Quantifying the effect of social networks in the context of agricultural climate change mitigation

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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). Switzerland for example aims at a 40% reduction of agricultural emissions till 2050 compared to 1990 levels in its so-called Long-Term Climate Strategy (The Federal Council, 2021).

To achieve GHG reduction goals, farmers must adapt current practices and implement effective and efficient mitigation measures. Consequently, understanding farmers' decision-making with respect to climate change mitigation is crucial for design and implementation of effective policy incentives. However, the reasons for (non-) adoption of mitigation measures remain poorly understood (Kreft et al., 2021a; Niles et al., 2016). Bio-economic modeling approaches are key tools used for (ex-ante) assessment of agricultural policies and their impact on actual GHG reduction potentials as well as production and farm incomes (Britz et al., 2014; De Cara et al., 2005; Lengers et al., 2014). Yet, they usually lack integration of behavioral factors and, in particular, social networks.

In this article, we integrate behavioral aspects of mitigation adoption with economic decision-making in an agent-based modeling approach. More precisely, accounting for farmers' individual preferences and farm level costs of mitigation measures, we quantify the impact of farmers' social networks on the effectiveness of a subsidy for mitigation in terms of overall GHG emissions reduced and income changes of 49 Swiss cattle farms.

Social networks have been widely recognized as important factor to explain adoption and diffusion of e.g., agricultural innovations (Bandiera and Rasul, 2006; Conley and Udry, 2001; Conley and Udry, 2010). However, the role of knowledge building in social networks through observation and interaction with peers (Šūmane et al., 2018; Wood et al., 2014) has not been addressed in the context of agricultural climate change mitigation efforts. Little is known about the economic importance of knowledge exchange within farmers' social networks and their impact on farmer decisions regarding climate change mitigation. Particularly, to the best of our knowledge, the effect of social networks on policies aiming at a reduction of agricultural GHG emissions has not been quantified in terms of GHG emissions reduced and resulting income changes.

To fill this research gap, we use 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 using a two-tiered decision-making mechanism that not only considers costs and benefits of individual measures but also behavioural factors such as risk preferences and socially oriented behaviour. This type of model is suited to address our research questions since it combines standard bio-economic modelling based on income maximization with farmers' social interactions while accounting for individual behavioral characteristics (Huber et al., 2018). Here, we use FARMIND in combination with the bio-economic farm optimization model FarmDyn (Britz et al., 2014) allowing us to calculate costs and GHG emissions associated with adoption of mitigation measures under the constraint that farm level production is not reduced. FARMIND and FarmDyn are calibrated based on farm census, detailed survey and empirical network data of 49 dairy, beef and suckler farms in a Swiss region (Kreft et al., 2021b; Kreft et al., 2020). We incorporate information on farmers' adoption of four GHG mitigation measures and their interactions, which do not reduce the overall production of milk and meat on the farm, i.e., the replacement of imported concentrate feed with legumes, an increase in the number of lactations per dairy cow, the use of emission reducing technologies for manure application (trail hoses) and the introduction of feed additives to reduce enteric fermentation of cattle.

We compare the influence of social and individual components affecting farmers' decision-making to quantify income changes and GHG reduction potential of agricultural climate change mitigation in a counterfactual simulation setting. To do so, we maximize the total GHG emissions reduction of dairy and beef farms in our sample given a payment of 120 Swiss francs (CHF) per ton of CO2eq abated, according to the current carbon price in the Swiss market. We simulate the amount of GHG emissions and income changes based on knowledge exchange within farmers' empirically observed social networks and compare it to two counterfactuals i.e., GHG mitigation in the absence of a social network and if all farms are linked to each other (complete network). The emerging phenomena of our simulations are the overall amount of GHG emissions due to individual adoption decisions when farmers receive a payment for mitigation and imitate mitigation measures implemented by their peers. This allows to quantify the extent to which social networks can broaden the diffusion of mitigation practices and hence increase the effectiveness of a payment to incentivize reduction of GHG emissions in agriculture. In addition, the simulation results quantify the income changes associated with the farm individual reduction in GHG emissions and thus indicate the economic value of observation and interaction with peers in social networks.

