Sustainable technology adoption: who and what matters in a farmer's decision?

Article

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Sustainable Technology Adoption: Who and What Matters in a Farmer's Decision?

Abstract

EU milk quota removal brings a renewed focus on continued adoption of sustainable technologies. This article explores spatial effects in their adoption using Bayesian spatial probit models employing a representative sample of Irish dairy farms. We consider global and local spatial effects, and overcome a missing neighbour problem by implementing census data in our spatial weight matrix. The findings reveal that spatial effects spill over to neighbours and better educated farmers with larger more intensively managed farms are more likely to adopt. The article concludes with policy recommendations that arise from our spatial analysis.

1 Introduction

Sustainable intensification is becoming increasingly important, which mainly stems from the recognition that the current growth path in agricultural production will lead to using natural resources beyond their capacity (OECD, 2012). A growing population, rising awareness of the impact of climate change on food production as well as an increasing realization that intensive agriculture has detrimental effects on the environment has added to the recognition of the importance of sustainable production methods (OECD, 2014). That is, there is increasing pressure on farmers to achieve productivity growth in a sustainable manner, which underlines the importance of continued adoption of new technologies (Salois, 2015).

The recent elimination of EU milk quotas in 2015 further adds to the existing challenge of increasing production in a sustainable way. Many EU farmers significantly expanded and intensified their milk production since quota removal and it is expected that milk production will further increase and intensify in regions with production advantages, such as mild short winters with longer grass-growing seasons (Donnellan et al., 2015). For example, in the 12 months period after the elimination of milk quotas, EU milk production has increased by 4.5 percent when compared to the year preceding quota removal[1]. However, post quota milk production changes vary significantly across EU Member States. Ireland, consistent with its favourable production conditions, increased its milk output by the largest percentage amount, 18.4 percent (CSO, 2016). The significant shifts in where and how much milk is produced in the EU since quota elimination suggest that fostering sustainable intensification is especially pertinent in regions with production growths.

In this article, we explore the adoption of milk recording by Irish dairy farmers. Milk recording provides information about yields, constituents, bacterial contamination and hygiene quality and is either done by a milk recorder who visits the farm or electronic DIY recording by the farmer. It is an important tool for improving productivity and profitability, but also has the potential to reduce negative environmental impacts and improve animal

[1] https://www.agriland.ie/farming-news/

health. These traits make the adoption of milk recording a good example to study farmers' preparedness for sustainable expansion. The central empirical question explored in this article is: What influences Irish dairy farmers to adopt sustainable technologies and what role do peers play? Answers to this question will help to prepare the Irish and EU dairy sector for the significant change and challenges that come with producing in a quota free environment.

Despite clear economic and societal benefits of milk recording, its adoption is quite low. For example, in 2008 38.6 percent of Irish dairy farmers practised milk recording, while this figure dropped to 36.6 percent in 2010. In 2012 still considerably less than half of all farms milk recorded (Dillon et al., 2015). When interpreting these uptake figures, it is important to consider that managing somatic cell counts (SCC) –an indicator of bacterial contamination– through milk recording is of major importance when planning to expand production, which the vast majority of Irish dairy farmers either plan to do (Thorne et al., 2015) or have already done given a growth in milk production of almost 20 percent since quota abolition. However, if farmers are not adopting simple, yet effective technologies to improve performance, concerns may arise in relation to whether the EU dairy sector is prepared for significant shifts and expansion in milk production. In general, credit constraints, risk considerations (Feder et al., 1985) or technical difficulties with implementation (Läpple and Kelley, 2013) are reasons for low adoption rates.

Milk recording requires very little or no technical skills, has low investment costs[2], is reversible and needs very little labour input from the farmer, characteristics that do not explain low adoption rates. Another possible factor is the influence of peers, which has been found to slow adoption rates[3] (Läpple and Kelley, 2013) and farmers are often influenced by the positive or negative opinions of their peers (Case, 1992). Hence, the impact of peers can act both ways, increasing or decreasing adoption rates, depending on neighbours' opinions

[2]Costs for milk recording are approx. €2 per cow and an annual fee of €60. It is recommended four times a year for a spring calving herd. This implies about €860 per annum for a herd of 100 cows, see www.progressivegenetics.ie

[3]This relates to the context of conversion to organic farming.

and experiences. While peer interaction is a well acknowledged component of the adoption process (Rogers, 2010), it is rarely formally considered in adoption studies. This study aims to fill this gap in the literature by accounting for peer effects in adoption decisions. From a policy perspective, peer effects can be very important as they may introduce positive multiplier effects in the uptake of technologies.

Therefore, this article explores the adoption of a sustainable technology of Irish dairy farmers during preparation for the 2015 milk quota abolition, when significant dairy expansion plans were introduced by the Irish government[4] (DAFF, 2010). It does so by utilizing a number of spatial econometric models that account for the influence of neighbours and exogenous spatial effects. It advances the empirical literature by distinguishing between global and local spatial effects and by enhancing the representative sample data with census data to overcome a *"missing neighbour problem"*. In addition to demonstrating that better educated farmers with larger holdings are more likely to adopt, we also find evidence of neighbourhood effects that spill over to other regions.

The reminder of the article is structured as follows: the next section introduces the conceptual background followed by an overview of the case study and technology under consideration. The data and descriptive statistics are presented next, followed by a description of empirical models. Section 6 describes and discusses the results, while the last section (section 7) offers some concluding remarks as well as policy recommendations.

2 Conceptual Background

The technology adoption literature in economics has its origin in the seminal work of Griliches (1957) who explained differences in technology adoption based on profitability. The main focus of this literature is on the importance of credit constraints, farm size, risk and uncertainty as well as access to information (Feder et al., 1985) and usually excludes the adoption choices

[4]Ireland announced ambitious growth targets in 2010, aiming to increase its milk production by 50 percent by 2020 relative to the 2007 to 2009 base.

by neighbours and how this affects technology uptake. In contrast, sociologists recognized the importance of peer influence in the adoption of new technologies quite early (see Rogers (2010)) and many studies cite anecdotal evidence that farmers adopt new technologies if they think it is beneficial and if their peers accept it (Case, 1992)[5]. This is a similar idea to the well-known concept of social norms in social-psychology, where an agent's behaviour is influenced by the opinion of his or her important others (Ajzen, 2005). In fact, many studies provide empirical evidence that social norms do indeed influence farmers' behaviour (Läpple and Kelley, 2013; Rehman et al., 2007).

