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Spatial dependence in the adoption of organic drystock farming in Ireland

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Abstract

This article analyses spatial dependence in the adoption of organic farming. Bayesian spatial Durbin probit models are applied to survey data of almost 600 Irish drystock farmers. The findings reveal that farmers located in close proximity exhibit similar choice behaviour. In addition, results show the importance of farmer interactions in adoption decisions as social norms and attitudes were identified to have spatial spill-over effects. Overall, the study highlights the importance of accounting for interdependence in farmers' decisions, which emerges as important in the formulation of agricultural policy.

Keywords: spatial dependence, Bayesian spatial Durbin probit model, organic farming, adoption decision

JEL classification: Q12, C11

1. Introduction

Organic farming has attracted increasing attention in recent decades as a means to sustain agricultural production while addressing the environmental problems caused by conventional agricultural methods (Lampkin and Padel, 1994; Klonsky and Tourte, 1998; Häring *et al.*, 2004). Throughout Europe, agri-environmental schemes have been introduced to encourage conventional farmers to convert to organic farming in order to facilitate its diffusion.

In support of those policy initiatives, a number of studies have attempted to gain insight into the organic farming adoption process (e.g. Pietola and Oude Lansink, 2001; Burton, Rigby and Young, 2003; Läpple, 2010). These empirical works demonstrated that output prices, policy changes, farm and household characteristics as well as information systems all contributed to the uptake of

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organic farming. Despite providing valuable insight into the importance of factors that affect the adoption of organic farming, the aforementioned studies ignore spatial dependence that can be important for adoption decisions. Spatial dependence implies that farmers located in close proximity exhibit similar choice behaviour. This may arise due to communication between farmers, which can, for example, raise awareness, reduce information costs or change preferences. This idea has its roots back to Manski's (1993) analysis of endogenous social effects where the propensity of an individual to behave in a certain way changes with the behaviour of the individual's social group, which is also known as neighbourhood effect. Alternatively, spatial dependence may arise due to favourable conditions for organic farming that can prevail in certain geographic areas. Ellison and Glaeser (1997) refer to this effect as natural advantage. Hence, when modelling adoption behaviour of farmers, it is important to control for spatial dependence, especially as policy implications may be biased when excluding spatial effects. This study applies Bayesian spatial Durbin probit models (SDMs), which account for spatial dependence in the adoption of organic farming among Irish drystock farmers.

Few studies have previously attempted to empirically explore spatial effects in an agricultural context, however precedents exist. One of the first studies that examined neighbourhood influence on technology adoption was Case (1992), focusing on sickle adoption in Indonesia. The results of a spatial probit model indicate strong neighbourhood effects in farmers' technology adoption decisions. The article concludes by arguing that not controlling for these spatial effects would result in biased estimates of the impact of factors determining adoption. Other examples include Holloway, Shankar and Rahman (2002) who study the adoption of high-yield varieties among Bangladeshi rice producers and Holloway and Lapar (2007), examining spatial dependence in market participation among Filipino smallholders. Employing Bayesian spatial probit models, the latter article also examines the size of the neighbourhood. Both articles show a positive neighbourhood effect on the likelihood of a farmer's adoption of technology or market participation, thereby highlighting the importance of controlling for spatial interactions.

In the context of organic farming, spatial dependence is important for several reasons: first, organic farming is an information-intensive farming technique and often farmers obtain technical information by communicating with other organic farmers (Egri, 1999; Padel, 2001). These neighbourhood effects may lower human capital investment costs when others have already adopted. Second, social norms in terms of views of other farmers on organic agriculture can either constrain or assist adoption. For example, Läpple and Kelley (2013) found that farmers' intentions to convert to organic farming are influenced by their own but, more importantly, by their important others' attitudes and views on organic farming. Durlauf (2004) describes this phenomenon as an intrinsic desire to behave like certain others. In general, farmers develop an opinion about organic farming that determines whether the farmer will adopt or not. This opinion can be influenced by neighbours' attitudes towards organic farming as farmers may communicate their enthusiasm or pessimism about organic farming with their neighbours (Case, 1992). Thus, for example, in an area where organic farming is a widespread and well-accepted farming method, farmers may be positively influenced to adopt or vice versa. Obviously, a widespread uptake of organic farming in one area can also be influenced by favourable geographic or economic conditions. For example, similar farming systems are often located in certain areas, influenced by soil quality suitable for a specific farm system or economic conditions such as the presence of a good processing facility or the availability of regional funds. Also, the quality of technical information available is often confined to certain areas due to the success of a good farm advisor working in that area.

There is a considerable variation in the uptake rate of organic farming in the EU both across and within Member States (Häring *et al.*, 2004). While the organic farming sector in the EU occupies 4.7 per cent of the agricultural land (Willer and Kilcher, 2011), Ireland has an uptake rate of just over 1 per cent of its agricultural area. In addition, organic farms are distributed quite unevenly throughout Ireland with clusters emerging in Co. Leitrim/Co. Roscommon, Co. Limerick and Co. Cork. This uneven spatial distribution in Ireland was influenced, among other things, by the impact of pioneering organic farmers, the availability of regional funds as well as access to information provision (Läpple and Cullinan, 2012). In addition, a number of key policy interventions, such as the introduction of organic support payments in 1995 or the decoupling of payments in 2004, had an impact on the overall growth of the organic sector in Ireland. In terms of demand, market opportunities exist for Irish organic producers, in particular export opportunities of red meat to the UK and Germany (DAFM, 2010). Furthermore, in line with the EU, the Irish government is committed to raise its share of organic area and has set a target to increase the sector to 5 per cent of the agricultural land by 2020 (DAFM, 2010).

Despite descriptive evidence of an uneven distribution of organic farming within countries and a theoretically sound case for the presence of spatial dependence in the adoption of organic farming, empirical studies relating the former observation to the latter are largely absent from the literature. One important exception is Schmidtner *et al.* (2011) which analyses secondary county-level data and explains the spatial distribution of organic farming in Germany. Employing a spatial model, the study reports regional agglomeration effects in the sense that regions with high organic uptake rates tend to be close to each other. In addition, Lewis, Barham and Robinson (2011) look at the extent to which spatial spill-overs impact the adoption of organic methods among south-western Wisconsin dairy farmers. The authors account for spatial interaction by using the number of organic farms surrounding each farm and control for endogenous effects by applying a Mundlak–Chamberlain panel data approach. The study also finds that the presence of neighbouring organic farmers positively influences adoption decisions.

