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Can information framing increase farmers' uptake of Eco-schemes? a randomised controlled trial

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Abstract

The overall success of voluntary agri-environmental programmes often hinges importantly on the level of farmer participation. Their enrolment decisions are shaped by a complex set of behavioural factors, which can be targeted by designing specific behavioural interventions—such as nudges—that aim to improve farmers' uptake of these schemes. However, the effectiveness of these approaches in real-world settings remains understudied. Here, we use two subsequent randomized controlled trials to evaluate the effect of information treatments on farmers' enrolment rates and enrolled area in a new Eco-scheme for establishing Skylark plots, which has been implemented as part of the EU's Common Agricultural Policy in Slovenia. The first trial framed enrolment as an environmental gain or loss, while the second trial framed enrolment as a negative or positive descriptive norm. In both trials, interventions had no direct effect on enrolment rates nor on the area enrolled. However, for large farms and for farms with prior enrolment in agri-environmental measures, interventions influenced the enrolment decision and the area enrolled. Our results imply that the provision of untargeted information framing alone may be insufficient to boost enrolment of all farmers in agri-environmental measures. However, such interventions may affect the behaviour of some groups of farmers. To improve enrolment, we recommend better targeting of behavioural interventions, coupled with system-level changes.

Keywords: Randomized controlled trial, Voluntary agri-environmental schemes, Nudges, Social norms, Gain–loss framing

Introduction

Sustainable use of natural resources and biodiversity conservation in agricultural ecosystems largely depends on voluntary agri-environmental schemes (AES) where farmers get paid for enrolling and conducting specific environmentally-friendly practices (Hasler et al. 2022). Such schemes include, for example, the Conservation Reserve Programme in the USA and Agri-environmental-climate measures (AECM)¹ and Eco-schemes in the European Union's Common Agricultural Policy (CAP) (Matthews 2013; Pe'er et al. 2022; Baylis et al. 2022). One of the limiting factors in the ability of such schemes to reach

¹ We distinguish in the rest of the manuscript between Agri-environmental schemes (AES) and agri-environmental-climate measures (AECM). While the first refer to all types of voluntary environmental programmes for farmers, AECM is a specific AES programme in the European Union.

environmental objectives is farmers' enrolment rate, as it is often relatively low, particularly for more demanding measures (Alliance Environment 2019; Buschmann and Röder 2019).

Improving information access, often achieved with information campaigns, is positively associated with farmers' enrolment into AES. They can increase enrolment by reducing farmers' transaction costs through making information more readily available (Canessa et al. 2024). Additionally, information campaigns can also increase alignment between the objectives of measures and farmers' perceptions by filling knowledge gaps and building trust (Taylor and Van Grieken 2015). However, their impact may also depend on contextual factors, including behavioural and socio-psychological variables (Schulze et al. 2024; Canessa et al. 2024). For example, evidence shows that provisioning of information by public agencies seems to be more effective than information campaigns run by extension services or financial entities (Canessa et al. 2024). Information campaigns can also serve as behavioural change tools by presenting information in ways that activate psychological drivers to encourage desired behaviours (Michie et al. 2008). An increasingly popular example of such tools are nudges, which influence behaviour by changing how information and choices are presented—without altering economic incentives (Thaler and Sunstein 2008). Nudges, therefore, tend to be simple interventions that can be implemented within existing policy programmes and are often also relatively cheap in terms of budgetary investment (Ferraro et al. 2017). Although nudges offer several appealing characteristics, their effect sizes remain uncertain—largely due to publication bias in the broader behavioural science literature (Mertens et al. 2022; Maier et al. 2022)—while the agricultural sector, in particular, still lacks rigorous experimental studies (Thoyer and Préget 2019; Ferraro and Messer 2025).

This study builds on two specific types of nudges: gain/loss framing and descriptive social norms. Gain or loss framing is based on prospect theory, which describes the decision-making under risk and shows that the pain humans experience from a loss is greater than the pleasure they derive from a gain of equal value (Kahneman and Tversky 1979). The predictions of prospect theory have been confirmed not only in consumers (Ruggeri et al. 2020), but also across European farmers from numerous countries, who are risk and loss averse, and underweigh large and overweigh small probabilities (Rommel et al. 2023; Finger et al. 2024). Nudges that frame information as a loss have successfully induced behavioural change both for private benefits (such as personal health) (Macapagal et al. 2017) as well as for public goods, including pro-environmental behaviour in consumers (Ropret Homar and Knežević Cvelbar 2021). While this framing effect has been widely validated in consumer behaviour, evidence from farmers, who make complex, risk-based decisions in business contexts, remains limited (Dessart et al. 2019).

As a social norm construct, descriptive norms describe the prevalent behaviour of others by statements such as “most people in this town cycle to work”. Findings within consumer behaviour research suggest that descriptive norms influence behaviour by representing a shortcut that reduces the cognitive effort in decision-making. This makes descriptive norms particularly effective in unfamiliar or uncertain situations (Cialdini 1998, 2009; Griskevicius et al. 2006; Jacobson et al. 2011). The effect of descriptive social norms depends on their positive or negative framing. A study by Cialdini et al. (2006) for example showed that positively framed descriptive norms (e.g. “The vast majority

of past visitors have left the petrified wood in the park, preserving the natural state of the Petrified Forest”) reduced the theft of petrified wood from a US national park. By contrast, negatively framed descriptive norms (e.g. “Many past visitors have removed the petrified wood from the park, changing the state of the Petrified Forest”) increased petrified wood theft from a US national park. Such a negative effect is called a boomerang effect and possibly arises due to moral licensing of such grey behaviour. Similar results have been replicated in a study examining healthy food choices (Mollen et al. 2021).

Social norms have been widely studied in economics and psychology, with interventions based on this nudge being used to change behaviour in health, social and environmental domains (Nyborg et al. 2016; Farrow et al. 2017; Dannenberg et al. 2024). Social norms also have a strong effect on farmers’ decisions regarding enrolment into AES, as shown by numerous studies (Burton 2004, 2013; Defrancesco et al. 2008; Villamayor-Tomas et al. 2019; Westerink et al. 2020; Klebl et al. 2023). In an experimental survey study, Kuhfuss et al. (2016) found that while including a descriptive norm increased farmers’ intentions to enrol into an AES, norm framing had no effect. A social comparison nudge decreased enrolment into an AES in a RCT conducted by Chabé-Ferret et al. (2023). Another RCT showed that a nudge providing information on individual and group consumption of irrigation water decreased the consumption of those irrigating the most. However, on average, the nudge also increased irrigation among those who did not consume any water before (Chabe-Ferret et al. 2019). Using an RCT to compare the effectiveness of a full information and average information social norms, Raineau et al. (2025) showed that only average information had a positive, but short-term, effect on optimising pesticide use. Overall, these studies show considerable variability regarding the effectiveness of social norm-based nudges.

Despite the theoretical appeal and cost-effectiveness of nudging, evidence of its effectiveness in the context of agri-environmental policy is lacking and inconclusive. Most existing studies have been conducted in consumer or public goods contexts, or have used hypothetical settings or small-scale experiments (Ropret Homar and Knežević Cvelbar 2021). There is a lack of large-scale, real-world evidence from farming populations—particularly regarding how farmers respond to behavioural interventions embedded in actual policy implementation (Lefebvre et al. 2021). Specifically, little is known about how gain/loss framing influences enrolment decisions in complex agri-environmental schemes (Ferraro et al. 2017), and no existing study has experimentally tested the impact of positive vs. negative framing of descriptive norms on farmers’ actual behaviour.

