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ORIGINAL ARTICLE

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

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Abstract

To reduce agricultural greenhouse gas (GHG) emissions, farmers need to change current farming practices. However, farmers' climate change mitigation behaviour and particularly the role of social and individual characteristics remains poorly understood. Using an agent-based modelling approach, 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. Our simulations are based on census, survey and interview data for 49 Swiss dairy and cattle farms to simulate the effect of social networks on overall GHG reduction and marginal abatement costs. We find that considering social networks increases overall reduction of GHG emissions by 45% at a given payment of 120 Swiss Francs (CHF) per ton of reduced GHG emissions. The per ton payment would have to increase by 380 CHF (i.e., 500 CHF/tCO_2eq) to reach the same overall GHG reduction level without any social network effects. Moreover, marginal abatement costs for emissions are lower when farmers exchange relevant knowledge through 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

agent-based modelling, agricultural policy, climate change mitigation,

First authorship is shared between Cordelia Kreft and Robert Huber.

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reduction of agricultural greenhouse gas emissions, social networks, Switzerland

JEL CLASSIFICATION
C63, D22, Q01, Q12

1 | INTRODUCTION

Agriculture is threatened by climate change, but at the same time it is also 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 the design and implementation of such policy incentives. However, the role of behavioural factors in general, and social learning in particular, remains poorly understood in this context (Kreft, Angst et al., 2023; Kreft, Finger et al., 2023; Kreft, Huber, et al., 2021; Niles et al., 2016). Although bio-economic modelling approaches are key tools used for the (ex-ante) assessment of agricultural policies and their impact on actual GHG reduction potential as well as production and farm incomes (e.g., De Cara et al., 2005; Lengers et al., 2014), they usually lack integration of individual behavioural factors and social interactions. To account for such factors in the simulation of farmers' decision-making, agent-based models have recently 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 model, 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; Schaub et al., 2023). 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 (e.g., Morgan & Daigneault, 2015; Šūmane et al., 2018; Wood et al., 2014). With regard to climate change adaptation and mitigation in agriculture, however, few studies have specifically accounted for social interactions of farmers (Berger & 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 largely unexplored. 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 reduced GHG emissions and associated marginal abatement costs.

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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., 2022). 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 optimisation model FarmDyn (Britz et al., 2021) 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 parametrised based on farm census, detailed survey and empirical network data for 49 dairy, suckler and bull-fattening farms located in a Swiss region (Kreft et al., 2020; Kreft, Angst, et al., 2021).

To assess the effect of social networks combined with payments 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, that is: (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 the payment to achieve the same reduction level across scenarios. This allows us to quantify the extent to which social networks could enhance the diffusion of mitigation practices and hence increase the effectiveness and efficiency of a payment to incentivise reduction of GHG emissions in agriculture. In addition, the simulation results quantify the income changes and marginal costs associated with the individual farm 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 results-based payments in the context of agricultural climate change mitigation. This quantifies the potential economic value of policies supporting social networks such as platforms for knowledge exchange in farming communities as well as information campaigns or farmer training 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 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.

2 | BACKGROUND AND CONCEPTUAL FRAMEWORK

2.1 | Agricultural climate change mitigation

Agriculture is a major source of GHG emissions, mainly methane (CH_4) and nitrous oxide (N_2O) (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

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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 changes in 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, Topp, 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 (e.g., Beach et al., 2008; Huber et al., 2023; 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 farmer (Ancev, 2011; Eory, Topp, 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 the low costs (McCarl & Schneider, 2000). On the other hand, strong self-efficacy (believing in one's own capabilities to successfully fulfil a given task) and a stronger innovation sense have been found to positively affect farmers' adoption of on-farm measures to reduce GHG emissions (Kreft, Huber, et al., 2021; Niles et al., 2016). Moreover, social learning through knowledge exchange within farmers' social networks and in particular frequent contact with knowledgeable peers can increase mitigation adoption (Kreft, Angst et al., 2023; Moran et al., 2013).

To enhance adoption and achieve a reduction of GHG emissions from agricultural production, different policy instruments have been proposed by the literature. These include financial incentives such as subsidies, taxes and tradable permits, binding standards, and regulations as well as information campaigns, training and advisory services (Eory, Topp, et al., 2018; Gerber et al., 2013). Although 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, for example, via a tax, we here apply the 'beneficiary pays' principle and focus on a results-based payment that farmers receive per ton of CO_2 equivalent reduced. Paying farmers for reducing emissions, as a results-based payment scheme, is often better accepted by farmers and policy-makers since it emphasises property rights of farmers who are compensated for profit reductions caused by the provision of positive externalities (e.g., Pretty & Ward, 2001).

