REFEREED ARTICLE

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Socio-economic factors affecting the adoption of GHG emission abatement practices; the case of spring slurry spreading

DOMNA TZEMI[1] and JAMES PATRICK BREEN[2]

ABSTRACT

The agricultural sector in Ireland contributes almost 33% of Ireland's total Greenhouse Gas (GHG) emissions with dairy cows and beef cattle being the biggest source of these emissions (EPA, 2016). Several studies exist indicating that changing the timing of slurry spreading from summer to early spring, would reduce the levels of ammonia emissions (Lalor and Schulte, 2008; Stettler *et al.*, 2003). A knowledge gap, however, exists on the extent to which Irish farmers would be willing to change the time they spread slurry. The main objective of this paper is to investigate the influence of selected personal, farm and economic characteristics on farmers' willingness to spread most of their slurry in early spring. In order to achieve that a binary probit model was used. The results showed that 50% of slurry spread in early spring in Ireland was positively influenced by advisory contact, investment in machinery per hectare and profitability of the farm. While off-farm income and the date farmers turn their cows out to grass had a significant negative effect. The findings of this study could assist advisors and policy makers in relation to the adoption of new practices by farmers.

KEYWORDS: probit model; technology adoption; dairy farmers

1. Introduction

The agricultural sector in Ireland contributed 33% of Ireland's total greenhouse gas (GHG) emissions in 2015. Although these emissions were 5.7% below their 1990 levels, the years 2012, 2013 and 2015 GHG emissions have seen an increase in GHG emissions levels from agriculture. The recent increase in emissions from the agricultural sector are largely due to the abolition of the EU milk quota system in 2015 which has led to higher animal numbers and an increase in milk production (EPA, 2016). Methane (CH_4) and Nitrous Oxide (N_2O) are the main greenhouse gases produced from agriculture with the bulk of these gases coming from the dairy and beef sectors in the case of Ireland. Dairy and beef production in Ireland are predominantly grass based with farmers engaged in rotational grass grazing from mid-spring to mid-autumn and a period of winter housing (3 to 6 months) when animals are fed a diet based largely on conserved grass forage or silage. In pasture-based dairy and beef livestock systems in Ireland, during the winter the majority of manures produced (approximately 80%) are managed as slurry (Hyde and Carton, 2005).

Ireland has been subject to two major global emission legislation protocols in order to diminish the pollution caused by agricultural activity and to regulate the management of nitrate and other nutrients. The Kyoto Protocol and the Gothenburg Protocol (and the subsequent National Emissions Ceilings Directive). Under the Kyoto Protocol Ireland has committed to reducing its GHG emissions and under the Gothenburg Protocol Ireland has committed to reducing emissions of four transboundary air pollutants (SO_2, NOX, VOCs and NH_3) which contribute to regional acidification, eutrophication and local air pollution across Europe.

Lalor and Schulte (2008), stated that of the total nitrogen applied in slurry, only 25% of the nitrogen is available to the grassland when the slurry is applied in the spring and just 5% is available when applied in the summer (Lalor and Schulte, 2008). However, a survey of Irish bovine farmers on slurry management practices conducted in 2003 found that only 31% of slurry was being applied in the spring, which was the optimum time of application in terms of availability of N to the plant, with 52%, 13% and 4% being applied in the summer, autumn and winter, respectively when recovery of nitrogen is poor (Hyde *et al.*, 2006).

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[1] Corresponding author: Lincoln International Business School, University of Lincoln, Brayford Pool, Lincoln, LN67TS, United Kingdom. Email: dtzemi@lincoln.ac.uk

[2] School of Agriculture and Food Science, University College Dublin, Ireland. Email: james.breen@ucd.ie

Several studies have reported that changing the timing of slurry spreading from summer to early spring, would reduce the levels of ammonia emissions (Lalor and Schulte, 2008; Stettler *et al*., 2003). Furthermore Schulte and Donnellan (2012) identified the potential for better utilisation of slurry to contribute to a reduction in GHG emissions. Little information exists, however, on the extent to which Irish farmers would be willing to change the time they spread slurry or the factors that influence current slurry spreading practices.