Despite these precedents, the general paucity of studies focusing on spatial dependence in the adoption of organic farming highlights the need for further research in this area. The current work provides both methodological and policy insights of broad relevance to the literature. To date, no other work has applied Bayesian spatial Durbin discrete choice models to thoroughly explore spatial dependence in the adoption of organic farming. Moreover, in contrast to Schmidtner *et al.* (2011), our analysis is conducted with individual farms based on a household survey. This allows consideration of specific characteristics, such as farm size or farmer attitudes, which are important for the adoption of organic farming. Our paper also differs from Lewis, Barham and Robinson (2011) in terms of methods and interpretations: we account for neighbourhood effects by including a spatial weight matrix. Importantly, employing spatial econometric techniques allows assessing spatial spill-over effects of explanatory variables, hence providing additional empirical evidence of neighbourhood effects. For example, our method quantifies the impact of a change in one farmer's characteristics on the adoption decisions of neighbouring farmers. This is another important feature that distinguishes our study from previous spatial econometric applications (e.g. Case, 1992; Holloway and Lapar, 2007). Specifically, marginal effects are calculated correctly, hence providing detailed insight into the effect estimates of explanatory variables on the own farmer's as well as neighbouring farmers' decisions.

The objective of this paper is to address the following research question: Is the adoption of organic farming spatially dependent and are there spatial spill-over effects on neighbouring farmers?[1]

The paper proceeds as follows: the theoretical and empirical framework is outlined in the next section, followed by a description of the survey and data. In the following section, the results are presented and discussed, whereas the final section offers some concluding remarks.

2. Theoretical and empirical framework

Besides the certification process that involves inspections and the conversion period, the adoption of organic farming can be challenging to the farmer, since significant changes in the farming system are necessary. A successful adoption of organic farming requires a high level of learning and knowledge, as well as some financial expenses.

Conceptually, it is assumed that a farmer adopts organic farming if the expected utility received from organic farming (U_{G}) is greater than the expected utility received from non-adoption (U_{C}), i.e. staying in conventional farming. The difference between the utility from organic farming and conventional farming is denoted as y^*, such that a utility maximising farmer will adopt organic farming if the utility gained from organic farming is greater than the utility associated with conventional farming, i.e. $y^* = U_{\mathrm{O}} - U_{\mathrm{C}} > 0$. More formally, an expected utility function including pecuniary and non-pecuniary factors is considered:

$$E[U_{\mathrm{O}}((\pi_{\mathrm{O}} - G + S_{\mathrm{O}}) + A)] - E[U_{\mathrm{C}}(\pi_{\mathrm{C}} + A)] > 0], \tag{1}$$

1 Please note that the term neighbourhood effect refers to the influence of neighbouring farmers' adoption decisions on farmer *i*'s decision, whereas the term spatial spill-over refers to the impact of a change in an explanatory variable of farmer *i* on farmer *j*'s decision, with $i \neq j$.

with $\pi_\mathrm{k}(k = O,\ C)$ being the farm-type-specific profit, which is defined subsequently. G are the costs of conversion to organic farming. These may include additional investments, information-gathering costs, initial loss of income due to trial errors or lower yields (Lampkin and Padel, 1994). The costs of conversion generally increase with the level of intensity of the farm system, suggesting that conversion to organic farming is more likely on farms with low-intensity livestock production (Pietola and Oude Lansink, 2001). $\mathrm{S_O}$ are organic-specific subsidies, which comprise a higher payment rate during the two-year conversion period in order to compensate for denied access to premium markets during this period, followed by a lower organic subsidy payment rate after full organic status is achieved. A represents the attitude of the farmer towards conversion to organic farming, which has a strong influence on the farmer's initial propensity to adopt organic farming but can also be adjusted, for example, through communication with other farmers. A can have a positive or negative impact on the adoption decision of the farmer (Case, 1992; Läpple and Kelley, 2013).

Profit π_k is derived as follows:

$$\pi_k = p_k \cdot q(f_k,\ F) - c_k \cdot f_k + s, \tag{2}$$

where P_k are farm-type-specific output prices, q is the quantity produced, which depends on input factors f_k and F production relevant factors, such as soil quality or proximity to market outlets and advisory services. c_k are farm-type-specific input prices, and S are subsidies received by the farm enterprise.

Given the assumption that farmers communicate with each other, a neighbour's j utility (U_{ki}) received from organic or conventional farming may also affect the own farmer's i utility (U_{ki}), (with $i \neq j$) underlining the importance to control for a neighbourhood effect. In addition, there may be unobserved favourable geographical and economic conditions at play, which influence adoption and are correlated over space. Assuming heterogeneity among farmers, all farmers receive different utility from farming and from their neighbours' influences and will make different adoption decisions based on their personal preferences and circumstances, which can also differ over space. For example, a less-risk averse farmer may adopt organic practices more easily than a more risk averse farmer as the less-risk averse farmer may perceive the risks associated with organic farming as less severe (Gardebroek, 2006). Thus, a modelling framework that controls for neighbourhood effects, farm and household characteristics as well as natural advantages that are correlated over space is required.

2.1. Bayesian spatial probit model

In order to assess spatial dependence, we estimate an SDM. Within this context, it is important to note that in situations involving any model uncertainty regarding the presence of spatial dependence in the dependent variable versus the disturbances, the SDM specification arises as the only appropriate specification. Please refer to LeSage and Pace (2009) for a formal line of argument.

The SDM takes the following form:

$$y^* = \rho W y^* + X\beta + WX\theta + \varepsilon, \tag{3}$$

with its corresponding data-generating process:

$$y^* = (I_N - \rho W)^{-1}(X\beta + WX\theta + \varepsilon), \tag{4}$$

where y^* is a $nx1$ vector representing the farmer's utility, X is an nxk matrix of explanatory variables comprising of farm, household and personal characteristics, β and θ are $kx1$ vectors of parameters to be estimated, ε is a $nx1$ vector normally distributed error term $\varepsilon \sim N(0,\ I_N), \rho$ is a scalar parameter indicating spatial dependence and I_N is an n-dimensional identity matrix. W is an $n \times n$ spatial weight matrix, which is defined subsequently.

