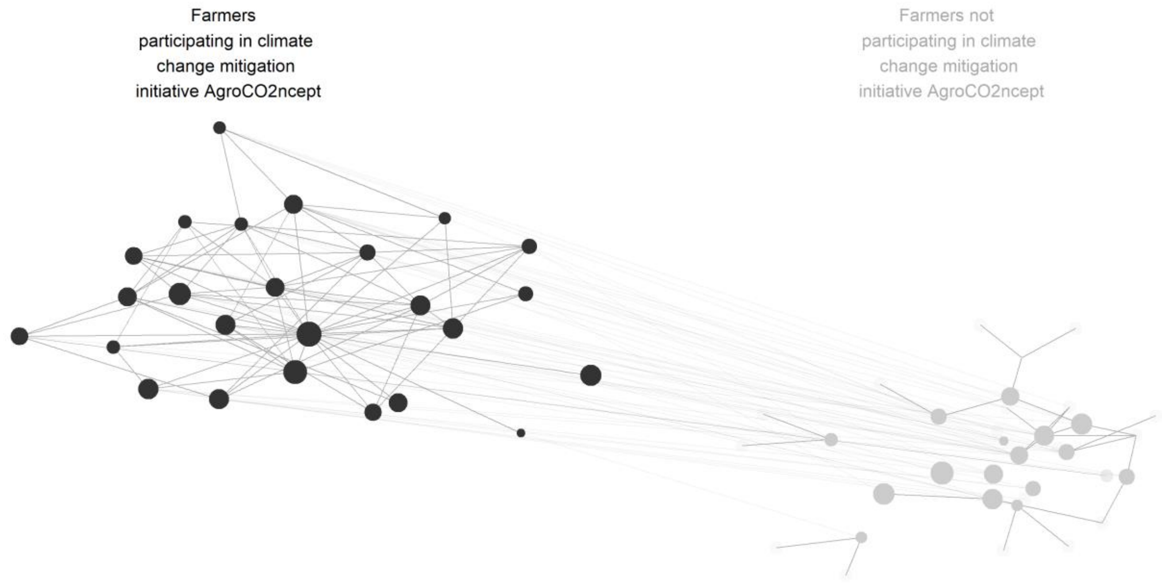

Figure 3.1: Total network ties regarding regular exchange on agricultural climate change mitigation. Black dots represent AgroCO2ncept participants, grey dots represent non-participants. The size of the nodes represents the share of adopted mitigation measures. The strength of the connecting lines represents the frequency of exchange.
.

Figure 3.2 shows four scatterplots capturing important features of farmers' individual networks in relation to their mitigation adoption. The size of the network (number of ties) increases along the mitigation gradient, i.e., farmers who adopt more mitigation measures have larger exchange networks. The mean strength of all ties in a farmers' network is relatively independent of mitigation adoption with most farmers exchanging on mitigation with their peers once or a few times per year. Betweenness centrality measures the number of shortest paths that go through a node, in other words the extent to which the actor controls the flow of information within the network (Freeman, 1979). In our sample, betweenness centrality of farmers increases with mitigation adoption, i.e., farmers adopting more mitigation measures have more shortest paths going through them.

Moreover, the mean mitigation share of contacts correlates with farmers' own mitigation: the contacts of high adopters have a higher share of adopted mitigation measures than the contacts of low adopters.

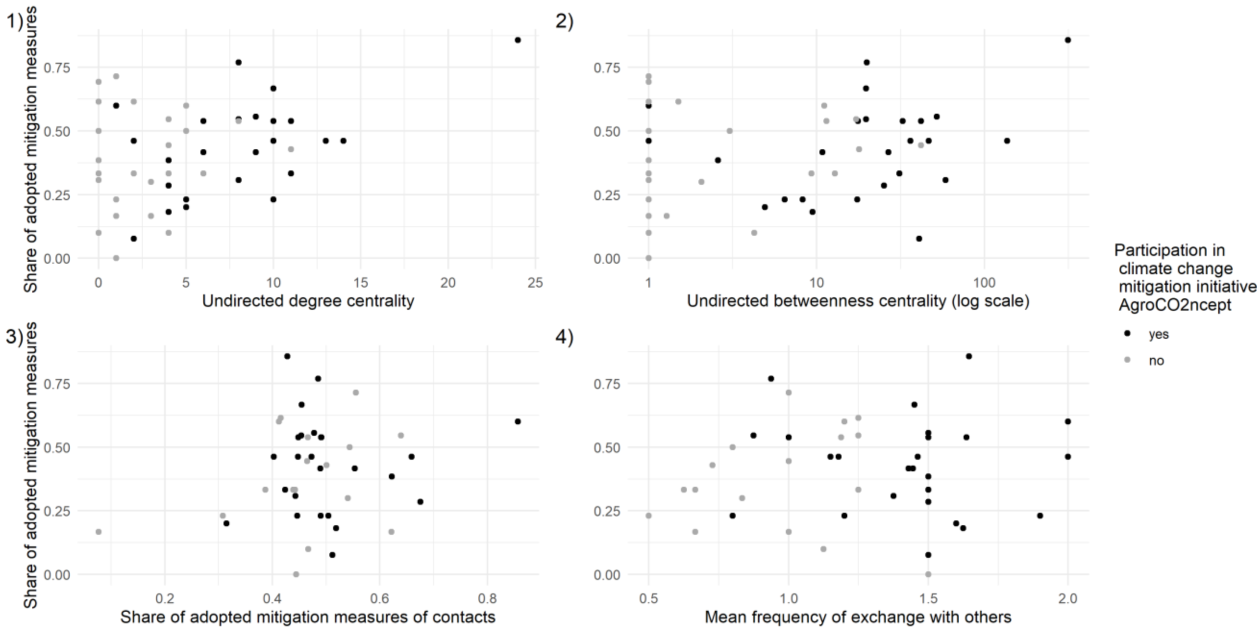

Figure 3.2: Farmers' individual mitigation adoption against different network traits. Black dots represent AgroCO2ncept participants and grey dots represent non-participants. The y-axis shows the share of adopted mitigation measures compared to the possibly relevant number of measures for the respective farm type. The x-axis represents four different characteristics of farmers' personal networks: 1) Undirected degree centrality (number of ties), 2) Undirected betweenness centrality (number of shortest paths going through the node), 3) Share of adopted mitigation measures of contacts and 4)Share of adopted mitigation measures of contacts.

3.6.2 Network autocorrelation estimation results

Figure 3.3 shows the results of the four network autocorrelation models in the form of a coefficient plot. Our report covers the network variables of greatest interest. A coefficient plot with all covariates and a detailed table showing the coefficient magnitude and confidence interval of all variables can be found in Appendix A3.7 and A3.8.

Our results indicate that there is uncertainty regarding both the sign and magnitude of the endogenous network association effect (H1) specified as a homogenous process across the whole network (averaged network influence). The averaged mean of the network influence is around zero in both the simple influence model and also after adjusting for knowledge diffusion ((1) and (2), Figure 3.3)). It is just as likely to be positive as it is to be negative and the 88% credible interval is evenly distributed around zero, containing both small and larger estimates.

We find a reliably positive effect for the association of aggregated knowledge about climate change mitigation in a farmer's network contacts (H2) throughout both models containing the parameter (knowledge diffusion model and fourth-order model plus knowledge diffusion ((2) and (4), Figure 3.3)). The probability of a positive association is high. In terms of magnitude, the posterior mean indicates a relatively significant effect (the effect should be interpreted as the ceteris paribus change given a one standard deviation increase and considering that values of y_i can range between 0 and 1). However, the credible interval also contains relatively small parameters.

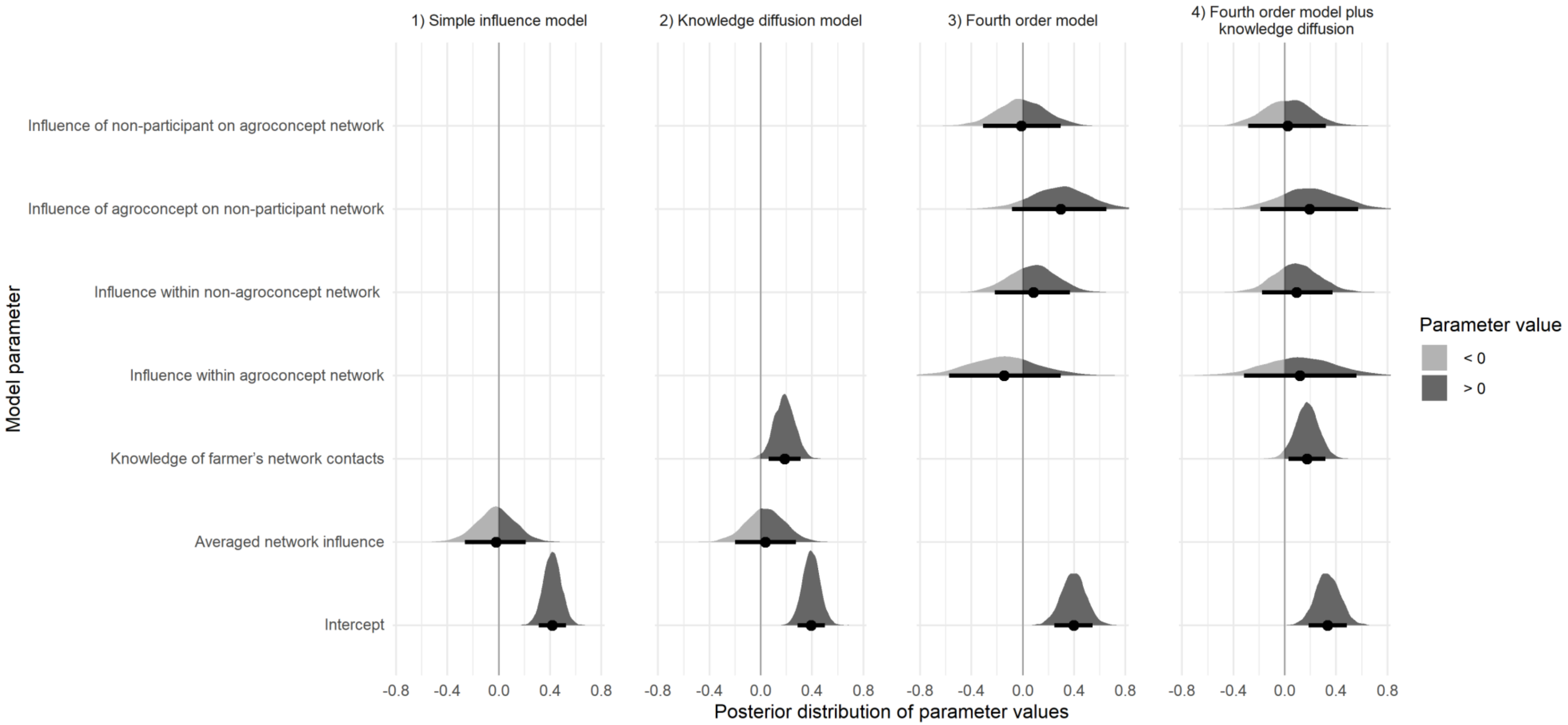

Figure 3.3: Estimated posterior distribution of network-related parameters for the four models tested. Network influence parameters each capture the impact of the adoption of climate change mitigation measures in a farmer's contact network on the farmer's own adoption of measures, either on average across the whole network (averaged network influence) or within and between sub-networks. The parameter for knowledge of network contacts can be interpreted as the marginal effect of a one unit increase in knowledge about mitigation measures among a farmer's network contacts on the share of adoption of climate change mitigation measures predicted for a farmer. Points represent median parameter estimates, horizontal spikes the 88% credible interval. Curves represent the distribution, with light grey areas for negative parameter values and dark grey areas for positive values. The posterior distribution for each parameter captures the uncertainty the model assigns to the parameter's influence. For example, a relatively wide distribution centered around zero indicates that the model fit neither supports a strong belief in the parameter having a certain sign (positive or negative), nor in the magnitude of its effect. In contrast, for example, if the posterior distribution covers a smaller range of large values and contains only few negative values, the model fit supports a stronger belief in the effect being both large and positive..

Moreover, we find evidence for the collective action hypothesis (H3) in both fourth-order models ((3) and (4), Figure 3.3)). It is almost certain that the relevant parameter ρ_{ab} (influence of AgroCO2ncept on non-participants network, Figure 3) is positive, given the proportion of its posterior distribution which is positive. Again, the magnitude of the effect is slightly uncertain, given our sample size. Nevertheless, our models justify the assumption of some, potentially influential, collective action spillover. Interestingly, the model results are much more inconclusive for all other network autocorrelation parameters in the fourth-order model. This would suggest that there is little endogenous network influence beyond the collective action spillover effect. This finding justifies the application of a network autocorrelation model that can differentiate various influence processes and does not assume a uniform process acting throughout the network.

3.7 Discussion

Based on a regional case study, this article investigates the suggestion that farmers' decisions on the adoption of climate change mitigation measures are influenced by the behavior and characteristics of their social network. We used a comprehensive data set comprising survey, census and interview data. This means that the sample was rather small given the task of face-to-face interviews. However, it suffices for the purpose of this study, which aims to explore a specific regional famers' network and local influence of the collective action initiative AgroCO2ncept. In our model, we account for this using a Bayesian approach, which is ideal for small networks as it does not rely on asymptotic approximations for standard errors (Dittrich et al., 2020). However, larger studies would be needed to provide more conclusive evidence and reduce any remaining doubts about the magnitude of estimated effects resulting from the smallness of our sample. The descriptive analysis of the entire network shows that AgroCO2ncept participants maintain closer connections with each other than non-participants. However, the comparison between the two groups must be treated with caution given the different approach applied for the network data collection: AgroCO2ncept members were provided with a full roster containing the names of all other participants from which they could select the exchange contacts they considered relevant. In addition, they could name any other persons they thought appropriate. Since there was no pre-defined network boundary for non-participants, they were asked to name, off-the-cuff, persons with whom they had regular exchanges on the topic. As it is far easier to identify names from a roster than to remember people spontaneously, this method can lead to potential recall bias (Brewer, 2000). During the interviews, this effect was counteracted by prompting respondents and repeating the question several times (Adams et al., 2021).

The descriptive analysis of farmers' individual networks revealed that, on average, farmers with a larger exchange network adopt more mitigation measures. This is in line with previous literature showing a positive influence of social networks on e.g., adoption of agri-environmental measures (e.g., Mathijs, 2003; Moschitz et al., 2015; Riley et al., 2018; Schneider et al., 2009; van Dijk et al., 2015, 2016).

In addition, our detailed data set enabled us not only to explore potential endogenous network effects, i.e., the influence of the mitigation behavior of peers, but also to investigate exogenous network effects, i.e., the influence of certain characteristics of farmers' contacts. This differentiation is quite important since we find no evidence for a uniform association between the mitigation adoption of peers and farmers' own adoption across the whole network. However, we do find a positive association between adoption and strong ties to farmers who are knowledgeable about agricultural climate change mitigation.

In contrast to previous studies (Matuschke and Qaim, 2009; Murendo et al., 2018), our findings indicate that adoption depends more strongly on mitigation knowledge existing within farmers' personal networks than on the actual mitigation behavior of peers. However, the type of technology or practice may determine the extent to which the characteristics of peers influence adoption (Murendo et al., 2018; Wuepper et al., 2017). We identify two main reasons which can possibly explain this phenomenon in the specific context of agricultural climate change mitigation. Firstly, the topic is still quite a relatively new, unexplored option for many farmers in Switzerland, and misconceptions regarding mitigation measures (e.g., their efficacy) represent one of the major barriers to adoption (Karrer, 2012; Peter et al., 2009). Consequently, information and social learning through knowledge exchange are crucial for mitigation adoption. Secondly, many agricultural mitigation practices are not specifically tailored to the reduction of GHG emissions but primarily target other agri-environmental objectives, e.g., no-tillage to increase soil fertility (Smith et al., 2007). This makes it difficult for farmers to recognize and imitate mitigation behavior of their peers and neighbors since it may not be easy to identify the implemented measures as such. Again, in this situation, an active exchange of knowledge could play a vital role in the adoption decision.

However, knowledge of peers is based on farmers' statements and can thus be prone to measurement error since farmers might not be able to accurately assess their contacts' mitigation knowledge. We try to counteract this potential inaccuracy by taking the mean of the knowledge ascribed to a person by all connected farmers in the network. Moreover, we argue that farmers' perception of their peers' knowledge is the relevant parameter for behavioral change (Matuschke and Qaim, 2009).

We also explored how the climate protection initiative AgroCO2ncept influenced mitigation behavior of non-participating farmers in the region. Our findings indicate that mitigation by farmers who belong to AgroCO2ncept has a positive impact on mitigation adoption of connected farmers who are not part of the initiative. Hence, in addition to our first results, we find evidence for an endogenous network effect in part of the network (i.e., only from AgroCO2ncept members to non-members). This is possibly explained by the fact that farming practices adopted by AgroCO2ncept farmers are more clearly related to climate change mitigation since the project and its climate protection objectives are well known in the region. Thus, identification of mitigation measures, observation and finally imitation of measures implemented by AgroCO2ncept members is easier than the observation of (potentially less obvious) mitigation behavior of peers who are not part of the initiative. Hence, our result suggests a local spillover effect of the collective action initiative. Therefore, we also see our study as a contribution to the literature on the spread of collective grassroots innovations, which is still relatively limited in the agricultural context (Ornetzeder and Rohracher, 2013; Seyfang and Smith, 2007; Vaiknoras et al., 2020).

Finally, social networks can help to overcome economic barriers of mitigation adoption through collaborative action (Bouamra-Mechemache and Zago, 2015). This is particularly relevant where potentially high investments, as well as transaction costs might prevent the adoption of climate change mitigation measures (Wreford et al., 2017).

3.8 Conclusions

In this article, we analysed social network data of 50 farmers in a region of Switzerland and explored the relationship between social relations regarding knowledge exchange and the uptake of on-farm climate change mitigation. In general, we find that farmers with larger networks adopt more climate change mitigation measures. Our results indicate that the level of mitigation knowledge present within a farmer’s network is crucial for mitigation adoption. However, it seems that farmers attach less importance to the actual mitigation behaviour of peers when deciding on their own adoption of mitigation measures. We also find that strong ties to members of the regional farmers’ initiative AgroCO2ncept Flaachtal are positively associated with mitigation uptake, suggesting a local spillover effect. In contrast to our findings regarding the whole network, the actual mitigation behaviour of AgroCO2ncept members is relevant for the mitigation adoption of connected non-members.

Our findings have policy implications. We show that social network integration, and especially knowledge diffusion within such networks, can contribute to a better understanding of farmers’ decision-making with regard to climate change mitigation. This is particularly important for effective policy designs aiming at a reduction of GHG emissions in agriculture. More specifically, policymakers should be aware of the relevance of social learning and informal knowledge exchange in farmers’ mitigation adoption. In a relatively new field of practice, such as on-farm climate change mitigation, accumulation and exchange of knowledge with well-informed peers and neighbours can contribute to behavioural change. Therefore, the creation of (regional) networks and platforms for farmers focusing on, and encouraging an active exchange about, the reduction of agricultural GHG emissions, is an essential step towards achieving the ambitious goals that have been set. Basically, while it is not possible to oblige people to learn from others, it is important to create the right environment for social learning to take place (Rist et al., 2007). Farmers’ overall mitigation knowledge could be improved if agricultural schools were to include climate change mitigation as a part of their general curriculum and extension agents included the topic regularly in their services.

Moreover, our findings suggest that promotion and support of regional (bottom-up) farmers’ initiatives can be a useful tool for policymakers as it can generate behavioural change beyond the scope of the project itself. To this end, the goals and measures of these schemes should be communicated more widely so that others can learn by observing members' practices. In addition to the benefits relating to social learning promotion and potential spillover effects, collective action is particularly promising as an effective and efficient path towards agricultural climate change mitigation since it also has considerable cost and risk reduction potential (Bouamra-Mechemache and Zago, 2015; Hodge and McNally, 2000).

Our study also has implications for future research. Findings show that social networks, and especially contact to well-informed peers, play an important role in farmers' behavioral change. This implies that relational data of this kind should be collected more regularly and included in future research also beyond climate change mitigation, e.g., to explain farmers' adoption of agri-environmental measures. Particularly, more studies on the influence of relevant characteristics of network connections (instead of their mere existence) can contribute to deeper understanding of farmers' decision making in response to their social environment. Additional data, e.g., on type of relationships or other sources of information, could also aid interpretation of results and help to explain network structures more thoroughly. Moreover, future research on the economic and ecological potential of farmers' collective action schemes is of particular relevance in the context of agricultural climate change mitigation.

3.9 Acknowledgements

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3.11 Appendix A3

A3.1: Hypotheses

Figure A3.1 illustrates the three hypotheses about the effect of social networks on adoption of climate change mitigation measures.

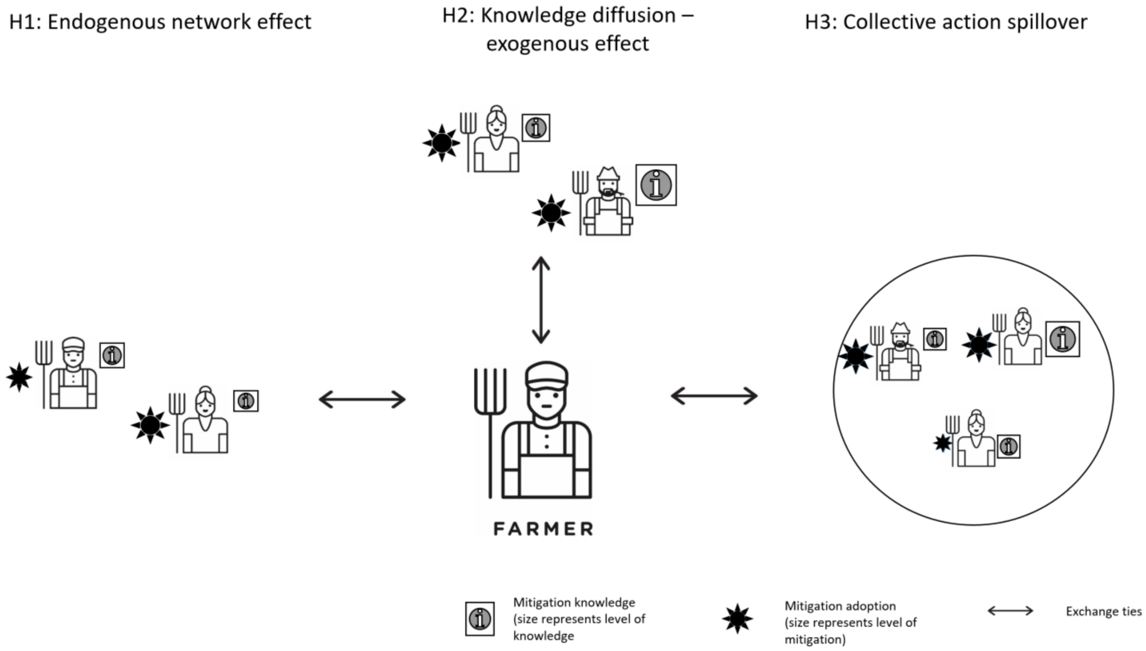

Figure A3.1: The hypothesized network effects on individual farmers' mitigation

A3.2: Location of farms

Figure A3.2 shows the approximate location of the farms reviewed, with red dots representing AgroCO2ncept participants and blue dots representing non-participants.

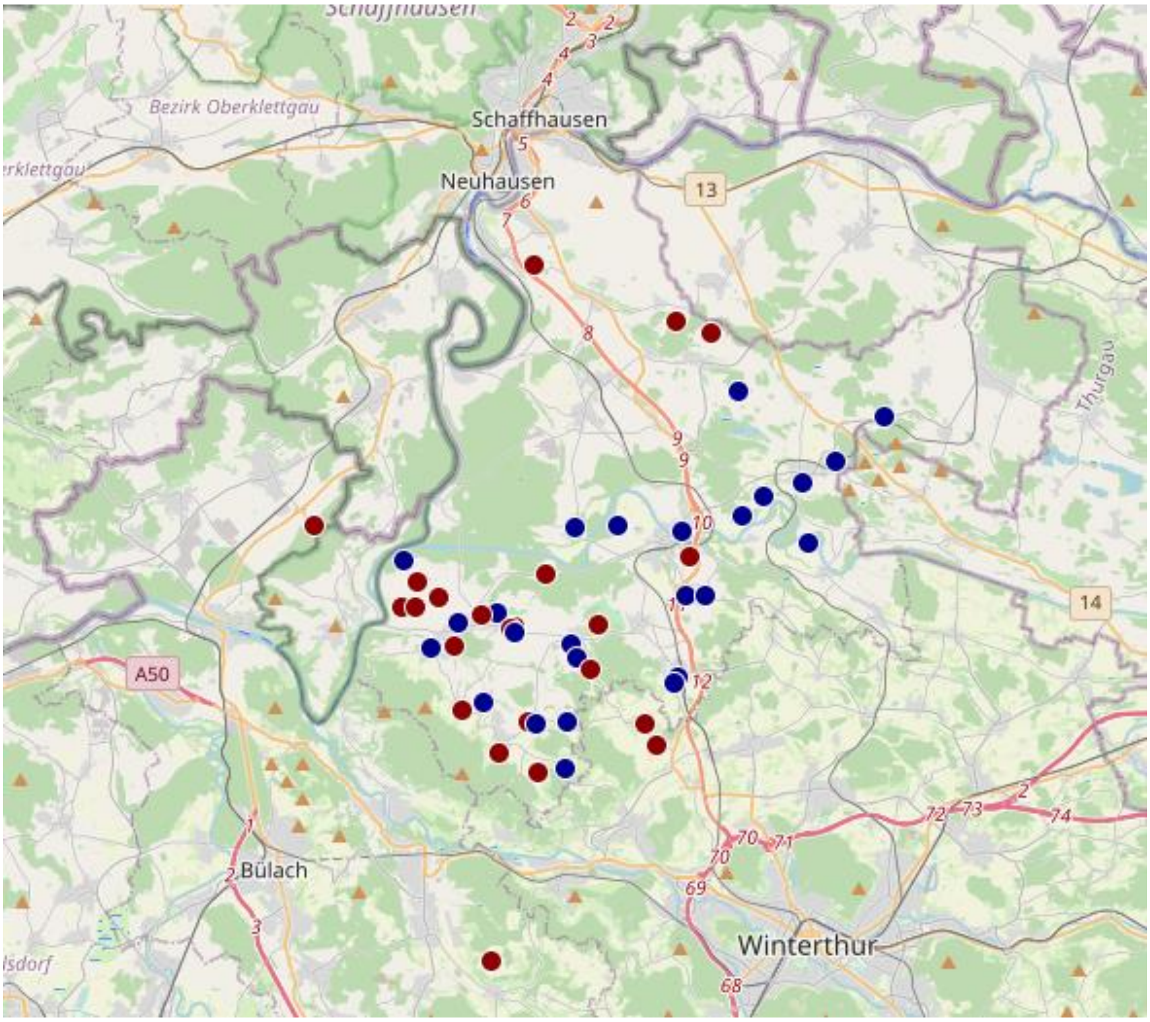

Figure A3.2: Approximate locations of the farms reviewed.

A3.3: Mitigation measures

Table A3.1 gives an overview on the mitigation measures included in the original survey. Seven measures related to livestock and manure management, three to crop production and three to energy production and use. The measures were chosen based on GHG reduction potential, relevance and suitability for Swiss agricultural systems.

	Mitigation measure	Main GHG reduction mechanism	References
Livestock and manure management	Replacement of (imported) concentrate feed with domestic legumes (e.g., peas, beans, lupines)	Reduced transport and land-use-changes for soy cultivation overseas	(Baumgartner et al., 2008; Hörtenhuber et al., 2011; Knudsen et al., 2014)
	Reduction of concentrate content to max. 10% of feed ration	Reduced concentrate production (e.g., mineral fertilizer, energy use)	(Schader et al., 2014)
	Increasing the number of lactations per dairy cow (min. 5)	Reduced CH4-emissions per kg milk over entire lifespan of cows and reduced replacement rate	(Mellado et al., 2011; Vijayakumar et al., 2017)
	Use of dual-purpose cattle breed (e.g., original Swiss brown)	Reduced number of animals needed for meat and milk production (mainly CH4)	(Schader et al., 2014; Zehetmeier et al., 2012)
	Introduction of feed additives (e.g., tannins, lipids etc.) to feed ration of cattle	Reduced enteric fermentation by partly inhibiting methanogenesis in rumen (reduced CH4-emissions)	(Jayanegara et al., 2020; Sinz et al., 2019; Wang et al., 2017)
	Coverage of manure storage	Reduced ammonia (NH3-) emissions due to anaerobic conditions under coverage	(Chadwick et al., 2011)
	Composting of manure	Reduced N2O-and CH4-emissions due to aerobic decomposition in compost	(Necpalova et al., 2018; Pattey et al., 2005)
Crop production	Manure application with drag hoses	Reduced NH3-emissions (i.e., N2O) from manure and slurry application	(Thomsen et al., 2010; Weiske et al., 2006; Wulf et al., 2002)
	Cover and catch crops in rotation	Carbon sequestration in soils	(Poeplau and Don, 2015)
	Min- or no-tillage	Reduced N2O emissions and increased soil carbon sequestration	(Alskaf et al., 2021; Mangalassery et al., 2014; Six et al., 2004)
Energy production and use	Solar panels for energy production	Reduced need for fossil fuels in heating and energy use of the farm	(Alig et al., 2015)
	Fermentation of manure in biogas-plant	Reduced need for fossil fuels and manure storage	(Massé et al., 2011; Meyer-Aurich et al., 2012)
	Drive tractors fuel-efficient (eco-drive mode)	Reduced fuel consumption of tractor driving	(Schader et al., 2014; Stadler and Schiess, 2000)

A3.4: Covariates

We use additional covariates derived from the previous survey (Kreft et al., 2020) and included in matrix X to adjust for potential associations between farmers' individual characteristics, their farm structures and their mitigation behavior.

We include a factor variable consisting of 5 items (questions) to measure farmers' non-cognitive skills, namely self-efficacy and locus of control, which have been shown to affect farmers' mitigation decisions (Kreft et al., 2021a). We also include a covariate measuring concerns about climate change and its consequences for agricultural production in Switzerland as well as for the future of the farmer's own farm. Climate change concerns are an arguably important factor for willingness to adopt mitigation practices (Haden et al., 2012). In addition, we adjust for farmers' age, level of education as well as farm size (log-transformed) and farm type (arable farming, livestock and other). These variables are among the standard variables investigated in research on farmers' adoption of sustainable practices (Defrancesco et al., 2008; Knowler and Bradshaw, 2007; Lastra-Bravo et al., 2015).

Most farmers in both subgroups (AgroCO2ncept participants and non-participants) focus on livestock production, mainly dairy or meat production. The second most common main activity is arable farming followed by special crops (e.g., viticulture) and others. The mean farm size of the whole sample is 34.7 hectares, whereby AgroCO2ncept farms are considerably larger (44.3 hectares) than non-AgroCO2ncept farms (24.7 hectares). However, the variation among farm sizes is quite large. On average, AgroCO2ncept participants are younger and their education level is slightly higher (most of them hold the agricultural master certificate) than that of non-participants (mostly agricultural apprenticeship). On average, farmers in our sample adopt 41 percent of the surveyed mitigation measures suitable for their farm type. In contrast to our initial hypothesis, the share of mitigation measures adopted by AgroCO2ncept participants (43%) is not much higher than that of non-participants (39%)[11].

Mean non-cognitive skills, namely self-efficacy and locus of control with regard to successful climate change mitigation, are higher in AgroCO2ncept farmers (3.74) than in non-participants (2.96)[12]. Concerns about the consequences of climate change for Swiss agriculture and the own farm do not differ much between the two groups. All covariates in matrix X were standardized by centering and dividing by two standard deviations (Gelman, 2008).

[11] To some extent, this could be because AgroCO2ncept members adopt additional measures (e.g., input of vegetable coal), which were not included in the survey. Also, we do not know the counterfactual scenario, i.e., how many mitigation measures farmers would adopt if they were not participating in AgroCO2ncept.

[12] For more details on the influence of non-cognitive skills on mitigation adoption, see also Kreft et al., 2021.

A3.5: Friends and work relations across entire network

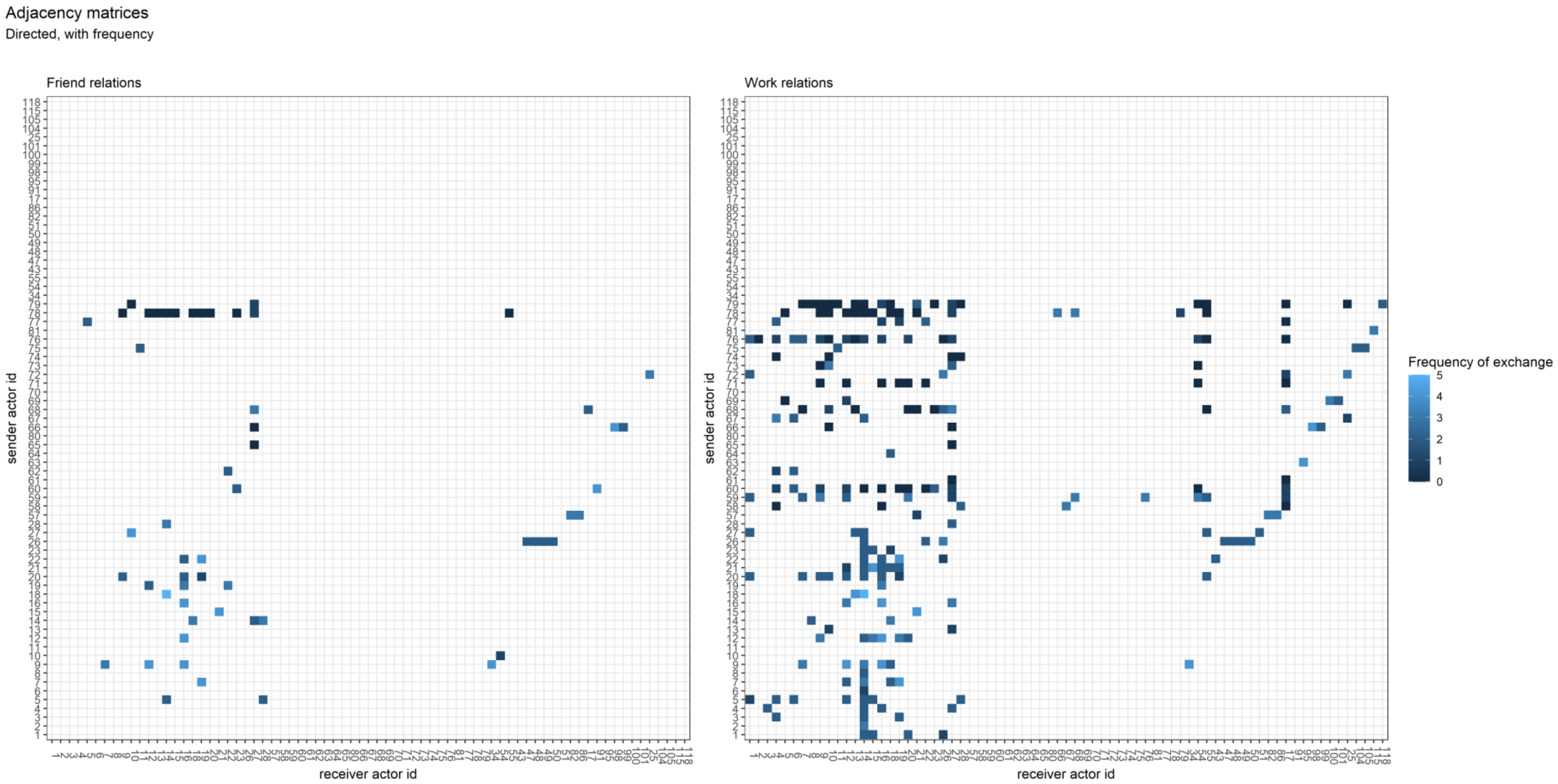

Figure A3.3: Adjacency matrix of friend relations (left) and work relations (right) in AgroCO$_2$ncept participants and non-participants.

A3.6: Distribution of centrality measures

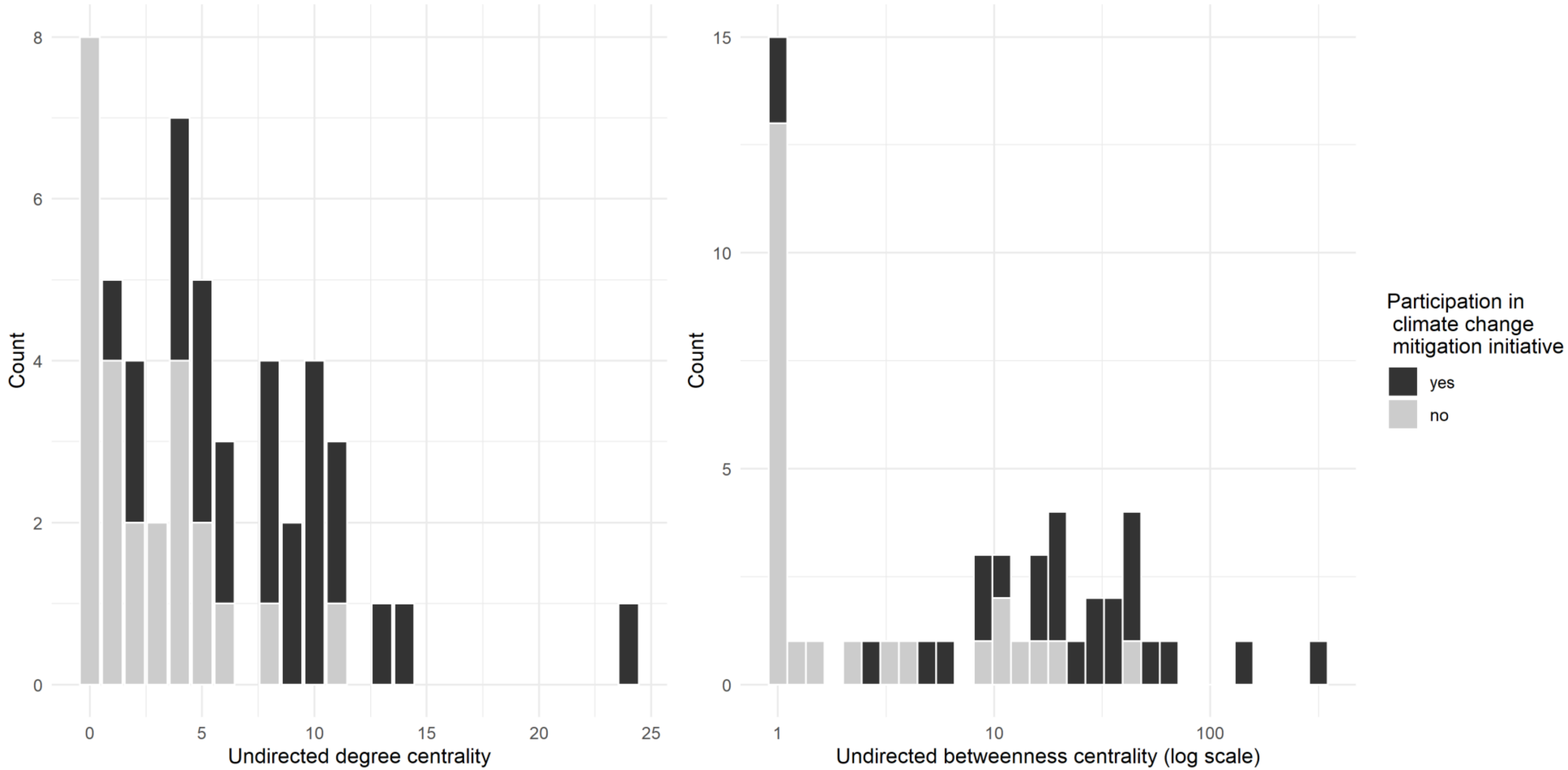

Figure A3.4: Distribution of undirected degree centrality (i.e., number of undirected ties) and undirected betweenness centrality (i.e., number of shortest paths going through a node). Black bars depict AgroCO₂ncept participants, grey bars represent non-participants.

A3.7: Plot of posterior distribution of parameters

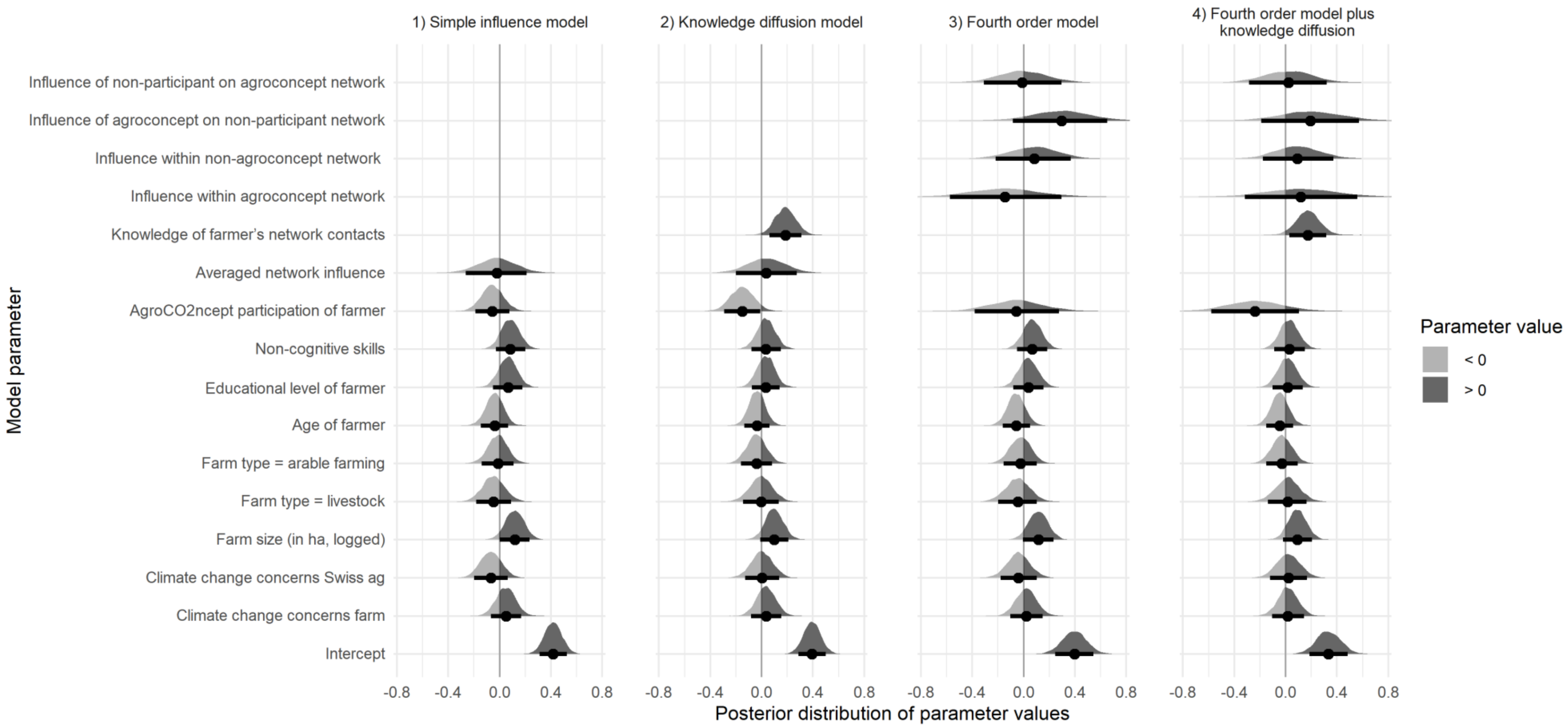

Figure A3.5: Estimated posterior distribution of parameters and all covariates for the four models tested. Points represent parameter estimates, horizontal spikes the 88% credible interval. Curves represent the distribution, with light grey areas for negative parameter values and dark grey areas for positive values.

A3.8: Detailed results: Posterior distribution of network autocorrelation model coefficients

Estimates / Models	(1) Simple influence (H1)	(2) Simple influence plus knowledge diffusion (H2)	(3) Fourth-order (H3)	(4) Fourth-order plus knowledge diffusion (H1 +H3)
Parameters associated with hypotheses				
ρ (average network autocorrelation)	-0.02 (0.44) [-0.26, 0.22]	0.04 (0.60) [-0.19,0.27]		
aggregated knowledge of network contacts		0.19 (0.99) [0.06,0.31]		0.17 (0.96) [0.03, 0.31]
ρ_{ab} (agroconcept to non-participant network autocorrelation)			0.31 (0.89) [-0.08, 0.69]	0.18 (0.78) [-0.19, 0.57]
Other covariates				
ρ_{aa} (within agroconcept network autocorrelation)			-0.10 (0.36) [-0.56, 0.34]	0.09 (0.64) [-0.36, 0.54]
ρ_{bb} (within non-agroconcept network autocorrelation)			0.08 (0.68) [-0.20, 0.37]	0.09 (0.69) [-0.19, 0.37]
ρ_{ba} (non-participant to agroconcept)			-0.02 (0.47) [-0.34, 0.29]	0.02 (0.54) [-0.28, 0.31]
Intercept	0.42 (1.00) [0.31, 0.53]	0.39 (1.00) [0.29,0.50]	0.38 (1.00) [0.22, 0.54]	0.34 (1.00) [0.19, 0.50]
Age	-0.04 (0.28) [-0.14, 0.07]	-0.04 (0.28) [-0.14,0.06]	-0.06 (0.20) [-0.17, 0.05]	-0.04 (0.25) [-0.15, 0.06]
Participation in AgroCO_2ncept	-0.06 (0.25) [-0.18, 0.07]	-0.15 (0.05) [-0.30, -0.01]	-0.09 (0.33) [-0.44, 0.27]	-0.23 (0.15) [-0.58, 0.13]
Farm type: arable farming	-0.01 (0.44) [-0.14, 0.11]	-0.04 (0.31) [-0.16,0.08]	-0.02 (0.41) [-0.15, 0.11]	-0.03 (0.35) [-0.16, 0.09]
Farm type: livestock	-0.05 (0.29) [-0.18, 0.09]	-0.01 (0.46) [-0.14,0.13]	-0.04 (0.33) [-0.19, 0.11]	0.01 (0.55) [-0.14, 0.16]
Concern about climate change impact on farm	0.05 (0.75) [-0.07, 0.17]	0.04 (0.69) [-0.08,0.15]	0.02 (0.60) [-0.11, 0.15]	0.02 (0.60) [-0.10, 0.14]
Concern about climate change impact on Swiss agriculture	-0.07 (0.21) [-0.20, 0.06]	0.00 (0.51) [-0.13,0.13]	-0.04 (0.34) [-0.18, 0.10]	0.02 (0.60) [-0.12, 0.16]
Education level	0.07 (0.82) [-0.05, 0.17]	0.03 (0.69) [-0.07,0.14]	0.03 (0.67) [-0.09, 0.15]	0.02 (0.59) [-0.10, 0.13]
Non-cognitive skills	0.08 (0.87) [-0.03, 0.20]	0.04 (0.69) [-0.08,0.15]	0.07 (0.81) [-0.05, 0.19]	0.03 (0.64) [-0.09, 0.14]
Log of total farm area (ha)	0.12 (0.94) [0.00, 0.23]	0.10 (0.92) [-0.01,0.21]	0.11 (0.94) [0.00, 0.23]	0.10 (0.91) [-0.02, 0.21]

Posterior distribution for the model parameters. We report the posterior mean, the probability of the coefficient being positive (as the percentage of positive values) and the 88% percent credible interval. Coefficient reporting format: Posterior Mean (Pr (>0)) [88% percent credible interval].

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Chapter 4: Quantifying the impact of farmers' social networks on the effectiveness of climate change mitigation policies in agriculture[13]

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Abstract

To effectively reduce agricultural greenhouse gas (GHG) emissions, farmers need to change current farming practices. Farmers' decision-making with respect to climate change mitigation and particularly the role of social and individual characteristics remain however poorly understood. We investigate how knowledge exchange within farmers' social networks affects the adoption of mitigation measures and the effectiveness of a payment per ton of GHG emissions abated using an agent-based modelling approach. Our simulations are based on census, survey and interview data of 49 Swiss dairy and cattle farms to simulate the effect of social networks on overall GHG reduction and marginal abatement costs using an agent-based modelling approach. We find that social networks increase overall reduction of GHG emissions by 42% at a given payment of 120 Swiss Francs per ton of reduced GHG emissions. The per ton payment would have to increase by 380 CHF (i.e. 500 CHF/t CO2eq) to reach the same overall GHG reduction level if no social networks are present. Moreover, marginal abatement costs of farms to mitigate emissions are lower when farmers exchange relevant knowledge in social networks. The effectiveness of policy incentives aiming at agricultural climate change mitigation can hence be improved by simultaneously supporting knowledge exchange and opportunities of social learning in farming communities.

Keywords

Agricultural policy, climate change mitigation, social networks, agent-based modeling, reduction of agricultural greenhouse gas emissions, Switzerland

[13] This chapter corresponds to the following article: Kreft, C., Huber, R., Schäfer, D., and Finger, R. (2022). Quantifying the impact of farmers' social networks on the effectiveness of climate change mitigation policies in agriculture. *Submitted*.

4.1 Introduction

Agriculture is threatened by the impacts of climate change, but at the same time is a considerable source of global greenhouse gas (GHG) emissions and thus has a key role in climate change mitigation through the implementation of various on-farm measures (Smith et al., 2008). Consequently, reducing agricultural GHG emissions has become a central policy goal in many countries. This is also reflected in national action plans under the Paris Agreement where 95% of the parties include the agricultural sector (Horowitz, 2016). At the same time, agricultural production must ensure a secure and healthy food supply for a growing world population.

To achieve GHG reduction goals while maintaining production levels, farmers must adapt current practices and implement effective and efficient mitigation measures. Policy incentives paying farmers for a reduction of GHG emissions can support the adoption of such measures. Understanding farmers' decision-making with respect to climate change mitigation is crucial for design and implementation of such policy incentives. However, the role of behavioural factors in general and social learning in particular remains poorly understood in the context of farmers' mitigation adoption (Kreft et al., 2021a; Niles et al., 2016). While bio-economic modeling approaches are key tools used for the (ex-ante) assessment of agricultural policies and their impact on actual GHG reduction potentials as well as production and farm incomes (Britz et al., 2021; De Cara et al., 2005; Lengers et al., 2014), they usually lack integration of individual behavioural factors and, in particular, social interactions. To account for such factors in the simulation of farmers' decision-making, agent-based models have been combined with social network analysis (Will et al., 2020).

In this article, we quantify the economic and policy relevance of social networks for efficient GHG emission reduction in agriculture. We integrate behavioural and social aspects of farmers' mitigation adoption based on a unique combination of census, survey and social network data with economic decision-making in a bio-economic agent-based modeling approach, using a Swiss case study. More precisely, we quantify the impact of farmers' social networks on the effectiveness of a results-based payment scheme for mitigation in terms of overall GHG emissions reduced and income changes, accounting for farmers' individual preferences and farm level costs of mitigation measures.

Previous literature has increasingly investigated the role of behavioural factors, namely cognitive, non-cognitive, social and dispositional aspects for farmers' adoption of sustainable practices (Dessart et al., 2019). In this context, social networks have been identified as an important factor to explain adoption and diffusion of agricultural innovations or participation in agri-environmental schemes (Bandiera and Rasul, 2006; Conley and Udry, 2001; Conley and Udry, 2010; Morgan and Daigneault, 2015; Šūmane et al., 2018; Wood et al., 2014). With regard to climate change adaptation and mitigation in agriculture, however, only few studies have specifically accounted for social interactions of farmers (Berger and Troost, 2014; Perosa et al., 2021; Zheng et al., 2022). Thus, the economic importance of knowledge exchange within farmers' social networks and its impact on decision-making regarding on-farm climate change mitigation remains unknown. Particularly, to the best of our knowledge, the effect of social networks on effectiveness and efficiency of policies aiming at a reduction of agricultural GHG emissions has not been quantified in terms of GHG emissions reduced and emerging marginal abatement costs.

To fill this research gap, we quantify and compare the influence of social and individual components affecting farmers' decision-making in the context of a results-based payment for GHG emissions reduction. To this end, we apply the agent-based modelling framework FARMIND (FARM Interaction and Decision-making) (Huber et al., 2021). In this framework, the adoption of climate change mitigation measures is simulated as a two-tiered decision-making mechanism that not only considers costs and benefits of individual measures but also behavioural factors such as risk attitudes, farming preferences and socially oriented behaviour in social networks. In our modelling framework, this means that farmers interact by imitating the mitigation measures adopted by their peers. We use FARMIND in combination with the bio-economic farm optimization model FarmDyn (Britz et al., 2014; Britz et al., 2019) allowing us to calculate marginal abatement costs and GHG emissions associated with adoption of mitigation measures under the constraint that farms maintain their current production level. FARMIND and FarmDyn are parametrized based on farm census, detailed survey and empirical network data of 49 dairy, suckler and bull-fattening farms located in a Swiss region (Kreft et al., 2021b; Kreft et al., 2020).

To assess the effect of social networks on the effectiveness of a payment for reducing GHG emissions, we simulate farmers' adoption decisions in four different scenarios and two modelling steps. We simulate the amount of GHG emissions and income changes based on personal knowledge exchange between socially connected farmers (here, we only refer to personal relations between farmers and do not consider broader types of networks such as social media platforms etc.). We compare this scenario to three counterfactuals i.e., i) GHG mitigation in the absence of a social network, ii) with ties between only few farmers (random network) and iii) with ties between all farms (complete network). We run the simulation with a subsidy per ton of GHG emissions reduced corresponding to the current carbon price in Switzerland and quantify the amount of reduced GHG emissions in each scenario. We then stepwise increase/decrease the payment to achieve the same reduction level across scenarios. This allows for quantifying the extent to which social networks can enhance the diffusion of mitigation practices and hence increase the effectiveness and efficiency of a payment to incentivize reduction of GHG emissions in agriculture. In addition, the simulation results quantify the income changes and marginal costs associated with the farm individual reduction in GHG emissions and thus indicate the economic value of information flow within farmers' social networks.

