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SPATIAL DEPENDENCE AND DETERMINANTS OF DAIRY FARMERS' ADOPTION OF BEST MANAGEMENT PRACTICES FOR WATER PROTECTION

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Introduction

Under "sustainable dairying: Water Accord" (the new Accord), dairy farmers have greater responsibilities to comply with Best Management Practices (BMPs) to meet the new targets for sustainable growth. Hence, farmer's choice should be considered as one of the most important determinants of the success of policy aimed at water quality protection. In this way, farmers may face a significant challenge of balancing profitability and the cost of adopting BMPs. However, main focus has been on the public's opinion on the impact of dairy farming on water quality. Studies have paid attention to either the public's perception of environmental degradation due to unsustainable agricultural practices or the NZ residents' willingness to pay for water quality protection (e.g. Tait et al., 2011). However, it is equally important to explore the issue of water quality degradation from the dairy farmers' perspective and to understand what factors determine farmers' decisions as to their compliance with water protection requirements. Failing to understand this may make it difficult to reach the new Accord targets by the expected date, let alone protect the environment.

To explore reasons for farmers' adoption and non-adoption of BMPs, the literature on this question provides insights into a number of determinants (Knowler & Bradshaw, 2007). These determinants can be summarized in several categories, including farmers' perceptions on environmental practices, farm characteristics, household characteristics, and other contextual factors (e.g. Moon & Cocklin, 2011). Notably, recent studies have started to focus on location effects (or spatial effects) on individual's choices, as individuals who benefit from environment improvement are located across a geographical area (Jørgensen, 2012). For policy makers, therefore, the choice of an instrument to regulate nutrient pollution should be considered in a spatial context because of differences in the physical environment in a given region (Whittaker et al., 2003). The importance of spatial effects has also been addressed in the literature on distance decay effects on individual's recreation demand for non-market products, such as clean rivers and free-entry parks. For example, willingness to pay to improve water quality is expected to decrease with the distance from residents' houses to rivers, as there are distance decay effects on their recreation demand for water quality (e.g. Jørgensen, 2012). For the same reason, I assume that dairy farmers' willingness to adopt/ improve BMPs may also decrease with the distance from the nearest water bodies as farmers have hedonic demands for beautiful views or clean water quality for household water use. In other words, the distance from dairy farm to water bodies will be considered as one of the determinants of dairy farmers' choices on BMPs.

Another spatial effect to be considered comes from spatial spillover effects regarding neighbouring farmers' choices. Although geographical locations of farms can be used to model the spatial dependence of choice between farmers, it is usually ignored. Recently, some studies have begun to address the spatial interactions in farmers' decision-making on participation in agri-environmental programs, farmers' adoption of clean technology and organic dairy farming (e.g. Läppl & Kelley, 2015). These studies have agreed that spatial spillover effects may reduce the fixed cost of learning about BMPs because farmers may economise by learning from their neighbours. Spillover effects may also reduce farmers' uncertainty of the environmental performance of BMPs after talking to their neighbours. Thus, interdependence in farmers' decisions should be considered when exploring dairy farmers' adoption of BMPs.

It is, therefore, the aim of this paper to explore determinants of dairy farmers' willingness to adopt BMPs for water quality protection. In addition, except for testing the commonly used determinants, such as farm characteristics, it will test for the hypothesis that spatial effects influence farmers' choices. Bayesian spatial Durbin probit models are applied to sample survey data in the Waikato region of NZ. Specifically, this paper will verify the above hypothesis from two aspects. Firstly, spatial effects will be modelled according to the distance from farm to the nearest water bodies. It is assumed that dairy farmers whose farms are located close to water bodies are more inclined to be willing to adopt BMPs. Secondly, spatial effects will be presented as the existence of spatial interdependency in dairy farmers' decision-making. It is hypothesised that dairy farmers observe or learn from nearby farmers thereby reducing the uncertainty of the performance of BMPs since BMPs are information-intensive farming techniques (Läppl & Kelley, 2015).

Methods

Modelling framework

Figure 1 shows the modelling framework of farmers' decision-making (on adoption/ non-adoption) under the circumstance of a standard choice modelling context (in the upper portion), and the extension of farmer choice in a spatial context (in the lower part). Here, the terms in blue rectangles represent unobservable variables, while those in orange boxes represent observable variables.