We expect that the empirically observed social network of farmers does increase the uptake of mitigation measures and thus the overall reduction of GHG emissions compared to a situation without any social ties. This increase is expected to be even larger when all farmers are interconnected. Moreover, we expect that social networks of farmers do increase the overall reduction of GHG emissions and hence enhance the effectiveness of a payment for agricultural climate change mitigation.

In this article, we build on a coherent framework and base on empirical in-depth data to shed light on the interactions of social networks with farmers' individual preferences and income optimization. Our analysis contributes to better understand the impact of social networks on famers' decision-making and effectiveness of payments in the context of agricultural climate change mitigation. This furthermore helps to inform 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. Section 3 describes the methodology. Section 4 presents the expected results of our simulation, followed by a short discussion and conclusions in sections 5 and 6, respectively.

2 Background and conceptual framework

2.1 Agricultural climate change mitigation

Agriculture is a major source of GHG emissions (mainly methane (CH4), nitrous oxide (N2O) and carbon dioxide (CO2)) (IPCC, 2019). Livestock production alone is 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 (Poore and Nemecek, 2018). Beef and milk production respectively account for 41 and 20 % of the entire livestock sectors emissions (Gerber et al., 2013). Hence, agriculture and especially the livestock sector can play a key role in 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 (MACC) 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, behavioural characteristics such as strong self-efficacy and a sense of innovativeness have been found to positively affect adoption (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., 2022; Moran et al., 2013).

To increase adoption rates of farmers and enhance agricultural climate change mitigation, 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. In Switzerland for example, farmers receive payments for emissions reducing manure application (mainly to reduce ammonia emissions) and for cultivating forage legumes (Swiss Federal Council, 2022a). A payment for increasing the number of lactations of dairy cows is currently being discussed (Swiss Federal Council, 2020). Another example of Swiss agricultural policy supporting climate change mitigation is the bottom-up initiative "AgroCO2ncept Flaachtal" aiming at a reduction of GHG emissions on farm and regional level which receives support by the Swiss government (AgroCO2ncept, 2016). Part of the farmers in our sample are members in the initiative.

2.2 Conceptual framework

Our analysis is based on the agent-based modelling framework FARMIND that integrates aspects of social network theory (Foster and Rosenzweig, 1995; Granovetter, 2005; Merton and Merton, 1968) 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 (see Figure 1 for an overview). In particular, 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). FARMIND simulates decision-making of farmers as a two-step procedure: Combining the individual levels of satisfaction (based on prospect value and individual reference income) and dissimilarity to other agents in the network with respect to mitigation measures, the farmer first chooses one of four strategies, namely repetition, imitation, optimization or opt-out. In a second step, based on the previous strategic choice, the farmer decides upon adopting mitigation measures based on the highest cost-benefit ratio (Huber et al., 2021).

The key assumption of our conceptual framework is that farmers are influenced by their social networks through the occurrence of social learning, i.e., learning from observation and interaction with others (Kreft et al., 2022; Morgan, 2011; Munshi, 2004; Skaalsveen et al., 2020; Wood et al., 2014). More precisely, we expect farmers to learn from exchanging on climate change mitigation and observing mitigation behavior of the farmers in their social network. We here assume that farmers will adopt the most cost-efficient mitigation measures that maximizes their total GHG abatement without reducing production and given a outcome-oriented payment per ton of GHG emissions reduced. Whether this kind of social learning takes place in our simulations, depends on how susceptible the farmer is to tolerate dissimilarity between him-/herself and others as well as on the number of ties to others (density of the network).

Furthermore, we assume that certain individual characteristics and preferences affect farmers' decisions (Dessart et al., 2019). In particular, we include farmers' risk attitudes and a preference for GHG mitigation measures. Farm structures such as farm size are also accounted for, mainly in the definition of a reference farm income based on which farmers calculate their prospect value and hence value gains and losses.

Based on these social and individual factors, the farmer decides whether to adopt one or several mitigation measures. The adoption decision finally determines benefits and costs, i.e., the amount of GHG emissions reduced as well as associated changes in farm income. Figure 1 gives a graphical overview of our conceptual framework.