2.2 | Conceptual framework

Our conceptual background is that farmers' individual decision on the uptake of GHG mitigation measures is influenced by four different components (Figure 1). First, uptake depends on heterogeneous cognitive, social and dispositional factors. Farmers might perceive the implementation of these measures as risky or 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 their peers. Third, whether a farmer will implement certain measures on the farm also depends on the underlying farm structures and processes, that is, farm size and type, that result in individual farm abatement costs. Finally, the adoption decision is also influenced by the policy measures, that is, the level of payment and how it changes the relation of costs and profits (Kreft, Finger et al., 2023)

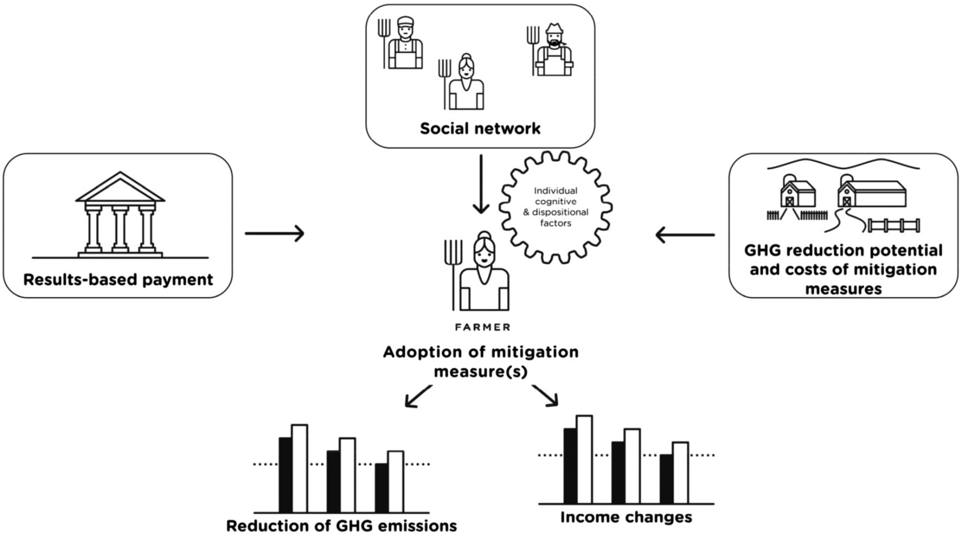

FIGURE 1 Conceptual framework. Farmers are influenced by their social networks, individual behavioural factors, costs and profits (i.e., income plus subsidy) of climate change mitigation as well as policies (payment per reduced ton of CO_2 equivalent). These factors affect the farmer's decision to adopt mitigation measures. The decision ultimately determines the reduction of GHG emissions and associated income changes.

Although 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, that is, learning from observation and interaction with others (e.g., Wood et al., 2014; Skaalsveen et al., 2020). 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 & Vorobeychik, 2019).

Here, we expect farmers to learn from others about climate change mitigation and to observe mitigation behaviour of the farmers in their social network and neighbourhoods. The assumed underlying mechanism of the social network effect is farmers' (and most people's) wish to conform to social norms, at least to a certain extent: If a farmer differs substantially from their peers in terms of mitigation adoption, they may seek to imitate the behaviour observed in the social network (Jager & Janssen, 2012). This initiates social learning processes as suggested by rural sociology studies describing the phenomenon of 'roadside farming', where farmers observe their neighbours' practices 'over the hedge' (e.g., Le Coent et al., 2021). Seeking conformity and a feeling of belonging has even been found to have stronger implications for behavioural change than financial incentives (Kuhfuss et al., 2013). Moreover, particularly in our case study region, farmers were found to learn from and imitate (perceived) knowledgeable peers (Kreft, Angst et al., 2023) and trust relationships can help to lower the perceived risks of adoption (Sligo & Massey, 2007).

Based on the framework described in Huber et al. (2022), we assume that farmers choose their practices based on individual risk attitudes and a preference for GHG mitigation measures that confines their choice options. The strategies to choose from are repetition, optimisation, imitation, and non-adoption (see Section 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.

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Whether imitation and social learning take place in our simulations depends on how tolerant the farmer is to 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 observed network data. Certain structural characteristics of networks such as density and centralisation have been shown to impact information flow, learning and ultimately behavioural outcomes (e.g., Bourne et al., 2017; Levy & Lubell, 2018). 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 enables us 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]

2.3 | Case study and mitigation measures

We analyse the effect of four distinct on-farm mitigation measures and their combinations on the reduction of 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 are situated in the region of 'Zürcher Weinland' in the northern part of Canton Zurich. Ten farms mainly produce beef from fattening bulls, 15 are suckler farms and 24 are dairy farms. The average farm size is 35 hectares (average farm size in Canton Zurich is 25 hectares) and 38 cattle livestock units (average cattle livestock units per farm in Canton Zurich is 30).

The simulated mitigation measures were selected based on the previous online survey and according to their relevance in Swiss agricultural systems (see Table 1 and Kreft et al., 2020). Costs and benefits (GHG emissions reduction) for each measure separately and for all possible combinations are derived from simulations with the bio-economic farm level model FarmDyn (Britz et al., 2021). Detailed information on the sub-model FarmDyn can be found in the ODD+D protocol (section 'Sub-model') in the Supplementary Material A.

As an 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 optimisation 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., increasing 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 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% compared to baseline GHG emissions.