One way of accounting for peer effects is via spatial proximity and Manski (1993) distinguishes between three effects that explain why agents in close proximity may exhibit similar choice behaviour. Probably the best known effect is the endogenous interaction effect, where the tendency of an agent to behave in a certain way depends on the behaviour of his or her social group. This effect is also known as neighbourhood effect. In relation to this particular context, Baerenklau (2005) stresses that neighbourhood effects are particularly relevant for smaller, less costly and reversible decisions (such as milk recording), where farmers may be immediately influenced by the simultaneously made decisions of their neighbours. As the name suggests, endogenous effects entail endogenous feedback, meaning that the impact spills from neighbours to their neighbours and so on. LeSage (2014) refers to spatial effects with endogenous feedback as global spillover.

The second effect, known as exogenous effect, implies that an agent's choice varies with the exogenous characteristics of the agent's social group. Stated differently, this, for example, implies that certain socio-economic groups are more likely to do certain things, such as go to the theatre, etc.

Manski's third effect is referred to as correlated effect, meaning that similar environmental surroundings may result in similar behaviour choices[6]. In an agricultural context, this could

[5] This is in addition to providing empirical evidence as well.

[6] Manski (1993) also considers endogenous group formation as a reason for correlated effects, however this effect is not relevant in spatial econometrics as spatial weight matrices are formed exogenously as they are based on location

be the impact of an extension specialist who only works in a certain area.

Nevertheless, most economic based studies are reluctant to formally acknowledge neighbourhood effects, but their omission can also be attributed to perceived identification issues (see Manski (1993) or Brock and Durlauf (2001) for an overview of this literature). Manski (1993) argues that endogenous and exogenous peer effects cannot be separately identified because of the so called "reflection problem". However, in Manski's model the identification issue arises as it is based on a non-generic model.[7]

Within the vast amount of literature on technology adoption, few studies however have recognized the importance of spatial dependence in technology adoption and one of the first studies that accounted for neighbourhood effects in agricultural technology adoption is Case (1992) by focusing on sickle adoption in Indonesia. By utilizing an innovative specification that implements a block diagonal spatial weights matrix that is applied to a random sample of 1,664 wet rice producing farms in 84 districts in Indonesia, she reports a clear spatial influence. Another example is Holloway et al. (2007), who analysed spatial dependence in market participation among Filipino farmers based on a random sample of 110 households. Läpple and Kelley (2015) explore spatial dependence in the adoption of organic drystock farming in Ireland based on a sample of almost 600 farms. Another contribution is, Wollni and Andersson (2014) who also focus on neighbourhood effects in the adoption of organic farming. Their study is conducted in Honduras and based on a sample of 241 farms.

All of the above mentioned studies utilize spatial econometric models in order to examine neighbourhood effects in various farmer adoption decisions in different countries and agree that neighbourhood effects are important in adoption choices. However, none of these studies explicitly distinguish between *local* and *global* spillovers. In fact, they implicitly assume global spillovers without considering that some spatial effects may be local (LeSage, 2014). Furthermore, all of the above mentioned studies are based on sample data, hence ignoring - what we call a – *"missing neighbour problem"*, namely the likely possibility that

[7] Please see section 5 for a more detailed discussion of the"reflection problem" in spatial econometrics.

some observations have fewer neighbours due to sampling issues but not due to actually having fewer neighbours. Based on these significant shortcomings of many studies that utilize spatial econometric models[8], the present article makes at least three very important contributions to the literature. Two contributions are directed to the spatial econometrics literature specifically, while one is an important policy contribution. First, we consider *local* and *global* spatial spillover effects, second we amend the spatial weight matrix to overcome a *"missing neighbour problem"* that arises if the data is based on a (random) sample and finally we address the adoption of a technology that has the potential to make an important contribution to sustainable production increases in the dairy sector, which given EU milk quota abolition is a very timely exercise.

In relation to the first contribution of this article, we are primarily concerned with spatial spillovers in the adoption of milk recording, where we distinguish between *local* and *global* spillovers (LeSage, 2014). For example, if a dairy farmer is located in a dairy intensive and progressive neighbourhood, exogenous characteristics of the neighbouring farms (i.e. stocking intensity, herd size, etc.) may have an impact on the farmer's technology choices in this neighbourhood, which, however, do not spill over to other regions and thus are local spillovers. That is, large farms have a higher probability to adopt new technologies that spill over to their direct neighbours (Storm et al., 2014). If adoption choices are (also) influenced by neighbours' adoption choices, they are likely to spill over to other neighbours, their neighbouring regions and so on and hence these are global spillovers.

In adoption choices it is likely that neighbours' choices as well as characteristics matter, but the type of spatial effect cannot be predicted a priori with certainty. Hence we test spatial models that allow for *local* and *global* spillovers and compare their performance. We find clear evidence for global spillovers in our study setting, that is consistent with theoretical considerations.

In relation to our second contribution, this article adds to the empirical challenge of

[8]This criticism can also be extended to social network studies that limit their network connections to sample members (see for example (Conley and Udry, 2010).

measuring neighbourhood effects. In spatial econometric applications, neighbourhood effects are generally measured by distance between (sample) members, with very little discussion of why specific weight matrices are chosen Halleck Vega and Elhorst (2015). While it is possible to add extra information in the spatial weight matrix (Case, 1992), few studies utilize more detailed information. In this context, (Maertens and Barrett, 2013) discuss several methods to collect farm level neighbourhood information. For example, they claim that a census approach is time intensive and only feasible for a small closed village context, which is then however not representative for the larger population. Agricultural census data generally provide geographic information only on electoral division or municipality level, hence not allowing individual farm level models. See for example Schmidtner et al. (2012) who model spatial distribution of organic farming on county level using German agricultural census data.

It emerges that sampling is the only feasible way for farm level studies that cover a larger geographic area. However, within a sample, not all farms are covered, hence leaving some farms with a potentially larger or smaller neighbourhoods, hence under- or over-representing the influence of neighbours. Several techniques have emerged to improve information in (small geographic confined) samples and (Maertens and Barrett, 2013) discuss several methods: one possibility is "snowball sampling" which means that each surveyed farmer suggests another farmer. While useful to gain detailed network information, it results in a non-representative sample. Other possible methods are "network within sample" or "random matching within sample" which, again, are confined to sample information, hence truncating the information. While all these techniques have advantages and disadvantages, they are based on directly eliciting information from farmers. There is no doubt that this provides very relevant and important information, but it is very time intensive and costly to attain. However, most importantly these techniques do not result in representative samples. Moreover, information is still confined to sample information only, bringing us back to the previously raised issue that farmers' neighbourhoods will differ in quantity and quality.

Hence, with the aim to have sample data on a larger scale that represents neighbourhoods well, we need new ways to increase information in our sample that does not truncate the information to sample members but still provides a feasible framework in relation to time and cost demands.