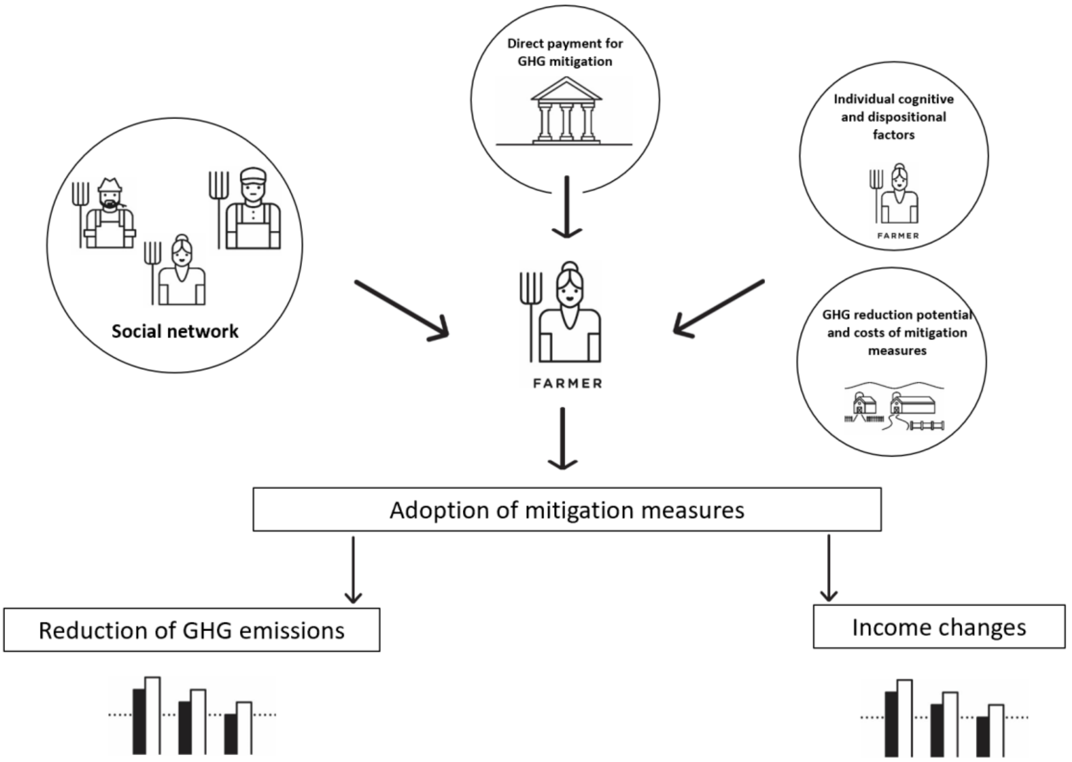


Figure 1: Conceptual framework: Farmers are influenced by their social networks, individual behavioural factors, costs and benefits of climate change mitigation as well as policies (direct payment). These factors affect the farmer's decision to adopt mitigation measures. The decision ultimately determines the reduction of GHG emissions and associated income changes.

For our analysis, we simulate a network of 49 farmers based on real network data of a subsample. Since certain structural characteristics of networks such as density and centralization have been shown to impact information flow, learning and ultimately behavioral outcomes (Bandiera and Rasul, 2006; Bodin and Crona, 2009; Bourne et al., 2017; Levy and Lubell, 2017; Lubell, 2004), we compare the effect of the empirically informed network to two hypothetical scenarios with different network structure: No social ties and ties between all farmers. Analyzing the difference in terms of total GHG emissions reduction and income changes between these network scenarios allows to quantify the impact of social networks on the effectiveness of a payment for GHG reduction and ultimately agricultural climate change mitigation. Figure 2 visualizes the four compared network scenarios in a stylized way:

