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

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Abstract

The agenda towards greenhouse gas mitigation within agriculture implies changes in farm management practices. Based on a survey of Scottish dairy farmers, this study investigates farmers' perceptions of how different GHG mitigation practices affect the economic and environmental performance of their farms, and the degree to which those farmers have adopted those practices. The results of the farm survey data are used to identify promising mitigation practices for immediate policy support based on their potential for additional adoption by farmers, their perceived contribution to the farm's financial and environmental performance and information on their cost-effectiveness. The study demonstrates the usefulness of including adoption behaviour and farmers' perception of mitigation practices to inform early stages of policy development. This would ultimately contribute to the robustness and effectiveness of climate change mitigation policies in the agricultural sector.

Keywords

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

Highlights

Best-Worst-Scaling is used to identify promising climate change mitigation practices

Preference data needs to be combined with information on current adoption patterns

The suggested practices in the dairy sector do not match current policy support

Best-Worst-Scaling is a useful tool especially in early stages of the policy planning process

1. Introduction

There has been an increasing policy interest in reducing greenhouse gas (GHG) emissions from agriculture in recent years (European Commission, 2008; Gerber et al., 2013; Scottish Government, 2009, 2013b; Smith et al., 2008; UNFCCC, 2008). 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 (DECC, 2013). Policy makers face a 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., 2011), combining both information on cost-effectiveness and abatement potential of a large number of mitigation practices. MACCs show the cost of reducing GHG emissions by one additional (marginal) unit as total GHG abatement increases. Therefore, mitigation practices are arranged in the order of their cost-effectiveness. The abatement potential is estimated against a baseline that represents business-as-usual adoption of mitigation practices. 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 large regions 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 scientific expert judgment, for example regarding adoption rates, effectiveness and costs (Eory et al., 2014a under review). 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 (De Cara and Jayet, 2000, Vellinga et al., 2011). Another result of MACC analysis is the significant mitigation potential of practices identified to have negative cost. These have been referred to as 'win-win' mitigation practices, the result of which has influenced several policy and industry documents (DSCF, 2008; TSB, 2013). 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 lack of uptake of practices with negative costs suggests that adoption behaviour is driven by a more complex set of motivating factors (Barnes et al., 2009; Barnes and Toma, 2012; 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 available in agriculture.

Accordingly, when advancing agricultural mitigation policy, MACC approaches may be of limited use as they are based on strong assumptions regarding current adoption rates and largely lack up-to-date information on farmers' views regarding the farm management practices. 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 and substantiating the information entailed in MACCs with information on adoption rates and on farmers' views regarding the farm management practices that are expected to result in considerable GHG emission reductions. Such information is important for informing targeting and for 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 (Weiske, 2005), 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 more intensive and technically advanced (Barnes, 2008; Barnes et al., 2010; Hadley, 2006) 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 rankings of mitigation practices is Best-Worst Scaling (BWS). In the type of BWS study applied here, respondents are asked to repeatedly choose from subsets of four to five different mitigation practices those that are perceived to be 'best' and 'worst' with respect to the farm's financial and environmental performance. The suitability to accommodate a large number of mitigation practices (Louviere et al., 2013) is a main reason for using BWS in this study – direct rankings of a large number of items can be too difficult for respondents to perform. BWS has been shown to have a number of other advantages over alternative rating and direct ranking techniques. For example, BWS does not suffer from rating scale bias (Auger et al. 2007) and is likely to better discriminate among objects that are perceived to be of similar importance (Lee et al. 2007). However, some respondents may dislike having to make repeated trade-offs (Hein et al. 2008), i.e. to repeatedly select the 'best' and 'worst' from different subsets of mitigation practices.