This model specification allows for the neighbours' decisions (through the term $\rho W y^*$), the farmer's characteristics (through the term $X\beta$) as well as a spatially weighted linear combination of neighbouring farmers' characteristics (through the term $WX\theta$) to exert an influence on adoption decisions.

The spatial lag $\rho W y^*$ implies that each farmer's utility is influenced by his or her neighbours' utilities received from adoption. Nevertheless, unobserved regional characteristics could trigger similar adoption choices without farmer interaction (Lewis, Barham and Robinson, 2011). In the modelling framework, this means that the spatial lag is endogenous due to correlation with unobserved effects, which needs to be taken into account in the estimation process (Anselin, 1980). The Bayesian approach implementing Markov Chain Monte Carlo (MCMC) estimation provides a powerful alternative to conventional sampling techniques in overcoming modelling issues in spatial econometrics as most of the available conventional methods involve multidimensional integration. The advantages of the Bayesian method entail, for example, non-reliance on asymptotic properties to ascertain valid standard errors as a consequence of the estimation algorithm (Holloway, Shankar and Rahman 2002).

The spatial lag $\rho W y^*$ is motivated by the assumption that the utility of farmer i is influenced by the utility received from adoption choices by neighbouring farmers in the past. More formally:

$$y_t^* = \rho W y_{t-1}^* + X_t\beta + \varepsilon_t, \tag{5}$$

where $W y_{t-1}^*$ is a time-lag of the average utility of neighbouring farmers observed in the previous time period $t-1$. Recursive substitution for past values over T periods shows that a cross-sectional model can be interpreted as a long-run equilibrium of diffusion, as follows (LeSage and Pace, 2009):

$$\lim_{T\to\infty} E(y_t^*) = (I_N - \rho W)^{-1} X\beta. \tag{6}$$

Our choice of an SDM specification is motivated by the likely possibility that spatially correlated omitted variables are correlated with included explanatory variables. In this particular context, certain landscape features or labour market situations are omitted but are likely to be correlated over space and correlated to observed explanatory variables, such as soil quality and off-farm job. If this is the case, the SDM has been shown to be the appropriate model. In fact, the SDM arises as the only appropriate specification in case of any uncertainty regarding the presence of spatial dependence (LeSage and Pace, 2009). Another important feature of the SDM is that it allows for spatial spill-overs to have different signs as the model includes β (coefficient on farmer characteristics) and θ (coefficient on spatially weighted explanatory variables) that do not necessarily have the same signs.

As previously mentioned, it is assumed that a farmer adopts organic farming if the utility received from organic farming is greater than the utility received from conventional farming. However, we do not observe the farmer's utility. Instead, we observe whether or not the farmer adopts organic farming. This leaves us with a binary choice variable (y) that equals one if $y^* = U_O - U_C > 0$ and zero otherwise. Estimation of binary choice models is well established in standard econometric techniques, but this is not the case for spatial econometric models. In spatial econometrics, the vast majority of work has focused on continuous econometric models, whereas spatial dependence in discrete choice settings has received less attention (Fleming, 2004). Nevertheless, earlier applications of discrete choice models suggest that a Bayesian technique implementing an MCMC approach is a powerful tool to estimate spatial probit models (LeSage, 2000; Holloway, Shankar and Rahman, 2002; LeSage and Pace, 2009).

Bayesian methods are based on a combination of the likelihood of the model $p(y|\tau)$ and prior distributional assumptions $p(\tau)$ for the unknown parameters $\tau = (\beta, \theta, \rho)$. The prior distribution represents how likely different values of the parameters are before seeing the data. That is, it characterises uncertainty about the unknown parameters (Gelman *et al.*, 2004). Prior distributions for the parameters need to be specified, which when combined with the likelihood via Bayes' rule yield the posterior distribution $p(\tau|y)$:

$$p(\tau|y) \propto p(y|\tau)p(\tau). \qquad (7)$$

Sampling from the resulting posterior distribution for the spatial probit models requires the use of an MCMC sampler approach as the posterior distributions are not amenable for analysis. Thus, conditional posterior distributions for all parameters are derived, which are then sampled sequentially.

The Bayesian approach to modelling binary choice models treats the observed binary-dependent variable as an indicator of unobserved utility, which is replaced with estimated parameters in order to fit the model (LeSage and Pace, 2009). Hence, the sampled continuous values y^* are used instead of the observed binary values y. Assuming y^* is known, it follows that $p(\beta,\ \theta,\ \rho|y^*) = p(\beta,\ \theta,\ \rho|y^*,\ y)$, which allows estimation of the remaining parameters using the same conditional posterior distributions as for a continuous model. Given the resulting conditional posterior distributions for the spatial probit model, the model is estimated in several steps. That is, the MCMC technique samples sequentially from the conditional posterior distributions for the model parameters, beginning with arbitrary values (please refer to LeSage and Pace (2009) for a more detailed description of model estimation and conditional distributions).

2.2. Spatial weight matrix

The specification of the spatial weight matrix is often arbitrary since exact information on the size of the neighbourhood does not exist. We follow Roe, Irwin and Sharp (2002) in the approach that we assume that beyond a certain distance, a spatial effect does no longer affect the adoption of organic farming. This implies that all spatial weights (w_{ij}) outside this distance are zero.[2] In order to allow for several neighbours per farm, 20 km was chosen as the minimum distance cut-off and we estimate models with 20-, 30-, 40- and 50 km distance cut-off. We apply an inverse distance matrix with $w_{ij} = 1/d_{ij}$, where d_{ij} is the Euclidian distance between farms i and j. The choice of an inverse distance matrix is motivated by the fact that with this specification, closer neighbours exert a stronger influence than more distant neighbours. This information would be lost by using a contiguity or k-nearest neighbour matrix. Following common practice, each weight matrix is row-stochastic, i.e. non-negative and each row sums to one (Holloway, Shankar and Rahman, 2002). Importantly, the matrix elements represent the pattern of correlation between sample units.