The purpose of this paper is to investigate the influence of selected personal, farm and economic characteristics on the current timing of slurry application on Irish dairy farms. In order to capture the impact of those characteristics on individual farmers' adoption decision, a binary probit model was used. Spreading of slurry is highly dependent on weather conditions and on farmer attitudes, therefore assuming that the spring in 2013 and 2014 were representative of typical spring weather in Ireland[3], it is hypothesised that farmers with better managerial skills (not too high stocking rate,), the ownership of slurry equipment and better land characteristics (date cows let out to grass) are more likely to spread most of their slurry in early spring. This section introduces the Irish agricultural sector and its contribution to GHG emissions focusing on slurry spreading techniques. The following section outlines the background to the research question based on the literature review of technology adoption. The third section introduces the applied methodology. Following this, the data used in the analysis are presented and the empirical results of the model are explained. The last section consists of the results of the model used followed by some final conclusions.

2. Background

Timing of spreading slurry

Timing of slurry application plays a major role in maximizing the availability of N contained within the slurry to the herbage. Winter and autumn are inappropriate months for spreading slurry due to high chances of high leaching losses to watercourses (Smith and Chambers, 1993; Schröder, 2005). Applications in the summer are not recommended as well, as they are more susceptible to losses of gaseous ammonia due to warmer and drier air and soil conditions (Smith and Chambers, 1993; Schröder, 2005). Early spring is deemed to be the best period in Ireland for slurry applications as nutrient uptake by herbage is in its peak and ammonia and leaching losses are relatively low (Carton and Magette, 1999). However, ground conditions (i.e. where the soils are too wet) may constitute a constraint for slurry application. For instance, Lalor and Schulte (2008) noted that in some parts of Ireland during a year of high rainfall, soils may only be dry enough to permit traffic with slurry application equipment for 25 days during the summer.

During the period of slurry storage anaerobic conditions in the slurry store produce methane emissions (Schulte *et al*., 2011). When more slurry is applied in spring the length of the slurry storage period has been found to be reduced by 3.1% on average resulting in a reduction in methane emissions from slurry storage (McGettigan *et al*., 2010; Schulte *et al.,* 2011).

There are a number of reasons for Irish farmers choosing to apply most of their slurry during the summer months, firstly farmers may choose to apply slurry after grass has been harvested for silage and the risks of contamination of pastures are less. Secondly most of the farmers use the splash plate method, however in the case of spring applications with the splashplate method farmers are restricted to only spreading when there is low herbage mass and this often coincides with soil conditions that do not allow soil trafficking without damage. As a result, applications are postponed until after the first cut of silage has been made, when risks of ammonia losses are higher and the N fertilizer replacement value is lower. Therefore, the use of low emission techniques such as trailing shoe and injection which allows slurry spreading in pastures with higher herbage mass, extend the period when slurry can be spread in spring when conditions are better resulting in lower ammonia emissions (Lalor and Schulte, 2008).

Factors affecting technology adoption

There is a large literature on the adoption and diffusion of new technology, with Rogers theory of adoption first being popularized in his book *Diffusion of Innovations (1962)* and widely applied. In general, the literature on the adoption of new agricultural and more environmentally friendly technologies suggests that farmers' decision making depends on a variety of factors, such as economic, structural characteristics of the farm, as well as demographic and personal characteristics (Austin *et al*., 1998; Rehman *et al*., 2007; OECD, 2012; Tornatzky and Klein, 1982)

To begin with, according to neo-classical economic theory individuals are profit maximisers. However, Willock *et al*. (1999) stated that farmers' decision making regarding environmental practices may not be influenced necessarily by the unique goal of profit; it depends on whether the farmer values farming as a way of life or as a business. This implies that farmers' personality, attitudes and objectives have to be considered when investigating the factors that influence their decision making. Therefore, as Vanclay (2004) argued farmers have different adoption behaviours as they think differently, use different methods and practices in their work and have other priorities.