Our analysis contributes to better understand the impact of social networks on famers' decision-making based on empirical data and to assess the impact of behavioural factors on the effectiveness of payments in the context of agricultural climate change mitigation. This allows to quantify the potential economic value of policies supporting social networks e.g., platforms for knowledge exchange in farming communities as well as information campaigns or farmers' trainings aiming at a reduction of agricultural GHG emissions.

The remainder of this article is as follows: Section 2 provides some background on agricultural climate change mitigation and introduces the conceptual framework of our simulation study. Section 3 describes the applied agent-based modelling framework FARMIND and its application in this study. Section 4 presents the results of our simulation, followed by a discussion and conclusions in sections 5 and 6, respectively.

4.2 Background and conceptual framework

4.2.1 Agricultural climate change mitigation

Agriculture is a major source of GHG emissions, mainly methane (CH4) and nitrous oxide (N2O) (IPCC, 2019). Livestock supply chains alone are responsible for 14.5% of anthropogenic GHG emissions (Gerber et al., 2013) and more than half of emissions attributed to the entire global food system (Xu et al., 2021). Beef and milk production account for 41 and 20% of the entire livestock sectors emissions, respectively (Gerber et al., 2013). Hence, agriculture and especially the livestock sector can play a key role in the reduction of GHG emissions. A broad range of possible mitigation measures has been proposed for global agriculture or specific regions (IPCC, 2014; MacLeod et al., 2015). Examples of measures in livestock production are improved herd management, manure handling or manipulation of feeding practices (Gerber et al., 2013).

Adopting mitigation measures is often associated with certain trade-offs for the farmer such as shifts or reduction of production and income losses due to (opportunity) costs of the measure (Eory et al., 2018). Marginal abatement cost curves that have been developed for agricultural GHG reduction in many countries and regions show that per unit costs of mitigation measures are quite heterogeneous (Beach et al., 2008; Jones et al., 2015; MacLeod et al., 2010; Moran et al., 2011; O'Brien et al., 2014; Pellerin et al., 2017). Most of these studies indicate that substantial GHG reduction (up to 25%) could be achieved at low costs or even at a net gain for the famer (Ancev, 2011; Eory et al., 2018). This raises the question why so-called "no-regret" options are not readily adopted. Besides transaction costs, farmers' individual characteristics such as risk attitudes and climate change perceptions or lack of certain skills might prevent farmers from adopting despite low costs (McCarl and Schneider, 2000). On the other side, strong self-efficacy (believing in one's own capabilities to successfully fulfil a given task) and a sense of innovativeness have been found to positively affect farmers' adoption of on-farm measures to reduce GHG emissions (Kreft et al., 2021a; Niles et al., 2016). Moreover, social learning through knowledge exchange within farmers' social networks and in particular frequent contact to knowledgeable peers can increase mitigation adoption (Kreft et al., 2023; Moran et al., 2013).

To enhance adoption of farmers and achieve a reduction of GHG emissions from agricultural production, different forms of policy instruments have been proposed by the literature. Among them are financial incentives such as subsidies, taxes and tradable permits, binding standards and regulations as well as information campaigns, trainings and advisory services (Eory et al., 2018; Gerber et al., 2013). While agriculture has so far mostly been excluded from emissions trading schemes, several countries pay farmers (indirect) subsidies for the adoption of mitigation practices (OECD, 2019). In contrast to the "polluter pays" principle implemented e.g., via a tax, we here apply the "beneficiary pays" principle and focus on a results-based subsidy (payment) that farmers receive per ton of CO2eq reduced. Paying farmers for reducing emissions, as a results-based payment scheme, is often better accepted by farmers and policy makers since it emphasizes property rights of farmers who are compensated for profit reductions caused by the provision of positive externalities (Pretty and Ward, 2001).

4.2.2 Conceptual framework

The conceptual background of our study is that farmers' individual decision on the uptake of GHG mitigation measures is influenced by four different components (Figure 4.1). First, the uptake depends on heterogeneous cognitive, social, and dispositional factors. Farmers might perceive the implementation of these measures as risky or they are simply resistant to change (Dessart et al., 2019). Second, the uptake decision is influenced by the farmers' social network and the adoption patterns of his/her peers. Third, whether a farmer will implement certain measures on the farm also depends on the underlying farm structures and processes i.e., farm size and type that result in farm individual abatement costs. Finally, the adoption decision is also influenced by the policy measures, i.e. the level of payment and how it changes the relation of costs and profits.

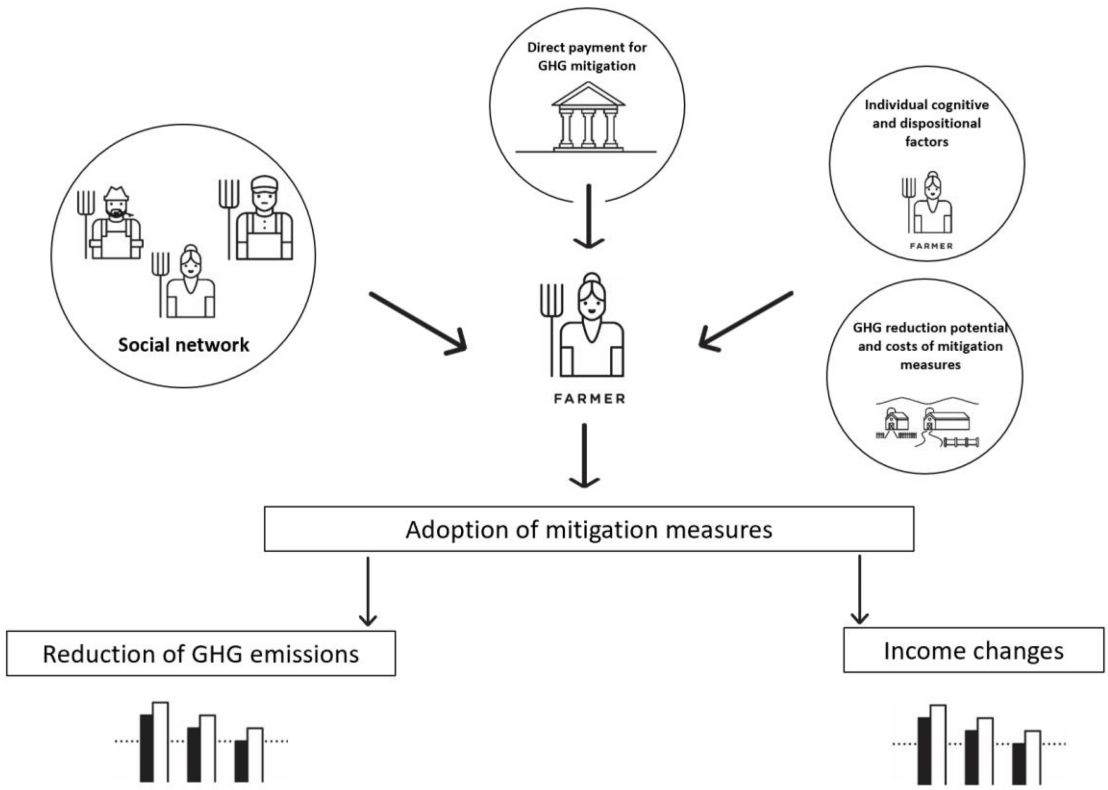

Figure 4.1: Conceptual framework. Farmers are influenced by their social networks, individual behavioural factors, cost and profits (i.e., income plus subsidy) of climate change mitigation as well as policies (direct payment). These factors affect the farmer's decision to adopt mitigation measures. The decision ultimately determines the reduction of GHG emissions and associated income changes.

While bio-economic modelling approaches can well represent farm specific abatement costs and the impact of a policy on the uptake of mitigation measures, the added value of our modelling framework is to combine the strength of farm-level modelling with behavioural factors and social network effects (see next Section).

The key assumption of our conceptual framework is that farmers' decisions on adopting GHG mitigation measures are also influenced by their social networks through the occurrence of social learning, i.e., learning from observation and interaction with others (Morgan, 2011; Munshi, 2004; Skaalsveen et al., 2020; Wood et al., 2014). Hence, social learning is a key driver of technology and innovation diffusion processes in agriculture (Rogers, 2010; Shang et al., 2021; Xiong et al., 2016; Zhang et al., 2019). Here, we expect farmers to learn from exchanging on climate change mitigation and observing mitigation behaviour of the farmers in their social network. The assumed underlying mechanism of the social network effect is farmers' (and most people's) wish to conform to social norms to a certain extent: If a farmer substantially differs from their peers in terms of mitigation adoption, they become uncertain and seeks to imitate the behaviour observed in the social network (Jager and Janssen, 2012). This initiates social learning processes and is also supported by rural sociology studies describing the phenomenon of "roadside farming", where farmers observe their neighbours' practices "over the hedge" (Beedell and Rehman, 2000; Burton, 2004; Le Coent et al., 2021). In fact, striving for conformity and a feeling of belonging was even found to sometimes have stronger implications for behavioural change than financial incentives (Kuhfuss et al., 2013). Moreover, farmers in the here considered case study region were found to particularly learn from and imitate (perceived) knowledgeable peers (Kreft et al., 2023) and trust relationships can help to lower the perceived risks of adoption (Sligo and Massey, 2007).

We assume that farmers choose a decision strategy based on individual risk attitudes and a preference for GHG mitigation measures that confines their choice options. The strategies to choose from are repetition, optimization, imitation, and non-adoption (see Section 4.3.2 for details). If a farmer chooses to imitate, they observe the mitigation measures adopted by their peers and will adopt the most cost-efficient mitigation measures given a certain payment level for GHG emission reduction. Whether imitation and social learning take place in our simulations, depends on how susceptible the farmer is to tolerate dissimilarity between themselves and others as well as on the number of ties to others (density of the network). Based on the decision strategy and these social and individual factors, the farmer decides whether to adopt one or several mitigation measures. The adoption decision finally determines changes in farm income through profits and costs as well as the associated amount of GHG emissions reduced.

To assess the impact of social networks on the effectiveness of the payments, we simulate a network of farmers based on real network data. Certain structural characteristics of networks such as density and centralization have been shown to impact information flow, learning and ultimately behavioural outcomes (Bandiera and Rasul, 2006; Bodin and Crona, 2009; Bourne et al., 2017; Levy and Lubell, 2017). To account for different network structures, we compare the effect of the empirically observed network to three hypothetical scenarios with different network structure: i) No social ties, ii) random ties between few farmers and iii) ties between all farmers. Choosing an extreme counterfactual scenario without any (context specific) knowledge exchange between farmers allows to quantify the impact of the observed social network (i.e., the empirical knowledge exchange) on the effectiveness of a payment for GHG reduction and ultimately agricultural climate change mitigation[1].

4.2.3 Case study and mitigation measures

We analyze the effect of four distinct on-farm mitigation measures to reduce GHG emissions from 49 Swiss dairy, suckler and bull-fattening farms who took part in a previous online survey[2] (Kreft et al, 2020). The farms of our sample are situated in the region of "Zürcher Weinland" in the Northern part of Canton Zurich. Ten farms are mainly producing beef from fattening bulls, 15 farms are suckler farms and 24 farms are dairy farms. The average farm size is 35 hectares (mean farm size in Canton Zurich is 25 hectares (Canton Zurich, 2018)) and 38 cattle livestock units (30 cattle livestock units per farm in Canton Zurich (Canton Zurich, 2018)).

[1] Stylized visualizations of the compared network scenarios can be found in the ODD+D protocol in Appendix A5.

[2] The full survey, the dataset and the codebook describing the variables are available in Kreft et al. (2020) as well as freely accessible on the ETH Zürich Research Collection: http://hdl.handle.net/20.500.11850/383116.

The simulated mitigation measures were selected based on the previous online survey and according to their relevance in Swiss agricultural systems (Kreft et al., 2020) (see Table 4.1). Costs and benefits (GHG emissions reduction) for each measure separately and for all possible combinations thereof are derived from simulations with the bio-economic farm level model FarmDyn (Britz et al. 2019). Detailed information on the sub-model FarmDyn can be found in the ODD+D protocol in Appendix A5 (section "Sub-model").

As important boundary condition of our analysis, we assume constant production levels of beef and milk. This assumption is in line with current policy goals in Switzerland to keep a high level of national self-sufficiency in milk and meat (BLW, 2022). Hence, the optimization of farm incomes with one or several adopted mitigation measures excludes options of non-agricultural income generation as well as switching to different production types. Thus, certain shifts in production can take place on farm-level (e.g., in- or decreasing specific crop area, reducing the number of heifers bought) but are limited to the main type and level of production. The technical GHG reduction potential of each measure was derived from the literature (Table 4.1) and validated in expert interviews. The simulated maximum technical mitigation potential (i.e., all farms adopt all suitable measures) amounts to a reduction of 13.8 percent compared to baseline GHG emissions.

Table 4.1 shows the four mitigation measures included in the model, the associated mechanism of GHG emissions reduction as well as main scientific references.

Table 4.1: Climate change mitigation measures included in the model and associated mechanisms of GHG emissions reduction. GHG reduction potentials and marginal abatement cost are based on simulations with the bio-economic farm level model FarmDyn (see section 4.3).

Measure description	Mechanism of GHG emissions reduction	Mean on-farm GHG reduction potential (t CO_2eq)	Mean marginal abatement cost (CHF/tCO_2eq)	References
a) Replacement of (imported) concentrate feed with legumes	Replacing concentrate feed such as soybean with on-farm produced legumes (e.g., peas or horse bean) mitigates up-stream CO_2-emissions due to reduced transport and land-use changes	4	1467	(Baumgartner et al., 2008; Hörtenhuber et al., 2010; Knudsen et al., 2014)
b) Increase of lactation number per dairy cow	Increasing the number of lactations per dairy cow reduces CH_4-emissions of a herd due to a reduced replacement rate, i.e., less upraising of calves and heifers	30	- 92	(Alig et al., 2015; Grandl et al., 2019; Schader et al., 2014)
c) Use of emissions reducing manure application technique	A close-to-ground application with drag hoses (or a similar technique) reduces N_2O-emissions of manure brought to the field and indirect N_2O emissions from other nitrogen compounds	3	116	(Thomsen et al., 2010; Weiske et al., 2006; Wulf et al., 2002)
d) Introduction of feed additives	Introducing feed additives such as linseed reduces the CH_4-emissions from enteric fermentation by inhibiting methanogenesis in ruminants$_2$	18	339	(Engelke et al., 2019; Hristov et al., 2013; Jayanegara et al., 2020)

We assume a results-based payment for GHG reduction based on the current CO_2 price in Switzerland of 120 CHF/tCO_2eq (Swiss Federal Council, 2022). To be able to compare the efficiency of the payment at the same overall GHG reduction level, we estimated the payment level at which the farms emit the same level of GHG emissions with and without social networks. To do so, we increased the payment in the counterfactual situation *without* social networks until GHG emissions reached the level observed in the simulation *with* social networks at 120 CHF/tCO_2eq. This is the case at a payment of 500 CHF/t CO_2eq, which also corresponds to the average marginal abatement costs if all farms were to adopt all measures. In our simulations, farmers thus receive a payment of a) 120 CHF and b) 500 CHF per ton of CO_2eq reduced due to adoption of one or several mitigation measures.

4.3 Methods: Agent-based modelling framework FARMIND

The purpose of our modelling framework is to simulate the adoption of climate change mitigation measures on cattle farms (dairy, suckler and bull-fattening) in a Swiss case study region. More specifically, the model simulates the effect of a social network on the adoption decision considering heterogeneous cognitive, social, and dispositional factors across individual farmers given a results-based payment for GHG emission reduction. Higher payments increase farmers' adoption of climate change mitigation measures but farm structural factors, and farmers' individual characteristics will constrain the uptake in our modelling framework.

We apply the agent-based modelling framework FARMIND that integrates aspects of social network theory and cumulative prospect theory (Kahneman and Tversky, 1992) to link farmers' heterogeneous cognitive, social, and dispositional factors to costs and benefits of climate change mitigation measures. FARMIND simulates decision-making of farmers as a two-step procedure: The farm individual decision-making includes first the choice of a strategy (i.e., repeating, optimizing, or imitating behaviour) and a subsequent (non-) adoption of the income maximizing mitigation measure. This type of model is suited to address our research questions since it combines standard bio-economic modelling based on farm optimization with farmers' social interactions while accounting for individual behavioural characteristics (Huber et al., 2018).

The key emerging phenomena of FARMIND in our analysis are the total amount of GHG emissions reduced by the adoption of farm individual mitigation measures and the change in income for the individual farm but also the whole farm community. To quantify the economic and environmental effect of social networks in the context of climate change mitigation efforts in agriculture, we compare the effect of empirical and hypothetical social networks in different scenarios. In the following, we describe our methodological approach in three steps i) agent characteristics, ii) agents' decision-making and iii) set up of simulation and scenarios (full details of the model as well as uncertainty and sensitivity analyses are provided in the ODD+D protocol in Appendix A5).

4.3.1 Agent characteristics

In FARMIND, each agent is characterized by three sets of state variables (cf. ODD+D protocol): (1) Farm specific costs and GHG emissions reduction potentials of four on-farm climate change mitigation measures. Those are exogenous parameters calculated with the bio-economic farm level model FarmDyn, i.e., a farm optimization model parametrized with farm-specific census data (Britz et al., 2019). Based on the calculated GHG emissions reduction, mitigation costs are partly compensated by a payment of per ton of CO_2eq reduced. (2) Each agent has personal characteristics including cognitive factors (i.e., loss aversion, valuation of gains and losses and probability weighting), social factors (i.e., tolerance for being dissimilar to other farmers), a reference income that determines whether they are satisfied with the current income situation, and dispositional factors (i.e., preferences for specific mitigation measures). These are exogenous parameters based on a farm survey (Kreft et al., 2020)[3]. (3) A social network between farmers representing personal exchange of knowledge on climate change

[3] The full survey, the dataset and the codebook describing the variables are available in Kreft et al. (2020) as well as freely accessible on the ETH Zürich Research Collection: http://hdl.handle.net/20.500.11850/383116.

mitigation derived from a social network analysis based on face-to-face interviews (Kreft et al., 2021b)[4]. Most individual and social factors could be taken into account without further transformation. Parameters based on survey questions with a Likert-scale (threshold levels) were transformed such that the relative proportion between agents was maintained (for details, see sections on input data, calibration and sensitivity analysis in the ODD+D protocol).

The simulated overall baseline GHG emissions (without adoption of mitigation measures) in our sample amount to 14 240 tons of CO_2eq, with a mean of 290 tons CO_2eq per farm. On average, farms emit 7.6 tons of CO_2eq per ha of agricultural land and 10.6 tons of CO_2eq per cattle livestock unit (see Appendix A4.1). However, total and per-unit emissions vary widely between farms. While the average simulated income of farms without adoption of mitigation measures (baseline income) is at 142 000 CHF per year, there is large heterogeneity of incomes across the whole sample. Mean farm income per ha of agricultural land is 3374 CHF and 6378 CHF per cattle livestock unit (see Appendix A4.1). Marginal abatement costs of adopting measures (without payments) are lowest for increasing number of lactations, in fact, several farms even save net costs by introducing this measure. Second most cost-effective is the use of drag hoses for manure application, followed by feed additives. Replacing concentrate feed by on-farm produced legumes is by far the most expensive measure overall and at the same time shows the highest dispersion of marginal costs (Figure 4.2).

[4] The questionnaires, the dataset and codebook describing the variables are available in Kreft al. (2021b) as well as through the ETH Zürich Research Collection: http://hdl.handle.net/20.500.11850/458053.

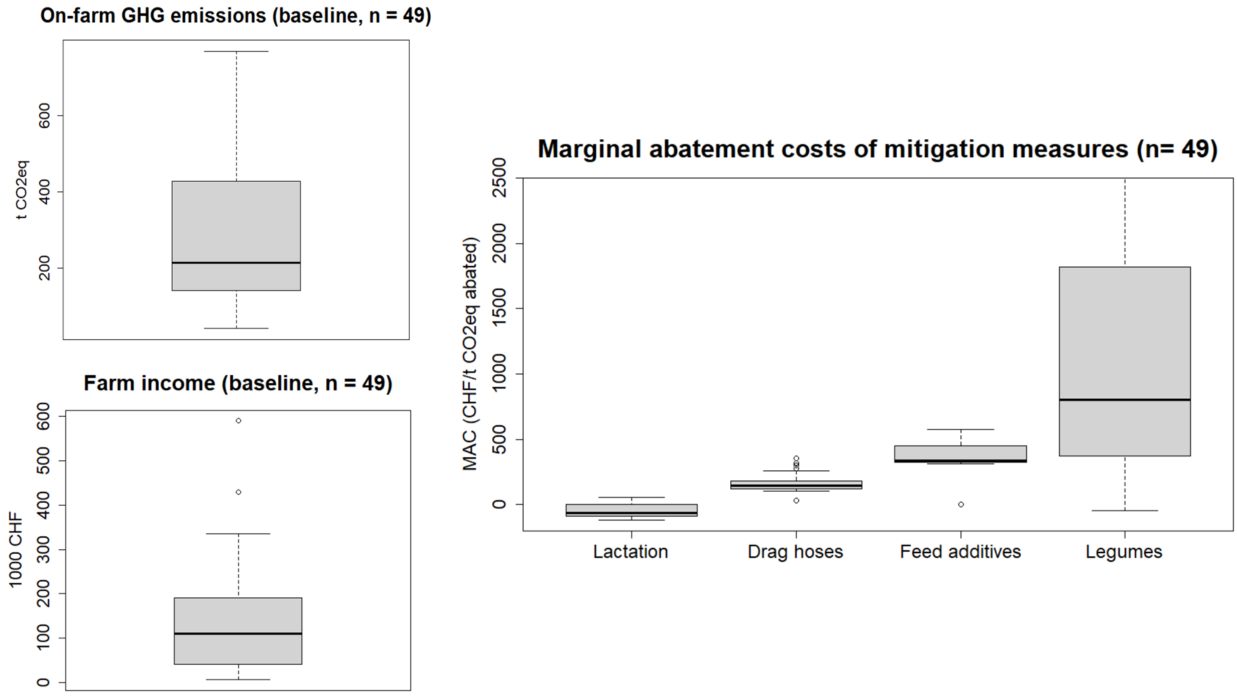

Figure 4.2: Distribution of baseline on-farm GHG emissions and farm income without adoption of mitigation measures as well as marginal abatement cost of single mitigation measures without any payments. Lower and upper boundaries of the grey box represent the 25th and 75th percentiles, respectively. Lower and upper error lines represent the 10th and 90th percentiles. The horizontal line inside the box depicts the median.

The highest total reduction of GHG emissions is achieved in our sample with increasing the number of lactations per dairy cow, followed by the introduction of feed additives, drag hoses and replacement of concentrate feed with legumes. However, the dispersion across farms in our sample is largest for the first two measures as well, while there is less heterogeneity for the measures with less GHG reduction potential. The highest mitigation is achieved if all farms adopt all four mitigation measures (i.e., all measures suitable to the farm type). Costs in terms of farm income losses are highest for feed additives and replacement of concentrate feed with legumes, followed by drag hoses. Increasing the number of lactations per dairy cow often results in net savings for the farmer. The measures with higher costs also have larger dispersion compared to the low-cost options in our sample (see Appendix A4.3).

4.3.2 Agents' decision-making and interactions

The described farm and farmer characteristics are used in FARMIND to simulate a two-tiered decision-making mechanism for managing farm resources (Huber et al., 2022). In a first step, agents choose a decision strategy i.e., repetition, optimization, imitation, and non-adoption. The choice of this strategy depends on the combination of two model endogenous variables: i) the agents' income satisfaction and ii) whether a farmer is inclined to engage in social processing with her/his peers or not. Since these parameters can vary depending on the price level and resulting income as well as the adoption dynamics within the social network of the farmer, the strategic choice can change endogenously with each model run.

In a second step, farm agents choose their actual production decision i.e., the adoption of a GHG mitigation measure based on the options provided in the corresponding strategy. This two-tiered decision-making is implemented in three coding steps (for a conceptual representation of the decision-making, refer to the ODD+D protocol).

In the first step, FARMIND calculates the agent's satisfaction based on the prospect value of the agent's income considering empirically observed risk preferences i.e., loss aversion, valuation of gains and losses and probability weighting (Kreft et al., 2020). The prospect value $V_i$is defined by the incomes x in year *t* and all previous years within the agents' memory length (here 5 years). Incomes above (below) the agents' individual reference income V_i^{ref} are considered as gains (losses). The prospect value is calculated based on empirically measured individual value and probability weighting functions using a lottery (Tanaka et al. 2010) and an individual reference income. If the prospect value is positive (negative), an agent is considered as satisfied (unsatisfied). Formally, assuming that a set of past incomes of farm i in year t are $\{x_1, \cdots, x_m\}$, and value function and decision weight are $v(x_t)$ and $\Phi(x_t)$, respectively, the prospect value for each farm is defined by

$$V_i = \sum_{t=1}^{m} v(x_t)\Phi(x_t) \qquad \textit{Equation 1}$$

The value functions in the gain (+) and loss (-) domain, respectively, are:

$$v^+(x) = {x_t}^{\alpha^+} \text{ for gains and } \quad v^-(x) = \lambda\, {x_t}^{\alpha^-} \quad \text{for losses,} \qquad \textit{Equations 2a/ 2b}$$

where λ is a measure of the agent's individual loss aversion.

The calculation of decision weight $\Phi(x_t)$ is based on the distribution of incomes from past income values. Assuming that historical incomes follow normal distribution over a given memory length *m*, we can identify the cumulative distribution function of income x_t, denoted by $F(x_t)$. We then calculate the decision weight of each income:

$$\Phi_{x_t}^{+/-} = w^{+/-}[1 - F(x_t)] - w^{+/-}[1 - F(x_t + \Delta)], \qquad \textit{Equation 3}$$

where $w^{+/-}$ is the probability weight function in the gain and loss domain respectively, and Δ is the difference between an income value and its adjacent value, e.g., 1 unit in the currency in which the income is expressed (here Swiss Francs CHF). The probability weight functions w^+ and w^- are defined as

$$w^{+/-}(p) = \frac{p^{\varphi^{+/-}}}{\left(p^{\varphi^{+/-}} + (1-p)^{\varphi^{+/-}}\right)^{1/\varphi^{+/-}}} \quad . \qquad \textit{Equation 4}$$

The interaction between agents in FARMIND is based on learning from observation and interaction with peers. To calculate whether a farmer will engage in such social processing or not, our model calculates the agent's dissimilarity to their peers i.e., whether the other agents also adopted climate change mitigation measures. To do so, we count the average number of mitigation measures in the agent network over the memory length. We then divide the average number for each measure that is adopted by the agent and the network by all mitigation measures performed in the corresponding network. The higher the value, the more similar an agent is to their peers i.e., the same GHG mitigation measures have been adopted.

Formally, assuming that a activities are performed by all the peers in the social network, agent i's activity dissimilarity is

$$d_i = \frac{1}{a}\sum_{j=1}^{a} \frac{\#\ of\ peers\ performing\ A_j}{n}\left(1 - P\left(A_j^i\right)\right) \qquad , \qquad \text{Equation 5}$$

where $P\left(A_j^i\right)$ is agent i's performance status for activity j; $P\left(A_j^i\right) = 1$ if A_i is performed and otherwise $P\left(A_j^i\right) = 0$ while n is the number of peers to whom an agent is linked. The higher the value of d_i, the greater the similarity between an agent and their peers (measured on a relative scale with 1 implying all farms engage in the same activity). Please note that the agents' dissimilarity also depends on the size of the network n and the number of activities a in the network. The larger the network and the smaller the number of activities within the network, the more likely it is that an agent will be dissimilar to their peers. The connection between the different agents in FARMIND is thereby based on an empirically informed social network (Kreft et al., 2021b).

The dissimilarity index is then compared to a tolerance level, representing the individual aptitude to consider deviating behaviour of other farmers. A low dissimilarity tolerance level d_i^{tol} implies that a farmer is more likely to comply with social norms, i.e., not being different from others. This value is derived from the survey using questions on how farmers assess the importance of peers in their decision-making on a Likert scale (Kreft et al. 2020).

Given the values for satisfaction and dissimilarity, four heuristic strategies are derived based on the theoretical framework CONSUMAT (see Jager and Jansen 2012 for details): If a farmer is satisfied and not socially oriented, they will abide by a production decision (Repetition). A satisfied but socially oriented farmer will search for additional information and start considering the behaviour they observe in their social network (Imitation). Those who focus on individual behaviour but are dissatisfied will strive to optimize their situation (Optimization). Finally, the combination of dissatisfaction and socially oriented behaviour leads to an examination of the behaviour adopted by other agents outside the direct social network (inquiring) (an overview of all possible cases can be found in section on "Scenarios" in the ODD+D protocol). In contrast to an uncertain but satisfied agent who will imitate the behaviour observed in the strongly connected social network to increase their "social well-being", the dissatisfaction leads agents to more extensive scrutinizing for other solutions, which will expectedly increase satisfaction.

Here, the choice of the agents' decision strategy results in a set of potential GHG mitigation measures that is transferred to the second simulation step. A repeating agent considers only those measures that had been applied in the last simulation run. An optimizing agent considers all available mitigation options. An imitating agent considers those mitigation measures that had been applied by agents in the social network. Finally, an agent that is socially oriented and at the same time unsatisfied will choose none of the mitigation measures. Since the adoption of the four mitigation measures represents only a small part of farmers' overall decision-making, the inquiring behaviour is implemented as "non-adoption". We assume that farmers will for example consider different mitigation measures or even other production options observed in the wider social environment. While such options are outside the scope of our study, the scenario "complete network" can be interpreted as a broader environment from where agents receive new information.

In the second step, the mitigation measures that are transferred from the strategic heuristic are weighted according to the personal preferences of the farmer (Kreft et al., 2020). Based on their stated intention to implement different mitigation measures, we apply the fuzzy out-ranking method to narrow down the options available to those preferred by the farmer. The higher the preference, the more likely the corresponding activity appears on the top of the fuzzy ranking and thus in the agents' choice set in the second tier of decision-making. This method allows to account for individual preferences for specific mitigation measures and further reduces the choice set of each agent transferred to the second stage of the decision-making process in FARMIND[5].

In the third step, based on the transferred choice sets and the ranking of the mitigation measures according to the farmers' individual preferences, FARMIND chooses those mitigation activities that maximize farm income. This represents the second tier of the farmers' individual decision-making. The results from the adoption decision (income and GHG mitigation measures) are then again transferred to the FARMIND strategic decision to update measures and income distribution of the agents. The cost and benefits (e.g., changes in GHG emissions) for each agent are based on the calculation of the bio-economic farm level model FarmDyn (Britz et al., 2019). This sub-model provides a matrix with all costs and potential GHG emissions reduction for all mitigation measures and their interactions for each agent.

4.3.3 Simulation set up and scenarios

We test and compare the effect of empirical and hypothetical social networks in four different scenarios. The scenarios reflect the different types of social networks i.e., from agents without ties to the agents with ties that were empirically measured to a network in which all agents are connected and a network with few random ties. This set up allows to compare the "observed network" to counterfactual situations without social ties, with few ties and with a complete social network. The difference in total GHG

[5] For more details on the fuzzy out-ranking method, please refer to section 2 (Individual decision-making) of the ODD+D protocol.

emissions reduction between the counterfactual “No social network” and the “Observe network” is then used to quantify and discuss the contribution of the network to overall GHG reduction. In addition, the comparison with the full network and the loose random network shows the potential of such a behaviour when only very few are connected and if social ties were scaled to all the farms, respectively. Thus, the comparison of simulation results gives quantitative insights into the relevance of social networks in climate change mitigation in agriculture.

For the initialization of the model, we allow optimizing agents in all scenarios to adopt initial mitigation measures (measures that would have been adopted by these agents also in the absence of social networks). We simulate farmers’ adoption decisions over several runs, each representing one year. In this period, agents endogenously choose a strategy and eventually adopt mitigation measures. We repeat the simulation over twelve runs (years) until FARMIND reaches a saturation state at which the number of mitigation measures does not change anymore (even though strategies might still vary). In each run, the income information is updated (according to different milk and beef price levels) and flows into the calculation of the prospect value, which ultimately defines the satisfaction of farmers when compared to the individual reference income.

We repeat this scenario over different payment levels for GHG emission reduction. With a payment of 0 CHF per ton of CO_2 equivalent, only those measures that have negative abatement costs (e.g., increasing the number of lactations per dairy cow) can enter the solution. With increasing payment levels, agents’ profits change depending on their GHG reduction potential and the farm individual opportunity costs.

A key methodological challenge in FARMIND is its parameterization given different potential pathways that result in the same level of adoption i.e., model equifinality (Williams et al., 2020). This implies that multiple structures and/or parameterizations in FARMIND exist that generate outputs consistent with the observed adoption pattern in our case study region. To address this challenge, we calibrated the behavioural parameters in FARMIND based on indicators of model performance with respect to how well the simulations allow to replicate the observed occurrence of adopted mitigation measures in our case study region, i.e. the observed number of mitigation measures currently adopted by farmers. In addition, we also performed an extensive output sensitivity analysis (i.e., with respect to the amount of GHG mitigation). The analyses showed that we can calibrate FARMIND to observed uptake of climate change mitigation measures in our case study region and that our simulation outcomes remain robust with respect to a meaningful variation in behavioural parameters (for details, see ODD+D protocol).

4.4 Results

We find that with a given payment for emission reduction, farmers’ social networks substantially increase the reduction of overall on-farm GHG emissions compared to a situation where farmers do not have social ties but are still influenced by individual preferences. At a payment of 120 CHF/tCO_2eq, overall aggregated GHG reduction is almost doubled from 262tCO_2eq to 511tCO_2eq due to the observed and the complete social network, and increased by 68% (to 440tCO_2eq) in case of the small random network (figure 3).[6] To be able to compare the effect of the social network to the same level of emission reduction in the scenario without social ties, we increased the payment in the counterfactual scenario until the reduction levels were comparable. The simulations show that a payment of 500 CHF/tCO_2eq would be necessary to reach the same reduction level without social networks as achieved at 120 CHF/tCO_2eq with social networks. This means that a similar amount of GHG emissions can be reduced with 380 CHF less (- 76%) due to knowledge exchange within farmers' social networks. When the payment is set to 500 CHF/tCO_2eq, overall GHG reduction increases by 118% (to 1123t CO_2eq) when farmers are connected in the observed social network compared to the scenario without social ties. At this payment level, a fully integrated social network reaches an additional 18% reduction of GHG emissions (to 1323 tCO_2eq) compared to the observed network while with a small random network, 13% less GHG reduction (982 tCO_2eq) is achieved. These findings can be explained by the two-tier decision-making process in our model. When social networks are present and the farmer chooses to imitate (choice of strategy), adoption is increased by providing information on mitigation measures through knowledge exchange. This is expressed by a larger choice set. At the second stage of the decision-making (income maximization), mitigation adoption can be increased due to a higher payment per ton of CO_2eq, which will increase farmers' income.

Comparing overall GHG emissions reduction of both payment levels (120 vs. 500 CHF/tCO_2eq), the increase due to the higher payment is larger when social networks exist as compared to a situation without networks. More precisely, an additional payment of 380 CHF/tCO_2eq (500 CHF instead of 120 CHF) increases GHG emissions reduction by 97% in the scenario without social networks and by 120% in the observed network scenario (respectively, 159% in the complete network scenario).

[6] A detailed overview of simulation results can be found in appendix 8.4. Boxplots showing the distribution of GHG reduction and income changes across farms are shown in appendix 8.5.

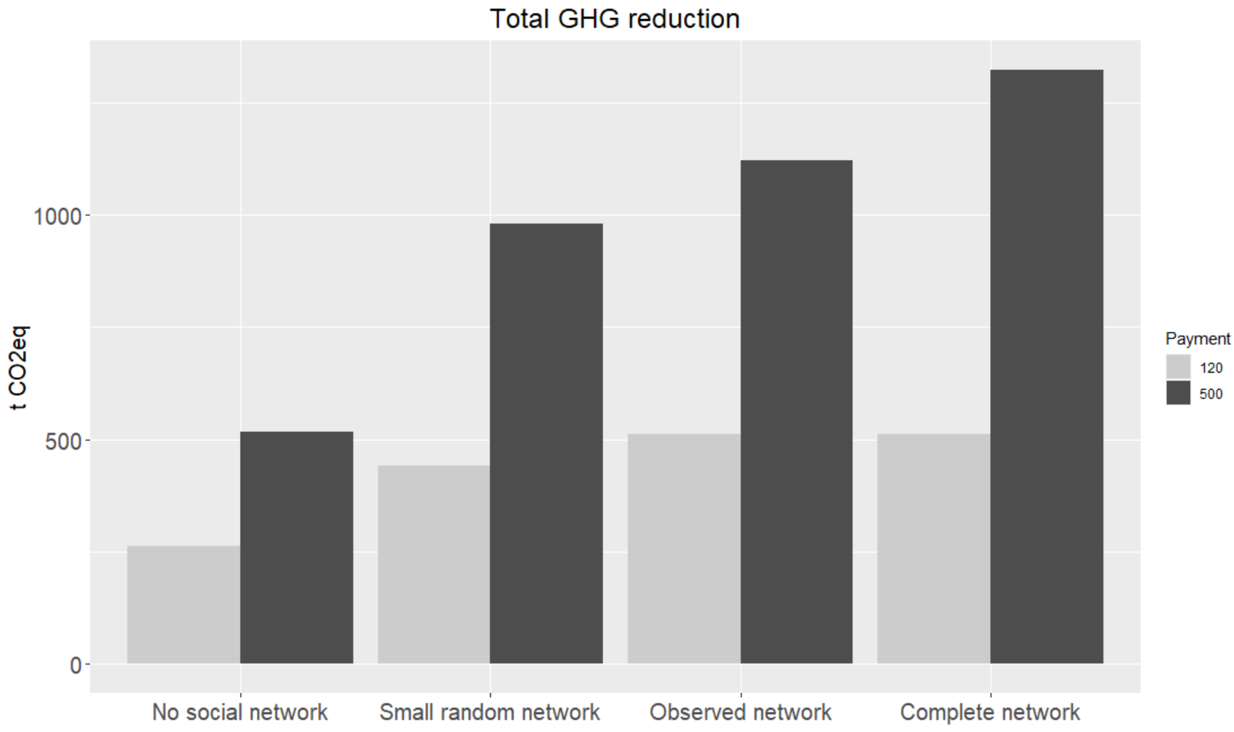

Figure 4.3: Total GHG reduction at two payment levels across all network scenarios. Grey bars correspond to GHG reduction at a payment of 120 CHF/t CO_2eq reduced. Black bars correspond to GHG reduction at 500 CHF/t CO_2eq reduced.

This is also reflected by marginal abatement costs of on-farm mitigation in our sample. Mean marginal abatement costs to achieve a similar amount of aggregated GHG reduction (approximately 500 tCO_2eq) are 190 CHF/tCO_2eq lower when farmers are socially interconnected in the observed network scenario. Without social network ties, mean marginal abatement costs are 325 CHF/tCO_2eq on average. In the observed and complete network scenario, marginal abatement costs amount to 135 CHF/tCO_2eq, and 192CHF/tCO_2eq in a situation with few random social ties (Figure 4.4).

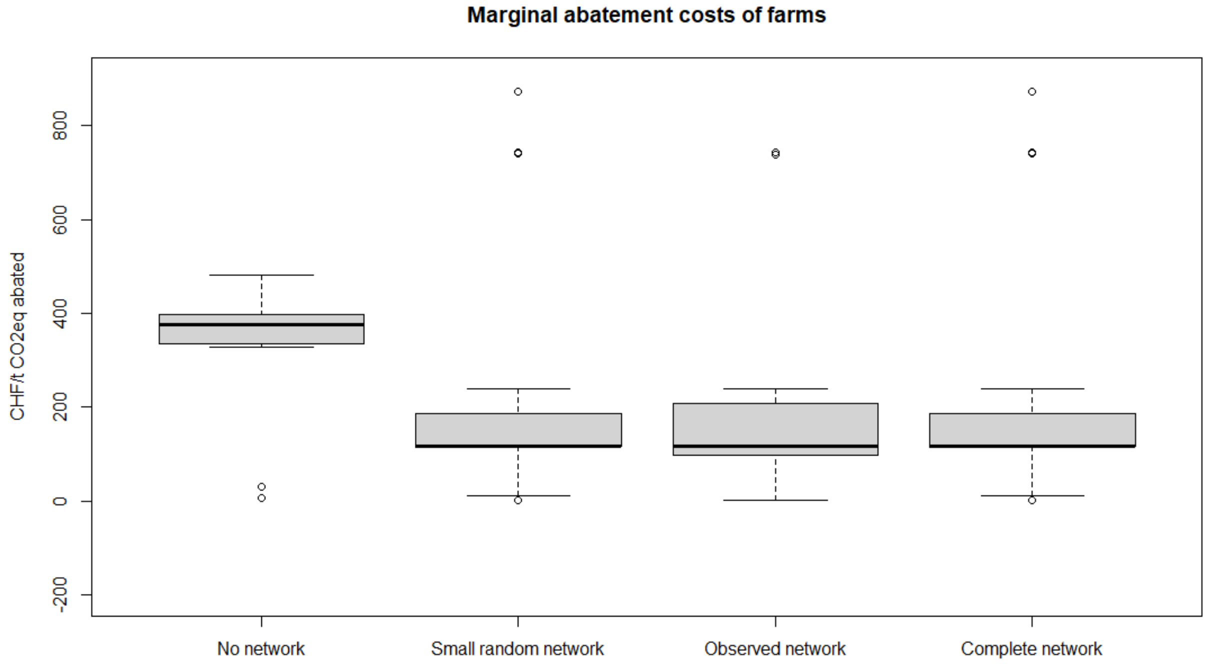

Figure 4.4: Distribution of marginal abatement costs of farms across the four network scenarios. To compare costs at a similar overall GHG reduction level (approximately 500 t CO_2eq), marginal abatement costs in the no network scenario are simulated based on a payment of 500 CHF/t CO_2eq, and on a payment of 120 CHF/t CO_2eq in the other scenarios where social ties are present.

With regards to the adoption of mitigation measures, we find that farmers adopt more mitigation measures when they have social ties to others compared to a scenario without any social networks. At a payment level of 120 CHF/tCO_2eq, increasing the number of lactations per dairy cow is the most widely adopted measure. Drag hoses are the second most adopted measure in the scenario without social networks and in the random network with few ties. In the observed and complete network scenario, feed additives to reduce enteric fermentation are more often adopted than drag hoses. This can be explained by the fact that the use of drag hose is less costly than introducing feed additives. It is thus more often adopted than feed additives when no social network or only few ties exist. However, when feed additives are adopted by peers in the social network, the measure gets into (imitating) farmers' choice set more often and is hence more often adopted. In all scenarios, replacing concentrate feed with locally grown legumes is the least adopted mitigation measure. At a payment of 500 CHF/t CO_2eq, overall mitigation adoption is substantially increased across all network scenarios. The higher payment mainly affects the adoption of drag hoses and feed additives which are now the most adopted measures (figure 5). In the three scenarios with social ties, the number of farms which replace concentrate feeds by legumes is increased as well while the number of farms introducing more lactations per dairy cow remains stable.

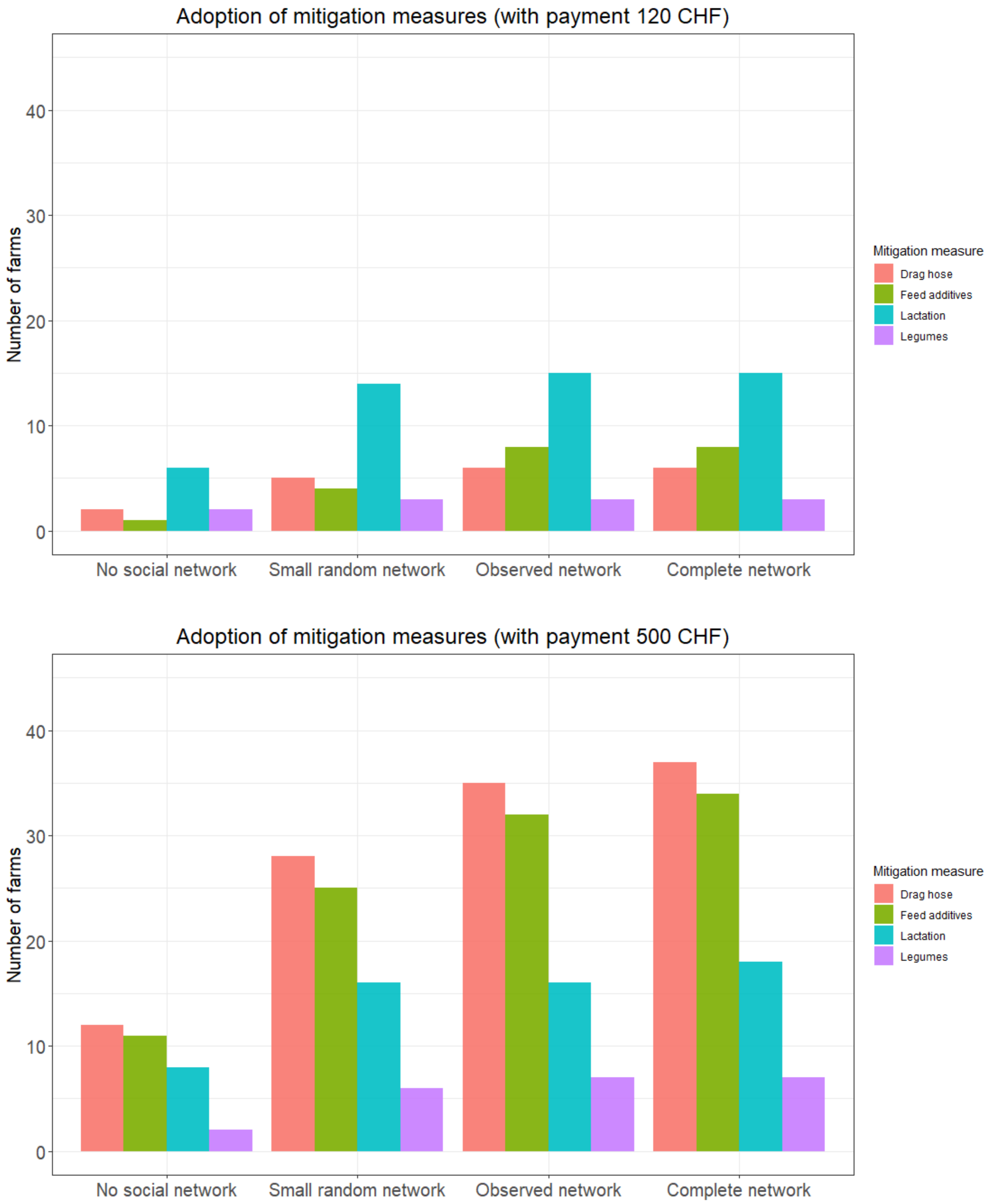

Figure 4.5: Adoption of mitigation measures in four network scenarios across the sample of 49 farms with payments of 120 CHF/tCO_2eq abated (upper graph) and 500 CHF/tCO_2eq (lower graph).

The overall technical GHG reduction potential in our sample, based on the considered GHG mitigation measures, is simulated to be at 13.8 % compared to baseline emissions, i.e., a reduction of 1967 t CO_2eq could be achieved if all farms were to reduce the maximum amount of GHG emissions possible independent from economic, individual behavioural and social constraints. However, when farmers strictly maximize incomes without behavioural constraints, the simulated reduction potential shrinks to

6.2% of baseline emissions at a payment of 120 CHF/t CO_2eq and 12.2% at 500 CHF/t CO_2eq. Accounting for individual behavioural characteristics (risk attitudes and farming preferences) further decreases the reduction potential in our model to 2.6 and 3.3%, respectively. Including social network ties increases overall reduction potential again to 3.8 and 8% of baseline emissions, respectively (Figure 4.6).

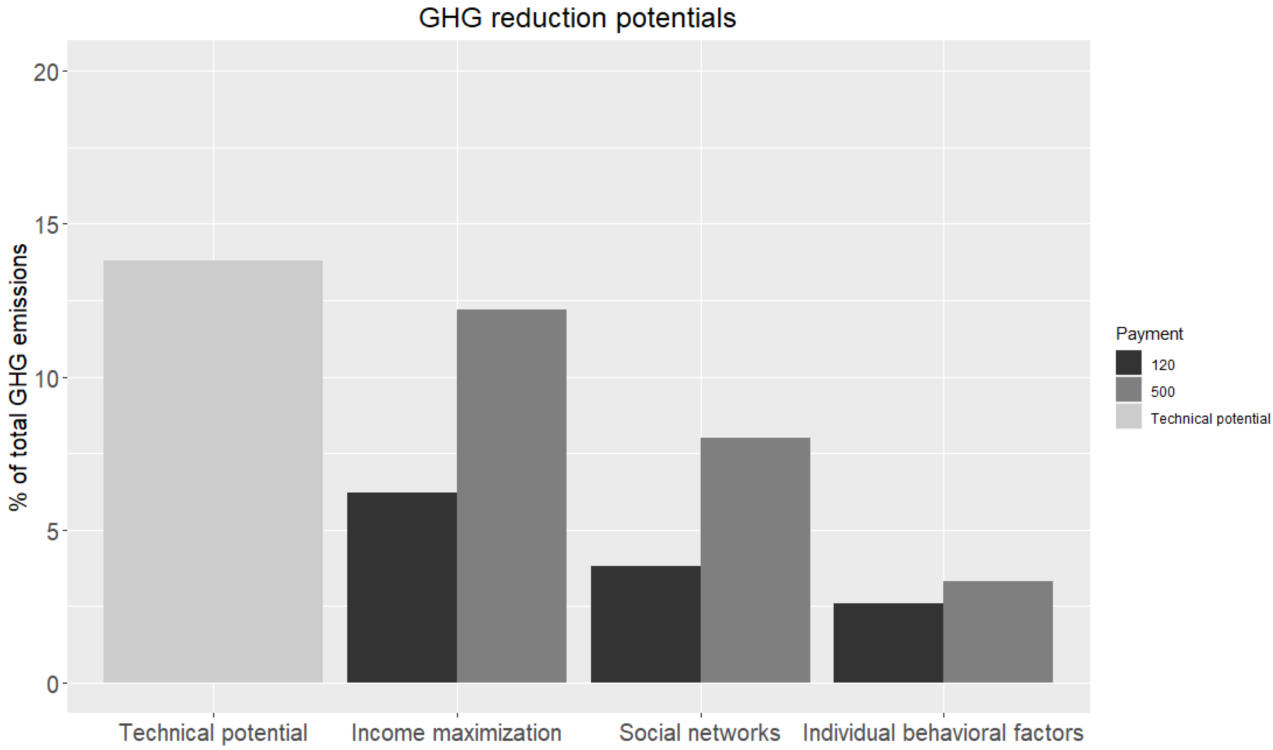

Figure 4.6: Comparison of GHG reduction potentials considering technical, economic, social and behavioural constraints. The technical potential is based on the here considered mitigation measures (cf. Table 4.1) without consideration of economic or behavioural constraints and with constant production levels.

4.5 Discussion

Our results show that social networks within which farmers exchange knowledge on climate change mitigation practices have a positive effect on farmers' adoption of such practices and hence increase the effectiveness of results-based payments for GHG reduction. This is in line with the literature investigating the effect of social networks and social learning on farmers' adoption of e.g., innovations or agri-environmental practices (Bandiera and Rasul, 2006; Conley and Udry, 2001; Conley and Udry, 2010). We add to the existing literature by simulating social network effects regarding the reduction of agricultural GHG emissions. Moreover, we quantify the effect of farmers' social relations in terms of outcomes, i.e., overall GHG emissions reduction and associated costs. Quantifying social network effects is particularly valuable to assess the potential effectiveness of policies aiming at a reduction of agricultural GHG emissions.

Social networks of farmers can act as facilitators of agricultural climate change mitigation by spreading knowledge and influencing farmers' preferences under given economic boundaries. We find that the empirically observed social networks of farmers almost double total mitigation in our sample at a given payment of 120 CHF/tCO_2eq reduced and by 118% at a payment of 500 CHF/tCO_2eq. The increase due to the higher payment is mainly explained by more farmers adopting drag hoses and feed additives, while the comparably low-cost measure 'increase of lactations' is already adopted by most (dairy) farms at 120 CHF/tCO_2eq. Our results furthermore show that the effectiveness of a payment per ton of CO_2eq reduced can be substantially increased due to knowledge exchange and social learning within farmers' social networks. The social network effect is higher at a payment of 500 CHF/tCO_2eq (+ 118% GHG reduction) compared to 120 CHF/tCO_2eq (+ 95% GHG reduction). This is explained by a model-intrinsic mechanism: A higher payment per ton of reduced CO_2eq implies that at the same "amount" of information flow due to the social network, more mitigation measures become profitable for the farmer.

Moreover, we find that social networks improve the cost-effectiveness of payments based on achieved GHG mitigation, i.e., paid per ton of CO_2eq reduced. In our model, a comparable level of mitigation is achieved with 380 CHF/tCO_2eq less (-76%) and average marginal abatement costs are 190 CHF/tCO_2eq lower (-58%) due to the observed network. Given our modelling framework, this can be explained by the fact that due to knowledge exchange between connected peers, socially oriented farmers have more choice options when deciding whether to adopt mitigation measures. Consequently, overall mitigation becomes more efficient due to the information flow within the social network. In previous literature, social networks have rather been shown to lower transaction costs of e.g. knowledge acquisition (Levy and Lubell, 2017) and enable cost-effective collaboration of farmers (Prager, 2015). While our model does not account for such types of transaction costs, they would increase the effect of the social network. Thus, our simulation results should rather be seen as a lower bound for the effect of social networks on policy effectiveness.

