Adoption of greenhouse gas mitigation in agriculture: an analysis of dairy farmers' preferences and adoption behaviour

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Abstract

Greenhouse gas mitigation in agriculture implies changes in farm management practices. Knowledge on farmers' current adoption of management practices aimed at reducing emissions, and their preferences regarding these, is important to inform the development of robust climate change mitigation policies in the agricultural sector. In the context of Scottish dairy farms, this study combines information on current adoption of mitigation practices with preference information based on Best-Worst-Scaling to facilitate the choice of mitigation practices to support via policy mechanisms that encourage and incentivise change. We find that current adoption plays an important role in understanding preference rankings of mitigation practices, and identify promising mitigation practices based on their potential for additional emission reduction, their perceived contribution to the farm's financial and environmental performance and information on their cost-effectiveness.

Keywords Climate change; Mitigation; Best-Worst-Scaling; Stated preferences; Technology adoption; Dairy farming

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1. Introduction

There has been an increasing policy interest in reducing greenhouse gas (GHG) emissions from agriculture in recent years (Smith et al. 2008; European Commission 2008; UNFCCC 2008; Scottish Government 2009). This can be attributed to the contribution of the agricultural sector to GHG emissions globally and nationally, and to the cost-effectiveness of agricultural GHG mitigation relative to emission reductions in other sectors. Policy makers face the challenge to develop and implement effective GHG abatement strategies for agriculture. This requires identifying those mitigation practices that are cost-effective and promise considerable potential for abatement, followed by a choice of suitable policy mechanisms to encourage their uptake.

A key tool for prioritising mitigation measures for policy support are marginal abatement cost curves (MACCs) for agriculture (Moran et al. 2010), combining both information on cost-effectiveness and abatement potential of a large number of mitigation practices. However, despite recent methodological refinements (Eory et al. 2012), MACCs developed at the national scale often draw on aggregate information and are therefore mainly useful to provide rankings of mitigation practices that can inform high-level strategic decisions and provide a rationale for investments in GHG abatement within a particular sector of the economy. For example, the MACCs developed for the UK model the whole country as one farm and thus largely ignore heterogeneity between farms and farm types. Further, outcomes of MACCs are sensitive to a large number of assumptions made via expert judgment, for example regarding adoption rates, effectiveness and costs. There is likely to be significant heterogeneity of adoption patterns, effectiveness and costs across farms, which can influence overall cost-effectiveness depending on their distribution around the mean values applied in MACCs. Another puzzling result of MACC analysis is the significant mitigation potential identified to have negative cost. These have been referred to as 'win-win' mitigation practices. These mitigation practices would be expected to be adopted by profit-maximising farmers without requiring any incentive as they reduce the cost burden of production. However, the (perceived) lack of uptake of practices with negative costs suggests that adoption behaviour is driven by a more complex set of motivating factors (Moran et al 2013) not accounted for in the MACC approach. Further, the currently developed MACCs only comprise a subset of the potential mitigation practices in agriculture.

Accordingly, when advancing agricultural mitigation policy, MACC approaches may be of limited use as information is needed to inform actual implementation strategies. There is thus a clear need for information directly obtained from land managers and farmers to complement and substantiate the results derived via MACCs. Consequently, the main aim of this paper is to contribute to filling the gap between national strategy development and implementation in agricultural GHG mitigation by complementing the information entailed in MACCs with information on adoption rates and on farmers' preferences for farm management practices that are expected to result in considerable GHG emission reductions. Such information is important for informing targeting and prioritisation of GHG mitigation practices for policy support, either via awareness raising campaigns or as part of positive financial incentive schemes within the agricultural policy architecture.

Given the large number (>100) of potential GHG mitigation practices in the agricultural sector, and the heterogeneity in farming systems, it is difficult to obtain comprehensive information across the whole industry in a single study. The research presented in this paper thus focuses on GHG abatement in dairy farms in Scotland. Scotland provides an example of a country with highly ambitious GHG reduction goals (Scottish Government 2009) relative to the rest of other developed country economies, and the dairying sector is generally quite intensive in these systems and therefore indicate considerable GHG mitigation potential (Barnes and Toma, 2012).

This paper presents results of a survey of dairy farmers aimed at deriving a ranking of mitigation practices that may be associated with their likely adoption. The methodological approach used to obtain preference-based rankings is Best-Worst Scaling (BWS), given its suitability to accommodate the larger number of practices (Louviere et al 2013), which have been suggested to be effective mitigation options for the dairy sector.

In recent years, Best-Worst Scaling (BWS) has been applied in a range of contexts related to food choice and agricultural management to derive rankings of long 'lists' of objects along various latent dimensions of interest (Lusk and Briggeman 2009; Erdem et al. 2012; Cross et al. 2011; Lagerkvist et al 2012; Jones et al. 2013). This study therefore contributes to the increasing body of literature applying BWS to understand and inform agricultural decision making, and assesses the usefulness of the BWS methodology to identify priorities for policy support, especially at early stages of planning when policy makers are faced with a choice amongst a large number of options. To our knowledge, only one study that applied BWS was concerned with GHG mitigation options (Jones et al. 2013). The authors investigated preferences for mitigation option of Welsh sheep farmers. A key advance of our study on Jones et al. (2013) is the explicit consideration of current adoption rates in the BWS choice model, which is expected to be of high significance for policy implications drawn from results.