Risk taking is one aspect of the personality that influences adoption decisions. Shapiro *et al*. (1992) argued that individuals that are risk averse avoid adopting new technologies that are seen as high risk, while according to Abadi Ghadim *et al.* (2005) farmers tend to adopt an innovation that is perceived as reducing risk.

In the context of the Irish literature, farm size is typically found to be positively associated with adoption depending on the technology. For instance, while Clancy *et al.* (2011) and Keelan *et al.* (2010) inferred positive relationship between farm size and adoption of energy crops and GM crops respectively, however, the adoption of organic farming was negatively related with farm size (Lapple and Van Rensburg, 2011). This can be explained by small farms' tendency to adopt more labour intensive systems, as small farms can rely on family labour (Hayami and Ruttan, 1985). In the case of organic

[3] Based on a review of weather data from 2008 to 2018 inclusive for 9 weather stations (cso.2018), rainfall levels in the spring of 2013 were slightly lower than average for the period 2008 to 2018, while rainfall levels for 2014 were higher than average but not out of line with other years that experienced high levels of rainfall.

farming specifically, smaller farms might be easier to manage, for instance in terms of meeting the required organic regulations (Lapple and Van Rensburg, 2011).

Economic variables, such as profit are hypothesized to have a positive effect on adoption. Howley *et al.*, (2012), found that profitable farms were more likely to use AI, as they acknowledged the benefits of using AI as a reproductive technology instead of natural mating. Other Irish studies, however, failed to conclude a significant relationship between adoption and profit (Clancy *et al.*, 2011; Keelan *et al.*, 2010).

3. Materials and Methods

The binary probit model

The use of probit and logit choice models to investigate the factors that affect the adoption of a new technology or innovation is widespread in the adoption literature (Feder *et al.*, 1985). Linear regression estimation is inappropriate as the basic assumptions of normality and homoskedasticity of the error term are violated (Greene, 2012) as they discern unequal differences between ordinal categories in the dependent variable (McKelvey and Zavoina, 1975 cited in Greene, 2012). When the dependent variable is binary, the appropriate econometric model is either the binary probit model or the binary logit model (Greene, 2012).

The main difference between the two models is that in the logit model the probability of an event is described by a logistic distribution while for the probit model a standard normal distribution is assumed. These models are based on the assumption that farmers will adopt and use the technology that allows them to achieve the highest level of utility (Davey and Furtan, 2008). For this study the probit model is chosen, which was also used in a number of other studies of adoption behaviour (Fernandez-Cornejo *et al.*, 2002; Boz and Akbay, 2005; Keelan *et al.*, 2010; Clancy *et al.*, 2011).

The binary probit model for Y_i is derived from a latent variable model. It is based on a latent variable intended to represent farmers' percentage of slurry spreading in spring. This latent variable is assumed to be determined by a normal regression structure:

$$Y_i^* = x_i^{'}\beta + \epsilon_i,\ \epsilon|\mathrm{x} \sim \mathrm{Normal}\,(0,1) \tag{1}$$

That is, for each person *i* the utility difference between spreading more than 50% of slurry in early spring and spreading less than 50%, is written as a function of personal and farm characteristics, x_i and unobserved characteristics, ϵ_i.

The binary probit model describes the probability that $y_i = 1$ as a function of the independent variables.

$$\begin{aligned} P(y_i = 1) &= P(y_i^* > 0) = P(x_i^{'}\beta + \epsilon_i > 0) \\ &= P(-\epsilon_i \le x_i^{'}\beta) = F(x_i^{'}\beta), \end{aligned} \tag{2}$$

This equation shows the probability that $y_i = 1$ for the given function $F(.)$. Where F is also a function of the cumulative distribution function, which is bound by the [0,1] interval. The parameter β is the parameter to be estimated. The model depends on the vector x_i which contains individual, economic and farm level characteristics.

Estimation of the parameters follows maximum log likelihood estimation

$$\begin{aligned} \mathrm{Log}\,L(\beta) = &\sum_{i=1}^{N} y_i \log F(x_i^{'}B) \\ &+ \sum_{i=1}^{N}(1-y_i)\log(1-F(x_i^{'}B)) \end{aligned} \tag{3}$$

Substituting the appropriate form for F gives an expression that can be maximized with respect to β (Verbeek, 2004).