[1]Stylised visualisations of the compared network scenarios can be found in the ODD+D protocol (Section 3.4), Appendix S1.

[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.

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TABLE 1 Climate change mitigation measures included in the model and associated mechanism of GHG emissions reduction. GHG reduction potentials and marginal abatement costs per measure are based on simulations with the bio-economic farm level model FarmDyn (see Section 3).

Measure description	Mechanism of GHG[a] emissions reduction	Mean on-farm GHG reduction potential (tCO_2eq)	Mean marginal abatement costs (CHF/tCO_2eq)	References
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)
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.	30	- 92	Alig et al. (2015), Grandl et al. (2019), Schader et al. (2014)
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	3	116	Thomsen et al. (2010), Weiske et al. (2006), Wulf et al. (2002)
Introduction of feed additives	Introducing feed additives such as linseed reduces the CH_4-emissions from enteric fermentation by inhibiting methanogenesis in ruminants	18	339	Grandl et al. (2019), Hristov et al. (2013), Jayanegara et al. (2020)

[a] *Note*: Details on emission source, types, and factors in FarmDyn can be found in the ODD+D protocol (Section 4.5) and in Huber et al. (2023). Mean values are calculated from the emissions and costs of the 49 farms.

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Table 1 shows the four mitigation measures included in the model, the associated mechanism of GHG emissions reduction as well as main scientific references. 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).[3] 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/tCO_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/tCO_2eq and (b) 500 CHF/tCO_2eq reduced due to adoption of one or several mitigation measures.

3 | METHODS: AGENT-BASED MODELLING FRAMEWORK FARMIND

Our 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 (Tversky & Kahneman, 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, optimising or imitating behaviour) and a subsequent (non-)adoption of the income-maximising mitigation measure. This type of model is suited to address our research questions since it combines standard bio-economic modelling based on farm optimisation with farmers' social interactions while accounting for individual behavioural characteristics (Huber et al., 2018).

The key FARMIND outputs 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, Section 3.6).

3.1 | Agent characteristics

In FARMIND, each agent is characterised by three sets of state variables: (1) Farm specific costs and GHG emissions reduction potentials of four on-farm climate change mitigation measures. These are exogenous parameters calculated with the bio-economic farm level model FarmDyn, that is, a farm optimisation model parametrised with farm-specific census data (Britz et al., 2021; Huber et al., 2023). Based on the calculated GHG emissions reduction, mitigation costs are partly compensated by a payment of per ton of CO_2eq reduced. (2)

[3]In another contribution, we assess the effect of different payment designs on the adoption of climate change mitigation measures (Kreft, Finger et al., 2023).

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).[4] (3) A social network between farmers representing personal exchange of knowledge on climate change mitigation derived from a social network analysis based on face-to-face interviews (Kreft, Angst et al., 2023; Kreft, Angst, et al., 2021).[5] 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, Appendix S1).

Since the farm-specific costs and GHG emissions reduction potentials of the four mitigation measures are exogenous input parameters in FARMIND, we give a brief overview of the underlying data that were calculated in the sub-model FarmDyn. For more details on the distribution of GHG emissions and incomes, we refer the reader to the ODD+D protocol (Supplementary Material A). 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. However, total and per-unit emissions vary widely between farms. Although the average simulated income of farms without adoption of mitigation measures (baseline income) is at 142,000 CHF per year, there is large vsample (see Supplementary material A in the ODD+D protocol). Mean farm income per ha of agricultural land is 3374 CHF and 6378 CHF per cattle livestock unit. Marginal abatement costs of adopting measures (without payments) are lowest for increasing the number of lactations, where several farms even save net costs by introducing this measure. The second most cost-effective practice 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 2).

The greatest 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 also largest for the first two measures, 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 ODD+D protocol A4.5).

3.2 | Agents' decision-making and interactions

The 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

[4]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.

[5]The questionnaires, the dataset and codebook describing the variables are available in Kreft, Angst et al. (2021) as well as freely accessible on the ETH Zürich Research Collection: http://hdl.handle.net/20.500.11850/458053.

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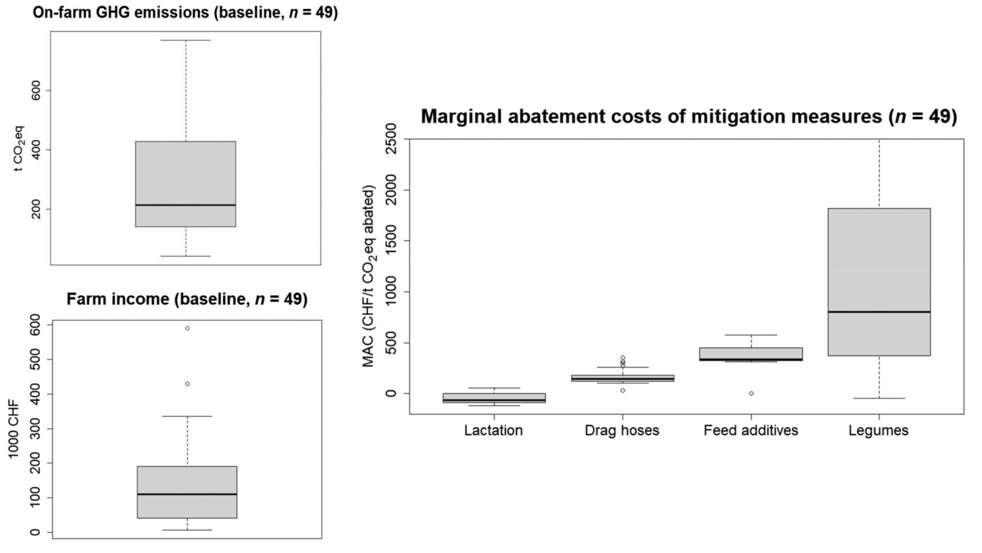

