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Spatial effects in investment decisions: Evidence from French dairy farms

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Abstract: This article analyses the spatial effects in farmers' investment decisions, in particular the role of neighbourhood effects, for the specific case of dairy farmers in a region of Western France. Investment decisions are measured by investment spikes, enabling the analysis to be linked to the literature on adoption of technology innovation. The main contribution is in accounting for the effect of the previous decisions of the farmers' neighbours, with the help of a spatial probit econometric model that includes investment age. Results show that farmers are not immediately influenced by the simultaneously-made decisions of their neighbours, but rather by the decisions taken by their neighbours in the year before. However, this positive influence does not compensate for the negative effect of own previous investment decisions.

Keywords: farm investment, spatial, neighbourhood effects, dairy, France.

JEL: C21, O13, R12, R42

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1. Introduction

The end of the European Union's (EU) dairy quota policy was confirmed in 2008 with milk quotas gradually increasing up to their abolition on 31 March, 2015. This change in agricultural policy may trigger substantial investment decisions by farmers in order to increase their production capacity through expansion or modernisation. From a policy perspective, understanding the determinants of farm investment in a changing policy and economic context can help draw policy recommendations on how best to support farmers throughout the changes.

In the economic literature on a firm's investment behaviour, the main determinants studied have been economic and financial determinants. These include: the output price, the capital price, the output quantity sold and, by extension, the output quantity produced (Chirinko, 1993); borrowing constraints and interest rates (Budina et al., 2000; Latruffe, 2005; O'Toole et al., 2014); the quasi-fixity of assets, irreversibility of investment, sunk costs and adjustment costs, in particular in the agricultural sector (Bokusheva et al., 2009; Chavas, 1994; Oude Lansink and Stefanou, 1997); and the influence of public policy, in particular agricultural subsidies (Bojnec and Latruffe, 2011; Sckokai and Moro, 2009). By contrast, neighbourhood effects, where neighbours have either a direct or indirect effect on individual behaviours (Wilson, 1987) have not been studied so far. One reason may be that it is usually believed that investment decisions, which are in fact input demands in the medium- or long-term, are governed by managers' profit-maximising behaviour and are thus only influenced by economic determinants. However, investment may be carried out to implement a new technology, and in this case an investment decision can be likened to the adoption of an innovation. In the agricultural literature, the importance of neighbourhood effects has recently been recognised in innovation adoption. Case (1992), for example, indicates that farmers are influenced by their neighbours when taking discrete choice decisions on the adoption of new technologies. Abdulai and Huffman (2005) show that a farmer's adoption of crossbred technology in Tanzania is positively influenced by the proximity of the farmer to other farmers using the same technology. The case of conversion to organic farming has also been studied in relation to neighbourhood effects, giving evidence worldwide of the role of neighbouring organic farms on the decision to adopt organic technology (e.g. Lewis et al., 2011; Wollni and Andersson., 2014; Laple and Kelley., 2014). This suggests that, after technology adoption, farmers develop a degree of 'positive or negative affect' towards the new technology, which they then spread to their neighbours (Case, 1992).

Manski (1993) explains that ‘neighbourhood effects’ can also be termed in the literature ‘peer influences’, ‘endogenous social effects’ or ‘social norms’, depending on the context (sociology, social psychology, economics, health). He provides a clear definition of such effects: ‘the propensity of an individual to behave in some way varies with the prevalence of that behaviour in some reference group containing the individual’. Such a ‘reference group’ may also be called a ‘social group’, where two or more people interact with one another, share similar characteristics, and collectively have a sense of unity (Turner, 1982).

Neighbourhood effects are due to interactions and information shared across agents within a group, and therefore depend on geographic proximity and network proximity. Information can be direct information or perceived information. The latter case relates to social norms theory as explained by Berkowitz (2005), as ‘situations in which individuals incorrectly perceive the attitudes and/or behaviours of peers and other community members to be different from their own when in fact they are not’. It also relates to social subjective norms in the theory of planned behaviour (TPB) (Ajzen, 1985) and the theory of reasoned action (TORA) (Fishbein, 1967), where an agent’s behavioural intention is influenced by his/her attitudes towards the behaviour, through social pressure or subjective norms, and by perceived behavioural control.