To rigorously assess the behavioural impact of nudges, randomised controlled trials (RCTs) offer a robust methodological approach by allowing causal inference through random allocation of treatments (Glennerster and Takavarasha 2013). Given the wide range of factors that affect farmers’ enrolment into AES (Schaub et al. 2023; Schulze et al. 2024; Sander et al. 2024; Canessa et al. 2024), establishing causality between a nudge and behavioural change with RCTs is especially valuable. Even though RCTs are considered the “gold standard” of economic research, there are only a handful of studies where they have been used to evaluate agri-environmental policy interventions in the developed world. In the USA, Wallander et al. (2017, 2023) showed that providing default options and sending reminder letters increased enrolment in US conservation auctions while anchoring affected the value of bids (Ferraro et al. 2024). The only RCT

evaluating EU's CAP policy interventions, to our knowledge, is the before-mentioned study by Chabé-Ferret et al. (2023) examining the impact of social comparison nudge and pre-paid postage envelopes. Although loss framing has previously been suggested as promising for encouraging enrolment into voluntary AES (Ferraro et al. 2017; Behaghel et al. 2019), this nudge has not yet been tested in agricultural context. Thus, both the external validity of behavioural theories in agricultural contexts and their policy relevance remain open questions.

To address these gaps, we implemented two randomized controlled trials (RCTs) to test the effectiveness of two information nudges on farmers' enrolment into a new eco-scheme for establishing Skylark plots² in Slovenia. In both experiments, the Slovenian Ministry for Agriculture, Forestry and Food (hereafter: the Ministry) sent standard information letters to all 4500 farmers who were eligible to enrol in the scheme. We used this campaign to set up a field experiment where we randomly assigned farmers to three groups that received differently framed letters. In the first trial, we examined the effect of gain and loss framing on enrolment, with two letters describing the consequences of enrolling as a gain or not enrolling as a loss for biodiversity conservation, compared to a control letter not mentioning these consequences. In our second trial a year later, we again set up a field experiment where the Ministry sent information letters to the same 4500 eligible farmers (except any that may have stopped farming in the meantime). We used positive and negative framing of descriptive norms that describe the desired behaviour (enrolment into the eco-scheme) as frequent or rare.

The objective of this study is to experimentally evaluate how two specific information-based behavioural interventions—gain/loss framing and positive/negative descriptive norm framing—influence farmers' decisions to enrol in a newly introduced eco-scheme under the EU's Common Agricultural Policy. Drawing on Prospect Theory and social norm theory, we examine whether these nudges affect uptake by altering how farmers perceive the environmental and social consequences of their decision. In doing so, we also assess the broader question of whether carefully framed policy communications can increase participation in voluntary AES programmes. By embedding these interventions into a real-world policy communication campaign and by using random assignment, we isolate the causal impact of the nudges and contribute to ongoing debates about the external validity and practical relevance of behavioural interventions in agricultural policy.

This study makes three key contributions to the literature. First, it provides rare real-world experimental evidence on the use of behavioural interventions in the context of the EU's agri-environmental policy. Second, it is, to our knowledge, the first field experiment to test gain/loss framing and descriptive norm framing (positive vs. negative) in AES enrolment. Third, our findings help clarify how the effects of nudges interact with other behavioural, agricultural and demographic variables. The results have practical implications for the design of more effective and behaviourally informed policy communication. The rest of this paper is structured as follows. In the next section, we present the context of our study. In Sect. "Material and methods", we describe the experimental

² Skylark plots are small patches (ca. 25 m²) of unsown ground on arable land that provide feeding and mating habitats for the Eurasian skylark. They are described in more detail in Context.

design and intervention and explain the empirical specification. In Sect. "[Results](#)" we describe the results and discuss them in Sect. "[Discussion](#)". In the final section, we summarise our findings and policy implications.

Context

In the 2023–2027 policy period, Eco-schemes were introduced as a new agri-environmental policy instrument within the CAP (Regulation (EU) 2021/2115, [2021](#)). Similarly to long-established Agri-environmental-climate measures (AECM), Eco-schemes are targeted CAP instruments that aim to achieve specific environmental goals (Pe'er et al. [2022](#)). Both Eco-schemes and AECM offer farmers fixed payments for implementing environmental measures. However, an important difference between the two is in the contract duration—while Eco-schemes are annual measures, AECM contracts are usually five years long. The effectiveness of both instruments in delivering environmental improvements will largely depend on achieving sufficient enrolment of farmers as well as continuation of their enrolment in the case of short-term Eco-schemes (Röder et al. [2024](#)).

One of the key EU environmental policy objectives is to halt biodiversity loss and improve the conservation status of protected species and habitats (European Commission [2020](#)). Despite numerous AES targeting farmland biodiversity, farmland bird species have been experiencing rapid population declines across the EU and in Slovenia (PECBMS [2022](#); Kmecl et al. [2023](#)). One of the most rapidly disappearing species in Slovenia is the Eurasian skylark (*Alauda arvensis*), whose population has decreased by 63% in the last 15 years (Kmecl et al. [2023](#)). High-density and fast-growing winter crops in intensively used agricultural areas, where skylarks struggle to find sufficient bare ground to feed and mate, are among the key causes for the species' poor breeding success (Chamberlain et al. [1999](#)). To address this issue, a targeted measure called "Skylark plots" was developed and successfully tested in several countries in Europe, where skylark habitat was improved by providing small patches of unsown ground on arable fields (Donald and Morris [2005](#); Fischer et al. [2009](#)).

In Slovenia, an Eco-scheme for establishing Skylark plots (hereafter: Skylark scheme) was introduced in 2023 for the first time. In the Skylark scheme, farmers are required to provide unsown patches on arable land, where cereals, oilseed rape, clover, crimson clover, or clover grass mixture are cultivated on the rest of the field. Each plot needs to be at least 25 m² large and at least 2.5 m wide, and should be provided at a density of one plot per half a hectare. Therefore, only about 0.5% of the cropping surface is usually lost per hectare. Additionally, while the use of herbicides and pesticides on the plots is discouraged, it is permitted when there is trouble with weeds. The establishment of Skylark plots is relatively easy for farmers and is usually done while sowing by switching off the sowing machine for several meters. As many eligible crops in Slovenia are sown in autumn, Skylark plots are most likely to be established during this time. However, formal enrolment into the scheme takes place in the following spring when farmers submit their annual CAP subsidy application. The payment agency then processes the payment of 60€ per ha (30€/patch) in late summer. There are no other administrative requirements. All enrolled farmers are controlled by remote sensing, and a sample is randomly selected for an additional control on the ground.

The scheme is implemented in five Slovenian lowland regions where skylarks feed and nest predominantly on arable land. In total, there are 37,852 ha of eligible arable land. However, since only arable land sown with specific crops can be enrolled, the actual area of eligible land is smaller and varies from year to year due to crop rotation. For example, in 2022, 16,787 ha (45%) of eligible land was sown with eligible crops. The contract duration for farmers is one year, which means all farmers, regardless of their previous enrolment, must decide annually whether to participate. In this way, enrolment in consecutive years and the location of plots may change based on the crop rotation practices of each farm.

Prior to implementation of the Eco-scheme, Skylark plots were tested on five farms, and field excursions were organised to demonstrate the practice and train agricultural advisors (Alif et al. 2024). Very few eligible farmers were aware of this practice before its implementation in the Slovenian National CAP strategic plan in 2023, and no similar schemes were available previously (MKGP 2023). Given that most farmers would find it the easiest to create the plots in autumn 2022, i.e. before the official introduction of the new CAP plan in January 2023, it was important for the Ministry to inform farmers about the scheme in advance to facilitate enrolment during the first year of scheme implementation. The enrolment targets outlined in the national strategic plan were set at 2,000 ha for 2023, 3,000 ha for 2024 and 4,000 ha for each subsequent year.

Material and methods

Intervention

We conducted the RCTs in two consecutive years, using the same design and procedure. In September 2022 (Experiment 1) and in September 2023 (Experiment 2), the Ministry sent information letters (which can be found in Supplementary information A and B of this paper) to all eligible farmers to raise farmers' awareness about the Skylark scheme and to invite them to enrol. The letters were sent just before the winter crops are usually sown, as most farmers would find it easiest to make the plots at that time (Fig. 1). While enrolment to the scheme was only available the following spring, the letters informed farmers of the general conditions of the Skylark scheme. To ensure fair access to information, we purposefully sent letters with identical information to all farmers, except for a short manipulated message in the middle or at the end of the letter that did not convey any essential information regarding the requirements and implementation of the scheme.