FIGURE 2 Distribution of baseline on-farm GHG emissions and farm income without adoption of mitigation measures as well as marginal abatement costs for adoption of measures without any payments. Lower and upper boundaries of the grey box represent the 25th and 75th percentiles, respectively. Lower and upper error lines represent the 10th and 90th percentiles. The horizontal line inside the box depicts the median.

choose a decision strategy, that is, repetition, optimisation, 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 their 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, that is, 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, that is, loss aversion, valuation of gains and losses and probability weighting (data based on 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:

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

The value functions in the gain (+) and loss (−) domains are:

$$v^+(x) = x_t^{\alpha^+} \text{ for gains and } \quad v^-(x) = \lambda\, x_t^{\alpha^-} \text{ for losses} \tag{2}$$

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The calculation of decision weight $\Phi(x_t)$ is based on the distribution of incomes from past income values. Assuming that historical incomes follow a 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:

$$\Phi_{x_t}^{+/-} = w^{+/-}\left[1 - F\left(x_t\right)\right] - w^{+/-}\left[1 - F\left(x_t + \Delta\right)\right], \tag{3}$$

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—for example, 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:

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

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—that is, 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—that is, 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 index is:

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

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 $P\left(A_j^i\right) = 0$ and 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). The dissimilarity index is calculated in each simulation run and may change for each agent depending on the decisions of their peers. Please note that the agents' dissimilarity index depends on the size of the network n and the number of activities in the network a. 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, Angst et al., 2023).

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, that is, not being different from others (i.e., the agent would be socially oriented). The tolerance level 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). This implies that the dissimilarity tolerance level is an individual attribute of each agent in the model, which is not changed

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during the simulation. The comparison between the dissimilarity index and the individual tolerance level results in a binary state, that is, either the agent is individually oriented (if the dissimilarity is lower than the tolerance level) or the agent is engaging in learning from observation and interaction with peers (if the dissimilarity is higher than the tolerance level).

Given the values for satisfaction and dissimilarity (and given the agents' social orientation), four heuristic strategies are derived based on the theoretical framework developed by Huber et al. (2022).[6] If a farmer is satisfied and individually oriented, they will abide by a production decision (Repetition). A satisfied farmer who is engaging in learning from observation and peers will search for additional information and start considering the behaviour they observe in their social network (Imitation). Those who are focusing on individual behaviour but are dissatisfied will strive to optimise their situation (Optimisation). Finally, the combination of dissatisfaction and social learning behaviour leads to an examination of the behaviour adopted by other agents outside the direct social network (an overview of all possible cases can be found in the 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 scrutinising for other solutions, which are expected to 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. Following Huber et al. (2022), a repeating agent considers only those measures that had been applied in the last simulation run. An optimising 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 opting for social learning processes and at the same time is 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, this strategy is implemented as 'non-adoption'. Thus, we follow Huber et al. (2022) and assume that farmers will consider different mitigation measures or even other production options observed in the wider social environment. The justification for this assumption is that agents who become unsatisfied after adopting a mitigation measure do not have to stick to this measure but would search for mitigation options that are not explicitly considered in the simulation framework.

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 outranking method (see, e.g., Dubois & Perny, 2016) 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. We then use the so-called non-dominance score (see Orlovsky, 1993) to endogenously determine a subset of the preferred measures (i.e., the best alternatives are cut off) which then enter the agents' choice set in the second tier of decision-making. This method accounts 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.[7]

[6]The framework described in Huber et al., 2022 was inspired by the CONSUMAT framework by Jager and Janssen (2012). Please note that the generic framework by Jager and Janssen (2012) provides a more holistic perspective on modelling decision-making and not all features discussed in the CONSUMAT are implemented in FARMIND. However, our chosen FARMIND approach captures the main mechanism used in our study on social networks and climate change mitigation, that is, to simulate individual satisfaction with an outcome (Jager & Janssen, 2012: 8) and socially oriented behaviour based on interacting with others and belonging to a group (Jager & Janssen, 2012: 6).

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

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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 maximise 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., 2021). This sub-model provides a matrix with all costs and potential GHG emissions reduction for all mitigation measures and their interactions for each agent.