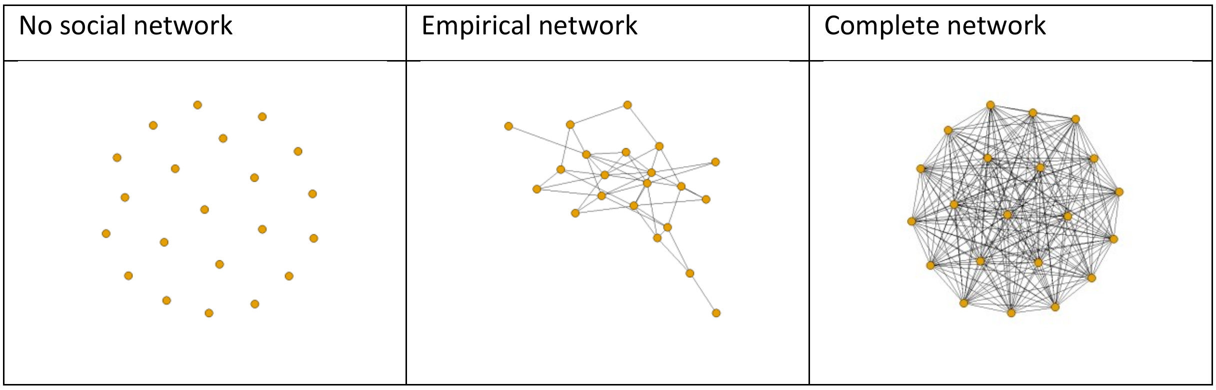


Figure 2: Stylized representation of four network scenarios: 1) No social ties between farmers; 2) The empirically informed simulated network with tendencies of a core-periphery structure, i.e., close interrelations within a core group of farmers and looser connections in the periphery; 3) A complete network with ties between all farmers.

2.3 Choice of mitigation measures

For this study, we analyze the effect of four distinct on-farm mitigation measures to reduce GHG emissions from 49 dairy and beef farms in Switzerland. The measures were selected based on a previous survey as well as relevance in Swiss agriculture (Kreft et al., 2020) (see Table 1). Costs and benefits (GHG emissions reduction) are simulated on farm level for each measure separately as well as for all possible combinations thereof. As important boundary condition of our analysis, 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 farm structures. The GHG reduction potential of each measure was derived from the literature (Table 1) and validated in expert interviews.

Table 1 shows the four mitigation measures included in the model, the associated mechanism of GHG emissions reduction as well as main scientific references.

Table 1: Climate change mitigation measures included in the model and associated mechanism of GHG emissions reduction

Measure description	**Mechanism of GHG emissions reduction**	**References**
a) Replacement of (imported) concentrate feed with legumes	Replacing concentrate feed such as soybean with locally produced legumes (e.g., peas or horse bean) mitigates up-stream CO_2-emissions mainly due to reduced transport and land-use changes	(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 primarily due to a smaller replacement rate, i.e., less "unproductive" calves and heifers	(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 trail hoses (or a similar technique) reduces N2O-emissions of manure brought to the field and indirect N2O emissions from other nitrogen compounds	(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 CH4-emissions from enteric fermentation by inhibiting methanogenesis in ruminants	(Engelke et al., 2019; Hristov et al., 2013; Jayanegara et al., 2020)

We here assume a results-oriented payment for GHG reduction based on the current CO2 market price in Switzerland, which amounts to 120 CHF per ton of CO2eq (Swiss Federal Council, 2022b). In our model, farmers thus receive a payment of 120 CHF per ton of GHG emissions reduced due to adoption of one or several mitigation measures.

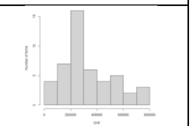
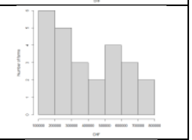
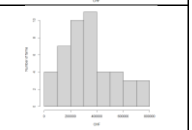
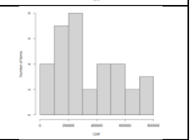
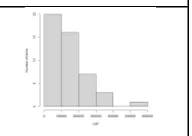
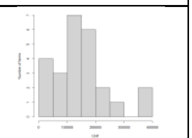
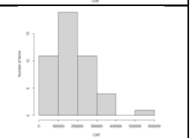
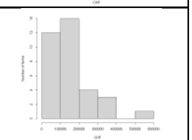
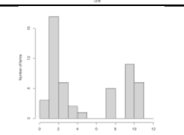
3 Methods: Agent-based modelling framework FARMIND