Using the agent-based modelling approach FARMIND has several advantages for addressing our research question: Beyond income optimization simulated with standard bio-economic modelling, it enables to additionally account for heterogeneous farmers' characteristics. Over the past decades, evidence is increasing that considering different behavioural traits is crucial when trying to explain farmers' decision-making in various contexts (Brown et al., 2017; Dessart et al., 2019). In particular, agricultural climate change mitigation is still an "unknown terrain" for most farmers and related costs and benefits are often rather uncertain. Therefore, individual risk attitudes, personal preferences, climate change perceptions and concerns as well as social relations can arguably play an even more decisive role (Haden et al., 2012; Kreft et al., 2021a; Niles et al., 2016). Linking FARMIND to the bio-economic farm model FarmDyn (Britz et al., 2019) furthermore allows to consider the emerging changes in GHG emissions and farm incomes.

While there is a considerable technical reduction potential of the four mitigation measures (13.8% of baseline emissions), farmers actually adopt much less due to economic constraints as well as individual risk attitudes and preferences for single mitigation measures (around 3%). The latter can for example lead to reluctance to change and even prevent farmers from adopting cost-saving mitigation measures (e.g., increasing the number of lactations per dairy cow). However, when considering social relations, individual behavioural barriers of adoption can be overcome to some degree due to the information flow within farmers' social networks. This helps to increase the total reduction potential (in our sample, up to 8%). This five percent point increase when considering social networks should be seen as an important leverage for increasing the effectiveness of payments for GHG emission reduction.

A challenge of ABM including farmers' behavioural characteristics and social interactions is the need for a data intensive and usually costly parametrization (Huber et al., 2022). For our analysis, we can draw from an extensive data basis. Additional to farm census data, we use empirical survey data including risk preferences derived from an incentive-based lottery as well as interview-based social network data, which were collected with the newest available version of the survey software Network Canvas (Kreft et al., 2023; Kreft et al., 2021b; Network Canvas, 2022). However, despite the empirical data we rely on, our analysis faces some important uncertainties. First, the use of thresholds for determining the decision strategies in FARMIND implies that the calibration of these parameters has an important effect on simulation outcomes (see also Huber et al. 2021). While the survey could identify relative differences between agents, the absolute level of these model parameters had to be determined by the income levels simulated in FarmDyn. We performed an extensive sensitivity analysis to assess the effect of farmers' reference income and their tolerance for being dissimilar on model outcomes (see ODD+D protocol). However, different approaches of sensitivity analysis, e.g., maintaining a set of parameter combinations for calibration (cf. Berger and Trost, 2014) could help to further assess the robustness of our results. Based on our subsequent model selection, FARMIND can reproduce the observed adoption of climate change mitigation measures in our case study region. Thus, we are convinced that using FARMIND is a valid approach to assess the effect of social networks in our case study region. Moreover, we believe that our model is transferable to other regions as it builds on a solid theoretical and conceptual foundation that can help to understand farmers' adoption decisions in the context of agricultural climate change mitigation. To make results more generalizable, however, increasing the scale and the consideration of other regions would be indispensable.

Second, there is large heterogeneity of simulated GHG emissions reduction and associated income changes across measures as well as between individual farms in our sample, which corresponds to findings of other studies (Jones et al., 2015; MacLeod et al., 2010; Moran et al., 2011; O'Brien et al., 2014; Vermont and De Cara, 2010) (cf. Appendix A4.5). Mean marginal abatement costs of the farms in our sample amount to almost 550 CHF/tCO_2eq (if all farms adopt all suitable measures). Particularly the measure of replacing concentrate feed with locally grown legumes is extremely costly for single farms. On the other side, increasing the number of lactations per dairy cow enables net savings for several farms in our sample. However, this assumption might not hold for all the farms since we assume a constant milk yield of longer lactating cows and do not account for potential fertility or health issues and resulting veterinary costs (Grandl et al., 2019; Mellado et al., 2011). Furthermore, increasing the number of lactations and consequently a lower replacement rate on one farm does not necessarily reduce overall GHG emissions of the entire sector. For instance, if newborn calves are sold for replacement or fattening on other farms, GHG emissions just occur elsewhere. Third, there is uncertainty in the scientific literature on the technical reduction potential of single measures (Eory et al., 2018). For example, injection and close-to-ground application of manure, e.g., with trail hoses has been found to reduce N_2O emissions compared to broadcasting (Weiske et al., 2006) but also to increase them due to denitrification processes in the soil (Wulf et al., 2002). Other studies did not find any effect of the application technique on N_2O emissions (Clemens et al., 1997; Velthof et al., 1996). However, it is undisputed that manure application with drag hoses reduces NH3 (ammonia) volatilization, which is an indirect source of N_2O emissions (Wu et al., 2021). Despite the scientific uncertainty about the mitigation potential, we included this measure since it is very relevant and widely adopted on Swiss farms (for the primary goal of reducing NH3 emissions). Regarding the introduction of feed additives, particularly those with high content of unsaturated fatty acids, there is good evidence of a reducing effect on methane emissions from enteric fermentation in cattle. Nevertheless, many different supplements have been investigated resulting in different reduction potentials (Hristov et al., 2013; Jayanegara et al., 2020). Our assumptions are based on supplementation with linseed, which is relatively well studied and easily available in Switzerland (Engelke et al., 2019; Poteko et al., 2020). Such uncertainties, heterogeneous mitigation potentials and (partially) high costs are among the major challenges of integrating agriculture in general climate policies (Fellmann et al., 2018). Further uncertainties are rooted in model validation and parametrization, which is based on (self-assessed) survey data. A thorough uncertainty and sensitivity analysis can be found in the ODD+D protocol and in (Huber et al., 2022), respectively.

Finally, the assumption of a “no-network”, i.e. that there are no social interactions between farmers in our counterfactual scenario implies that our estimation of the social network effect must be seen as an upper bound of the economic value of these networks.

We find that even in a hypothetical situation of a complete network integration and at a payment level of 500 CHF/tCO_2eq, total GHG emissions reduction in our sample is at maximally 12% of baseline emissions when accounting for individual farmer characteristics and social interactions. This suggests that a substantial reduction of agricultural GHG emissions, especially in the livestock sector, will probably be rather limited (and costly) if current production levels and consumption patterns are to be held constant (Poore and Nemecek, 2018). Hence, the here assumed restriction to keeping constant production levels reflects a rather short-term perspective.

4.6 Conclusion

We investigated the quantitative effect of farmers' social networks on agricultural climate change mitigation and respective policy incentives based on a case study in Switzerland. Despite heterogeneous costs and reduction potentials of mitigation measures across farms, we find that information flow and knowledge exchange within farmers' social networks can increase the diffusion of mitigation measures and consequently reduce GHG emissions of the dairy, suckler and bull-fattening farms in our sample. This would render policy incentives to increase adoption of mitigation practices more effective. Using the agent-based modelling framework FARMIND, we estimated the effect of social networks in terms of GHG reduction and income changes compared to a scenario without social ties. This constitutes an important contribution to the literature that has so far mainly assessed costs and benefits of agricultural mitigation measures without accounting for individual farmers' characteristics and social interactions. Based on our findings, farmers' knowledge exchange in social networks can increase the effectiveness of payments aiming at a reduction of agricultural GHG emissions.

Our results have some important implications for policymakers: First, in addition to financial incentives compensating for the costs of mitigation, policymakers should seek to support the creation of farmers' social networks targeted at information exchange related to climate change mitigation. Complementing payment schemes (e.g. to incentives uptake of climate change mitigation measures) with such additional effort can substantially increase the efficiency of policy measures. In particular, forming connections between early-adopters and those who have not yet adopted mitigation measures can be a promising way to support relevant information flow. Possible formats could be creating farmer networks, the organization of farm visits or regional workshops and events to support informal exchange. According to our simulations, such programs could save a considerable amount of governmental spending for paying farmers to reduce GHG emissions. Second and more generally, farmers need access to knowledge and expertise about agricultural climate change mitigation and respective on-farm practices. Common instruments are information campaigns as well as specific advisory services and trainings offered to farmers. The topic should also be integrated in regular curricula of farming schools. A combination of policies could hence be promising: a financial incentive to boost first adoption of some (pioneer) farmers accompanied by knowledge building and supporting the exchange among farmers to spread know-how and ultimately increase mitigation adoption (Le Coent et al., 2021).

Further research on the magnitude of social network effects on climate change mitigation is however needed to underpin our findings and recommendations and make them more generalizable. In particular, different and larger samples, a broader range of mitigation measures, accounting for transaction costs and potential changes in production as well as other regions would be a valuable extension of our research. Beyond a binary assessment of the social network effect, investigating the role of specific features of the networks could be another interesting extension. Along these lines, the definition of social networks could be extended to e.g. social media discussions. Moreover, estimating the effects of different policy interventions under consideration of social networks and farmer behavioural characteristics constitutes an interesting topic for future research.

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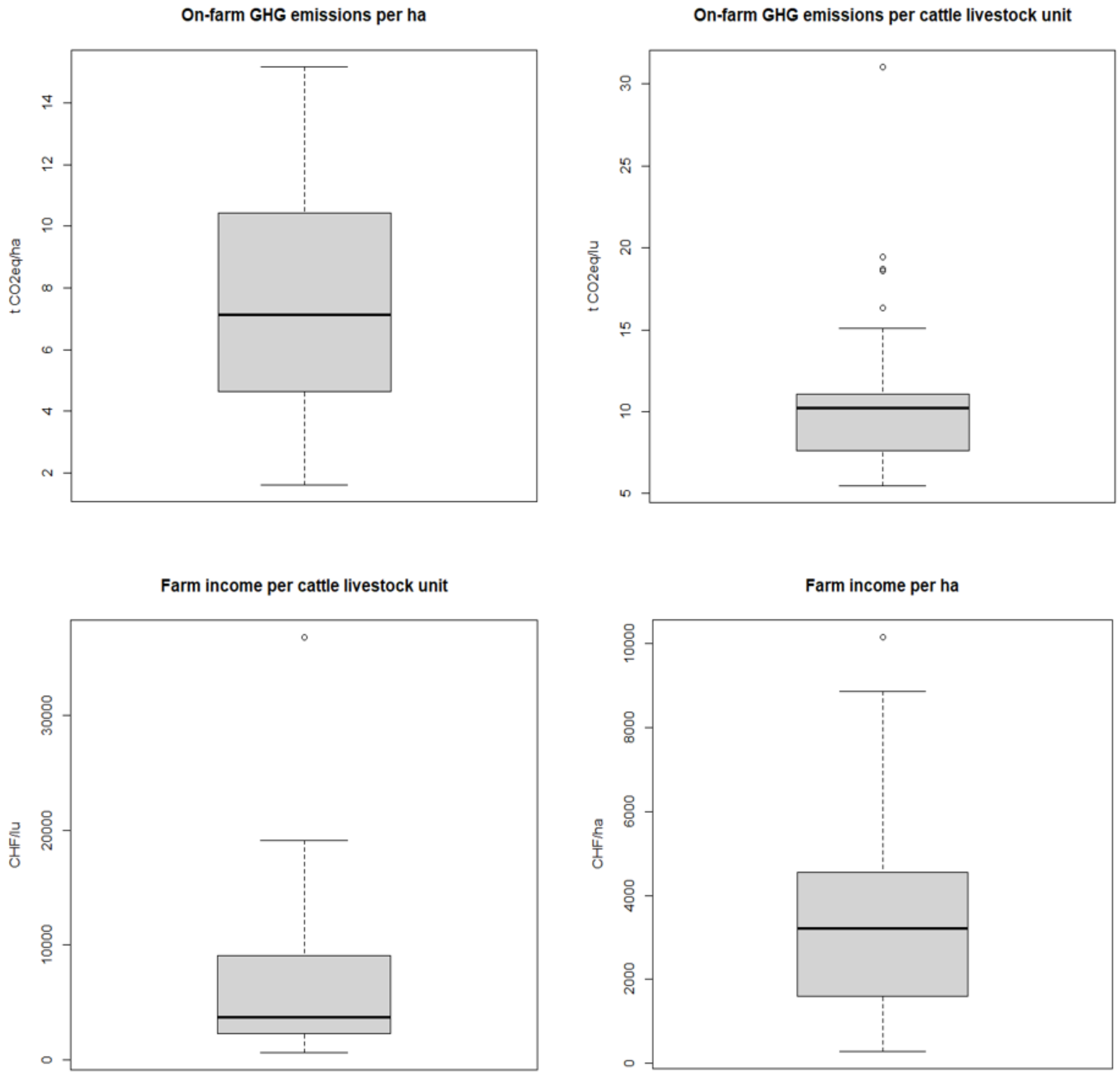
Appendix A4

A4.1: On-farm GHG emissions and farm income per area and livestock unit

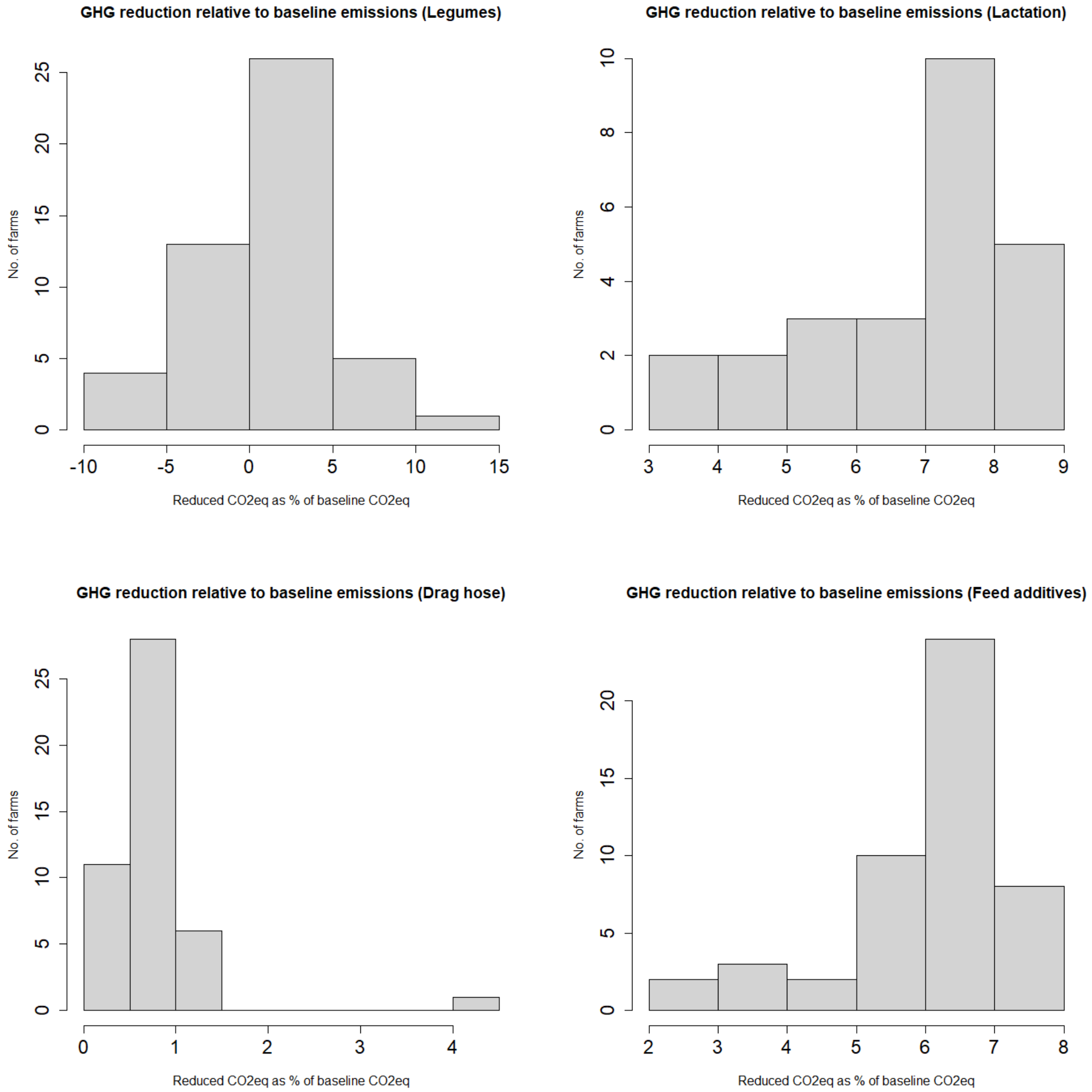
The following boxplots show the distribution of on-farm GHG emissions and farm income per ha and livestock unit across the simulated farms. Mean on-farm GHG emissions per ha of agricultural land are 7.6 tons of CO2eq. Mean on-farm GHG emissions per unit of cattle livestock are 10.6 tons of CO2eq. Mean farm income per ha of agricultural land is 3374 CHF. Mean farm income per unit of cattle livesto is 6378 CHF. Distribution of GHG reduction and farm income changes relative to baseline emissions



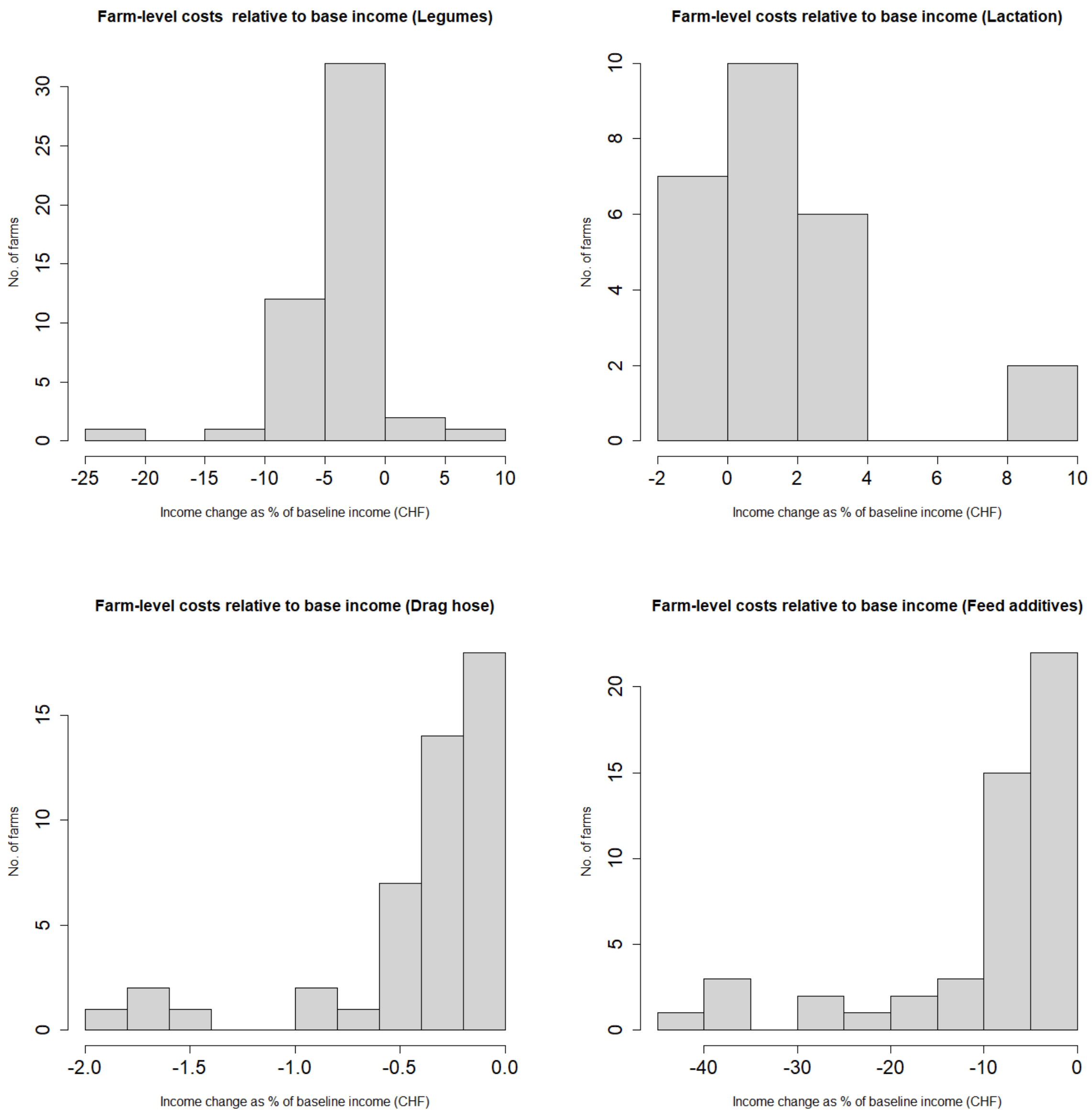
A4.2: Distribution of GHG reduction and farm-level costs

The following histograms show the distribution of GHG reduction and farm-level costs related to single mitigation measures across the simulated farms as percentage of baseline emissions and baseline farm income, respectively.

GHG reduction

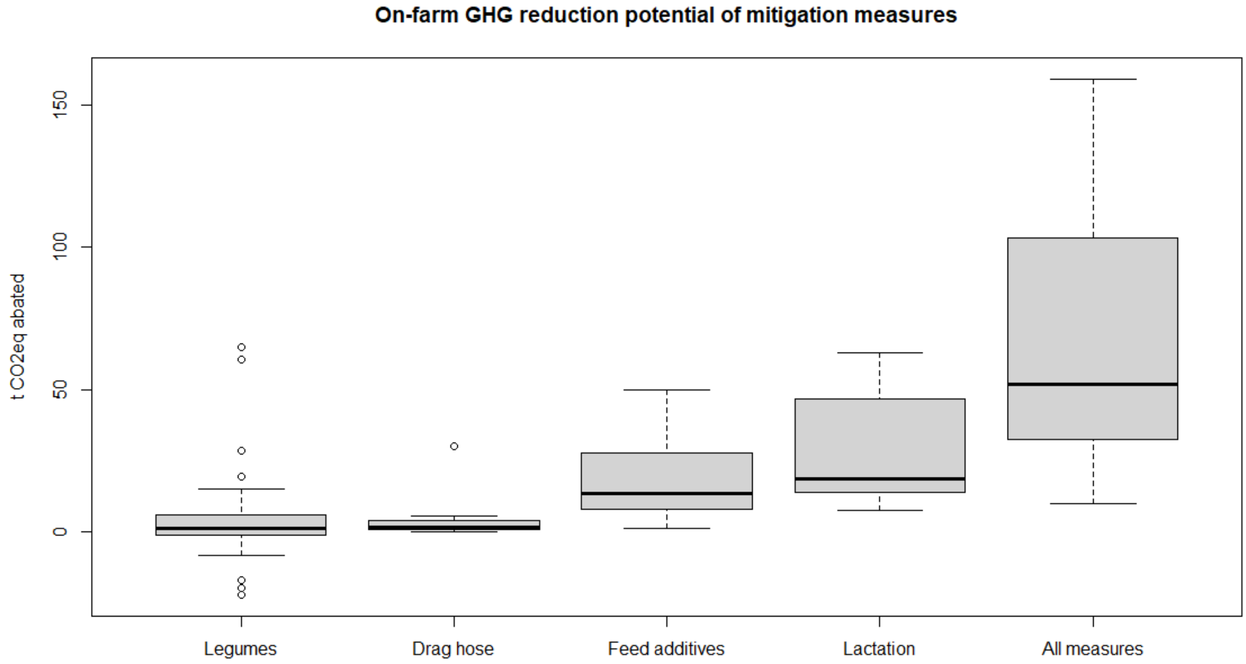


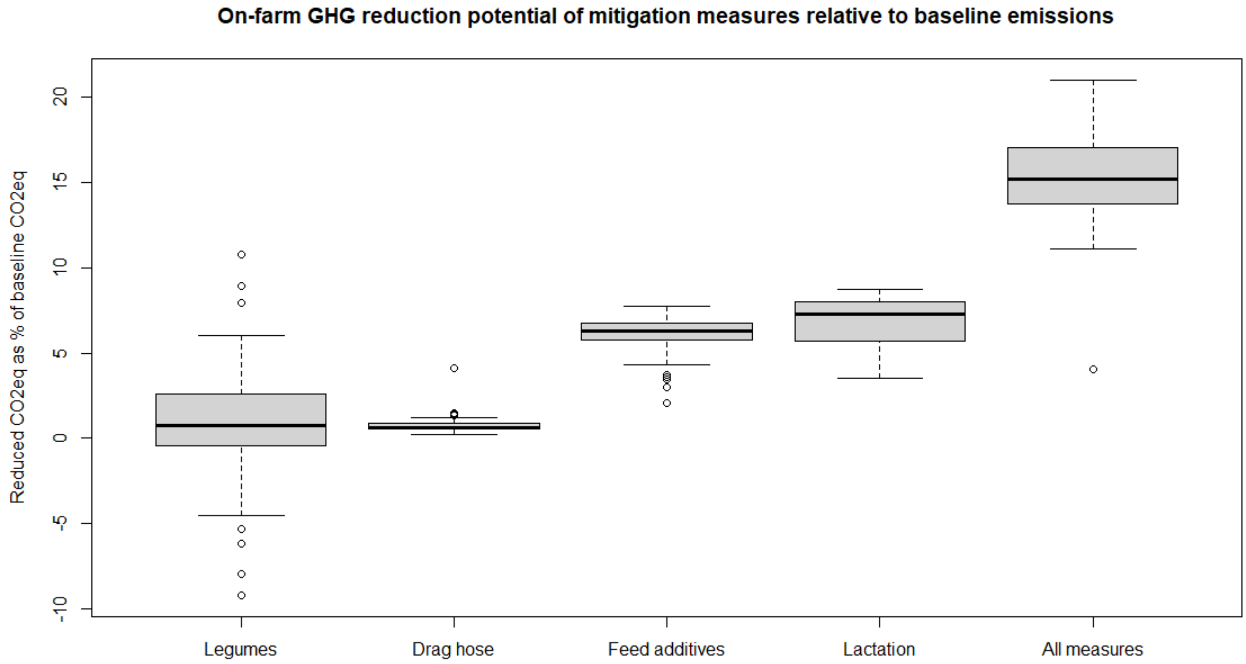
Farm-level costs

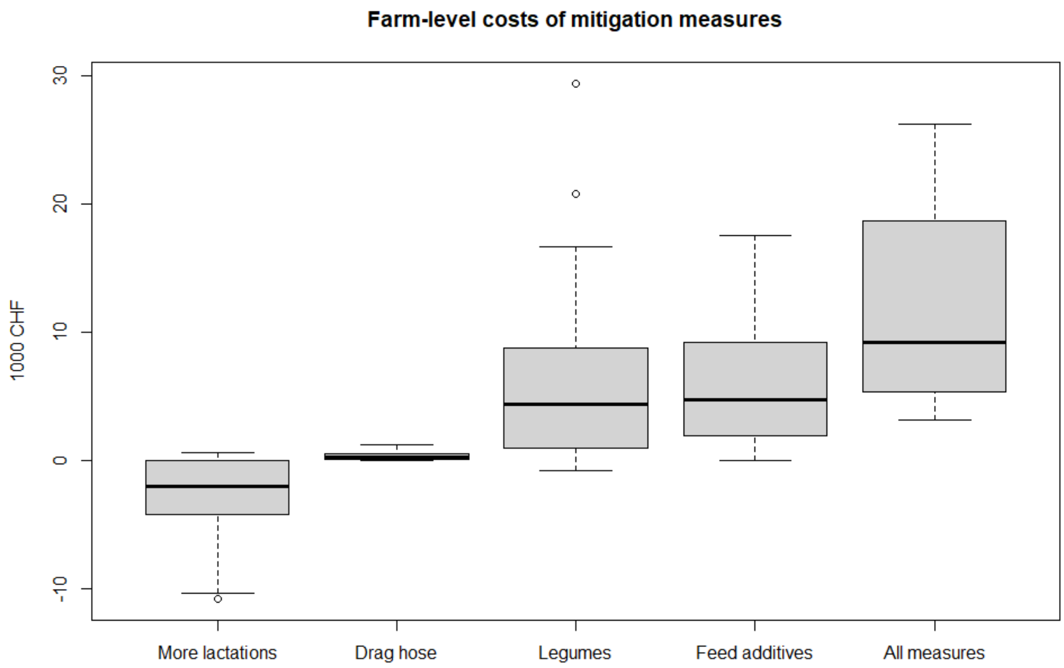


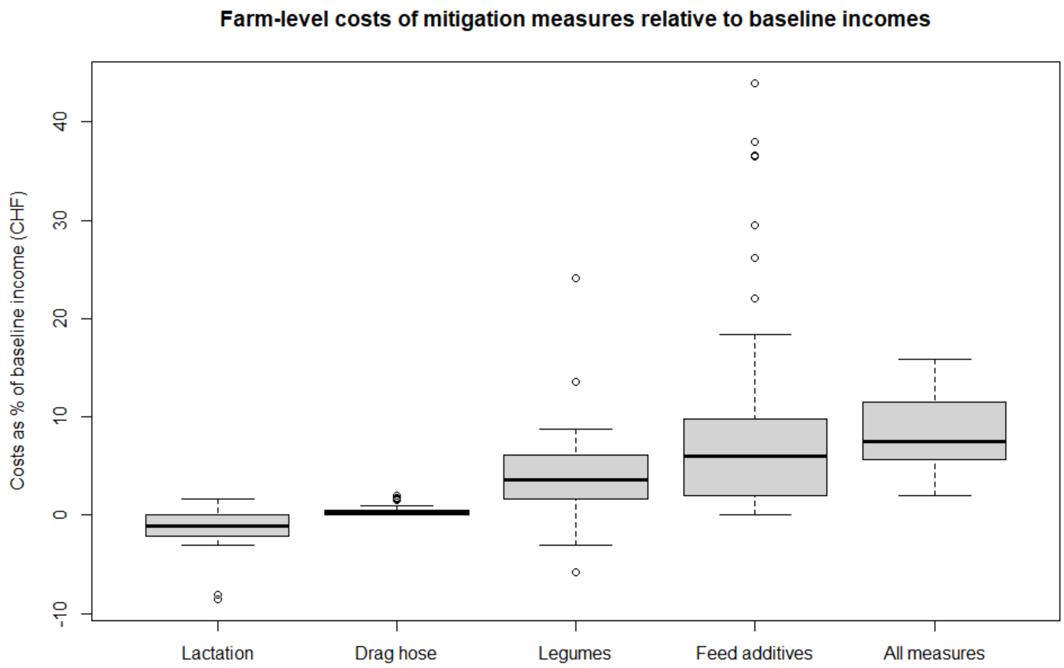
A4.3: Distribution of on-farm GHG reduction potential and costs across mitigation measures

The following boxplots illustrate the distribution of GHG reduction potentials as well as farm-level costs with adoption of single measures as well as all four measures. The first graphs are in absolute terms (tons of CO_2eq reduced and CHF) while the second graphs show the distribution relative to baseline GHG emissions and baseline farm-incomes (% of baseline CO_2eq and % of baseline CHF), respectively.


On-farm GHG reduction potential of mitigation measures
t CO2eq abated
150
100
50
0
Legumes
Drag hose
Feed additives
Lactation
All measures


On-farm GHG reduction potential of mitigation measures relative to baseline emissions
Reduced CO2eq as % of baseline CO2eq
20
15
10
5
0
-5
-10
Legumes
Drag hose
Feed additives
Lactation
All measures


Farm-level costs of mitigation measures
1000 CHF
30
20
10
0
-10
More lactations
Drag hose
Legumes
Feed additives
All measures


Farm-level costs of mitigation measures relative to baseline incomes
Costs as % of baseline income (CHF)
40
30
20
10
0
-10
Lactation
Drag hose
Legumes
Feed additives
All measures

A4.4: Detailed simulation results

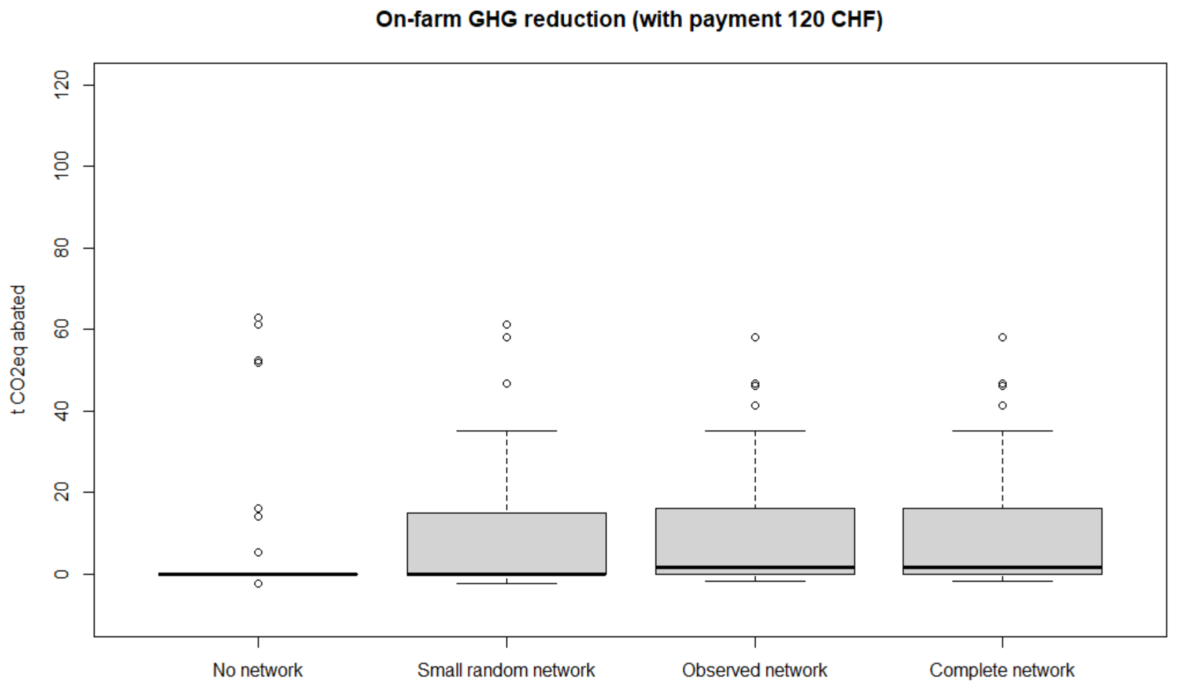
	Payment 120 CHF/t CO_2eq		**Payment 500 CHF/t CO_2eq**		**Mean marginal abatement costs (at similar GHG reduction level)**
	Overall GHG emissions reduction (tons)	Overall income change (1000 CHF)	Overall GHG emissions reduction	Overall income change	CHF/tCO_2eq
No network	262	49	516	194	325
Small random network	440	83	982	351	192
Observed network	511	100	1123	397	135
Complete network	511	100	1323	476	135

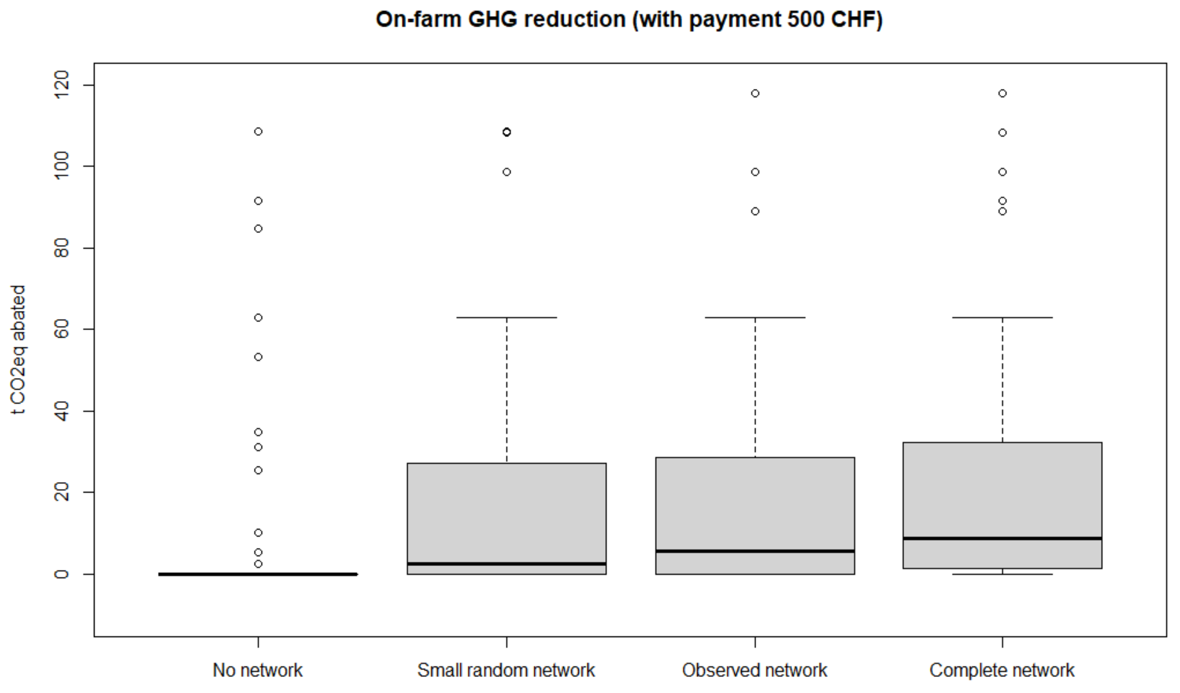
Detailed simulation results of overall GHG reduction, farm income changes and marginal abatement costs across four network scenarios at two payment levels. To compare based on similar GHG reduction levels, marginal abatement costs are simulated at a payment of 120 CHF/t CO_2eq for network scenarios and 500 CHF/t CO_2eq for the scenario without networks.

A4.5: Distribution of on-farm GHG reduction at different payment levels

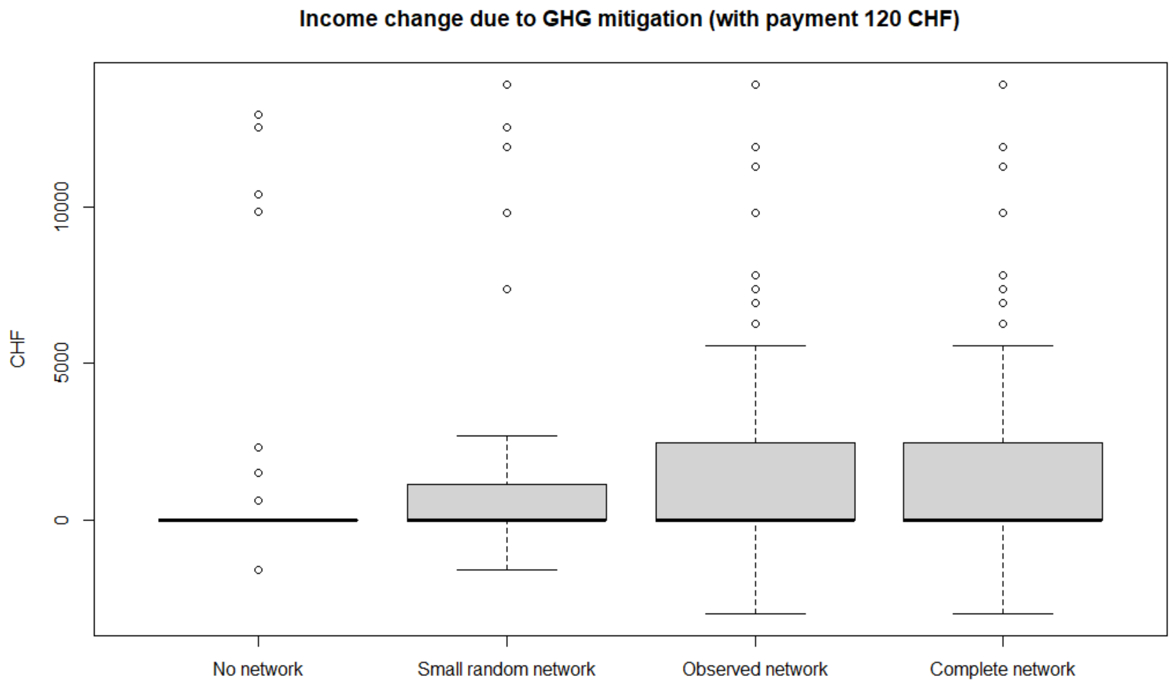
The following boxplots show the distribution of on-farm GHG reduction and farm income changes in the four simulated scenarios at both payment levels, 120 CHF/tCO_2eq and 500 CHF/tCO_2eq, respectively.

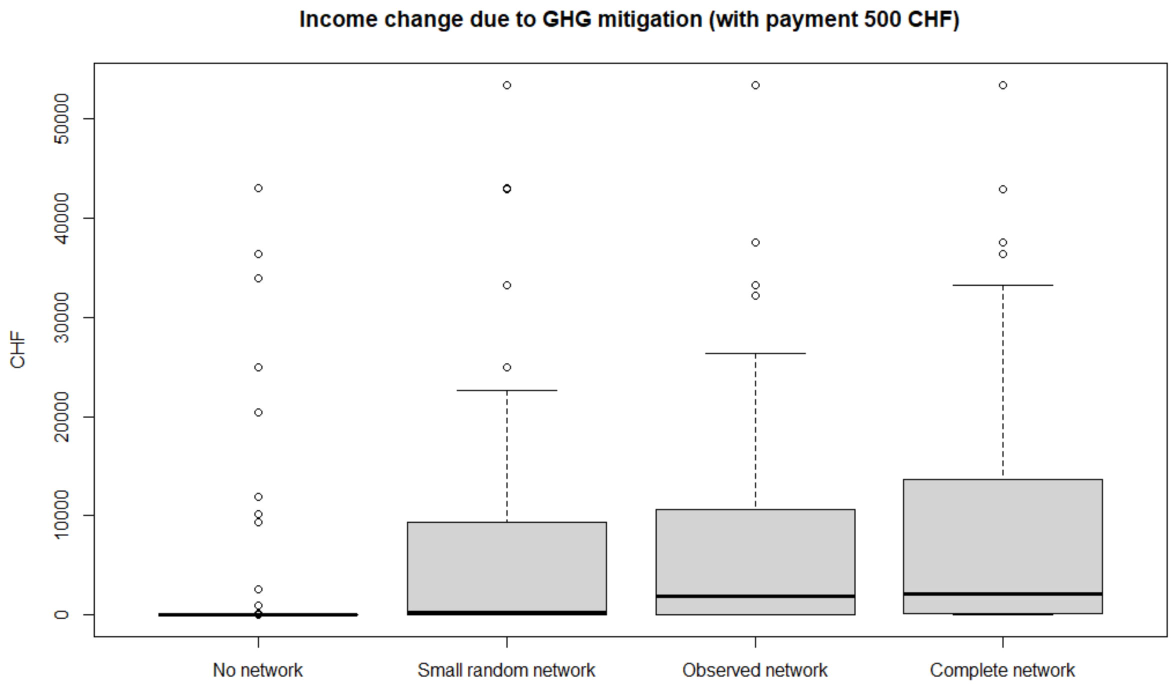
GHG reduction





Farm income changes





Appendix A5: ODD + D Protocol FARMIND

A5.1 Overview

Purpose

The purpose of the model is to simulate the effect of farmers' social networks on the adoption of climate change mitigation measures on Swiss dairy and beef cattle farms and on the effectiveness and efficiency of a public payment for greenhouse gas (GHG) emission reduction. More specifically, the model simulates the impact of the policy with and without social network effects on the adoption decision considering heterogeneous cognitive, social, and dispositional factors across individual farmers. Based on benefits and cost of four mitigation measures (replacement of concentrate feed in feeding rations, increased number of lactations per dairy cow, use of drag hoses for manure application and methane reducing feed additives), the model simulates farmers' individual adoption using survey data on farming objectives, risk preferences, and the tendency for social comparison. The emerging phenomena are the total amount of greenhouse gas (GHG) emissions reduced by the policy induced adoption of farm individual mitigation measures and the change in income for the individual farm as well as the whole farm community. Thus, the model allows to quantify the economic and environmental effect of social networks in the context of a public payment for GHG reduction in agriculture. By testing and comparing the effect of empirical and hypothetical social networks in different scenarios, the simulation results give quantitative insights into the relevance of social networks if the public supports climate change mitigation in agriculture.

Entities, state variables and scales (cf. Table A5.1)

Each agent represents an individual farmer. An agent has the following entities and state variables:

(1) Farm specific profits and cost as well as GHG emission reduction potentials for four on-farm climate change mitigation measures. These are exogenous parameters calculated in the sub-model FarmDyn (a farm optimization model parameterized with census data, see corresponding section below). Profits result from a payment for each ton of reduced CO_2 equivalents (CO_2eq). Farm specific cost emerge from implementing mitigation measures on each individual farm.

(2) Personal characteristics including cognitive factors (i.e., risk parameters based on cumulative prospect theory, and reference income), social factors (i.e., tolerance for being dissimilar to other farmers), and dispositional factors (i.e., preferences for specific mitigation measures). These are exogenous parameters based on a farm survey in our case study region (Kreft et al., 2020).

(3) A social network between farmers derived from an interview based on social network analysis (Kreft et al., 2021c).

(4) Income changes and GHG emission reduction potentials resulting from the choice of GHG mitigation options. The agents' income is used to calculate the prospect value based on the risk preferences of each individual farmer. The adoption choices of each farmer are used to calculate a dissimilarity index that drives social oriented behaviour. Income, GHG emissions, prospect value and dissimilarity index are model endogenous variables (see Table A5.1).

Table A5.1: State variables and parameters

Category	State variable / parameters	Abbreviation	Source for initialization
Farm	Adopted mitigation measures	A	Kreft et al. (2020)
	GHG emission reduction potential of measure A	y_{At}	Simulated in sub-model FarmDyn
	Income with adopted mitigation measures	x_{At}	
Personal characteristics	Loss aversion level	λ	Kreft et al. (2020)
	Valuation of gains and losses	$\alpha^{+/-}$	
	Probability weighting in gains and losses	$\phi^{+/-}$	
	Reference income to determine perceived gains and losses and calculate satisfaction	V_i^{ref}	
	Tolerance level for activity dissimilarity to determine information seeking behaviour	d_i^{tol}	
	Preference weight for mitigation measures	R^A	
Social network	Number of peers a farmer is linked to (number of social ties)	n	Kreft et al. (2021c)
Outcome variables	Prospect value	V_i	Model endogenous
	Agents' activity dissimilarity	d_i	
	GHG emission reduction (in simulation run t)	y_t	
	Income (in simulation run t)	x_t	

The underlying data on income changes and GHG emission reductions are calculated per farm on a yearly basis. Thus, a model run represents one year (i.e., the temporal resolution). To simulate the effect of knowledge diffusion through the social network, we repeat the simulation over twelve runs. Our main results, however, are comparative static in the sense that we compare final states of GHG emissions and incomes in different scenarios. The model simulates individual farms with heterogeneous farm sizes and locations. The farm size varies between 12 and 73 hectares (ha) with an average at 35 ha per farm. The sample consists of 24 dairy farms, 15 suckler farms and 10 bull fattening farms. On average, farms have 38 cattle livestock units.

Process overview and scheduling

FARMIND includes a two-tiered decision-making mechanism for managing farm resources (Huber et al., 2022b). In a first step, agents choose a decision strategy. The model includes four behavioural strategies: repetition, optimization, imitation, and opt-out (see section “Individual decision-making” below for details). In a second step, farm agents choose their actual production decision, i.e., the adoption of a GHG mitigation measure based on the options provided in the corresponding strategy. This two-tiered decision-making is implemented in three coding steps (cf. right panel in Figure A5.1).

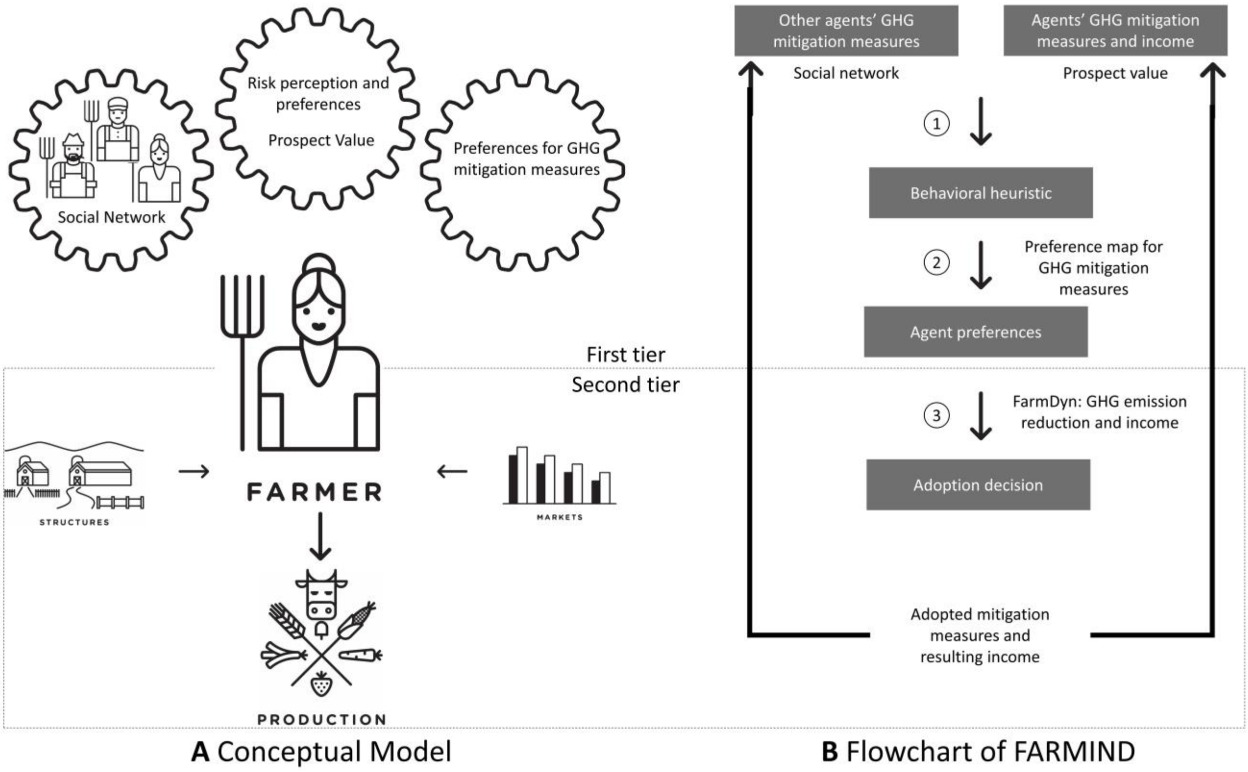


Figure A5.1: (a) Conceptual framework and (b) implementation flowchart of FARMIND

First, FARMIND calculates the income distribution over the farmers’ memory length and the income in the initialization year. On this basis, the model calculates the prospect value of the agent’s income considering the empirical based risk preferences (i.e., loss aversion, valuation of gains and losses and probability weighting). In addition, the model calculates the agents’ dissimilarity to the other agents in the network with respect to climate change mitigation measures. Prospect value and dissimilarity are then used to calculate a strategy of each individual farmer.

Second, mitigation measures are ranked according to the personal preferences of the farmer R^A (identified in the survey). A fuzzy logic algorithm identifies a sub-set of strictly preferred activities in the different strategies. This implies that an agent that dislikes one of the mitigation measures may not receive the corresponding option in the choice set even though it could be optimal for maximizing farm income.

Third, based on the transferred choice sets, FARMIND chooses those mitigation activities that maximise farm income from the available options. The results of the adoption decision (income and mitigation measures) are then again transferred to the FARMIND strategic decision to update measures and income distribution of the agents in the next model run.

A5.2 Design concepts

Theoretical and empirical background

We base our agent-based modelling framework on cumulative prospect theory and social network theory to link farmers' heterogeneous cognitive, social, and dispositional factors to cost and benefits of climate change mitigation measures. FARMIND is based on the so-called CONSUMAT framework, which integrates the different theoretical concepts into a structured sequence of modelling steps (Schaat et al., 2017). The parametrization of the model is based on the following empirical data: i) Risk preference parameters (based on the cumulative prospect theory) derived from a lottery included in an online survey with farmers in the case study region (Kreft et al., 2020). The lottery was based on Tanaka et al. (2010) and thus included values for risk aversion, valuation of gains and losses as well probability weighting (equal for gains and losses) ; ii) Stated preferences for mitigation options derived from the same survey (Kreft et al., 2020); iii) Information on the social network collected via face-to-face interviews using the survey software Network Canvas (https://networkcanvas.com); iv) Cantonal census data to calculate farm individual provision cost and GHG mitigation.

Individual decision-making

Following the CONSUMAT approach, agents make decisions on their behavioural strategies according to their satisfaction and willingness to engage in social processing. In FARMIND, an agent's satisfaction level in a year is reflected by the prospect value of incomes V_i in year *t* and all previous years within the memory length (here five years). Incomes above (below) the agents' individual reference income are considered as gains (losses). Based on these gains or losses, the prospect value is calculated using individual value and probability weighting functions. If the prospect value is positive (negative), an agent is considered as satisfied (unsatisfied). Formally, assuming a set of past incomes of farm i in year t $\{x_1, \cdots, x_m\}$, a value function $v(x_t)$ and decision weight $\Phi(x_t)$, the prospect value is defined for each farm by

$$V_i = \sum_{t=1}^{m} v(x_t)\Phi(x_t) \qquad \textit{Equation 6}$$

The value functions in the gain (+) and loss (-) domain, respectively, are:

$$v^+(x) = {x_t}^{\alpha^+} \text{ for gains and } v^-(x) = \lambda\, {x_t}^{\alpha^-} \text{ for losses,} \qquad \textit{Equations 7a/2b}$$

where λ is a measure of the agent's individual loss aversion.

