Spatial Dependence in the Adoption of Organic Drystock Farming in Ireland

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Abstract

This article analyzes spatial dependence in the adoption of organic farming. A Bayesian spatial Durbin probit model is applied to survey data of almost 600 Irish drystock farmers. The findings reveal that farmers located in close proximity exhibit similar choice behavior. More specifically, communication and interactions among farmers influence adoption decisions as for example attitudes and social norms were identified to have spatial spillover effects. Overall, the findings from this study highlight that it is important to account for spatial dependence when explaining adoption decisions as this also influences policy recommendations.

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

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 et al., 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 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 influence adoption decisions. Spatial dependence implies that farmers located in close proximity exhibit similar choice behavior. 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 behavior of the individual's social group, which is also known as neighborhood effect. Alternatively, spatial dependence may arise due to favorable conditions for organic farming that can prevail in certain geographic areas. Ellison and Glaeser (1997) refer to this effect as natural advantage. Hence, when modeling adoption behavior of farmers, it is important to control for spatial dependence, especially as policy implications may be biased when excluding spatial effects. This study applies a Bayesian spatial Durbin probit model that accounts for spatial dependence in the adoption of organic farming among Irish drystock farmers.

2. Theoretical and Empirical Framework

Theoretical 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. These may include additional investments, information gathering costs, initial loss of income due to trial errors, lower yields and denied access to premium markets during the two year conversion period (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).

Conceptually, it is assumed that a farmer adopts organic farming if the utility received from organic farming (U_O) is greater than the 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 maximizing farmer will adopt organic farming if the utility gained from organic farming is greater than the utility associated with conventional farming, i.e. $y^* = U_O - U_C > 0$. Given the assumption that farmers communicate with each other, a neighbor's utility received from organic or conventional farming may also affect the own farmer's utility, underlining the importance to control for a neighborhood effect. In addition, there may be unobserved favorable 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 neighbors' influences and will make different adoption decisions based on their personal preferences and circumstances, such as risk aversion or farm specific characteristics, which can also differ over space. Thus, a modeling framework that controls for neighborhood effects, farm and household characteristics as well as natural advantages that are correlated over space is required.

Bayesian spatial probit model

In order to assess spatial dependence, we estimate a spatial Durbin probit model (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:

$$y^* = \rho W y^* + X\beta + WX\theta + \varepsilon, \qquad (1)$$

where y^* is a $nx1$ vector representing the farmer's utility, X is a 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 $\varepsilon \sim N(0, I_N)$,and ρ is a scalar parameter indicating spatial dependence. W is a nxn spatial weight matrix, which is defined subsequently.

This model specification allows for the neighbors' 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 neighboring farmers' characteristics (through the term $WX\theta$) to exert an influence on adoption decisions.

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. The Bayesian approach implementing Markov Chain Monte Carlo (MCMC) estimation provides a powerful alternative to conventional sampling techniques in overcoming modeling issues in spatial econometrics as most of the available conventional methods involve multidimensional integration (LeSage, 2000; LeSage and Pace, 2009). 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 et al., 2002).

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 characterizes 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 $p(\tau|y)$:

$$p(\tau|y) \propto p(y|\tau)p(\tau) \qquad (2)$$

Sampling from the resulting posterior distribution for the spatial probit models requires the use of a 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 (please refer to LeSage and Pace (2009) for a more detailed description of model estimation and conditional distributions).

Spatial weight matrix

The specification of the spatial weight matrix is often arbitrary since exact information on the size of the neighborhood does not exist. We follow Roe et al. (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.[1] In this case we proceed with a 30km cut-off. We apply an inverse distance matrix with $w_{ij} = 1/d_{ij}$, where d_{ij} is the Euclidian distance between farm i and j. The choice of an inverse distance matrix is motivated by the fact that with this specification closer neighbors exert a stronger influence than more distant neighbors. This information would be lost by using a contiguity or k-nearest neighbor matrix. Following common practice, each weight matrix is row-stochastic, i.e. non-negative and each row sums to one (Holloway et al., 2002). Importantly, the matrix elements represent the pattern of correlation between sample units.

Interpretation of coefficients

The SDM accounts for neighborhood effects, which are also represented in the interpretation of model estimates, i.e. spatial spillover. More specifically, the model allows for dependence among farmers in the sense that changes in the explanatory variables x_{iv} with $v = 1, \dots k$ have an impact on the probability y_i that farmer i adopts organic farming as well as on the probability y_j that neighboring 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).

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 spillover, is derived by subtracting direct effects from total effects resulting in a measure of the impact of x_{iv} on y_j. Importantly, indirect effects cumulate spatial spillovers impacting on neighboring farmers and this effect is stronger for nearby neighbors and declines with distance (LeSage et al., 2011). When interpreting indirect effect estimates, it is important to note that since these reflect cumulative spillovers 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. 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 analyzed 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% was achieved due to an announcement in the Irish Farmers' Journal Newspaper and a reminder letter.