2.3. Interpretation of coefficients

The SDM accounts for neighbourhood effects, which are also represented in the interpretation of model estimates, i.e. spatial spill-over. More specifically, the model allows for dependence among farmers in the sense that changes in the explanatory variables x_{iv} with $v = 1, \ldots, k$ have an impact on the probability y_i that farmer i adopts organic farming as well as on the probability y_i that neighbouring farmers j with $i \neq j$ adopt organic farming. In other words, a change in an explanatory variable of farmer i can potentially influence the adoption decisions of all $n - 1$ other farmers (LeSage *et al.*, 2011). This is a logical consequence of the SDM specification as the model controls for other farmers' dependent and explanatory variables through the inclusion of Wy^* and WX (LeSage and Pace, 2009).

The idea of interpretation of spatial spill-over effects is best illustrated with an applied example: assume farmer i is considering adopting organic farming. A change in farmer i's environmental attitude has a positive effect on the probability that farmer i adopts organic farming (direct effect), but it also impacts on

2 The use of distance cut-offs also facilitates the estimation process as sparse matrix algorithms can be used.

farmer i's neighbours j's adoption decisions y_i, for example, due to communication between farmer i and j (indirect or spatial spill-over effect).

Overall, three effect estimates can be derived: direct effects measure the impact of a change in a variable x_{iv} on y_i. Total effects indicate how a change in variable x_{iv} impacts on the probability of all farmers in the sample adopting organic farming. Indirect effects, i.e. spatial spill-over, are derived by subtracting direct effects from total effects resulting in a measure of the impact of x_{iv}on y_i. Importantly, indirect effects cumulate spatial spill-overs impacting on neighbouring farmers, and this effect is stronger for nearby neighbours and declines with distance (LeSage *et al.*, 2011). When interpreting indirect effect estimates, it is important to note that since these reflect cumulative spill-overs falling on all farmers within the distance cut-off, the economic significance of these changes on the probability to adopt of an individual farmer may be very small, depending on the number of farmers within that distance cut-off.

In general, the interpretation of a spatial probit model is based on the 'usual' non-linear transformation of a probit model as well as changes of explanatory variables on adoption decisions over space (Lacombe and LeSage, 2013). More formally, assuming a continuous dependent variable for the moment, the derivative of y^* with respect to x_v results in an $n \times n$ matrix:

$$\partial y^* / \partial x_{\mathrm{v}}^{'} = A^{-1}(I_N \beta_v + W\theta_v), \tag{8}$$

where $A^{-1} = (I_N - \rho W)$.

In the case of the SDM, the effect of a change in farmer's i explanatory variable x_v on the adoption decision of farmer j, i.e. a single cross-derivative, can be expressed as follows:

$$\begin{aligned} \eta &= A^{-1}X(\beta + W\theta) = E(y^*), \\ \frac{\partial \Pr(y_i = 1)}{\partial x_{v,j}} &= \left(\frac{\partial F(\eta)}{\partial \eta} | \eta_i \right) A^{-1}_{i,j}(\beta_v + W\theta_v), \\ \frac{\partial \Pr(y_i = 1)}{\partial x_{v,j}} &= pdf\,(\eta_i) A^{-1}_{i,j}(\beta_v + W\theta_v), \end{aligned} \tag{9}$$

where $F(\eta)$ is the normal distribution CDF and $pdf\,(\eta_i)$ is the pdf of the normal evaluated at η_i (LeSage *et al.*, 2011). Please refer to LeSage *et al.* (2011) for a detailed explanation on how to calculate effect estimates for spatial autoregressive probit models.

3. Data

The main data source analysed in this study is based on a nationwide survey of Irish organic farmers conducted between July and November 2008. A list of all certified organic farmers was available from the Irish organic certification bodies, and a survey was sent to each farmer on this list. A response rate of

40 per cent was achieved due to an announcement in the *Irish Farmers' Journal* newspaper and a reminder letter. Data for conventional farmers were collected through an additional survey attached to the Teagasc National Farm Survey (NFS) (Connolly *et al.*, 2009). In general, the NFS is based on approximately 1,100 farms representing 110,000 farms nationally. The NFS data are EU-Farm Accountancy Data Network data for Ireland. The data for this study were restricted to farms that have cattle and/or sheep (drystock farms) since significant numbers of organic farms, necessary for an empirical analysis, can be found in this category. In fact, approximately 80 per cent of Irish organic farmers are engaged in drystock farming. Hence, a sub-sample of NFS data was merged with the survey data from the organic farms yielding 597 total observations, including 432 organic and 165 conventional farmers.

The very small number of organic farms in Ireland (just over 1 per cent) implies that complete random sampling would not have generated a large enough number of organic farms for an empirical analysis. Thus, these farms are well represented in the study, whereas the number of conventional farms in the sample is small considering the proportion of organic farms to the total number of farms in Ireland. Despite not being representative of the total farming population, the sample provides a good representation of the types of farm operators who participate in organic farming as well as the conventional drystock operators. In addition, the sample is geographically well represented across Ireland, and our sample of organic farms closely matches the geographic distribution of the Irish organic sector, see Appendix A1 for more details on regional distribution of the sample.

The questionnaire collected information on farm and household characteristics, information use and attitudes of the farmer. In addition to the survey data, information on the location of the farms was also utilised. The farms in the sample have been geo-coded, and the Euclidian distance between each farm has been calculated. This information was used to create the various spatial weight matrix specifications. Table 1 presents a description of variables used in the empirical analysis and their expected influence on the adoption of organic farming.

The attitudinal variables, described at the bottom four rows of Table 1, were initially derived from a set of 35 statements. Respondents were asked to express their agreement to each statement on a 7-point scale ranging from -3 (disagree very strongly) to $+3$ (agree very strongly). Principal Component Analysis with orthogonal (varimax) rotation was employed to the statements, and the attitude variables are based on the calculated component scores.

Table 2 presents summary statistics of the variables used in the empirical model, classified by adoption status. As is evident in Table 2, organic and conventional farmers differ in many characteristics. For example, organic farmers have smaller farms that are farmed in a less intensive way than conventional farms. Organic farmers are also younger, express a higher level of environmental attitude and are less-risk averse. The empirical analysis below will assess the association among these variables and the farmers' and their neighbours' adoption decisions.