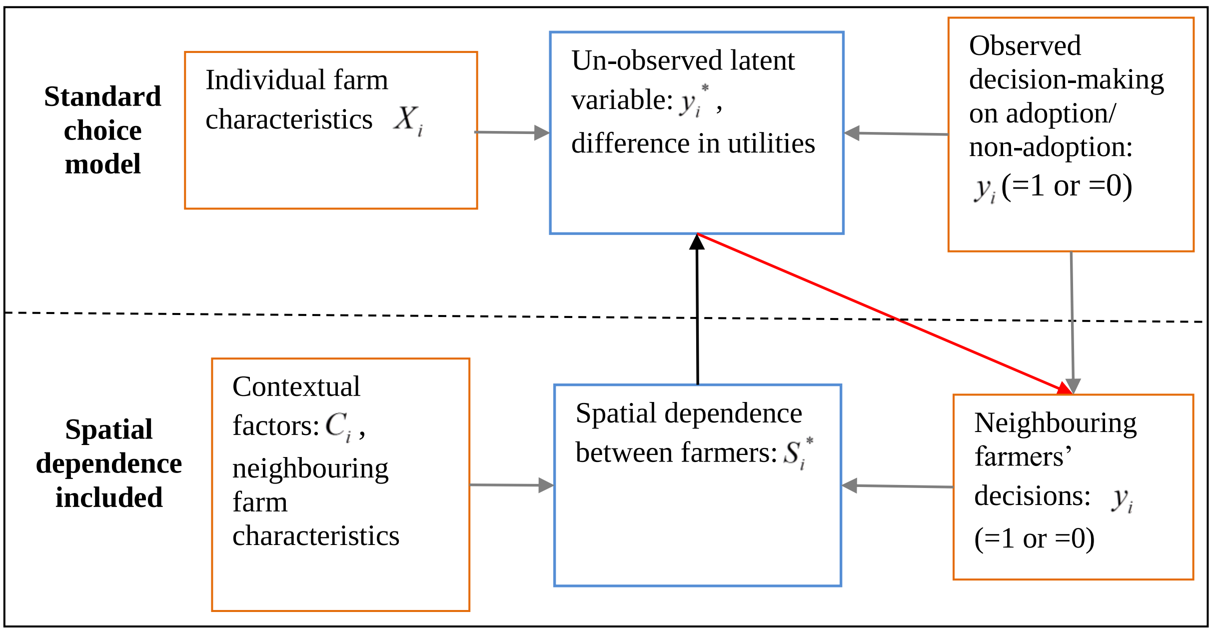

Figure 1 Modelling Framework of Farmers' Decision-making

The lower portion of the figure describes the contextual factors (also known as contextual effects in the sociological literature), i.e. characteristics of neighbouring farms, and spatial spillovers from neighbouring farmers' decisions. In other words, farmer decision depends on the own farm and household characteristics as well as on the spatial dependence between the farmer and his/ her neighbours.

Spatial Durbin Probit Model

Based on the framework depiced in the previous section, this paper uses a spatial Durbin probit model (SDM probit model) to analyse how interdependence in farmers' decisions contributes to their adoption of BMPs. The SDM probit model is regressed by using the Bayesian Markov Chain Monte Carlo (MCMC) estimation, and a detailed description of the estimation procedure for the model is provided in LeSage and Pace (2009) and Lesage et al. (2014). The range of the threshold values between farmers is from 1.5 km to 4 km (in intervals of 0.5 km), which is chosen on the basis of the distance band calculation in Arc GIS 10.2. This range is consistent with the previous studies, such as Srinivasan, Shankar & Holloway (2002) who indicate a reasonable radius for technology spillover is 2 to 3 km in rural areas. The model with the highest posterior probability with a threshold value of 1.5 km is the preferred model fitting the data best.

Data

This paper is based on a cross-sectional survey of data in the Waikato region of NZ. The data are used to empirically test and verify the hypothesis that spatial dependence exists in farmers' decision-making by using the spatial models presented in the previous section. The data are collected as a part of the study of the Upper Waikato Sustainable Milk Project held by DairyNZ. In this project, dairy farmers voluntarily committed to adopting BMPs at the beginning, and the reasons of adoption or non-adoption of the BMPs were collected by the means of face to face interview at the end of the project. Over 200 questionnaires were collected in 2013 by DairyNZ and 171 questionnaires were considered usable. The dependent variable is a binary variable, indicating farmer choice on the adoption or non-adoption of BMPs: coded as 1 representing the farmer has adopted BMPs as committed, and coded as 0 indicating the farmer has not adopted BMPs (set as the base category).

Likewise, dairy farmers also gave answers on what motivates them to adopt BMPs and what prevents them from implementing BMPs. Hence, drivers and barriers associated with the choices are grouped to form categorical variables considered as explanatory variables in this paper. For example, there are three main drivers, including self-initiated, access to industry information, such as access to the advice of experts, access to the knowledge of BMPs, and access to local government plans for BMPs, and other motivations. Other explanatory variables include variables of farm and household characteristics. The survey data on farm characteristics included farm size, farm contour and participation in dairy-related social activities. Unfortunately, the survey did not cover household characteristics of farms, which are regarded as important factors impacting farmers' decision-making. Meshblock data from the NZ 2013 census are used for the purpose of capturing household characteristics. Although the meshblock data cannot completely describe the variance of the individual (farm-level) data, 141 counts are collected from the meshblock data[1].