Empirically, there are two ways of investigating neighbourhood effects. The first is to evaluate those unobservable effects through direct revelation methods; namely, by directly questioning farmers through structured elicitation, in order to obtain measures of farmers’ beliefs (e.g. Läßle and Kelley., 2013; Rehman et al., 2007). The second way is to assess observed neighbourhood effects using spatial econometric techniques that account for spatial spillovers (e.g. Wollni and Andersson., 2014; Läßle et al., 2015). Two types of spatial spillover can be accounted for econometrically: spatial dependence where values observed at a location depend on values observed at nearby locations (in other words, neighbouring effects); and spatial heterogeneity where the econometric model’s coefficients vary across locations.

Here we focus on the specific role of neighbouring effects (i.e. spatial dependence) on large investment decisions that can be likened to the adoption of innovation. We assume that such decisions are observed in the data through investment spikes, which are ‘large, discrete investment episodes’ (Kapelko et al., 2015). Neighbourhood effects themselves may have two components: they can be effects due to neighbours’ simultaneous decisions (Baerenklau, 2005; Läßle et al., 2017), that is to say farmers are immediately influenced by the current decisions of their neighbours, or they can arise from their neighbours’ previous decisions (LeSage and Pace, 2009). The latter component is acknowledged by Läßle et al. (2017) in the limitations

of their study of neighbourhood effects of sustainable technology adoption in the Irish dairy sector, as follows: ‘farmers’ technology choices are analysed at one point in time, but there is a likely possibility that farmers are influenced by previous decisions of their peers’. This issue is indeed particularly relevant in the adoption context, as not all farmers adopt an innovation at the same time. There are pioneers and followers or, more precisely, there are five stages in the technology adoption lifecycle (Beal et al., 1957): innovators, early adopters, early majority, late majority and laggards. In general, only neighbourhood effects of simultaneous decisions are accounted for in empirical studies, because accounting for neighbours’ previous decisions requires panel data and dynamic spatial panel data modelling, entailing methodological difficulties. Our article contributes to the literature by assuming that it is possible to account for previous decisions without using a dynamic specification. Our strategy relies on the introduction of an explanatory variable ‘investment age’. This variable measures the time elapsed since the occurrence of the last investment spike, and can capture neighbours’ previous investment decisions.

The objective of our article is to examine the spatial determinants of farmers’ spike investment decisions, in particular the role of neighbourhood effects arising from both simultaneous and previous decisions of neighbours, for the specific case study of dairy farmers in a region of Western France in the period 2005-2014. The article is structured as follows: Section 2 explains the empirical framework and Section 3 describes the data. Section 4 presents the empirical results. Section 5 concludes.

2. Empirical framework

2.1. Econometric model

The dependent variable y is binary, taking the value 1 if there is an investment spike (adoption of innovation) and the value 0 if not (no adoption of innovation). A probit model is therefore needed, with the latent variable y^* capturing the difference in a farmer’s utility if adoption is undertaken or not. In other words, we assume that a farmer will have an investment spike if the expected utility of an investment spike (i.e. the utility of adoption) is higher than that of no investment spike (i.e. of no adoption). The general form of the probit model to be estimated is therefore:

$$\begin{cases} y_t = 1 & \text{if } y_t^* > 0 \\ y_t = 0 & \text{if } y_t^* \leq 0 \end{cases} \quad (1)$$

with t the time period; y_t the binary dependent variable; and y_t^* the latent variable which needs to be modelled in terms of several explanatory variables and accounts for neighbourhood effects.