Table 1. Description of variables

Variable	Description	Hypothesised sign
Farm characteristics		
Farm size	Utilisable agricultural area of the farm measured in hectares	±
Livestock density	Livestock units per hectare	−
Distance mart	Euclidian distance to nearest organic livestock mart in km	−
Soil	If farm is on good agricultural land = 1, 0 otherwise[a]	−
Household characteristics		
Off-farm job	If the farm household has an off-farm job = 1, = 0 otherwise	−
Household members	The size of the farm household (No.)	+
Age	Age of the farmer in years	−
Higher education	If the farmer has higher education (second level or higher) = 1, = 0 otherwise	+
Information characteristics		
Knows other organic farmer	If the farmer knows another organic farmer = 1, = 0 otherwise	+
Info advisory	Frequency of consultation with a farm advisor, attendance at information events and agricultural training courses, divided by 3[b]	+
Info media	Frequency of using magazines/press, TV/radio and the internet as a source of farming information, divided by 3[b]	+
Distance demo	Euclidian distance to nearest organic demonstration farm in km	−
Attitudinal characteristics		
Environmental attitude	Higher value = higher level of environmental concern	+
Risk attitude	Higher value = more risk averse,	−
Profit orientation	Higher value = higher profit orientation	±
Information-gathering attitude	Higher value = higher interest in information gathering.	+

Plus symbol implies a positive impact on the adoption of organic farming, whereas minus symbol implies a negative effect.
[a]Good agricultural land is classified as having no or minor limitations for use (Gardiner and Radford, 1980).
[b]The variables are divided by 3 as an equal influence of the three information sources is assumed.

4. Results and discussion

4.1. Spatial dependence

In order to motivate our spatial analysis, we first assess the strength of spatial dependence in the data. To this end, we employ a Moran scatter plot depicting

Table 2. Descriptive statistics for the sample

Variable	Organic ($n = 432$)	Conventional ($n = 165$)
Farm characteristics		
Farm size	38.39 (61.62)	54.09 (38.80)
Livestock density	0.81 (0.48)	1.08 (0.50)
Distance mart	52.85 (29.95)	58.18 (30.64)
Household characteristics		
Off-farm job	0.49 (0.47)	0.32 (0.46)
Household members	3.41 (1.66)	2.99 (1.57)
Age	50.12 (10.81)	53.07 (11.31)
Higher education	0.68 (0.47)	0.69 (0.46)
Information characteristics		
Knows other organic farmer	0.87 (0.48)	0.36 (0.34)
Info advisory	0.98 (0.79)	0.74 (0.74)
Info media	3.51 (1.69)	3.49 (1.30)
Distance demo	33.74 (19.27)	33.51 (17.77)
Attitudinal characteristics		
Environmental attitude	0.48 (0.62)	−1.13 (0.77)
Risk attitude	−0.05 (1.05)	0.17 (0.84)
Profit orientation	−0.01 (1.07)	0.03 (0.81)
Information gathering	0.05 (1.01)	−0.11 (0.96)

Mean and standard deviation in parentheses.

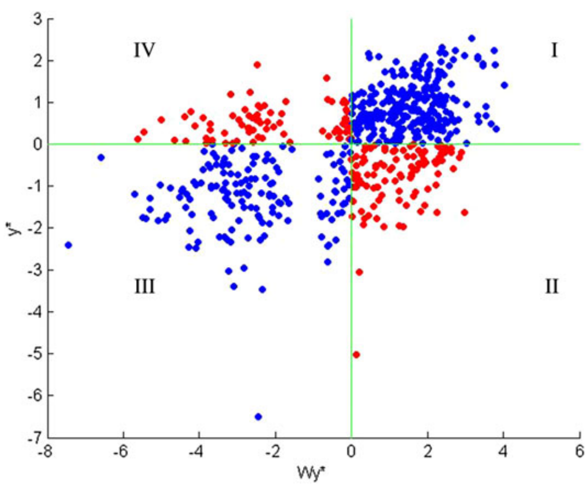

Fig. 1. Spatial dependence of observations.

the relation between y^* and the adoption decisions of neighbouring farms in terms of deviations from means, see Figure 1.

As is evident in Figure 1, there are a large number of points in quadrant I and quadrant III (blue dots) suggesting positive spatial dependence in the data

Table 3. Spatial parameter estimates for SDM

Model	Distance cut-off (km)	Spatial parameter posterior mean (95 % credible intervals)
Model 1	20	0.093 (0.002–0.32)
Model 2	30	0.104 (0.003–0.38)
Model 3	40	0.118 (0.003–0.33)
Model 4	50	0.135 (0.004–0.41)

(LeSage, 2004). More specifically, 44.4 and 24.8 per cent of the data are in quadrant I and III, respectively. In contrast, remarkably fewer data points are in quadrant II and IV, which imply negative spatial correlation (red dots): 18.1 and 12.7 per cent of data points, respectively. Given this visual evidence of spatial correlation in the Moran scatter plot, Bayesian probit spatial models are applied to account for spatial dependence, which will reveal the magnitude of this relationship.

A number of models that differ with regard to spatial weight matrix specifications were estimated and compared. As previously mentioned, we consider spatial dependence within a 20-, 30-, 40- and 50 km radius. These specifications assume that spatial dependence is confined to these radii. Each farmer in the sample has on average 11.8 neighbours within a 20 km radius, 25.1 neighbours within a 30 km radius, 42.1 neighbours within a 40 km radius and an average of 62.5 neighbours when the distance cut-off increases to 50 km.

Table 3 presents the spatial parameter estimates for the models with their corresponding 95 per cent credible intervals. All estimated SDMs exhibit positive and significant spatial correlation (ρ) values for neighbourhood effects. The values range from 0.09 for a 20 km neighbourhood to 0.14 for a 50 km radius and the 95 per cent credible intervals do not span zero for any of the parameter estimates.[3] Intuitively, this means that the adoption of organic farming by one farmer positively influences the adoption of neighbouring farmers. However, our findings indicate weaker spatial dependence in comparison with what others have previously reported in the context of spatial distribution of organic farming. For example, Schmidtner *et al.* (2011) report spatial dependence parameter estimates between 0.36 and 0.85 when modelling the share of land converting to organic farming in neighbouring counties in Germany.

