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The Role of Communication Framing in Agricultural Climate Action

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This paper investigates effective communication strategies to enhance farmers' engagement with climate change mitigation. Through an online survey experiment of over 500 Irish livestock farmers, it examines the impact of message framing–focused on reputation concern or expenses–on information engagement, knowledge, and intentions to adopt greenhouse gas mitigation measures. Findings reveal that while framing significantly reduces engagement with the information, it does not affect knowledge or implementation intentions. This underscores the complexity of motivating climate action, suggesting that advisory programs should employ positively framed messages to generate interest, despite challenges inherent in discussing climate change mitigation.

Key words: Greenhouse gas mitigation, livestock agriculture, economic experiment, climate change communication

Introduction

Meat consumption, followed by dairy, has increasingly become central to public debates on sustainable food consumption. In line with increasing concerns about and the urgency to address the climate crisis, greenhouse gas (GHG) emissions from livestock production have dominated those public debates. Overall, food systems are responsible for one third of global GHG emissions (Crippa et al., 2021). In industrialized countries, almost 50% of food system GHG emissions are land based (Crippa et al., 2021), and meat, aquaculture, eggs, and dairy are responsible for over half of those emissions (Poore and Nemecek, 2018).

Hence, the development and implementation of improved technologies on farms is seen as an important strategy to mitigate agricultural GHG emissions (Parlasca and Qaim, 2022). In fact, environmental impacts are often dominated by producers with very high impacts, which provides opportunities for mitigation at the farm-level (Poore and Nemecek, 2018). Key GHG mitigation strategies are the implementation of climate-smart practices, such as feed additives, improved grazing management, reduced fertilizer application, and improved breeding. How to facilitate widespread uptake is important for international food policies aiming to mitigate climate change. This underscores the necessity of effectively communicating climate change mitigation practices to farmers, highlighting their pivotal role in advancing agricultural sustainability.

In this paper, I study how to improve communicating climate action to farmers to facilitate a reduction in GHG emissions from agriculture. The urgency of adopting climate change mitigation technologies in the farming sector highlights the key role of effective knowledge transfer programs as policy responses to initiate widespread adoption. This is because in order to adopt new technologies, farmers not only need to be aware that these exist, they also need to be convinced of their merit (Chavas and Nauges, 2020). This is particularly important in the context of climate

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change as how to best encourage farmers to adopt climate-action practices is still an open question (Ferraro et al., 2021). In fact, most agricultural extension services focus on economic outcomes (Balaine et al., 2023). Moreover, communicating climate action goes beyond standard agricultural extension work as traditionally disengaged audiences need to be reached (Whitmarsh and Corner, 2017). This can be particularly challenging in the farming community (Arbuckle et al., 2013) as perceptions of agricultural emissions and their contribution towards GHG emissions can be disconnected (Hyland et al., 2016). Therefore, successfully communicating climate action measures to farmers is of major importance, but has received scant attention.

This is the focus and main contribution of this paper. Specifically, I test means to increase information engagement of farmers with climate change mitigation information by varying how the information is communicated. Particularly, I assess the effect of framing of messages on engagement with the information, knowledge and stated intentions to adopt and further intensify the use of farm practices. Farmers were randomly allocated into one of the two treatments or control group. One treatment focused on reputation concern by stating the importance to retain agriculture's sustainable image. This treatment is based on the idea of conditional co-operation, which means people are more likely to contribute to climate change if others also make an effort (Fischbacher, Gächter, and Fehr, 2001; Andre et al., 2024) and the 'working together norm' which invites people to join in to achieve a common goal (Howe, Carr, and Walton, 2021; Vlasceanu et al., 2024). The other treatment was based on loss aversion and focused on the potential to reduce expenses, following prospect theory (Kahneman and Tversky, 2013). This was motivated to challenge the effectiveness of the standard agricultural extension message that emphasizes gains in profit from adopting new farm practices.

The behavioural economics literature shows that framing of information can have an important impact on subsequent behaviour change (Kahneman, 2003; Tversky and Kahneman, 1974). A framing effect occurs if changes in the presentation induce changes of opinion (Chong and Druckman, 2007), and leads to better engagement. This has received limited attention in relation to agricultural extension, but precedents exist. A recent study by Balew et al. (2023), for example, explore loss-framed messages in relation to knowledge diffusion among farmers in Ethiopia, but do not find an effect. Wallander, Ferraro, and Higgins (2017) examined the effect of framed outreach messages on conservation program uptake in a field experiment. They provide evidence of inattentive behaviour and show that peer comparisons and social norm messaging do not affect contract enrolment. Yet, in relation to communications about climate change specifically, framing has been found to initiate constructive dialogue about climate change with audiences that are more difficult to reach (Whitmarsh and Corner, 2017) and to affect attitudes towards meat consumption (Graham and Abrahamse, 2017). However, no consensus has emerged on how to communicate climate change effectively (Ceyhan and Saribas, 2022). A recent study by Vlasceanu et al. (2024) found small effectiveness of different ways to communicate climate change, largely limited to non-climate skeptics. In relation to climate skeptics, Ferraro et al. (2021) study whether communicating the link between climate change and agricultural production discourages conservation action in a randomized control trial in the US. In contrast to their expectation, they find no evidence that this discourages the uptake of climate action. As such, how to effectively communicate climate change is still an open question, particularly in the agricultural sector, where scepticism may prevail (Arbuckle et al., 2013; Islam, Barnes, and Toma, 2013). This paper directly contributes to the scant research on farmer communication about climate change. As such, it adds to the important topic on how to encourage the update of climate change mitigation measures by farmers, as this is seen as one key step to reduce GHG emissions from food production (Parlasca and Qaim, 2022).

To this end, an online survey experiment with over 500 livestock farmers was conducted in Ireland to test ways to effectively communicate climate action among farmers. In Ireland, almost 40% of national GHG emissions arise from the agricultural sector, hence reducing agricultural GHG emissions is at the forefront of the political agenda. In the survey experiment, farmers were randomly allocated in two treatments and a control group to assess the effect of framing of messages on engagement with the information, knowledge and stated intentions to implement climate action measures. The findings show that information framing significantly affects engagement with the provided information. However, against expectations it reduces engagement. But, framing does not significantly impact knowledge or stated intentions. In addition, the data also suggests inattentive behavior of farmers.

The remainder of the paper is structured as follows: The next section provides background about the context of the study setting. In the methodology section, I describe the survey, experimental approach and data. This is followed by a results and discussion section, while the paper finishes with conclusions that outline policy implications.

The Irish Agricultural Sector

The Irish agricultural sector is livestock dependent, and dairy and beef are the dominant agricultural systems in terms of output. More specifically, about 87% of all 135,000 farms in Ireland have some livestock (CSO, 2022). With 74,000 farms, beef production is the dominant farm system in terms of farm numbers, while there are about 15,300 dairy farms and 17,000 sheep farms. The remaining farms are mixed grazing livestock, cereal farms, or pig and poultry farms.