Neighbourhood effects are classically modelled in three possible ways (which are not mutually exclusive): including a spatial lag of the explanatory variables; including a spatial lag of the dependent variable; and including a spatial lag of the error term. Whether the latter two forms of spatial lag should be included in the model can be tested through Moran's test of spatial autocorrelation of the observations (Moran, 1948). We thus perform such a test in a classic (i.e. non-spatial) probit model (that is, without accounting for neighbourhood effects) (Kelejian and Prucha., 2001). As shown in Appendix 1, the Moran's I test statistics calculated each year indicate that there is no spatial autocorrelation in our data except in years 2008 and 2013 where the value of the statistics is very close to zero. Hence, over the full period we consider that there is, on average, no spatial autocorrelation and we will not include spatial lags of the dependent variable nor of the error term. This means that there are no neighbourhood effects arising from neighbours' current decisions. We do, however, include spatial lags of explanatory variables to account for spatial effects due to neighbours' characteristics.

As regards neighbourhood effects arising from neighbours' previous decisions, this is non-testable with Moran's I test and such effects should therefore be directly modelled. The dynamic spatial panel data model can account for these effects (Elhorst, 2010) but this model may suffer from an identification problem and is difficult to implement in practice (Anselin et al., 2008; Manski, 1993). The important contribution of this article is to propose a new model, which is easier to implement. This model relies on the spatial lag of X model (SLX), which includes spatial lags of the explanatory variables. We use the probit version of the SLX, namely the spatial lag of X probit model (LeSage, 2014). In order to account for the neighbourhood effects of neighbours' previous decisions, we include investment age among the explanatory variables that are spatially lagged. The investment age measures the time elapsed since the occurrence of the last investment spike.

The latent variable of our SLX probit model thus takes the following form:

$$y_t^* = \alpha + \alpha_Y Y_t + \alpha_{WY} W_t Y_t + \alpha_X X_t + \alpha_{WX} W_t X_t + \varepsilon_t \quad (2)$$

where t is the time period; y_t^* is the latent variable of the SLX probit model; Y_t is the matrix of variables capturing investment age; X_t is a matrix of other explanatory variables;

$\alpha, \alpha_Y, \alpha_{WY}, \alpha_X, \alpha_{WX}$ are parameters to be estimated; ε_t is a normally distributed error term; and W_t is the spatial weight matrix.

Marginal effects are computed following Lacombe and LeSage (2018). They can be decomposed into direct effects and indirect effects. Direct effects, given by the non-lagged variables Y and X , show a change in farmer i 's behaviour due to a change in the farmer i 's own past investment behaviour (Y_{it}) and own current characteristics (X_{it}). Indirect effects, given by the spatially lagged variables (WY and WX), show a change in farmer i 's behaviour due to a change in his/her neighbour j 's past investment behaviour (Y_{jt}) and neighbours' current characteristics (X_{jt}). Total marginal effects are the sum of direct and indirect effects.

We use maximum likelihood to estimate the SLX probit model. The estimation requires the specification of the spatial weight matrix W as a first step.

2.2. Spatial weight matrix specification

One limitation of our database is the lack of precise farm geographical location, preventing the computation of the exact distance between two farms. As commonly used in the literature, to approximate the location of a farm we use the centroid of the smallest spatial unit the farm belongs to, here the farm's municipality. To approximate the geographic proximity between farms we use the Euclidean distance between centroids (Conley and Topa, 2002; Le Gallo, 2001; Saint-Cyr et al., 2018).

We use an inverse distance spatial weight matrix (W_D) with weights $w_{ij} = 1/d_{ij}$, where d_{ij} is the Euclidean distance between the municipalities of farm i and farm j . Similarly to Laple et al. (2017), Roe et al. (2002), and Wollni and Andersson (2014), we consider that beyond a specific distance the neighbourhood effects disappear. In other words, we assume that all spatial weights w_{ij} outside a given distance (d^*) are zero, i.e. $w_{ij} = 0$ if $d_{ij} > d^*$. Following Laple et al. (2017), we set d^* as 10 km because at this distance all farms in our sample have at least one neighbour. Using an inverse distance matrix implies that closer neighbours have a stronger influence than do more distant neighbours, which seems to conform to the reality. Since in our sample the smallest distance between two municipality centroids is 2.5 km, we assume that two farms i and j belonging to the same municipality are at a distance of 1 km on average, meaning that we set $w_{ij} = 1$ for them.