However, to date little work has been conducted to overcome this problem on a larger country scale. (Storm et al., 2014) also state that there is very limited availability of spatially explicit farm-level data for representative samples on country scale. Hence in this article we implement additional information in a "traditional" weight matrix. More specifically, we merge our sample data with census data. That is, we include agricultural census data in our spatial weight matrix, meaning that the strength of influence is based on *dairy livestock intensity* as well as proximity between farms. This provides a way of including information of every dairy farm in our estimation process, hence overcoming the issue that observations that have multiple neighbours that are not included in the sample will be erroneously treated as if they had fewer neighbours. We then compare this specification to a pure distance specification and find that both models provide quantitatively and qualitatively the same results.

In relation to the third contribution, we focus on a technology where concerns exist about low uptake rates, especially in the view of significant expansion plans within the EU milk quota abolition. Milk recording has the potential to improve productivity, whilst also providing environmental and animal health benefits and thus helps to balance resource use and increased production.

3 Contextual Background

Since April 2015, for the first time in three decades, EU dairy farmers can expand milk production without quota constraints. Expansion plans and achievements to date vary significantly across EU countries. For example, shortly after quota removal was confirmed in

2008, the Irish government announced progressive expansion plans aiming to achieve a 50 percent increase in milk production by 2020 (DAFF, 2010). Despite quota restrictions until 2015, moderate expansion was possible due to the so called "soft landing" of quota abolition and farmers in Ireland increased production by 7.6 percent between 2010 and 2015. With almost a 20 percent increase in milk production within the first year of quota removal, expansion of milk production in Ireland is well under-way. However, reaching the 50 percent increase in milk production will involve significant further intensification of dairy production methods.

In general, production is likely to expand most in countries or regions with a comparative advantage. In line with this, in Ireland milk production is expected to increase most in the south and south-west of the country, while much less milk production growth is expected in west and border regions. Despite these regional differences in growth, milk production is expected to increase in all regions (Läpple and Hennessy, 2012).

Irish dairy farming is characterized by a spring calving mainly grass-based system, where dairy cows are kept outside to graze for most of the year (Läpple et al., 2012). While worldwide New Zealand with its pasture based dairy system is seen as having the lowest cost milk production system, Ireland is generally regarded as similar in terms of production systems and costs (Donnellan et al., 2009; Dillon et al., 2008)[9].

New Zealand significantly increased its milk production during the EU milk quota era, mainly through increased cow numbers and yield increases resulting in more intensive production methods (Dillon, 2011). Given the rapid production increase of Irish milk production since quota removal, which is expected to continue, some argue that Ireland will experience a similar growth path to New Zealand by also increasing cow numbers, yields and stocking densities (Hurley and Murphy, 2015; Dillon, 2011). However, New Zealand's dairy expansion came at significant environmental costs resulting from nitrate contamination of drinking water, nutrient pollution of lakes, soil compaction and greenhouse gas emissions (Foote et al.,

[9]New Zealand still has slightly lower production costs than Ireland as more grass is utilized in the cow's diet (Dillon et al., 2008).

2015).

While the Irish dairy industry has the potential to benefit from its comparative advantage, it is important that farmers continuously adopt the latest technologies and processes to increase production in a sustainable way. This will be an important component to avoid environmental pitfalls as occurred in New Zealand.

However, farmers are often slow to adopt new technologies which is also the case in Ireland for milk recording. As previously mentioned, despite its clear advantages the uptake of milk recording is low. Milk recording is a low cost, easy to implement technology, which requires very little or no technical skills. There are two main options for milk recording which are "E-DIY milk recording", which automatically records all relevant information per cow, or "manual milk recording" where a milk recorder visits the parlour and takes samples[10].

The main advantage of implementing milk recording is from an economic perspective, i.e. milk recording helps to increase milk value by identifying cows that are most profitable [11] and it is an important aid in the early detection of mastitis based on SCC (O'Brien et al., 2009). Milk recording also provides important management information. For example, selecting suitable bulls for cows to address specific problems, such as high SCC or identifying cows with low milk solid content that can be replaced. This increases the value of the herd. Finally, milk recording can also be used for disease testing.

Benefits from milk recording are easily communicated among farmers. For example, a farmer may receive information from milk records that there is a SCC problem emerging in the herd and be in a position to start an intervention earlier than without the information received from milk recording.

Besides private benefits to the farmer, milk recording can also provide long-term environmental gains as well as animal health improvements. In relation to environmental gains, it is possible to identify the best cows for breeding based on the information received from

[10] Progressive Genetics, http://www.progressivegenetics.ie/milk-recording.

[11] which are generally cows that produce milk with the highest milk solid content which is important for the A+B-C pricing scheme

milk recording. It has been found that the genetic merit of the herd has an impact on greenhouse gas emissions from the dairy herd (O'Brien et al., 2010). In relation to animal health, management practices such as milk recording play an important part in the prevention of mastitis (O'Brien et al., 2009), and besides the animal health benefits, lower SCC content has also been found to be positively associated with farm profits (Dillon et al., 2015). In addition, managing SCC in the herd is an important component of successful expansion.

In summary, milk recording is a low-cost technology that is easy to implement with clear private and public benefits, however its uptake is below expectations. Understanding what and who matters in sustainable technology choices of farmers will provide an important step in achieving a more sustainable production growth of the dairy sector.

4 Data and Descriptive Statistics

The main data source used in this article is Irish Farm Accountancy Data Network (FADN) data for 2010 (Connolly et al., 2011). Irish FADN data are collected through the Irish National Farm Survey (NFS). The NFS was established in 1972 and has been published on an annual basis since. Overall, a statistically representative random sample of 1,100 farms, representing a farming population of approximately 110,000 farms, is surveyed each year through a series of face to face interviews with a professional data collection team. Farms are classified into farming systems based on the dominant enterprise which is calculated on a standard gross margin basis. The NFS distinguishes between six farming systems: specialized dairying, dairying other, cattle rearing, cattle other, mainly sheep and tillage. In this study we focus on dairy farms only. There are about 300 dairy farms in the NFS each year, representing a dairy farm population of approximately 17,000 dairy farms. The NFS dataset has a slight geographic bias toward south east of the country. This is not unexpected as the NFS is designed to give a representative national sample of the main farm enterprises, while in Ireland these enterprises are themselves geographically biased and localised. In relation to dairy enterprises, while spread across (most) of the country, these can predominately be found in the south and south west. However, dairy farms differ regionally in terms of intensity. The south and the south west are considered typical dairy regions, with more intensive farms due favorable soil and climatic conditions. The north west region is seen as a more disadvantaged dairying region that is characterized by lower stocking density due to higher rainfall areas and less suitable soil for intensive grazing Läpple and Hennessy (2015). The sample is not representative of smaller (in terms of output), less commercial farms, which are more concentrated in the north and west and around the coast, see Green and O'Donoghue (2013). Given these regional differences, farms in each region tend to be similar (in terms of size and intensity).