Beef and dairy production is mainly grass-based, with cows calving in the spring to maximize grass intake. At the end of 2023, there were over 6.5 m cattle in Ireland, and with an increase of 5.5% between 2008 and 2023, total cattle numbers have remained relatively stable over the last decade. In contrast, dairy cow numbers have increased by almost 50% between 2008 and 2023, while other cows (i.e. suckler cows) have decreased by 24% over the same time period (CSO, 2024).

This change in the composition of cattle population was initiated by the EU milk quota abolition, that came into effect in 2015. The ending of milk quotas was preceded by a 'soft landing' period, that allowed gradual increases in milk quota production in each EU Member State. In Ireland, dairy farming is generally associated with high farm incomes, while cattle farming achieves much lower incomes from farming (Carter and Läpple, 2019). Thus, due to the opportunity of unconstrained production growth, many dairy farmers expanded their milk production and significant intra and inter farm substitution from beef to dairy production took place.

In fact, Ireland was one of the few countries that significantly expanded its milk production. For example, milk production has increased by over 75% between 2008 and 2021 in Ireland, while total EU milk production increased only by about 7% between 2014 and 2020 (Eurostat, 2021).

However, Ireland's livestock focused agricultural production has implications on GHG emissions. Specifically, the Irish agricultural sector accounts for 37.5% of national GHG emissions, which is unique in a developed country context[1]. For example, agriculture accounts for about 10% of national GHG emissions in the EU and US. Ireland is committed to reduce GHG emissions as part of the EU target to be climate-neutral by 2050. In addition, Ireland has its own national target to reduce its GHG emissions by 51% by 2030 compared to 2018. In fact, the 2021 Climate Action Plan introduced sector specific targets, and the agricultural sector is required to reduce GHG emissions by 25% by 2030 compared to 2018.

A key measure to reduce agricultural GHG emissions is based on increased adoption of GHG mitigation measures by farmers, such as reduced fertilizer use, improved breeding, and low emission slurry spreading. To this end, a specific initiative has been launched in Ireland ('Signpost Program') in May 2021 to facilitate and support farmers in the adoption of climate action measures. The Signpost Program is run by Teagasc, the Irish agricultural and food development authority. As part of the Signpost Program, over 100 demonstration farms to showcase best practice were created. In addition, the Signpost Program hosts regular (online) seminars, and disseminates information via newsletters and on their website.

[1] One exception is New Zealand where nearly half of GHG emissions come from agriculture (Minstry for the Environment, 2022)

In general, information use in agriculture is a complex process. While farmers learn from many different sources, agricultural extension services and other farmers are seen as the most prevalent means of knowledge diffusion (Birkhaeuser, Evenson, and Feder, 1991; Case, 1992; Foster and Rosenzweig, 1995). Agricultural extension services provide information to farmers through a variety of means, such as one-to-one advice, farm visits, group advice, or information events, but information delivery has changed over time (Norton and Alwang, 2020), with an increasing focus on information and communication technology (Kahsay, Garcia, and Bosselmann, 2023). For example, online information provision has become more important over the last number of years, further stimulated due to Covid-19, when in-person (group) meetings were not possible. Given the fact that widespread farm level changes are required to mitigate climate change, online communication will likely further increase in importance over time, and is an important part of the Signpost Program, as it can be a cost effective means to reach a large number of farmers.

Methodology

Survey Experiment

An online survey experiment was conducted where farmers were randomly allocated into treatment or control group. In fact, as different livestock farm systems were included, I used stratified randomization to assign participants into one of the groups. Participants were stratified by farm system (dairy and drystock, i.e. beef and/or sheep) and assigned into blocks. Simple randomization was performed within each block to assign subjects to one of the two treatments or control group.

The treatments were based on the idea that the farmer is provided with a preview of information that is framed in a particular way. This is expected to influence the farmer's expected utility, and affects how attentively the farmer engages with the information. More attentive engagement with the information will increase knowledge about the promoted technologies. As such, the more closely the farmer engages with the provided information, the more likely it is that the farmer will perceive that the promoted technology will yield some benefit when implemented. In other words, it is important to convince the farmer of the merits of a new technology, i.e., he or she needs to believe that this new technology has some benefits. This is based on the assumption that the perceived and not the actual benefit of the new technology influences the adoption decision (Chavas and Nauges, 2020).

Treatment one motivated the information by aiming to generate reputation concerns of farmers by stating that *'Increasing concerns by society about agricultural GHG emissions threatens the reputation of the Irish agricultural sector. It is important that every farmer adjusts farm practices to help reduce agricultural GHG emissions. Every contribution, regardless how small, is valuable. Together we can make a difference and ensure Irish agriculture retains its environmentally sustainable reputation. In the following, we will give you some information on how you can contribute to this common goal.'* This treatment is influenced by the concept of conditional cooperation, suggesting that individuals are more inclined to take action against climate change when they observe similar efforts by others (Fischbacher, Gächter, and Fehr, 2001; Andre et al., 2024) and the 'working together norm' which invites people to participate to achieve a common goal (Howe, Carr, and Walton, 2021; Vlasceanu et al., 2024). As such, the treatment was aimed to enhance intrinsic motivation by highlighting the importance of working together to achieve a common goal. Altruism is seen as a motivator to provide a public good, and industry reputation concerns have been found to be related to altruism (Läpple and Osawe, 2023). Industry reputation of the agricultural sector is a public good in the sense that all farmers can benefit from it and it is also non-rivalrous. The idea for this treatment emerged based on previous research that revealed that Irish dairy farmers are concerned about the reputation of the Irish dairy industry, albeit in a different context (Osawe et al., 2021); general Irish media coverage that may impact the traditionally 'green' reputation of the Irish agricultural sector, as well as discussions with peers, farmers and agricultural advisers.

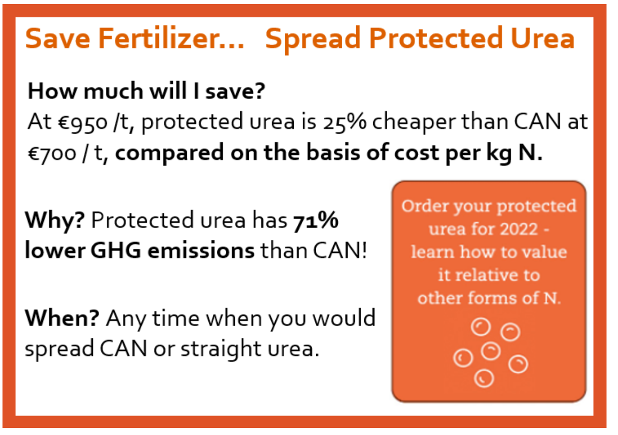

Figure 1. Infographic from survey

Treatment two focuses on expenses and introduced the information by reminding farmers to '*Avoid unnecessary expenses! ...and save the environment too. In the following, we will give you some information on how you can avoid reductions in your income by introducing simple measures on your farm.*' This treatment highlights loss aversion and is based on prospect theory (Kahnemann and Tversky, 1979), where losses have greater impact than gains. The main focus is also on economic outcomes, with environmental motivations included as a positive 'add-on'. The idea is to challenge and test conventional agricultural extension messages that focus on highlighting economic gains.