3. Data

3.1. Database

Our application is to dairy farms in an administrative region of Western France, namely Ille-et-Vilaine, which is a NUTS3¹ region in Brittany. We use farm-level data collected annually over 2005-2014 by a bookkeeping company, the private accountancy agency CER FRANCE d'Ille-et-Vilaine. After cleaning for inconsistent observations, the usable sample includes 2,112 dairy farms observed annually over the 10-year period or less, that is to say an unbalanced sample with a total of 14,127 farm-year observations.

The sample used is a relatively good representation of the full population of dairy farms present in the French Agricultural Census data. In fact, the yearly recovery rate, which is the number of dairy farms per municipality in our sample divided by the number of dairy farms per municipality in the Agricultural Census data, is on average 77% with a standard deviation of 20% over all the municipalities. This suggests that the 'missing neighbourhood problem', where the number of neighbours in the sample used does not represent the real number of neighbours in the population due to sampling issues, mentioned by Laple et al. (2017), is quite limited in our case.

Additional data are used in the estimation, namely data from the French Agricultural Census at the municipality level regarding the dairy farm population. The values of the Agricultural Census in 2010 are used for the whole period covering our farm-level data (2005-2014) since no other Agricultural Census was implemented during this period.

3.2. Dependent variable: definition of investment spikes

The dependent variable of our SLX probit model takes the value 1 if there is an investment spike and the value 0 if not. We consider that an investment spike occurs if the farm's gross investment in buildings, machinery and materials (between years t and $t-1$), divided by the capital value (of year $t-1$) exceeds a specific threshold of β per year. Here we consider the threshold to be 20%, enabling us to focus on large and significant investments. This choice of threshold value is based on local experts' advice and on the literature (Kapelko et al., 2015; Power, 1998; Licandro et al., 2004). Hence, the dependent variable is a dummy variable taking the value 1 if the farm's investment exceeds 20% of the value of the capital stock and 0 if not.

¹ 'The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory of the EU' (<https://ec.europa.eu/eurostat/web/nuts/background>).

Different thresholds β could be used to define investment spikes, and Table 1 shows the distribution of spikes depending on three thresholds (15%, 20% and 25%). For the selected threshold (20%), the share of spikes in total farm-year observations is 15.7%. This figure varies between 19.4% and 12.9% across the three different thresholds, as well as the number of farms with spikes (last part of Table 1). In order to check for the robustness of our results, the estimations will also be performed for the two other thresholds (15% and 25%).

Table 1: Comparison of investment spike definitions

	Threshold β		
	15%	20%	25%
Number of observations over the period:	14,127	14,127	14,127
no spike (a)	11,382	11,902	12,298
spike (b)	2,745	2,225	1,829
Share of spikes in total observations (%) (= $b \times 100 / a + b$)	19.4	15.7	12.9
Share of spikes' value in total investment value (%) (= aggregated value of all investment spikes over the period $\times 100 /$ total investment value over the period)	88.3	80.2	72.4
Number of farms with:			
0 spike	492	641	803
1 spike	792	869	871
2 spikes	582	466	364
3 spikes	203	123	67
4 or more spikes	43	13	7

Note: the threshold value β is when a farm's investment exceeds $\beta\%$ of the value of capital stock.

3.3. Explanatory variables

As explained above, we account here for the neighbourhood effects of neighbours' previous decisions by including in the explanatory variables some proxies for the investment age, Y_t . Following Kapelko et al. (2015) and Licandro et al. (2004), for each farm-year observation i, t we compute the number of years elapsed since the most recent spike has occurred for farm i . We then build investment age dummies ranging from 1 to 6-or-more years. For example, the dummy variable 'Investment age 1 year old' takes the value 1 if the most recent investment

spike took place one year ago, or, in other words, if one year has elapsed between two investment spikes.