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 (Cross et al., 2011; Erdem et al., 2012; Jones et al., 2013; Lagerkvist et al., 2012; Lusk and Briggeman, 2009). 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 perceptions of Welsh sheep farmers regarding the effectiveness and practicality of GHG mitigation options. 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' perceptions of the impact of mitigation practices on their farm's financial and environmental performance compare to cost-effectiveness and rankings in MACCs? In combination with available information on cost-effectiveness, the information on rankings of mitigation practices 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 is committed to GHG emission reductions of 42% by 2020, and an 80% reduction by 2050 compared to the 1990 baseline. Agriculture contributes approximately 20% to total emissions (Scottish Government, 2013a), and abatement in agriculture is pivotal for achieving this target: an emission reduction of 1.2 Mt CO_2 equivalent by 2020 is expected for the agricultural sector (Scottish Government, 2013b). Climate change mitigation has also been highlighted to be a key part of the multi-functional role Scottish agriculture is expected to play (Pack, 2010), which is in line with general direction the Common Agricultural Policy (CAP) post-2013 is expected to take (EC, 2010).

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. This is more than the consumption of any other agricultural product group, 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, 2013a; Sheane et al., 2011). Importantly, dairy farming is well-placed to offer many opportunities to reduce GHG emissions.

GHG emissions arising from land management associated with dairy farming can be reduced by altering nitrogen fertilisation practices, soil management, or crop types and varieties. The feed composition is another focal point of GHG mitigation efforts in the dairy sector: methane emissions from the rumen and both methane and nitrous-oxide emissions from manure can be significantly decreased by modifying the ration or by using feed additives (e.g. probiotics). Housing dairy cattle provides the basis for a set of GHG mitigation interventions related to 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, and therefore the GHG emissions embedded in the product. Dairy farmers represent the most technically advanced 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).

Currently there are three main pathways to provide policy support for increasing GHG abatement in the Scottish agricultural sector, using a mix of extension and awareness raising, regulation, and positive financial incentives. Farming for a Better Climate (FFBC) is an initiative aimed at increasing voluntary uptake of GHG mitigation and adaptation practices and is funded by the Scottish Government. The nitrogen use regulations in the designated Nitrate Vulnerable Zones (NVZs) are mandatory elements of cross-compliance under the CAP Single Farm Payment Scheme. They provide co-benefits in terms of N_2O emission reduction. Finally, the Scotland Rural Development Programme (SRDP) is the discretionary application of CAP Pillar 2 funds for financial support, and includes some measures with potential GHG co-benefits.

3. Methodology

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 dimension of interest (utility scale). In this study, the objects are management practices that have been identified as GHG mitigation options in dairy farms, and the latent utility scale is the contribution of each GHG mitigation practice to the farm's financial and environmental performance. The data on repeated best/worst choices of management practices allows us to derive 'impact scores' for each management practice on a 0-100 point scale. These scores reflect the farmers' evaluations of mitigation practices with respect to their contribution to the farm's performance. The interpretation of the scores is straightforward. 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. In deriving the 'impact scores', we consider that farmers differ regarding their perceptions of management practices. Some of this heterogeneity in perceptions can be explained by whether or not farmers have adopted a management practice at the time of the survey. This information is used to identify those practices that are ranked highly by non-adopters and exhibit fairly low current adoption rates and thus a relatively large potential for additional GHG mitigation.

In what follows, we provide a detailed description of the methodology and modelling approach used. 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. Following random utility theory, the utility respondent n derives from choosing a mitigation practice i from list t with $j= \{1,2,\ldots J\}$ practices can be decomposed into an observed or deterministic component, $V_{ni,t}$, and an unobserved random error term $\varepsilon_{ni,t}$ 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 $\pi^2/6$.

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

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:

$$V_{ni,t} = \alpha_{ni} I_{ni,t} + \gamma_{ni} I_{ni,t} A_{ni} \tag{2}$$

where α and γ are parameters to be estimated, $I_{ni,t}$ is an indicator variable for mitigation practice i being present in choice set t shown to farmer n, and A_{ni} is a dummy variable taking one if farmer n currently adopts a mitigation practice, else zero[1]. The coefficient α_{ni} represents the utility that the mitigation practice i provides to farmer n. γ_{ni} captures the difference in utility obtained from mitigation practice i resulting from its adoption by farmer n.