The information was introduced with the following sentences to all three groups: '*We are now interested in your opinion on how information is delivered to farmers. Please look at the information. We will then ask you some questions that will help us to improve how information is delivered to farmers.*' Farmers who were assigned into the control group received no further text and moved directly to the infographics. The two treatment groups received the previously described framing text after the introduction sentences before moving to the infographics.

Both treatments and the control group were shown the same three infographics that provided information on how to save chemical N fertilizer. Reducing the application of chemical N fertilizer was promoted as one of the main actions to reduce agricultural GHG emissions in Ireland at the time of data collection. Specifically, the focus was on the application of lime, the implementation of clover, and increased usage of protected urea. The application of lime is promoted as it increases soil pH, which reduces fertilizer requirement. The implementation of clover in grazing swards is a substitute for fertilizer, while protected urea is an 'environmentally friendly' fertilizer that releases fewer GHG emissions when compared to traditional fertilizers.

Figure 1 shows the infographic related to protected urea. All infographics followed the same structure, providing an economic and environmental motivation, as well as information on how to implement the practice.

The study was conducted in collaboration with a farm advisory service focused on climate action (Signpost Program). The provided information was aligned with messages that were due to be promoted by the program shortly after the study was completed. As part of the Signpost program strategy to initiate climate action relies on online newsletters, the treatments of this study are designed to test how engagement with information that is delivered online via text and graphics can be improved. Furthermore, the infographics were developed in collaborations with farm advisors and discussed with farmers in a small online focus group with four farmers and one advisor. The objective of the focus group was to design the infographics in an engaging and understandable way, and to decide on effective treatments to motivate engagement with climate change information. For example, during this discussion, farmers suggested to put the economic information before the environmental information, as the farmers in the focus group felt that economic information is more important to farmers. In addition, a social norms treatment was discussed, but the focus group farmers felt that the reputation and loss aversion treatment were more effective. Due to sample size constraints, it was not possible to include three treatments.

The outcome variables are information engagement, knowledge and stated intentions to change farm practices. Information engagement was elicited by measuring how many seconds farmers spent looking at each infographic. Participants' knowledge in relation to the provided information was assessed with multiple choice questions. Specifically, there were two multiple choice questions for each infographic, one question focused on management related issues and one focused on environmental implications. An example for an environmental related question is: 'How much fertilizer can you save by spreading lime?' followed by 5 choices: 30 kg/ha, 50 kg/ha, **70 kg/ha**, 90 kg/ha and don't know.[2]

Stated intention was measured by asking farmers about their plans for 2022 in relation to the three promoted farm practices (i.e. plans to increase lime application, clover and protected urea in 2022), and one general question about fertilizer application reduction plans, i.e., in 2022, I plan to reduce chemical N fertilizer. The answer choices were 'yes', 'no' and 'unsure', with follow up questions for reasons if 'no' or 'unsure' was selected.

The survey also elicited current farm practices, and farmers' attitudes towards agricultural GHG emissions and climate change, as well as farm information usage. The complete survey and experimental measure is provided in the online supplementary material. The survey has received ethical approval and has been pre-registered on Open Science Framework.[3]

Empirical Methods

I used econometric methods to estimate the treatment effect on the respective outcomes, i.e. engagement, knowledge and intention. Specifically, I estimated the following equations:

$$y_i = \alpha + \sum_{k=1}^{K} \beta_k T(x_i = x^k) + \beta_3 X_i + \epsilon_i, \tag{1}$$

where y_i is the respective outcome for each farmer i, i.e. engagement, knowledge and stated intention (outcome variables are described in more detail in the next sub-section). $T(x_i = x^k)$ is a dummy variable indicating that respondent i received treatment k, where k are the two treatments and the control group, which acts as the base category.

X_i is an nxm matrix of n observations for m control variables that includes farm size and system, use of best practices, climate change attitude, age, and awareness of the Signpost Program. α is a constant, β are parameters to be estimated and ϵ_i is a normally distributed error term. The coefficient of interest is β_k, and based on pre-the registered hypotheses I expect this to be positive and statistically significant.

Depending on the outcome variable y_i different estimators are used. For the models with the outcome variables engagement, overall knowledge and intention, an OLS estimator is used. The remaining models are based on maximum likelihood estimation. Specifically, ordered probit models are applied to estimate the impact of the treatments on overall knowledge and on knowledge in relation to the specific practices, i.e., lime, clover and protected urea, as well as on overall intention. In addition, binary probit models are used to estimate the impact of the treatments on intention to use the respective practices. All models described above estimate a causal impact as treatments have been randomly assigned.

[2] Correct answer in bold. The information needed to provide the correct answer was provided in the infographic. Participants did not have the option to return to the infographics to look for the information.

[3] Please see pre-registration details under this link: https://osf.io/qyvgt

Data

The study was conducted in January 2022 and was administered in Qualtrics. An online link was sent to farmers through their local advisor. An incentive of 30 €50 online gift vouchers was provided. The vouchers were randomly allocated to all respondents who opted to participate in the draw.

528 completed responses were received. Of those completed responses, 300 were dairy farmers, and 228 drystock farmers, comprising of 108 suckler (i.e. calf-cow operations), 92 cattle finishing and 28 sheep farmers. Dairy farmers in the sample have on average 129 dairy cows, which is significantly larger than the national average of 92 dairy cows (CSO, 2021).

Suckler farms have on average 31.74 suckler cows, cattle finishers have an average cattle herd of 91.22, while sheep farmers lambed on average 169.75 ewes/hoggets. When comparing this to the national average reveals that suckler farms have on average 36.9 livestock units. Cattle finishers have an average of 47 livestock units, while sheep farms have a national average of 140 ewes (Dillon, Moran, and Donnellan, 2022).

As mentioned, the outcome variables are engagement, knowledge and intention, and average values for our sample farmers are provided in table 1. In relation to engagement, as can be seen, farmers viewed the three infographics for an average time of 58 seconds. The first infographic (lime) was viewed for 26.46 seconds, the second one (clover) for 13.41 seconds, while the last infographic (protected urea) was viewed for 18.93 seconds, please see Appendix A table A1 for more details. Viewing times are consistent with what was expected. The first infographic was viewed the longest, which can be explained by the fact that respondents needed time to familiarize themselves with the way the information was presented in addition to reading the text. When looking at the second infographic, farmers were familiar with the format, and the clover infographic also included less text, which explains the shorter viewing times. Finally, the last infographic (protected urea) included more text which explains longer viewing times when compared to the clover infographic. It is re-assuring that viewing times for the last infographic increased again, as this suggest that survey fatigue may not be a serious issue.