Specifically, this study aims to address the following questions. How do farmers rank mitigation practices with respect to their farm's financial and environmental performance? How does current adoption affect rankings? How do rankings based on farmers' preferences compare to rankings derived from a MACC? In combination with available information on cost-effectiveness, the information on preferences and adoption behaviour can be used to evaluate plans for policy support that are currently in development. Practices ranked highly by non-adopters with fairly low current adoption rates but high effectiveness should be considered for immediate policy support. Other, less preferred practices that are still deemed to be cost-effective may benefit from continued awareness raising campaigns, and may still be relevant to particular sub-groups of farmers.

The paper proceeds with a description of GHG mitigation options in dairy farms and how GHG mitigation is embedded in the current policy framework and ongoing developments. This is followed by an introduction to BWS and the modelling approach taken. After describing the case study of Scottish dairy farms, the survey and the sampling procedure, we report the results of the survey data analysis and BWS modelling. We discuss the findings in the light of the current policy framework, develop policy recommendations based on the study's results and reflect on how rankings derived through BWS compare to previous MACC analyses.

2. GHG mitigation and dairy farms: policy context

Scotland has one of the most ambitious climate change mitigation targets with GHG emission reductions of 42% by 2020, and an 80% reduction by 2050. Agriculture contributes approximately

20% to total emissions, and abatement in agriculture is pivotal role for achieving this target: a 10% emissions reduction by 2020 is expected for the agricultural sector (Scottish Government 2009). Climate change mitigation has also been highlighted to be a key part of the multi-functional role Scottish agriculture is expected to play, which is in line with general direction the Common Agricultural Policy (CAP) post-2013 is expected to take.

Dairy farming is an important agricultural activity both globally and in Scotland, and its importance is going to increase as per capita consumption of fresh milk and milk products is projected to grow by 10% in the next 10 years – more than the consumption of any other agricultural product groups, including cereals, sugar, meat or fish (OECD-FAO Agricultural Outlook 2013-2022 database). In Scotland dairy farms occupy 4% of the agricultural land area (Shepherd et al. 2007), and fresh milk and milk products account for 13% of the total Scottish agricultural output of £2.8 billion (Scottish Executive 2013). At the same time, the dairy sector's contribution to global warming is also notable: globally 4% of the total anthropogenic GHG emissions originate in the dairy product chain (Gerber et al. 2010). Although the per litre GHG emissions of milk produced in Western Europe is only two-thirds of the global average (Gerber et al. 2010), the dairy product supply chain is responsible for 3% of the total Scottish GHG emissions (Scottish Government 2013; Sheane et al. 2011). Importantly, dairy farming is well-placed to offer many opportunities to reduce GHG emissions.

Dairy farms in developed countries often utilise good quality, fertilised land for growing forages, with cereals and high-protein crop products (often bought-in to the farm) also featured in the feed mixture. GHG emissions from these cropping areas often can be reduced by altering the nitrogen fertilisation practices, the types of crops, or the soil properties. The feed composition is another target point of GHG mitigation effort: methane emissions from the rumen and both methane and nitrous-oxide emissions from the manure can be significantly decreased by modifying the ration or using feed additives (e.g. probiotics). Housing dairy cattle, especially for the winter period, is common practice, and provides another point for interventions: improving manure management to reduce methane and nitrous-oxide emissions. Finally, the health and productivity of the animals and the herd structure affects the overall input use – milk production ratio, therefore the GHG emissions embedded in the product. Dairy farmers represent the most progressive producers within the Scottish agricultural sector (Barnes et al. 2010) and not much is known regarding their current behaviour and preferences regarding management practices aimed at climate change mitigation (Vellinga et al. 2011).

There are three main pathways to provide policy support for increasing GHG abatement in the Scottish agricultural sector that together use a mix of extension and awareness raising, regulation and positive financial incentives. First, Farming for a Better Climate (FFBC) is an initiative aimed at increasing voluntary uptake of GHG mitigation and adaptation practices funded by the Scottish Government. According to the public-private benefits framework developed by Pannell (2008), FFBC should ideally support the uptake of 'win-win' mitigation options, i.e. options that yield at least moderate benefits to both the public and the private firm. This is at least qualitatively attempted by giving priority to farm practices that result in GHG mitigation while at the same time increasing productivity and/or energy and resource use efficiency. FFBC operates a number of demonstration farms (Climate Change Focus Farms), organizes information events for farmers, distributes up-to-date knowledge and information on farming practices and successful case studies on its website and publishes practical guidance documents. Examples of featured mitigation measures include improving nitrogen use and feed efficiency, improving field drainage and installing renewable energy (including anaerobic digestion).

Second, the nitrogen use regulations in the designated Nitrate Vulnerable Zones (NVZs) are mandatory elements of cross-compliance under the CAP Single Farm Payment Scheme (CAP XC). They provide co-benefits in terms of N_2O emission reduction. Third, the Scotland Rural Development Programme (SRDP) is the discretionary application of CAP Pillar 2 funds for financial support, and includes some measures that lead to GHG co-benefits.