The calculation of decision weight $\Phi(x_t)$ is based on the distribution of incomes from past income values. Assuming historical incomes to follow normal distribution patterns over a given memory length

m (i.e., five years in our application), we can identify the cumulative distribution function of income x_t, denoted by $F(x_t)$. We then calculate the decision weight of each income.

$$\Phi_{x_t}^{+/-} = w^{+/-}[1 - F(x_t)] - w^{+/-}[1 - F(x_t + \Delta)] \qquad \textit{Equation 8}$$

where $w^{+/-}$ is the probability weight function in the gain and loss domain, respectively, and Δ is the difference between an income value and its adjacent value, e.g., 1 unit in the currency in which the income is expressed (here Swiss Francs CHF). The probability weight functions w^+ and w^- are defined as

$$w^{+/-}(p) = \frac{p^{\varphi^{+/-}}}{\left(p^{\varphi^{+/-}} + (1-p)^{\varphi^{+/-}}\right)^{1/\varphi^{+/-}}} \qquad \textit{Equation 9}$$

To calculate whether a farmer will engage in social processing or not, we calculate a dissimilarity index to represent the agent's deviating behaviour from other farmers. We count the average number of mitigation measures in the agent's network over the memory length. We then divide the average number for each measure that is adopted by the agent and the network by all mitigation measures performed in the corresponding network. The higher the value, the more similar an agent is to their peers, i.e., the same GHG mitigation measures had been adopted. This index is compared to a tolerance level, representing the individual aptitude to consider deviating behaviour of other farmers. A low dissimilarity tolerance level d_i^{tol} implies that a farmer is more likely to comply with social norms, i.e., not wanting to be different from others.

Formally, assuming that a activities are performed by all the peers in the social network, agent i's activity dissimilarity is

$$d_i = \frac{1}{a}\sum_{j=1}^{a} \frac{\#\ of\ peers\ performing\ A_j}{n}\left(1 - P\left(A_j^i\right)\right) \qquad \textit{Equation 10}$$

where $P\left(A_j^i\right)$ is agent i's performance status for activity j; $P\left(A_j^i\right) = 1$ if A_i is performed and otherwise $P\left(A_j^i\right) = 0$ while n is the number of peers to whom an agent is linked. The higher the value of d_i, the greater the similarity between an agent and their peers (measured on a relative scale with 1 implying all farms engage in the same activity). Please note that the agents' dissimilarity also depends on the size of the network n and the number of activities in the network a. The larger the network and the higher the number of activities within this network, the more likely it is that an agent will be dissimilar to their peers.

Based on the combination of the agents' satisfaction and dissimilarity, the strategic choice of the farmer is defined. If a farmer is satisfied and does not engage in social oriented behaviour, they will abide by a production decision (Repetition). A satisfied farmer who engages in information seeking behaviour will search for additional information and start considering the behaviour observed in the social network

(Imitation). Those who focus on individual behaviour but are dissatisfied will strive to optimize their situation (Optimization). Finally, the combination of dissatisfaction and social oriented behaviour leads to an examination of the behaviour adopted by other agents in general (Opt-out). Table A5.2 summarizes the four decision heuristics in FARMIND applied to the study of adopting climate change mitigation measures.

Table A5.2: Strategic decision and choice sets in FARMIND

		Satisfaction Prospect value with reference income as threshold for the determination of gains and losses	
		> 0: *satisfied*	< 0: *dissatisfied*
Information seeking behaviour Values for determining individual or social processing (threshold for activity dissimilarity)	< tolerance level: *individual oriented*	**Repetition** The agent only considers those mitigation measures performed in the year before.	**Optimization** The agent considers all mitigation measures only restricted by personal preferences.
	> tolerance level: *social oriented*	**Imitation** The agent considers those mitigation measures that are applied in the social network and satisfy personal preferences.	**Opt-out** The agent selects none of the mitigation measures.

The choice of the decision strategy results in a choice-set of potential GHG mitigation measures. A repeating agent considers only those measures that had been applied in the last simulation run. An agent that optimizes considers all available mitigation option. An imitating agent considers those mitigation measures that had been successfully applied by socially connected agents. Finally, an agent that strives for individual behaviour and who is unsatisfied will choose none of the mitigation measures. In addition, FARMIND considers farmers' individual preferences for mitigation measures. Based on their stated intention to implement specific mitigation measures, we apply the fuzzy out-ranking method to narrow down the options available to those preferred by the farmer. The higher the preference, the more likely the corresponding activity appears on the top of the fuzzy ranking and thus in the agent's choice set in the second tier of decision-making.

The ranking of mitigation measures is based on the following algorithm: For each mitigation activity and agent, we calculate a value R. This value is used as criterion to determine the so-called fuzzy concordance relations for each pair of mitigation measures. There are three types of relations: i) indifferent, ii) weakly preferred and iii) strictly preferred. If the difference between the normalized values of measure A_1 (e.g., increased number of lactations with a high value) and A_2 (e.g., replacement of concentrates in feeding ration with a low value) $R^{A_1} - R^{A_2}$ is smaller than an exogenously set lower threshold q^- these measures are regarded as indifferent, i.e., the agent has no preference between the two. If the difference is greater than the upper threshold q^+, A_1 (increased number of lactations) is strictly preferred over A_2 (replacement of concentrates). If the difference between the two activities falls within the interval of the lower and upper threshold [q^{-}, q^{+}], A_1 is weakly preferred over A_2. Formally, the matrix $f(A_1, A_2)$, describing the relation between the two activities A_1 and A_2, is defined by:

$$f(A_1, A_2) = \begin{cases} 0 & if\ R^{A_1} - R^{A_2} < q^{-} \\ \frac{(R^{A_1} - R^{A_2} - q\text{-})}{q^{+} - q^{-}} & if\ q^{-} < R^{A_1} - R^{A_2} < q^{+} \\ 1 & if\ R^{A_1} - R^{A_2} > q^{+} \end{cases} \qquad \textit{Equation 11}$$

This calculation allows that all mitigation activities for each agent can be ranked in a list. FARMIND then uses a non-dominance score (*ND*) algorithm (Equation 7) that endogenously defines a small sub-set of mitigation activities. A characteristic of the non-dominance score is that it reduces the number of mitigation measures to a small sub-set that is strictly preferred to all the other measures.

$$ND(A_1, X, f) = 1 - \max_{A_2 \in X} max\{R(A_2, A_1) - R(A_1, A_2), 0\}, \qquad \textit{Equation 12}$$

where X is the set of all mitigation measures, A_1 denotes the measures of interest, A_j denotes other measures in X and $f(A_1, A_j)$ denotes the fuzzy pairwise preference matrix. The non-dominance score results in a reduced choice set for each agent, which is then passed to the second-tier decision-making step.

The second tier of the agents' individual decision-making consists of the choice of mitigation strategies with the highest profit within the choice-set according to the decision strategy and preferences. The profit for each agent is calculated in the sub-model FarmDyn (see section Sub-model below). The sub-model provides a matrix with all profits, cost and potential GHG emission reduction for all mitigation measures as well as their interactions for each agent. FARMIND chooses the option with the highest profit in the available choice set of each agent.

Learning

Agents have a memory of the mitigation measures they have adopted. The length of memory is determined exogenously and is set to five years for each agent. The more experience an agent has with the corresponding mitigation measure, the higher its weight in the fuzzy preference ranking. More experience also increases the weight of the corresponding measure in the agent's social network. Thus, agents learn from their peers about mitigation behaviour performed over a longer time horizon. Thereby, the weight of experience, the learning rate, is represented as a logarithmic function that converges to one over the period of the memory length (i.e., five years). This mechanism of learning from peers increases the probability of adaption of a mitigation measure when more agents perform this measure over a longer time horizon.

Sensing

Agents can correctly observe the mitigation measures their peers perform and memorize the production activities in the past. They can also observe their own income. Agents memorize this information for periods of their memory length (i.e., five years). Assumptions about prices, yields or other information with respect to the adoption decision are condensed in the realised income (i.e., the results of the sub-model FarmDyn). In principle, agents do not have cost for gathering information. However, the learning rate slows the information exchange between agents in the social network and thus information from the peers is not directly and in every time step available for the individual agent.

Individual prediction

Agents change their decision strategy based on their individual prospect value. Using their realised income in the past and the individual value and probability weighting functions, agents "predict" the value of their realised income according to the cumulative prospect theory.

Interaction

Agents observe the behaviour of their peers in the case they choose to imitate. Thus, they exchange information on the performance of climate change mitigation measures.

Collectives

The social network allows to predefine a static collective that is more likely to observe and imitate mitigation behaviour from each other. The observed social network in our case study is derived from a bottom-up farmer initiative aiming at collectively reducing on-farm GHG emissions (Kreft et al., 2021b). There is, however, no dynamic mechanism from which collectives emerge or adapt.

Heterogeneity

Agents can differ with respect to all parameters presented in Table A5.1. This heterogeneity leads to different decision strategies for the individual agent, i.e., repetition, optimization, imitation, opt-out. Thus, agents are not fixed to a certain type of strategy but endogenously choose their strategy. Depending on the parametrization, agents can be fixed on a specific strategy, e.g., by setting high parameter values for reference income and dissimilarity tolerance, the agent will always choose "optimization" as strategy comparable to "econs" or "productivist" type of decision-making in ABMs using farmer typologies. In addition, the underlying sub-model FarmDyn also allows to differentiate the agents according to their production resources (labor, capital, land). This implies that each agent has the observed area, labor and capital endowment at disposal (derived from farm specific census data).

Stochasticity

There are no randomized variables or parameters in the calculation of satisfaction, information seeking behaviour and the choice sets. This implies that for each simulation run, one and only one solution exists. However, the model runs over several years. Between each simulation run, price levels for milk and meat products are randomly selected from a uniform distribution of prices between +/-15% of current price levels. This results in a certain randomness of the farmers' strategic choices based on the realised output prices over the whole simulation length (here 12 runs).

Observation

The model output of FARMIND are the type and amount of climate change mitigation measures and the corresponding reduction in GHG emissions as well as income changes depending on heterogeneous and individual farming decision strategies. The emergent phenomena are the impact of social networks on the distribution of GHG emissions across heterogeneous dairy and beef cattle farms in Switzerland and their total impact on climate change mitigation as well as farm incomes.

A5.3 Details

Implementation

FARMIND is written in Java. The model is available on Github: https://github.com/AECP-ETHZ/FARMIND. Code for the initialization and sensitivity analysis are written in R. The applied sub-model (FarmDyn) in this contribution is written in GAMS and Python and uses a CPLEX solver. A graphical user interface (GGIG) is available to steer the simulations and is written in Java and Python. The source code of the applied sub-model in this contribution can be made available upon request.

Figure A5.2 gives an overview of the implementation steps in our modelling approach. First, we prepared the input data sets (for details see Kreft et al., 2021b; Kreft et al., 2020) for the specific requirements of the FARMIND modelling environment. We used three input data sets: 1) Information about social networks which were collected using the survey software "Network Canvas". 2) Farmers' cognitive, social, and dispositional factors derived from an online survey in our case study region. 3) Census data by the Canton of Zürich on farm characteristics such as farm size, production activities and labor availability. To prepare the data matrix for the agents' income and GHG emissions for the four reduction measures, we used the single farm optimization tool FarmDyn (Britz et al., 2021). The resulting csv files were used in FARMIND as model input data.

We then run FARMIND in three steps: 1) We use the existing policy environment to calibrate the behavioural parameters "reference income" and "tolerance activity" to the observed adoption level of mitigation measures. 2) Based on different scenario set ups, the calibrated version of FARMIND is used to calculate the main results, i.e., the effect of different social networks on the effectiveness and efficiency of a payment for GHG emissions reductions (CHF/CO_2eq). 3) We use the scenario set-up for a sensitivity analysis quantifying the contribution of the behavioural model parameters on the model outcome (i.e., the level of GHG emissions). We here use the methods of standardized regression coefficient (SRC) and standardized rank regression coefficient (SRRC) based on Latin Hypercube Sampling (LHS) with 1000 samples to analyse the impact of the different parameters (Saltelli et al., 2008; Thiele et al., 2014). Finally, we analyse our simulation results and document our findings.

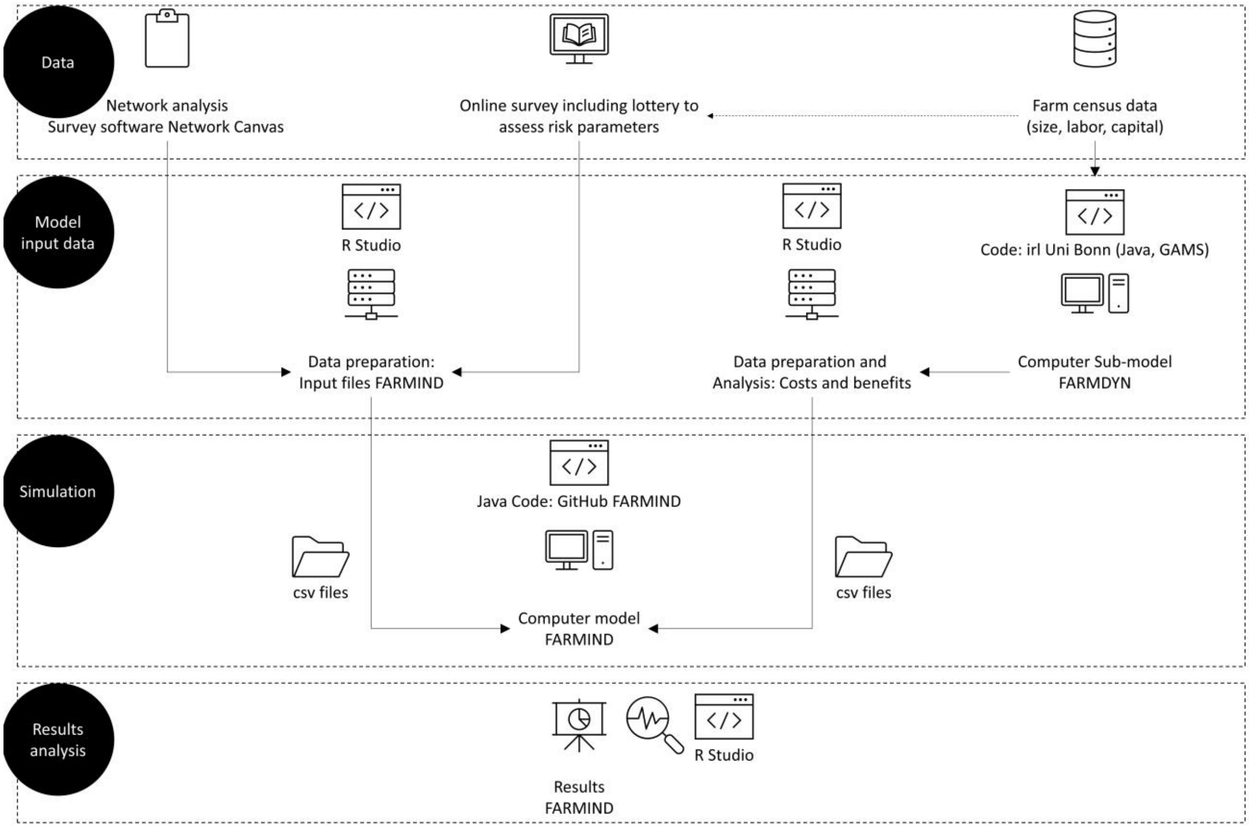


Figure A5.2: Overview of data flow and model interactions in FARMIND

In the following, we describe each of these steps in more detail. First, we provide description of the input data used in our modelling approach. Next, we present the initialization of the model and describe in detail the scenarios that we used in our main modelling exercise. Finally, we explain model selection (based on validating the model output against observed adoption patterns) and describe and present the results of our sensitivity analysis.

Input data

1) FARMIND uses six input data sets: 1) a social network including ties between agents; 2) a matrix of each agent's preferences for the relevant mitigation measures; 3) a table of the agent's individual characteristics (cf. Table A5.1); 4) a list of initial mitigation measures the agent performed; 5) a list of initial incomes over the memory length (i.e., five years); and 6) a list of years (corresponding each to a run of FARMIND) and output price levels. This input data is derived from the farm survey, the social network analysis, and the calculations in the sub-model FarmDyn. The input data for the social network was available for 21 farmers of the sample. We used an exponential random graph model (ERGM) to extend the empirical information to our social network. More precisely, we first fit an ERGM of the observed network of 21 farmers accounting for two important network characteristics, namely density and centralization. In a second step, social ties are simulated for the total network of 49 farmers based on the ERGM of the observed network. In general, an ERGM computes the overall probability of a network based on network statistics and takes the following general form:

$$log\big(exp\big(\theta' g(y)\big)\big) = \theta_1 g_1(y) + \theta_2 g_2(y) + \cdots + \theta_p g_p(y),$$

where $g(y)$ is the set of network covariates (here, density and centralization), θ captures size and direction of the effects of the covariates and p is the number of terms in the model (Statnet Development Team, 2021).

2) The input data for the agents' preferences were derived from the following survey question in Kreft et al. (2021): "Which of the measures that you do not currently implement could you imagine to adopt in the future, which not?" The survey participants then had to tick a box for all mitigation measures applied in the model. In the FARMIND input data, participants who answered that they could not imagine adopting a certain measure in the future received the value 1 for the corresponding measure and the value 5 otherwise. Given this parametrization, the non-dominance score will find that measures with a 5 are always preferred over those with the value of one. This implies that farmers who said that they will not implement this measure in the future will never get it as an option in their choice set, independently from their strategic choice (i.e., repetition, optimization, imitation, opt-out).

3) The Tanaka lottery applied in Kreft et al. (2021) allowed us to directly use the individual values for the risk parameters in FARMIND. Thus, each agent received the parameter value for the decision weight, loss aversion and the probability weighting directly from the survey. Please note that the lottery yields the same values for decision weights and probability weighting in the gain and loss domain. For the reference income and the threshold values for determining individual or social processing, we had to transform the survey data information to be able to use it as input data set in FARMIND. To do this, we did the following steps: First, we used individual information from each farmer with respect to the different questions. We asked the farmers about their current level of income and how satisfied they are with it (see Kreft et al., 2020). Then we asked the farmers to indicate at what income level they would no longer be satisfied (Question in the survey: "Below what agricultural income per year would you be no longer satisfied (in CHF per year)?"). With the help of this information, we categorized farmers according to their ratio between current income and the tolerated income reduction i.e., before getting unsatisfied. This allowed us to identify a relative measure of their reference income that we could apply to the simulation results of FarmDyn. For example, farmers who responded that already a minor reduction in income would make them unsatisfied, received in the input data a reference income set to a level for which incomes only little below the current income level were perceived as losses in the calculation of the prospect value.
A similar approach was taken for the threshold value for determining individual or social processing (i.e., threshold for activity dissimilarity). We used the farmers responses on the

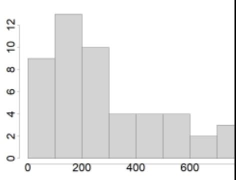
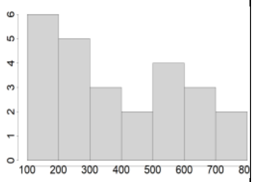
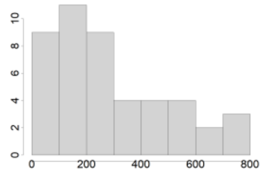
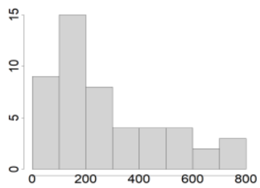
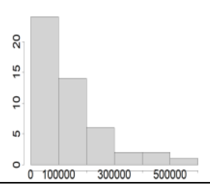
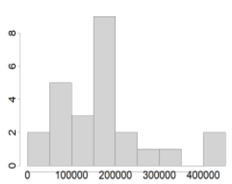
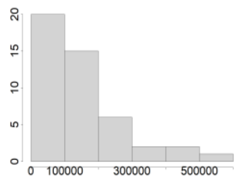
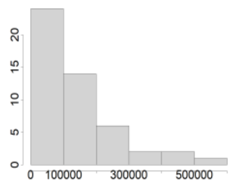
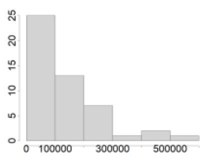
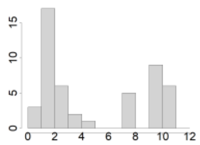
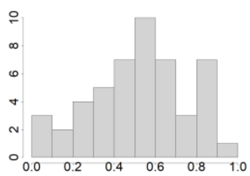
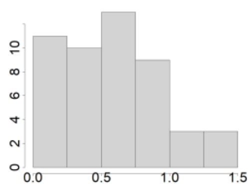
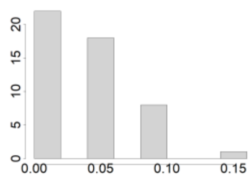
following survey question (based on a five-point Likert scale): “If other farmers in my environment implement climate change measures, I want to implement such measures on my farm as well.” The response was used to derive a relative measure of their tolerance to activity dissimilarity between 0.01 (small differences with respect to peers make the corresponding agent social oriented) and 0.15 (large differences to peers still do not make agent act socially oriented). Since these thresholds are key for the simulation outcome in FARMIND (see sensitivity analysis in Huber et al., 2022), we calibrated the levels of these two parameters to the observed adoption levels in our case study region (see sub-chapter on model selection and validation).

4/5) The model is initialized with agents that have not adopted any mitigation measures (see next section). Thus, the list of mitigation measures and the initial income for each agent (which are necessary to calculate the strategic choice in the first simulation run), are randomly drawn from the available baseline run in the FarmDyn model with variable output price levels).

6) FARMIND runs over several years, which is controlled by the input parameter “year_run”. This parameter can be set by the modeller e.g., to create a certain price scenario. In this simulation, however, we assume that this parameter is fluctuating over years and thus create stochasticity in the simulation outcome. Thus, the input parameter is randomly selected from a uniform distribution of prices between +/-15% of current price levels.

Table A5.3 illustrates the distribution of the raw data that was used to prepare the input parameters for FARMIND. Details on data collection can be found in Kreft et al. (2020) for the survey data, including a description of the applied Tanaka lottery, as well as in Kreft et al. (2021b) for the social network data. A description of the sub-model FarmDyn can be found below.

Table A5.3: Distribution plots of input variables from FarmDyn calculations (profits and GHG reduction potential), survey (behavioural variables) and social network analysis

Farm				
Adopted mitigation measures A	Replacing concentrate feed with legumes	Increased no. of lactations	Drag hoses	Feed additives
y_{At}				
Range (t CO_2eq)	39 – 775	154 – 707	42 – 764	41 – 722
x_{At} (with payment of 120 CHF)				
Range (CHF)	5553 – 568 648	32927– 434 801	6046 – 588 958	5471 – 589 301
Personal characteristics				
Reference income to determine perceived gains and losses and calculate satisfaction V_i^{ref}	Loss aversion level λ	Valuation of gains and losses $\alpha^{+/-}$	Probability weighting in gains and losses $\phi^{+/-}$	Tolerance level for activity dissimilarity to determine information seeking behaviour d_i^{tol}
				
5761 – 529 142	0.96 – 10.41	0.05 – 0.95	0.05 – 1.5	0.01 – 0.15
Social network				
	No social network	Empirical social network	Random social network	Complete social network
Number of peers a farmer is linked to (Mean (Sd))	0(0)	13.4 (1.4)	1.3 (1.2)	48(0)

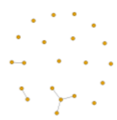
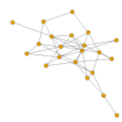
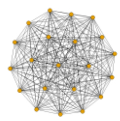
Initialization of simulation

We initialize the model with agents not implementing any of the mitigation measures. In this model set-up, agents have not performed any of the mitigation measures in the past, i.e., the list of mitigation measures an agent performed in the past is empty. Therefore, agents' realised income in the past, which is used to calculate the prospect value in the first model run, is based on farm incomes without any measures adopted. In this case, the initial income is randomly drawn from the simulated FarmDyn data over the price range. We then simulate 12 years (runs) in FARMIND. In this period, agents endogenously choose a strategy and eventually adopt mitigation measures. The 12-year period serves as a timespan that allows FARMIND to achieve a saturation state at which the number of mitigation measures does not change anymore (even though strategies might still vary).

Scenarios

To model the adoption decision considering heterogeneous cognitive, social, and dispositional factors across individual farmers, we test and compare the effect of empirical and hypothetical social networks in different scenarios. The scenarios reflect different types of social networks, i.e., from agents without ties to a network in which all agents are connected (see Table A5.4).

Table A5.4: Scenario definitions

Scenario	**No social network**	**Random network**	**Observed Network**	**Complete network**
	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Social network	No network (agents are not interlinked)	Small random network	Empirical Network	Full network (all agents are interlinked)
Farm parameters	Calibrated to survey data	Calibrated to survey data	Calibrated to survey data	Calibrated to survey data
Initial activities & performing years	No adoption (counterfactual)	Optimizing agents have initial activity	Optimizing agents have initial activity	Optimizing agents have initial activity
Payment level for GHG reduction (CHF/CO_2eq)	0-500	0-500	0-500	0-500
Exemplary illustration				

We run the four scenarios over the range of payment levels of 0 to 500 CHF per t of GHG reduced. We use an iterative process with a 20 CHF interval to calculate the payment level at which the simulation without social networks would provide the same GHG reduction level as in the case with networks. The underlying idea is that the effect of the social network on the efficiency of the payment can only be assessed if the same target reduction level is achieved with and without the network. With different reduction levels, a comparison of the scenarios would be biased since lower reduction levels would automatically imply lower cost. This scenario set-up allows to calculate the effect of different social networks on i) the total amount of emissions; ii) the payment level and marginal abatement cost, and iii) the number of mitigation measures adopted.

Overall, the specified scenarios allow to compare the empirically informed social network to counterfactual situations. The difference in total GHG emission reduction between the counterfactual “No social network” as well as the “Small random network” and the ”Complete network” can then be used to quantify and discuss the contribution of social networks to overall reduction of GHG emissions. Thus, the comparison of simulation results across scenarios gives quantitative insights into the relevance of social networks in agricultural climate change mitigation.

Model selection and validation

A key challenge in FARMIND is its parameterization given different potential pathways that result in the same level of adoption, i.e., model equifinality (Williams et al., 2020). This implies that multiple structures and/or parameterizations exist that generate outputs consistent with the observed adoption pattern in our case study region (e.g., Troost and Berger, 2015a). More specifically, while we were able to collect data on the underlying model parameters using census data, surveys and social network analysis, the strategic decisions, i.e., repetition, imitation, optimization and opt-out cannot be validated against observational data and different combinations of these strategies might result in the same model output. Consequently, the use of thresholds for determining the decision strategies in FARMIND implies that the calibration of these parameters has an important effect on simulation outcomes (see also Huber et al. 2021). The survey identified relative differences of the model parameters between agents. The absolute level of the reference income was determined by the income levels simulated in FarmDyn.

To address this challenge, we calibrated the threshold parameters in FARMIND based on a sensitivity analysis (please note that we also performed an extensive sensitivity analysis to assess the robustness of our results, see section below). Here, we parameterized the profit changes in FarmDyn using the current support for GHG emission reduction measures in Switzerland. Since there is currently no support for feed additives and only very few farms stated that they already experimented with additives, we did not consider this mitigation measure in the calibration of our agent-based approach. We ran FARMIND with increasing levels for both thresholds, i.e., reference income and dissimilarity tolerance, and compared the adoption pattern with the observed data. Given that we increased the thresholds for all agents simultaneously, the relation between the individual thresholds derived from the survey data was kept constant. To assess model performance, we calculated the standardized mean errors of the model:

$$ESAE = 1 - \frac{\sum_i \left| y_i^{obs} - y_i^{sim} \right|}{\sum_i y_i^{obs}},$$

with y_i^{obs} as the observed adoption of mitigation measures i. We calculated model performance by fixing one parameter and changing the second parameter starting with parameter levels that were insensitive to model output. We then changed the corresponding parameter levels which will first increase the goodness-of-fit. At a certain level, however, this goodness-of-fit (here measured by ESEA) starts to decrease. This allows to identify a “best” model that could explain the observed pattern with the simulated strategies in FARMIND.

The two threshold levels have the following impact on the adoption of climate change mitigation measures in our simulations. First, increasing the reference income implies that more agents become unsatisfied and thus increases the probability of them choosing the optimization or opt-out strategy. The increase in adoption through optimizing behaviour is represented in the left panel of figure.3. In the simulations with increasing reference income levels (R1-R5), farmers do not have a social network and the adoption of mitigation measures is driven by optimizing behaviour only. The results show that with optimizing behaviour, the simulated adoption overshoots the observed level for drag hoses and lactations with higher threshold levels for being satisfied. This implies that we should observe more of these mitigation measures if farmers were pure profit maximisers. Second, adding the social network to simulations in which farmers have a high reference income, the agents are pushed to the opt-out strategy since they are not only unsatisfied but also very different to their peers. This suggests that lower levels of the reference income are more suitable to represent the observed adoption levels. Given these lower levels of the reference income (R2-R3), we then tested the agent’s sensitivity with respect to the tolerance level (how much they consider the behaviour of their peers, i.e., how much they are inclined to engage in social processing).

Hence, we manipulated the levels of the threshold “tolerance activity” (N1-N5). This allowed us to compare adoption behaviour based on different combinations of reference income and dissimilarity tolerance (see right panel of figure 3). Overall, we find that models with social networks outperform models without interacting agents in terms of goodness-of-fit (we added R4 to the right panel of figure 3 to illustrate the outputs when agents are income maximisers only). If social networks are included, high and low levels of sensitivity towards social behaviour decrease model performance. The combinations of both threshold values in the middle of the possible ranges provide similar goodness-of-fit (Table A5.5). This allows us to meaningfully choose a single best model for the analysis since our findings are robust within a certain range of threshold values and only extreme assumptions can be discarded.

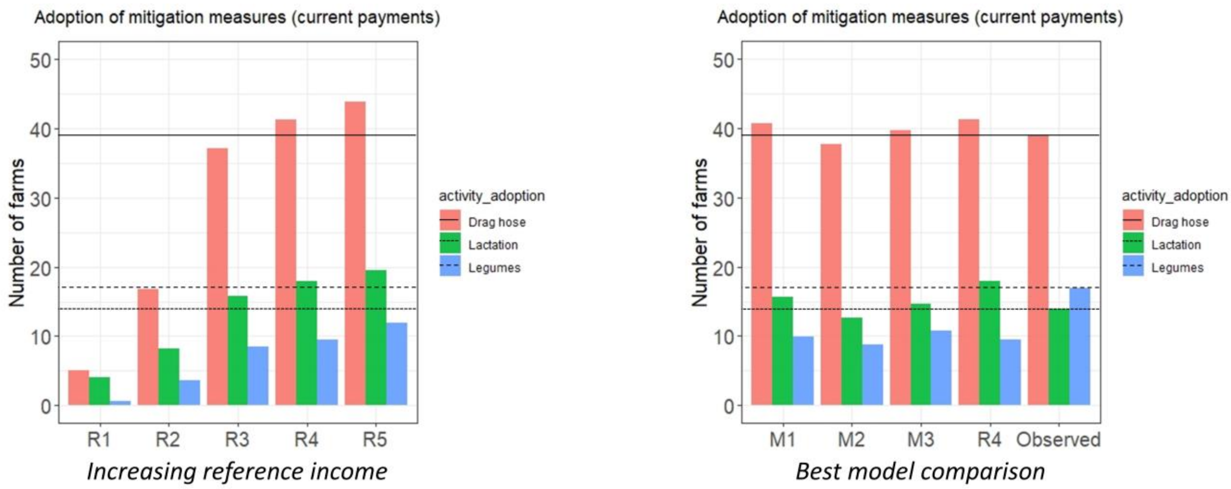


Figure A5.3: Visual comparison between simulated and observed adoption of climate change mitigation measures. The dashed lines refer to the corresponding observed level of adoption.

We are aware that other approaches exist such as pattern-oriented modelling (Grimm et al., 2005) or diverse model calibration (Williams et al., 2020) that relax some of the assumptions resulting from choosing a single best model. However, we here focused on model prediction, i.e., what if no social network existed (or it had different patterns). An equifinal model in our case would have to assume extreme values, i.e., all agents choose the same strategy (e.g., all were optimizers). Thus, our assumption is that farmers, in the context of adopting GHG mitigation measures, are not pure income optimizers. Indeed, the main purpose of our model is to include behavioural factors into simulating adoption decisions, and recent literature on farmers' behaviour suggests that optimization is only one of several types of decision-making strategies in agriculture (for a recent review see Bartkowski et al., 2022; Epanchin-Niell et al., 2022).

Table A5.5: Standardized mean absolute error from different model parameterizations

	Absolute error Legumes	Absolute error Lactation	Absolute error Drag hose	ESAE
R4 (no network)	5	-5.5	-4.8	0.78
R3 (no network)	7.5	-4	-2.2	0.80
R3 with N1	8.1	2	2.3	0.82
R3 with N3	9.4	1	1	0.84
M1: R3 with N4	8	1.2	1.3	0.85
R2 with N4	6.5	-1.3	-1.3	0.87
R3 with N5	7.9	0.4	0.7	0.87
M1: R2 with N2	6.1	-1	-1	0.88
M3: R2 with N3	6.3	-0.9	-0.9	0.88

Note: R1-R5 refer to increasing reference income levels. N1-N5 for decreasing sensitivity level for social oriented behaviour.

In addition, we also refrained from parameter screening and selection as described in Troost and Berger (2015a), i.e., a calibration of the important model parameters based on Latin Hypercube Sampling (LHS) over the whole parameter range. The reason is that we rely on individual data for each agent (based on the survey), and we do not have to make assumptions about the distribution of parameters in the initialization process of the model.

In summary, we can calibrate FARMIND to observed uptake of climate change mitigation measures in our case study region. Our simulation outcomes remain robust with respect to a meaningful variation in the threshold levels for determining the decision strategies in FARMIND. Thus, we are convinced that FARMIND is a valid approach to assess the effect of social networks on GHG mitigation in our case study region. To test external validity of FARMIND, however, more data and more case studies would be needed to generalize the effect of social networks on the effectiveness and efficiency of policy incentives to reduce farm-level GHG emissions.

Output sensitivity analysis

The main model outcomes are based on an uncertainty analysis, i.e., we run FARMIND with different social networks, output price levels and various levels of subsidies for CO_2 (CHF/CO_2eq) to achieve a given reduction level in GHG emissions.

To assess the robustness of our findings, we also performed an output sensitivity analysis. We here used the methods of standardized regression coefficient (SRC) as well as Sobols' method to assess the effects of behavioural parameters and model structures on GHG emission levels. We follow the protocol by Thiele et al., 2014 and calculate the contribution of farmers' individual behavioural parameters as well as different model structures on the total amount of GHG emissions (see Table A5.6):

Table A5.6: Parameter range for Latin Hypercube Sampling (LHS) in global sensitivity analyses

State variable / parameters	Abbreviation	Lower range LHS (Min value)	Upper range LHS (Max value)
Loss aversion level *% change for each agent*	λ	0.5	1.5
Valuation of gains and losses *% change for each agent*	$\alpha^{+/-}$	0.5	1.5
Probability weighting in gains and losses *% change for each agent*	$\phi^{+/-}$	0.5	1.5
Reference income *% change for each agent*	V_i^{ref}	0.8	1.2
Tolerance level for activity dissimilarity *% change for each agent*	d_i^{tol}	0.5	1.5
Preferences *1 = cannot imagine adopting* *5 = can imagine adopting*	R^A	1	5
Output price level *1 = 0.60 CHF/kg (milk) 7 CHF/kg (meat)* *20 = 0.79 CHF/kg (milk) 9 CHF/kg (meat)*		1	20
Fuzzy size *Maximum number of mitigation measures considered in choice set*		1	5
Social network *Connection probability for random network*		1	49

For each of the parameters, we use a uniform distribution of values with the observed value (i.e., taken from the survey) as the mean between a max. and a min. value (table 6). The mean values of behavioural factors are directly derived from the survey (and the corresponding lottery) or corresponds to the calibrated input values (in the case of the reference income and the tolerance for dissimilarity). Agent preference levels for different mitigation measures are set randomly in the sensitivity analysis. Price levels of beef and dairy products refer to the range of observed prices in Swiss agriculture. For the size of the choice set, the sensitivity analysis implies that either only the most preferred option appears in the choice set (if set to 1) or all options appear in the choice set (if set to 5). Thus, this factor tests for the effect of the fuzzy preference algorithm on the outcome. Finally, the overall impact of the network size is also tested by using a random network.

SRC Standardized regression coefficient

The standardized regression coefficient analysis includes two steps. First, a linear regression model is fitted to the simulation data generated from a Latin Hypercube Sample of the different parameters. The results from the standardized regression coefficient approach are here based on LHS with 1000 parameter sets (samples) and 100 repeated simulation samples.

Secondly, the regression coefficients are standardized. Thereby, the coefficients are multiplied with the ratio between standard deviations of the input parameter and the output value (Saltelli et al., 2004). Thus, the regression analysis shows the effect of an input on the output variables both normalized with a mean of zero and standard deviation of one. This allows to better interpret and communicate the absolute relationship between the inputs and output of FARMIND.

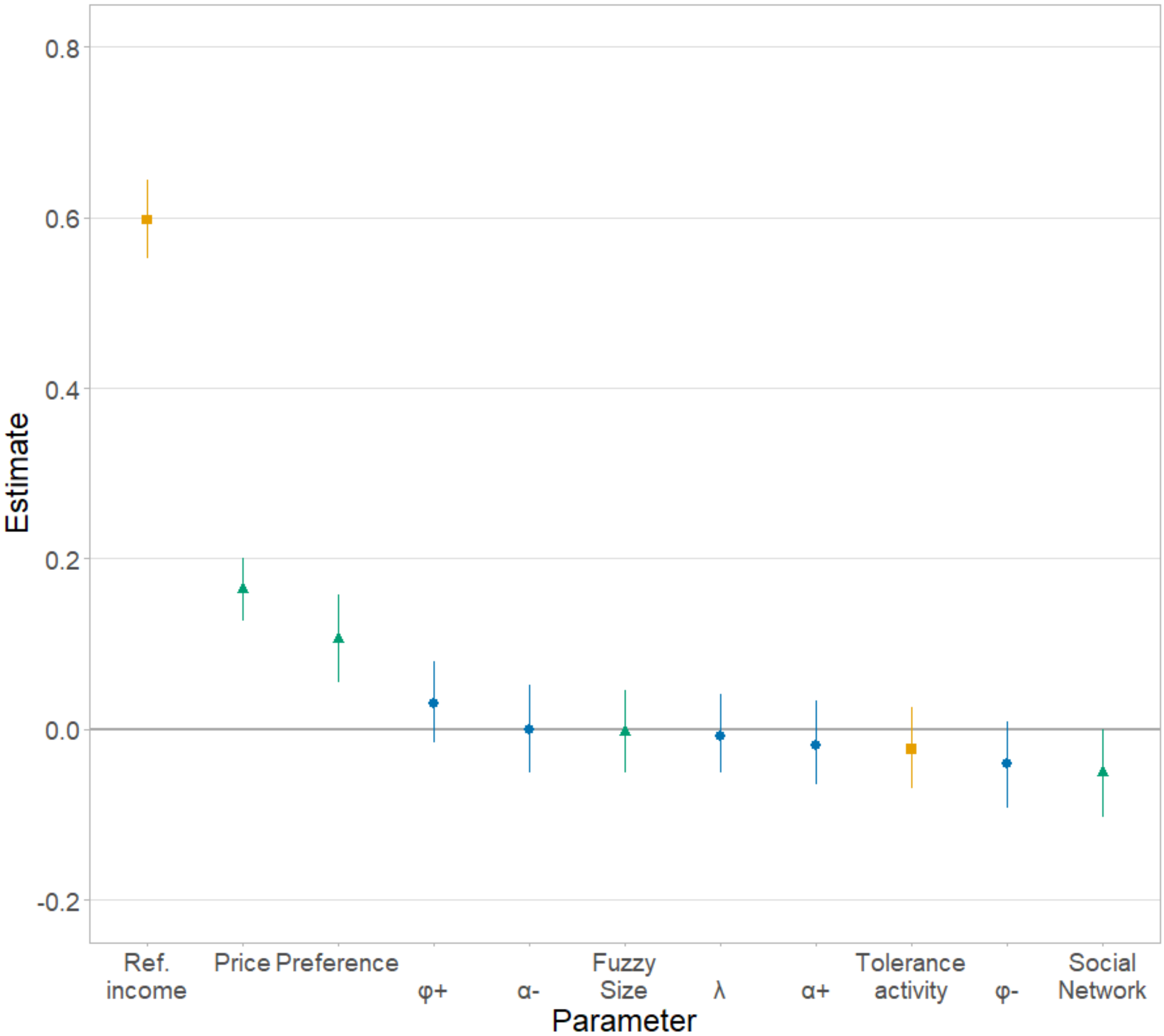


Figure A5.4: SRC for FARMIND in the context of adopting GHG mitigation measures in Swiss agriculture. Mark show mean SRC value. Sticks show maximum and minimal values of bootstrapped 95% confidence intervals of corresponding sensitivity indices. Parameter groups are represented in different colors. Yellow: threshold values that determine the choice between strategies i.e., reference income V_i^{ref} and dissimilarity tolerance $d_i^{tol}a$. Blue: Parameters used to calculate the cumulative prospect value for each agent. Green: Structural parameters including fuzzy size, price levels, preferences, and social networks.

Our sensitivity analysis provides four implications (cf. Figure A5.4): First, the reference income, i.e., the threshold parameter determining the choice between optimization and opt-out vs. imitation and repetition has the largest impact on the total amount of GHG emissions. An increase of the reference income by one standard unit increases the greenhouse gas emissions by approximately 0.6 standard deviation of all greenhouse gas emissions. The higher the reference income, the more likely agents are choosing the repetition or imitation strategy. Thus, theoretically, the sign of the threshold parameter could go in both directions since the imitation strategy would allow the agents to adopt mitigation measures whereas the repetition strategy would not. The results show that the effect of the repetition strategy, i.e., the agents' reluctance to change is more important for the overall level of GHG emissions.

Secondly, an increase of the behavioural factors describing cumulative prospect theory (α+, α-, ϕ+, ϕ-, and λ) have a much smaller impact on greenhouse gas emissions compared to the reference income. The main effect of an increase of these parameter values by one standard unit is, on average, close to zero. The maximum and minimum values of these estimates are between 5 and 8% (of the standard deviation). The parameter determining the curvature of the value function in the gain (α+) and loss (α-) domain, respectively (i.e., the decision weights), are identical for each agent given our Tanaka design of the lottery. Higher values for α+ imply that the value function reduces the depreciation of high incomes in the gain domain. Ceteris paribus, this increases the probability that agents are satisfied (since there is lower devaluation). Consequently, the probability of imitation increases and the total amount of GHG emissions decreases with higher values for α+. We can observe the opposite effect for α-, which devalues low incomes in the loss domain. Higher values for dissimilarity tolerance imply that agents, ceteris paribus, get less inclined to social oriented behaviour (i.e., imitation and opt-out). As in the case of the reference income, the sign of the dissimilarity tolerance parameter depends on which of the two remaining strategies (i.e., optimization and repetition) dominates. In our simulation, higher dissimilarity tolerance increases the weight of the optimization strategy and therefore the total amount of GHG emissions decreases on average.

Thirdly, the effect of structural variables such as the social network, the preference setting for mitigation measures or the price level for milk and meat have a larger effect on the total amount of GHG emissions compared to the cumulative prospect parameters, but a lower effect compared to the reference income. The higher the price levels, the higher the probability that agents are already satisfied without adopting mitigation measures and thus, ceteris paribus, the overall GHG emissions are higher. This suggests that exogenous assumptions on the price levels in FARMIND have an important effect on the adoption decision, but this is, compared to the threshold level, less important on the total level of GHG emissions. This is also an important consequence from using FarmDyn as a sub-model (see next Section for details). In FarmDyn, prices affect the income level relatively more than the amount of GHG emissions, i.e., the reduction potential of the different measures remains similar under different price scenarios.

Fourthly, we observe that the sign of behavioural factors is ambiguous. This has two underlying mechanisms. First, for probability weighting parameters ϕ+ (ϕ-), the effect can theoretically be positive or negative because it depends on the underlying income distribution (Huber *et al.*, 2020). Secondly, the behavioural parameters can decrease greenhouse gas emissions if they stimulate optimization or imitation and increase greenhouse gas emissions if they support repetition and opt-out (i.e., non-adoption of climate change mitigation measures). However, an increase in the parameter values of decision weights, for example, can increase both, the probability of optimization but also opt-out. Thus, the effect depends on the shares of agents that choose a certain strategy, which is in turn depends on the other parameter levels. To get more insights into this potential non-linear behaviour of the model, we also used Sobol's method to assess the sensitivity of FARMIND.

Sobol's method

To investigate non-linear relationships between the input parameters and outputs, we apply Sobol's method, a variance decomposition approach (Saltelli and Annoni, 2010). The underlying idea is to vary the input parameters and then to identify the effect of the individual parameter on output variance. In Sobol's method, the total variance is composed of the so called main and interaction effect, which is determined by evaluating the partial effects using Monte-Carlo methods (Thiele *et al.*, 2014).

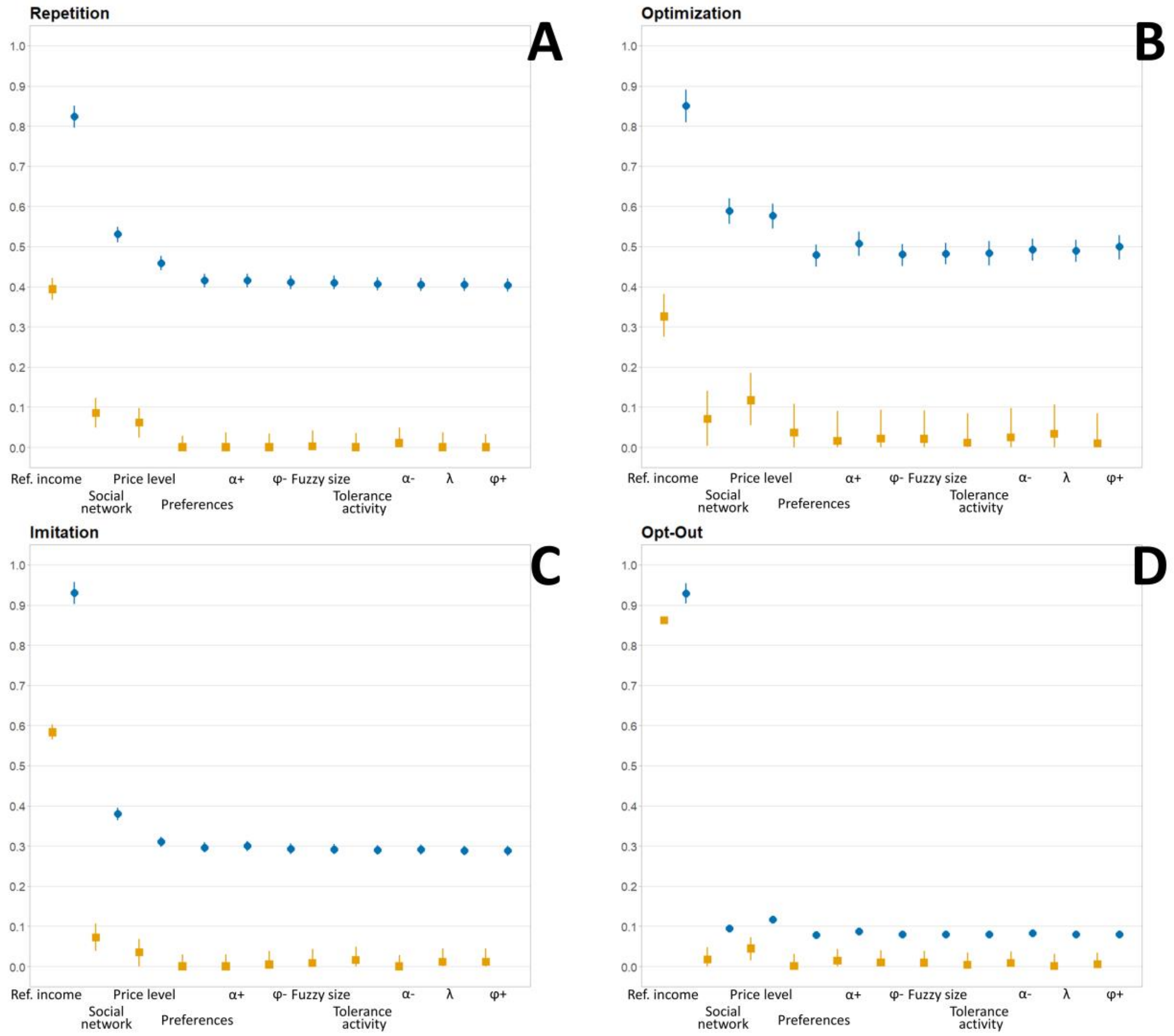


Figure A5.5: Results from Sobol sensitivity analysis for the four strategies. Dots represent the main effect of the parameter on the variability of the model outcome. Circles refer to the total effect, including interaction effects of the corresponding parameter on the strategy choice. Sticks show bootstrapped 95% confidence intervals of corresponding sensitivity indices.

As in the case of the regression analysis, we use a Latin Hypercube Sampling to generate the range of input parameters in the sensitivity analysis. We applied the soboljansen function to identify the expected non-linear effect of the model parameters (with 8000 bootstrap replicates).

The results from Sobol's method shows the importance of interaction effects in FARMIND (Figure A5.5). The main factors that drive the agents' behaviour in our model are the reference income and the social network. These two parameters drive the model especially for the repetition and imitation strategies. For the optimization strategy, the output price level is more important than the social network. For these three strategies, behavioural factors become much more important when looking at the interactions (i.e., the total effect of the parameter). This exemplifies that the main influence of the underlying behavioural factors such as risk preferences or dissimilarity tolerance is indirect (i.e., via the calculation of the prospect value and the social oriented behaviour).

In summary, the output sensitivity analysis shows that thresholds for determining the decision strategies in FARMIND are the key drivers in the simulation outcome. However, behavioural factors such as risk parameters or loss aversion are also sensitive with respect to the strategic decision and thus affect the amount of reduced GHG emissions. Given that our results are robust with respect to the choice of threshold levels in our data (see section above), the sensitivity analysis shows that the implications of our modelling results also remain with variation of the other factors within a large parameter space.

FARMIND requires a sub-model which is able to optimize a farm for two primary causes. On the one hand, for the case in which a farmer decides for the strategic decision of optimization and on the other hand to determine the satisfaction level of a farmer. For this purpose, we use the bio-economic single farm optimization model FarmDyn (Britz et al. 2021), which is described in more detail below.

Model introduction

FarmDyn is a highly detailed bio-economic farm scale optimization model, building on mixed integer linear programming. It contains detailed information on bio-physical and economic (e.g., cash flow, investments) processes linked to farming activities. This bio-economic model setup allows to determine the trade-offs between economic and environmental indicators considering the production of both agricultural outputs and environmental externalities (Janssen and van Ittersum, 2007).

FarmDyn has been extensively used for assessments of environmental policies such as the national implementation of the Nitrate Directive in Germany (Kuhn et al. (2019), Kuhn et al. (2020)) and the assessment of different greenhouse gas-indicators (GHG) and GHG mitigation measures for varying farming systems (Lengers et al. (2013), Lengers et al. (2014), Kokemohr et al. (2022)).

Case study and FarmDyn adjustments

The default version of FarmDyn is parameterized for the German agricultural sector. For this case study, FarmDyn's database was adjusted to reflect the Swiss agricultural sector. This includes new data on variable input and output costs (Agridea, 2020), fixed costs for buildings and machinery (Agridea, 2021), and relevant changes to farm (management) parameters such as yields (Agridea, 2021). In addition, a new FarmDyn module was developed to account for the Swiss cross compliance requirements (e.g. mandatory crop rotation, set aside rules) and the direct payment system (e.g. payments for land under food production, gras-based milk and meat production) (DZV, 2021).

Interplay of farm management and mitigation measures

FarmDyn maximizes the farm profits given certain boundary conditions such as farm endowments, prices, and policies. It finds the optimal farm management program including decisions about which crops to plant, how to fertilize them, how many animals to keep, and how to feed them. Each of these activities are linked to GHG-emissions on a very detailed technical level (see section "GHG emissions in the model"). Based on the limited farm endowments and the interplay between farm management decisions, each change in a boundary condition impacts the GHG emissions of the farm. This is true, if for example the price for a certain GHG-intensive crop increases, which shifts the cropping pattern towards a higher GHG emission in total. This effect is especially pronounced if mitigation measures become compulsory which aim at the reduction of GHG emissions.

For this study, four mitigation measures were implemented, which are described in detail in the following Table A5.7. The table shows for each of the measures the underlying assumption of how it reduces GHG emissions (means of mitigation). Further, the costs related to that measure are presented (associated costs) and finally the technical implementation (technical implementation) is described. To illustrate the complexity of the effect of a compulsory mitigation measure on GHG-emissions and associated costs, we have a look at the mitigation measure *a) replacement of (imported) concentrate feed with on-farm fodder*. The underlying assumption is that imported concentrate from overseas soybeans generate, due to its transport and land-use changes, high GHG emissions. To mitigate these emissions, the measure mandates that only on-farm fodder can be used leading to a production of protein fodder (legumes such as horse beans and peas). Due to the complexity of the model, the associated costs of the measure are a composition of multiple changes in the activities. First, the farm does not have to pay for the off-farm concentrate. Second, the required fodder has to be planted on-farm, leading to a costly production. Third, the production of on-farm fodder might replace previously grown cash crops, which diminish the overall farm income. This is a simple example on how these costs are generated. However, it can also have further on-farm effects if new crops such as legumes are more labour intensive, leading to a change in production elsewhere on the farm.