In each RCT, individual farms as experimental units were randomly assigned to three equally sized treatment arms: a control group that did not receive framed information,

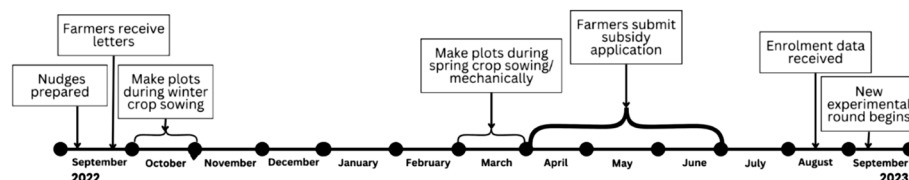


Fig. 1 Timeline of the experiment and enrolment into the scheme. The timeline was the same for both years, in which we conducted the experiment

Table 1 Framed messages used in information letters (note: the original text in Slovene was not bolded)

2022	<u>Gain framing:</u> “By implementing this scheme on your arable land, the breeding conditions for Skylark can improve and, hence, increase the chance for its chicks’ survival. Therefore, by implementing this scheme, you are contributing to the increase of the population of this endangered bird species and to biodiversity conservation in the Slovenian countryside.”	<u>Loss framing:</u> “By not implementing this scheme on your arable land, the breeding conditions for Skylark can deteriorate and, hence, decrease the chance for its chicks’ survival. Therefore, by not implementing this scheme, you are contributing to the decline of the population of this endangered bird species and to a biodiversity loss in the Slovenian countryside.”
2023	<u>Positive descriptive norm:</u> “In 2023, farmers in this area enrolled as much as 1,041 ha into the scheme and provided more than 2,000 Skylark plots.”	<u>Negative descriptive norm:</u> “In 2023, farmers in this area enrolled only 1,041 ha into the scheme and provided less than 2,100 Skylark plots.”

and two treatment groups that i) received gain and loss framed messages in Experiment 1 and ii) positively and negatively framed descriptive norms in Experiment 2.

In Experiment 1, we tested a nudge that framed enrolment into the scheme as a gain or a loss for the skylark population and nature conservation in Slovenia. There are three types of gain or loss framing, namely risky choice framing, attribute framing and goal framing. In risky choice framing that was originally researched by Kahnemann and Tversky (1979), the selection is between a “safe” choice that guarantees a certain success rate (e.g. 25% will survive the disease), and a risky choice with the same average outcome (e.g. 25% probability that all people survive and 75% that no one survives). This choice can be framed as a gain (the example above) or a loss (e.g. 75% of all people will die or 75% chance that everyone dies). In attribute framing, a specific characteristics of an object is described positively or negatively. Finally, goal framing emphasises gain or loss as a consequence of a specific action and is most commonly used (Levin et al. 1998). There are multiple permutations of messages in goal framing: in a positive frame, one can avoid loss (won’t-bad) or obtain gain (will-good), while in a negative frame, one can forego gain (won’t-good) or suffer loss (will-bad) (Levin et al. 1998). In both loss and gain framing, appeals that describe the action (will-good and will-bad) have been more effective in previous studies, possibly because individuals perceive the action to have an impact by itself (Patt and Zeckhauser 2000; Ropret Homar and Knežević Cvelbar 2021). In our intervention, farmers in two treatment groups received either a will-good (gain) framed message or a won’t-bad (loss) framed message (Table 1), while farmers in the control group received the information letter without any description of the consequences of their enrolment. Based on the literature review, we hypothesised that the farmers who received the loss-framed message would enrol more frequently than farmers in the other two groups. The experiment was preregistered on Aspredicted.³

In Experiment 2, a nudge based on descriptive norm framing was tested. The Ministry again sent information letters to all eligible farmers, where in addition to the material on the scheme the control group received, farmers in the two treatment groups were also provided with information on enrolment rates in the first year. In each group, the enrolment level was framed as high or low, respectively (Table 1). Based on previous studies,

³ Pre-registration can be found on <https://aspredicted.org/k6xy-6mvh.pdf>. Due to the very low response rate to the survey mentioned in the pre-registration, we did not include analyses related to the survey to this manuscript.

we expected positive descriptive norms to increase enrolment rates compared to both other groups (Mollen et al. 2021), while negative descriptive norms would have no effect. The experiment was pre-registered in the Centre for Open Science repository.⁴

Study samples

Our sample consisted of all farms in Slovenia that were eligible to enrol in the Skylark scheme. In Experiment 1, our sample included 4586 farmers, of which 1528 were in the control group, 1530 in the gain-framed group and 1528 in the loss-framed group. In Experiment 2, 1517 farmers received control letters, 1514 received positively framed letters and 1517 farmers received negatively framed letters, totalling 4548 recipients. The randomization was independent in both years and stratified by the five regions where the Eco-scheme is available (Ljubljansko barje, Ljubljanska kotlina, Krško-Brežiško polje, Dravsko-Ptujsko polje and Pomurje). As we relied on official data on enrolment, attrition could only occur with those farms that did not submit their annual subsidy application, but who would then also be unable to participate in the Skylark scheme or any other AECM/ Eco-scheme. As such cases were rare and likely due to discontinuation of farming, we consider our dataset complete.

Enrolment data for both experiments were obtained from the Ministry. The data included the area each farmer enrolled into the Skylark scheme, enrolment into AECM, enrolment into other Eco-schemes (only available in Experiment 2), total farm area and total area of eligible arable land for Skylark scheme, livestock units/ha, geographical region, gender and age.

Analysis

To evaluate the effectiveness of the framing treatments, we started by using a three-sample test of proportions to compare percentages of enrolment by treatment. We then used the Kruskal–Wallis non-parametric test to investigate if the median for treated and untreated units is the same. Next, we used a hurdle regression model, as this model aligns with the two decision-making processes that farmers undertake. To maximise their utility, farmers first decide whether to enrol into the scheme. If they decide to enrol, this influences their utility maximising choice regarding the amount of land to enrol. While the second decision is conditional on the first, this approach does not assume equality of covariate coefficients, i.e. a particular independent variable may have a certain effect on the decision to enrol, but a different effect on the amount of land to enrol. This matches the log-likelihood of a hurdle model, which is a sum of two separate log-likelihood functions, one modelling the probability of a binary process (zero versus positive outcomes), and the other being the log-likelihood function of the truncated-at-zero model:

$$f_{\text{hurdle}}(y; x, z, \beta, \gamma) = \begin{cases} f_{\text{zero}}(0; z, \gamma), & \text{if } y = 0 \\ (1 - f_{\text{zero}}(0; z, \gamma)) \cdot f_{\text{gamma}}(y; x, \beta) / f_{\text{gamma}}(0; x, \beta), & \text{if } y \geq 0 \end{cases}$$

⁴ The pre-registration can be found on <https://doi.org/10.17605/OSF.IO/CXV3G>. To examine the effect of the treatments, we opted for non-parametric rather than parametric tests (chi-squared and t-test) that were mentioned in the pre-registration due to non-normal data distribution.

(1)

Where β and γ are model parameters and x and z are covariates in the logistic and gamma regression model, respectively. The gamma distribution was used in the conditional part of the model due to the continuous but left-skewed nature of the enrolment data (Supplementary information C).