In addition to this dataset, we utilize data from the 2010 agricultural census. That is, data from the NFS were matched to agricultural census data, which allowed inference on dairy livestock density of each sample farm on an ED level. EDs are small legally defined administrative areas in the Ireland for which census data are available[12]. While there are 330 dairy farms in the NFS sample, the data has been reduced to farms that are geo-referenced and further reduced to farms that are matched to agricultural census data. Hence, a sub-sample of 280 dairy farms is used.

While these farms are specialized in dairy production, there is typically a significant alternative enterprise also operated on the farm. In addition to data on the farm business, the farm operator and household, data on technology adoption and extension participation is also recorded.

In relation to the cross-sectional nature of our data, a neighbourhood effect may arise as farmers are influenced by previous decisions of their neighbours (see LeSage and Pace (2009) how a cross-sectional model can be motivated as a long run equilibrium), but Baerenklau

[12]2010 is the latest year for which geo-referenced NFS data and Agricultural Census data are available. However, milk quota abolition was first announced in the 2003 Common Agricultural Policy (CAP)"Mid Term Review" and confirmed in the 2008 CAP "Health Check", hence preparation for production expansion was well under-way in 2010. In addition, the Irish government announced its ambitious growth target of a 50 percent increase in milk production in 2010. Moreover, the adoption of milk recording has not increased closer to milk quota abolition.

(2005) also notes that agents may be immediately influenced by the simultaneous decisions made by their peers.

The selection of explanatory variables to explain the adoption of milk recording is guided by the general literature on agricultural technology adoption (see for example Barham et al. (2004) or Sauer and Zilberman (2012)) as well as data availability. Table 1 presents summary statistics and a description of variables used in the empirical model for the full sample as well as classified by adoption status.

Table 1: Variable description and summary statistics

Variable	Description	Non-adopter	Adopter	All
		(n=164)	(n=116)	(n=280)
Herd size	Number of dairy cows	51.71 (35.41)	80.29 (36.05)	63.64 (38.31)
LU/ha	Livestock units per hectare	1.74 (0.48)	2.05 (0.47)	1.87 (0.50)
Specialization	Dairy cows as a proportion of all livestock	0.57 (0.17)	0.62 (0.12)	0.60 (0.15)
Soil	= 1 if good soil quality, 0 otherwise	0.54	0.62	0.57
Age	Age of the farmer	51.39 (10.60)	48.60 (10.19)	50.22 (10.50)
Agr. educ	= 1 if farmer has completed some level of agricultural education	0.63	0.86	0.73
Job	= 1 if main farm holder has an off-farm job	0.11	0.06	0.09
Household	Number of household members	3.52 (1.66)	3.75 (1.59)	3.63 (1.64)
Extension	Extension expenditure per cow in euro	5.72 (5.85)	7.02 (7.85)	6.47 (7.09)
Dairy intensity	Dairy livestock units per hectare at ED level	0.36 (0.25)	0.45 (0.22)	0.40 (0.24)

Mean and standard deviation in parentheses

It is clear from the summary statistics in Table 1, that there are differences between adopters and non-adopters in relation to a number of characteristics. For example, adopters have larger farms (measured in herd size), are younger and more likely to have completed some level of agricultural education. In addition, adopters are located in more dairying intensive locations, as indicated by the higher dairy intensity per ED for adopters. As previously mentioned, farms are geocoded and the Euclidian distance is calculated between all farms. This information is used to construct spatial weight matrices, which is explained in detail in the following section.

5 Empirical Framework

The adoption of milk recording differs between farmers due to their unique characteristics. The underlying assumption of our empirical framework is that farmers communicate with each other, meaning that they share their enthusiasm or pessimism about the new technology with their peers (Case, 1992). In addition, neighbours' choices can also lower the costs associated with adoption, i.e. they can significantly lower extension expenditure. More specifically, farmers with more neighbours who have already adopted the new technology may have lower learning costs than farmers with fewer or more distant neighbours (Lewis et al., 2011), which is based on the public good nature of information that spills over to other farmers. One argument for this phenomenon is knowledge spillover through communication. Communication among farmers is particularly fostered among Irish farmers through the support of farmer discussion groups, organisation of frequent farm walks, knowledge transfer events, etc. Moreover, several studies found that the probability of a farmer to adopt a new technology increases if a neighbour has already adopted the technology (Läpple and Kelley, 2015; Case, 1992; Holloway et al., 2007). It is easy to see that this type of spatial effect leads to an endogenous spatial effect, as neighbours speak to their neighbours who then speak to their neighbors and so on. Models that include an endogenous spatial effect are a global spillover models, due to their endogenous feedback effect.

While neighbours adoption decisions are important for ones own adoption, neighbouring characteristics are also important for technology diffusion. For example, large farms have a higher probability to adopt new technologies that spill over to their direct neighbours (Storm et al., 2014). This effect is a local spillover. Hence, in technology diffusion both characteristics are important, neighbours' choices as well as neighbours' characteristics (Storm et al., 2014). Thus, endogenous and exogenous spatial effects are likely to play a role in the adoption of milk recording, which given the endogenous feedback would lead to a global spillover specification.

Our theoretical considerations suggest a global model and we test the appropriateness of this model by comparing a number of global and local specifications.

That is, we estimate a spatial Durbin probit model (SDM), a spatial Durbin probit error model (SDEM), a spatial lag of X probit model (SLX) as well as a non-spatial probit model, for comparison purposes. That is, we are estimating the following specifications:

The first model is an SDM–assuming global spillovers–which takes the following form and nests the SLX model if $\rho = 0$:

$$y^* = \rho W y^* + X\beta + WX\theta + \varepsilon \tag{1}$$

where y^* is a $n \times 1$ vector representing the farmer's utility, X is a $n \times k$ matrix of explanatory variables comprising of farm and household characteristics, β and θ are $k \times 1$ vectors of parameters to be estimated, ε is a $n \times 1$ vector normally distributed error terms $N(0, \sigma^2 I_N)$, ρ is a scalar parameter indicating global spatial dependence, and I_N is an n-dimensional identity matrix. W is an $n \times n$ spatial weight matrix and we consider two different specifications, which are described subsequently. The term $\rho W y^*$ implies that the adoption choice of each farmer in the sample varies with a weighted average of the adoption choices of the remaining farmers in the sample, i.e. it accounts for global spillovers.