[1] The dummy variables relate to practices that a farmer may have already adopted and as such may introduce an endogeneity bias on the coefficients. To test the effect of this bias empirically we estimated both conditional logit and mixed logit models without the dummy variables for adoption. The population means for mitigation practices derived from these models were very similar to the ones that include the adoption dummies. This indicates that endogeneity – if present – has little impact on coefficients.

Under these assumptions, the probability that farmer *n* chooses mitigation practice *i* from choice set *t* with $j = \{1,2,\ldots J\}$ practices is described by a conditional logit model and has the following expression (McFadden, 1974):

$$L_n(y_{best} = i|\alpha_n, \gamma_n, t) \;=\; \frac{\exp(\lambda V_{ni,t})}{\sum_{j=1}^{J} \exp(\lambda V_{nj,t})}. \qquad (3)$$

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). 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[2]. 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):

$$L_n(y_{best} = b, y_{worst} = w|\alpha_n, \gamma_n, t_1, t_2) = \frac{\exp(V_{nb,t_1})}{\sum_{j=1}^{J} \exp(V_{nj,t_1})} \times \frac{\exp(-V_{nw,t_2})}{\sum_{j=1}^{J-1} \exp(-V_{nj,t_2})}. \qquad (4)$$

[2] 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.

Of course, farmers may have different views regarding the contribution of mitigation practices to their farm's performance. To accommodate this heterogeneity, we employ the mixed logit (MXL) model (McFadden and Train, 2000). In this model, each farmer has his or her own parameter $\tilde{\alpha}_{ni}$ which deviates from the population $\bar{\alpha}_i$ by the quantity η_{ni} ($\tilde{\alpha}_{ni} = \bar{\alpha}_i + \eta_{ni}$). η_{ni} is a random term, which introduces the heterogeneity in α by varying according to a random distribution $f(\eta_{ni} | \Omega)$[3].

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 α.

$$P_n(\alpha_n|\Omega) = \int_{\alpha_n} L_n(\alpha_n|\eta_n) f\,(\eta_n|\Omega) d\eta_n \qquad (5)$$

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 Hensher and Greene (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

[3] 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.

positive and negative values, and indicate impact relative to one management practice that has been omitted for 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:

$$Ratio - scaled\ impact\ score_i = \frac{\exp(V_i)}{(\exp(V_i) + J - 1)} \qquad (6)$$

where V_i is the zero-centred utility weight for management practice i derived from the MXL model, and J equates to the number of practices shown in each task. The thus converted scores are then scaled on a 0-100 point scale that can be interpreted as described above.

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 of scientists and managers of educational dairy farms, we subsequently narrowed down the number of practices based on whether an option can be readily implemented by farmers at present and whether it has a large technical potential for GHG emission reductions in the dairy industry. This excluded practices that are currently not possible due to legal restrictions (e.g. growth hormones), practices that require further research or technological advances (e.g. vaccination against methanogens), and practices that are a relatively minor source of GHG emissions with regard to the dairy farm (e.g. compaction of farm yard manure or using cover crops). 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 and are proposed for future policy support[4].

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

[4] Information on current policy support draws on the Farming for a Better Climate website (www.sruc.ac.uk/info/120175/farming_for_a_better_climate), the Scottish Rural Development Programme website (www.scotland.gov.uk/Topics/farmingrural/SRDP) and the Nitrate Vulnerable Zones website (www.scotland.gov.uk/Topics/farmingrural/Agriculture/Environment/NVZintro/NVZGuidanceforFarmers). Information on proposed policy support is based on Scottish Government (2013b) and relates to the time period 2013-2027.