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

Table 1. Descriptive statistics for the sample

Variable	Description	Organic n=432		Conventional n=165	
Farm characteristics					
Farm size	UAA in hectares,	38.39	(61.62)	54.09	(38.80)
Livestock density	livestock units per hectare,	0.81	(0.48)	1.08	(0.50)
Distance mart	Euclidian distance to nearest organic livestock mart in km,	52.85	(29.95)	58.18	(30.64)
Household characteristics					
Off-farm job	if the farm household has an off-farm job = 1, = 0 otherwise,	0.49	(0.47)	0.32	(0.46)
Household members	the size of the farm household (no.),	3.41	(1.66)	2.99	(1.57)
Age	age of the farmer in years,	50.12	(10.81)	53.07	(11.31)
Higher education	if the farmer has higher education (second level or higher) = 1, = 0 otherwise,	0.68	(0.47)	0.69	(0.46)
Information characteristics					
Knows other organic farmer	if the farmer knows another organic farmer = 1, = 0 otherwise,	0.87	(0.48)	0.36	(0.34)
Info advisory	frequency of consultation with a farm advisor, attendance at information events and agricultural training courses, divided by three,[2]	0.98	(0.79)	0.74	(0.74)
Info media	frequency of using magazines/press, TV/radio and the internet as a source of farming information, divided by three,[2]	3.51	(1.69)	3.49	(1.30)
Distance demo	Euclidian distance to nearest organic demonstration farm in km,	33.74	(19.27)	33.51	(17.77)
Attitudinal characteristics					
Environmental attitude	higher value = higher level of environmental concern,	0.48	(0.62)	-1.13	(0.77)
Risk attitude	higher value = more risk averse,	-0.05	(1.05)	0.17	(0.84)
Profit orientation	higher value = higher profit orientation,	-0.01	(1.07)	0.03	(0.81)
Information gathering	higher value = higher interest in information gathering.	0.05	(1.01)	-0.11	(0.96)

Note: mean and standard deviation in parentheses.

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 (FADN) 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% 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 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 utilized. 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 as well as summary statistics of the variables used in the empirical model, classified by adoption status. 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.

As is evident in Table 1, organic and conventional farmers differ in many characteristics. For example, organic farmers have smaller farms which 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 neighbors' adoption decisions.

4. Results and Discussion

We proceed with describing the effect estimates of our model with a 30km distance cut-off. The direct, indirect and total effects of the coefficients as well as the corresponding 95% credible intervals for this model are presented in Table 2. These are scalar summary estimates that are calculated as previously outlined. Seven of the included explanatory variables have 95% 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 spillover effect on all other neighboring farmers. In general, this implies that spatial spillover effects in the adoption of organic farming on an individual farmer are very small, but the effect is strongest on nearby neighbors and declines with distance. Here, the overall average distance to farms in this neighborhood is 19.4km and there are on average 25 farmers within a 30km radius.

Table 2: SDM effect estimates for a 30km neighborhood

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

Values in parentheses are 95% credible intervals.

In terms of farm characteristics, a higher livestock density seems to constrain adoption of organic farming, which is in line with previous literature (Schmidtner et al., 2011; Pietola and Oude Lansink, 2001). More specifically, for every additional livestock unit the adoption probability on this farm reduces by 4.9% (direct effect), while spatial spillovers reduce the probability of adoption on neighboring farms by a cumulative 0.7% (indirect effect), resulting in a total effect of 5.7% decrease in the probability of adoption on all farms. Intuitively, neighboring 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 spillover effect. In contrast, farm size and distance to organic livestock marts do not have a significant impact on adoption. Similarly, Hattam et al. (2012) and Burton et al. (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 exists 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, implying that younger farmers are more likely to adopt. More specifically, with every additional year the probability of adoption decreases by 0.2%. In contrast, whether or not the farmer has an off-farm job, number of household members as well as level of education do not show a significant effect on decision to adopt organic farming. Similar to our findings, Hattam et al. (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 et al. (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% higher probability to adopt organic farming. This also impacts on the farmer's neighbors' adoption decisions with a cumulative indirect effect of 1.7%, accumulating to a total effect of 12.6%. 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 are 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 utilized 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% and a cumulative 0.3% for neighboring farmers, accumulating to a total effect of 2.1%. Again, communication between farmers provides an explanation for the spatial spillover 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%, while it also impacts on the adoption of nearby farmers, with a cumulative indirect effect of

2.5%. The combined total effect on all farms is 18.7%. The positive effect of environmental attitude is in line with previous findings in the literature (Burton et al., 2003; Genius et al., 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% reduction in the probability of adoption, and a cumulative indirect effect of 0.6% decrease in probability. The total effect is a reduction of adoption probability of 4.5%. Similarly Gardebroek (2006) and Serra et al., (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 one standard deviation increase in profit orientation, which also has a spillover effect on neighbors of 0.5% decrease in probability with each increase of profit orientation by one standard deviation. The spatial spillover effects of the attitudinal variables provide empirical evidence, albeit small, that adoption decisions of farmers are influenced by their neighbors' attitudes. Nevertheless, the spatial spillover 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 a Bayesian spatial Durbin probit model (SDM), which takes 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 SDM confirm that farmers' adoption choices are dependent on their neighbors' decisions, i.e. neighborhood effects, but that neighbors' characteristics also exert an influence on adoption decisions, which highlights the importance of communication or interaction between 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 spillover. Our study reveals significant, albeit small, spatial spillover effects on neighboring farmers' choices. More specifically, by harnessing spatial spillover 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 neighbors' 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 neighborhood 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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