3. Methodology

BWS has been introduced by Jordan Louviere in 1987 (Flynn and Marley 2012) and can be related back to Thurstone's (1927) method of paired comparison. BWS is based on respondents repeatedly choosing the best and worst object from lists of objects that vary following an experimental design. The frequency of best and worst choices is indicative of the relative 'importance' respondents place on each object along a latent utility scale, in our case contribution of each GHG mitigation practice to the farm's performance. Following random utility theory, respondents are expected to make errors while choosing. The utility respondent *i* derives from choosing a mitigation practice *m* from list *t* with $j = \{1,2,\ldots J\}$ practices can be decomposed into an observed or deterministic component, $V_{im,k}$, and an unobserved random error term $\varepsilon_{im,t}$ assumed to be identically and independently distributed (iid) across the sample population and related to the choice probability with a type I extreme-value distribution with constant error variance $\pi^2/6$.

$$U_{im,t} = V_{im,t} + \varepsilon_{im,t} \tag{1}$$

In our case, the deterministic part is specified to include the mitigation practice's contribution to the latent utility scale and an interaction effect capturing differences in utility due to current adoption:

$$V_{im,t} = \beta'_{im} x_{m,t} + \gamma'_{im} x_{m,t} A_i \tag{2}$$

where *β′* and *γ′* are vectors of parameters to be estimated, $x_{m,t}$ is an indicator variable for mitigation practice *m* being present in choice set *t*, and A_i is a dummy variable taking one if the farmer currently adopts a mitigation practice, else zero. The coefficient β'_{im} represents the utility that the mitigation practice x_m provides to farmer *i*. γ'_{im} captures the difference in utility obtained from mitigation practice x_m resulting from its adoption by farmer *i*.

Under these assumptions, the probability that farmer *i* chooses mitigation practice *m* from choice set *t* is described by a conditional logit model and has the following expression (McFadden, 1974):

$$L_i \; y_{best} = m \; \beta_i, t \;\; = \frac{\exp(\lambda V_{im,t})}{\sum_{j=1}^{J} \exp(\lambda V_{ij,t})} \tag{3}$$

λ is a scale term inversely proportional to error variance and normalised to one. Equation (3) can be used to model 'best' choices. Different models can be used to jointly model 'best' and 'worst' choices, each implying different ways of how respondents process information and proceed through the BWS task (Louviere et al 2013)[1]. In this study we employ a model specification that assumes a sequential decision process with best choice being followed by worst choice as proposed by Lanscar (2009) and first applied in Lanscar and Louviere (2008). The sequential process is more likely to follow the 'true' decision process and is therefore the preferred choice in the context of this study. The sequential CL model entails a product of logit probabilities with each factor being a CL model of the best or worst choice in the sequence of best-worst choices.

Let b be the mitigation practice chosen as 'best' with respect to the farm's performance ($y_{best} = b$) from choice set t_1 with $j = \{1,2,\ldots J\}$ practices, and w be the mitigation practice subsequently chosen as 'worst' ($y_{worst} = w$) from choice set t_2 containing the remaining J-1 elements. The logit probability of observing this sequence can be expressed as (Lanscar et al. 2013):

$$L_i\left(y_{best} = b, y_{worst} = w \mid \beta_i, t_1, t_2\right) = \frac{\exp\left(V_{ib,t_1}\right)}{\sum_{j=1}^{J} \exp\left(V_{ij,t_1}\right)} \times \frac{\exp\left(-V_{iw,t_2}\right)}{\sum_{j=1}^{J-1} \exp\left(-V_{ij,t_2}\right)}. \qquad 4)$$

Of course, farmers may have different preferences for the contribution of mitigation practices to their farm's performance. To accommodate this heterogeneity, we employ the mixed logit (MXL) model (Revelt and Train 1997; Train 1998; McFadden and Train 2000). In this model, each farmer has his or her own vector of parameter β'_i which deviates from the population β by the quantity η_i ($\beta'_i = \beta + \eta_i$). η_i is a random term, which introduces the heterogeneity in β by varying according to a random distribution $f(\eta_i \mid \Omega)$[2].

The unconditional probability of choosing practice b as 'best' and subsequently practice w as 'worst' is the integral of the logit probabilities in equation 4 over all possible values of β_i.

$$P_i\left(\beta_i \mid \Omega\right) = \int_{\beta_i} L_i\left(\beta_i \mid \eta_i\right) f\left(\eta_i \mid \Omega\right) d\eta_i \qquad (5)$$

This integral does not have a closed form and thus requires approximation through simulation (Train 2003), in our case using 1,000 Halton draws.

Using information from repeated best-worst choices of the same individual, we can obtain 'individual-specific' parameter estimates from the individual's conditional distribution based on their (sequence of) choices using Bayes Theorem as described in Revelt and Train (1999) and Train (2003). Rather than representing unique sets of parameters for each individual, 'individual-specific' parameter estimates reflect the mean (standard deviation) estimate of those sub-sets of the sample that made the same choice facing identical choice sets. The 'individual-specific' parameter estimates can be used to investigate differences in rankings of mitigation practices at the individual level.

Sample-level or individual-specific coefficients indicate the relative impact of a management practice to be chosen as best and worst in the BWS task. These coefficients consist of both positive and negative values, and indicate impact relative to one management practice that has been omitted for

[1] The most common model is known as *maxdiff* (Sawtooth Software 2007). In this model, respondents are assumed to evaluate all possible pairs of best-worst combinations, from which they choose the one that maximises utility on the unobserved utility scale. Results obtained from the *maxdiff* model specification are very similar to the ones described in this paper.