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. The number of repetitions of each item within a block is relatively low. A larger number would have been desirable, but would have required more BWS tasks, likely resulting in respondent fatigue and potentially lower response rates. 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.

The sample drew on the June Agricultural Census database (RESAS, 2012). The census is administered every year in Scotland and covers the 50,000 plus holdings registered with agricultural land, of which 1,650 were classified as specialist dairy or mixed dairy farming in 2012. To be classified as a specialist dairy farm, at least two thirds of its income must come from the dairy enterprise (RESAS, 2012). 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 significantly 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 1,290. 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 the opt-out 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. These were evenly distributed across the experimental designed blocks (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 = 0.95), standard gross margins and economic size unit to reflect economic factors (t = 0.74 and t = 0.74 respectively). In addition, standard labour requirements were similar across the census and the sample (t=1). Table 2 shows the key indicators of the dairy farmers in the sample compared to the June Agricultural Census.

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 (P5, P6, P11, P12, P13 and P14). At the other end of the spectrum, P3, P9, P19, P16, and P20 all have adoption rates below 10%. Adoption levels are considerably higher in three out of the four domains (nutrition, productivity, soil and fertiliser management). Practices related to manure management have lower adoption rates and therefore a relatively large potential for further GHG reduction. On average, a respondent has reported to currently have adopted nine of the 20 practices (standard deviation 2.2), with significant heterogeneity in the patterns of adopted practices across respondents.

A probit regression model was run on the 20 separate mitigation practices, using structural and activity based factors from the survey and the matched census data. A surprisingly low and inconsistent number of explanatory factors were found across the 20 different mitigation practices. For example, age, education and the experience of farmers were only significant for four of the practices (P8, P11, P18, P16). Accordingly, whilst some studies do infer a relationship between adoption of on-farm environmental practices and these common factors (Vanslembrouck et al., 2002; Prokopny et al., 2008), the adoption of technologies related to carbon reduction may have different underlying and social motives, such as farmer networking and attitudes towards climate change (Barnes et al., 2013).

The CL and MXL model estimates are shown in Table 4. All mean parameter estimates are relative to the base effect of mitigation practice P17 (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 also confirmed by the magnitudes and statistical significance of all standard deviations of the random parameter distributions except for P15 (controlled/slow release fertiliser). All interaction terms with the dummy variable capturing differences in utility due to current adoption are positive and significantly different from zero. This demonstrates that stated current adoption had a large influence on the probability of choosing a practice as 'best'.

Table 5 reports the ratio-scaled impact scores for the sample average. It is apparent that impact scores tend to be highest for those practices that have the highest adoption rates. For example, the average impact scores for the five most adopted practices (P5, P6, P11, P13 and P14) is nine, while it is three for practices with the lowest adoption rates (P3, P9, P16, P19 and P20). Therefore, farmers perceive that the five most adopted practises contribute three times more to the farm's performance than the five least adopted practices.

In addition to scores for the sample average, we report scores for a stylised 'adopter' and 'non-adopter', 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'). These scores serve to illustrate overall differences in farmers' evaluation of the practices as a result of adoption. The model results (Table 5) generally suggest a positive influence of adoption on impact scores, but this influence may be stronger or weaker across the practices. General patterns in impact scores between a stylised 'adopter' and 'non-adopter' are similar. However, there are some notable differences. An 'adopter' has lower impact scores than a 'non-adopter' for five of the practices (P1, P12, P14, P15, P17). This means that for these practices adoption has had a less than average influence on farmers' perception of the contribution of mitigation practises on farm performance. Conversely, higher scores for an 'adopter' compared to a 'non-adopter' are found for four of the practices (P5, P9, P13, P19). In these cases, the influence of current adoption on farmers' perception of the contribution of mitigation practises on farm performance was greater than average.

Table 5 reveals how mitigation practices have been evaluated 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 in the actual sample and hence the resulting heterogeneity in scores for the mitigation practices across the sample well. For example, 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. This is important, because additional emission reductions can only be achieved by current non-adopters.