Table A5.7: Description of mitigation measures with underlying assumption of mitigating mechanism, its cost and the technical implementation in Farmdyn.

Measure description	**Means of mitigation**	**Associated costs**	**Technical implementation**
a) Replacement of (imported) concentrate feed with on-farm	Replacing concentrate feed such as soybean with locally produced legumes (e.g., peas or horse bean) mitigates up-stream CO_2-emissions due to reduced transport and land-use changes	• Replacement of cheap protein fodder by more costly own produced fodder • Cash crops replaced by legumes	Variable on purchasing off-farm concentrate equals zero
b) Increase of lactation number per dairy cow	Increasing the number of lactations per dairy cow reduces CH_4-emissions of a herd due to a reduced replacement rate, i.e., less upraising of calves and heifers	• No assumed costs • Reduced fodder costs and labor use due to reduced number of animals on farm	Increased lactation number per cow from 3 to value 7
c) Use of emissions reducing manure application technique	A close-to-ground application with trail hoses (or a similar technique) reduces N_2O-emissions of manure brought to the field and indirect N_2O emissions from other nitrogen compounds	• Purchasing of more costly application techniques such as drag hose compared to broad-spreader	Variable of the use of broadcast spreader equals zero
d) Introduction of feed additives	Introducing feed additives such as linseed reduces the CH_4-emissions from enteric fermentation by inhibiting methanogenesis in ruminants	• Costs for purchasing the feed additive	0.6 CHF per cow and day

GHG emissions in the model

For this study, FarmDyn considers the most relevant on- and off-farm GHG emission sources. This includes methane (CH_4) emissions from enteric fermentation and manure storage, nitrous oxide (N_2O) emissions from the application of manure and mineral fertilizer, as well as other nitrogen compounds leading to indirect N_2O emissions. To assess mitigation measures which aim to reduce inputs with a high carbon footprint, we use data for upstream emissions for purchased inputs such as feed concentrate or chemical fertilizer. A complete list of the source of emission, the methodology applied, and the corresponding emission factors can be seen in Table A5.8.

Table A5.8: Source of on- and off farm emissions, applied methodology and corresponding emission factors used in FarmDyn

Source of emission	Methodology Applied	Emission factor
CH_4 enteric fermentation	IPCC(2006)-10.30 f. tier 2+3	Haenel et al. (2018) p.140, p.145, p.155, p.168, p.214, p.194, IPCC p.10.30
CH_4 stable, storage and pasture	Haenel et al. (2018) p. 42 No. 3.28 and 3.29 Following IPCC (2006) eq. 10.23	Haenel et al. (2018) p.108 and p. 185. IPCC (2006) p.10.41
NH_3 emissions from stable and storage	EMEP (2016)	Haenel (2018) p.108, p. 109, Haenel et al. (2018) p.186 p.187
N_2O, NOx, N_2 emissions from stable and storage	EMEP (2016), Haenel (2018) p. 53	Haenel 2018 p. 110, HAENEL et al. (2012), JARVIS & PAIN (1994), Haenel et al. (2015) pp. 188
NH_3 from manure application	EMEP (2016)	Haenel et al. (2018), pp. 111-112, 189, 64
N_2O, NOx, N_2 emissions from manure application	EMEP (2016), Haenel et al. (2018), pp. 316-317	Haenel et al. (2018) p.326, Stehfest and Bouwman (2006) N2 Roesemann et al. (2015) pp. 316-317
NH_3 from excreta from pasture	EMEP (2016), Haenel et al. (2018) p.55	Haenel (2018) p.137/EMEP(2013): 3B , pp. 27
N_2O, NOx, N_2 emissions from excreta from pastures	EMEP (2016), Haenel et al. (2018) p.55	Haenel et al. (2018) p. 332; IPCC (2006) 11.11, table 11.1, Haenel et al. (2018) p. 332, Stehfest and Bouwman (2006) Roesemann et al. (2015), pp. 324
NH_3, N_2O, NOx, N_2 emissions from mineral fertilizer application	Haenel et al. (2018), pp. 316-317	Haenel et al. (2018) p.325, Haenel et al. (2018) p.326, Stehfest and Bouwman (2006) N2 Roesemann et al. (2015)
Indirect N_2O emissions from prior NOx, NH_3 and NO_3 emissions	IPCC (2006)	IPCC (2006)-11.24, Table 11.3
CO_2 emission from provision of inputs		KTBL (2021)

Source: http://www.ilr.uni-bonn.de/em/rsrch/farmdyn/FarmDynDoku/template/environmental_accounting_module/

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Chapter 5: Action- vs. results-based policy designs for agricultural climate change mitigation[20]

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Abstract

Reducing agricultural greenhouse gas (GHG) emissions is key to achieve overall climate policy goals. Effective and efficient policy instruments are needed to incentivize farmers' adoption of on-farm climate change mitigation practices. We compare action- and results-based policy designs for GHG reduction in agriculture and account for farmers' heterogeneous behavioural characteristics such as individual farming preferences, reluctance to change and social interactions. An agent-based bio-economic modelling approach is used to simulate total GHG reduction, overall governmental spending and farm-level marginal abatement cost of Swiss dairy and beef cattle farms under both action- and results-based policy designs. We find that total governmental spending associated with the compared policy designs depends on the cost and benefits of the considered measures as well as behavioural characteristics of farmers. More precisely, if farmers are reluctant to change, additional incentives are needed to increase adoption of a win-win measure. In such a case, targeting the payment on the cost of that particular measure (action-based design) instead of paying a uniform amount for abated emissions (results-based design) can lower governmental spending for agricultural climate change mitigation. Farm-level marginal cost of reducing GHG emissions are lower with results-based payments independent of the cost of measures. Moreover, we find that farmers' individual preferences and reluctance to change substantially lower the adoption of mitigation measures and hence overall GHG reduction potential of farms.

Keywords

Climate change mitigation, agricultural policy assessment, action- and results-based policy design, agent-based modelling, Switzerland

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5.1 Introduction

Agricultural production is among the major contributors to global warming. At the same time, agriculture has large potential to effectively mitigate greenhouse gas (GHG) emissions and help with achieving global temperature targets (Roe et al., 2019). Hence, reducing agricultural GHG emissions has become a key policy goal in many countries (OECD, 2019). To achieve these goals, farmers have to adopt GHG mitigation measures (IPCC, 2019). However, these measures and practices require a certain know-how and often cause additional investment and/or transaction cost. To date, policy instruments to incentivize mitigation of agricultural GHG emissions in European countries are usually designed as compensating payments for the adoption of specific farming practices (Wreford et al., 2017). So-called action-based designs enable to target payments based on estimated costs and benefits of specific GHG reduction measures. In general, however, action-based payment schemes have been criticized for being inefficient, leading to windfall effects and low additionality in the provision of environmental benefits due to asymmetric information and heterogeneous ecological potential (Claassen et al., 2018; Hanley et al., 2012; White and Hanley, 2016; Wunder et al., 2018). Instead, results-based policy designs have been suggested as cost-efficient alternative to tackle certain agri-environmental problems (Engel, 2016; Sidemo-Holm et al., 2018; Wuepper and Huber, 2021). However, such results-based designs have not been addressed for GHG emission reduction in agricultural production.

We compare action- vs. results-based policy designs to reduce GHG emissions in the agricultural sector, i.e., payments for practice adoption vs. payments based on mitigation performance. To this end, we use an agent-based bio-economic simulation framework considering farmers' behavioural characteristics, namely farming preferences, reluctance to change and social interactions. Agent -based models are used to simulate phenomena emerging from behaviour of individuals (agents) and their interactions (e.g., via land markets or exchange of knowledge). They allow to conduct computational experiments solving complex if-then scenario analyses based on data and theory. Since they enable to include heterogeneous individual characteristics such as personal preferences or social network ties, agent-based models are suitable tools to model the complexity of farmers' decision-making processes and quantify the respective outcomes (Huber et al., 2022). Such a modelling approach that integrates structural data, a detailed farm-level model as well as survey data and social network analysis, allows to consider specific characteristics of different mitigation measures as well as heterogeneous farms and farmers. This differentiation is highly relevant for the ex-ante assessment of agricultural policy designs that target the reduction of on-farm GHG emissions. Moreover, bridging behavioural tools and ex-ante policy assessments in an agent-based modelling framework provides a better understanding of the role of behavioural characteristics on climate change mitigation adoption in agriculture. Based on a Swiss case study, we specifically simulate the effect of the differently designed policy incentives on the adoption of GHG mitigation measures on dairy and beef cattle farms (suckler cows and bulls for fattening), particularly accounting for farmers' reluctance to change.

Previous studies have shown that subsidies for the implementation of emission mitigation practices could considerably reduce agricultural GHG emissions (Domínguez et al., 2016). However, existing greening policies of the Common Agricultural Policy in the EU are found to be rather ineffective with respect to GHG reduction in agriculture (Solazzo et al., 2016). In general, results-based designs in agricultural policy are found to be more efficient in achieving agri-environmental targets than action-based designs (see e.g., review by Burton and Schwarz, 2013b; Wuepper and Huber, 2021). However, it is suggested that the actual gain in efficiency from result-orientation of payments depends on the specific policy goal (e.g., whether the outcome is measurable), behavioural factors such as individual characteristics and social networks of decision-makers as well as underlying cost and benefits of the considered measures (Moxey and White, 2014; White and Sadler, 2012). For example, recent research in the context of behavioural economics suggests that reluctance to change, status quo bias or inertia are important barriers to behavioural change among farmers and that this is one of the most important reasons why more sustainable practices and GHG mitigation measures are not readily adopted (e.g., Dessart et al., 2019). This might especially explain the non-adoption of mitigation measures that could be cost saving for farmers, i.e., win-win or no-regret measures (Fleming et al., 2019, Moran et al., 2013). For example, increasing the number of lactations per dairy cow can create synergies between GHG reduction and farm profitability (Alig et al., 2015; Grandl et al., 2019). Moreover, individual preferences and social interactions can take a key role in farmers' decision-making regarding the adoption of climate change mitigation measures (Haden et al., 2012; Kreft et al., 2022a; Kreft et al., 2022; Kreft et al., 2021b; Niles et al., 2016). The consideration of behavioural factors in agri-environmental policy assessment is however still rare (e.g., Huber et al., 2018). The ex-ante assessment of action- vs. results-based policy designs under consideration of farmers' individual (behavioural) characteristics thus constitutes another important research gap.

We contribute to the existing literature by comparing action- and results-based policy designs for GHG emissions reduction. We use a case study of Swiss dairy and beef cattle farms accounting for farmers' individual preferences and social interactions in an agent-based bio-economic modelling approach. More precisely, we use the agent-based model FARMIND (Huber et al., 2022a) in combination with the bio-economic farm model FarmDyn (Britz et al., 2019) to simulate total governmental spending, aggregated changes in farm incomes as well as farm-level marginal abatement cost associated with action- and results-based payments.

To compare the efficiency of the different policy designs, we simulate a short-term reduction of 10% of baseline GHG emissions, assuming maintenance of current production levels and current numbers of livestock units. The simulations are based on a regional case study in Switzerland. We use a combination of census, survey, and detailed social network data of 49 Swiss dairy, suckler and bull-fattening farms.

Our analysis provides three contributions. First, we compare the efficiency of action- and results-based policy designs considering measures that have heterogeneous costs and reduction potentials on farm level. We consider four GHG mitigation measures in the analysis: i) replacing concentrate feed with legumes grown on the farm, ii) increasing the number of lactations per dairy cow, iii) applying manure using drag hoses and iv) introducing feed additives to reduce enteric fermentation of cattle. Second, we specifically investigate the role of a potential win-win measure (increased number of lactations, which may reduce GHG emission and increase profits) on the efficiency of action- and results-based policy designs. This provides quantitative results that can inform policymakers when choosing between policy designs to enhance climate change mitigation in agriculture. Third, we compare the overall reduction of GHG emissions achieved when accounting for farmers' reluctance to change, individual farming preferences, and social interactions to a case where farmers are profit maximizers. This provides a better understanding of the role of behavioural characteristics on mitigation adoption in agriculture.

Accordingly, our results are threefold: First, we find that total governmental spending to achieve a reduction of 10% of baseline GHG emissions is higher in the results-based policy design as compared to the action-based design. This suggests that an action-based payment would be more efficient from a governmental perspective. The result can be explained by the specific nature of the measure "increasing the number of lactations per dairy cow", which is a win-win measure that reduces GHG emissions while at the same time increasing farm profits. If farmers' behavioural characteristics such as reluctance to change prevent the adoption of win-win measures despite potential income gains, policy incentives are needed to overcome this inertia and enhance adoption. However, in such a case, targeting payments based on the cost of the specific win-win measure (action-based design) can lead to lower governmental spending than targeting it on farm-level cost-efficiency of GHG reduction (results-based design). This is particularly relevant in the context of agricultural climate change mitigation since recent research suggests that a considerable share of GHG emissions reduction in agriculture could be achieved at low cost or even net benefits due to such win-win measures (MacLeod et al., 2015; MacLeod et al., 2010; Moran et al., 2011). Second, when excluding the win-win measure from the simulations, we find that – in line with the existing literature – total governmental spending is lower in the results-based scheme than with action-based payments. Third, our results show that farmers' individual preferences and reluctance to change lower overall reduction of GHG emissions by roughly 20% in both action- and results-based payment schemes compared to simulations considering only profit maximizing behaviour. Our findings indicate that a combined consideration of the characteristics of mitigation measures and behavioural factors is key to assess the efficiency gain from differently designed policy incentives in agricultural climate change mitigation.

The remainder of this article is as follows: Section 2 provides information on action-and results-based payments as well as agricultural climate change mitigation and presents the conceptual framework. Section 3 introduces the agent-based modelling framework FARMIND, section 4 presents the results, which are discussed in section 5. Section 6 concludes.

5.2 Background and conceptual framework

5.2.1 Agricultural climate change mitigation and policy designs

Despite scientific evidence of agriculture's large potential to effectively reduce GHG emissions (Smith et al., 2008), respective mitigation measures are currently not widely adopted by farmers. Consequently, agricultural GHG emissions remained relatively stable over the past two decades (European Environment Agency, 2021). However, many countries have introduced the agricultural sector in their overall climate policy goals committed to under the Paris Agreement (OECD, 2019). Switzerland for example aims at a 40% reduction of agricultural GHG emissions by 2050 as compared to the level of 1990 (Swiss Federal Council, 2021). In the absence of binding standards and constraints regarding agricultural GHG emissions, policy instruments are required to incentivize and accelerate the uptake of climate-friendly farming practices. While agricultural policies explicitly targeting climate change mitigation are rare, the effectiveness and efficiency of differently designed policy instruments are well-studied with respect to other agri-environmental goals, i.e., conservation of biodiversity, maintenance of cultural landscapes or sustainable resource use (Pe'Er et al., 2019; Uthes and Matzdorf, 2013; Wuepper and Huber, 2021). The majority of these policy incentives pay farmers for the implementation of previously specified measures. Among the advantages of these so-called action-based policy designs are low monitoring cost and relatively good acceptance by farmers due to high certainty of payments (Vainio et al., 2021). However, action-based agri-environmental policy schemes have some important disadvantages regarding actual environmental improvements and cost-efficiency. Main problems relate to information asymmetry, moral hazard, and adverse selection of participating farmers (Moxey and White, 2014; White, 2002). It is argued that action-based payments incentivize farmers to minimize opportunity cost of adoption and hence fail to achieve environmental goals (Dicks et al., 2014; Velten et al., 2018). Instead, paying farmers based on achieved environmental outcomes has been suggested as effective and efficient alternative. So-called results-based policy designs are found to have several advantages over action-based designs: Since they allow for flexible and innovative solutions by individual farmers, results-based payments can potentially achieve environmental improvements at lower public and private costs (Burton and Schwarz, 2013b; Moxey and White, 2014; Sidemo-Holm et al., 2018; Wuepper and Huber, 2021). However, results-based payments often have high administrative cost for monitoring outcomes, especially when the desired policy goal is hard to measure as is the case with GHG emissions on farm level. Moreover, farmers face higher uncertainty of payments with results-based designs.

5.2.2 Conceptual framework

The conceptual framework of our analysis is captured in Figure 5.1. It integrates aspects of behavioural theories such as prospect theory accounting for heterogeneous risk preferences and subjective valuation of gains and losses (Kahneman and Tversky, 1979) and social network theory (Foster and Rosenzweig, 1995; Borgatti and Ofem, 2010). Moreover, we draw from a large body of empirical literature on economic, individual, and social factors affecting farmers' (non-) adoption of sustainable farming practices (e.g., Defrancesco et al., 2008; Dessart et al., 2019; Finger and Möhring, 2022; Kreft et al., 2021; Lastra-Bravo et al., 2015; Niles et al., 2016). Building on this theoretical and empirical background, we essentially assume that farmers are influenced in their decision to adopt climate change mitigation measures by three main factors: the design of policy incentives (action- or results-based design), the profitability of mitigation depending on the specificities of different types of mitigation measures, heterogeneous farm-level cost and GHG reduction potential, as well as farmers' behavioural characteristics such as individual preferences for certain mitigation measures, reluctance to change and social interactions. Farmers' adoption decisions determine the overall reduction of GHG emissions, total governmental spending and farm incomes. These outcomes in turn define the efficiency of the policy.

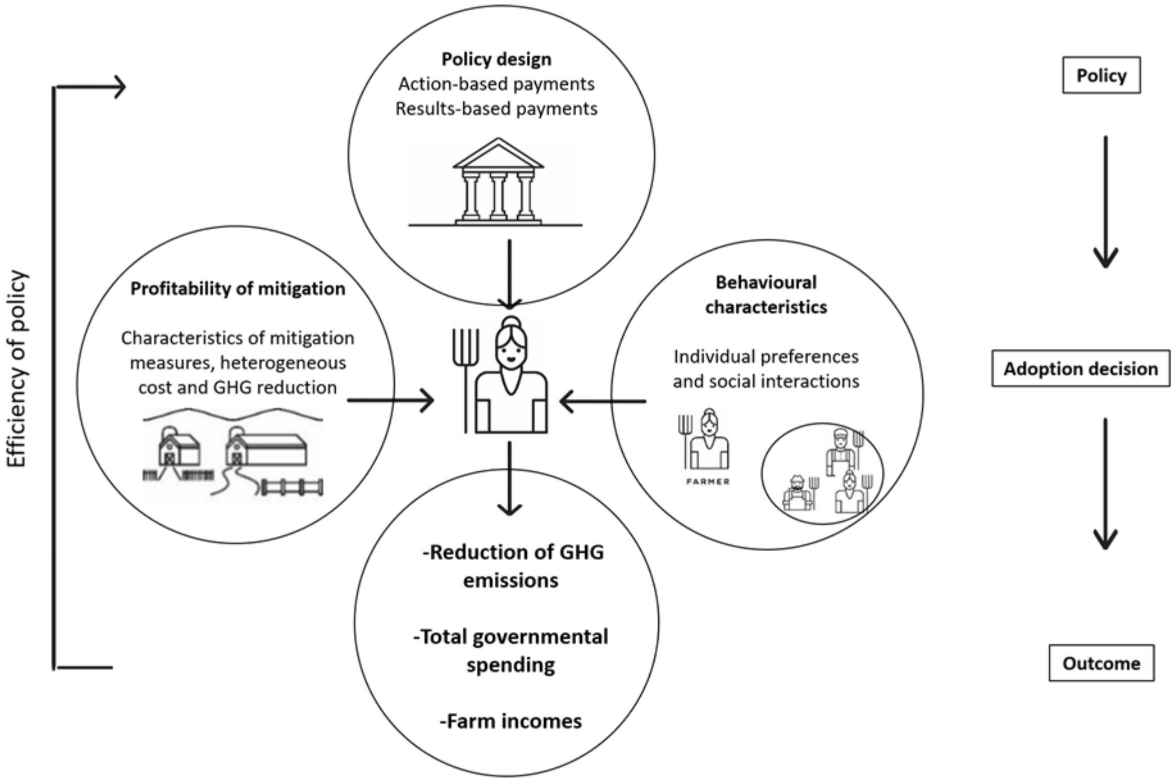

Figure 5.1: Conceptual framework.

An important boundary condition of our analysis is the assumption of constant production levels, i.e., farmers' adoption decisions do not substantially change production type and yields. The motivation for this assumption is that keeping milk and meat production constant results in an effective reduction of GHG emissions per unit of production (e.g., kg of milk or meat). This is in line with current policy goals in Switzerland aiming at a reduction of GHG emissions while maintain a high degree of self-sufficiency in milk and meat (BLW 2022a).

5.3. Data and mitigation measures

We simulate the adoption of four distinct mitigation measures, associated governmental spending, farm-level marginal abatement cost and overall GHG emissions from 49 dairy and beef cattle farms in Switzerland. Our case study is located in the northern part of Canton Zurich (region of "Zürcher Weinland") and comprises 24 dairy and 25 beef cattle, i.e., 15 suckler cow and 10 bull-fattening farms, in that region. With an average of 35 hectares (ha) and 38 cattle livestock units, the farms in our sample are larger than the average farm in Canton Zurich, which has 25 ha (Canton Zurich, 2018). We parametrize our model with census data on farm structures, survey data on farmers' individual preferences (Kreft et al., 2020) and detailed social network data based on personal interviews (Kreft et al., 2021c).

The here considered mitigation measures were selected based on scientific evidence (e.g., mitigation potential) and their suitability to Swiss dairy and beef cattle systems (Kreft et al., 2020). The current GHG emissions level, the mitigation potential of each measure as well as associated implementation cost are heterogeneous across farms and calculated for each farm with the bio-economic model FarmDyn (Britz et al., 2019). For the calculation of GHG reduction potentials and cost associated with mitigation measures, we assume constant production of milk and meat levels (however, FarmDyn allows farms to adjust crop areas and herd management) Underlying information on economic and bio-physical processes is based on planning data, IPCC emission factors, official statistics, and expert knowledge (Britz et al., 2019).

The simulated overall baseline GHG emissions (without adoption of mitigation measures) in our sample amount to 14'240 tons of CO2 equivalents (t CO2eq), with a mean of 290 t CO2eq per farm. Figure 5.2

shows the distribution of marginal abatement cost across farms for the four analyzed measures.

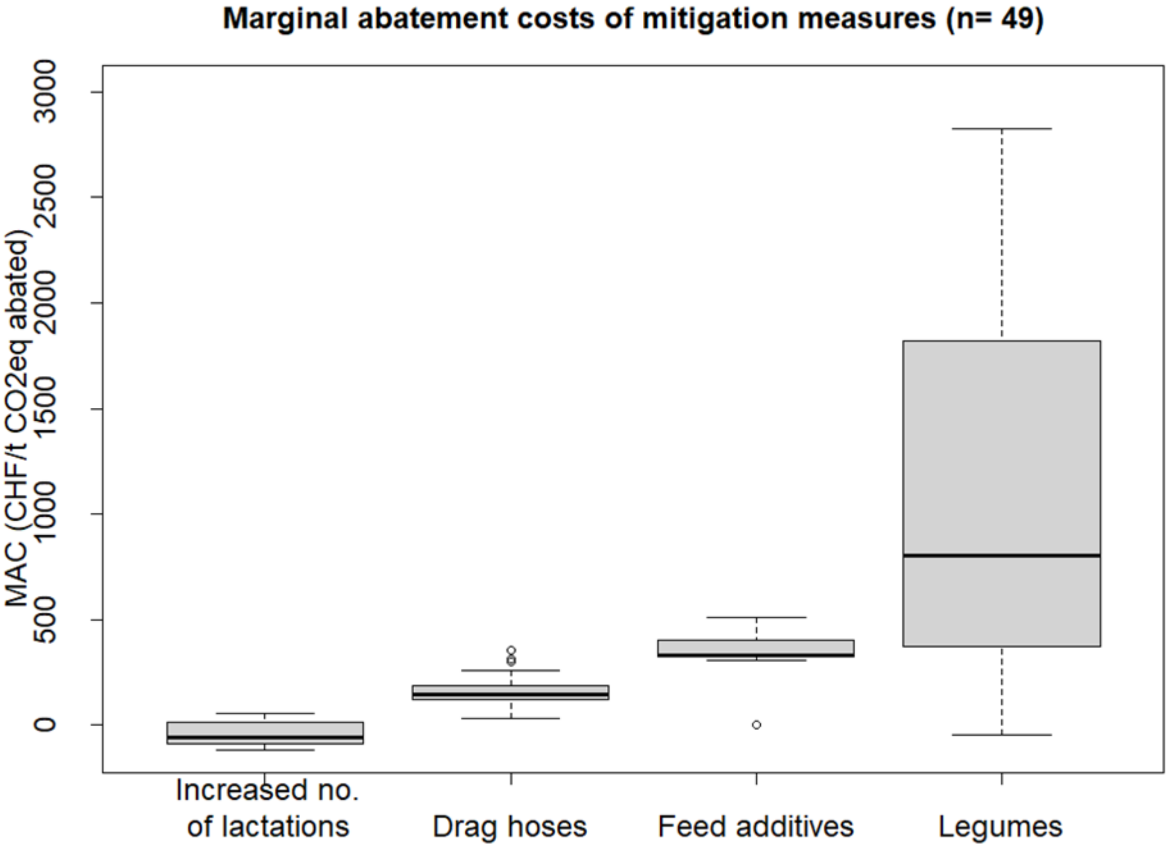

Figure 5.2: Distribution of marginal abatement costs for adoption of measures on individual farm-level without payments. Lower and upper boundaries of the grey box represent the 25th and 75th percentiles, respectively. Lower and upper error lines represent the 10th and 90th percentiles. The horizontal line inside the box depicts the median. Points represent individual farms.

Replacing concentrate feed with legumes such as protein peas or horse beans produced on the farm is the most expensive measure (Swiss Francs/t CO2eq abated) on the modelled farms. It mainly reduces upstream emissions occurring in production and transportation of imported concentrate feed. Farmers in Switzerland receive a subsidy of 1000 Swiss Francs (CHF) per hectare (ha) of such legumes (Swiss Federal Council, 2022). Increasing the number of lactations is the most effective and efficient measure in our sample as it actually provides net benefits for most farmers while reducing GHG emissions mainly due to lower replacement rates in the herd. It is thus a win-win measure and will therefore be separately analyzed as such. A direct payment scheme for this measure is planned as part of a revised agricultural policy program in Switzerland as of 2024 (Swiss Federal Council, 2020). In our model, this measure is only relevant for farms that keep dairy cows. The use of drag hoses for manure application is the second most efficient measure in terms of marginal abatement cost, the absolute mitigation potential is, however, rather low. To date, farmers receive a payment of 30 CHF/ha for implementing this measure[21].

[21] As of 2024, it will be mandatory to use drag hoses or a similar technique to reduce emissions from manure application (BLW, 2022b).

Including certain additives in the feed ration of ruminants that reduce enteric fermentation is a rather expensive measure and there is currently no policy directly supporting the use of such feed additives. We base the assumed payment on the market price of a feed additive product available in Switzerland. Table 5.1 summarizes the information on measures, mean GHG reduction potential and marginal abatement cost in our sample as well as assumed action-based payments and scientific references.

Table 5.1: Climate change mitigation measures included in the analysis (table based on Kreft et al., 2021).

Measure description	**Mechanism of GHG emissions reduction**	**Mean on-farm GHG reduction potential (t CO_2eq per unit)**	**Mean marginal abatement costs (CHF per t CO_2eq)**	**Assumed action-based payment**	**Base for assumed payment**	**References**
a) Replacement of (imported) concentrate feed with legumes	Replacing concentrate feed such as soybean with on-farm produced legumes (e.g., peas or horse bean) mitigates up-stream CO_2-emissions due to reduced transport and land-use changes	2.4 t CO_2eq per ha of legumes produced	1467	1000 CHF per ha of legumes produced	Existing direct payment in Swiss agricultural policy	(Baumgartner et al., 2008; Hörtenhuber et al., 2010; Knudsen et al., 2014; Mellado et al., 2011)
b) Increase of lactation number per dairy cow	Increasing the number of lactations per dairy cow reduces CH_4-emissions of a herd due to a reduced replacement rate, i.e., less upraising of calves and heifers	0.8 t CO_2eq per dairy cow	- 92	80 CHF per dairy cow	Payment currently debated in parliament (10 to 200 CHF/cow depending on no. of lactations)	(Alig et al., 2015; Grandl et al., 2019; Schader et al., 2014 ; Hansen et al., 2021)
c) Use of drag hoses for manure application	A close-to-ground application with drag hoses (or a similar technique) reduces N_2O-emissions of manure brought to the field and indirect N_2O emissions from other nitrogen compounds	0.07 t CO_2eq per ha of total land	116	30 CHF per ha and application (here: average 60 CHF)	Existing direct payment in Swiss agricultural policy (mandatory as of 2024)	(Thomsen et al., 2010; Weiske et al., 2006; Wulf et al., 2002 ;Huguenin-Elie et al., 2018)
d) Introduction of feed additives	Introducing feed additives such as linseed reduces the CH_4-emissions from enteric fermentation by inhibiting methanogenesis in ruminants	0.6 t CO_2eq per cattle unit	339	250 CHF per cattle unit	Product available on Swiss market	(Engelke et al., 2019; Hristov et al., 2013; Jayanegara et al., 2020 ; Poteko et al., 2016)

5.4 Modelling framework

Our modelling framework aims to simulate the efficacy and efficiency of action- and results-based policy designs for climate change mitigation on Swiss dairy and beef cattle farms. The key emerging phenomena of the model are the overall achieved reduction of GHG emissions, associated governmental spending and farm marginal abatement cost in both policy designs accounting for heterogeneous cognitive, dispositional and social factors across individual farmers.

We apply the agent-based bio-economic modelling framework FARMIND (Huber et al., 2022a). This framework integrates aspects of cumulative prospect theory (Kahneman and Tversky, 1992) and social network analysis to link farmers' individual behavioural characteristics and social interactions to effectiveness and efficiency of policy designs for GHG reduction in agriculture. FARMIND simulates individual decision-making of farmers as a two-step procedure: The farm decision-making includes the choice of a strategy (i.e., repeating, imitating, optimizing or opting-out) and a subsequent (non-) adoption of the income maximizing mitigation measure (Kreft et al., 2022).

To additionally quantify the effect of behavioural characteristics on climate change mitigation in agriculture, we compare the total GHG reduction in two scenarios, i.e., with and without consideration of farmers' reluctance to change, individual preferences for mitigation measures, and social networks. The methodological approach is further explained in three steps: i) agent characteristics, ii) agents' decision-making and iii) set up of simulation and scenarios[22].

5.4.1 Agent characteristics

In FARMIND, each agent is characterized by three sets of state variables: (1) Farm specific cost and GHG reduction potentials of four on-farm climate change mitigation measures. These exogenous parameters are calculated for each single farm with the bio-economic farm optimization model FarmDyn (Britz et al., 2019). This model was parametrized with farm-level census data. In our set-up, farmers receive a payment either for the adoption of a mitigation measure (action-based policy design) or for the achieved GHG reduction (results-based policy design). (2) Each agent has personal characteristics. These include cognitive factors (i.e., loss aversion, valuation of gains and losses and probability weighting), dispositional factors (i.e., preferences for specific mitigation measures), and social factors (i.e., tolerance for being dissimilar to other farmers and a reference income that determines whether they are satisfied with the current income situation). These exogenous parameters are derived from a farm survey (Kreft et al., 2020). (3) Social ties to other farmers based on social network data derived from face-to-face interviews (Kreft et al., 2021c).

5.4.2 Decision-making process and agents' interactions

FARMIND simulates a two-tiered decision-making process of farmers (Huber et al., 2022a). First, farm agents make a strategic decision by choosing among four possible strategies, namely repetition, optimization, imitation, and opting-out (here: non-adoption of mitigation measures). Second, farm agents make a production decision and choose whether or not to adopt one or several GHG mitigation measures.

[22] Full details of the model as well as uncertainty and sensitivity analyses are provided in the ODD + D protocol in Appendix A7.

The strategic choice is determined by the combination of two model endogenous variables: i) the agents' income satisfaction based on their reference income and ii) whether a farmer is inclined to engage in social processing with their peers or not. Table 5.2 summarizes the decision heuristics in FARMIND[23].

Table 5.2: Decision heuristics in FARMIND

		Satisfaction Prospect value with reference income as threshold for the determination of gains and losses	
		> 0: *satisfied*	< 0: *dissatisfied*
Information seeking behaviour Values for determining individual or social processing (threshold for activity dissimilarity)	< tolerance level: *individual oriented*	**Repetition** The agent only considers those mitigation measures performed in the year before.	**Optimization** The agent considers all mitigation measures only restricted by his personal preferences.
	> tolerance level: *social oriented*	**Imitation** The agent considers those mitigation measures that are applied in the social network and satisfy personal needs.	**Opt-out** The agent selects none of the mitigation measures.

The satisfaction of a farmer is defined by the farm-specific prospect value calculated based on an individual reference income and risk preferences. The latter comprise farmer specific information on valuation of gains and losses, loss aversion, and probability weighting, all derived from the survey and a multiple price list (i.e., a lottery) (Kreft et al., 2020; Tanaka et al., 2010). Whether a farmer is inclined in social processing is defined by the dissimilarity to the peers in their social networks, i.e., whether connected farmers adopt GHG reduction measures as well. This is compared to a tolerance level, which captures the individual aptitude to consider deviating behaviour of peers. The value of the tolerance level is derived from farmers' response to a respective survey question and not related to the actual adoption behaviour (Kreft et al., 2020, and see ODD+D protocol in Appendix A7 for details).

The levels of satisfaction and dissimilarity determine the strategic choice (see Jager and Jansen 2012 for details): If a farmer is satisfied and does not engage in social comparison, they will stick to the current production (Repetition). This behaviour reflects farmers' reluctance to change. A satisfied farmer who is engaged in social comparison will search for additional information and consider the behaviour observed in their social network (Imitation). Farmers who are dissatisfied but focus on individual behaviour will strive to optimize their situation (Optimization). Those who are both dissatisfied and socially oriented will examine the behaviour adopted by other agents in general (Opt-out).

Depending on the strategy chosen, a set of potential GHG mitigation measures is transferred to the second simulation step. Repeating agents only consider measures already applied in the last simulation run. Optimizing agents consider all mitigation measures available. Imitating agents consider mitigation measures successfully applied by their peers, and agents who opt-out choose none of the mitigation measures. The so transferred mitigation measures are then ranked with a fuzzy out-ranking method

[23] See also ODD + D protocol in Appendix A7.

according to the personal preferences of the farmer derived from survey data (Kreft et al., 2020). Based on this, the agent in FARMIND chooses the mitigation activities that maximize farm income. The resulting income and adopted GHG mitigation measures are then again transferred to the FARMIND strategic decision level to update measures and income distribution of the farm agents.

We conducted a specific sensitivity analysis to calibrate the two threshold parameters (individual reference income and dissimilarity tolerance) based on observed adoption of mitigation measures. The sensitivity analysis allowed to identify a model that reproduced the observed adoption patterns in our case study region (i.e., allowing for a minimal error between simulated and observed adoption decisions). This supports the validity of the model to assess the efficiency of different payment schemes under consideration of behavioural influences. (For more details on model selection and validation as well as further sensitivity analyses, please refer to the ODD + D protocol in Appendix A7.)

As mentioned above, the GHG emission reduction and cost associated with the different mitigation measures as well as all combinations thereof are simulated for each agent with the bio-economic farm level model FarmDyn (Britz et al., 2019). Therein, farmers are assumed to be fully informed and rational decision-makers who maximise profits given a rich set of constraints. The model contains detailed information on bio-physical (e.g., nitrogen flows, GHG emissions) and economic (e.g., cash flow, investments) processes linked to farming activities based on official statistics, IPCC emission factors, planning data, and expert knowledge.

5.4.3 Scenario description and simulation set-up

We test and compare the cost-efficiency of different policies incentivizing agricultural climate change mitigation in four scenarios. These reflect the type of policy (action- or results-based payments) and whether behavioural aspects, i.e., reluctance to change, personal preferences and social networks are included or not. The assumed action-based payments per mitigation measure are based on current (or planned) policies in Switzerland. With these payments, a reduction of 10% of GHG emissions is reached. To compare the efficiency of the different policy designs, the results-based payment is stepwise in-/decreased until a similar level of GHG reduction (i.e., 10% of baseline emissions) is achieved under both policy schemes. This is the case with a results-based payment of 370 CHF/tCO2eq. Both action- and results-based payments are designed to compensate farmers for the costs incurring from adoption of mitigation measures. Moreover, creating a counterfactual situation of strictly profit maximizing farm agents (who are risk neutral and don't have any other behavioural characteristics nor social interactions) allows to assess the effect of behavioural factors on overall GHG reduction and associated cost. Thus, the comparison of simulation results gives quantitative insights into the relevance of behavioural economic factors for policies aiming at climate change mitigation in agriculture.

The model is initialized with agents who do not implement any of the mitigation measures. FARMIND then simulates farmers' adoption decisions over 12 years in which the agents endogenously choose a strategy and adopt mitigation measures. The number of runs is set such that FARMIND reaches an equilibrium state where the adopted mitigation measures do not change anymore. Stochasticity is created by random selection of producer prices for milk and meat (+/- 15% of current price levels). This price range represents observed market conditions in our case study region (see BLW, 2021) and allows to consider the uncertainty of farmers' strategic choices based on market developments. Over the entire simulation length of 12 runs, this allows for a certain randomness of farmers' strategic choices based on their reference incomes realized (or not) under different price levels. We run the model with two scenarios, namely with the action- and results-based policy design. Farm profits change depending on farm individual opportunity cost and the adoption of measures or the GHG reduction achieved, respectively. To create the counterfactual situation without considering behavioural aspects, the reference income of each agent is set such that all agents start to maximize profits independent of individual preferences or social influences. This is also done for both policy scenarios. We finally run the same simulations while excluding the measure of increasing the number of lactations per dairy cow. This measure does increase farm profits while reducing GHG emissions and is hence a so-called win-win measure. Paying farmers for an already profitable measure leads to windfall effects, which can be higher or lower depending on the payment scheme.

5.5 Results

We find that total governmental spending to achieve a GHG reduction of approximately 10% of baseline emissions is higher in the results-based policy design (+26%) than in the action-based design (Figure 5.3)[24]. Figure 5.3 furthermore shows the contribution of each mitigation measure to the overall expenditure. Governmental spending to incentivize farmers to increase the number of lactation ("Lactation") is much higher in the results-based scheme compared to the action-based scheme. The underlying mechanism in our model is the following: a win-win measure enters the farmer's choice set if they choose a profit maximization strategy or if it is adopted by peers in the social network (with an imitation strategy) and fits the farmer's personal preferences. Once it is in the choice set, a win-win measure will be adopted independent of the policy design. In that case, a lower (or even no) compensation would suffice to incentivize the adoption. This potentially renders an action-based policy more efficient from a governmental perspective. More precisely, the composition of adopting farms and adopted measures changes with the payment scheme: The results-based scheme incentivizes farms with comparably low abatement costs to adopt mitigation measures (i.e., farms that can efficiently mitigate GHG emissions). In contrast, the action-based scheme supports farms with low adoption costs per measure independent of the GHG reduction potential. In the case of the win-win measure, however, most farms do not have costs when adopting this measure. Thus, if this measure enters the farmer's choice set, it will be adopted under both policy schemes irrespectively of the magnitude of the incentive since it is profitable per se. Therefore, the number of farms that adopt the win-win measure "increased

[24] Detailed simulation results as well as additional figures on GHG reduction, farm income changes and mean marginal abatement cost by measure can be found in Appendix A6.

number of lactations per dairy cow" does not change between the results- and action-based policy designs in our simulations (see Figure 5.5 below). Since the action-based scheme addresses specific measures, a low payment for increasing the number of lactations is already sufficient for adoption. A homogeneous payment per ton of CO2eq reduced (i.e., results-based scheme), in contrast, is independent of the specific measure. In our simulations, the payment to achieve a 10% reduction level is 370 CHF / per t CO2 equivalent and the measure has a large potential to decrease GHG emissions. Consequently, the governmental support for the results-based payment is higher because it cannot does not consider the cost of the specific measure (i.e., in the case of the win-win measure the profit from adoption). Overall, this leads to lower governmental expenditures of action-based policy designs in our simulations when considering all four measures.

However, mean marginal abatement cost[25] of farms to reach an overall 10% GHG reduction are substantially lower with the results-based policy as compared to the action-based design (-85%). Moreover, dispersion across farms and hence the uncertainty of marginal abatement cost is higher in the action-based scheme (Figure 5.3). This can be explained by the fact that with action-based payments, farmers adopt measures that have relatively low opportunity cost independent of the associated GHG reduction potential. Consequently, farmers do not consider the amount of GHG emissions reduced in the action-based scheme, which potentially leads to the adoption of measures with low mitigation potential on the specific farm. This leads to a larger distribution and higher average marginal abatement cost in action-based designs. In contrast, when farmers are paid based on the achieved GHG reduction, the mitigation potential of measures is a key part of the adoption decision since it defines the profitability of adopting. Hence, farmers strive to minimize their marginal abatement cost, which is reflected in lower average marginal cost and less dispersion.

[25] Marginal abatement cost are defined as the difference between a counterfactual base income without adoption of mitigation measures and the farm incomes including governmental payments for climate change mitigation.

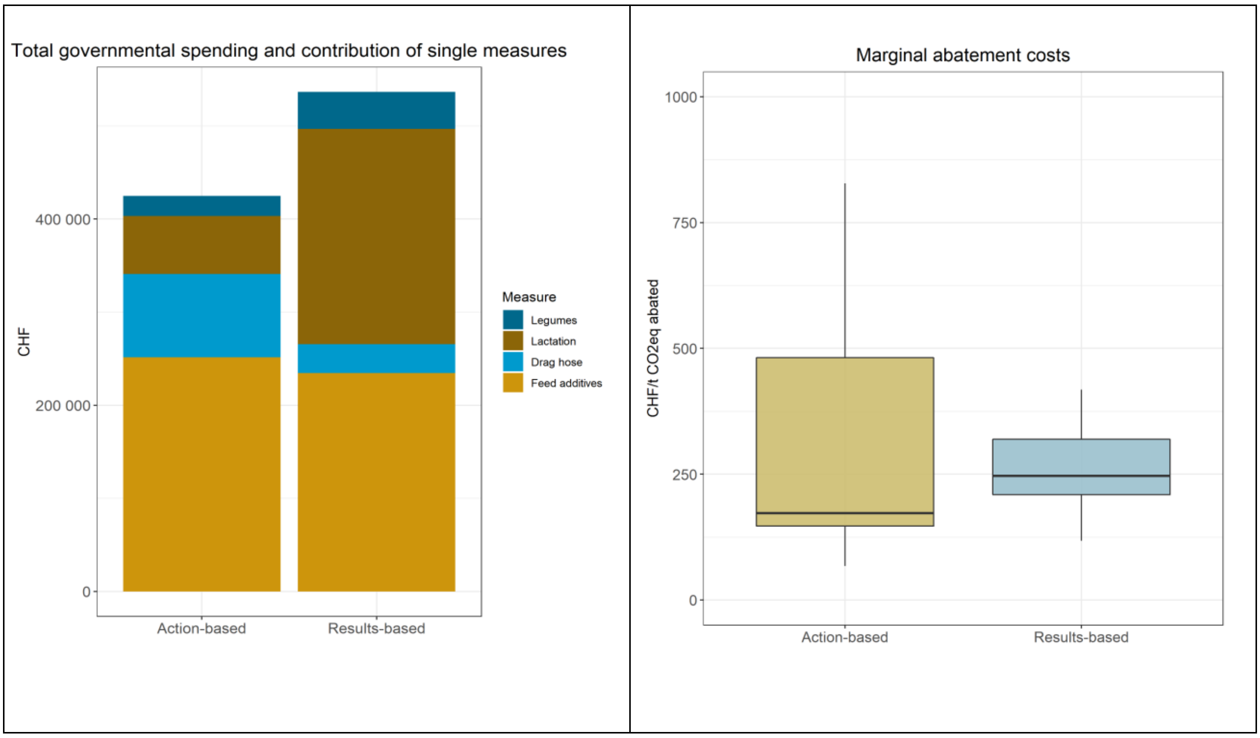

Figure 5.3: Governmental spending and marginal abatement cost of four mitigation measures (including a win-win measure).

Note: Total governmental spending by measure and distribution of total marginal abatement cost for a 10%-reduction of on-farm GHG emissions under action- and results-based policy designs. Four mitigation measures are included in the analysis: i) replacement of concentrate feed by legumes, ii) increased number of lactations per dairy cow (win-win measure), iii) drag hoses for manure application, iv) feed additives to inhibit enteric fermentation of cattle. Governments spend a total amount of CHF 424 782 under the action-based and CHF 536 473 under the results-based policy design to achieve an approximate 10% reduction of baseline GHG emissions. Mean marginal abetment cost of farms is at CHF 1398 (Sd 3899) with action-based payments and CHF 247 (Sd: 78) with results-based payments.

When the win-win measure is excluded from the analysis, we find that a results-based design is more efficient in terms of lower governmental spending (-21%). This would be expected from a theoretical perspective. As in the above case, average marginal abatement cost on farm-level are lower in the results-based design than in the action-based design (Figure 5.4).

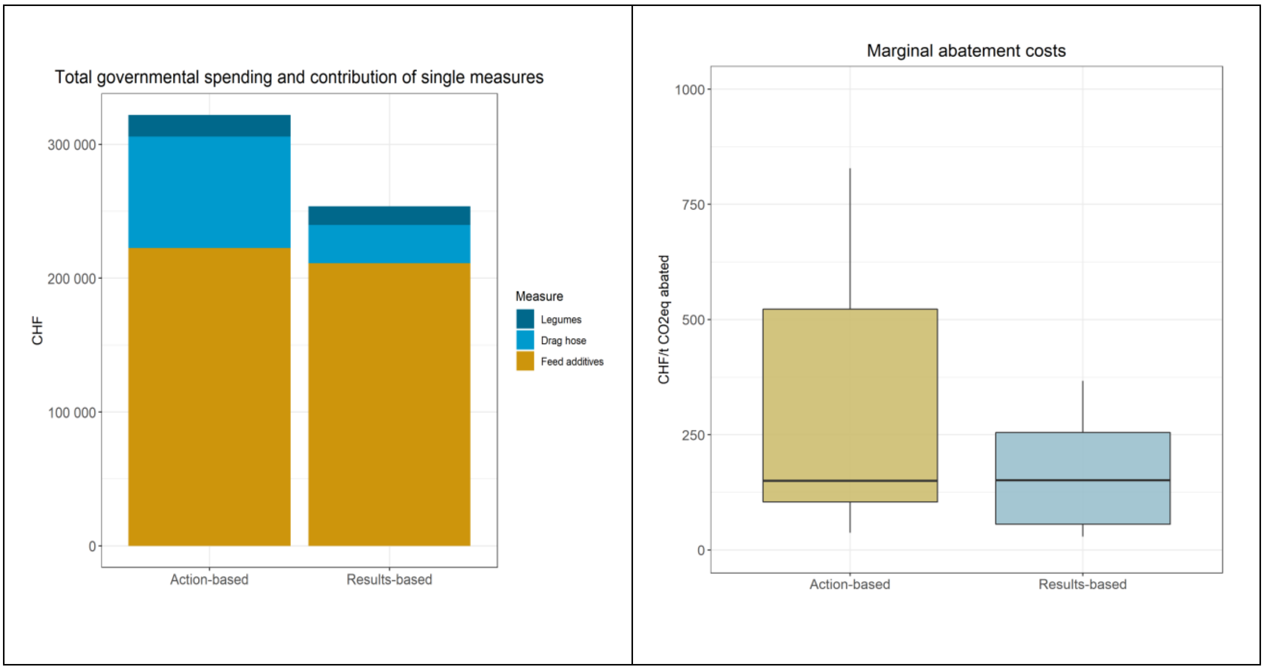

Figure 5.4: Governmental spending and marginal abatement cost of three mitigation measures (without win-win measure).

Note: Total governmental spending by measure and distribution of total marginal abatement cost for a 10%-reduction of on-farm GHG emissions under action- and results-based policy designs. Three mitigation measures are included in the analysis: i) replacement of concentrate feed by legumes, ii) drag hoses for manure application, iii) feed additives to inhibit enteric fermentation of cattle. Governments spend a total amount of CHF 321 948 under the action-based and CHF 253 525 under the results-based policy design. Mean marginal abetment cost of farms is at CHF 1443 (Sd: 3996) with action-based payments and CHF 132 (Sd: 178) with results-based payments.

Moreover, we find that the inclusion of behavioural factors, namely farmers' individual preferences for certain mitigation measures as well as social networks substantially decreases adoption of mitigation measures and consequently the overall GHG reduction potential in our sample as compared to a scenario where farmers are profit maximizers. This holds for both compared policy designs. When the win-win measure is included, almost all farmers implement at least one mitigation measure in the case of profit maximization since adoption is profitable with the payments. Almost all farmers in our model that keep dairy cows would increase the number of lactations under profit maximization behaviour. However, when accounting for individual characteristics and preferences, less mitigation measures are adopted and up to 12 farmers do not adopt any measures. With both action- and results-based payments, the use of drag hoses for manure application is most widely adopted, followed by feed additives, increased number of lactations, and replacing concentrate feed by legumes. The same patterns of adoption show when the win-win measure is excluded from the analysis (Figure 5.5).

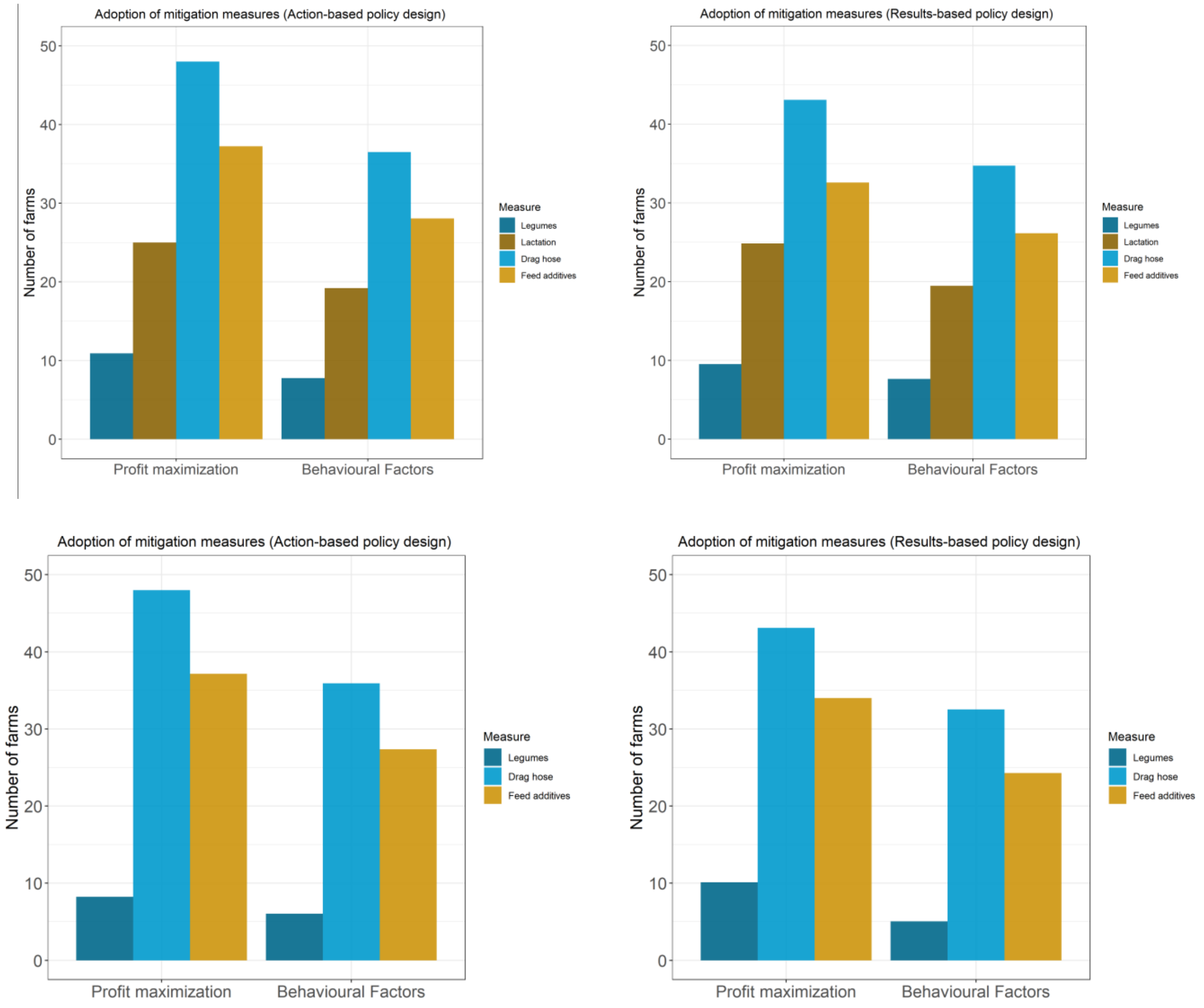

Figure 5: Comparison of the adoption with four and three mitigation measures under action- and results-based payment schemes

These findings can essentially be explained by two mechanisms in our model: 1) Because of a combination of different behavioural characteristics and/or preferences for certain mitigation measures, farmers are reluctant to change. This leads agents to repeat their current farming practices instead of choosing an optimization strategy. Hence, in FARMIND, no new mitigation measures are available in the agent's choice set. 2) When farmers are susceptible to social influences and choose an imitation strategy, only the measures already adopted by peers in the network are available in the choice set of the individual agent. Hence, not all potential mitigation measures are necessarily considered as would be the case with a fully rational and informed agent.