[2] In the application reported in this paper, we use a normal distribution. We tested several distributional forms, amongst them triangular and uniform distributions, but normal distribution yielded the highest Log-Likelihood values. More complex distributional forms such as S_b-Johnson that allows for bimodality were considered, but models did not converge.

model identification purposes. Interpretation of these coefficients does not follow intuitively. Therefore, they are converted to ratio-scaled probabilities (% of times a management practice is chosen as best) or impact scores using the probability-based rescaling procedure described in Sawtooth Software (2007) and the following equation:

$$Ratio - scaled\ impact\ score = \frac{\exp(\beta_{ij})}{(\exp\ \beta_{ij}\ + a-1)} \tag{6}$$

where β_{ij} are zero-centred parameter scores for individual *i* and management practice *j* derived from the MXL model, and *a* equates to the number of items shown in each task. The thus converted scores are then scaled on a 0-100 point scale. The rescaling allows a straightforward interpretation and comparison of the farmers' evaluations of mitigation practices with respect to their contribution to the farm's performance. If, for example, practice j_1 receives a score of 5 and practice j_2 a score of 10 for an individual, we can say that j_2's contribution to the farm's performance is perceived to be twice as large as j_1's contribution – the probability of j_2 being chosen as best is twice as large as those of j_1.

4. Case Study

The data used in this paper is based on a mail survey of Scottish dairy farms. The questionnaire administered to respondents consisted of three parts. The BWS choice tasks were followed by a question on current adoption of the management practices and finally collected a range of farm and farmer characteristics. As a first step towards developing the survey instrument, a long list of potential GHG mitigation practices in dairy farms was identified (N=85). Using expert advice, we subsequently narrowed down the number of practices based on whether an option can be readily implemented by farmers at present. This excluded practices that were currently not possible due to legal restrictions, practices that required further research or technological advances, and practices that were prohibitively expensive to implement. The short list of 20 practices (Table 1) can be grouped into practices associated with animal nutrition, animal productivity, soil and fertiliser management or manure storage. All identified mitigation practices may, depending on the circumstances, enhance the farm's financial performance due to reductions in input costs and/or enhanced productivity. Only a sub-set of the practices are considered in the current policy framework (including the basic provision of information on a measure on the FFBC website), or are under consideration for CAP post-2013.

Table 1. List of GHG mitigation practices used in BWS choice tasks

Measure	Description	**Consideration in policy framework**
Animal Nutrition		
M1	Planting high sugar content (high WSC) ryegrass (e.g. Aber HSG)	-
M2	Reducing grass in the diet and feeding more concentrates/grains/total mixed rations	RPP2-FFBC
M3	Adding oily seeds (e.g. canola, sunflower) at 10% to the diet	-
M4	Adding a live microbial feed supplement (e.g. Lactobacillus sp.) to the complete diet directly	-

M19	Applying feed and ration management (including forage/fodder analysis) with a feed company or advisor involved to optimise nutrient use of animals	FFBC - as on webpage
Animal productivity		
M5	Working with veterinary surgeons to optimise biosecurity, vaccination and herd health	-
M6	Using bull semen from high PLI indexed bulls	RPP2-FFBC
M7	Using sexed semen to increase proportion of females born	-
M13	Moving from 2 to 3 times milking per day	-
Soil and fertiliser management		
M8	Using high-clover swards (20% of dry matter)	FFBC - as on webpage
M9	Applying fertiliser according to fertiliser recommendations	NVZ, FFBC - as on webpage, RPP2-FFBC, RPP2-90%uptake
M10	Make manure management plans taking full account of nutrients available in the manure	NVZ, FFBC - as on webpage, RPP2-FFBC, RPP2-90%uptake
M11	Maintaining old drainage system (or installing a new one if needed) to improve drainage on fields	FFBC - as on webpage
M12	Preventing soil compaction (e.g. avoiding the use of heavy machinery and livestock poaching when soils are wet or saturated)	-
M16	Using the type of fertiliser that breaks down and releases nutrients slowly (controlled or slow release fertiliser)	-
M17	Using chemicals to prevent loss of N due to nitrification (nitrification inhibitors)	-
M18	Changing to crops which require less nitrogen fertilisation	FFBC - as on webpage, RPP2-FFBC
Manure storage		
M14	Frequently (twice-a-week) removing manure from the cattle shed to outside storage (e.g. to manure heap; slurry tank or lagoon)	-
M15	Installing and using an anaerobic digester to treat animal waste	SRDP (2013), FFBC - as on webpage
M20	Covering the manure storage (e.g. straw, plastic film, tent, or lid in case of slurry and plastic film in case of farm yard manure)	SRDP (2013)

Table 1 contains descriptions of the short-listed management measures, which were tested for understanding and refined in a series of focus groups with dairy farm researchers and dairy farmers. Participants of pre-tests confirmed that all included descriptions were clear and associated with concrete management actions on the farm. In this process, specific attention was given to the choice of the latent dimension used to frame best-worst choices. An obvious candidate was 'likelihood of adoption'. However, it became evident that most farmers actually adopted at least one of the 20 measures at present, and could thus not discriminate between two (or more) measures adopted at present when being asked about the highest likelihood of adoption. Several different formats were tested with the aim of capturing the farmers' genuine evaluation of a particular measure in terms of being beneficial to the farm's business. As discussions revealed, this objective could not be equated with maximising financial profits. Interestingly, several farmers stated that environmental considerations increasingly play a role in their investment decisions, motivated to a large degree by increasing demands of large buyers, including supermarket chains. In the final survey, farmers were therefore asked to choose the best or worst measure in terms of their farm's performance, which included both economic and environmental considerations. It was also clearly stated that the management practices extend beyond minimum requirements for Cross Compliance under the Single Farm Payment scheme.