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. In addition to considering the impact scores, Table 6 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) P1 (High sugar content ryegrass); ii) P8 (Sexed semen); iii) P10 (High-clover swards); iv) P15 (Controlled/slow release fertiliser); and v) P17 (Lower N-requiring crops). P12 (Manure management plans) is ranked highly, but has limited potential for further adoption with stated current adoption being 80%. P9 (3 times milking per day) has a very wide distribution of ranks and an overall low impact score for a stylised 'non-adopter', 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. P7 (Semen from high PLI indexed bulls) and P16 (Nitrification inhibitors) may show some potential that can be developed. Both have 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.

The last column of Table 5 reports available estimates of a mitigation practice's cost-effectiveness. Six practices are associated with a negative cost-effectiveness estimate (P4 Adding live microbial feed supplement to diet; P7 Semen from high PLI indexed bulls; P8 Sexed semen; P11 Following fertiliser recommendations; P12 Manure management plans and P17 Lower N-requiring crops), which would suggest that on most of the farms these practices are associated with a (financial) gain and should thus have already been adopted by a large number of profit maximising farmers. However, only P11 and P12 show a very high adoption rate (87% and 80%, respectively) and a relatively high score at the sample average. P7 and P8 are reported to having been taken up by 50-60% of the sample and have mid-range impact scores. Due to their negative cost-effectiveness, however, they deserve further investigation regarding their inclusion into policy support measures. P4 and P17 have both been adopted roughly by fifth of the sample (21%), which might indicate the existence of non-financial barriers. The low scores assigned to P4 by non-adopters may be due to unfamiliarity with the novel practice of adding live microbial feed supplement. P17 has a relatively high score, signalling a potential for an increased uptake with additional policy support. For the majority of practices, lower cost-effectiveness tends to be reasonably associated with higher adoption rates and higher impact scores for the non-adopters, and vice versa.

6. Discussion

Jones et al. (2013) used BWS to inform decision making in GHG mitigation within the English and Welsh sheep industry. Their approach is similar to the one presented in this paper 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 choices made in 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 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. Importantly, only two of these promising practices are currently put forward for future policy support: Lower N-requiring crops and Semen from high PLI indexed bulls. Based on our findings, we suggest that the policy 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.

In addition, the transfer of information regarding these technologies may also benefit from recent discussions on future advisory service models, where there may be more of a focus on providing free public good advice on climate change topics (House of Lords, 2011). Further, the heterogeneity in adoption patterns and impact scores suggests that there is a need to remain flexible with respect to how GHG mitigation can be best achieved on individual farms. Therefore, it is important that information and advice platforms such as FFBC continue to promote a wider set of practices beyond those identified as promising in this study.

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 policy mechanisms to achieve further GHG emission reductions. It reveals that those practices that appear to have received the greatest policy attention thus far (P11 Following fertiliser recommendations; P12 Manure management plans) have a high rate of stated current uptake. Based on the results of the BWS study, P11 and P12 have relatively high impact scores, indicating that dairy farmers perceive them to be beneficial to their farms' 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. P19 (Anaerobic digester) and

P20 (Covering the manure storage) are currently available for financial support via the SRDP, but have not been put forward for future policy support. 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 P19, 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 future policy framework if barriers prove to be feasible to overcome.

The comparison of impact scores with cost-effectiveness estimates derived from MACC studies shows some consistency, although the derived rankings do not 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 (P4 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 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. The analysis of these limiting factors of uptake of cost-effective GHG reduction practices is a promising avenue of further research.