In relation to knowledge, the data arising from the multiple choice questions were converted into an ordinal score. A correct answer was coded as 1 while all other answer choices were coded as 0. All six questions were added to form an overall knowledge score, ranging from 1 to 6. Since only eight farmers answered no question correctly (i.e. score of 0) the first two categories were merged, which explains the range from 1 to 6, see table 1. Similarly, scores for the two knowledge questions relating to each infographic were added, resulting in a range from 0 to 2 (shown in table A3). On average, farmers answered 3.7 questions correctly, with no significant difference between treatment and control groups see table 1. Importantly, farmers answered management related questions better than questions related to environmental implications of the respective farm practice, see Appendix B table A2. This may suggest selective attention (Schwartzstein, 2014). In addition, only 10% of respondents answered all questions correctly, which suggests that inattention may be an issue.

The third outcome variable is stated intention, which was also converted in an ordinal score. If the respondent indicated that it is planned to improve the use of the respective practice in 2022 (i.e. reduce fertilizer; apply more lime; increase the amount of clover/mixes species; increase the use of protected urea) the answer was coded as 1. All other answer choices were coded as 0. All four intention questions were added to form an overall intention score, ranging from 0 to 4, see table 1. In addition, scores for the individual intention questions were calculated, resulting in dummy variables that equal one if the farmer indicated to use the practice in 2022 and zero otherwise (shown in table A4 expressed as percentages). On average, farmers plan to use 2.7 of the practices to reduce chemical N fertilizer (including the general intention to reduce chemical N fertilizer), with no significant difference between treatment and control groups, see table 1. In general, farmers expressed great intentions for reducing chemical N fertilizer, which may partly be driven by high fertilizer prices at the beginning of 2022. Just under 60% of dairy farmers plan to increase the use of protected urea, while less than 40% of drystock farmers plan to use more protected urea. Overall, dairy farmers have

Table 1. Outcome variables by treatment

Outcome variables	Reputation	Expenses	Control	Full sample	Difference
Engagement	50.47 (48.02)	57.54 (46.99)	65.92 (44.24)	58.06 (46.76)	p=0.0001
Knowledge	3.63 (1.40)	3.82 (1.37)	3.72 (1.52)	3.72 (1.43)	p=0.293
Intention	2.84 (1.12)	2.64 (1.16)	2.71 (1.08)	2.73 (1.12)	p=0.372
Observations	174	174	180	528	

Notes: Difference: Kruskal Wallis test between groups for continuous variables, and χ^2 tests for categorical variables.

Table 2. Control variables by treatment

Control variables	Reputation	Expenses	Control	Full sample	Difference
Farm size	60.56 (49.61)	56.77 (37.16)	64.96 (55.32)	60.81 (48.08)	p=0.314
Farm system (% dairy farms)	57.47	57.47	55.55	56.82	p=0.915
Age 18-35 (% in category)	15.52	14.37	16.11	15.34	p=0.899
Age 36-45	23.56	20.69	23.89	22.27	p=0.734
Age 46-55	31.03	32.18	28.33	30.49	p=0.721
Age 56-65	22.99	20.69	25.56	23.11	p=0.554
Age 65+	6.09	12.07	6.11	8.33	p=0.090
Signpost (% aware)	72.41	65.52	65.00	67.61	p=0.252
Reduced N application in last 3 years (% yes)	45.40	48.85	43.33	45.83	p=0.576
Protected urea (% of fertilizer N in 2021)	21.72 (31.72)	23.92 (31.18)	20.61 (27.32)	22.07 (30.08)	p=0.554
Clover (% of farmers having any clover in 2021)	91.38	89.08	88.89	89.77	p=0.693
Lime (% of farmers applied lime in 2021)	68.97	68.97	63.89	67.23	p=0.500
Climate change attitude (range: 4 to 20)	14.62 (3.33)	14.77 (3.42)	14.77 (3.43)	14.68 (3.37)	p=0.886
Observations	174	174	180	528	

Notes: Difference: Kruskal Wallis test between groups for continuous variables, and χ^2 test for proportions.

significantly greater intentions to increase the use of environmentally friendly measures, and more detail is provided in Appendix C.

I hypothesised that the outcome variables would be significantly influenced by the treatments, and table 1 also provides an overview of the outcome variables divided by treatment. Beginning with engagement, it is evident that framing of information influenced how long farmers viewed the infographics, but the direction of the effect is against the initial hypothesis. In fact, the time farmers spent looking at the infographics is shorter for the treatment groups. This difference is confirmed by a Kruskal Wallis test. While, as mentioned, there is no significant difference between the treatment and control groups in relation to knowledge and stated intention. I test these effects in more detail with econometric methods, but before presenting the results from the econometric analysis, control variables are described.

Control variables divided by treatment and for the full sample are reported in table 2, while control variables divided by farm system are reported in the Appendix in table B1. Kruskal Wallis and χ^2 tests reveal that there are no statistically significant differences between the three treatment groups in relation to control variables (see last column of 2). As such, this confirms that farmers were randomly assigned into treatment groups.

Survey respondents farm 60.81 ha on average, see table 2. 15% of sample farmers are younger than 35 and 8% of sample farmers are older than 65. This implies that sample farmers are significantly younger than the national average, where almost one third is older than 65 (CSO, 2021). The majority of farmers (almost 70%) are aware of the Signpost Program. However, this differs between farm systems. For example, over 80% of dairy farmers are aware of the Signpost Program, while just half of drystock farmers know of the Signpost Program.

Of particular interest are current usage rates of the practices that are promoted by the infographics, and table 2 provides an overview of current practices on our sample farms. As mentioned, reductions in chemical N fertilizer is one of the key measures to reduce agricultural GHG emissions in Ireland at present. Spreading lime and implementing clover are steps to achieve lower fertilizer application rates, while protected urea is marketed as 'environmentally friendly' fertilizer.

About 45% of sample farmers reduced chemical N fertilizer application over the last three years. In relation to protected urea, 22% of fertilizer of sample farms was applied as protected urea. This differs between farm systems: Almost 30% of fertilizer spread by dairy farmers was applied as protected urea, while only 12% of fertilizer applied by drystock farmers was applied as protected urea. When interpreting this difference, it is important to realize that absolute fertilizer applications of dairy farmers are generally much higher than application rates of drystock farmers. However, in relation to GHG mitigation, the target is that 100% of chemical N fertilizer is applied as protected urea. This indicates that there is great potential within sample farmers to further increase this practice. In fact, 47% of sample farmers indicated that they are not using any protected urea, while only 3.41% of sample farmers indicated that more than 95% of their fertilizer application is protected urea. These statistics indicate that the infographic about protected urea is relevant for almost all farmers (96.6%) of the sample.