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[1] A Meshblock is defined as the smallest geographic unit for which statistical data is collected by Statistics NZ. Meshblocks vary in size from part of a city block to large areas of rural land.

A detailed description of all the explanatory variables is shown in Table 1. Accordingly, the expected signs of the coefficients associated with the variables are also given in the third column of Table 1. Where it is a priori difficult to set the expected sign of coefficients, "+ or –" and "– or +" are used. However, the preference of the signs are offered given the orders, for example, DR1, "+ or –" indicates self-motivated farmers are more likely to adopt BMPs compared to farmers who find other reasons as the primary motivation to adopt BMPs.

Table 1 Descriptions of Variables

Explanatory variables	Descriptions	Expected signs
Drivers for adopting BMPs (DR)	Categorical variables: DR1: self-initiated, coded as 1; DR2: industry information, coded as 2; DR3: others, coded as 3 (set as the base).	 + or - + or -
Barriers to adopting BMPs (BA)	Categorical variables: BA1: financial problems, coded as 1; BA2: lack of information, coded as 2; BA3: personal reasons and others, coded as 3 (set as the base).	 - or + - or +
Farm size	Effective areas of dairy farms (hectares).	+
Farm contour	Percentage of flat areas over total farm areas.	-
Social activities	The number of dairy-related activities, such as discussion group and field days that the farmer participated in the past year (2012).	+
Distance	The distances from dairy farms to the nearest water bodies (metres). To control for the non-linear relationship between distance and the farmer's adoption of BMPs, the distances are natural log transformed in the empirical analysis.	-
Staff training	Binary variable=1, if there are staffs (the farmer himself/ herself is also counted as a staff) who have been trained or are being trained toward BMPs.	+
Income (Proximity)	The median income of people, who are greater than 16, in meshblocks.	+
Age (Proximity)	The average age of people, who are greater than 16, in meshblocks.	-
Education level (Proximity)	Education level, which is the proportion of people (who are greater than 16) educated at and over level 5, in meshblocks.	+

Results and Discussions

In the non-spatial probit model, marginal effects are estimated at the mean for continuous variables and for a change from zero to one for dummy variables. The SDM probit model, however, accounts for both direct and indirect effects. The direct effects represent the impact of a change in the explanatory variables of farmer *i* on the adoption probability of farmer *i*, and the indirect effects (spillovers) express the cumulative effect of a change in the explanatory variables of neighbouring farms on the adoption probability of farmer *i*. The indirect effects come from the interdependence in decision-making among farmers, i.e., a change in the independent variable has an effect on farmer *j's* probability to adopt BMPs and thereby also on farmer *i's* probability to adopt. To what extent changes in the neighbourhood influence the adoption probability of farmer *i* is dependent on the spatial proximity defined by the spatial weights matrix. The total effect of an explanatory variable is thus the sum of its direct effect and its indirect effect (LeSage and Pace, 2009).

Table 2 shows the marginal effect estimates, including direct, indirect and total effects as well as Bayesian 95 percent credible intervals for total effect estimates. The results show that for all explanatory variables, direct effects are about 1.5 times larger than the indirect (spatial spillover) effects. According to the magnitudes of the total effects, the most influential determinants are access to industry information (in the category of drivers), financial constraints (in the category of barriers), and participation in dairy related social activities.

Table 2 Direct, Indirect and Total Effects Estimates of the SDM Probit Model

Variable	Direct effects	Indirect effects	Total effects
DR1: self-initiated	0.123	0.082	0.205 [0.005, 0.405]
DR2: industry information	0.223	0.041	0.264 [0.236, 0.702]
BA1: financial problems	-0.367	-0.098	-0.465 [-0.585, -0.345]
BA2: lack of information	-0.049	-0.017	-0.066 [-0.089, -0.043]
Farm size	0.062	0.031	0.093 [0.001, 0.185]
Farm contour	-0.014	-0.009	-0.023 [-0.053, 0.007]
Social activities	0.313	0.021	0.334 [0.114, 0.554]
Log Distance	-4.42	-1.95	-6.37 [-8.18, -4.16]
Staff training	0.173	0.115	0.288 [0.101, 0.475]
Income	0.004	0.002	0.006 [-0.002, 0.014]
Age	-0.041	-0.019	-0.06 [-0.08, -0.04]
Education level	0.156	0.104	0.27 [0.145, 0.395]
Source: authors' elaboration based on Matlab software.			