There are some limitations to our study that deserve to be pointed out. Although our sample matches well with key characteristics of Scottish dairy farms, a higher response rate would have been desirable. In the light of general time constraints faced by Scottish farmers and frequent complaints about an increasing amount of administrative work, however, the achieved response rate is of a reasonable magnitude. Because 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 influences both stated adoption rates and BWS impact scores. For example, P11 (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 and high impact score of P13 (Improve drainage on fields), even though this practice can be associated with high costs. We do not know, however, whether farmers' response implied a one-off intervention to prevent the worst, or whether they have been investing in the drainage systems' maintenance on a regular basis. 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.

7. Conclusions

The main purpose of this study is to inform decision making on policy support for management practices aimed at reducing GHG emissions from the dairy sector. The post-2014 CAP and Rural Development Programmes are under development, which makes this paper a timely and important contribution to help mainstreaming climate change considerations in European agricultural policies. Current adoption rates of potential GHG saving practices and perceptions of the contribution of the practices to the farm's performance amongst non-adopters are both important in this respect. 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. Using BWS in combination with information on farmers' current adoption patterns allowed the identification of a number of promising mitigation practice in the dairy sector.

Our study therefore provides important insights for policy makers and farm advisory bodies in a domain that thus far has largely been reliant on scientific 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 and through expert opinion by providing a richer picture of farmers' perceptions of different mitigation practices and can therefore support the development of more robust agricultural climate change policies.

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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)	☐

Figure 1. Example of BWS choice task

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

Measure	Description	Current policy support	Proposed policy support
Animal nutrition			
P1	Planting high sugar content (high WSC) ryegrass (e.g. Aber HSG)	-	-
P2	Reducing grass in the diet and feeding more concentrates/grains/total mixed rations	-	V
P3	Adding oily seeds (e.g. canola, sunflower) at 10% to the diet	-	-
P4	Adding a live microbial feed supplement (e.g. Lactobacillus sp.) to the complete diet directly	-	-
P5	Applying feed and ration management (including forage/fodder analysis) with a feed company or advisor involved to optimise nutrient use of animals	V	-
Animal productivity			
P6	Working with veterinary surgeons to optimise biosecurity, vaccination and herd health	V	-
P7	Using bull semen from high PLI indexed bulls	V	V
P8	Using sexed semen to increase proportion of females born	-	-
P9	Moving from 2 to 3 times milking per day	-	-
Soil and fertiliser management			
P10	Using high-clover swards (20% of dry matter)	V	-
P11	Applying fertiliser according to fertiliser recommendations	V, M	V, M
P12	Make manure management plans taking full account of nutrients available in the manure	V, M	V, M
P13	Maintaining old drainage system (or installing a new one if needed) to improve drainage on fields	V	-
P14	Preventing soil compaction (e.g. avoiding the use of heavy machinery and livestock poaching when soils are wet or saturated)	V	-
P15	Using the type of fertiliser that breaks down and releases nutrients slowly (controlled or slow release fertiliser)	-	-
P16	Using chemicals to prevent loss of N due to nitrification (nitrification inhibitors)	-	-
P17	Changing to crops which require less nitrogen fertilisation	V	V
Manure storage			
P18	Frequently (twice-a-week) removing manure from the cattle shed to outside storage (e.g. to manure heap; slurry tank or lagoon)	-	-
P19	Installing and using an anaerobic digester to treat animal waste	FI, V	-
P20	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)	FI, V	-

Note: V: voluntary (through FFBC), M: mandatory, FI: financial incentives

Table 2. Descriptive statistics of dairy sample compared to June agricultural census, mean and standard deviation

	Census (N=1,290)	**Survey (N=235)**
Standard Gross Margin (k£)	167.5	168.2
	(474.5)	(117.1)
Economic Size Unit (£/ha)	139.6	140.1
	(395.1)	(97.6)
Standard Labour Requirement (Labour Units)	5.5	5.4
	(4.3)	(4.1)
Area (Ha)	125.4	137.7
	(98.7)	(103.9)