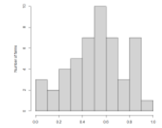
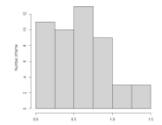
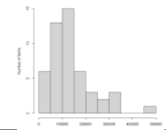
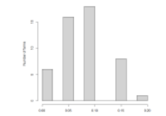
The purpose of the model is to simulate the adoption of climate change mitigation measures on Swiss cattle farms (dairy and beef). More specifically, the model simulates the effect of a social network on the adoption decision considering heterogeneous cognitive, social, and dispositional factors across individual farmers given a payment for emissions reduction. The farm individual decision-making includes the choice of a strategy (i.e., repeating, optimizing, or imitating behaviour) and a subsequent (non-)adoption of the income maximizing mitigation measure. The emerging phenomena of FARMIND are the total amount of greenhouse gas 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 scenario simulation (full details of the model are provided in the ODD+D protocol).

3.1 Agent characteristics

In FARMIND, each agent is characterized by three sets of variables (cf. Table 2). (1) Farm specific costs and greenhouse gas emission reduction potentials for five on-farm climate change mitigation measures. These costs and GHG reduction potentials are exogenous parameters calculated in the bio-economic farm level model FarmDyn i.e., a farm optimization model calibrated with census data for each specific farm. Based on the calculated GHG emissions reduction, mitigation costs are partly compensated by a payment of 120 CHF per ton of CO2eq 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 and a reference income that determines whether he is 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) A social network between farmers derived from an interview based social network analysis (Kreft et al., 2021b).

Table 2. State variables and parameters in FARMIND

Category	State variable / parameters	Ab-brevi-ation	Descriptive statistics	Source
Farm	Adopted mitigation measures	A		Kreft et al. (2020)
	Greenhouse gas emissions with adopted measure	y_{At}		Simulated in Sub-model FarmDyn based on Britz et al. (2021)
	Greenhouse gas emissions with adopted measure (No external concentrate) (38 903 – 775 437)			
	Greenhouse gas emissions with adopted measure (Increased no. of lactations) (154 766 – 707 316)			
	Greenhouse gas emissions with adopted measure (Drag hoses) (42 100 – 764 154)			
	Greenhouse gas emissions with adopted measure (Feed additives) (40 750 – 721 715)			
	Income with adopted mitigation measures A and payment of 120 CHF/t GHG reduced (based on GHG reduction results)	x_{At}		
	Income with adopted mitigation measures (No external concentrate) (20 386 – 568 548)			
	Income with adopted mitigation measures (Increased no. of lactations) (22 427 – 384 401)			
	Income with adopted mitigation measures (Drag hoses) (22 805 – 588 858)			
	Income with adopted mitigation measures (Feed additives) (19 681 – 589 201)			
Personal characteristics	Loss aversion level (0.96 – 10.41)	λ		Kreft et al. (2020)

	Valuation of gains and losses (0.05 – 0.95)	$\alpha^{+/-}$		
	Probability weighting in gains and losses (0.05 – 1.5)	$\varphi^{+/-}$		
	Reference income to determine perceived gains and losses and calculate satisfaction (17 456 – 471 431)	V_i^{ref}		
	Tolerance level for activity dissimilarity to determine information seeking behavior (0.01 – 0.2)	d_i^{tol}		
	Preference weight for agricultural activities (Mean (Sd))	β_P	1.0 (0.0)	
Social network	Number of peers a farmer is linked to (Mean (Sd))	*n*	13.4 (1.4)	Kreft et al. (2021b)

3.2 Agents' decision-making

These farm and farmers 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. The model includes four behavioural strategies: repetition, optimization, imitation, and opt-out. In a second step, farm agents choose their actual production decision i.e., the adoption of a greenhouse gas mitigation measure based on the options provided in the corresponding strategy. This two-tiered decision-making is implemented in three coding steps (for a formal representation of the decision-making see Appendix).