The next model, the SDEM–assuming local spillovers–takes the following form and it is easy to see that this model also nests the SLX model if $\lambda = 0$ and the spatial error model if $\theta = 0$:

$$y^* = X\beta + WX\theta + u \tag{2}$$

$$u = \lambda Wu + \varepsilon \tag{3}$$

It is important to realise when considering different spatial models with and without spatial error component that the SDM can be derived from the spatial error model (SEM) as shown in **?**, which we recreate here for convenience.

We first start out with a standard SEM with autoregressive errors of the following form:

$$y = X\beta + u \tag{4}$$

$$u = \lambda Wu + \varepsilon \tag{5}$$

The next step in the derivation is to write the SEM model in reduced form as follows:

$$y = X\beta + (I_n - \lambda W)^{-1}\varepsilon \tag{6}$$

Next, we multiply through both sides of the equation by $(I_n - \lambda W)$:

$$(I_n - \lambda W)\, y = (I_n - \lambda W)\, X\beta + \varepsilon \tag{7}$$

The next step is to multiple through by $(I_n - \lambda W)$ as follows:

$$y - \lambda W y = X\beta - \lambda\beta W X + \varepsilon \quad (8)$$

$$y = \lambda W y + X\beta - \lambda\beta W X + \varepsilon \quad (9)$$

The final step is to let $\theta = -\lambda\beta$ and rewrite the above equation as follows:

$$y = \lambda W y + X\beta + W X\theta + \varepsilon \quad (10)$$

The last equation is the familiar SDM model which as shown can be easily derived from the SEM. The SDM specification is also motivated by the possibility that spatially correlated variables are omitted that are correlated with included explanatory variables. Moreover, in situations involving any model uncertainty regarding the presence of spatial dependence in the dependent variable versus the disturbances, the SDM specification is often seen as the only appropriate specification (**?**).

As common in modelling technology choices, we assume that a farmer will adopt the new technology if the expected utility of adopting the technology (U_A) is higher than that of non-adoption (U_N). However, we only observe whether or not the farmer adopts milk recording instead of observing expected utility. This leaves us with a binary choice variable (y) that equals one if $y^* = U_A - U_N > 0$ and zero otherwise. While binary choice models are a very common modelling framework in standard econometrics, binary choice models have received less attention in a spatial framework (Calabrese and Elkink, 2014). However, there is a growing number of spatial binary choice applications (see for example Wollni and Andersson (2014) and Läpple and Kelley (2015)) that apply Bayesian MCMC estimators as suggested by LeSage and Pace (2009).

In general, Bayesian methods are based on a combination of the likelihood of the model $p(y \mid \tau)$ and prior distributional assumptions $p(\tau)$ for the unknown parameters, which in our case are $\tau = (\beta, \theta, \rho)$. The prior distribution represents a priori expected values of the parameters, hence it depicts uncertainty about the unknown parameters (Gelman et al., 2014). Prior distributions are combined with the likelihood via Bayes' rule, which yield the posterior distribution $p(\tau|y)$:

$$p(\tau|y) \propto p(y|\tau)p(\tau) \tag{11}$$

In the case of the SDM, the resulting posterior distribution is not available in closed form, hence am MCMC sampler approach is used and conditional posterior distributions for all parameters are derived, which are then sampled sequentially. Additional information regarding MCMC estimation of spatial econometric models is contained in LeSage and Pace (2009).

The Reflection Problem

One point of concern that has been raised regarding the use of spatial econometric models comes originally from Manski (1993), but has later been reiterated by Gibbons and Overman (2012). In the seminal article by Manski (1993), he outlines what is referred to as the "reflection problem". Using standard spatial econometric notation, the reflection problem is one where the endogenous spatial effects (as given by Wy), the exogeneous effects (as given by WX), and the contextual effects (as given by $W\varepsilon$) are not separately identified in the model. Using a linear–in–means model specification, Manski (1993) shows that it is not possible to separate out the different spatial effects. By way of example, suppose that a farmer is trying to decide whether or not to adopt a certain technology. The reflection problem states that it is impossible to tell empirically whether that adoption is due to another farmer's adoption of the same technology (i.e. the neighbourhood–effect), the characteristics of the other farmers in the system (i.e. the exogenous effects), or the spatially–correlated unobserved factors in the model (i.e. the correlated effect).

The identification of spatial econometric models with an endogenous effect, such as the spatial autoregressive model and SDM as discussed in Gibbons and Overman (2012) extend this idea by noting that it is impossible to determine if exogenous changes are caused by neighboring outcomes, i.e. Wy and not by changes in neighboring characteristics, as defined by WX (Gibbons and Overman, 2012).

Although the reflection problem seems as first glance to be obvious, we argue that there is one crucial assumption in the work of Manski (1993) and Gibbons and Overman (2012) that if changed, allows for the separate identification of the endogenous spatial effects, the exogenous effects, and the correlated effects.

Proposition 1 as noted in Bramoullé et al. (2009) shows that when $WW = W$ (i.e. the spatial weight matrix is idempotent) the model is not identified and Manski (1993)'s critique holds. However, as noted in (Bramoullé, 2013, p. 266), "the property that $WW = W$ only holds when the mean is inclusive and is computed over everyone in the peer group including i." In practical terms, the reflection problem only manifests itself when the spatial weight matrix has 1's on the main diagonal, i.e. the mean is inclusive. It is worth quoting Bramoullé (2013) at length regarding this issue:

"Assuming that an individual is one of his own peers seems a bit strange, and applied researchers typically consider *exclusive means*, where the average is computed over everyone in the peer group except i. As it turns out, this minor distinction has key implications for identification." (emphasis original)

In other words, the reflection problem is vitiated when one uses a standard spatial weight matrix, i.e. one where the main diagonal consists of zeros so that no one is a neighbor to themselves. This is a standard assumption that is made in the spatial econometric literature, e.g. LeSage (2014).

In addition to the above studies mentioned, Bramoullé et al. (2014) develop a game theoretic model and show that for any ρ (i.e. spatial autocorrelation parameter) and any W (i.e. spatial weight or network matrix) there exists a unique Nash equilibrium that depends only on a single network measure, which is the lowest eigenvalue of the network (spatial) weight matrix.

In short, the current study avoids the reflection issue by utilizing a spatial weight matrix that is *exclusive* of the mean of the own individual, i.e. a spatial weight matrix that has zeros on the main diagonal, which is standard practice in the spatial econometrics literature.