Note: Standard deviations in parentheses

Table 3. Stated current adoption rates of practices

Measure	Short descriptor	Currently adopted (%)
Animal nutrition		
P1	High sugar content ryegrass	51.9
P2	Reducing grass and more concentrates in diet	30.2
P3	Adding oily seeds to diet	3.8
P4	Adding live microbial feed supplement to diet	20.9
P5	Applying feed and ration management	94.9
Animal productivity		
P6	Working with veterinary surgeons	93.2
P7	Semen from high PLI indexed bulls	60.4
P8	Sexed semen	51.9
P9	3 times milking per day	9.8
Soil and fertiliser management		
P10	High-clover swards	34.9
P11	Following fertiliser recommendations	86.4
P12	Manure management plans	79.6
P13	Improve drainage on fields	89.4
P14	Preventing soil compaction	92.8
P15	Controlled/slow release fertiliser	26.8
P16	Nitrification inhibitors	4.3
P17	Lower N-requiring crops	20.9
Manure storage		
P18	Frequent removal of manure	46
P19	Anaerobic digester	0.9
P20	Covering the manure storage	3.8

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	
P1	-0.15		1.46	***	-0.07		1.81	***	0.96	***
P2	-1.77	***	1.96	***	-2.37	***	2.74	***	1.14	***
P3	-1.39	***	1.17	**	-1.89	***	1.67	***	0.70	***
P4	-1.46	***	1.3	***	-1.90	***	1.81	***	0.86	***
P5	0.4		2.59	***	0.41		4.09	***	2.42	***
P6	0.86	**	1.57	***	1.18	**	2.28	***	1.67	***
P7	-0.9	***	2.03	***	-1.06	***	2.61	***	0.86	***
P8	-0.25		2.08	***	-0.32		2.87	***	1.43	***
P9	-1.48	***	4.09	***	-2.13	***	6.81	***	2.85	***
P10	-0.05		1.96	***	-0.05		2.63	***	1.01	***
P11	-0.52	*	2.11	***	-0.74	**	2.82	***	0.67	**
P12	0.92	***	1.04	***	1.26	***	1.44	***	1.08	***
P13	0.52	*	2.48	***	0.51		3.93	***	1.96	***
P14	0.78	**	1.39	***	1.24	**	1.75	***	1.52	***
P15	0.02		1.13	***	0.02		1.63	***	0.13	
P16	-0.92	***	1.67	***	-1.20	***	2.56	***	0.75	***
P17	0 (fixed)		1.09	***	0 (fixed)		1.48	***	-	
P18	-1.51	***	1.62	***	-1.91	***	2.12	***	1.03	***
P19	-1.67	***	2.14		-2.29	***	4.97	***	1.56	***
P20	-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 10%, 5% and 1% level