We conducted three different hurdle models. In the first model, only the treatment group was included as a predictor. In the second model, gender, age, livestock density, enrolment in AECM, enrolment in other Eco-schemes (only in 2024), and area of eligible arable land that were obtained from the Ministry (see Sect. "Study samples") were included in the model for control purposes. In the third model, interactions between covariates and a treatment group were included as a part of exploratory analysis. We included the covariates listed above in the regression analyses to better understand their influence on enrolment decisions. This knowledge can be used for future message targeting, whereby the alignment of message discourses (e.g., a focus on economic vs. nature conservation consequences) with farm characteristics may lead to increased effectiveness of interventions for different types of farms (as was done in e.g. Offord-Woolley 2017). As we had no prior beliefs about the effect of farm characteristics on enrolment in the second and third models, all covariates and interactions were included in both parts (enrolment decision and area enrolled) of the model.

We tested four hypotheses in each hurdle model (e.g., Treatment 1 vs Control and Treatment 2 vs Control in both enrolment decision and enrolled area model parts). Consequently, we applied Bonferroni correction for multiple testing, considering p-values below 0.0125 as significant for direct treatment effects in both model parts. As covariates and interactions were used for control and exploratory analysis, we did not adjust the p-value for them and used $p=0.05$ as the statistical significance threshold.

As the Skylark scheme first became available in 2023, all farmers in Experiment 1 had the same base state of non-enrolment. However, in Experiment 2, some farmers had already enrolled in the scheme. The treatment in Experiment 2 may thus have affected their decision to enrol differently from those farmers who had not enrolled in the first year. We, therefore, split farmers according to their enrolment status in 2023 (not enrolled vs enrolled) and ran a separate logistic regression for each group to compare the impact of treatments in Experiment 2 on (re)enrolment decision where the dependent variable was binary, with value 1 if a farmer enrolled in the scheme in 2023 and 0 if they did not, as shown in Eq. 2.

$$\ln \left(\frac{p}{1-p} \right) = \beta_0 + \beta_1 m_i + \beta_2 n_i + \beta_3 g_i + \beta_4 l_i + \beta_5 AEM_i + \beta_{10} Arable_i + \beta_{11} Gender_i + \beta_{12} Age_i + \beta_{13} livestock_i \quad (2)$$

where i denotes the i^{th} individual farmer, and m is the indicator variable which takes the value of 1 if the farmer received a positively framed descriptive norm, and 0 if otherwise. n is an indicator variable which takes the value of 1 if the farmer received a negatively framed descriptive norm, and 0 otherwise. g and l are indicator variables that take the value of 1 if the farmer received gain-framed or loss-framed message in 2022, respectively, and 0 if the farmer was in control group in 2022. All other variables are covariates included to examine other determinants of enrolment and include enrolment into

AECM and other Eco-schemes (not including the Skylark Eco-scheme), size of eligible arable land, gender, age and livestock units/ha.

After running regression models, average marginal effects of treatments were estimated for all models. Additionally, plots of average predicted probabilities were produced for all interaction terms to compare the effects of treatment in different population subgroups.

Results of the power analysis using the R package *pwrss* (Bulus 2023) show that with our sample size of around 4500 farmers, we have sufficient power (>0.8) to detect any impact of the intervention when its standardized effect size is larger than 0.225 (logistic regression coefficient) for enrolment rate. For the conditional part of the hurdle model, the power analysis could only be conducted ex-post, as we did not know what the sample size (e.g. the number of enrolled farmers) would be in advance.

The analyses were done in R version 4.2.1. (R Core Team 2022), using package *glmTMB* for gamma hurdle models (Brooks et al. 2017) and package *marginalEffects* for average marginal effect estimation (Arel-Bundock et al. 2024).

Results

Experiment 1

In 2023, only 110 out of 4,357 farmers enrolled into the Skylark scheme, together providing plots on 1004.3 ha of arable land. In gain treatment (1437 farms), 32 farmers enrolled 442.0 ha, in loss treatment (1460 farms), 35 farmers enrolled 275.0 ha and in the control group (1460 farms), 44 farmers enrolled 292.0 ha of land. 220 farmers who received the letter did not submit their subsidy application. There were no statistically significant differences in the characteristics of the three experimental groups (Table 2). The distribution of all population variables can be found in Supplementary information D. Three-sample test of equal proportions showed no statistically significant differences in enrolment rates between the three treatment groups ($\chi^2 = 2.16$, $df = 2$, $p\text{-value} = 0.339$), while Kruskal–Wallis test shows that there were also no statistically significant differences in area enrolled among the three groups ($\chi^2 = 2.12$, $df = 2$, $p\text{-value} = 0.347$).

Given our sample size for the conditional part of the hurdle model (110 farmers) and standard deviation in the area enrolled, we only have sufficient power (>0.8) for detecting effects (unstandardized linear regression coefficient) larger than 8.4 when no covariates are included in the model. Given the coefficient sizes we detect, our study is significantly underpowered for conditional parts of all hurdle models due to the low enrolment of farmers.

We find that in hurdle model 1, where no covariates are included, our treatments had no statistically significant effects on the decision to enrol (Table 3 (A)) and extremely small marginal effects (probability of enrolment for gain and loss treatment was reduced by 0.6% (95% CI -1.95, 0.38) and 0.6% (95% CI -1.85, 0.05), respectively). However, gain framing statistically significantly increased the amount of land enrolled (Table 3 (B)) with an average marginal effect of 7.18 ha (95% CI 1.67, 12.68) of more land enrolled. Loss framing had no statistically significant effect and a much lower average marginal effect (1.32 ha (95% CI -2.21, 4.84) of land additionally enrolled).

In model 2, where covariates were also included, neither of the two treatments had a statistically significant effect in either the zero-inflated (decision to enrol) or conditional

Table 2 Demographic and farm characteristics of all farmers (regardless of their enrolment) in the three experimental groups in Experiment 1

Characteristic	Overall n = 4357 ¹	Control n = 1460 ¹	Gain n = 1437 ¹	Loss n = 1460 ¹	p-value ²
Age	59.3, 60.0 (14.1)	58.8, 59.0 (13.8)	59.2, 60.0 (14.5)	59.9, 60.0 (13.9)	0.087
Gender					0.6
Male	3266 (75.0%)	1069 (74.4%)	1088 (75.5%)	1109 (76.0%)	
Female	1091 (25.0%)	368 (25.6%)	372 (25.5%)	351 (24.0%)	
Eligible arable land	7.3, 3.2 (14.5)	7.5, 3.2 (14.4)	7.4, 3.3 (14.5)	7.2, 2.9 (14.5)	0.8
Farm size	15.2, 7.5 (26.7)	15.3, 7.8 (22.9)	15.7, 7.6 (34.0)	14.6, 7.2 (21.6)	0.5
Region					> 0.9
Dravsko-ptujsko polje	794 (18.2%)	264 (18.4%)	267 (18.3%)	263 (18.0%)	
Krško-brežiško polje	354 (8.1%)	117 (8.1%)	119 (8.2%)	118 (8.1%)	
Ljubljanska kotlina	446 (10.2%)	147 (10.2%)	151 (10.3%)	148 (10.1%)	
Ljubljansko barje	235 (5.4%)	74 (5.1%)	79 (5.4%)	82 (5.6%)	
Pomurje	2528 (58.0%)	835 (58.1%)	844 (57.8%)	849 (58.2%)	
Livestock units/ha	0.5, 0.1 (0.9)	0.5, 0.1 (0.8)	0.5, 0.1 (1.1)	0.5, 0.1 (0.8)	0.7
Agri-environmental climate measure enrolment					0.4
Yes	1,541 (35.4%)	515 (35.8%)	497 (34.0%)	529 (36.2%)	
No	2834 (64.6%)	922 (64.2%)	963 (66.0%)	931 (63.8%)	
Enrolled farmers	110 (2.5%)	44 (3.0%)	32 (2.2%)	34 (2.3%)	0.3
Area enrolled	0.2, 0.0 (2.6)	0.1, 0.0 (1.8)	0.3, 0.0 (3.5)	0.1, 0.0 (2.2)	0.4

¹ n (%); Mean, Median (standard deviation)² One-way ANOVA / Pearson's Chi-squared test for differences between groups

(enrolled area) part of the model. Their average marginal effects were of similar magnitude as in model 1, as they decreased the probability of enrolment for 0.7% (95% CI – 2.59, 0.09) and 0.25% (95% CI – 1.72, 1.22) and increased the amount of land enrolled by 3.1 ha (95% CI – 2.59, 8.73) and 0.6 ha (95% CI – 3.16, 4.37) for gain framing and loss framing, respectively.