Spatial Weight Matrix Specifications

We consider two different spatial weight matrix specifications. The geographic proximity is calculated based on Euclidean distances between farm i and j in our sample. While close proximity to each other does not necessarily imply that communication takes place, there is evidence that location matters and Maertens and Barrett (2013) found that living close to another farmer increases the probability of a social link by up to 50 percent. Utilizing a sample implies that spatial interaction is confined to sample members, rather than to all farms within the farm's proximity. Stated differently, some farms within the sample may have fewer neighbours due to sampling issues, rather than due to being in a remote region. Hence, a pure distance weight matrix does not take into account whether or not the farm is in a dairy intensive location. To address this problem, we amend W to account for *dairy livestock intensity* within the electoral division (ED) of the farm. That is, we overcome the missing neighbour problem by incorporating census data in our estimation process. The main intuition of the reason why dairy livestock intensity is incorporated in the weight matrix is motivated by the finding that larger, more intensively stocked farms are found to be more likely to adopt milk recording. Therefore, we consider dairy intensity to be more important for milk recording decisions than, for example, using the number of surrounding farms. Hence, we construct a *"dairy intensity distance"* (α_{ij}) that measures the average livestock intensity (κ) of farm i and farm $j's$ ED, such that $(\alpha_{ij}) = (\kappa_i + \kappa_j)/2$, which is then normalized on the maximum across the sample.

In this spatial weight matrix specification farmers are considered neighbours if they live within a certain distance, but the strength of the spatial weight is determined by the average dairying intensity of the ED of farm i and farm j. Hence, our *"dairy intensity matrix"* W_{DI} is calculated as a multiple of a contiguity distance matrix and α_{ij}. Importantly, the contiguity matrix is based on a distance cut-off, which is outlined below.

In addition, we also apply an inverse distance spatial weight matrix (W_D) with $w_{ij} = 1/d_{ij}$, where d_{ij} is the Euclidean distance between farm i and j. We follow common practice to use a cut-off d^* that implies that all spatial weights w_{ij} outside this distance are zero, i.e. $w_{ij} = 0$ if $d_{ij} < d^*$, see for example Roe et al. (2002). We set d^* as the minimum distance that all farms in our sample have at least one neighbour, which is 45 km in our sample. An inverse distance matrix implies that closer neighbours exert a stronger influence than more distant neighbours, which may resemble reality more closely than a contiguity matrix where each neighbour regardless of proximity has the same influence. We follow common practice and row-normalize all spatial weight matrices.

Interpretation of Coefficients

Besides accounting for spatial dependence, spatial econometric models also differ substantially from standard econometric models with respect to the interpretation of coefficients. Several empirical studies erroneously use point estimates of the parameters (e.g. β and θ) to draw conclusions on spatial relationships (Elhorst, 2014). However, spatial econometric models that have a spatially–lagged dependent variable (such as the SDM used in this article) need to be interpreted with care. **?** have developed a methodology to handle the case for continuous y outcomes as well as discrete outcomes for the dependent variable.

We begin our discussion by writing the SDM in reduced form as follows:

$$y = (I_n - \rho W)^{-1} X\beta + WX\theta + (I_n - \rho W)^{-1}\varepsilon \qquad (12)$$

The reduced form of the SDM can now be used to illustrate the calculation of the effects estimates. If we take the partial derivative of y with respect to X we obtain the following expression:

$$\partial y / \partial X_r = (I_n - \rho W)^{-1}(\beta_r + W\theta_r) \tag{13}$$

where r delineates the r^{th} explanatory variable. Note that since the $(I_n - \rho W)^{-1}$ term in an $n \times n$ matrix, the partial derivative results in a matrix of what LeSage and Pace (2009) refer to as effects estimates. Using this result, we can derive three different types of effects estimates: the direct effect, the indirect and the total effect.

If we define the quantity $S\left(W\right) = (I_n - \rho W)^{-1}(\beta_r + W\theta_r)$ we can now define the own–partial derivative (i.e. the direct effect) and the cross–partial derivative (i.e. the indirect effect):

$$\partial y_i / \partial x_{ir} = S(W)_{ii} \tag{14}$$

$$\partial y_i \Big/ \partial x_{jr} = S(W)_{ij} \tag{15}$$

The own–partial derivative is how a change in an explanatory variable in location i affects the dependent variable in location i and the cross–partial derivative is how a change in an explanatory variable in location j affects the dependent variable in location i (where $i \neq j$). The total effect is defined as the sum of the direct and indirect effects.

Given that there is a partial derivative effect for each observation, LeSage and Pace (2009) recommend that one calculates scalar summaries of the effects. The average direct effect is the average of the diagonal elements of the $S\left(W\right)$ matrix, while the indirect or spillover effects are the average of the off–diagonal elements of the $S\left(W\right)$ matrix. The summary effect for the indirect effect is either taken as the average of the row or column sums, which result in different interpretations. More specifically, the average *row* effect provides the impact on a specific y_i based on a change in all elements of the explanatory variable, while in contrast the average *column* effect shows the impact of a change in x_{ki} on the dependent variable of all farmers (Elhorst, 2014). While average row and column sums result in the same value, intuitively in some cases either the row or the column effect makes more sense in the interpretation. Additional details regarding the calculation of the effects estimates are given in LeSage and Pace (2009), and in the case of the spatial probit model, Lacombe and LeSage (2013)

6 Results and Discussion

This section presents the results from the empirical models. However, before we embark on the interpretation of various econometric models we discuss neighbourhood relationships. Farmers in our sample have on average 33 neighbours within a 45km radius. This figure varies between one to 67 neighbours. On average, the distances to neighbouring farms are 28 km. The shortest distance is 420 meter, while minimum distances are on average 6.9km[13].

To recall, we estimate and compare SDM, SDEM as well as SLX models[14] in order to identify whether spatial spillovers are of global or local nature. All spatial models are estimated with the following two spatial weight matrix specifications, in order to identify whether adding additional information on missing neighbours improves our specification.

1. W_{DI}: a multiple of a contiguity distance matrix and the *"dairy intensity distance"*.
2. W_D: an inverse distance matrix[15].

In addition, we also include a non-spatial probit model in our comparison exercise. That means, we compare seven models based on percentages correctly predicted weighted by the proportion of adopters and non-adopters in the sample, such that: $\hat{p} = (1-\bar{y})\hat{p}_0 + \bar{y}\hat{p}_1$, where $\hat{p}$ is the overall percentage correctly predicted, $\hat{p}_0$ and $\hat{p}_1$ are the percentages for non-adopters and adopters, respectively, while $\bar{y}$ is the mean adoption rate in the sample (Wooldridge, 2012). The results of the model comparison exercise are shown in Table 2.