Driver and Barrier Variables:

Among all the drivers, access to industry information is regarded as the most important determinant of dairy farmers' adoption of BMPs. Compared to farmers choosing other motivations, farmers, who deem access to industry information as the most important driver, are 26.4 percent more likely to adopt BMPs. The 26.4 percent total effects can be further broken down to 22.3 percent direct effects and 4.1 percent indirect effects. This finding is consistent with results of previous studies on technology adoption as information exchange between neighbours is an important determinant of technology diffusion (e.g. Wollni & Andersson, 2010).

Relative to personal and other reasons, financial problems, such as capital shortage and high expenditures, seem to be the biggest obstacle that prevents dairy farmers from adopting BMPs. Farmers stuck in the dilemma of financial problems are 46.5 percent less possible to adopt BMPs, and about 9.8 percent is from neighbouring farmers who are also constrained by their budget.

Farm Characteristic Variables:

Among all the farm characteristics, staff training and participation in social activities that are related to dairy farming, such as discussion groups and workshops, are important determinants of farmers' decision-making on the adoption of BMPs. A farmer's adoption likelihood increases by 33.4 percent in total when he/ she participated in one more social activities in the previous year. A farmer, whose staff have been trained or are being trained to master BMPs, is 28.8 percent more likely to adopt BMPs. Thereinto, part of the increase in the probability, about 40 percent (indirect effects divided by total effect), is because the farmers' neighbours are also keen to train staffs toward BMPs.

Impacts of the physical characteristics of farms, including farm size and farm contour, are less significant compared to the above variables.

As expected, the hypothesis that farmers who live closer to water bodies tend to be more willing to adopt BMPs to protect the water quality is true. Here, with one-meter increase in the distance from a farm to the nearest water body, the probability of the farmer's adoption of BMPs increases by about 6.4 percent.

Household Characteristic Variables

Higher education level and median income have positive impacts on farmers' adoption of BMPs. In particular, education level has the greatest impact. With a 1 percent increase in education level, a farmer located in the meshblock is 27 percent more likely to adopt BMPs. The adoption probability only increases by 0.6 percent with a rise in one dollar in median income in the meshblock. The average age in the meshblock negatively affects the adoption. 6 percent decrease is observed in the probability of adoption due to one year increase in age.

Conclusions

This paper uses a spatial Durbin probit model to empirically analyse the spatial dependence and determinants of dairy farmers' adoption of BMPs. Data were obtained from a survey of 171 farms in the Waikato region of New Zealand; socioeconomic data were drawn from the 2013 Census. Spatial spillovers are observed through the impacts of neighbouring farmers' adoption choice as well as their characteristics. In addition, a farmer's willingness to adopt BMPs decay with the increase in the distance from the farm to the nearest water bodies.

This paper also highlights the importance of information acquisition for dairy farmers to adopt good practices. Firstly, the existence of spatial dependence in decision-making between farmers indicates the information exchange among farmers. Secondly, the results show that access to industry information, as a driver, has the greatest impact on farmers' adoption of BMPs. Thirdly, participation in different (dairy-related) social activities also promotes farmers' adoption of BMPs, as it is another way of obtaining relative knowledge and exchange information with others.

Based on the results and findings presented in this paper, policy implications can be made as follows. To begin with, an understanding of dairy farmers' drivers and barriers to adopting BMPs could assist policy makers to specific strategies and deliver support to solve the problems that are badly in the need of help. For example, financial problems are regarded as the biggest obstacle for farmers to adopt BMPs in the empirical analysis, which is consistent with reality not only in the Waikato region but elsewhere of NZ. Thus, it is worthwhile for regional governments to figure out ways of reducing the cost of dairy farmers to adopt BMPs, such as offering free channels for information acquisition, which could significantly reduce the uncertainty of adoption BMPs. Joint neighbourhood initiatives are also most appropriate to address the positive externalities of sustainable management practices. Although individual farmers could not internalize the full benefits of the adoption of BMPs and, therefore, incline to delay adoption, integrated activities in one community can help to overcome such problems of collective action. Assuming all farmers in a neighbourhood commit to establishing measures against water pollution, individuals do not have to fear that neighbouring farmers may free ride on their investments into BMPs. Lastly, the existence of a distance decay effect in dairy farmers' adoption of BMPs provides a different point of view of education as a vehicle for regional governments to use in the promotion of BMPs. That is, during the education and promotion process, instead of treating dairy farmers as polluters, they could also be seen as individuals who also demand good water quality for recreation purposes. Stimulating dairy farmers' desire for clean waterways may encourage them to re-evaluate their farming practices and adjust to the requirements of sustainable dairy.

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