In model 3, where all interactions were also tested, neither treatment had a statistically significant effect on the decision to enrol and average marginal effects were similarly small (– 1.23% (95% CI – 2–56, –0.11) for gain and – 0.03% (95% CI – 1.74, 1.20) for loss framing, respectively). After correcting for multiple hypothesis testing ($\alpha = 0.0125$), treatments do not have statistically significant effects on enrolled area despite the large average marginal effects (– 226 ha (95% CI – 974, 522) for gain and – 232 ha (95% CI – 980, 516) for loss treatment, respectively). However, multiple interactions were statistically significant, including between gain framing and gender, and between both types of framing and enrolment in AEEM and eligible arable land, all of which were affecting the amount of land enrolled, but not enrolment decision. Plots of average marginal effects for all interaction terms, shown in Supplementary information E, point to a lack of differences in effect sizes between treatment groups in most population subsamples. However, those who received gain or loss framed letters enrolled on average about 5 ha more land in the Eco-scheme if they were also enrolled in AEEM, while there was no such difference for the control group. Additionally, women who received a gain-framed letter enrolled on average about 6 ha of land more than any other group of participants.

Table 3 Results of three hurdle regressions on enrolment in Experiment 1; part (A) shows the regression of enrolment decision, while Part (B) is the conditional part regarding the amount of land enrolled

(A) Enrolment decision (zero–inflated)						
	Model 1		Model 2		Model 3	
	Estimate	p–value	Estimate	p–value	Estimate	p–value
(Intercept)	–3.47	<0.001	–4.07	<0.001	–4.67	<0.001
Gain framing	–0.31	0.187	–0.54	0.074	0.77	0.649
Loss framing	–0.26	0.252	–0.09	0.740	0.51	0.729
Eligible arable land			0.01	0.003	0.01	0.261
Age			–0.00	0.777	–0.00	0.987
Gender—Female			–0.28	0.397	–0.01	0.981
AECM—Yes			1.50	<0.001	2.02	<0.001
LU/ha			–0.18	0.286	–0.08	0.767
Gain:eligible arable land					0.01	0.240
Loss:eligible arable land					–0.00	0.638
Gain:Age					–0.02	0.366
Loss:Age					0.01	0.777
Gain:Female					–0.55	0.545
Loss:Female					–0.48	0.513
Gain:AECM					–0.33	0.694
Loss:AECM					–1.09	0.098
Gain:LU/ha					–0.02	0.959
Gain:LU/ha					–0.29	0.487
(B) Land allocation decision (conditional)						
	Model 1		Model 2		Model 3	
	Estimate	p–value	Estimate	p–value	Estimate	p–value
(Intercept)	1.89	<0.001	0.07	0.866	0.73	0.153
Gain framing	0.73	0.003	0.25	0.183	–2.06	0.047
Loss framing	0.18	0.457	0.05	0.745	–1.61	0.052
Eligible arable land			0.03	<0.001	0.04	<0.001
Age			0.01	0.359	0.00	0.766
Gender—Female			0.23	0.274	0.01	0.975
AECM—Yes			0.80	<0.001	0.15	0.571
LU/ha			–0.07	0.531	–0.01	0.933
Gain:eligible arable land					–0.02	0.026
Loss:eligible arable land					–0.02	0.007
Gain:Age					0.03	0.056
Loss:Age					0.02	0.067
Gain:Female					1.85	0.004
Loss:Female					–0.19	0.631
Gain:AECM					1.31	0.017
Loss:AECM					1.40	<0.001
Gain:LU/ha					–0.13	0.587
Gain:LU/ha					–0.30	0.147

Model fit and sample size for all three models are shown at the bottom of part B. Bolded values indicate statistically significant results. Note that $p < 0.0125$ was used as a significance threshold for direct treatment effects due to multiple comparison corrections. N (all models) = 4375

Model 1 fit: AIC = 1732.9, BIC = 1777, logLik = –859.4

Model 2 fit: AIC = 1078.2, BIC = 1180.2, logLik = –522.1

Model 3 fit: AIC = 1081.3, BIC = 1303.2, logLik = –503.6

Looking at the direct effects of covariates, enrolment in AECM is statistically significantly positively associated with enrolment in the Skylark scheme, while the amount of eligible arable land has a statistically significant positive effect on the amount of land enrolled.

Experiment 2

In 2024, 292 farms enrolled 3,020 ha into the Skylark scheme out of 4376 farmers that submitted their general CAP subsidy application. 172 farmers (out of 4548 farmers in total that received a letter) did not submit their subsidy application. While the total share of farmers (6.7%) and land enrolled into the scheme (7% of eligible arable land) still remains low, the enrolment rate almost tripled compared to 2023.

In this trial, 83 farmers receiving positive descriptive norms enrolled 815 ha, 98 farmers receiving negative descriptive norms enrolled 865 ha and 111 farmers from the control group enrolled 1,339 ha. There were no statistically significant differences in the characteristics of the three experimental groups (Table 4). The three sample test of equal proportions showed that there are no statistically significant differences among the three treatment groups in terms of enrolment rates ($\chi^2=4.18$, $df=2$, $p\text{-value}=0.124$), while

Table 4 Demographic and farm characteristics of all farmers, regardless of their enrolment, in the three experimental groups in Experiment 2

Characteristic	Overall, n = 4376 ¹	Control, n = 1464 ¹	Positive frame, n = 1,456 ¹	Negative frame, n = 1,456 ¹	p-value ²
Age	59.3, 60 (14.4)	59.5, 60 (14.4)	59.4, 60 (14.0)	59.1, 60 (14.8)	0.7
Missing data	50	13	17	20	
Gender					0.5
Business	62 (1.4%)	18 (1.2%)	21 (1.4%)	23 (1.6%)	
Male	3239 (74.0%)	1064 (72.7%)	1091 (74.9%)	1084 (74.5%)	
Female	1075 (24.6%)	382 (26.1%)	344 (23.6%)	349 (24.0%)	
Eligible arable land	8.7, 3.1 (57.2)	7.4, 3.1 (19.4)	11.1, 3.0 (95.4)	7.4, 3.2 (18.3)	0.13
Farm size	18.1, 7.6 (92.2)	15.8, 7.4 (34.9)	22.4, 7.2 (150.8)	16.2, 7.9 (39.6)	0.10
Region					> 0.9
Dravsko—Ptujsko polje	943 (21.5%)	312 (21.3%)	317 (21.8%)	314 (21.6%)	
Krško brežiško polje	350 (8.0%)	116 (7.9%)	120 (8.2%)	114 (7.8%)	
Ljubljanska kotlina	467 (10.7%)	156 (10.7%)	157 (10.8%)	154 (10.6%)	
Ljubljansko barje	229 (5.2%)	75 (5.1%)	77 (5.3%)	77 (5.3%)	
Pomurje	2385.0 (54.5%)	804.0 (55.0%)	784.0 (53.9%)	797.0 (54.7%)	
Livestock units/ha	0.7, 0.1 (13.4)	0.5, 0.1 (2.4)	0.5, 0.1 (0.8)	1.1, 0.1 (23.1)	0.4
AECM enrolment					0.13
Yes	1589 (36.3%)	558 (38.2%)	503 (34.6%)	528 (36.3%)	
No	2784 (63.7%)	904 (61.8%)	952 (65.4%)	928 (63.7%)	
Other Eco-scheme enrolment					0.5
Yes	2290 (52.4%)	765 (52.3%)	747 (51.3%)	778 (53.4%)	
No	2083 (47.6%)	697 (47.7%)	708 (48.7%)	678 (46.6%)	
Area enrolled	0.69, 0.00 (5.92)	0.92, 0.00 (8.44)	0.56, 0.00 (4.59)	0.59, 0.00 (3.55)	0.2
Farmers enrolled	292 (6.7%)	111 (7.6%)	83 (5.7%)	98 (6.7%)	0.12

¹ n (%); Mean, Median (Standard deviation)

² Pearson's Chi-squared test; One-way ANOVA for differences between groups

Kruskal–Wallis test showed no statistically significant differences in area enrolled among the three groups ($\chi^2 = 4.30$, $df = 2$, p -value = 0.117).