[13] The largest minimum distance is 45km, which is our cut-off for the distance matrix

[14] The SLX model is nested in either of the specifications.

[15] Both $W's$ are subject to a distance cut-off that ensures that every farm has at least one neighbour.

Table 2: Comparison of Model Performance

	SDM	**SDEM**	**SLX**	**Probit**
W_DI	0.9857	0.7214	0.7536	–
W_D	0.9821	0.7107	0.7464	–
no W	–	–	–	0.7179

As can be seen in Table 2, the SDM model shows a clearly superior model performance when compared to all other models. The SLX model performs marginally better then the more flexible SDEM model, which can be explained by the fact that the SLX model is a more parsimonious model. While both SDMs have much higher percent correctly predicted than the remaining models, the difference within the same group of models (i.e. based on the different weight matrix specification) is less pronounced. In fact, the models utilizing the *"dairy intensity distance"* perform marginally better in all specifications. The non-spatial probit performs worse in terms of predictive power than most spatial specifications. More specifically, when compared to the spatial specifications, the non-spatial probit model performs worse in five out of six cases and is only marginally better in one case, implying that accounting for spatial spillovers improves the accuracy of the model. Despite differences in predictive power, all models show very similar effects of explanatory variables, for example, herd size, livestock density and agricultural education have a significant and positive effect in all spatial models as well as the non-spatial probit. The non-spatial probit model is the only model that also shows a significant positive impact of dairy specialization. Overall, this confirms robustness of estimation, which given complexity of the estimation process is re-assuring.

Overall then, the figures clearly suggest that the spatial spillover is a global process, as the SDMs dominate. This implies that endogenous and exogenous spatial effects matter, which is consistent with our theoretical considerations. However as the difference in performance between both W specification is only marginal, Table 3 provides effect estimates for the SDM with both weight matrix specifications. Specifically, the direct, indirect and total effects of the estimated coefficients as well as the corresponding 95 percent credible intervals of the *"dairy intensity distance"* SDM are shown in Table 3.

The values are scalar summary estimates of the previously outlined calculation of the effect estimates. In terms of interpretation, any effect estimate whose credible interval does not cross zero is regarded as having a statistically significant effect on the probability to adopt milk recording.

Before embarking on interpretation of the results, we compare both SDM models based on differences in effect estimates. This will provide further insight into potential differences between the two specifications and whether or not adding additional information in the weight matrix actually improves our estimates.

In fact, direct, indirect and total effect estimates of both models are remarkably similar and all effect estimates of the *"inverse distance"* SDM are within the 95 percent credible intervals of the *"dairy intensity distance"* SDM. Given the similarities of both models, it appears that including more detailed information in our W does not significantly improve or alter our results. This is in line with findings by LeSage and Pace (2014) who compare spatial econometric models with different $W's$ and conclude that fine-tuning adjustments of the W does not make a difference in the estimates and inferences. However, this could also be a special feature of our sample, which is a representative sample of Irish dairy farms.

Hence, the interpretation of results applies to both models that are presented in Table 3. Overall, three of the included explanatory variables have 95 percent credible intervals that do not cross zero. In addition, the indirect effect estimates are smaller in magnitude than the direct estimates. This makes sense, given the interpretation of the indirect effects.

In terms of farm characteristics, the size of the dairy cow herd is positively associated with the adoption of milk recording, which is in line with previous literature findings that larger farms are more likely to adopt new technologies (Barham et al., 2004; Feder et al., 1985; Sauer and Zilberman, 2012). More specifically, each additional dairy cow on farm i increases the probability of adoption of milk recording by 0.4 percent on the $i'th$ farm (direct effect), while - considering the indirect row effect here- a one cow increase in herd size of

Table 3: Effect estimates of SDM

Variable	*Lower 5% credible interval*	*"Dairy Intensity Distance"*	*"Inverse distance"*	*Upper 95% credible interval*
Direct effects				
Herd size	0.002	**0.004**	**0.004**	0.005
LU/ha	0.065	**0.165**	**0.178**	0.262
Specialization	-0.105	0.231	0.265	0.57
Soil	-0.186	-0.084	-0.095	0.029
Age	-0.006	-0.001	-0.001	0.004
Agr. Educ	0.063	**0.188**	**0.176**	0.316
Off farm job	-0.271	-0.102	-0.125	0.061
Household	-0.041	-0.004	-0.005	0.027
Extension	-0.011	-0.002	-0.002	0.005
Indirect effects				
Herd size	0.000	**0.002**	**0.002**	0.005
LU/ha	0.004	**0.077**	**0.109**	0.25
Specialization	-0.039	0.107	0.161	0.438
Soil	-0.15	-0.038	-0.058	0.006
Age	-0.004	0	-0.001	0.003
Agr. Educ	0.003	**0.087**	**0.111**	0.284
Off farm job	-0.193	-0.045	-0.076	0.03
Household	-0.022	-0.002	-0.003	0.03
Extension	-0.006	-0.001	-0.001	0.007
Total effects				
Herd size	0.002	**0.005**	**0.006**	0.006
LU/ha	0.062	**0.243**	**0.286**	0.363
Specialization	-0.022	0.339	0.426	0.867
Soil	-0.197	-0.122	-0.153	0.072
Age	-0.007	-0.001	-0.002	0.006
Agr. Educ	0.118	**0.274**	**0.287**	0.45
Off farm job	-0.437	-0.147	-0.201	0.029
Household	-0.062	-0.006	-0.008	0.027
Extension	-0.014	-0.003	-0.003	0.007
Rho		0.284***	0.342***	

Please note: 95% credible intervals are from "Dairy intensity distance" model
Bold font indicates that the variable is associated with the dependent variable at 95% level

all other farmers leads to a 0.2 percent increase of the probability of adoption of farmer i. Overall, this results in a total effect of 0.6 percent increase of adoption probability of all farms.

Similarly, livestock density has a positive effect on the probability of adopting a new technology. For example, an increase of one livestock unit per hectare increases the probability of adoption on the same farm by over 16 percent, while an increase in livestock density of neighbouring farms increases farmer $i's$ adoption probability by almost 8 percent (indirect row effect), accumulating to a total increase in probability of adoption of all farms of 25 percent.[16] The significant indirect effects of herd size and livestock density suggest that adoption choices vary with the observable characteristics of the farmer's neighbourhood, such as larger more intensively farmed holdings. Intuitively, it makes sense that farms of similar size and intensity are in close proximity and farm holders of similar farms are part of the same neighbourhood.