The β coefficients in the probit model do not have a meaningful interpretation. Thus, marginal effects were calculated to determine how much each explanatory variable affects the likelihood of spreading or not in early spring. The marginal effects for an ordered probit can be calculated as

$$\begin{aligned} \frac{\partial P(y=1x)}{\partial x_j} &= \frac{\partial P(y=1x)}{\partial x\beta} \cdot \frac{\partial x\beta}{\partial x_j} \\ &= \psi^{'}(x\beta)\cdot\beta_j = \psi(x\beta)\cdot\beta_j \end{aligned} \tag{4}$$

A change in factor x_j does not induce a constant change in the $P(y = 1\ |x)$ because $\psi()$ is a non-linear function of x (Baum, 2006). For instance, an increase in x_j increases (decreases) the probability that $y=1$ by the marginal effect.

Data

The main data source used in this analysis is the Irish National Farm Survey (NFS). The NFS collects data on Irish farms on behalf of the Farm Accountancy Data Network of the European Union on an annual basis since 1972, providing a representative sample of Irish farms. The data used in this study is taken from the NFS for the years 2013 and 2014. Many farmers stay in the sample for several years and the sample has an annual turnover rate of approximately 15-20%. That is, after a specific period, some farms drop out and others replace them, so that the sample is kept representative. In 2013 911 farms participated in the NFS survey representing a national population of 79,103 farms (Hanrahan *et al.*, 2014). And in 2014, 798 farms participated in the NFS survey representing 78,641 farms nationally (Hennessy and Moran, 2014).

Data from an NFS supplementary survey provides more detailed information on slurry spreading management for both years 2013 and 2014. It includes among other information data on the type of slurry application method used by farmers as well as the percentage of slurry spread during different periods of the year. This provided a cross-section sample of 639 farms for 2013 and 2014 to be used in this study.

The dependent variable of the binary probit model has two responses; 0 for the farmers that spread 49% or less of their slurry during January to April and 1 for the farmers that spread more than 49% of their slurry from January to April. According to the Food Harvest 2020 Report[4] (DAFF, 2010) farmers who spread 50% or more

[4] The Food Harvest 2020 report outlines a strategy for the development of the Irish agri-food sector for the period to 2020. The report outlined a series of strategic targets for the different sub-sectors of Irish agriculture.

Table 1: Definitions of socioeconomic variables and descriptive statistics

Variable definition and codes	Variable name	N	Mean	Standard Deviation	Minimum	Maximum
Independent variables						
Advisory contact; 0=None; 1=Yes	ADVISORY_CONTACT	639	0.77	0.42	0	1
Date cows let out to grass (in numbers of weeks)	DATE_COWS_GRASS	639	9.31	3.48	1.86	21.29
Slurry spreaders owned by farmers; 1 = equipment present; 0 otherwise	OWN_SLURRY_EQUIPMENT	639	0.77	0.42	0	1
Stocking rate (total livestock units divided by utilized agricultural area in hectares	STOCKING_RATE	639	1.89	0.53	0.39	3.95
Land owned in hectares	LAND_OWNED	639	52.78	31.39	4	243.72
Region South East; 0=farm is located in the Border Midland West; 1=farm is located in South & East	REGION_SE	639	0.75	0.43	0	1
Off-farm employment; 0=no off farm activity; 1=wage/salary or self-employed off-farm	OFF_FARM_EMPLOY	639	0.07	0.25	0	1
Investment in machinery per hectare	INVEST_MACHINERY_HA	639	1017	748.30	0	5177.49
Profitability (farm gross margin in euro[5] per total livestock units)	PROFITABILITY	639	1068.51	285.44	202.53	2438.01
Environmental subsidies; 0=no env/al subsidies; 1=farmers received env/al subsidies	ENV/AL_SUBS	639	0.29	0.45	0	1
Year; 0 = 2013; 1=2014	YEAR_DUMMY	639	0.51	0.50	0	1
Dependent variable	HALF_SPRING_SLURRY	639	0.61	0.49	0	1
Slurry application in Jan-Apr; 0 = 0-49%; 1 = 50-100%						

of their slurry in early spring perform better both environmentally and financially than those who spread less than 50% (Schulte and Donnellan, 2012). Reduced NH_3 losses due to favourable weather conditions, increases the fertiliser replacement value of slurry, which leads to reduction in the total N fertiliser inputs.