3.3 | Simulation set-up and scenarios

We test and compare the effect of empirical and hypothetical social networks in four different scenarios, which compare the 'observed network' to counterfactual situations without social ties, with few ties and with a complete social network. The difference in total GHG emissions reduction between the counterfactual 'No social network' and the 'Observed network' quantifies the contribution of the network to overall GHG reduction. In addition, 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 initialisation of the model, we allow optimising agents in all scenarios to adopt initial mitigation measures (measures that would have been adopted by these agents in the absence of social networks). We simulate farmers' adoption decisions over several runs, each representing 1 year. In this period, agents endogenously choose a strategy and eventually adopt mitigation measures. We repeat the simulation over 12 runs (years) until FARMIND reaches a saturation state at which the number of mitigation measures does not change (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. The results of each model run are deterministic, that is, there is one result for each simulation over 12 runs. To consider the uncertainty of prices, we simulate 100 price vectors randomly selected from a uniform distribution of milk and beef price levels (see ODD+D protocol for details). This results in a certain randomness of the farmers' strategic choices based on the realised output prices over the whole simulation length. GHG emissions and income changes are based on the mean adoption pattern over these 100 simulations.

We repeat these simulations over each scenario (i.e., different social networks) and different payment levels for GHG emission reduction.[8] 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) 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 parameterisation given different potential pathways that result in the same level of adoption, that is, model equifinality (Williams et al., 2020). This implies that multiple structures and/or parameterisations in

[8]A replication package of our simulation is freely acccessible on the ETH Research Collection (http://hdl.handle.net/20.500.11850/613176)

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FARMIND exist, which 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 replicate the observed occurrence of adopted mitigation measures in our case study region, that is, the observed number of mitigation measures currently adopted by farmers.

In addition, we also checked the robustness of our simulation results by testing different assumptions with respect to the behavioural strategies (i.e., income maximisation and excluding the non-adoption strategy) and 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 | 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 increased from 330 tCO_2eq to 416 tCO_2eq with a small random network, to 603 tCO_2eq given the observed network and to 638 tCO_2eq under the assumption of a complete social network (Figure 3).[9] 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 raised 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 a similar 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 from 628 tCO_2eq without social networks to 1194 tCO_2eq (i.e., by 90%) when farmers are connected in the observed social network. At this payment level, a fully integrated social network reaches an additional 17% reduction of GHG emissions (to 1392 tCO_2eq) compared to the observed network, but with a small random network, 34% less GHG reduction (786 tCO_2eq) is achieved.

These findings reflect 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 maximisation), 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 90% in the scenario without social networks, by 98% in the observed network scenario and by 118% in the complete network scenario.

[9]A detailed overview of simulation results and percentage changes can be found in the supplementary material B including boxplots showing the distribution of GHG reduction and income changes across farms.

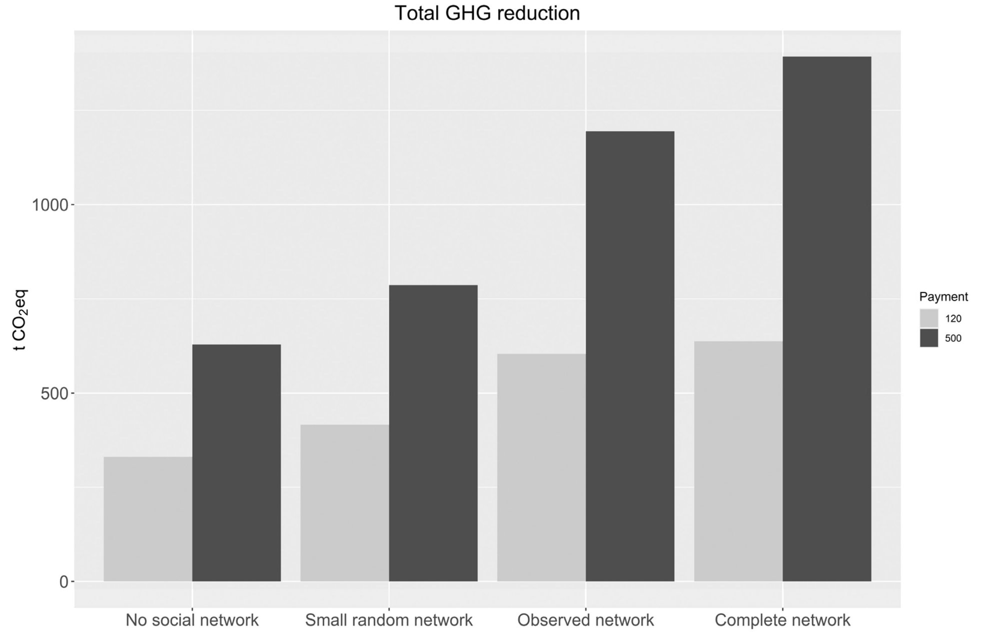

FIGURE 3 Total GHG reduction at two payment levels across all network scenarios. Grey bars correspond to GHG reduction at a payment of 120 CHF/tCO_2eq reduced. Black bars correspond to GHG reduction at 500 CHF/tCO_2eq reduced.