There is no significant effect of soil quality and off-farm job on technology adoption. The latter finding is in contrast to previous findings by Sauer and Zilberman (2012), who report a negative effect of off-farm income on dairy technology adoption. Since there may be initial learning costs involved in the adoption of milk recording (if the farmer adopts the E-DIY option), a larger number of household members may be beneficial for the adoption of milk recording. However, the number of household members does not show a significant effect on technology adoption.

Our results do not confirm that younger farmers are more likely to adopt new technologies (Barham et al., 2004; Feder et al., 1985), as suggested by the non-significant effect estimates of age. However, our findings support earlier studies highlighting the importance of farmer's education on technology adoption (Foltz and Chang, 2002). For example, having completed agricultural education increases the probability of adopting milk recording by almost 19

[16] Some may argue that milk recording causes higher livestock intensity, but as milk recording helps to improve the performance of individual cows, stocking density should not increase, as the farmer can produce more from existing cows.

percent (direct effect), and also increases the probability of adoption of neighbouring farmers by a cumulative 9 percent, adding to a total effect of 28 percent increase in probability of adopting milk recording. The indirect effect of this variable is interpreted as the average column effect and intuitively suggests that farmers share their knowledge with each other.

Finally, in contrast to the general consensus that agricultural extension increases the adoption of new technologies (Birkhaeuser et al., 1991) our model does not confirm this as the coefficient of extension expenditure per cow is not significant. However, before concluding that extension services are not successful in inducing technology adoption it is important to remember that based on data availability, extension expenditure per cow is included but no information on the type of extension service is accounted for. Moreover, (Krishnan and Patnam, 2014) report that extension services are important initially, but the effect diminishes after some time, while learning from neighbours remains important. This could be a situation we are also observing, as milk recording is available since several years. In a similar vein, Barham et al. (2015) conclude that farmers' learning styles are quite heterogeneous based on their finding of no strong relationship between learning styles and the uptake of a new technology.

7 Concluding Remarks

The adoption of sustainable technologies by farmers can play an important role in achieving a sustainable growth path, which was explored in this article. More specifically, this article analysed farmers' adoption decisions of a simple, yet effective sustainable technology, where uptake rates are below expectations. We specifically explored whether spatial effects in the adoption of a dairy technology matter and whether they are of local or global nature. In addition, in order to overcome the issue that we only observe a sample of farmers, we implemented census data in our spatial weight matrix specification. That is, the article addressed two important issues in the spatial econometrics literature that have been subject to recent discussion (see LeSage (2014) and LeSage and Pace (2014)), but also addresses an important and very topical policy question, where our spatial analysis provides more detailed insight and advanced policy recommendations.

The findings from this study reveal that there are neighbourhood effects in the adoption of milk recording, confirming that farmers do take their peers' decisions into account when making technology adoption decisions. The results also show that exogenous spatial effects are important, in the sense that observable characteristics have spatial spillover effects. More specifically, farmers with larger more intensively farmed holdings who have completed agricultural education are more likely to adopt milk recording and those characteristics also have positive spatial spillover effects on neighbours' adoption decisions. For example, having completed agricultural education increases the own farmer's as well as neighbours' adoption decisions, providing empirical evidence for knowledge spillover due to communication among farmers.

Focusing specifically on spatial spillovers, the findings of this article also show that spatial spillover effects in dairy technology adoption are of global nature. This is important as the majority of previous spatial econometric applications routinely assume spatial effects are of global nature, without testing for or considering local spatial effects (see, for example, Schmidtner et al. (2012); Wollni and Andersson (2014)). More importantly, knowledge about global or local spillover effects also has important policy implications, as the former encompasses endogenous feedback, while the latter does not. In this context, the significant positive neighbourhood effect implies that farmers are influenced by their peers, which in turn, given the global spatial spillover effect, can have a positive multiplier effect on adoption rates of neighbours. By merely assuming global spillover effects, but not testing which spillover effects actually exist, policy recommendations assuming multiplier effects may be wrong.

Another important contribution from this study is that amending the spatial weight matrix does not have a significant effect on the inferences from the model. Nevertheless, our *"dairy intensity distance"* models are superior to the ones that are based on sample data only (i.e. *"inverse distance"* models). However, an alternative explanation of the finding is that our sample- which is a representative sample- represents the spatial structure of the Irish dairy sector well, hence little new information is added by implementing census data. Overall, the similarity of both model specifications corroborates LeSage and Pace (2014) that fine-tuning spatial weight matrices does not alter or improve the results.

In relation to policy recommendations for sustainable expansion of the agricultural sector, our findings revealed that better educated farmers, who manage larger more intensively stocked farms, are more likely to adopt milk recording. It appears that the already "better performing" farmers are also the ones adopting new technologies. This may be a cause of concern as milk recording could play an important role in helping more marginal farmers to catch up, but these farmers have been identified to be less likely to engage with new technologies.

Based on our spatial models, the results provide direct and indirect avenues to achieve higher uptake rates. In relation to direct avenues, there is a significant neighbourhood effect in the adoption of milk recording, where the adoption of one farmer induces adoption decisions of others. Hence, we do find positive multiplier effects that should be harnessed by policy makers. Increasing farmer interaction, for example through farm open days, etc. may be a good way to increase adoption of milk recording, hence taking advantage of the likely positive global spillover effect. In relation to indirect ways, based on significant exogenous effects, we find that if neighbouring farmers intensify or expand their dairy enterprise, this also impacts on other farmers milk recording uptake decisions. This means that the generally observed trend in Irish dairy farming of intensifying and expanding milk production may trigger further sustainable technology uptake rates. Finally, again an indirect avenue, our study showed that education not only increases the own farmer's but also neighbouring farmers'adoption rates, which - we argue- may be through direct communication. Hence, incentivising agricultural education and adding sustainable technologies to the curriculum will add to increased uptake rates, not only of the participating farmers, but also their neighbours.

Finally, there are a few limitations in the current study, which have to be taken into consideration. First, farmers' neighbourhoods are based on spatial proximity only, but no information is available on whether or not these farmers do really communicate with each other. While distance is certainly a good proxy for social networks, it has also been shown that neighbourhood effects are weaker when based on distance than on actual network measures (Bandiera and Rasul, 2006). Also, it can be argued that our measure of extension services is quite crude and more detailed work on the effect of extension services on technology adoption choices - especially when simultaneously considering neighbourhood effects- would make an interesting topic for further research. Moreover, it is important to consider that farmers who chose to participate in agricultural education may also be more likely to adopt milk recording, hence the effects reported in our study may be subject to slight bias. Finally, farmers' technology choices are analysed at one point in time, but there is a likely possibility that farmers are influenced by previous decisions of their peers. Hence, extending this work to a panel data model would also be a potential avenue for future research.

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