The experimental design for the BWS tasks was a Balanced Incomplete Block Design (BIBD) that contained 29 choice tasks that were blocked into 3 versions. One block contained 9 BWS choice tasks, of which 4 sets comprised 5 management practices (objects), while the remaining sets featured 4 practices. The remaining 2 blocks included 10 choice tasks with 4 practices per task. Across the whole design, each item is shown 6 times, and each pair of items appears together once. Each item appears twice within each block. To avoid that an item appears in the same position in consecutive tasks, and to minimise the occurrence of the same item in consecutive tasks, the order of items in each task was randomised. An example of a typical BWS choice task is shown in Figure 1.

Figure 1. Example of BWS choice task

Best for your farm's performance	**Set 1**	**Worst** for your farm's performance
☐	Working with veterinary surgeons to optimise biosecurity, vaccination and herd health	☐
☐	Frequently (twice-a-week) removing manure from the cattle shed to outside storage (e.g. to manure heap; slurry tank or lagoon)	☐
☐	Using sexed semen to increase proportion of females born	☐
☐	Using the type of fertiliser that breaks down and releases nutrients slowly (controlled or slow release fertiliser)	☐

The sample drew on the June Agricultural Census database (Scottish Government 2012). The census is administered every year in Scotland and covers over 50,000 agricultural holdings, of which 1,650 were classified as specialist dairy or mixed dairy farming in 2012. A specialist dairy farm generates at least two thirds of its income from dairy production. In the census, a mixed dairy farming type is identified simply by the presence of dairy cows, even if their contribution to the farm's income is marginal. However, mixed farms with a substantial herd size can contribute substantially to climate change mitigation. Therefore, we included mixed farms, but omitted those farms holding less than five dairy cows, resulting in an effective sample size of 1290. The majority of more intensive dairying units tends to concentrate in the South-West of Scotland, where naturally conducive biophysical conditions prevail.

A mail survey was administered between November 2012 and February 2013, following best practice on follow-ups and reminders as detailed in Dillman (2000). The survey was carried out in two waves, with approximately 5 weeks between each wave. However, based on advice from focus group participants, we abstained from sending out further reminders, being mindful of the large amount of postal information and survey requests received by Scottish farmers. Farmers were given the opportunity to opt-out after the first wave. A total of 327 farmers responded (25%). Six farmers made use of this without stating further reason, while 36 opted out because of having recently given up dairy farming, or because they do not consider themselves as a dairy farmer. We received 285 questionnaires (22%), of which 36 contained BWS tasks that were either incomplete (N=14) or showed more than two choices (one 'best' and one 'worst') in some or all of the tasks (N=22) despite having received a carefully worded guide to completing the tasks. Of the remaining 249 farmers, 14 returned incomplete responses regarding current adoption of management practices, leaving data from 235 questionnaires (18%) for final analysis (Experimental design block 1: N=80; Block 2 N=83; Block 3 N=73).

The data were cleaned and compared with sample statistics for the whole population, as provided by the June Agricultural Census. These proved to be similar (at 5% levels of significance) using a two-sample t-test with respect to area (t=1.97), standard gross margins and economic size unit (to reflect economic factors (t= 1.33 and 1.34 respectively). In addition, standard labour requirements were similar across the census and sample (t=0.29). Table 2 reports the key indicators of the dairy farmers in the sample compared to the June Agricultural Census.

Table 2 Descriptive statistics of dairy sample compared to June agricultural census, mean and t-statistics

	Census	**Survey**
Standard Gross Margin (£)	170,254	160,681
Economic Size Unit (£/ha)	141.9	133.9
Standard Labour Requirement (Labour Units)	5.4	5.3
Area (Ha)	136.2	124.3

5. Results

Table 3 reports the stated adoption rates for the 20 practices included in the BWS choice tasks. There is a lot of heterogeneity in the level of stated current adoption within the sample. Current stated rates of adoption are greater than 80% for six of the practices (M19, M5, M9, M10, M11 and M12). At the other end of the spectrum, M3, M13, M15, M17, and M20 all have adoption rates below 10%. Adoption levels are considerably high in all of the four domains (nutrition, productivity, soil and fertiliser management and manure management). On average, a respondent has reported to currently adopt nine of the 20 practices (standard deviation 2.2), with significant heterogeneity in the patterns of adopted practices across respondents.

Table 3. Stated Current adoption rates of practices

Measure	**Short descriptor**	**Currently adopted (%)**
Animal Nutrition		
M1	High sugar content ryegrass	51.9
M2	Reducing grass and more concentrates in diet	30.2
M3	Adding oily seeds to diet	3.8
M4	Adding live microbial feed supplement to diet	20.9
M19	Applying feed and ration management	94.9

Animal productivity		
M5	Working with veterinary surgeons	93.2
M6	Semen from high PLI indexed bulls	60.4
M7	Sexed semen	51.9
M13	3 times milking per day	9.8
Soil and fertiliser management		
M8	High-clover swards	34.9
M9	Following fertiliser recommendations	86.4
M10	Manure management plans	79.6
M11	Improve drainage on fields	89.4
M12	Preventing soil compaction	92.8
M16	Controlled/slow release fertiliser	26.8
M17	Nitrification inhibitors	4.3
M18	Lower N-requiring crops	20.9
Manure storage		
M14	Frequent removal of manure	46
M15	Anaerobic digester	0.9
M20	Covering the manure storage	3.8

The CL and MXL model estimates are shown in Table 4. All mean parameter estimates are relative to the base effect of mitigation practice M18 (*Lower N-requiring crops*), which was left out in order for the model to be identified. An increase in the value of the log-likelihood function by over 200 points for the MXL model compared to the CL model confirms the presence of substantial unobserved heterogeneity in the probability of choosing a mitigation practice as 'best'. We therefore focus on MXL results for the remainder of this paper. Except for M16 (*controlled/slow release fertiliser*), all standard deviations of the random parameter distributions are statistically significant. All interaction terms with the dummy variable capturing differences in utility due to current adoption are positive, statistically significant and large in magnitude relative to base effects. This demonstrates that stated current adoption had a large influence on the probability of choosing a practice as 'best'.