Given our sample size for the conditional part of the hurdle model (292 farmers) and standard deviation in the enrolment area, we only have sufficient power (> 0.8) to detect effects (unstandardized linear regression coefficient) larger than 7.1 when no covariates are included in the model. Despite higher enrolment in 2024, our study thus remains underpowered for detecting medium or small effect sizes.

In model 1 with no covariates, neither treatment had a statistically significant effect on enrolment decision nor on the amount of land enrolled after using $\alpha = 0.0125$ to account for multiple hypothesis testing (Table 5). On average, positive and negative framing decreased the probability of enrolment by 2.37% (95% CI – 4.3, 0.44) and 1.13% (95% CI – 3.13, 0.87), with those who received positive framing on average enrolling 0.14 ha more (95% CI – 3.44, 3.72) and those who received negative framing 3.24 ha less (95% CI – 6.19, – 0.28) in the Skylark scheme.

When covariates were added to model 2, there were again no statistically significant results and average marginal effects remained similarly small and statistically insignificant (probability of enrolment changes by – 1.91% (95% CI – 3.79, – 0.02) and – 0.5%, while area enrolled changes by – 1.02 ha (95% CI – 2.18, 0.137) and 0.28 ha (95% CI – 0.89, 1.45) for positive treatment and negative treatment, respectively) (Table 5).

In model 3 with interactions, there were again no direct statistically significant effects of our treatments neither on enrolment decision (average marginal effect for positive treatment: – 1.95% (95% CI – 3.85, 0.06); for negative treatment: – 0.66% (95% CI – 2.58, 1.26)) nor on area enrolled (statistically insignificant average marginal effect for positive treatment: – 4.25 ha (95% CI – 10.9, 2.34), for negative treatment = 12.27 ha (95% CI – 14.1, 38.59)) (Table 5). However, positive norm statistically significantly interacted with eligible arable land. There was also a statistically significant interaction between negative norm and livestock unit per ha, which negatively affected the decision to enrol. Finally, those who received a negatively-framed message and were enrolled in AECM enrolled statistically significantly less land in the scheme. The average marginal effects of all interactions, displayed in Supplementary information E, show that within different population subgroups, effects of the different treatment groups were similar. The most prominent difference in marginal effects among the treatment groups is for eligible arable land, where enrolment probability increases much faster for the control group than for the positively framed group and is thus around 60% higher in the control group for farms with around 150 ha of eligible arable land. Among the covariates, enrolment in AECM and other Eco-schemes and more eligible arable land were consistently statistically significantly positively associated with both enrolment decision and the amount of land enrolled.

Re-enrolment analysis

Among the 110 farmers who enrolled in the scheme in 2023, 27 received a positively framed descriptive norm, 41 received a negatively framed descriptive norm, and 39 were in the control group, while four did not submit their subsidy application. As 80 farmers out of 110 re-enrolled, the total re-enrolment rate was 72%. We found that negatively framed norm reduced enrolment rates, as 68% of farmers in that group re-enrolled

Table 5 Results of three hurdle regressions on enrolment in Experiment 2; part (A) shows the regression of enrolment decision, while Part (B) is the conditional part regarding the amount of land enrolled

(A) Enrolment decision (zero-inflated)						
	Model 1		Model 2		Model 3	
	Estimate	p value	Estimate	p value	Estimate	p value
(Intercept)	− 2.31	< 0.001	− 4.82	< 0.001	− 4.32	< 0.001
Positive norm	− 0.33	0.017	− 0.30	0.049	− 1.57	0.106
Negative norm	− 0.15	0.269	− 0.08	0.580	− 0.76	0.397
Gender—F			0.10	0.519	− 0.05	0.854
Age			0.00	0.338	− 0.00	0.852
LU/ha			− 0.27	0.005	− 0.06	0.630
AECM—Yes			1.59	< 0.001	1.47	< 0.001
Eco-schemes—Yes			1.60	< 0.001	1.15	< 0.001
Eligible arable land			0.02	< 0.001	0.03	< 0.001
2023 Loss framing			− 0.06	0.709	− 0.09	0.712
2023 Control			0.13	0.379	− 0.11	0.664
Positive norm:AECM					0.28	0.491
Negative norm:AECM					0.08	0.843
Positive norm:Other Eco-schemes					0.79	0.103
Negative norm:Other Eco-schemes					0.71	0.122
Positive norm:eligible arable land					− 0.02	0.012
Negative norm:eligible arable land					− 0.01	0.114
Positive norm:Female					0.36	0.348
Negative norm:Female					0.11	0.775
Positive norm:Age					0.01	0.368
Negative norm:Age					− 0.00	0.824
Positive norm:LU/ha					− 0.24	0.295
Negative norm:LU/ha					− 0.44	0.036
Positive norm:2023 loss					0.06	0.868
Negative norm:2023 loss					0.07	0.855
Positive norm:2023 control					0.14	0.712

Table 5 (continued)

(A) Enrolment decision (zero-inflated)						
	Model 1		Model 2		Model 3	
	Estimate	p value	Estimate	p value	Estimate	p value
Negative norm:2023 control					0.52	0.140
(B) Land allocation decision (conditional)						
	Model 1		Model 2		Model 3	
	Estimate	p value	Estimate	p value	Estimate	p value
(Intercept)	2.53	< 0.001	0.42	0.041	− 0.10	0.744
Positive norm	0.01	0.939	− 0.14	0.071	1.00	0.038
Negative norm	− 0.30	0.031	0.03	0.637	0.45	0.331
Gender—F			− 0.02	0.763	− 0.15	0.231
Age			0.00	0.121	0.00	0.680
LU/ha			− 0.03	0.545	− 0.06	0.456
AECM—Yes			0.68	< 0.001	0.91	< 0.001
Eco-schemes—Yes			0.61	< 0.001	0.63	< 0.001
Eligible arable land			0.03	< 0.001	0.03	< 0.001
2023 Loss framing			− 0.01	0.908	− 0.02	0.898
2023 Control			− 0.03	0.700	0.03	0.807
Positive norm:AECM					− 0.16	0.442
Negative norm:AECM					− 0.45	0.024
Positive norm:Other Eco-schemes					− 0.40	0.122
Negative norm:Other Eco-schemes					0.19	0.443
Positive norm:eligible arable land					− 0.01	0.109
Negative norm:eligible arable land					0.00	0.232
Positive norm:Female					0.23	0.264
Negative norm:Female					0.16	0.400
Positive norm:Age					− 0.01	0.139
Negative norm:Age					− 0.01	0.231
Positive norm:LU/ha					0.04	0.710
Negative norm:LU/ha					− 0.02	0.879
Positive norm:2023 loss					− 0.06	0.758
Negative norm:2023 loss					0.09	0.639

Table 5 (continued)**(B) Land allocation decision (conditional)**

	Model 1		Model 2		Model 3	
	Estimate	p value	Estimate	p value	Estimate	p value
Positive norm:2023 control					− 0.16	0.385
Negative norm:2023 control					0.01	0.951

Model fit and sample size for all three models are shown at the bottom of part B. Bolded values indicate statistically significant results. Note that $p < 0.0125$ was used as a significance threshold for direct treatment effects due to multiple comparison corrections