Definitions and descriptive statistics for explanatory variables hypothesised to affect timing of slurry spreading are presented in Table 1. Farm characteristics such as the hectares of land owned by farmers (LAND_OWNED) and the region farms are located are hypothesised to influence farmers' decision to spread more than half of their slurry in early spring. The variable region South & East captures geographical, soil and climatic characteristics of farms. The economic characteristics of the farms were captured by the off-farm income, investment in machinery per hectare as well as farm's profitability and the binary variable for the reception of environmental subsidies. The *YEAR_DUMMY* variable was added in order to capture any possible effect that the specific weather effects in the two years 2013 or 2014 might have had on the timing of farmers' slurry spreading.

Table 2: Results of the binary probit model on the probability of early slurry spreading

Variable	Coefficient	P value
ADVISORY_CONTACT	0.22*	0.078
DATE_COWS_GRASS	-0.05***	0.004
OWN_SLURRY_EQUIPMENT	-0.05	0.699
STOCKING_RATE	-0.08	0.449
LAND_OWNED	0.002	0.315
REGION_SE	0.15	0.238
OFF_FARM_EMPLOY	-0.44**	0.027
INVEST_MACHINERY_HA	0.0001*	0.067
PROFITABILITY	0.0003*	0.089
ENV/AL_SUBS	0.143	0.217
YEAR_DUMMY	0.007	0.943
Loglikelihood	-405.5498	
LR chi2(11)	44.26	
Pseudo R2	0.0517	

Notes:
(***) Indicates the variable is significant at the 1% level.
(**) Indicates the variable is significant at the 5% level.
(*) Indicates the variable is significant at the 10% level.

4. Results

As mentioned above, a binary probit model on the possibility of the farmer considering to spread more than half of their slurry in early spring (January to April) was applied. Table 2 presents the estimation results of the probit model. The statistical significance of the model is defined at 10%, 5% and 1% level. The chi-squared for the probit model is 44.26 and statistically significant, indicating that the hypothesis that all slope coefficients equal zero is rejected. An overall result shows that farmer characteristics, individual and managerial have significant impact on the likelihood of early slurry spreading. The marginal effects from the probit model are presented in Table 3.

Beginning with farmers' individual characteristics, farmers who had contact with some agricultural advisors, either from Teagasc or private agricultural advisors, were more likely to spread slurry in early spring. In general, literature has shown that advisory contact along with activities such as participation in discussion groups has a positive influence on famer' decision making (Hennessy and Heanue, 2012).

Only one of the variables that were used to capture farmers' managerial skills showed significant effect on slurry spreading. The result for *DATE_COWS_GRASS*

[5] May 2017, €1 was approximately equivalent to £0.84 and $1.09.

Table 3: Marginal Effects of the probit model on the probability of early spring slurry spreading

Variable	coefficient	p-value
ADVISORY_CONTACT	0.079*	0.076
DATE_COWS_GRASS	-0.018**	0.003
OWN_SLURRY_EQUIPMENT	-0.018	0.699
STOCKING_RATE	-0.031	0.448
LAND_OWNED	0.000	0.314
REGION_SE	0.055	0.236
OFF_FARM_EMPLOY	-0.161**	0.025
INVEST_MACHINERY_HA	0.0001*	0.065
PROFITABILITY	0.0001*	0.086
ENV/AL_SUBS	0.052	0.216
YEAR_DUMMY	0.002	0.943

Notes:
(***) Indicates the variable is significant at the 1% level.
(**) Indicates the variable is significant at the 5% level.
(*) Indicates the variable is significant at the 10% level.