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

Measure	Short descriptor	Sample average	'Adopter'	'Non-adopter'	Cost-effectiveness
Animal nutrition					
P1	High sugar content ryegrass	4.6 (3.9;5.4)	3.2 (2.4;4.1)	6.3 (5.1;7.5)	not available
P2	Reducing grass and more concentrates in diet	1.0 (0.8;1.3)	1 (0.6;1.4)	1.0 (0.8;1.3)	++
P3	Adding oily seeds to diet	1 (0.6;1.5)	0.6 (0.2;1.3)	1.5 (1.2;1.9)	++
P4	Adding live microbial feed supplement to diet	1 (0.7;1.3)	0.6 (0.4;1)	1.5 (1.2;1.9)	-
P5	Applying feed and ration management	10.6 (8.7;12.3)	12.1 (11.1;13.1)	8.1 (4.3;11.8)	not available
Animal productivity					
P6	Working with veterinary surgeons	10.1 (8.4;11.6)	9 (7.8;10.1)	10.7 (7.9;13.2)	not available
P7	Semen from high PLI indexed bulls	3 (2.5;3.6)	2.8 (2.1;3.5)	3.2 (2.4;4)	-
P8	Sexed semen	5.7 (4.8;6.6)	5.7 (4.4;7)	5.4 (4.3;6.6)	-
P9	3 times milking per day	6.5 (4.8;8.8)	12.3 (9.1;14.3)	1.3 (0.9;1.7)	not available
Soil and fertiliser management					
P10	High-clover swards	6.1 (5.3;7.0)	5.8 (4.4;7.2)	6.4 (5.4;7.4)	+
P11	Following fertiliser recommendations	4.2 (3.3;5.1)	4.1 (3.3;5)	4.1 (2.7;5.7)	-
P12	Manure management plans	8.8 (7.8;9.8)	6.2 (5.1;7.3)	11.1 (9.5;12.6)	-
P13	Improve drainage on fields	10.7 (9.2;12.1)	12 (10.9;13)	8.5 (5.6;11.2)	++
P14	Preventing soil compaction	9.2 (7.5;10.9)	7.2 (6.1;8.3)	10.9 (7.9;13.3)	not available
P15	Controlled/slow release fertiliser	4.6 (3.8;5.4)	3 (2.1;4.0)	6.6 (5.7;7.6)	++
P16	Nitrification inhibitors	2.6 (1.7;3.8)	2.6 (1.1;4.7)	2.8 (2.3;3.4)	++
P17	Lower N-requiring crops	4.3 (3.5;5.1)	2.6 (1.7;3.7)	6.6 (5.7;7.5)	-
Manure storage					
P18	Frequent removal of manure	1.1 (0.9;1.4)	0.8 (0.6;1.2)	1.5 (1.1;2.0)	not available
P19	Anaerobic digester	3.4 (1.1;6.9)	6.7 (1;13.0)	1.1 (0.8;1.4)	++
P20	Covering the manure storage	1.5 (0.8;2.5)	1.7 (0.5;3.8)	1.4 (1.1;1.8)	++

Note: Based on 235 respondents. All impact scores based on MXL model results. 95% confidence intervals based on a Krinsky and Robb (1986) procedure with 2,000 draws in parentheses. 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. (2014b under review).

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

Rank	**Mitigation practice**																			
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
1	20	0	0	0	3	8	0	28	28	35	0	30	8	10	37	1	19	1	1	6
2	24	1	1	1	3	2	5	22	12	24	2	13	5	4	46	5	59	0	2	4
3	15	0	1	1	2	3	10	15	13	34	5	1	4	0	41	19	52	2	6	11
4	26	1	3	9	0	0	11	9	11	26	5	2	1	1	29	44	33	1	12	11
5	12	7	34	16	1	1	19	8	6	18	7	0	1	1	14	41	17	4	8	20
6	6	11	28	27	0	1	11	6	9	6	8	1	3	0	4	43	4	17	27	22
7	4	13	40	25	1	1	14	6	12	6	3	1	2	0	1	22	2	23	29	27
8	2	29	40	31	1	0	9	6	14	1	1	0	0	1	0	23	0	22	24	21
9	3	24	27	27	0	0	8	4	19	3	0	0	1	0	0	16	0	14	32	30
10	1	29	24	21	0	0	4	1	19	0	1	0	0	0	0	5	0	16	30	21
11	0	19	14	11	0	0	0	5	23	0	0	0	0	0	0	4	0	14	28	18
12	0	11	9	9	0	0	0	1	19	0	0	0	0	0	0	1	0	5	14	21
13	0	5	4	2	1	0	2	0	15	0	0	0	0	0	0	1	0	5	12	7
14	0	10	0	5	0	0	0	1	4	0	0	0	0	0	0	0	0	0	2	5
15	0	3	0	1	0	0	0	1	4	0	0	0	0	0	0	0	0	1	3	0
16	0	1	1	0	0	0	0	0	3	0	0	0	0	0	0	0	0	1	1	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
19	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Sum (# of non-adopters)	113	164	226	186	12	16	93	113	212	153	32	48	25	17	172	225	186	127	233	226