In relation to clover, almost 90% of sample farmers indicated that they have some clover in their grassland swards. However, this measure does not give detailed insights into the intensity of clover uptake.[4] Current recommendations for farmers are to establish at least 20% clover content in all of their grassland area (Hennessy et al., 2022). The incorporation of clover into grazing swards is a key farm practice to reduce GHG emissions due to reduced fertilizer application needs (Lanigan et al., 2018), yet the uptake of clover in grazing swards has remained low (Environmental Protection Agency, 2022), underlining the importance of this infographic for sample farmers.

In relation to spreading lime, 67% of sample farmers spread lime in 2021. Exploring this by farm system reveals the vast majority (81%) of dairy farmers spread lime on their fields last year, while only about half of drystock farmers spread lime. In general, the application of lime is strongly encouraged for all farmers, but correct application rates depend on soil pH and are thus hard to assess by a survey. Table A5 in the appendix shows control variables divided by farm system.

Farmers were also asked about their opinions in relation to GHG emissions from agriculture and climate change, and a 'climate change attitude' variable was created based on the sum of the following four statements: 'GHG emissions from agriculture are an important issue', 'GHG emissions from agriculture are cause for alarm', 'Addressing climate change is urgent' and 'I can make a contribution to mitigating climate change on my farm', which were all assessed by a 5-point Likert scale ranging from strongly disagree to strongly agree[5]. The choice of the statements was informed by the Cronbach's alpha value, which was highest for the selected four statements. Specifically, the four statements achieved a Cronbach's alpha of 0.715. The average score of the sample farmers is 14.68.

Overall, the sample is biased towards larger farms operated by younger farm holders. This is similar to other studies that rely on online survey with farmers, see Kuhfuss et al. (2016) and Läpple and Osawe (2023) for examples. This also reflects the difficulty in reaching farmers in the absence of panel providers for agriculture in many countries. Nevertheless, this sampling bias is considered in the analysis and interpretation of the results.

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[4] While the survey asked the proportion of grassland swards that contained clover and/or mixed species, answers indicated that this question was not interpreted correctly by all farmers. Hence, only whether or not the farmer implemented any clover/ multi species is used.

[5] The full set of questions can be found in the survey provided in Appendix D.

Table 3. Regression results: Information engagement

Information engagement	All Model 1	Lime Model 2	Clover Model 3	Pr. urea Model 4
Reputation	-15.450***	-8.322***	-4.405***	-2.409
	(4.860)	(3.113)	(1.268)	(1.965)
Expenses	-9.420*	-5.620**	-1.867	-1.386
	(4.822)	(2.773)	(1.575)	(1.668)
Farm size	0.014	0.006	0.018	-0.004
	(0.043)	(0.026)	(0.019)	(0.011)
Farm system	-2.437	2.181	-1.962	-0.135
	(5.119)	(2.661)	(1.417)	(1.712)
Pr. urea usage	0.079			-0.029
	(0.081)			(0.022)
Liming	6.085	2.676		
	(4.485)	(2.253)		
Clover	3.948		0.176	
	(5.561)		(2.061)	
Climate change attitude	0.961	0.841*	0.137	0.098
	(0.642)	(0.431)	(0.165)	(0.229)
Age (36 - 45)	9.247	4.581	1.256	2.838
	(6.677)	(4.697)	(1.484)	(2.323)
Age (46 - 55)	10.051*	2.791	3.564*	3.258
	(5.830)	(3.635)	(1.860)	(2.329)
Age (56 - 65)	20.384***	8.333**	5.578***	6.076**
	(6.910)	(4.095)	(1.847)	(2.615)
Age (65+)	24.018***	9.817**	6.782***	6.654**
	(6.961)	(4.020)	(1.940)	(2.849)
Signpost	-3.471	-1.743	1.162	-2.070
	(4.757)	(2.513)	(1.314)	(1.876)
Constant	33.766***	11.828	9.301***	16.785***
	(12.068)	(7.367)	(2.961)	(3.880)
Observations	528	528	528	528
R-squared	0.054	0.040	0.050	0.026

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Results and Discussion

In line with the pre-registered hypotheses, I test the impact of the treatments on the time spent looking at the infographics (engagement), knowledge and stated intentions. Table 3 reports the results of a linear regression model with overall information engagement as dependent variable and separate models for engagement with each infographic (i.e., the time spent looking at lime, clover and protected urea infographics). As outlined in equation 1, treatments are included as dummy variables with the control group as base category. The following control variables are also included in the models: farm size and system; climate change attitude, use of the respective practice (i.e. lime, clover, protected urea), farmer's age measured in categories, and awareness of the Signpost Program.

As can be seen in table 3, the reputation treatment significantly affects the time participants viewed the infographics, but the direction of the effect differs to what was expected. In contrast to prior expectations, the treatments significantly reduced the time farmers engaged with the provided information. More specifically, the reputation treatment significantly reduced total engagement by 15 seconds. Exploring this effect by infographic (models 2 to 4) reveals that the effect is mainly due to a reduction in viewing the lime infographic (8 seconds reduction), followed by a 4 seconds reduction in viewing the clover infographic. However, the treatment did not significantly impact how long farmers viewed the protected urea infographic.

A similar pattern is evident with the expenses treatment. Overall, the expenses treatment reduces engagement with all infographics by almost 10 seconds. Focusing on the individual infographics reveals that the loss aversion treatment significantly reduced viewing time of the lime infographic, but did not significantly influence how long farmers viewed the remaining two infographics.

The results from table 3 suggest that the treatment effect diminishes over time, as the effect is stronger for the first infographic (lime) and neither treatment significantly influences how long the last infographic (protected urea) is viewed. While this is not encouraging in relation to the strength of the treatment effect, it suggests that the additional reading related to the treatments over the control group does not cause additional survey fatigue. Otherwise, we would see a significant shorter engagement in the treatment groups compared to the control group in the infographics that were presented later. Furthermore, there is no statistically significant difference between the two treatment effects, and both significantly reduce engagement.