Table 4. CL and MXL model results

	CL				**MXL**					
	Base effects		Interactions with stated adoption dummy		Base effects		Interactions with stated adoption dummy		Standard deviation of random parameters	
M1	-0.15		1.46	***	-0.07		1.81	***	0.96	***
M2	-1.77	***	1.96	***	-2.37	***	2.74	***	1.14	***
M3	-1.39	***	1.17	**	-1.89	***	1.67	***	0.70	***
M4	-1.46	***	1.3	***	-1.90	***	1.81	***	0.86	***
M19	0.4		2.59	***	0.41		4.09	***	2.42	***
M5	0.86	**	1.57	***	1.18	**	2.28	***	1.67	***
M6	-0.9	***	2.03	***	-1.06	***	2.61	***	0.86	***
M7	-0.25		2.08	***	-0.32		2.87	***	1.43	***
M13	-1.48	***	4.09	***	-2.13	***	6.81	***	2.85	***
M8	-0.05		1.96	***	-0.05		2.63	***	1.01	***

M9	-0.52	*	2.11	***	-0.74	**	2.82	***	0.67	**
M10	0.92	***	1.04	***	1.26	***	1.44	***	1.08	***
M11	0.52	*	2.48	***	0.51		3.93	***	1.96	***
M12	0.78	**	1.39	***	1.24	**	1.75	***	1.52	***
M16	0.02		1.13	***	0.02		1.63	***	0.13	
M17	-0.92	***	1.67	***	-1.20	***	2.56	***	0.75	***
M18	0 (fixed)		1.09	***	0 (fixed)		1.48	***	-	
M14	-1.51	***	1.62	***	-1.91	***	2.12	***	1.03	***
M15	-1.67	***	2.14		-2.29	***	4.97	***	1.56	***
M20	-1.48	***	2.45	***	-2.01	***	2.84	***	1.56	***
Log-L		-3768.73					-3568.22			
AIC		1.68					1.6			
BIC		1.73					1.68			

Note: *,**,***: significantly different from zero at 90%, 95% and 99% level

Table 5 shows the ratio-scaled impact scores for the sample average, assuming A_i in equation 2 is one for all practices, i.e. that all of the practices have been reported to be currently adopted ('adopter'), and assuming A_i is zero for all practices ('non-adopter'). For the sample average, it is apparent that impact scores tend to be highest for those practices that have the highest adoption rates. Although general patterns in impact scores between a stylised 'adopter' and 'non-adopter' are similar, there are some notable differences. An 'adopter' has higher impact scores for five of the practices (M1, M10, M12, M16, M18), and lower scores for four of the practices (M11, M13, M15, M19).

Table 5. Means and 95% confidence intervals for ratio-scaled impact scores

Measure	Short descriptor	Sample average	'Adopter'	'Non-adopter'	Cost-effectiveness
Animal Nutrition					
M1	High sugar content ryegrass	5	3.2	6.3	Not available
M2	Reducing grass and more concentrates in diet	0.7	1	1	++
M3	Adding oily seeds to diet	0.5	0.6	1.5	++
M4	Adding live microbial feed supplement to diet	0.7	0.6	1.5	-
M19	Applying feed and ration management	13.3	12.3	8.1	Not available
Animal productivity					
M5	Working with veterinary surgeons	12.2	9.1	10.9	Not available
M6	Semen from high PLI indexed bulls	3.9	2.8	3.1	-
M7	Sexed semen	6	5.7	5.4	-
M13	3 times milking per day	0.7	12.7	1.2	Not available
Soil and fertiliser management					
M8	High-clover swards	4.9	5.8	6.3	+
M9	Following fertiliser recommendations	7.8	4.2	4.0	-
M10	Manure management plans	10.1	6.3	11.1	-
M11	Improve drainage on fields	13.1	12.1	8.5	++

M12	Preventing soil compaction	11.3	7.3	11.1	Not available
M16	Controlled/slow release fertiliser	3.7	3	6.6	++
M17	Nitrification inhibitors	1	2.4	2.8	++
M18	Lower N-requiring crops	3.3	2.6	6.5	-
Manure storage					
M14	Frequent removal of manure	1.2	0.8	1.5	Not available
M15	Anaerobic digester	0.3	6.2	1.1	++
M20	Covering the manure storage	0.5	1.5	1.4	++

Note: Based on 235 respondents. All impact scores based on MXL model results. Cost-effectiveness in £ (t CO_2eq)$^{-1}$: ++ ≥ 50; +: 0 to 50; - < 0. All cost-effectiveness estimates are based on Moran et al. (2008), Pellerin et al. (2013) and Eory et al. (2014 under review).

Table 5 reveals preference patterns at the sample level, and can guide some general recommendations for promising further mitigation action in the dairy sector. However, the scores for stylised 'adopters' and 'non-adopters' do not reveal the heterogeneity of adoption patterns and the resulting heterogeneity in scores for the mitigation practices well. A high score for a particular practice may be driven by a few observations of non-adopters with a very positive evaluation of that practice's contribution to their farms' performance. Given the significant amount of unobserved heterogeneity in the MXL model, a low score may mask a considerable proportion of non-adopters who perceive a particular practice as beneficial to their farms' performance.