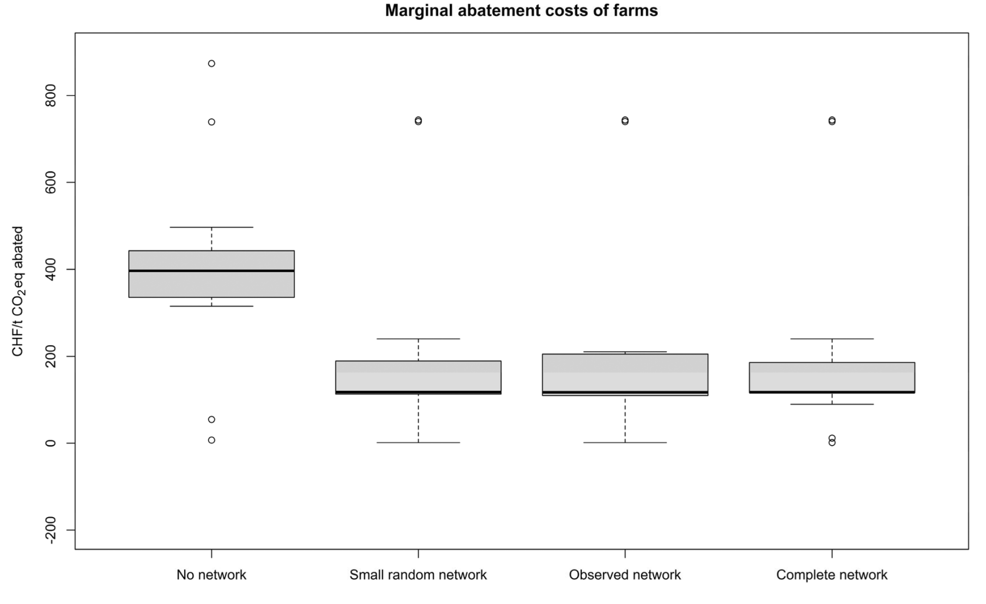

FIGURE 4 Distribution of marginal abatement costs of farms across the four network scenarios. To compare costs at a similar overall GHG reduction level (approximately 500 tCO_2eq), marginal abatement costs in the no network scenario are simulated based on a payment of 500 CHF/tCO_2eq, and on a payment of 120 CHF/t CO_2eq in the other scenarios where social ties are present.

This is also reflected by marginal abatement costs of on-farm mitigation in our simulation. Mean marginal abatement costs to achieve a similar amount of aggregated GHG reduction (approximately 600 tCO_2eq) are 183 CHF/tCO_2eq lower when farmers are socially

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interconnected in the observed network scenario. Without social network ties, mean marginal abatement costs are 377 CHF/tCO_2eq on average. In the observed and complete network scenario, marginal abatement costs amount to 194 CHF/tCO_2eq, respectively (Figure 4).