Overall, it appears that a close link between framing of the message and the infographic is required to exert an effect in the desired direction, i.e. increase information engagement. For example, Graham and Abrahamse (2017) suggest framing of the message to align with people's value sets as an important factor of communicating climate change messages. Despite close collaboration with farm advisors and farmers, the treatments may not have been aligned with farmers' pre-existing beliefs, leading them to reduce engagement with the information.[6]

In addition, Golman, Hagmann, and Loewenstein (2017) state that the expectation of bad news leading to negative feelings can increase inattention[7]. For example, some media articles blame farmers for climate change[8] and it has also been shown that Irish farmers are concerned about climate change and see climate change as an overstated problem (Läpple, 2023). This could be an indication that farmers may perceive climate change as bad news. As such, the reputation treatment may have triggered pre-existing beliefs (i.e., blame for climate change) and therefore evoked negative feelings, a feeling which has also been found to be associated with information avoidance of farmers (Läpple and Arpinon, 2024). Furthermore, this may have even been aggravated by confirmation bias, where people confirm their pre-existing beliefs (Rabin and Schrag, 1999), i.e., the feeling of being blamed for climate change. In this context, Reisch, Sunstein, and Kaiser (2021) describe that confirmation bias can reduce information engagement. Moreover, negative news seems to have no impact on preferences, indicating that respondents may be unwilling to process adverse information. These findings align with recent studies, suggesting that people are more inclined to accept positive news over negative news (Cerroni, Notaro, and Raffaelli, 2019).

In relation to the expenses treatment, it may be the case that the phrase 'avoid unnecessary expenses' evoked negative emotions as opposed to triggering the anticipated loss aversion effect, and as such reduced engagement. In this instance, it would be desirable to have detailed information on reasons for increased disengagement. However, the literature provides clear evidence that financial concerns reduce information engagement (Golman, Hagmann, and Loewenstein, 2017) and bad news (i.e., unnecessary expenses) also reduce information engagement (Sharot and Sunstein, 2020; Reisch, Sunstein, and Kaiser, 2021). An alternative explanation may be receiving discouraging

[6] One possible explanation is that the focus group farmers did not represent the general opinion of the farming population, due to self-selection.

[7] In our data, only 7 farmers looked at each infographic less than 3 seconds, while only 10% of farmers answered all knowledge questions correctly. This suggests that inattention (i.e., people not paying attention while viewing the information) may be more important than information avoidance, i.e., deliberately avoiding the information by skipping the information. However, it is also important to note that our experiment was not set up to measure information avoidance per se. In addition, in our sample the majority of farmers express concern about agricultural GHG emissions and 70% of farmers stated that they are interested in information about climate actions, which further suggests that active information avoidance is likely not a concern.

[8] Please see IrishExaminer, and IrishTimes and TheJournal for examples.

advice, for example Möbius et al. (2022) show that people follow advice more when they receive a positive signal about their ability to when they receive a negative signal.

In relation to control variables, farm size and farm system, as well as current use (intensity) of the promoted practices are not significantly related to engagement with the information. In contrast, with increasing age, infographics are viewed for longer. This is in line with findings that reading is a process that changes throughout the lifespan (Locher and Pfost, 2020).

Next, I test the effect of the treatments on knowledge[9], see table 4. Model 1 and 2 relate to overall knowledge: Model 1 is an ordered probit model, while model 2 is a linear regression model. Models 3 to 5 focus on each specific practice promoted by the infographics. Based on the ordinal nature of the knowledge score, these are ordered probit models. The highest category means that the farmer answered all questions correctly (see table A3). As before, treatments are included as dummy variables, and all models include a set of control variables comprising of farm size and system, lime, clover and protected urea usage, climate change attitude, age categories and whether or not the farmer is aware of the Signpost Program.

As can be seen, neither of the treatments have a significant impact on knowledge. Thus, despite impacting engagement in terms of viewing times, the treatments do not influence knowledge. However, considering that farmers in the reputation treatment viewed the infographics for a shorter time with no significant difference in knowledge to the other treatment groups, may suggest that farmers in the reputation treatment focused better (but shorter) on the task.

In relation to control variables, the models focusing on overall knowledge (Model 1 and 2) indicate that increasing farm size and usage of protected urea is positively related to knowledge. In contrast, current usage of clover or liming is not significantly related to knowledge on these practices. Greater concern about climate change and being aware of the Signpost Program is also positively related to overall knowledge, while some differences emerge in relation to the individual practices. For example, climate change attitude is not statistically significant in model 3, which focuses on knowledge of liming. Despite the fact that liming is pushed as a climate change mitigation strategy in Ireland, a stronger climate change attitude does not seem to be related to knowledge about the practice. In addition, being aware of the Signpost program is not significantly related to knowledge about protected urea. While increased use of protected urea is promoted by the Signpost Program, the knowledge questions in this survey may not adequately pick up this effect. Finally, in relation to overall knowledge, knowledge on these practices declines with increasing age.

In relation to the last outcome variable (stated intention), the results of the treatment effect on stated intention are reported in table 5. Model 1 and 2 focus on overall intention. Model 1 is an ordered probit model, while Model 2 is a linear regression model. Models 3 to 5 are binary probit models and focus on each specific practice promoted by the infographics. Treatments are included as dummy variables with the control group as base category, and all models include the following control variables: Farm size and system, lime, clover and protected urea usage[10], climate change attitude, age categories and whether or not the farmer is aware of the Signpost Program.

As can be seen, neither of the treatment variables significantly affect stated intentions, which is against the pre-registered hypothesis. Considering the previous finding that the treatments affected viewing times with diminishing effect for subsequent infographics, may suggest that the treatments were not strong enough to influence farmer decisions in a lasting way. However, it is important to note that the variables controlling for current extent of the use of the respective practices are all significantly and positively related to the overall stated intention to increase the use of the practices. It is also interesting to note that being aware of the Signpost Program is significantly related to a higher stated intention to use the promoted practices, and that age is not significantly related to intentions.[11].

[9] Please note that increased knowledge may also reflect better attention.

[10] In each model the respective practice is included as control variable.

[11] I also tested whether the treatment effect on intention differs with the use of the current practice (by including interaction terms), but the effects are not statistically significant.

Table 4. Regression results: Knowledge

Knowledge	All Model 1	All Model 2	Lime Model 3	Clover Model 4	Pr urea Model 5
Reputation	-0.101	-0.103	-0.052	-0.179	0.062
	(0.111)	(0.151)	(0.124)	(0.121)	(0.121)
Expenses	0.084	0.114	0.064	-0.008	0.186
	(0.112)	(0.151)	(0.125)	(0.121)	(0.122)
Farm size	0.002*	0.002**	0.002	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Farm system	-0.070	-0.105	-0.056	-0.191*	-0.045
	(0.110)	(0.147)	(0.119)	(0.114)	(0.118)
Pr. Urea	0.004**	0.005**			0.004**
	(0.002)	(0.002)			(0.002)
Liming	0.129	0.183	0.264**		
	(0.106)	(0.146)	(0.117)		
Clover	-0.125	-0.179		-0.067	
	(0.150)	(0.204)		(0.163)	
Climate change attitude	0.037***	0.046**	0.012	0.041***	0.031**
	(0.014)	(0.019)	(0.015)	(0.015)	(0.015)
Age (36 - 45)	-0.287*	-0.380**	-0.217	-0.401**	-0.054
	(0.151)	(0.192)	(0.170)	(0.165)	(0.164)
Age (46 - 55)	-0.358**	-0.481***	-0.260	-0.448***	-0.192
	(0.142)	(0.185)	(0.161)	(0.157)	(0.156)
Age (56 - 65)	-0.277*	-0.362*	-0.170	-0.411**	-0.068
	(0.150)	(0.192)	(0.169)	(0.165)	(0.164)
Age (65+)	-0.584***	-0.765***	-0.307	-0.702***	-0.378*
	(0.202)	(0.269)	(0.225)	(0.219)	(0.219)
Signpost	0.226**	0.294*	0.210*	0.307***	0.027
	(0.107)	(0.153)	(0.119)	(0.115)	(0.116)
Constant		3.158***			
		(0.450)			
Observations	528	528	528	528	528
R-squared		0.092			