showed that farmers who let their cows out to grass earlier are more likely to spread a larger proportion of their slurry in early spring. One could consider it as a proxy for soil traficabillity and overall weather conditions as farmers let their cows out only when the soil is not too wet (saturated) or heavy. Therefore, the timing of cows' turnout has a positive significant effect on the timing of spreading slurry. *OWN_SLURRY_EQUIPMENT* had no significant effect, although it was expected that farmers who own their slurry spreading machinery are more likely to spread more of their slurry in early spring. As it was assumed that farmers who own their own slurry spreading equipment are likely to have more opportunity to avail of spells of good weather in the spring compared with those farmers who are using contractors as their ability to avail of relatively short periods of suitable weather conditions is linked to the availability of the contractor.

The effect of animal stocking intensity was captured by the variable *STOCKING_RATE* which showed no evidence of a significant effect on slurry spreading. However, a negative relationship between stocking rate and early slurry spreading was expected based on the hypothesis that those farmers with higher stocking rate are less willing to apply more of their slurry in early spring due to concerns in relation to the trafficability of the soil and the implications that this may have in terms of damaging the sward and reducing the future grass availability. A dummy variable for year was used in order to see if there was any significant difference in the early application of slurry between 2013 and 2014, this could have been expected if the weather conditions between the two years were not comparable However the results showed no significant effect.

With regard to farm characteristics, land ownership and the regional location of the farm did not demonstrate any significant influence on slurry spreading. It was expected that farms located in the South and East region would have a positive effect on early slurry spreading. In terms of climatic and soil conditions farms located in SE region are considered more advantaged than the farms located in BMW. That is, better weather conditions and better quality soils are likely to be more trafficable in the early spring, therefore making slurry application easier during periods of less favourable weather conditions when compared with farms with poor soil quality. Ownership of land was assumed to have a positive effect on early slurry spreading based on previous studies. Fernandez-Cornejo *et al.* (2002; 2007) showed that land owners are more likely to adopt new practices because they directly avail of the benefits.

The effect economic variables have on early slurry spreading is examined in this section. Investment in machinery was positively related to technology adoption suggesting that farmers with greater economic capacity and more investments in machinery tend to be more risk takers and make new investments, therefore more likely to adopt new technology or practices. Farmers' employment off the farm showed that farmers who receive salary/wage or they are self-employed off the farm are less likely to spread more than half of their slurry in early spring. This negative relationship can likely be attributed to time constraints with those farmers who are employed off the farm having limited time to spend on spreading slurry during the spring time which is a particularly busy time of the year for Irish dairy farms which are predominantly 100% spring calving.

Farm's profitability was found to be significant in determining changing management practice. As expected, farms with higher profitability are more likely to spread their slurry earlier. A potential explanation could be that more profitable farms tend to perform better than less profitable farms. The environmental subsidies variable failed to show any significant effect on early spreading, although it was assumed that farmers who receive environmental subsidies from their participation in rural environment protection scheme (REPS) were more environmentally aware than those who did not receive any.

The marginal effects from the ordered probit were computed and are presented in Table 3. More details on their computation are explained in Williams (2012). In the case of continuous variables, these results show the effect that a unit change of a continuous variable has on the probability of the farmer spreading more than half of their slurry in early spring. In the case of binary independent variables, marginal effects measure how predicted probabilities change as the binary variable changes from 0 to 1. The marginal effect for advisory contact indicates that farmers who will change from not using to using advisory contact are more likely to spread more than 50% of their slurry in the January to April period by seven percentage points when compared with farmers who do not engage in contact with the advisory services. Likewise, for each delay of one week in the date that farmers let their cows out to grass the probability of spreading more than 50% of their slurry in early spring is reduced by almost 2%. Both investment in machinery and profitability have a positive effect on slurry spreading with the marginal effects being very small numbers, as the unit change refers to €1. If income coming from off-farm sources would be increased by one unit, the probability of spreading more than 50% of farmers' slurry in early spring would be decreased by 16%.