With regards to 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 a drag

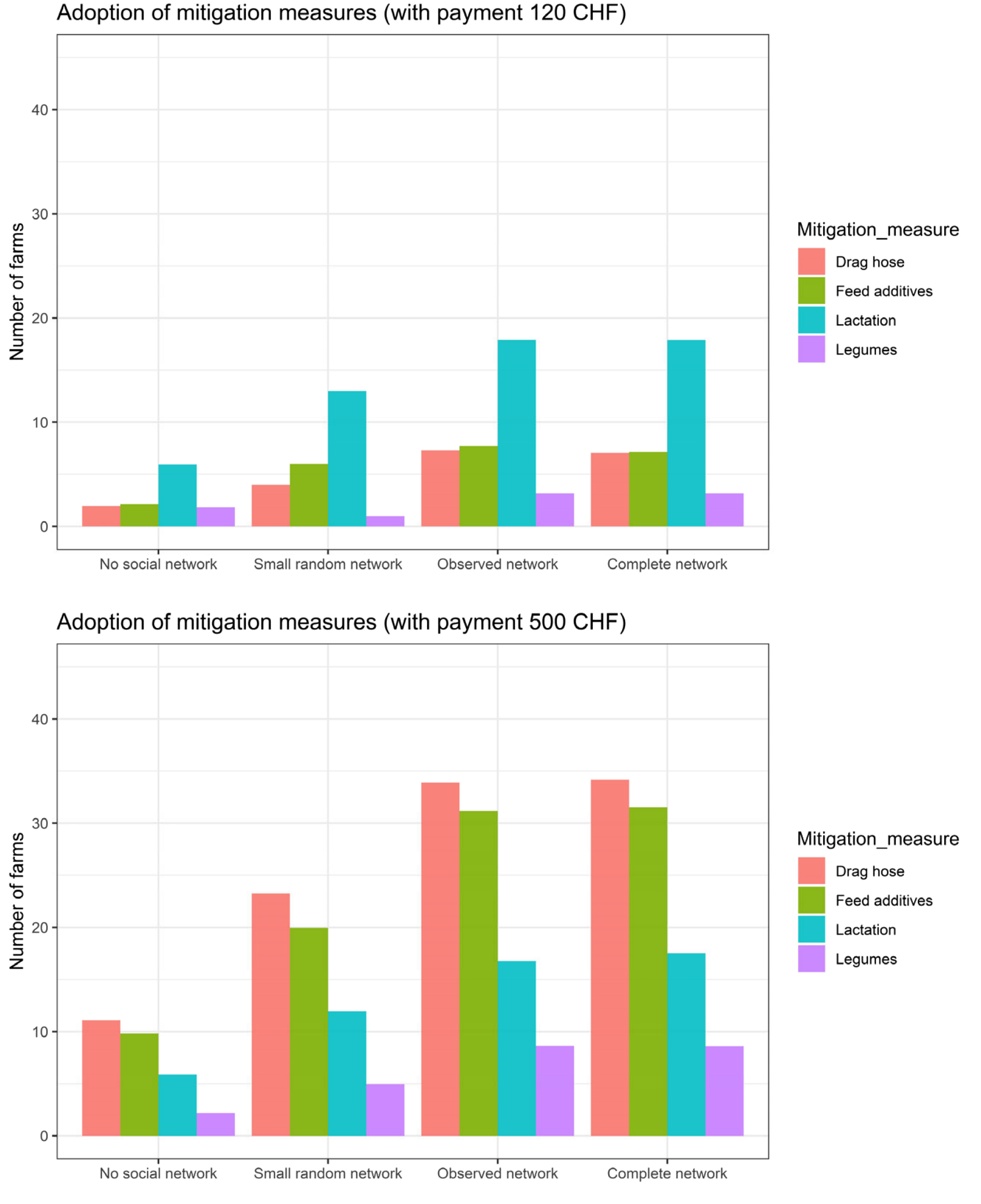

FIGURE 5 Adoption of mitigation measures in four network scenarios across the sample of 49 farms with payments of 120 CHF/tCO_2eq reduced (upper graph) and 500 CHF/tCO_2eq (lower graph). [Colour figure can be viewed at wileyonlinelibrary.com]

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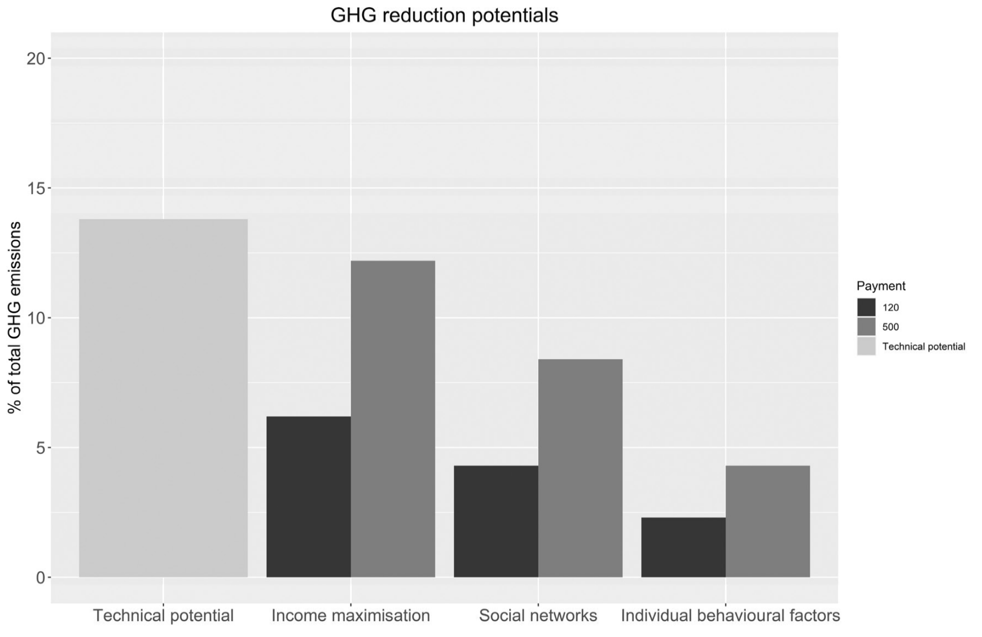

FIGURE 6 Comparison of GHG reduction potentials considering technical, economic, social and behavioural constraints. The technical potential is based on the here considered mitigation measures (cf. Table 1) without consideration of economic or behavioural constraints and with constant production levels.

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/tCO_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 that replace concentrate feeds by legumes is increased as well while the number of farms introducing more lactations per dairy cow remains stable.

The overall technical GHG reduction potential in our sample is simulated to be at 13.8% compared to baseline emissions, that is, a reduction of 1967 tCO_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 maximise incomes without behavioural constraints, the simulated reduction potential shrinks to 6.2% of baseline emissions at a payment of 120 CHF/tCO_2eq and 12.2% at 500 CHF/tCO_2eq. Accounting for individual behavioural characteristics (risk attitudes and farming preferences) further decreases the reduction potential in our model to 2.3% and 4.3%, respectively. Including social network ties increases overall reduction potential again to 4.3% and 8.4% of baseline emissions, respectively (Figure 6).