Model 1 fit: N = 4464, AIC = 4884.6, BIC = 4929.4, logLik = -2435.3

Model 2 fit: N = 4461, AIC = 3736.8 BIC = 3882.5, logLik = -1845.4

Model 3 fit: N = 4461, AIC = 3756.5, BIC = 4104.7 logLik = -1823.2

Table 6 Results of logistic regressions (odds ratios) predicting enrolment decision (Yes/No) into the Skylark scheme in 2024 for farmers that enrolled and did not enrol in the scheme in 2023

Term	Enrolled in 2023		Not enrolled in 2023	
	Estimate	p-value	Estimate	p-value
(Intercept)	− 1.46	0.324	− 1.63	< 0.001
Positive norm	− 1.39	0.083	− 0.21	0.209
Negative norm	− 0.94	0.173	− 0.05	0.762
Female	− 0.94	0.173	− 0.05	0.609
Age	0.81	0.252	0.09	0.820
Eligible arable land	0.16	0.005	0.02	< 0.001
Livestock units/ha	− 0.34	0.433	− 0.28	0.009
AECM enrolment	0.90	0.260	− 1.66	< 0.001
Other Eco-scheme enrolment	− 1.57	0.040	− 1.60	< 0.001

compared to 84% in the control group, decreasing the probability of enrolment by 17.7% on average (95% CI − 37.1, 1.61) after controlling for the effect of other variables. However, this difference was not statistically significant (Table 6). While the probability of enrolment was reduced by 11.4% (95% CI − 2.70, 4.30) also for farmers who received a positively-framed descriptive norm, this difference was again not statistically significant (Table 6). Among the covariates, eligible arable land had a statistically significant positive effect on re-enrolment probability. Enrolment in other eco-schemes was negatively and statistically significantly associated with re-enrolment likelihood.

Looking at farmers who did not enrol in the scheme in 2023, our treatments did not affect their enrolment rates. Their average marginal effects for both positive framing (− 1.12; 95% CI − 2.86, 0.62) and negative framing (− 0.28; 95% CI − 2.05, 1.50) were also much smaller than for re-enrolling farmers. Farmers were more likely to enrol in the Skylark scheme for the first time if they were not enrolled in other Eco-schemes or AECM and if they had more eligible arable land (Table 6).

Discussion

The economic literature is increasingly focusing on behavioural factors influencing farmers' decisions to adopt sustainable environmental practices (Dessart et al. 2019). This knowledge can be used to tailor policy design so that barriers to enrolment due to behavioural factors are lessened, e.g. by increasing the scheme's flexibility and reducing perceived non-compliance risk (Espinosa-Goded et al. 2010; Greiner 2015). Additionally, the understanding of behavioural factors can also be used for developing behavioural change interventions that could increase enrolment rates through information provisioning or framing (Chabé-Ferret et al. 2023). Despite the increasing interest in such nudges, there is still debate regarding in which contexts and to what extent these approaches yield meaningful results in real-world settings (Mertens et al. 2022; Maier et al. 2022; Chater and Loewenstein 2023).

In this paper, we evaluate the effectiveness of two types of information provision nudges in increasing enrolment in a new Eco-scheme for Skylark conservation in Slovenia. Our focus is on the effect of gain and loss framing (Experiment 1) and descriptive norms framing (Experiment 2) on enrolment rates and amount of land enrolled. In Experiment 2, we also separately analyse the relationship between the initial enrolment during Experiment 1 and the re-enrolment behaviour within Experiment 2. Our results reveal a complex relationship, with significant variations across different subgroups of farmers.

In Experiment 1, we found that while gain framing had a positive statistically significant effect on the amount of land enrolled in the model without covariates, there were no statistically significant effects on enrolment rates in the Skylark scheme when covariates and interactions were added to the model. Given that in the case of enrolment decision modelling, we had sufficient power to detect statistical significance even for the small effect sizes that we discovered, our results indicate that there is no meaningful direct effect between gain or loss framing and the decision to enrol in the Skylark scheme. However, looking at the direction of the effects, it is interesting to note that while the effects are positive in the model without covariates and with covariates, their direction reverses to negative when interactions are included. As the literature shows both gain and loss framing have predominantly positive effects (Ropret Homar and Knežević Cvelbar 2021), the negative direction of effects in the interaction model is unexpected. Due to the low enrolment rate that leads to low power of our model on enrolled area, our statistically insignificant results in the conditional part of the hurdle model on the amount of land enrolled may not prove a null relationship between the two framing types and the amount of land enrolled. Particularly given the relatively large average marginal effects detected, such statistically insignificant results may be due to the low power of this model.

In the exploratory analysis in model 3 with all covariates and interactions, we found several statistically significant interactions affecting the amount of land enrolled, showing that the effect of our nudge may depend on farm characteristics. Firstly, the negative interaction between both framing types and the amount of eligible arable land points to an interesting dynamic that is not in line with the literature which shows that framing increases enrolment. Larger farms, often more oriented towards productivity or economic results and with a different decision-making process regarding AECM enrolment

(Bojnec and Latruffe 2013; Unay Gailhard and Bojnec 2015; Leonhardt et al. 2022), may perceive public-good framing as misaligned with their economic goals, leading to decreased engagement. Marginal effect plots show that this effect grows exponentially and is highest for farms far larger than the average Slovenian farm (7.0 ha, Travnikar et al. 2023). To increase the amount of land that large farms enrol, interventions may need to be re-tailored to better resonate with their farming goals and economic realities.

Secondly, we found that farmers who received gain or loss treatments enrolled 5 ha more in the Skylark scheme, on average, if they were enrolled in AECM as well. This increased responsiveness to nudges by farmers enrolled in AECM is invariable across both experiments, as a statistically significant negative interaction was also found between negative descriptive norms and AECM enrolment in Experiment 2. Furthermore, as a covariate, AECM enrolment statistically significantly increases enrolment probability and the amount of land enrolled in both experiments. Positive previous experience with AECM might reduce transaction costs and the perceived risk of joining the Skylark scheme as a new programme. Equally, similar underlying decision factors for enrolment into both AECM and Skylark scheme can lead to the positive association between enrolment into the two types of schemes (Schaub et al. 2023; Schulze et al. 2024; Canessa et al. 2024). For example, previous studies have found that farmers who enrol in AECM tend to have more positive environmental attitudes and may also be more aware of the negative impacts of farming on the environment (Dessart et al. 2019; Cusworth 2020; Westerink et al. 2021; Klebl et al. 2023). This suggests that these farmers may have a stronger environmental ethos or be more attuned to conservation messaging (Dessart et al. 2019; Leonhardt et al. 2022), which could lead to greater sensitivity to nudges that focus on conservation outcomes. The importance of environmental attitudes for the effectiveness of information campaigns has also been detected in previous studies on nudges. For example, Zachmann et al. (2023) found that when farmers with negative attitudes towards fungicide-resistant varieties are provided with personalized information on the use of environmentally toxic fungicides, their intended land devoted to such varieties strongly declines.

We also found that there was a statistically significant interaction between gender and area enrolled, whereby women who received gain framing enrolled on average 6 ha more land than men. While only a handful of studies have examined differences between genders in response to gain or loss framing, their results show either no differences (Ezquerria et al. 2018) or the opposite direction of the effect, where women react more strongly to loss framing (Kim 2012; Cochard et al. 2020). It is unclear what could drive the interaction in the opposite direction in our study.

Similarly to Experiment 1, the descriptive norm framing used in Experiment 2 showed no overall significant effect on enrolment. However, the effect of both frames had a negative direction for enrolment probability and a positive direction for the amount of land enrolled. While previous studies have consistently found a positive effect of a positive descriptive norm (Cialdini et al. 2006; Mollen et al. 2021), the effects of negative norms tended to be neutral or negative. One reason why the two frames worked similarly in our study is that farmers might have paid more attention and responded more to the actual enrolment numbers that were the same in both frames, rather than the framing text. Again, however, the power of our study was too low to detect effects of even medium

magnitudes on area enrolled due to the low number of farmers enrolled. Therefore, we cannot rule out possible weaker effects of these two nudges on the enrolled area. Similarly to the direct effects, there were also no statistically significant effects of our treatments on farms re-enrolling or those not yet enrolled before.