5.6 Discussion

The success of effective climate change mitigation in agriculture depends on farmers' adoption of farming practices that can reduce GHG emissions from agricultural production. We provide an ex-ante analysis of different policy designs to reduce GHG emissions on 49 Swiss dairy and beef cattle farms accounting for different types of mitigation measures and farmers' behavioural characteristics in the agent-based bio-economic modelling framework FARMIND (Huber et al., 2022). Our results show that the cost-efficiency of action- and results-based policy incentives for agricultural climate change mitigation depends on the specific cost structure and mitigation potential of the considered measures. Especially, if a policy aims to incentivize the adoption of a win-win measure by farmers who are otherwise reluctant to change (but learn from their peers and are eventually triggered to consider new measures due to adoption dynamics within their social networks), an action-based design can lead to lower governmental spending than a results-based design.

This finding seems counterintuitive at first given that previous literature has usually found results-based policy designs to be more cost-efficient than action-based designs (e.g., Sidemo-Holm et al., 2018; Wuepper and Huber, 2021). However, in the case of a win-win situation where emissions are reduced while farm profits are increased, targeting payments to the cost and benefits of specific measures (i.e., defining the amount of the payment based on the measure specific characteristics) can be more efficient from a governmental perspective than targeting the policy to desired outcomes and cost-efficiency on farm-level. Accordingly, we find that when the win-win measure is excluded from the policy, the results-based design achieves GHG reduction at lower public costs than the action-based, which corresponds to theory (e.g., Engel, 2016) and empirical literature (Claassen et al., 2018; Sidemo-Holm et al., 2018; White and Hanley, 2016; Wuepper and Huber, 2021). Yet, results-based policy designs for agricultural GHG reduction constitutes a challenge since the outcome is hard to measure. A promising way to overcome this challenge could be to (ex-ante) model the results instead of measuring them (Bartkowski et al., 2021).

Independent of the type of measures (i.e., win-win or not), we find that the results-based policy design is more efficient on farm level as it leads to lower average marginal abatement cost than the action-based design. Moreover, the action-based policy results in larger dispersion of marginal cost across farms and is thus more uncertain compared to a results-based design. When farmers are paid for the adoption of mitigation measures independent of the actual GHG reduction potential of the farm, the adoption behaviour is mainly influenced by individual opportunity cost. Hence, farmers potentially adopt mitigation measures that barely reduce GHG emissions, which increases the cost per ton of CO2eq reduced. For the same reason, marginal abatement cost are very heterogeneous across individual farms when GHG reduction is not part of the adoption decision. These results provide a differentiated picture of the cost-efficiency of action- and results-based policy designs for agricultural climate change mitigation and shed light on potential trade-offs between different policy goals related to GHG reduction on one hand and supporting viable farm incomes on the other hand. Looking at the abatement cost without compensating payments for the adopted measures, the win-win measure of increasing the number of lactations creates overall net benefits while the introduction of feed additives produces the highest overall cost for farms (see Appendix A6, Figure A2).

We do not account for potential changes in overall production intensity as a response to mitigation incentives since our model assumes fixed production levels. This enables to estimate GHG reductions per kg of milk and beef, which is a relevant measure since Switzerland is a net importer of food. If domestic production of milk and beef is reduced without major changes in consumption patterns, these products will be imported and hence, GHG emissions will occur elsewhere instead (Vellinga and de Vries, 2018). Clearly, this assumption reflects a rather short-term perspective since substantial reductions of GHG emissions from agriculture and food production will be limited under current consumption levels of animal-based proteins (Poore and Nemecek, 2018). However, the approach reflects current (short-term) Swiss policy goals to keep self-sufficiency in milk and meat at a high level. Moreover, we do not expect major incentives to increase or decrease production since the assumed payments for the selected measures only compensate farmers for the associated costs and are decoupled from production. Since adoption is not mandatory, only farms that remain profitable and can keep up production levels (with given payments) will implement a specific measure in our model. Moreover, the here analyzed GHG mitigation measures have been shown to not impact yield levels (Mellado et al., 2011; Hansen et al., 2021; Huguenin-Elie et al., 2018; Poteko et al., 2016).

Our results furthermore show that individual behavioural characteristics, and particularly farmers' reluctance to change lower the overall GHG reduction potential of action- and results-based policy incentives. Such behavioural characteristics even prevent farmers from considering so-called win-win (or no-regret) measures that reduce emissions and increase farm profits at the same time as is the case with increasing the number of lactations of dairy cows. In our model, this is reflected by a two-step procedure of decision-making. Based on a farmer-specific combination of (dis-) satisfaction and (un-) certainty, the farmer decides for a strategy which determines the set of potential mitigation measures to choose from in the second step. So even if adoption of a certain measure would be profitable for the farmer in the second step of the decision-making, they could refrain from doing so because of their personal preferences and/or their reluctance to change. In our simulation, aggregated farm profits forgone due to such behavioural influences amounts to roughly 1 156 CHF per farm (on average, 56’700 CHF in total over all farms)) in the action-based scheme and to 1 272 CHF per farm (on average, 63’300 CHF in total over all farms) in the results-based scheme. This is in line with research showing that up to 25% of GHG emissions from agricultural production could be mitigated at very low cost or even net gains, yet respective mitigation measures are still not readily adopted by farmers (Ancev, 2011; Eory et al., 2018). Our findings help to explain non-adoption of win-win GHG mitigation measures due to farmers’ reluctance to change and inertia, which are known to be among the most dominant barriers when it comes to adoption of agri-environmental measures (Dessart et al., 2019). In our model, inertia can be overcome by learning within farmers’ social networks. Especially, farmers who are reluctant to change but to some degree susceptible to social influences, start to consider the adoption of new mitigation measures when exchanging respective knowledge with connected peers (Kreft et al., 2022a; Kreft et al., 2022b).

While we can parametrize our model drawing from a thorough data basis that includes detailed information on farm structural characteristics, farmers’ individual preferences and social interactions, our analysis faces some uncertainties. In general, the agent-based model FARMIND relies on certain parameter thresholds to simulate farmers’ decision-making. While risk preferences, sensitivity to social dissimilarity and farming preferences could be directly taken from the survey data, the absolute levels of the reference incomes are based on simulations with the bio-economic model FarmDyn (Britz et al., 2019). However, the sensitivity analysis conducted in previous work based on the same model parametrization showed that FARMIND can well reproduce the observed adoption patterns in our case study region (see ODD+D protocol in Appendix A7). Another uncertainty concerns the amount of the results-based payment. To compare both policy designs based on the same level of achieved reduction of GHG emissions, the results-based payment was stepwise approximated until the same GHG reduction as with the action-based payments was reached. This leads to the payment of 370 CHF/tCO_2eq, which is rather high when compared to e.g., the current CO_2 tax on fossil fuels in Switzerland, which is at 120 CHF/tCO_2eq (Swiss Federal Council, 2022). There is furthermore uncertainty regarding the technical and economic potential of the mitigation measures included (for a detailed discussion of uncertainty related to GHG reduction potential of measures, see Kreft et al., 2022). In particular, the here highlighted win-win measure of increasing the number of lactations of dairy cows could for example increase veterinary costs due to health or fertility issues of older cows (Grandl et al., 2019; Mellado et al., 2011), which could also explain farmers’ non-adoption. Our model does not account for these types of costs or for potentially associated changes in milk yield. Finally, our analysis does not include potential transaction cost nor administrative cost, e.g., for the monitoring of result- but also action-based schemes.

5.7 Conclusion

In this article, we compare action- vs. results-based policy designs to incentivize climate change mitigation in agriculture. Our ex-ante policy analysis accounts for heterogeneous behavioural characteristics of farmers, i.e., reluctance to change, personal preferences, and social interactions. We use an agent-based model in combination with a bio-economic model to simulate total governmental spending, farm-level marginal abatement cost and overall GHG reduction considering different types of mitigation measures.

Our results suggest that cost-efficiency of action- and results-based policy designs depends on the characteristics of the considered measures. In particular, if farmers learn about a win-win measure (which reduces emissions while increasing farm incomes) within their social networks but reluctance to change prevents them from adopting it, an action-based policy to incentivize adoption of particular measures can be superior in terms of cost-efficiency from a governmental perspective. Our findings furthermore highlight that behavioural characteristics of farmers help to understand (non-) adoption of GHG reduction practices in agriculture.

Our results have some important implications for the design of policies that aim at an effective and efficient reduction of GHG emissions from agricultural production. First, despite many advantages and theoretical efficiency gains, result-orientation of policies might not necessarily lead to higher efficiency and savings of public cost per se. Rather, underlying heterogeneity of structures, cost and characteristics of measures must be addressed and thoroughly analysed to achieve desired GHG reduction most efficiently (Moxey and White, 2014). For example, when the adoption of measures leads to profit gains of farms, targeting payments to the specific cost and mitigation potential of these measures can lead to lower cost for society than a design that primarily targets cost-efficiency on farm-level. Second, ex-ante analyses of policies should account for behavioural characteristics such as personal preferences and social networks of farmers, which are important determinants of decision-making and hence influence the effectiveness of policy instruments. Especially, farmers' tendency to inertia or "status-quo bias" with respect to adoption of new practices must be overcome by information and appropriate policy incentives. This can be of particular relevance in the rather new field of agricultural climate change mitigation.

Our analysis also has implications for future research. The efficiency of policies to incentivize agricultural GHG emissions based on larger samples and in different regions is needed to generalize findings and implications. Moreover, more mitigation measures shall be considered. Future studies should especially test the effect of different win-win measures on the efficiency of action- and results-based policy incentives for agricultural climate change mitigation. Moreover, accounting for transaction and administrative cost of individual measures and payment designs could contribute important insights into the efficiency of climate change mitigation policies in agriculture.

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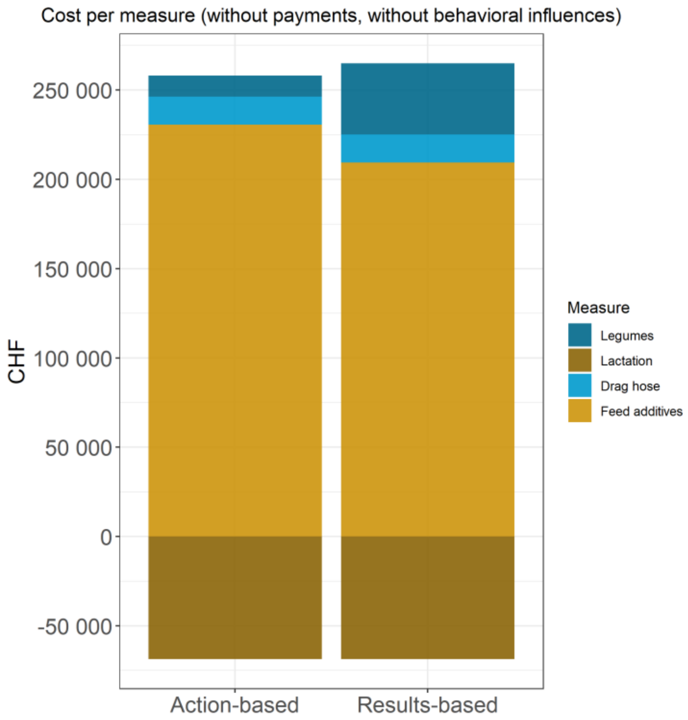
5.10 Appendix A6

A6.1: Detailed simulation results

Table A6.1: Detailed simulation results with and without including the win-win measure of increasing the number of lactations per dairy cow for action-and results-based policy designs. Two scenarios are compared, namely with and without including behavioural characteristics of farmers. Note that totals might differ from the sum of numbers by measure due to interaction effects when combining single measures.

	4 mitigation measures (including win-win measure)				3mitigation measures (excluding win-win measure)			
	Action-based		Results-based		Action-based		Results-based	
	Profit maximization	Behavioural factors	Profit maximization	Behavioural factors	Profit maximization	Behavioural factors	Profit maximization	Behavioural factors
Total GHG reduction (tCO_2eq)	**1623**	**1412**	**1697**	**1396**	**943**	**705**	**1056**	**685**
Legumes	23	46	101	108	7	31	224	37
Lactation	800	624	800	624				
Drag hose	129	84	128	83	129	78	128	77
Feed additives	806	658	758	634	806	595	773	571
Total change in farm incomes (CHF)	**328 499**	**271 814**	**420 304**	**357 976**	**183 255**	**149 362**	**133 131**	**88 545**
Legumes	14 791	11 351	7 738	6 600	16 431	12 991	54 697	9 716
Lactation	149 794	119 060	367 212	288 000				
Drag hose	84 865	72 710	31 643	17 755	84 865	67 570	31 643	16 513
Feed additives	77 511	68 693	71 164	65 017	77 511	65 748	71 432	62 345
Total governmental spending (CHF)	**541 098**	**424 782**	**627 924**	**536 473**	**436 271**	**321 948**	**390 876**	**253 525**
Legumes	27 210	21 710	37 315	39 907	21 700	16 200	82 869	13 852
Lactation	78 414	62 094	295 843	231 043				
Drag hose	106 178	89 561	47 381	30 793	106 043	83 245	47 381	28 510
Feed additives	309 693	251 418	281 191	234 729	304 528	222 503	285 840	211 251
Mean marginal abatement costs (Sd) (CHF/tCO_2eq)	**1203 (3591)**	**1398 (3899)**	**241 (99)**	**247 (78)**	**1143 (3611)**	**1443 (3996)**	**131 (166)**	**132 (178)**

A6.2 Total abatement cost on farm-level by measure without payments



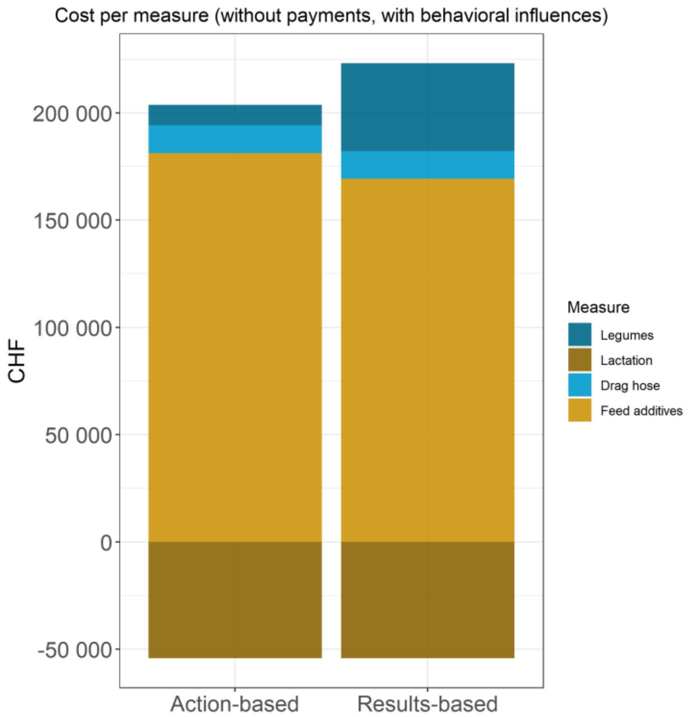
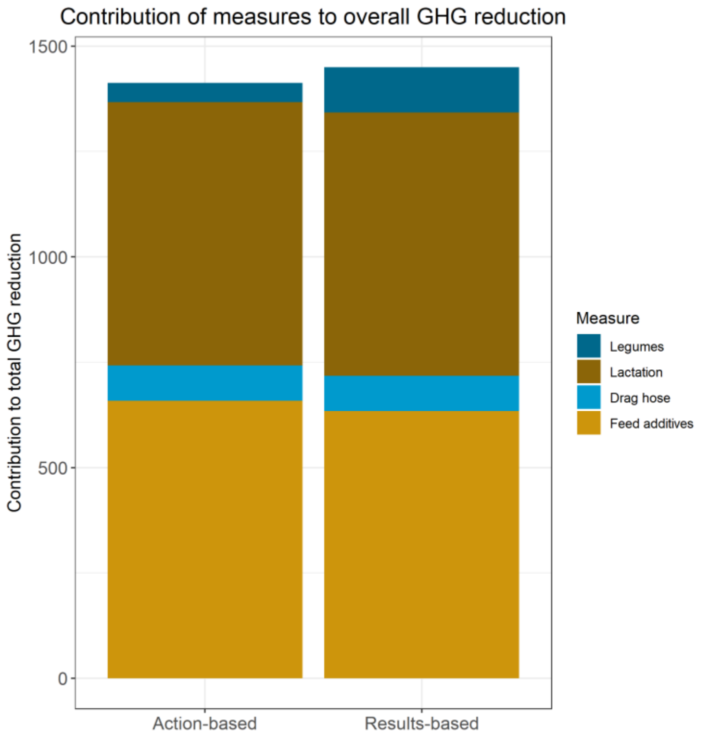


Figure A6.2: Total abatement cost (income changes) on farm-level without payments. The underlying adoption choices are based on both the action- and results-based scheme. The upper graph shows costs without consideration of farmers' behavioural characteristics, the lower graphs shows costs with consideration of behavioural characteristics. The win-win measure (increasing the number of lactation) creates net profits for farms without any payments and introducing feed additives creates highest cost in all scenarios. Since the underlying adoption choices are based on assumed payments, the profit maximization scenario (upper graph) creates slightly higher overall costs than when considering behavioural influences. This is due to the fact that farmers adopt more in the profit maximization scenario with payments.

A6.3: Total reduction of GHG emissions by measure under action- and results-based policy designs



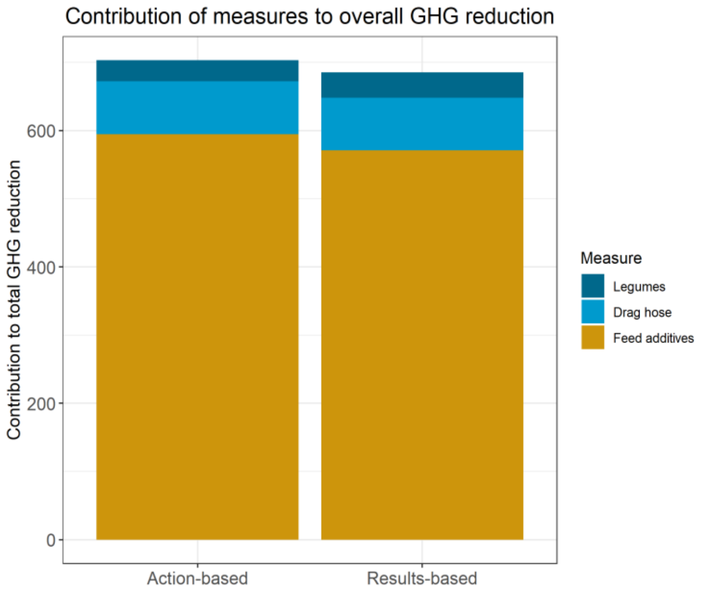
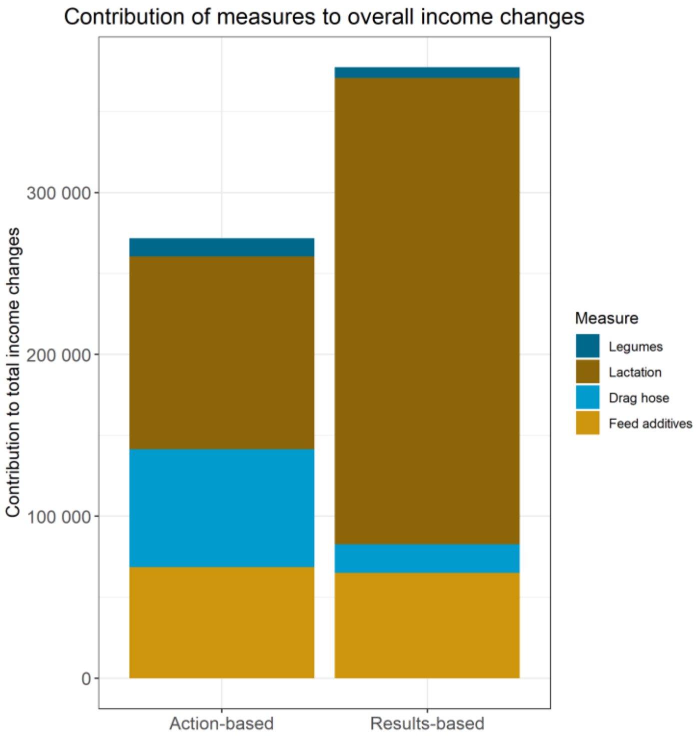


Figure A6.3: Simulated total reduction of GHG emissions due to adoption of four and three mitigation measures in action- and results-based payment schemes. The upper part of the graph shows GHG reduction including a win-win measure in the payment scheme (increasing the number of lactations of dairy cows), the lower part of the graph shows GHG reduction without the win-win measure.

A6.4 Total changes in farm incomes by measure under action- and results-based policy designs



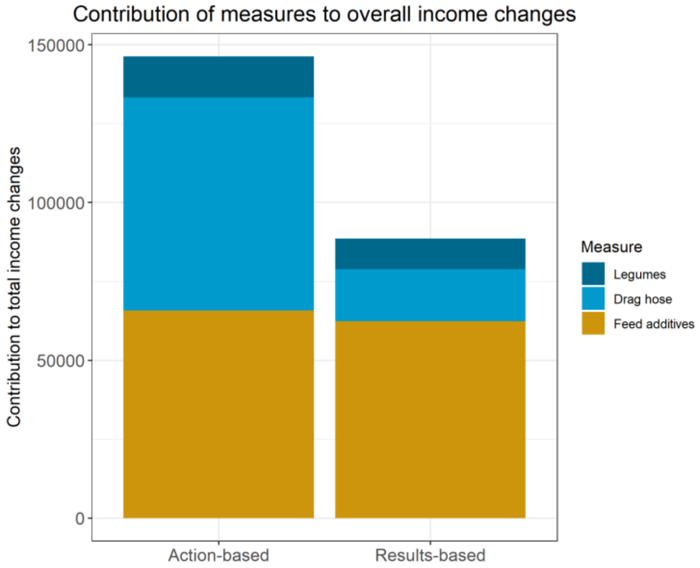


Figure A6.4: Simulated total income changes (increases) due to adoption of four and three mitigation measures in action-and results-based payment schemes. The upper part of the graph shows income changes including a win-win measure in the payment scheme (increasing the number of lactations of dairy cows), the lower part of the graph shows income changes without this win-win measure.

A6.5 Mean marginal abatement cost by measure under action- and results-based policy designs

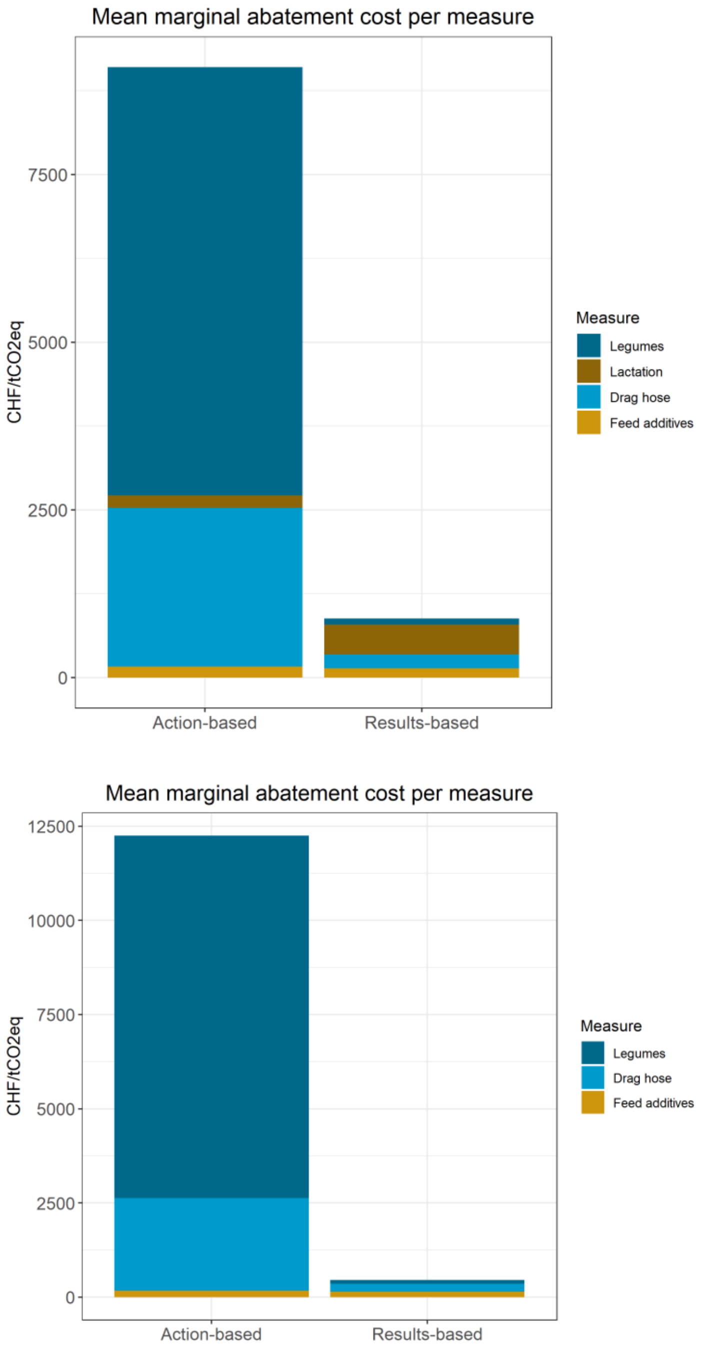


Figure A6.5: Simulated mean marginal abatement costs of single measures in action-and results-based payment schemes. The upper part of the graph shows mean marginal abatement costs including a win-win measure in the payment scheme (increasing the number of lactations of dairy cows), the lower part of the graph shows mean marginal abatement costs without this win-win measure.

5.11 Appendix A7: ODD+ D Protocol FARMIND

A7.1 Overview

Purpose

The purpose of the agent-based model FARMIND is to simulate and compare the effect of action and results-based payments on farmers' adoption of climate change mitigation measures on Swiss dairy and beef cattle farms. Thereby, the model considers heterogeneous cognitive, social, and dispositional factors across individual farmers. More specifically, we simulate the effect of individual farming preferences, reluctance to change and social interactions on the adoption decision of four climate change mitigation measures i.e., 1) replacement of concentrate feed in feeding rations, 2) increased number of lactations per dairy cow, 3) use of drag hoses for manure application and 4) methane reducing feed additives. The model is parameterized with survey data including a lottery to identify risk preferences and a social network analysis as well as cost and benefit calculations from the farm-level optimization model FarmDyn (see Britz *et al.*, 2021). The emerging phenomena are the total amount of greenhouse gas (GHG) emissions reduced by the policy induced adoption of farm individual mitigation measures and the change in income for the individual farm as well as the whole farm community. Thus, the model allows to quantify the economic and environmental effect of behavioural factors on the cost-efficiency of differently designed public payments for GHG reduction in agriculture.

Entities, state variables and scales

Each agent represents an individual farmer. An agent has the following entities and state variables:

(1) Farm specific profits and cost as well as GHG emission reduction potentials for four on-farm climate change mitigation measures. These are exogenous parameters calculated in the sub-model FarmDyn (a farm optimization model parameterized with census data, see corresponding section below). Profits result from either a payment for each ton of reduced CO_2 equivalents (CO_2eq) i.e., a results-based payment or from a payment for the implementation of the measure implemented on the farm i.e., an action-based payment. Farm specific cost emerge from implementing mitigation measures on each individual farm. The cost and benefits are calculated for an output price range of +/- 15% of current milk and meat prices.

(2) Personal characteristics including cognitive factors (i.e., risk parameters based on cumulative prospect theory, and reference income), social factors (i.e., tolerance for being dissimilar to other farmers), and dispositional factors (i.e., preferences for specific mitigation measures, reluctance to change). These are exogenous parameters based on a farm survey in our case study region (Kreft et al., 2020).

(3) A social network between farmers derived from an interview based on social network analysis (Kreft et al., 2021c).

(4) Income changes and GHG emission reduction potentials resulting from the choice of GHG mitigation options. The agents' income is used to calculate the prospect value based on the risk preferences of each individual farmer. The adoption choices of each farmer are used to calculate a dissimilarity index that drives social oriented behaviour. Income, GHG emissions, prospect value and dissimilarity index are model endogenous variables (see Table A7.1).

Table A7.1: State variables and parameters of FARMIND

Category	State variable / parameters	Abbreviation	Source for initialization
Farm	Adopted mitigation measures	A	Kreft et al. (2020)
	GHG emission reduction potential of measure A	y_{At}	Simulated in sub-model FarmDyn
	Income with adopted mitigation measures	x_{At}	
Personal characteristics	Loss aversion level	λ	Kreft et al. (2020)
	Valuation of gains and losses	$\alpha^{+/-}$	
	Probability weighting in gains and losses	$\phi^{+/-}$	
	Reference income to determine perceived gains and losses and calculate satisfaction	V_i^{ref}	
	Tolerance level for activity dissimilarity to determine information seeking behaviour	d_i^{tol}	
	Preference weight for mitigation measures	R^A	
Social network	Number of peers a farmer is linked to (number of social ties)	n	Kreft et al. (2021c)
Outcome variables	Prospect value	V_i	Model endogenous
	Agents' activity dissimilarity	d_i	
	GHG emission reduction (in simulation run t)	y_t	
	Income (in simulation run t)	x_t	

The underlying data on income changes and GHG emission reductions are calculated per farm on a yearly basis. Thus, a model run represents one year (i.e., the temporal resolution). To simulate the effect of knowledge diffusion through the social network, we repeat the simulation over twelve runs. Our main results, however, are comparative static in the sense that we compare final states of GHG emissions and incomes in different scenarios. The model simulates individual farms with heterogeneous farm sizes and locations. The farm size varies between 12 and 73 hectares (ha) with an average at 35 ha per farm. The sample consists of 24 dairy farms, 15 suckler farms and 10 bull fattening farms. On average, farms have 38 cattle livestock units. Given milk prices range between 0.60 and 0.79 Swiss francs per kilogram. Beef prices range between 7 and 11 Swiss francs per kilogram.

Process overview and scheduling

FARMIND includes a two-tiered decision-making mechanism for managing farm resources (Huber et al., 2022b). In a first step, agents choose a decision strategy. The model includes four behavioural strategies: repetition, optimization, imitation, and opt-out (see section "Individual decision-making" below for details). In a second step, farm agents choose their actual production decision, i.e., the adoption of a GHG mitigation measure based on the options provided in the corresponding strategy. This two-tiered decision-making is implemented in three coding steps (cf. right panel in Figure A7.1).

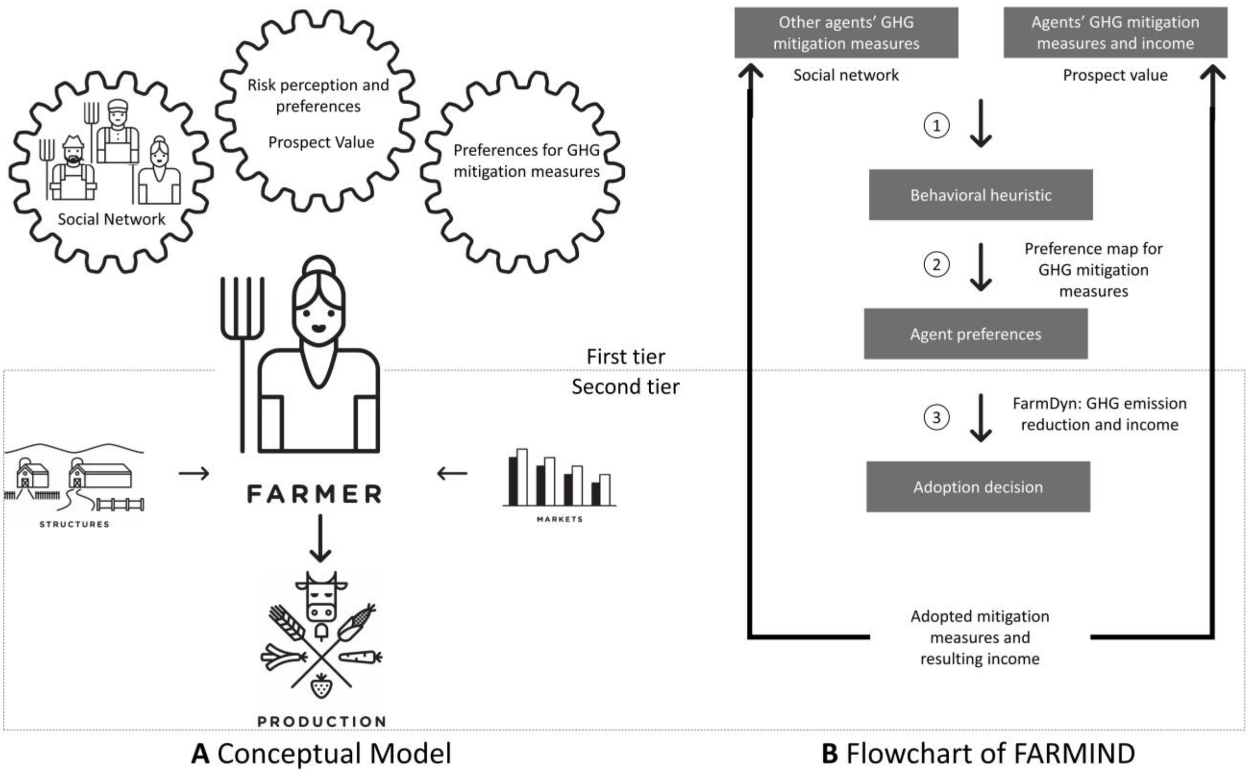


Figure A7.1: (a) Conceptual framework and (b) implementation flowchart of FARMIND

First, FARMIND calculates the income distribution over the farmers' memory length and the income in the initialization year. On this basis, the model calculates the prospect value of the agent's income considering the empirical based risk preferences (i.e., loss aversion, valuation of gains and losses and probability weighting). In addition, the model calculates the agents' dissimilarity to the other agents in the network with respect to climate change mitigation measures. Prospect value and dissimilarity are then used to calculate a strategy of each individual farmer. The strategy is calculated endogenously in the model for every agent and every year (i.e., behavioural strategies are not fixed).

Second, mitigation measures are ranked according to the personal preferences of the farmer R^A (identified in the survey). A fuzzy logic algorithm identifies a sub-set of strictly preferred activities in the different strategies. This implies that an agent that dislikes one of the mitigation measures may not receive the corresponding option in the choice set even though it could be optimal for maximizing farm income.

Third, based on the transferred choice sets, FARMIND chooses those mitigation activities that maximise farm income from the available options. The results of the adoption decision (income and mitigation measures) are then again transferred to the FARMIND strategic decision to update measures and income distribution of the agents in the next model run.

A7.2 Design Concepts

Theoretical and empirical background

We base our agent-based modelling framework on cumulative prospect theory and social network theory to link farmers' heterogeneous cognitive, social, and dispositional factors to cost and benefits of climate change mitigation measures. FARMIND is based on the so-called CONSUMAT framework, which integrates the different theoretical concepts into a structured sequence of modelling steps (Schaat et al., 2017). We here specifically use on aspect of the CONSUMAT framework: The strategic choice in our first-tier decision-making concept includes the heuristic strategy of "repetition" which implies that an agent chooses his/her production portfolio only based on the experiences in the past. We here relate this behavioural strategy with the concept of "reluctance to change" (e.g., Burton *et al.*, 2008; Dessart *et al.*, 2019). In addition, preferences for specific activities may also make farmers "reluctant to chance". For example, farmers might dislike a certain mitigation measure, which in this case would not be adopted even though it could be profitable.

The parametrization of the model is based on the following empirical data: i) Risk preference parameters (based on the cumulative prospect theory) derived from a lottery included in an online survey with farmers in the case study region (Kreft et al., 2020). The lottery was based on Tanaka et al. (2010) and thus included values for risk aversion, valuation of gains and losses as well probability weighting (equal for gains and losses) ; ii) Stated preferences for mitigation options derived from the same survey (Kreft et al., 2020); iii) Information on the social network collected via face-to-face interviews using the survey software Network Canvas (https://networkcanvas.com); iv) Cantonal census data to calculate farm individual provision cost and GHG mitigation.

Individual decision-making

Following the CONSUMAT approach, agents make decisions on their behavioural strategies according to their satisfaction and willingness to engage in social processing. In FARMIND, an agent's satisfaction level in a year is reflected by the prospect value of incomes V_i in year *t* and all previous years within the memory length (here five years). Incomes above (below) the agents' individual reference income are considered as gains (losses). Based on these gains or losses, the prospect value is calculated using individual value and probability weighting functions. If the prospect value is positive (negative), an agent is considered as satisfied (unsatisfied). Formally, assuming a set of past incomes of farm i in year t $\{x_1, \cdots, x_m\}$, a value function $v(x_t)$ and decision weight $\Phi(x_t)$, the prospect value is defined for each farm by

$$V_i = \sum_{t=1}^{m} v(x_t)\Phi(x_t) \quad \textit{Equation 13}$$

The value functions in the gain (+) and loss (-) domain, respectively, are:

$v^+(x) = {x_t}^{\alpha^+}$ for gains and $v^-(x) = \lambda\, {x_t}^{\alpha^-}$ for losses, *Equations 14a/7b*

where λ is a measure of the agent's individual loss aversion.

The calculation of decision weight $\Phi(x_t)$ is based on the distribution of incomes from past income values. Assuming historical incomes to follow normal distribution patterns over a given memory length m (i.e., five years in our application), we can identify the cumulative distribution function of income x_t, denoted by $F(x_t)$. We then calculate the decision weight of each income.

$$\Phi_{x_t}^{+/-} = w^{+/-}[1 - F(x_t)] - w^{+/-}[1 - F(x_t + \Delta)] \quad \textit{Equation 15}$$

where $w^{+/-}$ is the probability weight function in the gain and loss domain, respectively, and Δ is the difference between an income value and its adjacent value, e.g., 1 unit in the currency in which the income is expressed (here Swiss Francs CHF). The probability weight functions w^+ and w^- are defined as

$$w^{+/-}(p) = \frac{p^{\varphi^{+/-}}}{\left(p^{\varphi^{+/-}} + (1-p)^{\varphi^{+/-}}\right)^{1/\varphi^{+/-}}} \quad \textit{Equation 16}$$

The use of the prospect value for determining farmers' satisfaction has the following implications for the agent's decision-making in the context of climate change mitigation measures. For agents with a low reference income, the probability that a certain income is considered as a gain is higher compared to agents with high reference incomes. Thus, satisfaction (the sum of gains and losses over the memory length) is more likely to be positive for the former and the agent consequently is more likely to choose either repetition or imitation. In other words, agents with low reference incomes are more likely to be "reluctant to change" and thus not to adopt climate change mitigation measures. High risk aversion or loss aversion parameters affect the "contribution" of each income to the prospect value. For example, if one of the incomes is perceived as loss (event though the absolute income would be above the reference income), the calculation of the prospect value might switch from positive to negative, triggering an optimization or opt-out strategy.

To calculate whether a farmer will engage in social processing or not, we calculate a dissimilarity index to represent the agent's deviating behaviour from other farmers. We count the average number of mitigation measures in the agent's network over the memory length. We then divide the average number for each measure that is adopted by the agent and the network by all mitigation measures performed in the corresponding network. The higher the value, the more similar an agent is to their peers, i.e., the same GHG mitigation measures had been adopted. This index is compared to a tolerance level, representing the individual aptitude to consider deviating behaviour of other farmers. A low dissimilarity tolerance level d_i^{tol} implies that a farmer is more likely to comply with social norms, i.e., not wanting to be different from others. The implementation of the dissimilarity index implies that the agents' strategic choice is not only affected by the individual characteristics towards social and individual behaviour (i.e., the tolerance level) but also by the diffusion of other agents' adoption of climate change mitigation measures. For example, an agent with a high tolerance for social dissimilarity might still consider the strategy "imitation" once many of his/her peers have adopted climate change mitigation measures.

Formally, assuming that a activities are performed by all the peers in the social network, agent i's activity dissimilarity is

$$d_i = \frac{1}{a}\sum_{j=1}^{a} \frac{\#\ of\ peers\ performing\ A_j}{n}\left(1 - P\left(A_j^i\right)\right) \qquad \textit{Equation 17}$$

where $P\left(A_j^i\right)$ is agent i's performance status for activity j; $P\left(A_j^i\right) = 1$ if A_i is performed and otherwise $P\left(A_j^i\right) = 0$ while n is the number of peers to whom an agent is linked. The higher the value of d_i, the greater the similarity between an agent and their peers (measured on a relative scale with 1 implying all farms engage in the same activity). Please note that the agents' dissimilarity also depends on the size of the network n and the number of activities in the network a. The larger the network and the higher the number of activities within this network, the more likely it is that an agent will be dissimilar to their peers.

Based on the combination of the agents' satisfaction and dissimilarity, the strategic choice of the farmer is defined. If a farmer is satisfied and does not engage in social oriented behaviour, they will abide by a production decision (Repetition). A satisfied farmer who engages in information seeking behaviour will search for additional information and start considering the behaviour observed in the social network (Imitation). Those who focus on individual behaviour but are dissatisfied will strive to optimize their situation (Optimization). Finally, the combination of dissatisfaction and social oriented behaviour leads to an examination of the behaviour adopted by other agents in general but not specifically with respect to climate change mitigation measures (Opt-out). The underlying assumption is that agents' who are unsatisfied and dissimilar have the highest commitment to change their behaviour and would engage in searching for farming options beyond the four climate change mitigation options provided in our simulation.

Table A7.2 summarizes the four decision heuristics in FARMIND applied to the study of adopting climate change mitigation measures. It is important to note that the agents' strategic choice is model endogenous, i.e., it depends on price developments (simulated in the sub-model) and the adoption behaviour of the peers. For example, agents might first choose to repeat and only after their peers have adopted mitigation measures, they might consider the imitation strategy because of the emerging dissimilarity. This implies that all agents can endogenously switch back and forth between strategies.

Table A7.2: Strategic decision and choice sets in FARMIND

		Satisfaction Prospect value with reference income as threshold for the determination of gains and losses	
		> 0: *satisfied*	< 0: *dissatisfied*
Information seeking behaviour Values for determining individual or social processing (threshold for activity dissimilarity)	< tolerance level: *individual oriented*	**Repetition** The agent only considers those mitigation measures performed in the years before.	**Optimization** The agent considers all mitigation measures only restricted by personal preferences.
	> tolerance level: *social oriented*	**Imitation** The agent considers those mitigation measures that are applied in the social network and satisfy personal preferences.	**Opt-out** The agent selects none of the mitigation measures but searches for other production activities.

The choice of the decision strategy results in a choice-set of potential GHG mitigation measures. A repeating agent considers only those measures that had been applied in the last simulation runs. An agent that optimizes considers all available mitigation option. An imitating agent considers those mitigation measures that had been successfully applied by socially connected agents. Finally, an agent that strives for individual behaviour and who is unsatisfied will choose none of the mitigation measures in the corresponding simulation run.

In addition, FARMIND considers farmers' individual preferences for mitigation measures. Based on their stated intention to implement specific mitigation measures, we apply the fuzzy out-ranking method to narrow down the options available to those preferred by the farmer. The higher the preference, the more likely the corresponding activity appears on the top of the fuzzy ranking and thus in the agent's choice set in the second tier of decision-making.

The ranking of mitigation measures is based on the following algorithm: For each mitigation activity and agent, we calculate a value R. This value is used as criterion to determine the so-called fuzzy concordance relations for each pair of mitigation measures. There are three types of relations: 1) indifferent, 2) weakly preferred and 3) strictly preferred. If the difference between the normalized values of measure A_1 (e.g., increased number of lactations with a high value) and A_2 (e.g., replacement of concentrates in feeding ration with a low value) $R^{A_1} - R^{A_2}$ is smaller than an exogenously set lower threshold q^- these measures are regarded as indifferent, i.e., the agent has no preference between the two. If the difference is greater than the upper threshold q^+, A_1 (increased number of lactations) is strictly preferred over A_2 (replacement of concentrates). If the difference between the two activities falls within the interval of the lower and upper threshold [q^-, q^+], A_1 is weakly preferred over A_2. Formally, the matrix $f(A_1, A_2)$, describing the relation between the two activities A_1 and A_2, is defined by:

$$f(A_1, A_2) = \begin{cases} 0 & if\ R^{A_1} - R^{A_2} < q^- \\ \frac{(R^{A_1} - R^{A_2} - q^-)}{q^+ - q^-} & if\ q^- < R^{A_1} - R^{A_2} < q^+ \\ 1 & if\ R^{A_1} - R^{A_2} > q^+ \end{cases} \qquad \textit{Equation 18}$$

This calculation allows that all mitigation activities for each agent can be ranked in a list. FARMIND then uses a non-dominance score (*ND*) algorithm (Equation 7) that endogenously defines a small sub-set of mitigation activities. A characteristic of the non-dominance score is that it reduces the number of mitigation measures to a small sub-set that is strictly preferred to all the other measures.

$$ND(A_1, X, f) = 1 - \max_{A_2 \in X} max\{R(A_2, A_1) - R(A_1, A_2), 0\}, \qquad \textit{Equation 19}$$

where X is the set of all mitigation measures, A_1 denotes the measures of interest, A_j denotes other measures in X and $f(A_1, A_j)$ denotes the fuzzy pairwise preference matrix. The non-dominance score results in a reduced choice set for each agent, which is then passed to the second-tier decision-making step. The use of the non-dominance score has the following implications for the agents' decision-making with respect to the adoption of climate change mitigation measures in our model. An agent might dislike a certain measure for personal reasons but is open to all the other mitigation options. Consequently, the fuzzy ranking algorithm will put this specific measure at the end of the list and the dominance score will cut off the list before this final measure. This implies that the corresponding agent will not have this specific measure as a choice option in the optimization or imitation strategy, even though it would be potentially profitable (when optimizing) or had been adopted by peers (in the case of imitating).

The second tier of the agents' individual decision-making consists of the choice of mitigation strategies with the highest profit within the choice-set according to the decision strategy and preferences. The profit for each agent is calculated in the sub-model FarmDyn (see section Sub-model below). The sub-model provides a matrix with all profits, cost and potential GHG emission reduction for all mitigation measures as well as their interactions for each agent. FARMIND chooses the option with the highest profit in the available choice set of each agent.

Learning

Agents have a memory of the mitigation measures they have adopted. The length of memory is determined exogenously and is set to five years for each agent. The more experience an agent has with the corresponding mitigation measure, the higher its weight in the fuzzy preference ranking. More experience also increases the weight of the corresponding measure in the agent's social network. Thus, agents learn from their peers about mitigation behaviour performed over a longer time horizon. Thereby, the weight of experience, the learning rate, is represented as a logarithmic function that converges to one over the period of the memory length (i.e., five years). This mechanism of learning from peers increases the probability of adaption of a mitigation measure when more agents perform this measure over a longer time horizon.

Sensing

Agents can correctly observe the mitigation measures their peers perform and memorize the production activities in the past. They can also observe their own income and the average income of their peers. Agents memorize this information for periods of their memory length (i.e., five years). Assumptions about prices, yields or other information with respect to the adoption decision are condensed in the realised income (i.e., the results of the sub-model FarmDyn). In principle, agents do not have cost for gathering information. However, the learning rate slows the information exchange between agents in the social network and thus information from the peers is not directly and in every time step available for the individual agent.

Individual prediction

Agents change their decision strategy based on their individual prospect value. Using their realised income in the past and the individual value and probability weighting functions, agents "predict" the value of their realised income according to the cumulative prospect theory.

Interaction

Agents observe the behaviour of their peers in the case they choose to imitate. Thus, they exchange information on the performance of climate change mitigation measures.

Collectives

The social network allows to predefine a static collective that is more likely to observe and imitate mitigation behaviour from each other. The observed social network in our case study is derived from a bottom-up farmer initiative aiming at collectively reducing on-farm GHG emissions (Kreft et al., 2021b). There is, however, no dynamic mechanism from which collectives emerge or adapt.

Heterogeneity

Agents can differ with respect to all parameters presented in Table A7.1. This heterogeneity leads to different decision strategies for the individual agent, i.e., repetition, optimization, imitation, opt-out. Thus, agents are not fixed to a certain type of strategy but endogenously choose their strategy. Depending on the parametrization, agents can be fixed on a specific strategy, e.g., by setting high parameter values for reference income and dissimilarity tolerance, the agent will always choose "optimization" as strategy comparable to "econs" or "productivist" type of decision-making in ABMs using farmer typologies (Bartkowski *et al.*, 2022). In addition, the underlying sub-model FarmDyn also allows to differentiate the agents according to their production resources (labour, capital, land). This implies that each agent has the observed area, labour, and capital endowment at disposal (derived from farm specific census data).

Stochasticity

There are no randomized variables or parameters in the calculation of satisfaction, information seeking behaviour and the choice sets. This implies that for each simulation run, one and only one solution exists. However, the model runs over several years. Between each simulation run, price levels for milk and meat products are randomly selected from a uniform distribution of prices between +/-15% of current price levels. This results in a certain randomness of the farmers' strategic choices based on the realised output prices over the whole simulation length (here 12 runs). This also implies that the strategic choice is not always the same for each agent in every model run. Depending on the sequence of randomly selected prices, more or fewer agents might be satisfied or not with subsequent consequences also for social (dis-)similarity.

Observation

The model output of FARMIND are the type and amount of climate change mitigation measures and the corresponding reduction in GHG emissions as well as income changes depending on heterogeneous and individual farming decision strategies. The emergent phenomena are the impact of social networks on the distribution of GHG emissions across heterogeneous dairy and beef cattle farms in Switzerland and their total impact on climate change mitigation as well as farm incomes.

A7.3 Details

Implementation

The results presented in this contribution can be replicated from the following repository[26]. The replication package contains a "readme" file that gives detailed instructions how to replicate our simulations on any computer (only requiring R Studio and Java). FARMIND is written in Java. The model is available on Github: https://github.com/AECP-ETHZ/FARMIND. Code for the initialization and sensitivity analysis are written in R. The applied sub-model (FarmDyn) in this contribution is written in GAMS and Python and uses a CPLEX solver. A graphical user interface (GGIG) is available to steer the simulations and is written in Java and Python. The source code of the applied sub-model in this contribution can be made available upon request. The result files of the sub-model are exchanged between FARMIND and FarmDyn using csv files. Thus, a replication of the simulation results is possible without paying fees for GAMS and CPLEX.

[26] The replication package is part of the submission. It will be made public after the publication process in the ETH Research Collection (see also the FARMIND repository: https://www.research-collection.ethz.ch/handle/20.500.11850/456722)

Figure A7.2 gives an overview of the implementation steps in our modelling approach. First, we prepared the input data sets (for details see Kreft et al., 2021b; Kreft et al., 2020) for the specific requirements of the FARMIND modelling environment. We used three input data sets: 1) Information about social networks which were collected using the survey software "Network Canvas". 2) Farmers' cognitive, social, and dispositional factors derived from an online survey and a lottery in our case study region. 3) Census data by the Canton of Zürich on farm characteristics such as farm size, production activities and labour availability. To prepare the data matrix for the agents' income and GHG emissions for the four reduction measures, we used the single farm optimization tool FarmDyn (Britz et al., 2021). The resulting csv files were used in FARMIND as model input data.

We then run FARMIND in three steps: 1) We use the existing policy environment to calibrate the behavioural parameters "reference income" and "tolerance activity" to the observed adoption level of mitigation measures. 2) Based on different scenario set ups, the calibrated version of FARMIND is used to calculate the main results, i.e., the effect of different policy designs on GHG emissions reductions (CHF/CO_2eq), governmental spending and marginal abatement costs. 3) We use the set-up of the results-based payment for a sensitivity analysis quantifying the contribution of the behavioural model parameters on the model outcome (i.e., the level of GHG emissions). We here use the methods of standardized regression coefficient (SRC) and standardized rank regression coefficient (SRRC) as well as Sobols' method based on Latin Hypercube Sampling (LHS) to analyse the impact of the different parameters (Saltelli et al., 2008; Thiele et al., 2014). Finally, we analyse our simulation results and document our findings.

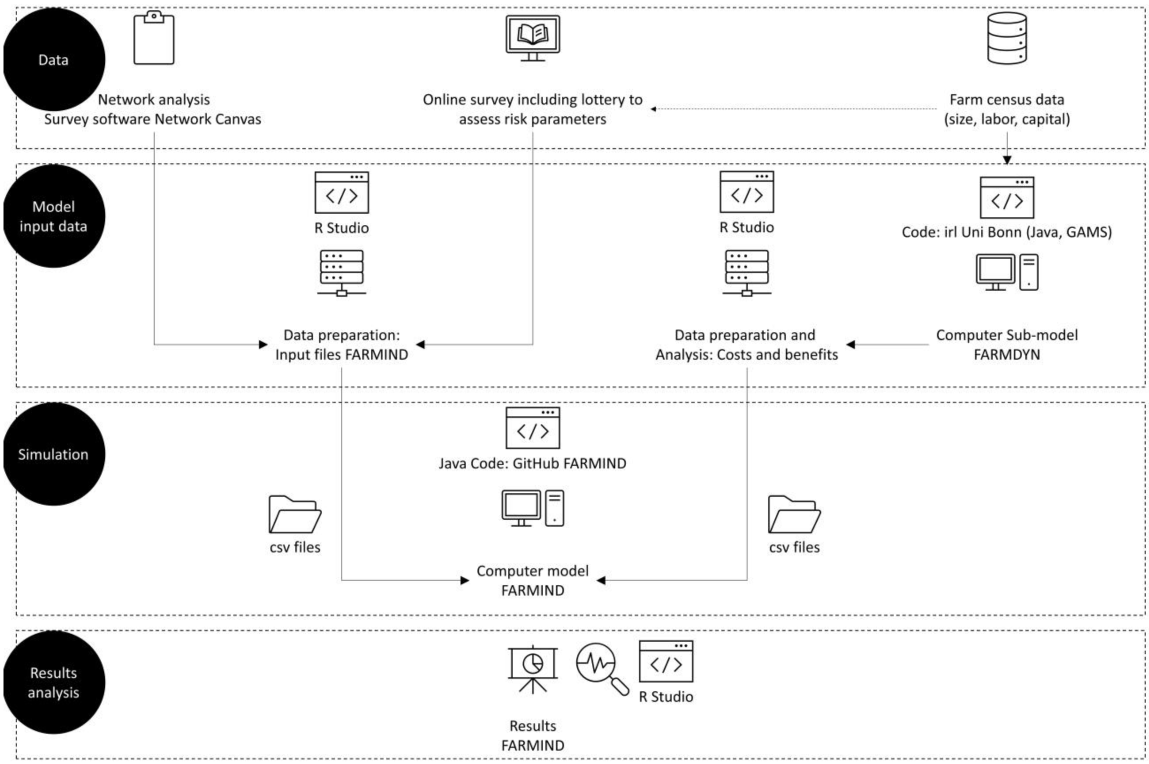


Figure A7.2: Overview of data flow and model interactions in FARMIND

In the following, we describe each of these steps in more detail. First, we provide description of the input data used in our modelling approach. Next, we present the initialization of the model and describe in detail the scenarios that we used in our main modelling exercise. Finally, we explain model selection (based on validating the model output against observed adoption patterns) and describe and present the results of our sensitivity analysis.