Table 6. Ranking of non-adopted practices based on individual-specific impact scores

Rank	Mitigation practice																			
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19	M20
1	20	0	0	0	8	0	28	35	0	30	8	10	28	1	1	37	1	19	3	6
2	24	1	1	1	2	5	22	24	2	13	5	4	12	0	2	46	5	59	3	4
3	15	0	1	1	3	10	15	34	5	1	4	0	13	2	6	41	19	52	2	11
4	26	1	3	9	0	11	9	26	5	2	1	1	11	1	12	29	44	33	0	11
5	12	7	34	16	1	19	8	18	7	0	1	1	6	4	8	14	41	17	1	20
6	6	11	28	27	1	11	6	6	8	1	3	0	9	17	27	4	43	4	0	22
7	4	13	40	25	1	14	6	6	3	1	2	0	12	23	29	1	22	2	1	27
8	2	29	40	31	0	9	6	1	1	0	0	1	14	22	24	0	23	0	1	21
9	3	24	27	27	0	8	4	3	0	0	1	0	19	14	32	0	16	0	0	30
10	1	29	24	21	0	4	1	0	1	0	0	0	19	16	30	0	5	0	0	21
11	0	19	14	11	0	0	5	0	0	0	0	0	23	14	28	0	4	0	0	18
12	0	11	9	9	0	0	1	0	0	0	0	0	19	5	14	0	1	0	0	21
13	0	5	4	2	0	2	0	0	0	0	0	0	15	5	12	0	1	0	1	7
14	0	10	0	5	0	0	1	0	0	0	0	0	4	0	2	0	0	0	0	5
15	0	3	0	1	0	0	1	0	0	0	0	0	4	1	3	0	0	0	0	0
16	0	1	1	0	0	0	0	0	0	0	0	0	3	1	1	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	2
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Sum (# of non-adopters)	113	164	226	186	16	93	113	153	32	48	25	17	212	127	233	172	225	186	12	226

We therefore estimated individual-specific parameter estimates based on MXL model results, and subsequently calculated ranks of non-adopted measures for each individual. The results of ranks of non-adopted practices are shown in Table 6. Because all respondents have reported to currently adopt at least one of the practices, the table only includes ranks from one to 19. Together with the scores of a stylised non-adopter, the table reveals a set of practices that have both considerable rates of non-adoption and thus further potential for mitigation, and have a high density at the top of the distribution of ranks and thus are promising prospects for policy support to stimulate uptake. These practices are i) M1 (*High sugar content ryegrass*); ii) M7 (*Sexed semen*); iii) M8 (*High-clover swards*); iv) M16 (*Controlled/slow release fertiliser*); and v) M18 (*Lower N-requiring crops*). M10 (*Manure management plans*) is ranked highly, but has limited potential for further adoption with stated current adoption being 80%. M13 (*3 times milking per day*) has a very wide distribution of ranks and an overall low impact score, but approximately 25% of the 212 non-adopted recorded for this practice rank it in the top-three non-adopted practices. This result may be related to farm-specific labour constraints that are less restrictive for farmers who see an increase in the milking frequency as a particularly beneficial practice. Following these practices, M6 (*Semen from high PLI indexed bulls*) and M17 (*Nitrification inhibitors*) may show some potential that can be developed with both having the mode of the distribution of ranks within the top five of non-adopted practices. However, any decision related to supporting the uptake of particular practice should additionally consider the practice's (cost-)effectiveness.

Table 5 reports available estimates of a mitigation practice's cost-effectiveness in addition to impact scores. Three practices are associated with a negative cost-effectiveness estimate (M4 *Adding live microbial feed supplement to diet*; M6 *Semen from high PLI indexed bulls*; and M9 *Following fertiliser recommendations*), which would suggest that these practices are associated with a (financial) gain and should thus have already been adopted by profit maximising farmers. However, only M9 shows a very high adoption rate (89%) and a relatively high score at the sample average. M6 is reported to having been taken up by 60% of the sample and has mid-range impact scores. Due to its very low cost-effectiveness, however, it deserves further investigation regarding its inclusion into policy support measures. This is in contrast with M17 (*Nitrification inhibitors*), which had impact scores similar to M6, but has been associated with a very high cost-effectiveness. The adoption rate of M4 is at 20% fairly low, and impact scores are only at the lower end. For the majority of practices, lower cost-effectiveness tends to be reasonably associated with lower impact scores for the sample average. A notable difference is M4, however, which received a very low impact score while cost-effectiveness is low, too.

6. Discussion and conclusions

The main of this study is to inform decision making on policy support for management practices aimed at reducing GHG emissions from the dairy sector. An important aspect in this respect is knowledge on the current adoption rates regarding the wide range of identified management practices that are potential candidates for inclusion into policy mechanisms. Current adoption rates provide information on the effectiveness of current policy considerations, and are crucial in determining the potential for additional emission reductions over and above current levels.

Jones et al. (2013) used BWS to inform decision making in GHG mitigation within the English and Welsh sheep industry. Their approach is similar in that BWS was used to derive impact scores. Farmers are asked to evaluate 26 mitigation practices considering their 'practicality', while a sample of experts was used to provide impact scores regarding the practices' 'effectiveness'. For several of the mitigation practices, the distribution of the 'practicality' impact scores derived by Jones et al. (2013) is very wide, and often appears to be bimodal. This is an indication that current adoption rates may have played a significant role in farmers' evaluation.