4.2. Estimation results

Model results are quite robust between the different weight matrix specifications, and no difference in the economic significance of the results arises. In

3 When interpreting the magnitude of the parameter, it is important to note that the theoretical upper bound for this parameter is 1 (LeSage *et al.*, 2011).

addition, it also means that direct and indirect effects estimates do not vary much for the different distance cut-offs. We proceed with describing the effect estimates of the model with a 30 km distance cut-off. The coefficient estimates β and θ are relegated to Appendix A2 as these cannot be interpreted as representing how changes in the explanatory variables affect the adoption of organic farming.

The direct, indirect and total effects of the coefficients as well as the corresponding 95 per cent credible intervals for this model are presented in Table 4. These are scalar summary estimates that are calculated as previously outlined. Seven of the included explanatory variables have 95 per cent credible intervals that do not cross zero. In addition, as one would expect the indirect effect estimates are smaller in magnitude than the direct effect estimates. In fact, the indirect estimates are quite small in magnitude, with the largest effect being 0.025 for the coefficient estimate for environmental attitude. As previously mentioned, indirect effects are the cumulative spatial spill-over effect on all other neighbouring farmers, which are on average 25 farmers within a 30 km radius. In general, this implies that spatial spill-over effects in the adoption of organic farming on an individual farmer are very small, but the effect is strongest on nearby neighbours and declines with distance. Here, the overall average distance to farms in this neighbourhood is 19.4 km. A more detailed analysis of the average distance for each farmer to neighbouring farmers can be found in Appendix A3.

In terms of farm characteristics, a higher livestock density seems to constrain adoption of organic farming, which is in line with previous literature (Pietola and Oude Lansink, 2001; Schmidtner *et al.,* 2011). More specifically, for every additional livestock unit, the adoption probability on this farm reduces by 4.9 per cent (direct effect), whereas spatial spill-overs reduce the probability of adoption on neighbouring farms by a cumulative 0.7 per cent (indirect effect), resulting in a total effect of 5.7 per cent decrease in the probability of adoption on all farms. Intuitively, neighbouring farms can be impacted by a more intensive farm system from an adjoining farm, leading to a lower probability that these farms convert, which may explain the negative spill-over effect. In contrast, farm size and distance to organic livestock marts do not have a significant impact on adoption. Similarly, Hattam, Lacombe and Holloway (2012) and Burton, Rigby and Young (2003) also do not find a significant effect of farm size on the adoption of organic production techniques. The explanation for a non-significant effect for distance to organic market outlets may relate to the fact that organic cattle is either sold unfinished through livestock marts or sold directly to other farmers through local networks, which has become more important in recent years. In addition, other marketing opportunities for finished organic livestock exist such as organic livestock processors or approved abattoirs, which may further explain why distance to organic marts is not significant in this application.

In terms of household characteristics, age of the farmer is the only variable that exhibits a significant effect. Here, age has the expected negative effect,

Table 4. SDM effect estimates for a 30 km neighborhood

Variable	Direct effect	Indirect effect	Total effect
Farm characteristics			
Farm size	−0.0001 (−0.0004 to 0.0001)	−0.00002 (−0.0001 to 0.0000)	−0.0002 (−0.0004 to 0.0001)
Livestock density	−0.049 (−0.083 to −0.019)	−0.007 (−0.027 to −0.0002)	−0.057 (−0.096 to −0.023)
Distance mart	−0.0002 (−0.0009 to 0.0005)	−0.00003 (−0.0002 to 0.0001)	−0.0002 (−0.0009 to 0.0005)
Household characteristics			
Off-farm job	0.017 (−0.002 to 0.056)	0.003 (−0.004 to 0.018)	0.19 (−0.025 to 0.066)
Household members	0.009 (−0.022 to 0.021)	0.001 (−0.002 to 0.006)	0.01 (−0.002 to 0.023)
Age	−0.002 (−0.004 to −0.0005)	−0.0003 (−0.001 to −0.00001)	−0.0026 (−0.005 to −0.0007)
Higher education	−0.039 (−0.083 to 0.004)	−0.006 (−0.032 to 0.0004)	−0.046 (−0.105 to 0.0042)
Information characteristics			
Knows other organic farmer	0.109 (0.073 to 0.146)	0.017 (0.0005 to 0.063)	0.126 (0.081 to 0.178)
Info advisory	0.019 (−0.006 to 0.041)	0.0029 (−0.0005 to 0.012)	0.021 (−0.007 to 0.049)
Info media	−0.018 (−0.033 to −0.005)	−0.003 (−0.012 to −0.001)	−0.0214 (−0.039 to −0.005)
Distance demo	0.0002 (−0.0008 to 0.001)	0.0001 (−0.0004 to 0.0001)	0.0002 (−0.001 to 0.001)
Attitudinal characteristics			
Environmental attitude	0.162 (0.137 to 0.188)	0.025 (0.0008 to 0.087)	0.187 (0.159 to 0.249)
Risk attitude	−0.039 (−0.063 to −0.017)	−0.006 (−0.025 to −0.002)	−0.045 (−0.077 to −0.019)
Profit orientation	−0.034 (−0.055 to −0.013)	−0.005 (−0.02 to −0.0002)	−0.039 (−0.068 to −0.015)
Information gathering	0.006 (−0.013 to 0.025)	0.0009 (−0.002 to 0.007)	0.007 (−0.015 to 0.028)

Values in parentheses are 95 per cent credible intervals.

implying that younger farmers are more likely to adopt. More specifically, with every additional year, the probability of adoption decreases by 0.2 per cent. In contrast, whether or not the farmer has an off-farm job, number of household members as well as level of education does not show a significant effect on decision to adopt organic farming. Similar to our findings, Hattam, Lacombe and Holloway (2012) also do not find a significant effect of income sources, education as well as age on the adoption of organic farming. In general, being engaged in off-farm work can increase or decrease the probability of conversion to organic farming, as an off-farm income provides more freedom for on-farm decisions but simultaneously limits the time available for farming, which can act as a constraint for conversion.