In contrast to the statistically insignificant direct effects, we found a negative statistically significant interaction between livestock units/ha and negative framing on enrolment rates, indicating that this message backfired for more intensive farms. Such backfiring also appeared in the interaction between positive framing and eligible arable land. Large farms may have perceived the provided enrolment rates as less successful than smaller farms, as they could have provided a large share of the entire enrolled area themselves. As larger farms may, therefore, perceive enrolment as less widespread than small farms and the positively framed nudge as potentially deceiving, this could lead to the negative interaction observed. These findings underscore the risk of behavioural interventions backfiring. Such a negative effect, also called the “boomerang” effect, has been previously observed as a potential consequence of social norms, particularly when the desired behaviour is rare (Cialdini et al. 2006; Chabé-Ferret et al. 2023). Such a response arises because when the norm describes a behaviour that is not prevalent, it can reduce the individual’s motivation to perform the behaviour as well as make individuals feel less responsible for the consequences of the (lack of) behaviour (Mollen et al. 2021; Ai and Rosenthal 2024). Therefore, while descriptive norms in our study do not seem to be effective in changing farmers’ behaviour, special caution is required when using social norms in contexts where desired behaviours are not yet widespread. This finding is consistent with previous research on social norm nudges in agricultural contexts, which generally report null, mixed, or short-lived effects, suggesting that this approach may have limited and context-dependent effectiveness (Kuhfuss et al. 2016; Peth et al. 2018; Chabe-Ferret et al. 2019; Chabé-Ferret et al. 2023; Raineau et al. 2025; Vella et al. 2025).

Given that 7% of total eligible land was enrolled in 2024, there is still potential to increase enrolment rates. Our results show that to improve enrolment rates, behavioural change interventions based on framed information provision may not suffice and other barriers and concerns farmers face may need to be addressed. Previous research has identified farmers’ concerns regarding loss of yields, growth of weeds on the plots and more difficult cultivation as reasons why they would be reluctant to enter the scheme (Alif et al. 2024). Furthermore, the payment of 60€/ha may not be a sufficiently high incentive for some farmers to trade off time dedication, cognitive effort and yield loss. More generally, numerous other factors can act as barriers to enrolment into AES, such as structural factors, including the inability to enrol due to old age, health issues and ownership structure (Šumrada et al. 2022). Behavioural factors, such as negative attitudes toward the measure and its objective, lack of trust in institutions, or risk-aversion, can also prevent farmers’ participation in voluntary schemes (Schaub et al. 2023; Schulze et al. 2024; Canessa et al. 2024). Particularly in Experiment 1, the fact that farmers needed to make Skylark plots before the government officially confirmed the scheme may have dissuaded risk-averse farmers from enrolling due to concerns about possible policy or payment changes. Equally, no official information on the scheme was available online at the time of our first experimental intervention, thus the difficulty of obtaining

additional information (farmers would need to call their agricultural advisor) may have deterred other farmers. More research is needed to determine which of these factors formed the main bottleneck in enrolment to the Skylark scheme. Such work could also help illuminate why some groups of farmers reacted differently to our nudge, thus enabling the preparation of nudges that are better targeted at those specific groups. At the same time, this adds to the evidence that the effect of behavioural change interventions is limited and that system-level changes, such as increased payment levels or more flexible scheme designs, may be necessary to drive broader participation (Nemati and Penn 2020; Maier et al. 2022; Chater and Loewenstein 2023; Chabé-Ferret et al. 2023).

A significant limitation of our study is the low power for detecting the effects of treatments on the area enrolled. As our sample included the entire population of farmers eligible for the Skylark eco-scheme, it is not possible to increase the power without first increasing farmers' enrolment into the scheme. As such, randomized controlled trials that target schemes where larger populations of farmers exist or are eligible for enrolment, or enrolment rates are higher, may be more beneficial. At the same time, this limitation represents a conundrum, as nudges and other behavioural interventions are most needed to increase the enrolment precisely in measures with very low enrolment rates.

As the RCT was conducted in a real-world setting, we have no way of knowing whether farmers actually read and attended to all or parts of the letters, nor how they psychologically reacted to it. There is little reason to suspect that the attention that farmers paid to the letter would differ between treatment groups, as randomization worked well at least for the observed variables. However, in case our intervention disturbed or annoyed farmers, this could lead to different rates of attending to the letter. We regard this as unlikely, as in both experiments our intervention was placed towards the end of the letter. Therefore, there is no reason to suspect that farmers would not have at least read the first part of the letter with the most important information on the scheme before being exposed to (or affected by) the treatment. Additionally, if attention differed between treatment groups, we would expect that to also affect enrolment rates, as particularly in the first experiment, the letter was the primary source of information for farmers about the scheme. With no such differences detected between treatment groups, we believe the question of whether farmers read the letter or not is not so relevant for our experiment as their behaviour was natural and our effect sizes represent the real world.

Conclusions

The two experiments we present in this paper are among the first randomized controlled experiments conducted on agricultural policies in Europe. We used two nudges that have been previously studied in consumer research and assessed their effectiveness on farmers' behaviour for the first time. A particular strength of our approach is its high external validity compared to other experimental methods in economics (e.g. lab experiments, lab-in-the field experiments or discrete choice experiments), as the experiment was conducted in the real world. Furthermore, our experiments were conducted at the national level, including the entire population of eligible farmers, thus preventing any biases resulting from sample selection. Despite that, due to low enrolment rate, we had limited statistical power to detect the effects of our intervention on the amount of land enrolled. Although RCTs have very high external validity compared to other impact

evaluation methods, our study was placed in a specific national context and may therefore not generalise to other political or cultural contexts. Previous studies have shown that particularly social norm-based nudges are less effective in individualistic than collectivistic societies. Particularly given the different agri-political settings, conducting cross-cultural studies on nudge effectiveness in agriculture may be especially relevant.

We examined the effect of a gain and loss, and a descriptive norm framing nudges on farmers' enrolment into a new Eco-scheme. While the treatments overall had no statistically significant effects, they affected specific groups of farmers. Our study suggests that the effectiveness of information nudges on farmers' enrolment decisions in AES is thus highly contingent on the target audience and context. As such, future policy efforts should tailor interventions to specific subgroups of farmers to increase their impact.

The results suggest that behavioural interventions alone may be insufficient to substantially increase enrolment in AES and may, in some cases, even have adverse effects. To enhance enrolment, such approaches should be complemented by structural and systemic changes that address other key barriers. These could include greater flexibility in scheme requirements (e.g., reduced administrative burdens), provision of adequate financial incentives, and improved extension approaches (e.g., participatory methods, on-farm demonstrations, and field visits). Future research should examine how behavioural change interventions can be better tailored to distinct farmer groups, based on characteristics found to influence responses in this study (e.g., prior AES participation, farm size). In addition, more evaluations of strategies that combine structural adjustments with targeted behavioural interventions are needed to identify effective ways of increasing AES participation.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s40100-025-00417-y>.

Additional file A

Additional file B

Additional file C

Additional file D

Additional file E

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Author contributions

All authors contributed to conceptualization of the study and reviewed the manuscript. Ž.A., A.N. and T.Š. designed the methodology. Ž.A. analysed the data, prepared all figures, and wrote the original draft. T.Š. administered the project, acquired funding and together with C.J.L. supervised the study.

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Availability of data and materials

The data that support the findings of this study are available at the Ministry of Agriculture, Forestry and Food of Republic of Slovenia, but restrictions apply to the availability of these data, and so are not publicly available. Data are, however, available from the authors upon reasonable request and with permission of Ministry of Agriculture, Forestry and Food of Republic of Slovenia.

Declarations

Ethical approval

The study was not submitted to an Internal Review Board.

Competing interests

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