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

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in line with the literature investigating the effect of social networks and social learning on farmers' adoption of, for example, innovations or agri-environmental practices (Bandiera & Rasul, 2006; Conley & Udry, 2001; Conley & 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, that is, 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.

Farmers' social networks can act as facilitators of agricultural climate change mitigation by spreading knowledge and influencing farmers' preferences under given economic boundaries. This means that the effectiveness of a payment per ton of CO_2eq reduced can be substantially increased with knowledge exchange and social learning within farmers' social networks. In our sample, the observed social network increases mitigation by 83% at 120 CHF/tCO_2eq and by 90% at 500 CHF/tCO_2eq. The stronger network effect at 500 CHF/tCO_2eq 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. Compared to 120 CHF/tCO_2eq, a payment of 500 CHF/tCO_2eq increases mitigation by 90% without social networks and by 98% with the observed social network. 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.

Moreover, we find that social networks improve the cost-effectiveness of payments based on achieved GHG mitigation, that is, CHF 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 (−70%) due to the observed network. Given our modelling framework, this can be explained by the fact that due to knowledge exchange between connected peers, farmers that learn through observations and interactions with peers 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 been shown to lower transaction costs of, for example, knowledge acquisition (Levy & Lubell, 2018) and enable cost-effective collaboration of farmers (Prager, 2015). Although 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 optimisation simulated with standard bio-economic modelling, it also accounts for heterogeneous farmers' characteristics. Over the past decades, evidence is increasing that considering different behavioural traits is important when trying to explain farmers' decision-making in various contexts (Brown et al., 2017; Dessart et al., 2019; Schaub et al., 2023). 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 arguably play an even more decisive role (Haden et al., 2012; Kreft, Angst et al., 2023; Niles et al., 2016). Linking FARMIND to the bio-economic farm model FarmDyn furthermore allows the emerging changes in GHG emissions and farm incomes to be more completely considered.

Although there is a considerable technical reduction potential of the four mitigation measures (13.8% of baseline emissions), farmers' actual adoption is reduced 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

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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-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 to including farmers' behavioural characteristics and social interactions within an ABM is the need for a data intensive and usually costly parametrisation (e.g., Troost 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, Angst et al., 2023; Kreft, Angst, et al., 2021). However, despite the empirical data we rely on, our analysis rests on the conceptual underpinning of the model described in Huber et al. (2022) and 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., 2022). Although 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 to sensitivity analysis, for example, maintaining a set of parameter combinations for calibration (e.g., Troost & Berger, 2015) 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 generalisable, however, increasing the scale and the consideration of other regions is indispensable.

Second, the validity of our simulation builds on the theoretical arguments underlying the conceptual background of FARMIND (see, e.g., Troost et al., 2023). For example, we assume that farmers who are dissatisfied and eager to learn through observation and interaction with peers will search for activities beyond the four mitigation measures simulated in this study. This rests on the assumption that agents can reverse their adoption decision and may not stick to a mitigation measure if they become unsatisfied. We tested the consequences of this assumption in a robustness check of our simulations allowing dissatisfied agents that opt for social learning to remain with the options to adopt mitigation measures (for similar implementations of this strategy see, e.g., Malawska & Topping, 2016; Pacilly et al., 2019; van Duinen et al., 2016). Allowing unsatisfied farmer to remain with adopted measures increases the value of the social network in our simulations (see Supplementary material B). Given the same payment levels, the social network increases GHG mitigation by 26–46%. Thus, our main conclusion remains robust also under different operationalisations of the behavioural strategies in FARMIND.

Third, 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 (e.g., Huber et al., 2023; Jones et al., 2015; O'Brien et al., 2014). 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

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hand, 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, Pellerin, et al., 2018). For example, injection and close-to-ground application of manure, such as 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). Earlier 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 NH_3 (ammonia) volatilisation, 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 NH_3 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 parametrisation, 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, 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 & Nemecek, 2018). Hence, our assumed restriction to keeping constant production levels reflects a rather short-term perspective.

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 make 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. The main mechanism is that socially oriented farmers can observe the adoption of mitigation measures of their peers. 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.

The use of empirically rich agent-based models such as FARMIND come with an important limitation. The validity of our simulation builds on the theoretical arguments outlined in the conceptual background of FARMIND. Although our approach includes a broad range of behavioural factors using a unique combination of survey, social network and farm structural data, the model remains an abstraction of the reality and not all behavioural drivers could be considered here. Nevertheless, our findings are robust with respect to different implementations of behavioural strategies and parameterisations.

Our results have some important implications for policy-makers. First, in addition to financial incentives compensating for the costs of mitigation, policy-makers 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 incentivise 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 organisation of farm visits or regional workshops and events to support informal exchange. According to our simulations, such programmes 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 training offered to farmers. The topic should also be integrated in regular curricula of farming schools. A combination of policies could 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 needed to underpin our findings and recommendations and make them more generalisable. In this context, our findings are confined to the scope of our conceptual boundaries. Comparing our approach to different operationalisations and social network theories would be an important next research step. Moreover, including additional behavioural drivers in 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, for example, 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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