Input data

FARMIND uses six input data sets: 1) a social network including ties between agents; 2) a matrix of each agent's preferences for the relevant mitigation measures; 3) a table of the agent's individual characteristics; 4) a list of initial mitigation measures the agent performed; 5) a list of initial incomes over the memory length; and 6) a list of years (corresponding each to a run of FARMIND) and output price levels. This input data is derived from the farm survey, the social network analysis, and the calculations in the sub-model FarmDyn.

1) The input data for the social network was available for 21 farmers of the sample. We used an exponential random graph model (ERGM)[27] to extend the empirical information to our social network. More precisely, we first fit an ERGM of the observed network of 21 farmers accounting for two important network characteristics, namely density and centralization. In a second step, social ties are simulated for the total network of 49 farmers based on the ERGM of the observed network. In general, an ERGM computes the overall probability of a network based on network statistics and takes the following general form:

$$log\big(exp\big(\theta' g(y)\big)\big) = \theta_1 g_1(y) + \theta_2 g_2(y) + \cdots + \theta_p g_p(y),$$

where $g(y)$ is the set of network covariates (here, density and centralization), θ captures size and direction of the effects of the covariates and p is the number of terms in the model (Statnet Development Team, 2021).

2) The input data for the agents' preferences were derived from the following survey question in Kreft *et al.* (2021): "Which of the measures that you do not currently implement could you imagine to adopt in the future, which not?" The survey participants had to tick a box for all mitigation measures applied in the model. In the FARMIND input data, participants who answered that they could not imagine adopting a certain measure in the future received the value 1 for the corresponding measure and the value 5 otherwise. Given this parametrization, the non-dominance score will find that measures with a 5 are always preferred over those with the value of 1. This implies that farmers who said that they will not implement this measure in the future will not get his measure as an option in their choice set, independently from their strategic choice (i.e., repetition, optimization, imitation, opt-out).

[27] We here use the ergm-function of the R package statnet. For more details on the functioning of ERGMs, refer to: http://statnet.org/Workshops/ergm_tutorial.html#1_Statistical_network_modeling_with_ERGMs

3) The Tanaka lottery applied in Kreft *et al.* (2021) allowed us to directly use the individual values for the risk parameters in FARMIND. Thus, each agent received the parameter value for the decision weight, loss aversion and the probability weighting directly from the survey. Please note that the lottery yields the same values for decision weights and probability weighting in the gain and loss domain. For the reference income and the threshold values for determining individual or social processing, we had to transform the survey data information to be able to use it as input data set in FARMIND.

To do this, we did the following steps: First, we used individual information from each farmer with respect to the different questions. We asked farmers to rank six personal goals (e.g., high income, high yield, climate protection, environmental protection etc.) according to the importance they attributed to it (see Kreft *et al.*, 2020) We used individual farmers' ranking score of the "income goal" to identify a relative measure of their reference income that we could apply to the simulation results of FarmDyn. For example, farmers who ranked "high income" as most important goal, received in the input data a reference income set to a level for which incomes only little below the current income level were perceived as losses in the calculation of the prospect value.

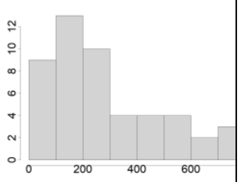
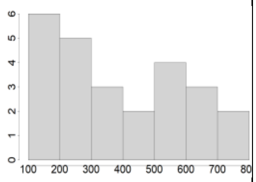
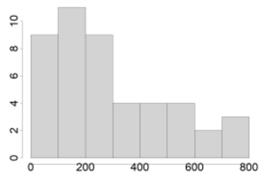
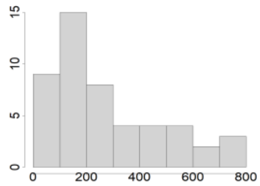
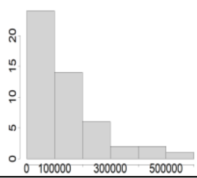
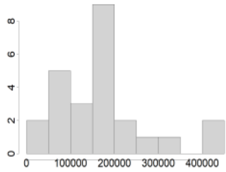
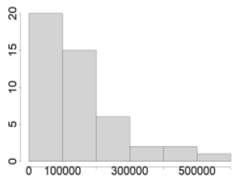
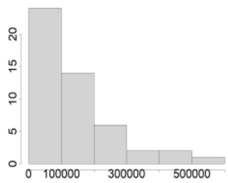
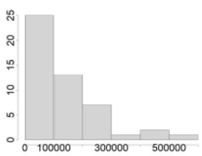
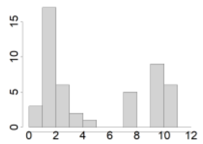
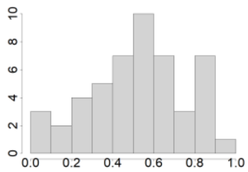
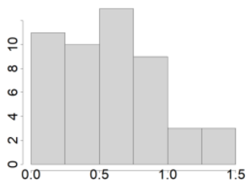
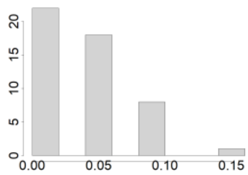
A similar approach was taken for the threshold value for determining individual or social processing (i.e., threshold for activity dissimilarity). We used the farmers' responses on the following survey question (based on a five-point Likert scale): "If other farmers in my environment implement climate change measures, I want to implement such measures on my farm as well." The response was used to derive a relative measure of their tolerance to activity dissimilarity between 0.01 (i.e., if a farmer has 10 ties, he will start check for climate change mitigation options once 1 out of these 10 peers has adopted a mitigation measure) and 0.15 (i.e., he/she will only start to imitate if 8 out of 10 peers adopted a measure, which means that large differences to peers still do not make the agent act socially oriented). Since these thresholds are key for the simulation outcome in FARMIND (see sensitivity analysis in Huber *et al.*, 2022), we calibrated the levels of these two parameters to the observed adoption levels in our case study region (see sub-chapter on model selection and validation).

4 / 5) The model is initialized with agents that have not adopted any mitigation measures (see next Section). Thus, the list of mitigation measures and the initial income for each agent (which are necessary to calculate the strategic choice in the first simulation run), are randomly drawn from the available baseline run in the FarmDyn model with variable output price levels).

6) FARMIND runs over several years, which is controlled by the input parameter "*year_run"*. This parameter can be set by the modeller, e.g., to create a certain price scenario. In this simulation, however, we assume that this parameter is fluctuating over years and thus create stochasticity in the simulation outcome. Thus, the input parameter is randomly selected from a uniform distribution of prices between +/-15% of current price levels.

Table A7.3 illustrates the distribution of the raw data that was used to prepare the input parameters for FARMIND. Details on data collection can be found in Kreft et al. (2020) for the survey data, including a description of the applied Tanaka lottery, as well as in Kreft et al. (2021b) for the social network data. A description of the sub-model FarmDyn can be found below.

Table A7.3: Distribution plots of input variables from FarmDyn calculations (profits and GHG reduction potential), survey (behavioural variables) and social network analysis

Farm				
Adopted mitigation measures A	Replacing concentrate feed with legumes	Increased no. of lactations	Drag hoses	Feed additives
y_{At}				
Range (t CO_2eq)	39 – 775	154 – 707	42 – 764	41 – 722
x_{At} (with payment of 120 CHF)				
Range (CHF)	5553 – 568 648	32927– 434 801	6046 – 588 958	5471 – 589 301
Personal characteristics				
Reference income to determine perceived gains and losses and calculate satisfaction V_i^{ref}	Loss aversion level λ	Valuation of gains and losses $\alpha^{+/-}$	Probability weighting in gains and losses $\phi^{+/-}$	Tolerance level for activity dissimilarity to determine information seeking behaviour d_i^{tol}
				
5761 – 529 142	0.96 – 10.41	0.05 – 0.95	0.05 – 1.5	0.01 – 0.15
Social network				
	Empirical social network	Random social network	Complete social network	
Number of peers a farmer is linked to (Mean (Sd))	13.4 (1.4)	1.3 (1.2)	48(0)	

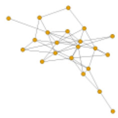
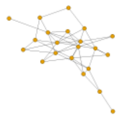
Initialization of simulation

We initialize the model with agents not implementing any of the mitigation measures. In this model set-up, the agents did not perform any of the mitigation measures in the past, i.e., the list of mitigation measures the agent performed in the past contains no mitigation measure. Therefore, the agents' realised income in the past, which is used to calculate the prospect value in the first model run, is only based on incomes without any measures adopted. In this case, the initial income is randomly drawn from the simulated FarmDyn data over the price range. We then simulate 12 years (runs) in FARMIND. In this period, agents endogenously choose a strategy and eventually adopt mitigation measures. The 12-year period serves as a timespan that allows FARMIND to achieve a saturation state at which the number of mitigation measures does not change anymore (even though strategies might still vary).

Scenarios

We run the model with two scenarios, namely with the action- and results-based policy design. Farm profits change depending on farm individual opportunity cost and the adoption of measures or the GHG reduction achieved, respectively. To create the counterfactual situation without considering behavioural aspects, the reference income of each agent is set such that all agents start to optimize independent of individual preferences or social influences. This is also done for both policy scenarios. We finally run the same simulations while excluding the measure of increasing the number of lactations per dairy cow (see Table A7.4). Overall, the specified scenarios allow to compare the two policy designs including/excluding the win-win measure to each other and to the counterfactual situation with income maximizing agents.

Table A7.4: Scenario definitions. Note: The payment level in the results-based payment scenario was increased until the reduction in GHG emission reached the same level as in the action-based payment scenario.

Scenario	**Action-based**	**Results-based**
Social network	Empirical Network	Empirical Network
		
Farm parameters	Calibrated from survey data	Calibrated from survey data
Initial activities & performing years	No adoption	No adoption
Payment	Legumes produced: 1000 CHF/per ha	0-400 CHF/CO_2eq
	Longer lactation: 80 CHF/cow	
	Use of drag hose: 60 CHF/ha	
	Feed additives: 250 CHF/cattle	
Counterfactual	Farmers are income maximizers (Optimization strategy)	Farmers are income maximizers (Optimization strategy)
Sub-scenario to test for impact of “win-win” measure	3 measures (without consideration “longer lactation”)	3 measures (without consideration “longer lactation”)

Model selection and validation

A key challenge in FARMIND is its parameterization given different potential pathways that result in the same level of adoption, i.e., model equifinality (Williams et al., 2020). This implies that multiple structures and/or parameterizations in FARMIND exist that generate outputs consistent with the observed adoption pattern in our case study region (e.g., Troost and Berger, 2015a). More specifically, while we were able to collect data on the underlying model parameters using census data, surveys and social network analysis, the strategic decisions, i.e., repetition, imitation, optimization and opt-out cannot be validated against observational data and different combinations of these strategies might result in the same model output. Consequently, the use of thresholds for determining the decision strategies in FARMIND implies that the calibration of these parameters has an important effect on simulation outcomes (see also Huber et al. 2021). The survey identified relative differences of the model parameters between agents. The absolute level of the reference income was determined by the income levels simulated in FarmDyn.

To address this challenge, we calibrated the threshold parameters in FARMIND based on a sensitivity analysis (please note that we also performed an extensive sensitivity analysis to assess the robustness of our results, see section below). Here, we parameterized the profit changes in FarmDyn using the current support for GHG emission reduction measures in Switzerland. Since there is currently no support for feed additives and only very few farms stated that they already experimented with additives, we did not consider this mitigation measure in the calibration of our agent-based approach. We ran FARMIND with increasing levels for both thresholds, i.e., reference income and dissimilarity tolerance, and compared the adoption pattern with the observed data. Given that we increased the thresholds for all agents simultaneously, the relation between the individual thresholds derived from the survey data was kept constant. To assess model performance, we calculated the standardized mean errors of the model:

$$ESAE = 1 - \frac{\sum_i \left| y_i^{obs} - y_i^{sim} \right|}{\sum_i y_i^{obs}},$$

with y_i^{obs} as the observed adoption of mitigation measures i. We calculated model performance by fixing one parameter and changing the second parameter starting with parameter levels that were insensitive to model output. We then changed the corresponding parameter levels which will first increase the goodness-of-fit. At a certain level, however, this goodness-of-fit (here measured by ESEA) starts to decrease. This allows to identify a “best” model that could explain the observed pattern with the simulated strategies in FARMIND.

The two threshold levels have the following impact on the adoption of climate change mitigation measures in our simulations. First, increasing the reference income implies that more agents become unsatisfied and thus increases the probability of them choosing the optimization or opt-out strategy. The increase in adoption through optimizing behaviour is represented in the left panel of Figure A7.3. In the simulations with increasing reference income levels (R1-R5), farmers do not have a social network and the adoption of mitigation measures is driven by optimizing behaviour only. The results show that with optimizing behaviour, the simulated adoption overshoots the observed level for drag hoses and lactations with higher threshold levels for being satisfied. This implies that we should observe more of these mitigation measures if farmers were pure profit maximisers. Second, adding the social network to simulations in which farmers have a high reference income, the agents are pushed to the opt-out strategy since they are not only unsatisfied but also very different to their peers. This suggests that lower levels of the reference income are more suitable to represent the observed adoption levels. Given these lower levels of the reference income (R2-R3), we then tested the agent’s sensitivity with respect to the tolerance level (how much they consider the behaviour of their peers, i.e., how much they are inclined to engage in social processing).

Hence, we manipulated the levels of the threshold “tolerance activity” (N1-N5). This allowed us to compare adoption behaviour based on different combinations of reference income and dissimilarity tolerance (see right panel of Figure A7.3). Overall, we find that models with social networks outperform models without interacting agents in terms of goodness-of-fit (we added R4 to the right panel of Figure A7.3 to illustrate the outputs when agents are income maximisers only). If social networks are included, high and low levels of sensitivity towards social behaviour decrease model performance. The combinations of both threshold values in the middle of the possible ranges provide similar goodness-of-fit (Table A7.5). This allows us to meaningfully choose a single best model for the analysis since our findings are robust within a certain range of threshold values and only extreme assumptions can be discarded.

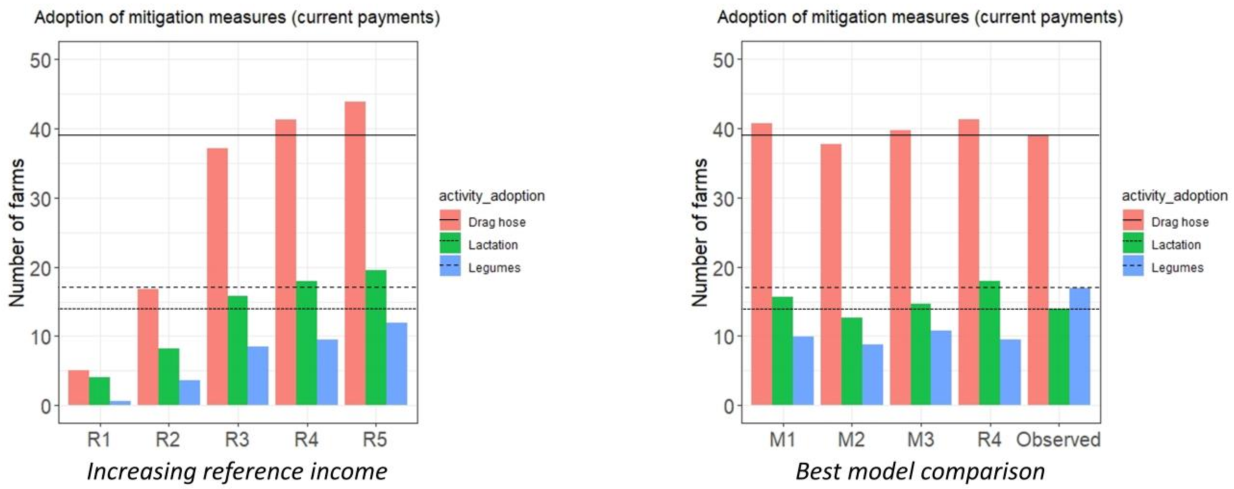


Figure A7.3: Visual comparison between simulated and observed adoption of climate change mitigation measures. The dashed lines refer to the corresponding observed level of adoption.

We are aware that other approaches exist such as pattern-oriented modelling (Grimm et al., 2005) or diverse model calibration (Williams et al., 2020) that relax some of the assumptions resulting from choosing a single best model. However, we here focused on model prediction, i.e., what if no social network existed (or it had different patterns). An equifinal model in our case would have to assume extreme values, i.e., all agents choose the same strategy (e.g., all were optimizers). Thus, our assumption is that farmers, in the context of adopting GHG mitigation measures, are not pure income optimizers. Indeed, the main purpose of our model is to include behavioural factors into simulating adoption decisions, and recent literature on farmers' behaviour suggests that optimization is only one of several types of decision-making strategies in agriculture (for a recent review see Bartkowski et al., 2022; Epanchin-Niell et al., 2022).

Table A7.5: Standardized mean absolute error from different model parameterizations

	Absolute error Legumes	Absolute error Lactation	Absolute error Drag hose	ESAE
R4 (no network)	5	-5.5	-4.8	0.78
R3 (no network)	7.5	-4	-2.2	0.80
R3 with N1	8.1	2	2.3	0.82
R3 with N3	9.4	1	1	0.84
M1: R3 with N4	8	1.2	1.3	0.85
R2 with N4	6.5	-1.3	-1.3	0.87
R3 with N5	7.9	0.4	0.7	0.87
M1: R2 with N2	6.1	-1	-1	0.88
M3: R2 with N3	6.3	-0.9	-0.9	0.88

Note: R1-R5 refer to increasing reference income levels. N1-N5 for decreasing sensitivity level for social oriented behaviour.

In addition, we also refrained from parameter screening and selection as described in Troost and Berger (2015a), i.e., a calibration of the important model parameters based on Latin Hypercube Sampling (LHS) over the whole parameter range. The reason is that we rely on individual data for each agent (based on the survey), and we do not have to make assumptions about the distribution of parameters in the initialization process of the model.

In summary, we can calibrate FARMIND to observed uptake of climate change mitigation measures in our case study region. Our simulation outcomes remain robust with respect to a meaningful variation in the threshold levels for determining the decision strategies in FARMIND. Thus, we are convinced that FARMIND is a valid approach to assess the effect of different policy designs on adoption of climate change mitigation measures in our study region and associated governmental spending. To test external validity of FARMIND, however, more data and more case studies would be needed to generalize the effect of social networks on the effectiveness and efficiency of policy incentives to reduce farm-level GHG emissions.

Output sensitivity analysis

The main model outcomes are based on an uncertainty analysis, i.e., we run FARMIND with different social networks, output price levels and various levels of subsidies for CO_2 (CHF/CO_2eq) to achieve a given reduction level in GHG emissions.

To assess the robustness of our findings, we also performed an output sensitivity analysis. We here used the methods of standardized regression coefficient (SRC) as well as Sobols' method to assess the effects of behavioural parameters and model structures on GHG emission levels. We follow the protocol by Thiele et al., 2014 and calculate the contribution of farmers' individual behavioural parameters as well as different model structures on the total amount of GHG emissions (see Table A7.6):

Table A7.6: Parameter range for Latin Hypercube Sampling (LHS) in global sensitivity analyses

State variable / parameters	Abbreviation	Lower range LHS (Min value)	Upper range LHS (Max value)
Loss aversion level *% change for each agent*	λ	0.5	1.5
Valuation of gains and losses *% change for each agent*	$\alpha^{+/-}$	0.5	1.5
Probability weighting in gains and losses *% change for each agent*	$\phi^{+/-}$	0.5	1.5
Reference income *% change for each agent*	V_i^{ref}	0.8	1.2
Tolerance level for activity dissimilarity *% change for each agent*	d_i^{tol}	0.5	1.5
Preferences *1 = cannot imagine adopting* *5 = can imagine adopting*	R^A	1	5
Output price level *1 = 0.60 CHF/kg (milk) 7 CHF/kg (meat)* *20 = 0.79 CHF/kg (milk) 9 CHF/kg (meat)*		1	20
Fuzzy size *Maximum number of mitigation measures considered in choice set*		1	5
Social network *Connection probability for random network*		1	49

For each of the parameters, we use a uniform distribution of values with the observed value (i.e., taken from the survey) as the mean between a max. and a min. value (Table A7.6). The mean values of behavioural factors are directly derived from the survey (and the corresponding lottery) or corresponds to the calibrated input values (in the case of the reference income and the tolerance for dissimilarity). Agent preference levels for different mitigation measures are set randomly in the sensitivity analysis. Price levels of beef and dairy products refer to the range of observed prices in Swiss agriculture. For the size of the choice set, the sensitivity analysis implies that either only the most preferred option appears in the choice set (if set to 1) or all options appear in the choice set (if set to 5). Thus, this factor tests for the effect of the fuzzy preference algorithm on the outcome. Finally, the overall impact of the network size is also tested by using a random network.

SRC Standardized regression coefficient

The standardized regression coefficient analysis includes two steps. First, a linear regression model is fitted to the simulation data generated from a Latin Hypercube Sample of the different parameters. The results from the standardized regression coefficient approach are here based on LHS with 1000 parameter sets (samples) and 100 repeated simulation samples.

Secondly, the regression coefficients are standardized. Thereby, the coefficients are multiplied with the ratio between standard deviations of the input parameter and the output value (Saltelli et al., 2004). Thus, the regression analysis shows the effect of an input on the output variables both normalized with a mean of zero and standard deviation of one. This allows to better interpret and communicate the absolute relationship between the inputs and output of FARMIND.

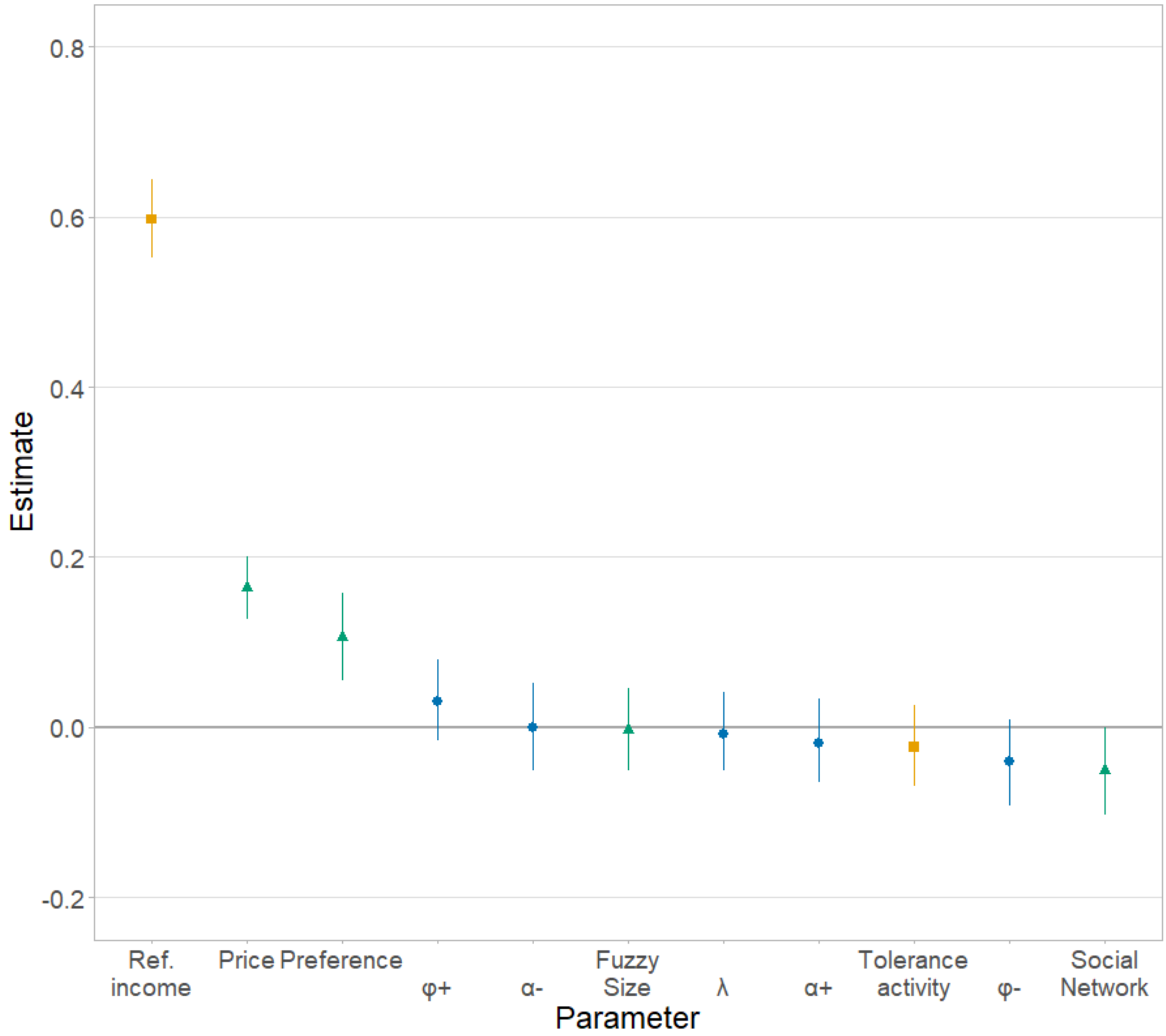


Figure A7.4: SRC for FARMIND in the context of adopting GHG mitigation measures in Swiss agriculture. Mark show mean SRC value. Sticks show maximum and minimal values of bootstrapped 95% confidence intervals of corresponding sensitivity indices. Parameter groups are represented in different colors. Yellow: threshold values that determine the choice between strategies i.e., reference income V_i^{ref} and dissimilarity tolerance d_i^{tol}a. Blue: Parameters used to calculate the cumulative prospect value for each agent. Green: Structural parameters including fuzzy size, price levels, preferences, and social networks.

Our sensitivity analysis provides four implications (cf. Figure A7.4): First, the reference income, i.e., the threshold parameter determining the choice between optimization and opt-out vs. imitation and repetition has the largest impact on the total amount of GHG emissions. An increase of the reference income by one standard unit increases the greenhouse gas emissions by approximately 0.6 standard deviation of all greenhouse gas emissions. The higher the reference income, the more likely agents are choosing the repetition or imitation strategy. Thus, theoretically, the sign of the threshold parameter could go in both directions since the imitation strategy would allow the agents to adopt mitigation measures whereas the repetition strategy would not. The results show that the effect of the repetition strategy, i.e., the agents' reluctance to change is more important for the overall level of GHG emissions.

Secondly, an increase of the behavioural factors describing cumulative prospect theory (α+, α-, ϕ+, ϕ-, and λ) have a much smaller impact on greenhouse gas emissions compared to the reference income. The main effect of an increase of these parameter values by one standard unit is, on average, close to zero. The maximum and minimum values of these estimates are between 5 and 8% (of the standard deviation). The parameter determining the curvature of the value function in the gain (α+) and loss (α-) domain, respectively (i.e., the decision weights), are identical for each agent given our Tanaka design of the lottery. Higher values for α+ imply that the value function reduces the depreciation of high incomes in the gain domain. Ceteris paribus, this increases the probability that agents are satisfied (since there is lower devaluation). Consequently, the probability of imitation increases and the total amount of GHG emissions decreases with higher values for α+. We can observe the opposite effect for α-, which devalues low incomes in the loss domain. Higher values for dissimilarity tolerance imply that agents, ceteris paribus, get less inclined to social oriented behaviour (i.e., imitation and opt-out). As in the case of the reference income, the sign of the dissimilarity tolerance parameter depends on which of the two remaining strategies (i.e., optimization and repetition) dominates. In our simulation, higher dissimilarity tolerance increases the weight of the optimization strategy and therefore the total amount of GHG emissions decreases on average.

Thirdly, the effect of structural variables such as the social network, the preference setting for mitigation measures or the price level for milk and meat have a larger effect on the total amount of GHG emissions compared to the cumulative prospect parameters, but a lower effect compared to the reference income. The higher the price levels, the higher the probability that agents are already satisfied without adopting mitigation measures and thus, ceteris paribus, the overall GHG emissions are higher. This suggests that exogenous assumptions on the price levels in FARMIND have an important effect on the adoption decision, but this is, compared to the threshold level, less important on the total level of GHG emissions. This is also an important consequence from using FarmDyn as a sub-model (see next Section for details). In FarmDyn, prices affect the income level relatively more than the amount of GHG emissions, i.e., the reduction potential of the different measures remains similar under different price scenarios.

Fourthly, we observe that the sign of behavioural factors is ambiguous. This has two underlying mechanisms. First, for probability weighting parameters ϕ+ (ϕ-), the effect can theoretically be positive or negative because it depends on the underlying income distribution (Huber *et al.*, 2020). Secondly, the behavioural parameters can decrease greenhouse gas emissions if they stimulate optimization or imitation and increase greenhouse gas emissions if they support repetition and opt-out (i.e., non-adoption of climate change mitigation measures). However, an increase in the parameter values of decision weights, for example, can increase both, the probability of optimization but also opt-out. Thus, the effect depends on the shares of agents that choose a certain strategy, which is in turn depends on the other parameter levels. To get more insights into this potential non-linear behaviour of the model, we also used Sobols' method to assess the sensitivity of FARMIND.

Sobol' method

To investigate non-linear relationships between the input parameters and outputs, we apply Sobol' method, a variance decomposition approach (Saltelli and Annoni, 2010). The underlying idea is to vary the input parameters and then to identify the effect of the individual parameter on output variance. In Sobol' method, the total variance is composed of the so called main and interaction effect, which is determined by evaluating the partial effects using Monte-Carlo methods (Thiele *et al.*, 2014).

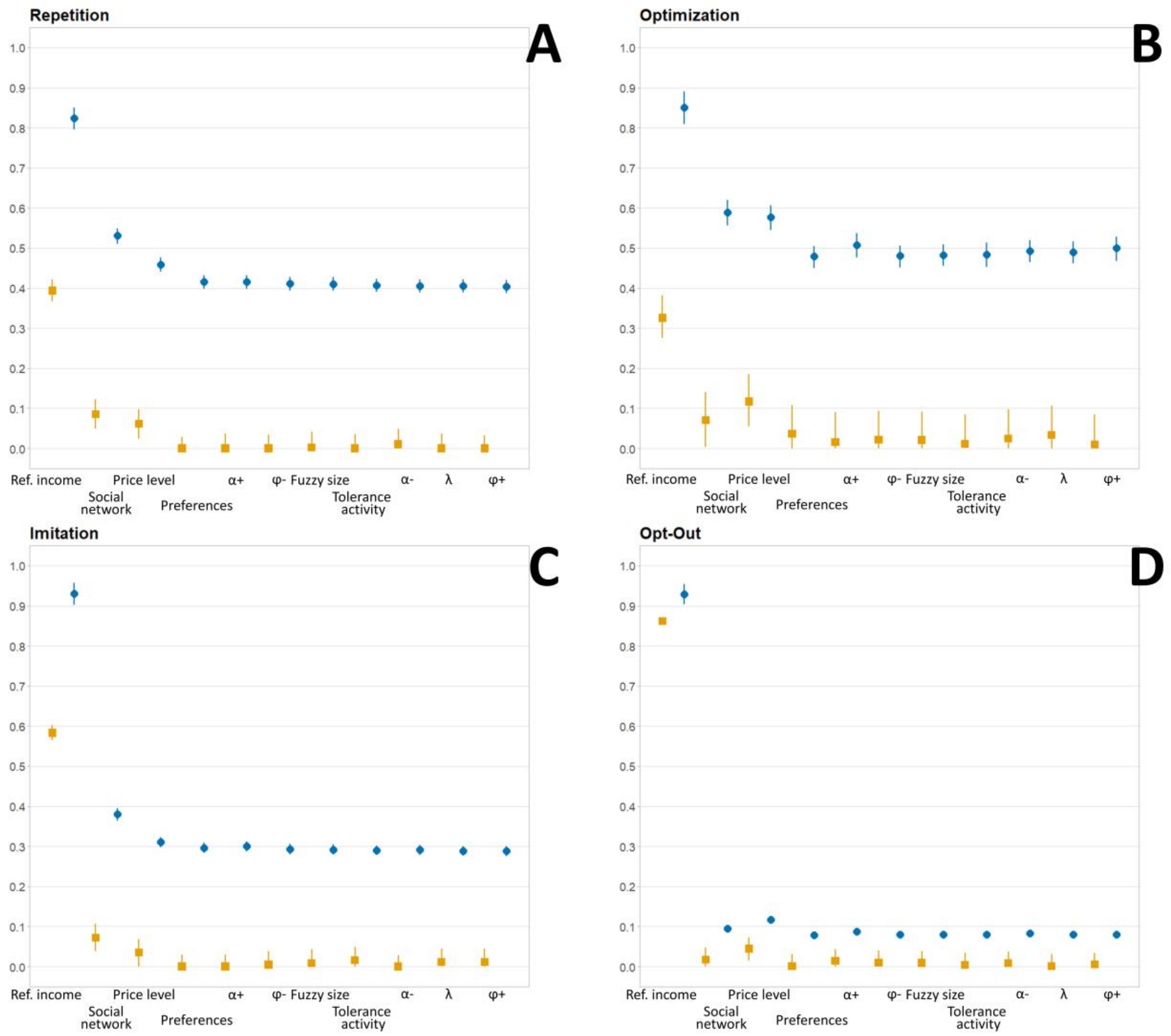


Figure A7.5: Results from Sobol-Sensitivity analysis for the four strategies. Dots represent the main effect of the parameter on the variability of the model outcome. Circles refer to the total effect, including interaction effects of the corresponding parameter on the strategy choice. Sticks show bootstrapped 95% confidence intervals of corresponding sensitivity indices.

As in the case of the regression analysis, we use a Latin Hypercube Sampling to generate the range of input parameters in the sensitivity analysis. We applied the soboljansen function to identify the expected non-linear effect of the model parameters (with 8000 bootstrap replicates).

The results from Sobol' method shows the importance of interaction effects in FARMIND (Figure A7.5). The main factors that drive the agents' behaviour in our model are the reference income and the social network. These two parameters drive the model especially for the repetition and imitation strategies. For the optimization strategy, the output price level is more important than the social network. For these three strategies, behavioural factors become much more important when looking at the interactions (i.e., the total effect of the parameter). This exemplifies that the main influence of the underlying behavioural factors such as risk preferences or dissimilarity tolerance is indirect (i.e., via the calculation of the prospect value and the social oriented behaviour).

In summary, the output sensitivity analysis shows that thresholds for determining the decision strategies in FARMIND are the key drivers in the simulation outcome. However, behavioural factors such as risk parameters or loss aversion are also sensitive with respect to the strategic decision and thus affect the amount of reduced GHG emissions. Given that our results are robust with respect to the choice of threshold levels in our data (see section above), the sensitivity analysis shows that the implications of our modelling results also remain with variation of the other factors within a large parameter space.

Sub-model FarmDyn

FARMIND requires a sub-model which is able to optimize a farm for two primary causes. On the one hand, for the case in which a farmer decides for the strategic decision of optimization and on the other hand to determine the satisfaction level of a farmer. For this purpose, we use the bio-economic single farm optimization model FarmDyn (Britz et al. 2021), which is realised as a mixed-integer linear programming model in the programming language GAMS (General Algebraic Modelling System). FarmDyn assumes a fully informed and rational decision maker maximizing profits given a rich set of constraints. The model contains detailed information on bio-physical (e.g., nitrogen flows, GHG emissions) and economic (e.g., cash flow, investments) processes linked to farming activities. Data on the bio-physical and economic processes are taken from planning data, official statistics, and expert knowledge.

In this study, all relevant economic parameters of dairy, suckler and bull-fattening farms are parameterized for Switzerland. This includes the in- and output prices, investment cost for machinery and stables, crop yields as well as feeding factors and output for animals. Additionally, FarmDyn was adapted to the complex cross compliance and premium system of the Swiss agricultural sector. For cross compliance this entails mandatory crop rotations and set aside levels, whereas the premium system provides payments for the general production of food (ensuring food supply, payments for arable land) or for the use of specific feeding patterns such as grass-based milk and meat production.

We implemented four different mitigation measures with each one being able to be switched on and off, separately. Each mitigation measure has a distinct impact on the optimal farm management with links to related (opportunity) cost and a certain mechanism of GHG mitigation (see Table A7.7). The option to independently make each measure mandatory allows to construct scenarios with different combinations of mitigation measures for each single farm.

Table A7.7: Mitigation measures in FarmDyn

Measure	Short description of impact on the farm management decisions	Im- and explicit cost	Mechanism of GHG mitigation
No external concentrates	This measure prohibits the farmer in FarmDyn to purchase any non-roughage products on the market including e.g., concentrates, grain products, legumes.	The farmer reduces his purchasing cost for concentrate, at the same time the cost of fodder production on-farm increases. Further, area devoted to cash crops has to be replaced by fodder production.	Up-stream CO_2-eq. emissions associated with purchased non-roughage products are reduced to zero, whereas emissions on-farm can increase when arable land is diverted from cash crop production to fodder production.
Increased number of lactation periods	Lactations are exogenously extended to at least 5 (from 4) lactation periods per dairy or mother cow for farmers	There are no relevant im- or explicit cost.	The increased number of lactation periods leads to less required replacements in the cow herd, which means fewer heifers and calves on-farm and thus less CO_2-eq. emissions from the herd.
Alternative fertilizer application	Mandatory use of drag hose or trailing shoe for organic fertilizer/manure are linked to new investment in machinery	The farmer faces investment cost for the new machinery.	Application of organic fertilizer close to or directly injected into the soil reduces nitrous oxide and indirect nitrous oxide from other nitrogen compounds.
Feed additive	This measure prescribes farmers in Farmdyn to apply feed additives for ruminants which intervene in the digestive system. These feed additives are linked to purchasing cost and	For each unit of feed additives used for cows, the farmer must purchase the feed additive on the market.	The use of feed additives aims to reduce the methane emissions from the ruminant

FarmDyn runs a simulation for each farm in each scenario. Every farm is calibrated based on its given farm land (arable- and grassland), available working units, available crops, and animal numbers. For each simulation, FarmDyn returns results of farm profits and GHG emissions based on their source (crops, herds etc.).

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Appendix Chapter 1: Data on farmers' adoption of climate change mitigation measures, individual characteristics, risk attitudes and social influences in a region of Switzerland[28]

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Abstract

We present survey data on the adoption of agricultural climate change mitigation measures collected among 105 farmers in a region in Switzerland in 2019. We surveyed measures farmers use to reduce greenhouse gas emissions on the farm level. The list comprised 13 measures related to energy production and use, herd and manure management as well as crop production. Additionally, data was collected with regard to farmers' individual concerns and perceptions of climate change, attitudes and goals, self-efficacy and locus of control, income satisfaction and social influences. Moreover, risk preferences as well as loss aversion and probability weighting were elicited using a multiple price list. The survey data was matched with cantonal farm census data, containing information on farm size, farm type and age of the farmers.

Keywords

Agricultural climate change mitigation, farmers' climate change attitudes and perceptions, risk attitudes, non-cognitive skills, social networks, Switzerland

[28] This chapter is published as: Kreft, C. S., Huber, R., Wüpper, D. J., and Finger, R. (2020). Data on farmers' adoption of climate change mitigation measures, individual characteristics, risk attitudes and social influences in a region of Switzerland. *Data in brief* **30**, 105410.

Specifications Table

Subject	Agricultural economics
Specific subject area	Adoption of agricultural climate change mitigation measures, non-cognitive skills, social influences, risk preferences
Type of data	CSV file
How data were acquired	Online survey combined with farm census data Limesurvey R
Data format	Raw and partly filtered (for reasons of confidentiality)
Parameters for data collection	The survey targeted farmers of all production types in a specific region of Canton Zurich, Switzerland
Description of data collection	The online questionnaire was distributed via Limesurvey to 389 farmers registered in the region of Zürcher Weinland, Canton Zurich, Switzerland. Risk preferences, loss aversion and probability weighting were elicited using a multiple price list. Participation was incentivized. In total, 105 respondents completed the survey. The data was anonymized.
Data source location	Zürcher Weinland, Canton Zurich, Switzerland
Data accessibility	Data is accessible via ETH Zürich Research Collection: http://hdl.handle.net/20.500.11850/383116

Value of the Data

- The data highlights which measures are taken by farmers to reduce greenhouse gas emissions and elicits climate change related perceptions, attitudes, self-efficacy, locus of control, social influences as well as risk preferences. Risk preferences, loss aversion and probability weighting were elicited by a multiple price list.
- The data enables to understand the adoption of climate change mitigation measures in agriculture and associate it to farmers' individual characteristics as well as farm structural characteristics.
- The data can be used to analyse drivers of agricultural mitigation measures including a wide range of behavioural factors and farm characteristics. This allows for a broad range of control variables.
- The data allows to interlink different individual factors, e.g., non-cognitive skills and risk preferences or climate change perceptions and concerns.

6.1 Data Description

We collected survey data on climate change mitigation measures adopted by farmers and combined them with cantonal farm census data. Mitigation measures in the survey were selected based on relevant literature and suitability for Swiss agriculture [1, 2]. The here presented data is based on a combination of census and survey data, which were matched by farmers' email addresses[29]. It contains information on the adoption of greenhouse gas reduction measures, on farm structure and production as well as individual farmers' characteristics. For reasons of confidentiality, any personally identifiable information (i.e., all qualitative data, names and contact details of respondents, names of other persons as well as personal feedback) was removed from the dataset. Risk preferences, loss aversion and probability weighting were elicited using a multiple price list following the approach of Tanaka et al. [3]. The original questionnaire[30], the dataset and the codebook describing the variables are available on the ETH Zürich Research Collection: http://hdl.handle.net/20.500.11850/383116

6.2 Experimental Design, Materials, and Methods

The online survey (in German) was distributed in March 2019 via a link sent by email to all 389 farmers in the region of Zürcher Weinland, Canton Zurich, Switzerland, that were registered with cantonal authorities. The region includes 24 municipalities and is part of the political district of Andelfingen.

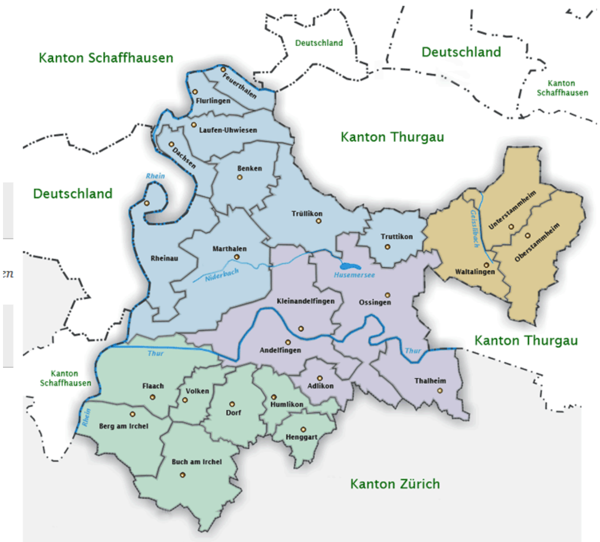


Figure 6.1: Map of the region of Zürcher Weinland including 24 municipalities (https://www.feuerthalen.ch/tourismus/umgebung/zuercher-weinland.html/323)

The email was accompanied by a supporting letter of the Cantonal Farmers Union. We used the online platform Limesurvey[31] to design the survey and collect the data. The questionnaire was tested and

[29] For three of the farmers who completed the survey, there were no entries in the farm census data for the period of question (e.g. because they did not apply for direct payments in the respective period).
[30] Please also find the full survey questionnaire in the supplementary material to this Appendix Chapter.
[31] www.limesurvey.org

improved in two rounds of pre-tests. First, we tested general wording, understanding and user-friendliness with six students of agricultural sciences. In a next step, we obtained content-related feedback from ten farmers at the farming school of the Canton of Zurich. The survey was online for eight weeks. Two reminders were sent to farmers who had not filled out the questionnaire after two and four weeks. As an incentive to participate, we provided summary information on the first survey results. Moreover, farmers were given CHF 10 for answering all questions. Additionally, farmers had the chance to win up to CHF 190 based on real payouts from the lottery (multiple price list).

The questionnaire contained 26 questions and on average, farmers needed 40 minutes to complete the survey. The survey was structured in following sections:

(i) Expected consequences and perceptions of climate change
(ii) Perceived self-efficacy and locus of control (non-cognitive skills)
(iii) Current implementation and expected effectiveness of mitigation measures
(iv) Education, personal preferences, goals and innovativeness
(v) Income satisfaction
(vi) Personal social networks and social comparison
(vii) Risk preferences, loss aversion and probability weighting (multiple price list)

6.2.1 Expected consequences and perceptions of climate change

Farmers were asked if they expected negative or positive consequences of climate change with regard to the overall agricultural sector in Switzerland and the economic future of their own farm. Moreover, farmers were asked to indicate whether over the past 10 years they had experienced decreases or increases in occurrence of hail, permanent droughts, frost in autumn and spring, heavy precipitation, long rainy periods and heat waves. Here, we are primarily interested in climatic changes perceived by the farmers as we assume perception of climate change to be an important factor in decision-making regarding mitigation efforts. However, as the data relate to one specific region, real climate data could be easily matched to the survey data.

6.2.2 Perceived self-efficacy and locus of control (non-cognitive skills)

We included a question containing five items on self-efficacy (3 items) and locus of control (2 items) based on [4] and [5]. All items were related to the domain of agricultural climate change mitigation.

6.2.3 Current implementation and expected effectiveness of mitigation measures

Farmers were asked to indicate which measures they undertook to reduce GHG emissions on the farm. In total, 13 measures could be selected and respondents had the option to add additional measures they adopted[32]. For reasons of identifiability, we did not include these additional measures in the raw data. Measures were carefully chosen regarding effectiveness, relevance and suitability for Swiss agriculture based on [1, 2]. The following measures were included:

- Energy production and use
    - Solar panels
    - Biogas plant
    - Ecodrive mode for tractor
- Livestock and manure management
    - Replacement of (imported) concentrate feed by domestic legumes
    - Reduction of concentrate feed to max. 10 percent of the ration
    - At least 5 lactation periods per dairy cow
    - Double purpose cattle breed
    - Feed of additives to reduce methane emissions from enteric fermentation
    - Coverage of manure storage
    - Composting of manure
- Crop production
    - Emissions reducing fertilizer application technique (e.g., drag hoses)
    - Cover and catch crops in rotation
    - Tillage without plough

For farms where a certain measure was not eligible (e.g., livestock measures for pure crop farms), respondents could chose the option “not relevant for my farm type”. Farmers were furthermore asked to indicate how effective for climate change mitigation they rated each measure (regardless of whether they adopted the measure or not). We also included a question on the potential adoption of each non-adopted measure where farmers had to indicate whether they could imagine to adopt the measure in the future or not.

6.2.4 Education, personal preferences, goals and innovativeness

After a question about level of education, respondents were asked to indicate which agricultural activities they could generally imagine for their farms, namely dairy cows, cattle fattening, pig fattening, poultry, crop farming, specialized culture or options outside the agricultural sector. Each activity had to be rated. We also included a question on personal values, where farmers were asked to rate six different goals concerning agricultural production, namely protection of natural resources, reduction of GHG emissions, preservation of animal and plant biodiversity, high yields, generation of high agricultural income and acknowledgement from other farmers. This was followed by a question on the level of attainment of the six goals. To collect data on farmers’ innovativeness, a question containing five items was included regarding the pioneer character of respondents.

[32] Other measures mentioned by farmers were for example use of vegetable carbon, dilution of cattle slurry, younger age of cow at first calving, reduction of pesticides, fungus-resistant varieties, regular maintenance of machines etc.

6.2.5 Income satisfaction

This section of the questionnaire contained two questions referring to the satisfaction with the agricultural income (including direct payments) and two questions referring to satisfaction with the total household income (including employment outside the agricultural sector). We asked farmers to indicate at which yearly income level (on a scale from CHF 160 000 to CHF 40 000) they would not be satisfied anymore (note that the average total income of Swiss farms is CHF 97 000, consisting of CHF 65 000 farm income and CHF 32 000 off-farm income, see e.g., www.agrarbericht.ch). We also queried the share (in percentage) of agricultural in total household income.

6.2.6 Personal social networks and social comparison

We included a question regarding the subjective importance respondents placed on the opinion of others about their own farm and farming abilities. Another question in this section concerned the importance of social comparison expressed by needs of superiority or conformity with regard to agricultural income and climate change mitigation.

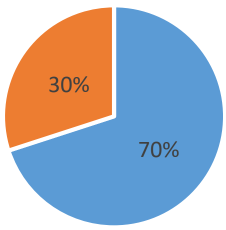
Respondents were furthermore asked to list the names (acronyms and nicknames were allowed as well) of up to ten persons in their direct social network with whom they regularly exchanged about general agricultural matters and agricultural climate change mitigation. To specify the type of relation, we further queried how the respondent was connected to each person listed, namely neighbour, colleague, friend, family member, partner, club colleague, veterinary, extension service or other. In the latter case (other), respondents were asked to specify the type of connection. Lastly, we included a question on how important the opinions, attitudes and activities of each person listed were for decision-making on the farm.

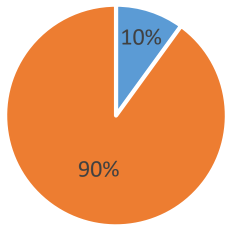
6.2.7 Risk preferences, loss aversion and probability weighting (multiple price list)

To elicit risk preferences, loss aversion and probability weighting, we added three multiple price lists (lottery tasks) proposed by [3] (see also [6] for an overview). The wording and level of payouts were adapted to the farming context and climate change mitigation. More precisely, farmers' were presented the following introductory text:

"In order to implement climate change mitigation on your farm, you can decide between investing in either measure A or measure B. Both investments offer a certain return, e.g., due to higher efficiency and cost reduction. Both investments have the same price and the respective return will be paid out at the same time. In three out of ten cases (30%), investment A offers a return of CHF 40 000 and in 7 out of ten cases (70%), investment A offers a return of CHF 10 000. Investment B offers a return of CHF 68 000 in one of ten cases (10%) and in nine of ten cases (90%) a return of only 5000 CHF is offered.

The return of investment B with the lower probability (10%) is increased in the following tables. At which level of return would you be willing to take the higher risk and invest in B instead of the more stable alternative A. Note that there are no right or wrong answers – decide only according to your personal preferences.”





	Investment A		Investment B	
	30%	70%	10%	90%
1 ☐	40.000 CHF	10.000 CHF	68.000 CHF	5000 CHF
2 ☐	40.000 CHF	10.000 CHF	75.000 CHF	5000 CHF
3 ☐	40.000 CHF	10.000 CHF	83.000 CHF	5000 CHF
4 ☐	40.000 CHF	10.000 CHF	93.000 CHF	5000 CHF
5 ☐	40.000 CHF	10.000 CHF	106.000 CHF	5000 CHF
6 ☐	40.000 CHF	10.000 CHF	125.000 CHF	5000 CHF
7 ☐	40.000 CHF	10.000 CHF	150.000 CHF	5000 CHF
8 ☐	40.000 CHF	10.000 CHF	185.000 CHF	5000 CHF
9 ☐	40.000 CHF	10.000 CHF	220.000 CHF	5000 CHF
10 ☐	40.000 CHF	10.000 CHF	300.000 CHF	5000 CHF
11 ☐	40.000 CHF	10.000 CHF	400.000 CHF	5000 CHF
12 ☐	40.000 CHF	10.000 CHF	600.000 CHF	5000 CHF
13 ☐	40.000 CHF	10.000 CHF	1.000.000 CHF	5000 CHF
14 ☐	40.000 CHF	10.000 CHF	1.700.000 CHF	5000 CHF
Never ☐				

Figure 6.2: Example of multiple price list

For ease of understanding, farmers were additionally presented a short explanatory video clip (the clip is available on the ETH research collection: http://hdl.handle.net/20.500.11850/383116).

Concerning the real payout modalities, we followed [7] and [8]. They were instructed that real payouts were based on their decisions. For every lottery, one row was randomly chosen using a macro-enabled Excel spreadsheet. Based on the decision in this randomly chosen row (investment A or B), the lottery was drawn. The final amount of all three tasks was summed up and divided by 10 000. As the third lottery could also entail a loss of up to CHF 5, participants were provided a secure endowment of CHF 5 beforehand such that they could not lose any money for real.

Participants could chose whether they wanted to receive the real gains from the lottery and give contact and bank details. All participants who chose this option were later informed about their gains via email. The theoretical minimum was CHF 3.9 (including CHF 5 security endowment from the third lottery) and the maximum win was CHF 190 (including CHF 5 security endowment). The expected return of each participant was approximately CHF 11.