In this study, we collected information on adoption rates of proposed mitigation practices through a survey of Scottish dairy farmers, and considered how current adoption impacts on preferences for the practices elicited through a BWS exercise. We found current adoption to have a significant positive impact on the probability to choose a practice as 'best'. Not controlling for current adoption patterns in the choice model would have severely limited the usefulness of impact scores for deriving policy recommendations. For example, we would not have been able to investigate the relative ranking of non-adopted practices based on individual-specific impact scores, which, together with information on the level of uptake across the sample, form the basis for identifying promising mitigation practices. Information on current adoption should therefore be gathered and used in BWS studies aimed at informing policy support for *further* uptake of management practices.

Based on low or moderate rates of non-adoption and thus further potential for mitigation, and a high density at the top of the distribution of ranks of non-adopted practices, we were able to identify a number of candidates that should be considered for (further) policy support aimed at reducing GHG emissions. These practices are *High sugar content ryegrass*, *Sexed semen*, *High-clover swards*, *Controlled/slow release fertiliser*, and *Lower N-requiring crops*. Additionally, there is limited potential for *3 times milking per day* and *Semen from high PLI indexed bulls*. Of all of these, only three are finding consideration in the current policy framework: information on *High-clover swards* and *Lower N-requiring crops* is provided on the FFBC website, and *Lower N-requiring crops* and *Semen from high PLI indexed bulls* are considered in FFBC-RPP2. Based on our findings, we suggest that the current framework needs to be revisited and possibly be expanded to include the practices identified above. Of course, these practices should first be screened for effectiveness drawing on empirical research or with the help of experts in the field.

A comparison of adoption rate information with the currently available and planned policy support for management practices shown in Table 1 is also of interest to assess the potential of current policy mechanism to achieve further GHG emission reductions. It reveals that those practices that appear to receive the greatest policy attention (M9 *Following fertiliser recommendations*; M10 *Manure management plans*) have a high rate of current uptake. Based on the results of the BWS study, M9 and M10 have relatively high impact scores, indicating that dairy farmers perceive them to be beneficial to their farm's performance. The high uptake may partially demonstrate the success of past initiatives and the regulatory environment in particular concerning NVZs, but it equally points to a limited scope for further emission reductions through these practices. M15 (*Anaerobic digester*) and M20 (*Covering the manure storage*) are part of the revised SRDP (2013). Both show low levels of current uptake and hence theoretically large scope for further GHG reductions. Importantly, however, both practices' impact scores are at the lower end. In the case of M15, low rates of current uptake and low impact scores of non-adopters may be due to large capital investments needed for installing anaerobic digesters, constraints associated with the current system of managing the slurry or manure, and the quantity of slurry generated by a farm. Regarding the covering of the manure storage, however, it would be worth to further investigate the range of existing farm-specific barriers to uptake in order to possibly revise the SRDP (2013) if barriers prove difficult to be overcome.

The comparison of impact scores with cost-effectiveness estimates derived from MACC studies shows some consistency, although the derived rankings don't match well for all practices where cost-effectiveness information is available. The mismatch between adoption rate and cost-effectiveness scores in at least one of the cases with negative cost (M4 *Adding live microbial feed supplement to diet*) indicates that farmers' decision making may not be entirely driven by profit maximisation provided the assumptions made in the cost-effectiveness analysis apply. Alternatively, such a divergence may be related to the farm specific production constraints, which include geographical dependencies, for example on the suitability of surrounding land to produce different types of fodder, and farm-specific constraints, for example with respect to labour or access to technology.

There are some limitations to our study that deserve to be pointed out. Given that our survey included 20 practices, it was not possible to provide farmers with a very detailed account of each practice. While we took great care in generating clearly understandable descriptions of the mitigation practices, we cannot deny the possibility that some farmers' perceptions of the practices may have differed from our understanding, and that this resulted in both an upward bias in stated adoption rates and BWS impact scores. For example, M9 (*Following fertiliser recommendations*) describes the application of specific information packages on fertiliser use that have been developed by agricultural extension services and government bodies. However, some farmers may have perceived this to imply following generally known guidelines and legal restrictions (for example related to NVZs) for fertiliser application, although this was not the case in the focus groups preceding the survey. Further, both adoption rates and impact scores could have been affected by recent issues farmers faced. For example, 2012 was an unusually wet year in Scotland, causing concerns about drainage systems. Many farmers reacted to that, which is reflected in the high adoption rate for M11 (*Improve drainage on fields*). We do not know, however, whether farmers' response implied a one-off intervention to prevent the worst, or whether they invested in large scale structural changes in the drainage system that will need to be maintained on a regular basis. It is also impossible to predict whether as a consequence of 2012, farmers will indeed maintain a functioning drainage system, or whether their response was entirely adaptive to the weather shock. Further, it is reasonable to assume that higher impact scores are associated with a greater likelihood of actual uptake. However, there is no guarantee that a practice that is evaluated as being *relatively* beneficial to the farm's environmental and financial performance will indeed be adopted in the face of a wide range of barriers to uptake and farm constraints. The above concerns imply that the results need to be carefully interpreted, and that our recommendations should be validated and investigated in greater depth, possibly through a combination of qualitative interviews and workshops with farm advisors and farmers.

Our study provides important insights for policy makers and farm advisory bodies in a domain that thus far has largely been reliant on expert information. BWS, in combination with information on adoption rates, can serve as a useful tool especially at an early stage of a mitigation policy planning process. It complements information derived via MACCs by providing a richer picture of farmers' preferences and can therefore support the development of more robust agricultural climate change policies.

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