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Conclusion

Agricultural advisory services are not always successful in convincing farmers to implement changes on their farms (e.g., Aker (2011); Birkhaeuser, Evenson, and Feder (1991); Läpple and Hennessy (2015)). Also, just providing information sometimes has very little impact (Karlan, Knight, and Udry, 2015). This issue is particularly pertinent considering that reaching climate targets will require large scale adoption of GHG mitigation practices by farmers, which calls for effective climate change communication. Many farmers certainly use new information and are willing to embrace changes on their farms. However, reaching enough farmers with information and asking them to change their farm practices to contribute to achieving climate targets will be challenging. Therefore, ways to increase engagement with information provision and encourage climate action is important.

Utilizing an online survey experiment with over 500 farmers, this study assessed the impact of framing of information with the aim to achieve more effective climate change communication that promotes agricultural GHG mitigation. Specifically, by randomly allocating farmers into treatment and control groups, I estimated a causal effect of information framing on engagement, knowledge

Table 5. Regression results: Intention

Intention	All Model 1	All Model 2	Lime Model 3	Clover Model 4	Pr urea Model 5
Reputation	0.096	0.088	0.034	0.090	0.074
	(0.115)	(0.111)	(0.149)	(0.143)	(0.137)
Expenses	-0.083	-0.092	-0.001	-0.141	-0.015
	(0.115)	(0.115)	(0.149)	(0.141)	(0.137)
Farm size	0.001	0.001	0.001	0.003**	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Farm system	0.308***	0.321***	0.091	0.301**	0.358***
	(0.114)	(0.113)	(0.145)	(0.136)	(0.131)
Pr. Urea usage	0.005***	0.005***			0.005***
	(0.002)	(0.001)			(0.002)
Liming	0.231**	0.229**	0.218		
	(0.109)	(0.110)	(0.137)		
Clover	0.334**	0.347**		0.829***	
	(0.153)	(0.163)		(0.187)	
Climate change attitude	0.010	0.010	-0.017	0.018	0.006
	(0.014)	(0.014)	(0.019)	(0.017)	(0.017)
Age (36 - 45)	-0.208	-0.220	-0.187	-0.331*	-0.257
	(0.155)	(0.147)	(0.202)	(0.195)	(0.184)
Age (46 - 55)	0.063	0.035	0.091	-0.192	0.056
	(0.147)	(0.128)	(0.198)	(0.187)	(0.175)
Age (56 - 65)	0.027	-0.003	-0.200	-0.146	0.001
	(0.155)	(0.142)	(0.201)	(0.196)	(0.184)
Age (65+)	-0.099	-0.110	-0.296	-0.252	-0.133
	(0.206)	(0.212)	(0.261)	(0.254)	(0.247)
Signpost	0.231**	0.234**	0.407***	-0.054	0.244*
	(0.110)	(0.112)	(0.140)	(0.136)	(0.130)
Constant		1.671***	0.492	-0.708**	-0.516*
		(0.293)	(0.337)	(0.359)	(0.303)
Observations	528	528	528	528	528
R-squared		0.133			

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

and stated intention to adopt and increase the use of GHG mitigation practices. One treatment aimed to generate reputation concern of the agricultural industry, while the second treatment focused on avoiding unnecessary expenses. As hypothesised, I found that the treatments significantly affect information engagement, but the direction of the effect was negative against expectations. In addition, I did not find significant effects of the treatments on knowledge or stated intention. In relation to knowledge, positive attitude towards climate change mitigation and awareness of the Signpost Program was positively related, while the farmer's age was negatively related to knowledge. The findings also revealed that farmers have much greater knowledge on management related issues of GHG mitigation practices then environmental implications.

There are a number of findings from this study that are worth highlighting. First, the results show that framing of information influences engagement with the information. However, the negative impact of the treatments seems to suggest that the framing of the information may have initiated expectation of bad news, which is related to increased inattention (Golman, Hagmann, and Loewenstein, 2017). For example, Möbius et al. (2022) show that people follow advice more when they receive a positive signal about their ability to when they receive a negative signal. In addition, a reduction in engagement may be further aggravated by confirmation bias (Rabin and Schrag, 1999), that makes people reinforce pre-existing beliefs, i.e. farmers are blamed for climate change (as suggested by several media articles), which triggers negative feelings that the reputation treatment may have reinforced and caused further disengagement. As such, empirical evidence from this study in combination with previous literature findings suggest that climate change communication may need to be motivated in a way to trigger expectations about positive news in order to increase information engagement. If confirmation bias is at play, this bias can also have a positive impact on information engagement (Reisch, Sunstein, and Kaiser, 2021).

Second, the negative impact of the reputation treatment may point towards a social dilemma. Addressing climate change is a collective action problem, where immediate short term gains are known to outweigh long-term collective strategies (Ostrom, 2010). However, working together – inviting people to join in to achieve a common goal (Vlasceanu et al., 2024) – does not seem to enact interest in climate change mitigation of Irish farmers.

Finally, results from the knowledge questions provide useful insights in potential issues with inattention. Shorter engagement in the reputation treatment did not reduce knowledge, suggesting that attention may be higher for a shorter time. However, the findings also reveal that all farmers have significantly better knowledge of how to implement new farm practices, as opposed to their environmental impact. This may suggest that information on how to implement practices is more important to engage farmers than highlighting the environmental performance of new farm practices. nevertheless, these findings also suggest inattentive behaviour.