Two of the information-relevant variables are significant. In line with Hattam, Lacombe and Holloway (2012), whether or not the farmer knows another organic farmer has a positive significant impact on the adoption decision. In terms of magnitude of this effect, a farmer who knows another organic farmer has a 10.9 per cent higher probability to adopt organic farming. This also impacts on the farmer's neighbours' adoption decisions with a cumulative indirect effect of 1.7 per cent, accumulating to a total effect of 12.6 per cent. The indirect effect of this variable suggests an influence of social norms in the sense that farmers communicate their experiences with organic farming with each other. This provides further empirical evidence that communication between farmers and social acceptance is important for the adoption of organic farming, which has previously been stressed by Musshoff and Hirschauer (2008) and Läpple and Kelley (2013). Distance to organic demonstration farms, a proxy for access to organic information and information utilised from advisory services do not show a significant effect. However, information received from the media exhibits a significant negative effect. The variable info media reduces the probability of adoption of the farmer by 1.8 per cent and a cumulative 0.3 per cent for neighbouring farmers, accumulating to a total effect of 2.1 per cent. Again, communication between farmers provides an explanation for the spatial spill-over effect for this variable. The counterintuitive negative effect can be explained by a general paucity of information provision on organic farming through this information channel.

The attitudinal variables environmental and risk attitude as well as profit orientation have a significant impact on the probability to adopt. An increase in the level of environmental attitude by one standard deviation raises the probability of adoption of this farmer by 16.2 per cent, whereas it also impacts on the adoption of nearby farmers, with a cumulative indirect effect of 2.5 per cent. The combined total effect on all farms is 18.7 per cent. The positive effect of environmental attitude is in line with previous findings in the literature (Burton, Rigby and Young, 2003; Genius, Pantzios and Tzouvelekas, 2006). Risk attitude of the farmer has a negative effect on the probability to adopt organic farming, implying that more risk averse farmers are less likely to adopt. A one standard deviation increase in risk attitude, i.e. more risk averse, produces a direct effect of 3.9 per cent reduction in the probability of adoption, and a cumulative indirect effect of 0.6 per cent decrease in probability. The total effect is a reduction of adoption probability of 4.5 per cent. Similarly, Gardebroek (2006) and Serra, Zilberman and Gil (2008) argue that organic farmers are more willing to take risks and Musshoff and Hirschauer (2008) report that risk aversion induces conversion reluctance. In relation to profit orientation, more profit-focused farmers have a lower probability to adopt that decreases by 3.4 per cent per one standard deviation increase in profit orientation, which also has a spill-over effect on neighbours of 0.5 per cent decrease in probability with each increase of profit orientation by one standard deviation. The spatial spill-over effects of the attitudinal variables provide empirical evidence, albeit small, that adoption decisions of farmers are influenced by their neighbours' attitudes. Nevertheless, the spatial spill-over effect, especially from information and attitudinal variables, is a very important finding in this study as it empirically supports anecdotal knowledge that farmers influence each others' decisions by communicating with each other.

5. Concluding remarks

This study examined spatial dependence in the adoption of organic farming among Irish drystock farmers. To this end, we employ Bayesian SDMs, which take other farmers' dependent and explanatory variables into account. The model choice was motived by the fact that the SDM arises as the only appropriate specification in the case of any uncertainty regarding the type of spatial dependence. Overall, if there is spatial dependence, it is important to control for it as policy inferences change in the presence of spatial dependence.

Our findings reveal that the adoption of organic farming in Ireland exhibits spatial dependence. More specifically, the Bayesian SDMs confirm that farmers' adoption choices are dependent on their neighbours' decisions, i.e. neighbourhood effects, but that neighbours' characteristics also exert an influence on adoption decisions, which highlights the importance of communication or interaction between farmers.

Focusing on neighbourhood effects, an important contribution of this study is in providing new empirical evidence on the impact of spatial interdependence in the adoption of organic farming. Our SDM specifications account for neighbourhood influences within distances of a 20-, 30-, 40- and 50 km radius. All models show a positive neighbourhood effect, implying that the adoption of one farmer positively influences the adoption of neighbouring farmers.

Another important contribution of this study is that marginal effect estimates are calculated correctly. That means that we are able to assess how changes in values of an explanatory variable of farmer i impact the own farmer's choice, i.e. direct effect, as well as other farmers' j choices, i.e. indirect effect or spatial spill-over. Our study reveals significant, albeit small, spatial spill-over effects on neighbouring farmers' choices. More specifically, by harnessing spatial spill-over effects, our results provide empirical evidence that social norms and attitudes play a role in spreading the uptake of organic farming. For example, a positive environmental attitude enhances the own farmer's as well as neighbours' adoption decisions, underlining that communication between farmers is important for the adoption of organic farming. The latter result has not received much attention in the literature yet but provides additional empirical evidence of the importance of communication among farmers in adoption decisions over and above the general neighbourhood effect picked up by the spatial parameter.

These results are of particular relevance for policy-makers, as our findings suggest new avenues for increasing the uptake of organic farming, which is a policy objective within Ireland's agri-food growth targets (DAFM, 2010). Based on our results, participatory extension methods, such as farm walks or discussion groups, could be a successful way in increasing the uptake rate of organic farming, since these extension methods foster communications between farmers. Considering that it has been previously found that negative perceptions of farmers hamper the uptake of organic farming (Läpple and Kelley, 2013), bringing organic and conventional farmers together in participatory extension methods could be an effective means to change those negative perceptions and thereby increase uptake rates. In addition, this is in line with Irish policy support measures for other agricultural sectors, where the implementation and financial support of discussion groups has become an important means of increasing farm profitability and efficiency.

There are of course limitations of our analysis, which should be taken into consideration when interpreting the findings from this analysis. We investigated the decision of farmers to adopt organic farming at one point in time. However, while adoption is a spatial process, it is also dynamic. For example, it is possible that pioneering organic farmers had a greater influence on the diffusion of organic farming than later adopters or that the spatial extent of the network may change with investment in broadband infrastructure through time. This limitation, which is driven by data constraints, also implies that one has to exercise caution when drawing causal effects from our results. Hence, a dynamic analysis that takes spatial aspects into account could be a potential avenue for further research.