5. Conclusions

The purpose of this study was to investigate the effect that farm and farmer individual characteristics have on the timing of slurry application on Irish dairy farms, with a particular focus on the proportion of slurry spread in early spring due to the capacity for early slurry application to help mitigate GHG emissions. Technology adoption theory was used as a theoretical framework and taking into account the fact that this framework was developed to empower agricultural advice and policy, the findings of this study provide useful information for those interested in influencing changes in farm management practices that may contribute to reducing environmental externalities such as slurry spreading timing. A probit model was developed to determine any potential influence the selected explanatory variables may have on farmers' decision on spreading slurry in early spring.

Overall the results from the probit model endorse the hypothesis that a number of economic and individual, managerial characteristics can play an influential role in farmer's decision making. Consistent with the results of previous studies (Boz and Akbay, 2005; Islam *et al*., 2013; Lapple and Van Rensburg, 2011) this research has shown that Irish farmers provided with agricultural information are more likely to spread slurry in early spring. This would support previous research that has shown that advisory contact has the potential to instigate technology adoption amongst farmers.

The date farmers turn their cows out to grass showed a negative significant effect. This variable reflects to a large extent the physical characteristics of the farm in terms of the soil quality and drainage as well as the infrastructure on the farm in terms of pathways or roadways for herding cows to and from the fields and local weather effects. Previous research has determined that economic factors such as a farm's profitability or the off-farm income available will positively affect the probability of adopting a new technology (Clancy *et al*, 2011; Keelan *et al*., 2010; Clancy *et al*., 2011). In accordance with these findings this research showed that farm profitability had a positive significant effect on the probability of a farmer spreading more of their slurry in early spring. Despite the expectation for significant effect of farm characteristics, like the region or the land ownership both of them showed no significant effect on slurry spreading.

A lot of attention has been placed on the capacity for changes in management practices to contribute to reducing agricultural GHG emissions, this paper identifies some of the potential challenges to such a strategy, as these changes in management practices may be curtailed by the physical resources or attributes of the farm (e.g., soil quality or date cows can be turned out to grass), the capital resources (e.g. the capacity to invest in machinery) and the perceived riskiness of the change in management practice (e.g. the capacity of the new management practice to support higher stocking rates). The research findings outlined in this paper suggest that national governments have a role to play in encouraging change in practices amongst farmers such as spreading their slurry in early spring. Based on the results of this research, policy makers could take into consideration that more profitable farms are more receptive to changes in management practices. These farms may be more open to changing farm management practices in order to increase their profitability further, or as noted by Levinthal and March (1981) profitable farms with high aspirations are more receptive to changes when their performance expectations are not being met. Therefore, this may require the presence of an agri-environmental scheme for low profitability farms. Incentivising advisory contact could be considered by policy makers as it could possibly influence farmers in changing management practices.

The findings of this study also has implications for the marginal abatement cost curve (MACC) for Irish agriculture studied by Schulte and Donnellan (2012) in terms of redefining the assumptions. More specifically, Schulte and Donnellan (2012) in their estimation of the MAC curve as with MAC curves in general quantified the volume of emissions that could be abated through timing of slurry application on the basis of what is technically feasible to achieve, this approach to the estimation of MAC curves can fail to reflect the likely level of adoption of GHG abatement measures by farmers that will be influenced by a farmers individual characteristics. Therefore, farmer and farm characteristics that this study indicated to influence the adoption of new management practices could be taken into consideration in any future updates of the MAC curve or as part of a sensitivity analysis to consider the abatement potential under levels of adoption. Further research recommended could be on factors that affect farmers adopting new spreading slurry technology since evidence from literature (Lalor and Schulte, 2008) has shown that spreading slurry in early spring using low emission techniques (e.g. trailing shoe) maximizes N- efficiency and minimizes ammonia loss.

About the authors

Domna Tzemi is a PhD candidate in the School of Agriculture and Food Science in the University College Dublin. Her research interests include farm-level modelling and specifically the impact of alternative GHG abatement practices on farms.

James Breen is Assistant Professor in the School of Agriculture and Food Science, in the University College Dublin. His research interests are predominantly in the area of farm-level modelling and specifically in the examination of the impact of alternative agricultural and environmental policies on Irish farmers.

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