The other explanatory variables, X_t , are based on the literature on agricultural technology adoption (Barham et al., 2004; Laple et al., 2017; Roussy et al., 2017; Sauer and Zilberman, 2012) and investment behaviour (Budina et al., 2000; Latruffe, 2005; O'Toole et al., 2014; Storm et al., 2014). They include the farm's dairy herd size, livestock density (proxied by the number of livestock units per hectare of utilised agricultural area), labour to capital ratio, degree of specialisation in milk production (proxied by milk gross margin divided by total gross margin), and the reliance on fodder maize (proxied by the share of fodder maize in forage area). These variables are observed yearly for each farm and are measured at the farm level, while two additional explanatory variables are observed in 2010 only (as they are extracted from the Agricultural Census) and are measured for the municipality where the farm is located: dairy cow density and dairy farm density.

Finally, we include four control variables. One control variable is the number of occurrences of the farm during the period (to control for the fact that the probability of observing an investment spike increases with the number of times that the farm appears in the sample). The three other control variables aim at controlling for economic conditions: the farm's milk price; a dummy variable for the year 2008; and the farm's rate of growth of milk quota. Both latter variables allow for the announcement of the termination of the EU's dairy quota policy to be taken into account.

To avoid endogeneity issues, the variables dairy herd size, livestock density, labour to capital ratio, milk specialisation, and reliance on fodder maize, are included lagged over one period (i.e. $t-1$), while the other variables are used in t .

The descriptive statistics of all explanatory variables are presented in Table 2.

Table 2: Description and summary statistics of explanatory variables

Variable		Mean	Standard deviation	Min	Max
<i>Investment age (Y)</i>					
Investment age 1 year old	Dummy = 1 if 1 year between two investment spikes	0.117	0.321	0	1
Investment age 2 years old	Dummy = 1 if 2 years between two investment spikes	0.096	0.295	0	1
Investment age 3 years old	Dummy = 1 if 3 years between two investment spikes	0.075	0.263	0	1
Investment age 4 years old	Dummy = 1 if 4 years between two investment spikes	0.059	0.235	0	1
Investment age 5 years old	Dummy = 1 if 5 years between two investment spikes	0.043	0.202	0	1
Investment age 6 years old	Dummy = 1 if 6 years between two investment spikes	0.042	0.205	0	1
<i>Other explanatory variables (X)</i>					
Dairy herd size	Number of dairy cows in the farm	48.7	19.5	7.6	198.5
Livestock density	Livestock units per hectare of agricultural utilised area of the farm	1.6	0.4	0.5	7.8
Milk specialisation	Milk gross margin/total gross margin of the farm	0.62	0.15	0.01	1
Labour to capital ratio	Number of annual working units per Euro of capital of the farm	0.000029	0.000181	0	0.017396
Reliance on fodder maize	Share of fodder maize in forage area of the farm	39.2	12.6	0	100
Dairy cow density	Number of dairy cows per km ² in the farm's municipality	0.41	0.15	0.05	0.87
Farm cow density	Number of dairy farms per km ² in the farm's municipality	0.0059	0.0025	0.0007	0.0168
<i>Control variables</i>					
Number of occurrences	Number of times that the farm appears in the sample	7.4	1.8	3	9
Milk price	Milk price of the farm in Euros per 1,000 litres	316.4	28.4	251.9	511.4
Dummy year 2008	Variable taking value 1 for year 2008 and 0 otherwise	0.1253	0.3311	0	1
Rate of growth of milk quota	Change in milk quota between years t and $t-1$, divided by the quota in $t-1$	0.043	0.309	-0.926	15.56

Note: 'Dairy cow density' and 'Farm cow density' are observed in year 2010 and taken from the Agricultural Census, while all other variables are observed each year at the farm level and taken from the farm-level accountancy database during 2005-2014. The number of observations for each variable is 14,127.