First, 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). In addition, the model calculates the agent's dissimilarity to his peers i.e., whether the other agents also adopted climate change mitigation measures. The connection between the different agents in FARMIND is based on an empirically informed social network (Kreft et al., 2021b). Each agent has a threshold value for these two aspects i.e., satisfaction and dissimilarity, that determine the strategic heuristic of the agent.

If a farmer is satisfied and does not engage in social comparison, he/she 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 he/she observes in his/her 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 in general (no adoption of mitigation measures).

The choice of the agents' decision strategy results in a set of potential greenhouse gas mitigation measures that is transferred to the next simulation step. A repeating agent considers only those measures that he had 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 agents in his social network. Finally, an agent that strives for individual behaviour and who is unsatisfied will choose none of the mitigation measures.

Secondly, the mitigation measures that are transferred from the strategic heuristic are ranked 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.

Thirdly, 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 greenhouse gas emission reduction. The results from the adoption decision (income and greenhouse gas mitigation measures) are then again transferred to the FARMIND strategic decision to update measures and income distribution of the agents. The cost and benefits (i.e., changes in greenhouse gas emissions) for each agent are based on the calculation of the bio-economic farm level model FarmDyn. This sub-model provides a matrix with all costs and potential greenhouse gas emission reduction for all mitigation measures and their interactions for each agent. 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, greenhouse gas 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.

3.3 Simulation 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 three 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. This set up allows to compare the hypothetical the "empirical network" in scenario 2 to counterfactual situations without social ties and with a complete social network.

The difference in total GHG emissions reduction between the counterfactual "No social network" and the "Empirical 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 shows the potential of such a behaviour if social ties would be scaled to all the farms. Thus, the comparison of simulation results gives quantitative insights into the relevance of social networks in climate change mitigation in agriculture.

We initialize the scenario runs with agents not implementing any of the mitigation measures. This serves as a counterfactual situation for the assessment of social network effects on the adoption. We then simulate in FARMIND 12 years (runs). 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 an equilibrium state at which the number of mitigation measures do not change anymore (even though strategies might still vary).

4 Expected results

We expect that farmers' social networks lead to more adoption of climate change mitigation measures and thus have a positive effect on overall GHG emissions reduction compared to a scenario without any social ties. This implies that social networks, i.e., knowledge exchange among farmers, increases the effectiveness of an incentive paid to farmers per ton of CO2eq abated. Moreover, we expect to find considerable heterogeneity of GHG emissions reduction and income changes across mitigation measures and farms in our sample.

5 Preliminary Discussion

(In this version of the paper, we only discuss some aspects of our study, i.e., mainly underlying assumptions and implications based on expected results. A complete discussion of the actual results will be available in the full version of the article.)

In this article, we estimate the effect of farmers' social networks on agricultural climate change mitigation and respective policy incentives using agent-based modelling. We expect our results to show that the existence of social networks within which farmers exchange knowledge on climate change mitigation practices has a positive effect on farmers' adoption of such practices and hence increases 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 this by quantifying the effect of knowledge exchange within farmers' social networks in terms of outcomes, here overall GHG emissions reduction and total costs.

The underlying assumed 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 his or her peers in terms of mitigation adoption, he or she becomes uncertain and seeks to imitate the observed behaviour (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). Striving for conformity and a feeling of belonging can even have stronger implications for behavioural change than financial incentives (Kuhfuss et al., 2013).

In line with literature on agricultural climate change mitigation, we expect to find heterogeneity of reduction and associated income changes across measures (and combinations thereof) as well as between individual farms (Beach et al., 2008; Jones et al., 2015; MacLeod et al., 2010; Moran et al., 2011; O'Brien et al., 2014; Vermont and De Cara, 2010). This constitutes one of the major challenges of integrating agriculture in general climate policies (Fellmann et al., 2018).

Moreover, agricultural mitigation can be comparably expensive. Here, 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 to five per dairy cow results in negative marginal costs for several farms in our sample. Based on literature investigating the effects of increased lifespan of dairy cows, we here assume a constant milk yield of longer lactating cows (in fact, milk yield has even been shown to increase with number of lactations) and do not account for potential fertility or health issues and resulting veterinary costs (Grandl et al., 2019; Mellado et al., 2011). However, this assumption might not hold for all the farms. Furthermore, increasing the number of lactations and consequently a lower replacement rate on one farm does not necessarily reduce overall GHG emissions of the sector. If the newborn calves are sold for replacement or fattening on other farms, GHG emissions simply occur elsewhere.