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Appendix A1

Table A1 compares the regional distribution of organic and conventional farmers in our sample. Region 5 and Region 8 include clusters of organic farms, which explain the higher proportion of organic farms in those regions in our sample. See Läpple and Cullinan (2012) for more details on regional distribution of organic farms in Ireland.

Table A2 compares our sample of organic farms to the population of organic farms in Ireland at the end of 2010. For example, comparing the proportion of organic farms in the three areas with clusters in organic farming (Co. Leitrim/Co. Roscommon, Co. Limerick and Co. Cork) shows that our sample proportions are very close to the proportion of the population. Overall, we conclude that our sample provides a good geographical representation of the population of organic farms.

Table A1. Regional distribution of sample farms across Ireland

Region	Organic (%)	Conventional (%)
1	16.9	19.5
2	1.1	0.6
3	7.6	9.4
4	9.3	15.1
5	18.8	10.1
6	10.0	12.6
7	20.6	22.6
8	15.7	10.1

Region 1: counties – Louth, Leitrim, Sligo, Cavan, Donegal, Monaghan; Region 2: county – Dublin; Region 3: counties – Kildare, Meath, Wicklow; Region 4: counties – Laois, Longford, Offaly, Westmeath; Region 5: counties – Clare, Limerick, Tipperary North; Region 6: counties – Carlow, Kilkenny, Wexford, Tipperary South, Waterford; Region 7: counties – Cork and Kerry; Region 8: counties – Galway, Mayo, Roscommon.

Appendix A2

Table A2. Comparison of geographical distribution of sample and population of organic farms

County	% in county		County	% in county	
	Population (n=1385)	Sample (n = 432)		Population (n = 1385)	Sample (n = 432)
Leitrim	5.19	5.09	Kerry	4.98	5.55
Limerick	8.44	7.87	Tipperary	6.21	6.94
Cork	14.22	15.05	Louth	0.04	0
Roscommon	7.72	6.71	Laois	1.87	1.15
Sligo	3.46	5.09	Galway	7.14	6.48
Monaghan	2.02	1.15	Kilkenny	2.45	2.08
Mayo	2.59	2.54	Waterford	2.81	2.08
Longford	1.15	1.85	Wexford	2.59	2.31
Carlow	0.05	0	Cavan	2.52	2.77
Wicklow	2.31	3.0	Clare	5.84	7.40
Dublin	1.08	1.15	Donegal	1.66	2.77
Kildare	2.31	1.15	West Meath	4.11	3.70
Offaly	3.03	2.54	Meath	3.17	3.47

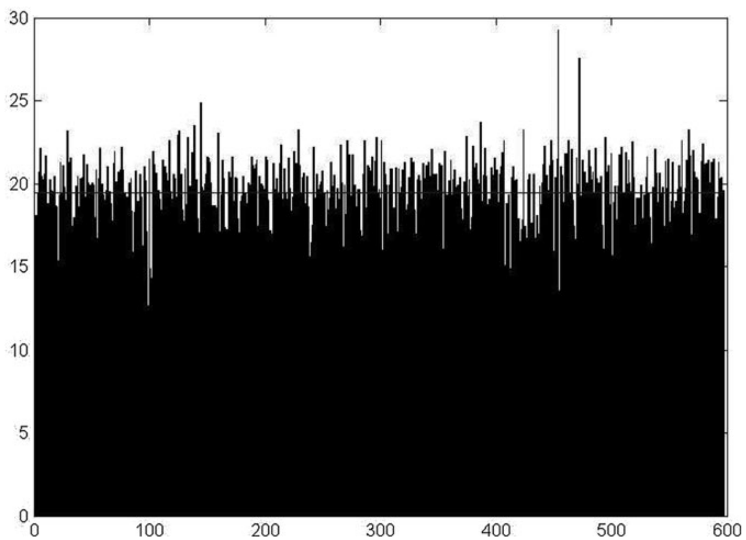

Fig. A1. Average distance within a 30 km neighbourhood. Please note that the horizontal line indicates the overall average distance to neighbouring farms, whereas the vertical bars indicate the average distance to neighbouring farms for each farmer in the sample.

Appendix A3

Table A3. SDM model estimates

Variable	β Posterior mean (95 % credible intervals)	Variable	θ Posterior mean (95 % credible intervals)
Constant	4.51 (9.66 to 0.92)	–	–
Farm characteristics			
Farm size	−0.002 (0.001 to −0.004)	W-farm size	0.02 (0.03 to 0.006)
Livestock density	−0.59 (−0.24 to −0.97)	W-livestock density	−2.53 (−1.04 to −4.14)
Distance mart	−0.002 (0.006 to −0.011)	W-distance mart	0.02 (0.04 to 0.001)
Household characteristics			
Off-farm job	0.20 (0.71 to −0.26)	W-off-farm job	−0.52 (1.11 to −2.2)
Household members	0.10 (0.25 to −0.02)	W-household members	0.04 (0.50 to −0.35)
Age	−0.03 (−0.01 to −0.05)	W-age	0.002 (0.05 to −0.06)
Higher education	−0.47 (0.05 to −0.96)	W-higher education	−0.17 (1.42 to −1.85)
Information characteristics			
Knows other organic farmer	1.29 (1.77 to 0.86)	W-knows other organic farmer	0.36 (2.35 to −1.36)
Info advisory	0.22 (0.48 to −0.07)	W-info advisory	−1.31 (−0.27 to −2.31)
Info media	−0.22 (−0.05 to −0.39)	W-info media	0.05 (0.60 to −0.47)
Distance demo	0.002 (0.01 to −0.01)	W-distance demo	−0.01 (0.02 to −0.05)
Attitudinal characteristics			
Environmental attitude	1.93 (2.31 to 1.55)	W-environmental attitude	0.90 (1.63 to 0.09)
Risk attitude	−0.47 (−0.19 to −0.75)	W-risk attitude	−0.34 (0.48 to −1.15)
Profit orientation	−0.41 (−0.16 to −0.66)	W-profit orientation	0.69 (1.45 to 0.004)
Information gathering	0.08 (0.29 to −0.16)	W-information gathering	−0.25 (0.61 to −1.05)
ρ	0.104 (0.376 to 0.003)		