6.3 Acknowledgments

We greatly appreciate the support and input from Ladina Knapp as well as various consulted experts for the design and technical implementation of the survey. We particularly thank the farmers who participated in the survey. Financial support for the project AgroCO2ncept provided by the Federal Office of Agriculture is acknowledged.

6.4 Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary material

Survey on agricultural climate change mitigation in the region of Zürcher Weinland 2019

Introduction

Dear farmers,

Against the background of global warming, we are dealing with the options of climate protection in Swiss agriculture. In particular, we are interested in better understanding farmers' decision-making with regard to practical climate change mitigation. Your assessments and personal network information, preferences and risk attitudes are central to this. Since it is about your very personal assessments, there are no wrong answers.

Completing the questionnaire takes about 30 minutes. As a reward for answering all questions, you will receive CHF 10 at the end of the survey. You can also win up to CHF 190 in the last part. If you are interested, we will gladly send you a summary of the survey results.

Your data and information will of course be kept strictly confidential and will be used anonymously for scientific purposes only.

We thank you very much for your participation!

Assessments of climate change

These questions deal with the consequences of climate change for Swiss agriculture and your farm. There are no right or wrong answers. It's all about your own personal assessments.

Q1. Do you think that climate change will have consequences for agriculture in Switzerland?

Please select the appropriate answer for each item:

Very negative consequences 1	2	No consequences 3	4	Very positive consequences 5
☐	☐	☐	☐	☐

Q2. How did you perceive the frequency of extreme weather events over the past 10 years on your farm?

	Strong increase 1	2	No change 3	4	Strong decrease 5
Hail events	☐	☐	☐	☐	☐
Continuous dry phases	☐	☐	☐	☐	☐
Frost in autumn and spring	☐	☐	☐	☐	☐
Heavy rain	☐	☐	☐	☐	☐
Long rainy periods	☐	☐	☐	☐	☐
High temperatures and heat waves	☐	☐	☐	☐	☐

Q3. How do you assess the consequences of climate change for the economic development of your farm?

Very negative consequences 1	2	No consequences 3	4	Very positive consequences 5
☐	☐	☐	☐	☐

Q4. How would you rate the following statements regarding your role as a farmer in climate change mitigation?

Please choose your answer on the scale from 1 ("strongly disagree") to 5 ("fully agree").

	I do not agree at all 1	2	3	4	I fully agree 5
I can do something about climate change on my farm by reducing greenhouse gases.	☐	☐	☐	☐	☐
My behaviour as a farmer influences climate change.	☐	☐	☐	☐	☐
How successfully I can reduce greenhouse gases on the farm depends mainly on my skills as a farmer.	☐	☐	☐	☐	☐
I am confident that I can reduce greenhouse gases and at the same time produce successfully.	☐	☐	☐	☐	☐
Climate change is a problem I can not change.	☐	☐	☐	☐	☐

Agricultural climate change mitigation

In this part of the survey, we would like to find out which climate change mitigation measures you implement on your farm and how you assess the effectiveness of the single measures.

Again, there is no right or wrong, it is all about your very personal assessment.

Q5: Which of the following measures do you currently implement on your farm and do you consider the measures effective for climate change mitigation?

Please indicate the appropriate answers for each measure.

	Do you currently implement the measure?			How effective do you think the measure is for climate change mitigation?					
	Yes	No	Not relevant for my type of farm.	Not effective at all. 1	2	3	4	Very effective 5	I don't know
I substitute some of the (imported) concentrates for my animals with native grain legumes (e.g., peas, lupines, field beans, European soya).	☐	☐	☐	☐	☐	☐	☐	☐	☐
I reduce the concentrate content to a maximum of 10 percent of the ration for my animals.	☐	☐	☐	☐	☐	☒	☐	☐	☐
I keep my cows for at least 5 lactation periods.	☐	☐	☐	☐	☐	☐	☐	☐	☐
I keep cattle of a dual-purpose breed (for example, original brown cattle).	☐	☐	☐	☐	☐	☐	☐	☐	☐
I feed my cattle tannins, flaxseed or similar feed additives to reduce methane emissions from digestion.	☐	☐	☐	☐	☐	☐	☐	☐	☐

The manure storage on my farm is covered.	☐	☐	☐	☐	☐	☐	☐	☐	☐
I compost the farm manure.	☐	☐	☐	☐	☐	☐	☐	☐	☐
I apply the fertilizer close to the ground with a drag hose or a similar technology.	☐	☐	☐	☐	☐	☐	☐	☐	☐
I include cover or catch crops in my rotation.	☐	☐	☐	☐	☐	☐	☐	☐	☐
I do not use the plough for tillage.	☐	☐	☐	☐	☐	☐	☐	☐	☐
I have solar panels for energy production.	☐	☐	☐	☐	☐	☐	☐	☐	☐
Manure from my farm is fermented in a biogas plant.	☐	☐	☐	☐	☐	☐	☐	☐	☐
When working with the tractor I drive in eco-drive mode (fuel-efficient).	☐	☐	☐	☐	☐	☐	☐	☐	☐

Q5a: Are you currently implementing any other measures to reduce greenhouse gases on your farm?

Please write this in the text field.

Q6: Which of the measures that you do not currently implement could you imagine to adopt in the future, which not?

	I can imagine to adopt this measure on my farm.	I can not imagine to adopt this measure on my farm.
I substitute some of the (imported) concentrates for my animals with native grain legumes (e.g., peas, lupines, field beans, European soya).	☐	☐
I reduce the concentrate content to a maximum of 10 percent of the ration for my animals.	☐	☐
I keep my cows for at least 5 lactation periods.	☐	☐
I keep cattle of a dual-purpose breed (for example, original brown cattle).	☐	☐
I feed my cattle tannins, flaxseed or similar feed additives to reduce methane emissions from digestion.	☐	☐
The manure storage on my farm is covered.	☐	☐
I compost the farm manure.	☐	☐
I apply the fertilizer close to the ground with a drag hose or a similar technology.	☐	☐
I include cover or catch crops in my rotation.	☐	☐
I do not use the plough for tillage.	☐	☐
I have solar panels for energy production.	☐	☐
Manure from my farm is fermented in a biogas plant.	☐	☐
When working with the tractor I drive in eco-drive mode (fuel-efficient).	☐	☐

Personal values and preferences

The following questions serve to assess your personal values and preferences regarding agriculture and climate change. We also want to find out how you assess your farm and yourself in agricultural climate protection.

Q7: What is the highest education you have completed?

☐ Agricultural apprenticeship
☐ Agricultural mastership examination

☐ Agri-technician
☐ Technical college, university, ETH
☐ Other: ………………………………………….

Q8: Which activities can you prinicipally imagine for your company and which not?

To answer the question, it does not matter what you currently produce on your farm.

	I would definitely do that ☺☺☺ 1	☺☺ 2	☺☹ 3	☹☹ 4	I would definitely not do that ☹☹☹ 5
Dairy farming	☐	☐	☐	☐	☐
Cattle fattening	☐	☐	☐	☐	☐
Pig fattening	☐	☐	☐	☐	☐
Poultry	☐	☐	☐	☐	☐
Arable farming	☐	☐	☐	☐	☐
Specialized crops	☐	☐	☐	☐	☐
Off-farm activity	☐	☐	☐	☐	☐

Q9: Please rank the following goals according to how important they are to you when making decisions on the farm.

Put the items on the right-hand side (highest rating above). The elements can be moved with the mouse. Double-click moves an element to the other list.

To protect the environment and natural resources.	
To reduce greenhouse gases on the farm.	
To achieve the highest possible yield.	
To be acknowledged by other farmers in the region.	
To generate the highest possible income from agriculture.	
To preserve a high biodiversity of animals and plants on my land.	

Q10: How well do the following statements apply to you and your farm?

Please choose your answer on the scale from 1 ("does not apply at all") to 5 ("fully applies").

	Does not apply at all 1	2	3	4	Fully applies 5
With the management of my farm, I make a contribution to climate change mitigation.	☐	☐	☐	☐	☐
I regularly achieve high yields.	☐	☐	☐	☐	☐
The biodiversity of animals and plants on the land I cultivate is high.	☐	☐	☐	☐	☐
My soil is healthy and fertile.					
My agricultural income allows me and my family a good life.	☐	☐	☐	☐	☐
I feel acknowledged by the farmers in the region.	☐	☐	☐	☐	☐

Q11: How well do the following statements apply to you personally?

Please choose your answer on the scale from 1 ("does not apply at all") to 5 ("fully applies").

	Does not apply at all 1	2	3	4	Fully applies 5
I am a pioneer in climate change mitigation and implement appropriate measures, even if they involve economic risks.	☐	☐	☐	☐	☐

I am ready to implement climate change mitigation measures earlier than other farmers in the region.	☐	☐	☐	☐	☐
I am open to climate change mitigation, but I want to think through all aspects first. While doing so, I focus on the experiences of other farmers.	☐	☐	☐	☐	☐
In principle, I only implement climate change mitigation measures if they have already been implemented by others for a while and have proven themselves.	☐	☐	☐	☐	☐
I rely on the tried and tested. Implementing climate change mitigation measures on my farm is economically too risky for me.	☐	☐	☐	☐	☐

Income and satisfaction

This part is about your satisfaction with your current income. The first two questions refer to the purely agricultural income per year (including direct payments, excluding off-farm income). The third and fourth questions relate to your total earned income per year (agricultural income, self-employment and other off-farm income).

Q12: How satisfied are you currently with your annual agricultural income (including direct payments, excluding off-farm income)?

☺☺☺ Very satisfied 1	☺☺ Satisfied 2	☺☹ So-so 3	☹☹ Unsatisfied 4	☹☹☹ Very unsatisfied 5
☐	☐	☐	☐	☐

Q13: Below what agricultural income per year would you be no longer satisfied (in CHF per year)?

130 000	120 000	110 000	100 000	90 000	80 000	70 000	60 000	50 000	40 000	30 000	20 000	10 000
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Q14: How satisfied are you currently with your total earned income (agricultural income, self-employment and other off-farm income)?

☺☺☺ Very satisfied 1	☺☺ Satisfied 2	☺☹ So-so 3	☹☹ Unsatisfied 4	☹☹☹ Very unsatisfied 5
☐	☐	☐	☐	☐

Q15: Below what total income per year would you be no longer satisfied (in CHF per year)?

160 000	150 000	140 000	130 000	120 000	110 000	100 000	90 000	80 000	70 000	60 000	50 000	40 000
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Q16: What is the share of your purely agricultural income (including direct payments, excluding off-farm income) of your total earned income?

☐ 0-25%
☐ 26-50%
☐ 51-75%
☐ 76-100%

The social network

The following questions will help us to understand the role that farmers' social relationships and networks play in agricultural climate change mitigation (e.g. by sharing knowledge and sharing experience or information).

Q17: How important is it to you what people around you think about the success of your farm and your farming skills?

Very important 1	2	3	4	Not important at all 5
☐	☐	☒	☐	☐

Q18: How well do the following statements apply to you personally?

Please choose your answer on the scale from 1 ("does not apply at all") to 5 ("fully applies").

	Does not apply at all 1	2	3	4	Fully applies 5
It is important to me to impress other farmers with my farm.	☐	☐	☐	☐	☐
I feel confirmed if I earn more than other farms.	☐	☐	☐	☐	☐
On my farm, I want to produce more environmentally and climate-friendly than other farmers in my area.	☐	☐	☐	☐	☐
If other farmers in my environment earn more than I do, it bothers me.	☐	☐	☐	☐	☐
If other farmers in my environment implement climate change measures, I want to implement such measures on my farm as well.	☐	☐	☐	☐	☐

Q19: With whom do you regularly discuss general agricultural topics and agricultural climate protection?

Please enter the names (also abbreviations or nicknames possible) of a maximum of 10 people who come to your mind.

Person 1
Person 2
Person 3
Person 4
Person 5
Person 6

Person 7
Person 8
Person 9
Person 10

Q21: Please indicate how you know the person or how you relate to the person (to be completed per person).

Neighbour	Workmate	Friend	Family member	Partner	Club-/association colleague	Extension Service	Other
☐	☐	☐	☐	☐	☒	☐	☐

Q23: How important are the opinions, attitudes and activities of these people when making decisions on your farm?

For example, imagine you are faced with deciding whether or not to implement a new climate change mitigation measure on your farm. How important for your decision is what the named person thinks, says or does on his own behalf?

Very important	Important	Not important
☐	☐	☐

Risk preferences

The last three questions are about how you assess risks. Findings on farmers' risk attitudes help to better understand practical decisions on the farm - for example, in agricultural climate change mitigation.

To answer these last questions lasts a maximum of 10 minutes and you can win up to 190 CHF.

Please have a look at our short explanatory video or carefully read the text below.

Lottery-Explanation.mp4 (Command Line)

- Imagine you want to implement climate change mitigation on you farm.
- To this end, you can invest in either measure A or measure B.
- Both investments promise a certain return, e.g. through higher efficiency and cost savings. Both investments cost the same amount and the respective return is paid out at the same time.
- Investment A generates a return of CHF 40,000 in 3 out of 10 cases (or 30%) and a return of CHF 10,000 in 7 out of 10 cases (or 70%).
- Investment B generates a return of 68,000 CHF in 1 out of 10 cases (or 10%), but only 5,000 CHF in 9 out of 10 cases (90%).
- In the following tables, the less likely return on investment B increases with each series.
- For each question, ask yourself for which return of B you are willing to take the higher risk and invest in B instead of the safer variant A.
- There are no right or wrong answers – it is all about your personal preferences.

<u>Your decisions determine how much money you can actually win:</u>

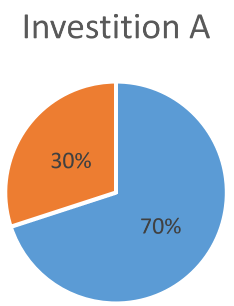
For each of the following three questions, a row is randomly drawn.

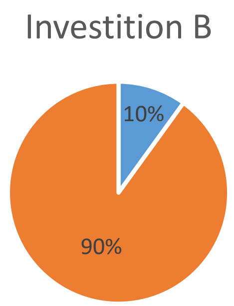
- Based on your decision in exactly this row, investment A or B will be used for this question.
- According to the probabilities of the investment (A or B) your profit will be drawn (in question 3 it may also be a loss).
- The amounts from each question are added together and divided by 10,000.

You can choose between investment A and investment B in each row. Both have the same costs and the respective return is paid out at the same time. However, A and B differ in their predictability: Investment A is stable across the rows. Investment B is less stable, but the potential return from row to row increases.

Q24: Please indicate from which row you choose investment B.

You can make a selection by clicking on the row in the table. This corresponds to the first row in which you select B.

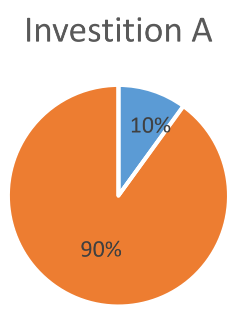
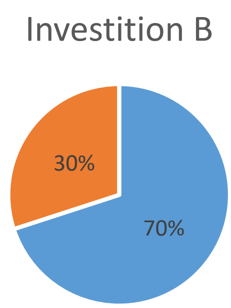




	Investition A		Investition B	
	30%	**70%**	**10%**	**90%**
1 ☐	40.000 CHF	10.000 CHF	68.000 CHF	5000 CHF
2 ☐	40.000 CHF	10.000 CHF	75.000 CHF	5000 CHF
3 ☐	40.000 CHF	10.000 CHF	83.000 CHF	5000 CHF
4 ☐	40.000 CHF	10.000 CHF	93.000 CHF	5000 CHF
5 ☐	40.000 CHF	10.000 CHF	106.000 CHF	5000 CHF
6 ☐	40.000 CHF	10.000 CHF	125.000 CHF	5000 CHF
7 ☐	40.000 CHF	10.000 CHF	150.000 CHF	5000 CHF
8 ☐	40.000 CHF	10.000 CHF	185.000 CHF	5000 CHF
9 ☐	40.000 CHF	10.000 CHF	220.000 CHF	5000 CHF
10 ☐	40.000 CHF	10.000 CHF	300.000 CHF	5000 CHF
11 ☐	40.000 CHF	10.000 CHF	400.000 CHF	5000 CHF
12 ☐	40.000 CHF	10.000 CHF	600.000 CHF	5000 CHF
13 ☐	40.000 CHF	10.000 CHF	1.000.000 CHF	5000 CHF
14 ☐	40.000 CHF	10.000 CHF	1.700.000 CHF	5000 CHF
Never ☐				

Q25: Please indicate from which row you choose investment B.

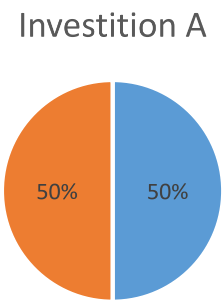
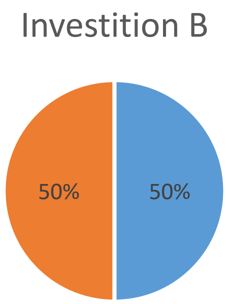
You can make a selection by clicking on the row in the table. This corresponds to the first row in which you select B.

				
	90%	**10%**	**70%**	**30%**
1 ☐	40.000 CHF	30.000 CHF	54.000 CHF	5000 CHF
2 ☐	40.000 CHF	30.000 CHF	56.000 CHF	5000 CHF
3 ☐	40.000 CHF	30.000 CHF	58.000 CHF	5000 CHF
4 ☐	40.000 CHF	30.000 CHF	60.000 CHF	5000 CHF
5 ☐	40.000 CHF	30.000 CHF	62.000 CHF	5000 CHF
6 ☐	40.000 CHF	30.000 CHF	65.000 CHF	5000 CHF
7 ☐	40.000 CHF	30.000 CHF	68.000 CHF	5000 CHF
8 ☐	40.000 CHF	30.000 CHF	72.000 CHF	5000 CHF
9 ☐	40.000 CHF	30.000 CHF	77.000 CHF	5000 CHF
10 ☐	40.000 CHF	30.000 CHF	83.000 CHF	5000 CHF
11 ☐	40.000 CHF	30.000 CHF	90.000 CHF	5000 CHF
12 ☐	40.000 CHF	30.000 CHF	100.000 CHF	5000 CHF
13 ☐	40.000 CHF	30.000 CHF	110.000 CHF	5000 CHF
14 ☐	40.000 CHF	30.000 CHF	130.000 CHF	5000 CHF
Never ☐				

Q26: Please indicate from which row you choose investment B.

You can make a selection by clicking on the row in the table. This corresponds to the first row in which you select B.

Please note: You can also lose money in this question. Therefore, you will now receive 5 CHF, from which any losses due to this task will be deducted when calculating your total gain. In no case can you lose more than this CHF 5.

				
	50%	**50%**	**50%**	**50%**
1 ☐	25.000 CHF	- 4000 CHF	300.000 CHF	- 21.000 CHF
2 ☐	4000 CHF	- 4000 CHF	300.000 CHF	- 21.000 CHF
3 ☐	1000 CHF	- 4000 CHF	3000 CHF	- 21.000 CHF
4 ☐	1000 CHF	- 4000 CHF	3000 CHF	- 16.000 CHF
5 ☐	1000 CHF	- 8000 CHF	3000 CHF	- 16.000 CHF
6 ☐	1000 CHF	- 8000 CHF	3000 CHF	- 14.000 CHF
7 ☐	1000 CHF	- 8000 CHF	3000 CHF	- 11.000 CHF
Never ☐				

Q27: After completing the survey, would you like to receive 10 CHF in return for your participation and profit?

Yes	No
☐	☐

Q28: If so, please provide your account details so that we can transfer you CHF 10 and your profit after the poll has ended.

Account holder:
IBAN:

Q29: Would you like to receive a summary of the survey results?

Yes	No
☐	☐

Q30: Do you have any final feedback or comments?

Thank you very much for your participation!

Your details and personal data will of course be kept strictly confidential and will be used exclusively for scientific purposes.

After the survey, we will determine your gains from the last part of the survey. If you answered "Yes" to the question and provided your account details, we will transfer your winnings to your account.

We will also gladly send you a summary of the survey results, if you have indicated your interest accordingly.

Appendix Chapter 2: Social network data of Swiss farmers related to agricultural climate change mitigation[33]

Cordelia Kreft[a], Mario Angst[b], Robert Huber[a], Robert Finger[a]

[a] ETH Zurich, Agricultural Economics and Policy Group, Switzerland

[b] University of Zurich, Digital Society Initiative, Switzerland

Abstract

We present social network data of Swiss farmers, focusing on exchange and advice relations regarding agricultural climate change mitigation. The data were generated via face-to-face interviews in 2019 using the survey software Network Canvas (https://networkcanvas.com). We interviewed 50 farmers, with 25 of these participating in a regional climate protection initiative in Switzerland as well as 25 farmers located in the same region who did not participate in the initiative. Farmers were asked to indicate the persons with whom they regularly exchanged on topics related to climate change and mitigation in agriculture. The farmers assessed the type and strength of their relationships and were asked to rate the knowledge of their contacts regarding climate change mitigation. We also collected data on the perceived influence of farmers and other persons on farming decisions. Information on farmers' adoption of climate change mitigation measures and behavioural characteristics was collected in a previous online survey. Farm characteristics were obtained from census data.

Keywords

Farmers' social networks, agricultural climate change mitigation, grassroots initiative, social learning, Network Canvas software, Switzerland

[33] This chapter is published as: Kreft, C. S., Angst, M., Huber, R., and Finger, R. (2021c). Social network data of Swiss farmers related to agricultural climate change mitigation. *Data in Brief* **35**, 106898.

Specifications Table

Subject	Agricultural Economics; Climate Change
Specific subject area	Farmers' social networks with regard to agricultural climate change mitigation
Type of data	Table
How data were acquired	Face-to-face interviews using Network Canvas Software on tablets, online surveys, farm census data
Data format	Raw and partly filtered (for reasons of confidentiality)
Parameters for data collection	Interviews were conducted with farmers participating in a regional climate protection initiative as well as with non-participating farmers in the same region
Description of data collection	Interviews with farmers were scheduled by telephone and conducted face-to-face on site (usually on the farm) by four trained interviewers. Questions were asked using the network survey tool Network Canvas installed on tablets. Farmers were asked to directly place named contacts on different sociograms on the tablet. The data was anonymized.
Data source location	Region of Zürcher Weinland, Canton Zurich, Switzerland
Data accessibility	Data is accessible via ETH Zürich Research Collection: http://hdl.handle.net/20.500.11850/458053

Value of the data

- The data provides detailed information on farmers' social networks and their potential role in reduction of agricultural greenhouse gas emissions. The combination with farm census data as well as data from a previous online survey on adoption of mitigation measures and behavioural characteristics represents a comprehensive data basis.

- The data allows for in-depth insights in famers' decision-making in the context of climate change mitigation.

- The data can be used to analyse the role of social networks in adoption of climate change mitigation measures. A wide range of behavioural factors and farm characteristics allows for a comprehensive set of control variables.

- The data enables the use of social network analysis techniques in combination with econometric analyses and/or mathematical modelling.

7.1 Data Description

We collected data on social networks of farmers with regard to climate change mitigation in the region of Zürcher Weinland, Canton Zurich, Switzerland. Interviews were conducted face-to-face with 25 farmers participating in the bottom-up climate protection initiative AgroCO2ncept Flaachtal [1] (hereafter: AgroCO2ncept) as well as with 25 farmers in the same region who were not participating in the initiative. The two interview questionnaires were slightly different for AgroCO2ncept participants and non-participants, e.g., participants were specifically asked about the project. Both questionnaires[34], all resulting datasets as well as the codebooks describing the variables are available through the ETH Zürich Research Collection: http://hdl.handle.net/20.500.11850/458053.

10 datasets resulted from the interviews as listed in Table 7.1.

Table 7.1: Overview of datasets

Farmers interviewed	Dataset ID	Data content	Complete datasets available	Data file name
AgroCO2ncept participants (n=25)	1	Farmers' personal attributes derived from interviews ("ego attributes")	25	Atts_agroconcept_int.csv
	2	Additional farmers' attributes from online survey and census data	24 (ID 16 has not answered survey)	Atts_agroconcept_survey.csv
	3	Ties between AgroCO2ncept farmers only (complete network)	25 senders, 25 receivers	Edges_agroconcept_complete.csv
	4	Ties between AgroCO2ncept farmers as well as with non-members (external contacts)	25 senders, 53 receivers	Edges_agroconcept_and_external_contacts.csv
	5	Influential people in the region named by AgroCO2ncept farmers	24 senders, 32 receivers	Influence_agroconcept.csv
Farmers not participating in AgroCO2ncept (n=25)	6	Farmers' personal attributes derived from interviews ("ego attributes")	25	Atts_nonpart_int.csv
	7	Additional farmers' attributes from online survey and census data	22	Atts_nonpart_survey.csv
	8	All ties named by non-participants	25 senders, 74 receivers	Edges_nonpart_all.csv
	9	Ties from non-participants to AgroCO2ncept members only	25 senders, 30 receivers (including some co-managers of AgroCO2ncept farms)	Edges_nonpart_to_agroconcept.csv
	10	Influential people in the region named by non-participants	16 senders, 25 receivers	Influence_nonagroconcept.csv

The presented data contain information on farmers' social ties to AgroCO2ncept members as well as to non-members. The ties are defined by regular exchange on agricultural climate change mitigation. Also, the strength of the ties and the type of relationship were assessed (datasets 3,4,8,9). Moreover, farmers were asked about some personal characteristics including attitudes towards climate change mitigation,

[34] Please also find the questionnaires in the supplementary material S1 and S2 to this Appendix Chapter.

assessment of the AgroCO2ncept project and their own mitigation behaviour (datasets 1, 6). Farmers were furthermore asked to identify the perceived social influence of previously named contacts as well as (optionally) of additional persons (datasets 5, 10). For reasons of confidentiality, any comments, qualitative data or other personal information such as contact details of farmers were removed from the data.

The obtained interview data were matched with previously collected survey data[35] on farmers' adoption of mitigation measures, farmers' behavioural characteristics as well as cantonal census data on farm structures and demographics (datasets 2, 7). In the survey, mitigation behaviour was assessed by asking farmers to indicate which out of 13 selected mitigation measures they had adopted on their farm.

7.2 Experimental Design, Materials and Methods

Out of the 50 interviewed farmers, 46 had previously participated in an online survey on behavioural factors of agricultural climate change mitigation, which was conducted by the authors in March and April 2019 [2]. The farms were located in the region of Zürcher Weinland, Canton Zurich in Switzerland. The region includes 24 municipalities and is part of the political district of Andelfingen. Interview appointments were individually scheduled on the phone. AgroCO2ncept farmers were chosen based on their participation in the initiative. Additionally, we aimed to interview 25 farmers who did not participate and had ideally answered the online survey [2]. We asked approximately 60 farmers in the region out of which 25 were willing to participate.

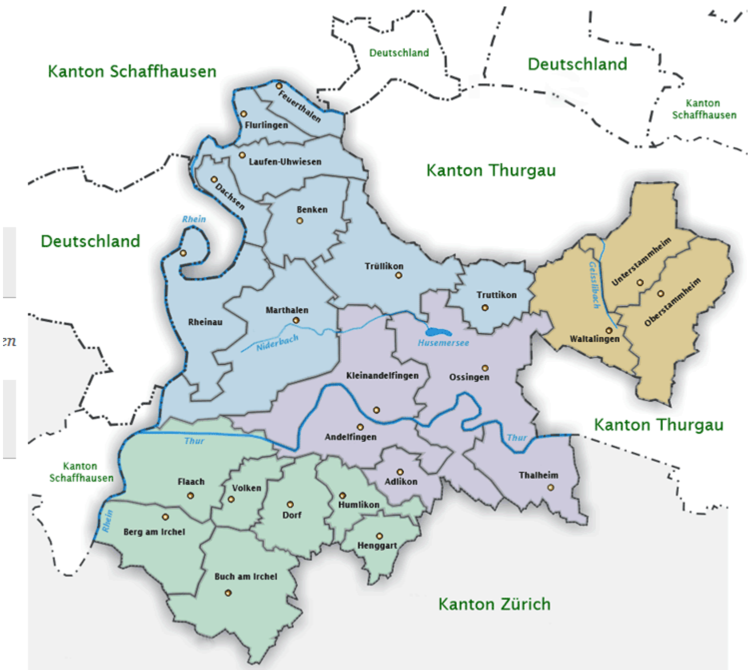


Figure 7.1: Map of the region of Zürcher Weinland including 24 municipalities (https://www.feuerthalen.ch/tourismus/umgebung/zuercher-weinland.html/323; see also [2])

[35] For a detailed description of the survey data used see [2].

The participating farmers were interviewed in November and December 2019 face-to-face by four trained interviewers on-site (usually on the farm). We used the free and open source network data collection software Network Canvas to design the questionnaire on tablets [3]. A touchscreen based data collection has been found to be more efficient than paper based methods of network data collection. The chosen Network Canvas software is a particularly modern, scientific and at the same time intuitive and user friendly tool [4]. Figure 7.2 and Figure 7.3 show examples of the touchscreen based questions.

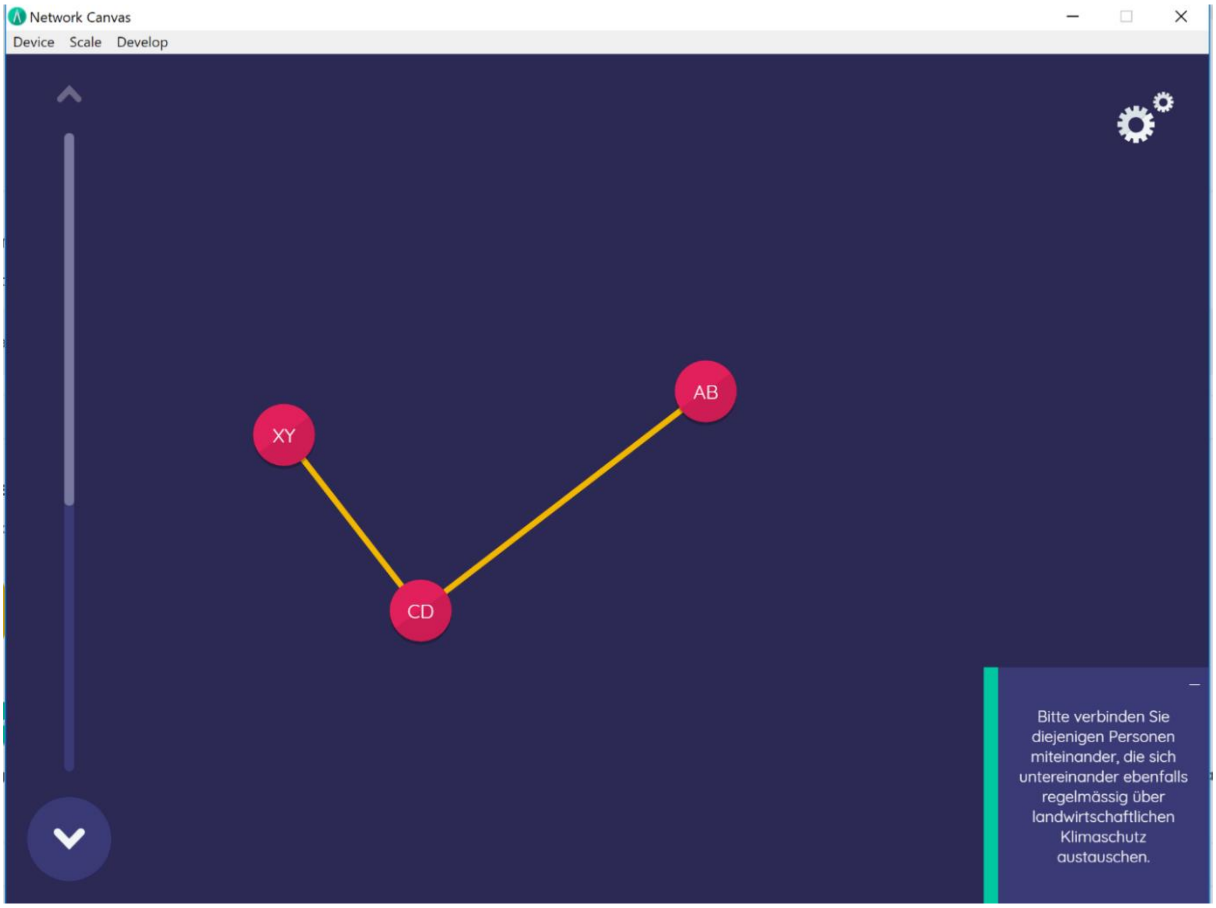


Figure 7.2: Alter-alter relations ("Please draw lines between the persons of whom you think they regularly exchange about agricultural climate change mitigation")

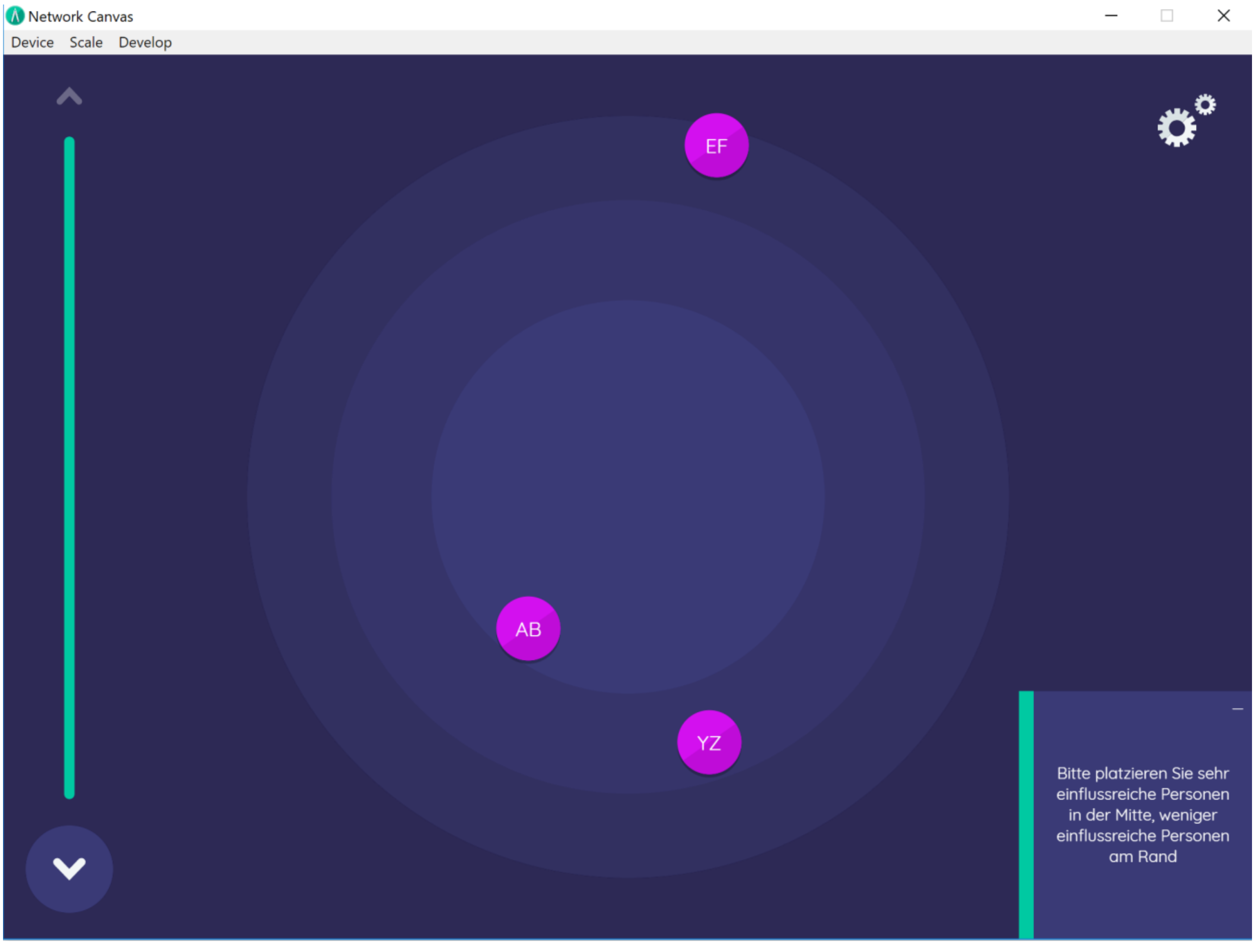


Figure 7.3: Influence ranking ("Please place people whom you perceive as very influential in the center of the concentric circle, less influential persons on the outer boundaries")

Questions were read aloud by interviewers and simultaneously shown to farmers on the tablet. Most answers were inserted in the questionnaire by the interviewer. Some network related tasks (e.g., to draw ties between contacts or place persons on a concentric circle according to their influence) were directly executed by the interviewees on the tablet. Both questionnaires (for AgroCO2ncept participants and non-participants) were pre-tested for understanding, wording and user-friendliness with six students of agricultural sciences and three experts of social network research.

The questionnaire contained 29 questions for AgroCO2ncept participants and 25 questions for non-participants. On average, interviews lasted for about 30-40 minutes. The questionnaire for AgroCO2ncept farmers was structured in the following subsections:

i) Personal characteristics and AgroCO2ncept participation
ii) Agricultural climate change mitigation on the farm
iii) Name generator for regular exchange on agricultural climate change mitigation
iv) Name interpreter questions
v) Alter-alter relations
vi) Influential people

Similarly, the questionnaire for farmers not participating in AgroCO2ncept contained the following subsections:

vii) Personal characteristics and agricultural climate change mitigation on the farm
viii) Name generator for regular exchange on agricultural climate change mitigation
ix) Name interpreter questions
x) Alter-alter relations
xi) AgroCO2ncept project
xii) Contact to AgroCO2ncept participants
xiii) Name interpreter questions to AgrCO2ncept contacts
xiv) Influential people

7.2.1 AgroCO2ncept participants

i) Personal characteristics and AgroCO2ncept participation

Farmers participating in AgroCO2ncept were asked about the year in which they joined the initiative and how happy they were with it so far. Moreover, we asked whether they felt that their personal interests and opinions were sufficiently taken into account in the decision-making process of AgroCO2ncept and how they assessed the success of the project regarding the overall greenhouse gas reduction target. All questions had to be answered on 3- or 5-point Likert Scales.

ii) Agricultural climate change mitigation on the farm

We asked farmers to answer questions related to agricultural climate change mitigation. First, farmers were asked whether they considered to adopt (additional) mitigation measures on their farm. Next, we wanted to know how they assessed their success regarding the personal greenhouse gas reduction target committed to within AgroCO2ncept. Moreover, we asked farmers how important climate change mitigation was for their farming decisions in general and how that importance changed compared to 10 years ago. All questions had to be answered on 3- or 5-point Likert Scales.

iii) Name generator for regular exchange on agricultural climate change mitigation

Farmers were asked to indicate with whom they regularly exchanged about agricultural climate change mitigation. We here based on the existing literature on the important role of social networks in farmers' adoption decisions, as for example shown in [5] and [6]. Interviewees (egos) were presented a roster with the names of all other AgroCO2ncept participants (alters). In order to choose a person as a contact, interviewees had to draw the name from the roster to an empty box on the touchscreen of the tablet. In addition, farmers had the option to name any other external person with whom they exchanged on the topic.

iv) Name interpreter questions

The following questions served to obtain information on the chosen alters and on the type and strength of the relationships [7]. Farmers were asked about the frequency of the exchange with the chosen contacts today and before joining AgroCO2ncept. Next, we asked them to indicate how they were currently related to them (e.g., friend, workmate, neighbour, family member etc.) and how they were related before joining AgroCO2ncept. We further asked participants how strongly every alter had influenced ego's decision to join the initiative. The following questions covered the alters' perceived knowledge about agricultural climate change mitigation, how often the ego would ask the alters for advice on farming decisions and how much they would trust them. All questions had to be answered on 3- or 5-point Likert Scales.

v) Alter-alter relations

Here, farmers were asked to indicate whether the chosen alters would regularly exchange on agricultural climate change mitigation amongst each other. Knowing alter-alter relations allows for a deeper analysis of so-called "egocentric" networks (individual actors networks) [8]. To this end, interviewees had to randomly place the alters on the tablet and draw lines between those who were connected (see Figure AC2.2).

vi) Influential people

Lastly, we asked farmers to indicate whom they perceived as influential for decision-making of farmers in the region. Interviewees were presented the roster with all AgroCO2ncept participants again and could additionally name any external person who came to their mind in this context. In a next step, farmers were asked to rank the influence of the named persons on a concentric circle (see Figure AC2.3).

7.2.2 Farmers not participating in AgroCO2ncept

vii) Personal characteristics and agricultural climate change mitigation on the farm

First, farmers not participating in AgroCO2ncept were asked about the main production focus of their farm (in case no survey data was available for these farmers). Next, we asked whether they considered to adopt (additional) mitigation measures on their farm. As for AgroCO2ncept farmers in section *ii)* above, we asked about the importance of climate change mitigation for farming decisions today and 10 years ago.

viii) Name generator for regular exchange on agricultural climate change mitigation

Farmers were asked to indicate with whom they regularly exchanged about agricultural climate change mitigation. Interviewees (egos) could name any person (alter) by adding their name to a field on the tablet.

ix) Name interpreter questions

We asked for the same information about alters as presented in the AgroCO2ncept questionnaire above, see section *iv)*. The questions about influence on the decision to join AgroCO2ncept as well as about the relationship before joining were left out.

x) Alter-alter relations

See *v)* for AgroCO2ncept participants.

xi) AgroCO2ncept project

Farmers not participating in AgroCO2ncept were asked whether they knew the project and whether they had ever considered to join the project.

xii) Contact to AgroCO2ncept participants

Interviewees were presented a roster containing all AgroCO2nept participants, and asked to indicate whom they had regular contact with. In order to choose a person, they had to be clicked on the tablet.

xiii) Name interpreter questions to AgrCO2ncept contacts

Interviewees were asked to specify the type of relationship (e.g., friend, workmate, neighbour, family member etc.) and the frequency of exchange on agricultural climate change mitigation with the chosen AgroCO2ncept contact.

xiv) Influential people

See section *vi)* for AgroCO2ncept participants.

7.3 Ethics statement

All participating interviewees were thoroughly informed about the content and the scope of the study before participation. Thus, informed consent was obtained from the participants prior to the interviews. Participation was completely voluntary. Moreover, anonymity of the data is guaranteed by excluding all personal identifiable information of respondents.

7.4 CRediT Author Statement

Cordelia Kreft: Conceptualization and design of questionnaires, conducting of interviews, data cleaning, writing manuscript ; **Mario Angst:** Conceptualization, methodology, editing; **Robert Huber:** Conceptualization, pretests, editing, supervision; **Robert Finger:** Conceptualization, pretests, editing, supervision

7.5 Acknowledgments

We greatly appreciate the support of Kate Banner and the whole team of the Network Canvas software for their support and advice with the technical implementation of the interview questionnaire. Moreover, we thank Christoph Stadtfeld and Timon Elmer for their valuable input on the content and design of the questionnaire. Our thanks furthermore go to Jasmin Brunner, Vera Steiner and Elisabeth Tanner for helping us to conduct the interviews. We particularly thank the farmers who participated in the interviews. Financial support for the project AgroCO2ncept provided by the Federal Office for Agriculture is acknowledged.

7.6 Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships, which have or could be perceived to have influenced the work reported in this article.

7.7 References

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Supplementary material

S1: Questionnaire for AgroCO2ncept participants (designed with software Network Canvas)

Personal characteristics and AgroCO2ncept participation

Q1. Please insert your pre- and surname

Q2. In what year have you joined the project AgroCO2ncept Flaachtal?

Q3. What were most important reasons to join the project?

Q4. How happy are you with the project?

Very happy 5	Rather happy 4	Partly 3	Rather unhappy 2	Very unhappy 1
☐	☐	☐	☐	☐

Q5. What are you particularly happy with?

Q6. What are you particularly unhappy with?

Q7. Do you feel that your interests and opinions are taken into account in the decision-making processes within AgroCO2ncept?

Yes, absolutely 5	Rather yes 4	More or less 3	Rather not 2	No, not at all 1
☐	☐	☐	☐	☐

Q8. Do you think AgroCO2ncept has so far been successful regarding its greenhouse gas reduction targets?

Yes, absolutely 5	Rather yes 4	Partly 3	Rather not 2	No, not at all 1
☐	☐	☐	☐	☐

Q9. Would you decide to participate again today?

Yes	No	Maybe
☐	☐	☐

Q10. If no, why not?

Agricultural climate change mitigation on the farm

Q11. Do you consider to implement further mitigation measures on your farm?

Yes	No	Maybe
☐	☐	☐

Q12. If yes, which measures do you plan to adopt?

Q13. How well have you reached your personal greenhouse gas reduction targets agreed upon in AgroCO2ncept?

Fully reached 5	Mostly reached 4	Partly 3	Mostly not reached 2	Not reached at all 1
☐	☐	☐	☐	☐

Q14. How important is climate change mitigation for your decisions on the farm?

Sehr wichtig 5	Eher wichtig 4	To some extent 3	Eher nicht wichtig 2	Gar nicht wichtig 1
☐	☐	☐	☐	☐

Q15. How important is climate change mitigation for your decisions on the farm today compared to 10 years ago?

Much more important 5	More important 4	Equally important 3	Less important 2	Much less important 1
☐	☐	☐	☐	☐

Name generator

Q16. With whom of the following persons do you regularly exchange on agricultural climate change mitigation?

(To choose from the roster with the names of all farmers participating in AgroCO2ncept, click on the circle with the respective name and draw it to the free space on the right. Please also consider additional external contacts and add them with pre-and surname using the symbol on the bottom right).

Name interpreter questions

We now ask you to answer the following questions to the persons you have just named.

Q17. How often do you exchange with this person on agricultural climate change mitigation?

Every day 5	Once per week 4	Once per month 3	Every other month 2	Once per year 1
☐	☐	☐	☐	☐

Q18. Please indicate how you are currently related to the person (multiple answers possible).

Friend	Workmate	Neighbour	Family member	Partner	Association colleague	Other
☐	☐	☐	☐	☐	☐	☐

Q19. If other, please specify

Q20. How often did you have contact with the person before joining AgroCO2ncept?

Every day 5	Once per week 4	Once per month 3	Every other month 2	Once per year 1	Never 0
☐	☐	☐	☐	☐	☐

Q21. Please indicate how you were related to the person before joining AgroCO2ncept (multiple answers possible).

Friend	Workmate	Neighbour	Family member	Partner	Association colleague	Other
☐	☐	☐	☐	☐	☐	☐

Q22. If other, please specify

Q23. How strong was the person's influence on your decision to join AgroCO2ncept?

Very strong 5	Strong 4	Rather weak 3	Weak 2	The person did not influence me 1
☐	☐	☐	☐	☐

Q24. In your perception, how much does the person know about agricultural climate change mitigation?

Very much 5	Much 4	Rather little 3	Little 2	Nothing 1
☐	☐	☐	☐	☐

Q25. How often do you consult the person for advice on decisions regarding your farm?

Every day 5	Once per week 4	Once per month 3	Every other month 2	Once per year 1	Never 0
☐	☐	☐	☐	☐	☐

Q26. How much do you trust the persons' knowledge and advice?

Very much 5	Much 4	To some extent 3	Rather little 2	Not at all 1
☐	☐	☐	☐	☐

Alter-alter relations

Q27. Please connect the persons you have chosen before if you think that they exchange regularly about agricultural climate change mitigation.

Influential people

Q28. Which persons do you perceive as influential for decision-making of other farmers in the region?

(To choose from the roster with the names of all farmers participating in AgroCO2ncept, click on the circle with the respective name and draw it to the free space on the right. Please also consider additional external persons and add them with pre-and surname using the symbol on the bottom right).

Q29. Please place very influential persons in the center of the concentric circle, place less influential persons towards the outer margins of the circle.

S2: Questionnaire for farmers not participating in AgroCO2ncept (non-participants) (designed with software Network Canvas)

Farm characteristics and agricultural climate change on the farm

Q1. Please insert your pre- and surname

Q2. Please indicate the main production focus on your farm

Suckler cows	Arable farming	Dairy cows	Cattle fattening	Forest	Vegetables	Fruits	Other
☐	☐	☐	☐	☐	☐	☐	☐

Q3. If other, please specify

Q4. Do you plan to implement (additional) greenhouse gas reduction measures on your farm?

Yes	No	Maybe
☐	☐	☐

Q5. If yes, which measures do you plan to adopt?

Q6. How important is climate change mitigation for your decisions on the farm?

Very important 5	Rather important 4	To some extent 3	Rather not important 2	Not important at all 1
☐	☐	☐	☐	☐

Q7. How important is climate change mitigation for your decisions on the farm today compared to 10 years ago?

Much more important 5	More important 4	Equally important 3	Less important 2	Much less important 1
☐	☐	☐	☐	☐

Name generator

Q8. With whom do you regularly exchange on agricultural climate change mitigation?

(Please add any persons that come to your mind with pre-and surname using the symbol on the bottom right).

Name interpreter questions

We now ask you to answer the following questions to the persons you have just named.

Q9. How often do you exchange with the person on agricultural climate change mitigation?

Every day 5	Once per week 4	Once per month 3	Every other month 2	Once per year 1
☐	☐	☐	☐	☐

Q10. Please indicate how you are currently related to the person (multiple answers possible).

Friend	Workmate	Neighbour	Family member	Partner	Association colleague	Other
☐	☐	☐	☐	☐	☐	☐

Q11. If other, please specify

Q12. In your perception, how much does the person know about agricultural climate change mitigation?

Very much 5	Much 4	Rather little 3	Little 2	Nothing 1
☐	☐	☐	☐	☐

Q13. How often do you consult the person for advice on decisions regarding your farm?

Every day 5	Once per week 4	Once per month 3	Every other month 2	Once per year 1	Never 0
☐	☐	☐	☐	☐	☐

Q14. How much do you trust the persons' knowledge and advice?

Very much 5	Much 4	To some extent 3	Rather little 2	Not at all 1
☐	☐	☐	☐	☐

Alter-alter relations

Q15. Please connect the persons you have named before if you think that they exchange regularly about agricultural climate change mitigation.

AgroCO2ncept project

Q16. Do you know the climate change mitigation initiative AgroCO2ncept Flaachtal?

Yes	No
☐	☐

Q17. Have you considered to join the project?

Yes	No
☐	☐

Q18. Why have you decided against joining AgroCO2ncept?

Contact to AgroCO2ncept participants

Q19. With whom of the farmers participating in AgroCO2ncept do you have regular contact?

Please choose from the roster with the names of all AgroCO2ncept participants.

Name interpreter questions to AgroCO2ncept contacts

We now ask you to answer the following questions to the AgroCO2ncept participants who have chosen.

Q20. Since when do you know the person?

Q21. Please indicate how you are currently related to the person (multiple answers possible).

Friend	Workmate	Neighbour	Family member	Partner	Association colleague	Other
☐	☐	☐	☐	☐	☐	☐

Q22. If other, please specify

Q23. How often do you exchange with the person on agricultural climate change mitigation?

Every day 5	Once per week 4	Once per month 3	Every other month 2	Once per year 1	Never 0
☐	☐	☐	☐	☐	☐

<u>Influential people</u>

Q24. Which persons do you perceive as influential for decision-making of other farmers in the region?

(To choose from the roster with the names of all farmers participating in AgroCO2ncept, click on the circle with the respective name and draw it to the free space on the right. Please also consider additional external persons and add them with pre-and surname using the symbol on the bottom right).

Q25. Please place very influential persons in the center of the concentric circle, place less influential persons towards the outer margins of the circle.

Curriculum Vitae

Cordelia Sophie Kreft

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I am an agricultural scientist currently working on my PhD about the economic dimension of climate change mitigation in agriculture at ETH Zurich. I have several years of work experience in agricultural trade policy and hold an additional diploma of journalism. My core competencies are thus at the interconnection of agricultural science and communication, and I am passionate about finding solutions for a more sustainable and resilient food system.

Education

2018 – 2022	**PhD in Agricultural Economics, ETH Zurich** *Title of dissertation: "Behavioural economics of climate change mitigation in Swiss agriculture: The role of farmers' individual characteristics and social networks"*
2016 – 2018	**Diploma of Journalism, Swiss School of Journalism (MAZ), Luzern**
2010 – 2013	**MSc in Agricultural Sciences, ETH Zurich** Major in Agricultural Economics and Policy Master Thesis: *Food waste in Swiss vegetable production and value chains*
2007 – 2010	**Bsc in Organic Agricultural Sciences, University of Kassel**
2006 – 2007	**Law studies, University of Freiburg (Germany)**

Work Experience

2016 – 2018	**Publishing house KiMedia, Zurich** **Journalist** Research and writing of articles for several Swiss consumer magazines
2013 – 2016	**Swiss Federal Office for Agriculture, Bern** **Employee in International Trade section** Negotiations of bilateral free trade agreements, WTO negotiations, agricultural export, and internal markets
2013	**Agency for International Cooperation (GIZ), Bonn** Intern in Sustainable Agriculture section
2011 – 2013	**Office for Equal Opportunities (Equal!), ETH Zurich** Student assistant
2011	**Institute for Environmental Decisions, ETH Zurich** Student assistant

2010	**German Parliament, Berlin** Intern at Committee for Economic Cooperation and Development

Further Experience

Since 2021	Board member at parents' association of local daycare (Kita Rumpelkiste, Zürich)
2015 – 2017	Member in organizational team of the Alumni Association of the German National Academic Foundation in Switzerland
2009 – 2013	Board member at human rights organization FIAN for the Right to Food (German section)
2007 – 2010	Several internships on organic farms and alpine farms

Language and software skills

Languages	German (native), English (fluent), French (basic)
Software	MS Office, R

Extracurricular activities

Yoga	Yoga teacher
Music	Piano, choir singer
Farming and outdoor	Member and involvement in community based farm, hiking

Personal information

Nationality	Germany
Birth date	29.09.1987