Besides the uncertainty regarding actual costs, there is no scientific consensus on the technical reduction potential of single measures either (Eory et al., 2018). For example, injection and close-to-ground application of manure e.g. with trail hoses has been found to reduce N2O 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 N2O emissions (Clemens et al., 1997; Velthof et al., 1996). However, it is undisputed that manure application with trail hoses reduces NH3 (ammonia) volatilization, which is an indirect source of N2O emissions (Wu et al., 2021). Despite the scientific uncertainty about the mitigation potential, we still 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).

There is ongoing research concerning potential synergies and trade-offs of agricultural climate change mitigation measures regarding other policy goals, e.g., reduction of other pollutants such as nitrate, particulate matter, sulfur dioxide or phosphorus (Eory et al., 2018; Schneider et al., 2007; Wagner et al., 2012). Another potential conflict of interests is between climate change mitigation in the livestock sector and animal welfare. For instance, increasing the productivity of animals in order to reduce emissions per unit of product can result in decreased health (Shields and Orme-Evans, 2015) while other propositions such as reduced grazing time to mitigate N2O losses (Schils et al., 2013) can negatively affect animal welfare. Ultimately, the implementation of mitigation measures can affect agricultural yields and markets and thus global food security (Frank et al., 2017; Fujimori et al., 2019).

6 Conclusion

Reduction of agricultural GHG emissions is indispensable to reach the temperature goal of the Paris Agreement to limit global warming to 1.5° C (IPCC, 2019). However, despite agriculture being mentioned in many countries' overall climate policy goals, no country has so far exposed its agricultural sector to a mandatory carbon price and agriculture has not been included in emissions trading schemes (Leahy et al., 2020). Among the obstacles are uncertainties regarding cost-effectiveness of mitigation measures as well as comparably high public and individual efforts associated with reduction and monitoring of agricultural GHG emissions (Lynch et al., 2021; Maraseni, 2009).

Despite heterogeneous costs and reduction potential of mitigation measures across farms, we expect our results to show that learning and knowledge exchange within farmers' social networks can increase the diffusion of mitigation measures and consequently reduce GHG emissions on dairy and beef farms in Switzerland. This would render policy incentives to increase adoption of mitigation practices more effective. Using the agent-based modelling framework FARMIND, we quantify 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 which has so far mainly estimated costs and benefits of agricultural mitigation measures without accounting for individual farmers' characteristics and social interactions. Future research on adoption, costs and benefits of agricultural climate change mitigation should therefore consider the important role of farmers' social and individual properties more regularly.

Based on our findings, farmers' knowledge exchange in social networks is expected to increase the effectiveness of payments aiming at a reduction of agricultural GHG emissions. This has some important implications for policymakers: First, in addition to financial incentives compensating for costs of mitigation, farmers need access to knowledge and know-how about agricultural climate change mitigation and respective on-farm practices. Possible instruments could be information campaigns as well as specific advisory service and trainings offered to farmers. The topic should also be integrated in regular curricula of farming schools. Second, policymakers should seek to support social networks and knowledge exchange, particularly between early-adopters and those who have not yet adopted mitigation measures. 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). Estimating the effects of different policy interventions under consideration of social networks and farmer behavioural characteristics constitutes an interesting topic for future research.

However, we find that even in a hypothetical situation of a complete network integration, total GHG emissions reduction potential due to adoption of the analyzed mitigation measures stays well below 10% of baseline emissions on the farms in our sample. This indicates that a substantial reduction of agricultural GHG emissions, especially in the livestock sector, will be quite limited if current production levels are to be held constant. To reach higher levels of emission reductions in the food system, there is no way around reducing animal stocks, and hence moving dietary patterns from milk and meat to more plant-based protein sources (Poore and Nemecek, 2018).

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