There are a number of limitations in relation to internal and external validity that are important to consider in relation to this study. First, in relation to internal validity, the absence of an active control group (i.e., providing text of similar length without relevant information) implied different reading times and cognitive burden for survey respondents. This could mean that the treatment effect is also picking up survey fatigue. While longer engagement with the last infographic compared to the second infographic does not point towards survey fatigue, without an active control, this possibility cannot be excluded for certain. Second, the order of the infographics has not been randomized. However, as the order is exactly the same in both treatments and the control group, this should not cause any concerns in relation to the treatment effect. In relation to external validity, the study also suffers from a common problem of studies that rely on convenience sampling of farmers, see Kuhfuss et al. (2016) and Läpple and Osawe (2023) for examples. As is often observed, the sample is not representative of the farming population but rather represents the behavior of younger farmers who manage larger farms. As these farmers may have a different attitude about the need for climate change mitigation, it is possible that the negative treatment effect may even be larger in the wider farming population. However, despite those limitations, the study provides interesting insights and underlines the importance of successfully communicating GHG mitigation measures among farmers to combat the climate crisis. Hence, pursuing further research in this area is needed. One interesting possibility would be to devise and explore positive framing of climate change information to establish if this piques interest in climate change mitigation among farmers. This could include economic benefits such as access to premium prices and new markets, adapting to market demands, or emphasizing co-benefits of climate change mitigation such as biodiversity of water quality enhancements. Another interesting option would be to assess whether it is possible to devise tailored information based on farmers' values and how this impacts engagement and subsequent behavior changes. Options would be to let farmers endogenously choose information or test information provision as narratives or science-based facts as in Yang and Hobbs (2020).

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Appendix A

Engagement

Table A1. Engagement by infographic

	Reputation	Expenses	Control	All
All infographics	50.47 (48.02)	57.54 (46.99)	65.92 (44.25)	58.06 (46.76)
Lime	22.56 (31.76)	25.70 (24.08)	30.97 (27.55)	26.46 (28.13)
Clover	11.03 (11.46)	13.66 (17.23)	15.47 (12.83)	13.41 (14.14)
Pr. urea	16.88 (20.45)	18.17 (15.82)	19.48 (15.44)	18.19 (17.37)
Observations	174	174	180	528

Notes: Time spent looking at infographic measured in seconds. Mean and standard deviation in parentheses.

Knowledge

Farmers were asked to answer six multiple choice questions about the information provided in the infographics. We ensured farmers that this is not a test of their knowledge, but rather a test of how successful information is provided. The questions and % correctly answered are provided in table A2.

It is evident that farmers answered management related questions better than questions that related to environmental implications of the respective farm practice.

Table A2. Knowledge questions

	Dairy	Drystock	All
How much fertilizer can you save by spreading lime?	59.33	46.93	53.98
Where should you apply lime?	86.00	83.33	84.85
How much fertilizer can you save by incorporating clover?	39.33	25.44	33.33
When should you sow clover?	80.33	70.18	75.95
By how much does protected urea reduce GHG emissions when compared to CAN?	40.33	37.72	39.20
Protected urea is cheaper than CAN when compared per	86.33	79.82	83.52

Notes: Numbers refer to % of correct answers.

Table A3. Knowledge categories

Knowledge categories	Lime	Clover	Pr. urea
0 (both wrong)	8.52	19.51	12.69
1 (one correct)	44.13	51.70	51.89
2 (both correct)	47.35	28.79	35.42
Observations	528	528	528

For the analysis, the knowledge questions were coded as follows: a correct answer received a score of 1, all other answers received a score of 0. For the individual knowledge questions (i.e. two questions related to each infographic), this resulted in the categories shown in table A3. These are used for the ordered probit models shown in table 4. Farmers knowledge in relation to the information provided in the infographics differs. Specifically, in relation to the lime infographic, almost half of the sample farmers (47%) answered both questions correctly. This is quite different in relation to clover, where less than one third of sampled farmers (29%) answered both questions correctly, and also to protected urea where 35% of farmers answered both questions correctly.

Intention

Farmers were asked about their intentions to implement the promoted practices on their farms in 2022. Figure A1 provides an overview of farmers' intentions. As can be seen, almost all farmers plan to reduce fertilizer applications in 2022. While this is an important step to reduce GHG emissions, it is also important to realise that fertilizer prices were very high at the time the data were collected. This likely influenced farmers' motivations to reduce fertilizer applications.

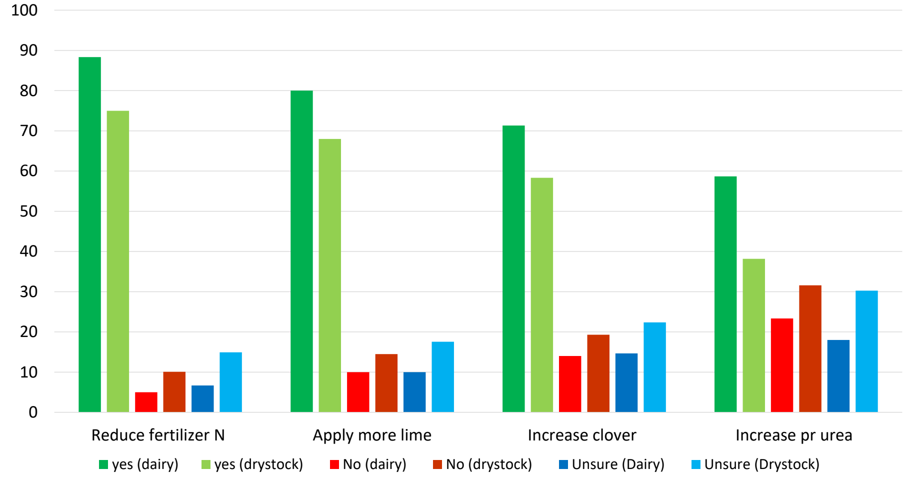

Figure A1. Stated intentions for 2022

Farmers' stated intentions were then converted into a dummy variable, where positive intentions were coded as one, and no and unsure were coded as zero. While this was used to calculate overall intention scores (see table 1), this data was also used to calculate intentions in relation to the respective farm practices as shown in table A4, which is the used for the models presented in table 5.

Table A4. Intention by farm practice and treatment

Intention	Reputation	Expenses	Control	All
Reduce fertilizer (% indicated yes)	85.63	80.46	81.67	82.57
Lime (% indicated yes)	76.44	74.14	73.89	74.81
Clover (% indicated yes)	69.54	60.92	66.67	65.72
Pr. Urea (% indicated yes)	52.29	48.85	48.33	49.81
Observations	174	174	180	528

Appendix B: Control Variables by Farm System

Table B1. Control variables

Control variables	Dairy	Drystock	All
Farm size	74.50 (44.06)	42.79 (47.30)	60.81 (48.08)
Age 18-35 (% in category)	17.33	12.71	15.34
Age 36-45	23.67	21.49	22.27
Age 46-55	33.67	26.31	30.49
Age 56-65	21.00	25.88	23.11
Age 65+	4.33	13.6	8.33
Signpost (% aware)	82.33	48.24	67.61
Reduced N application in last 3 years (% yes)	43.67	48.68	45.83
Protected urea (% of fertilizer N in 2021)	29.98 (32.16)	11.65 (23.39)	22.07 (30.08)
Clover (% of farmers having any clover in 2021)	89.00	90.79	89.77
Lime (% of farmers applied lime in 2021)	81.33	48.68	67.23
Climate change attitude (range: 4 to 20)	14.60 (3.22)	14.79 (3.56)	14.68 (3.37)
Observations	300	228	528