4. Results

4.1. Spatial versus non-spatial probit model

We estimate the SLX probit model of equations (1) and (2) on the pooled sample (i.e. all years pooled together). Before presenting the results, we firstly compare the performance of the SLX probit model with that of the non-spatial probit model in order to assess whether accounting for spatial effects improves the quality of the model prediction.² The comparison is based on the percentage of correctly predicted observations using Wooldridge (2015):

$$\hat{p} = (1 - \theta)\hat{p}_0 + \theta\hat{p}_1 \quad (3)$$

where \hat{p} is the overall percentage of correctly predicted observations, \hat{p}_0 is the percentage of correctly predicted observations with no spike, \hat{p}_1 is the percentage of correctly predicted observations with spike, and θ is a specific threshold.

This threshold θ may be defined as 0.5 but this can lead to misleading results, because it is possible to get high percentages of correctly predicted observations even when the least likely outcome (spike or no spike) is very poorly predicted (Wooldridge, 2015). This is the case for our sample where there are only 15% of spike observations. Thus, we may use 0.15 as the value for the threshold θ , but this would increase the number of predicted observations with spike and would incorrectly predict the observations with no spike. Thus, in terms of the overall percentage correctly predicted, we may do worse than when using the 0.5 threshold.

A third possibility, suggested by Wooldridge (2015), is to choose the threshold such that the number of predicted spikes is exactly equal (or close) to the number of observed spikes in the sample. In our case, after several trials we found that the value 0.18 for the threshold θ is the most appropriate for our sample.

Table 3 presents the results of the percentage of correctly predicted observations for several thresholds tested. One can note that, in all cases, the SLX probit model performs better, even if marginally, than the non-spatial probit in terms of predictive power. This implies that taking into account spatial effects improves the accuracy of the model, as found by Laple et al. (2017).

² Results of the non-spatial probit are shown in Appendix 2.

Table 3: Comparison of model performance

Threshold θ	Percentage of correctly predicted observations \hat{p} with the SLX probit	Percentage of correctly predicted observations \hat{p} with the non-spatial probit
0.18	68.99015	68.84245
0.15	56.54231	55.40857
0.5	84.26331	84.23519

Note: the threshold value θ and the percentage \hat{p} refer to equation (3).

4.2. Results of the spatial probit model

Table 4 presents the results of the spatial probit model, namely the SLX probit model, in terms of marginal effects. Firstly looking at results for the investment age (variables Y), we find that all direct marginal effects are negative. This indicates that, for a farm i , having an investment spike in previous years (whatever the year(s)) decreases the probability of having an investment spike in the current year t . This is an intuitive result as farms do not innovate each year. It takes time to fully implement an innovation and large investments result in adjustment costs for the farm (Bokusheva et al., 2009; Levi et al., 2017). Also conforming to intuition, the probability of having an investment spike is reduced more when an investment spike has occurred the year before ($t-1$) than when it has occurred in earlier years ($t-2$ up to $t-6$). Adjustment costs are indeed stronger in the first year(s) following an investment.

More importantly, when looking at the indirect marginal effects of investment age, we found that the probability of observing an investment spike significantly increases (by about 12%) if investment spikes occur in neighbouring farms in the previous year ($t-1$). There are no significant effects for earlier years. In other words, farmers influence their neighbours with a time lag of one year only, revealing that farmers keep in mind mainly the most recent investment decisions of their neighbours. This is consistent with findings in experimental economics trying and eliciting subjective probability. They find that individuals are asymmetrically influenced by good and bad events and by late and recent events (Tversky and Kahneman, 1981). However, our results show that overall the total (own plus neighbours') effect of investment age of one year old is negative, suggesting that the positive influence of neighbours does not compensate for the negative impact of adjustment costs of previous investments on own farm.

Looking at the direct effects for the other explanatory variables (X), results indicate that dairy herd size decreases the probability of having investment spikes, while livestock density, milk

specialisation, and labour to capital ratio increase it. There is no significant effect of the farm's own reliance on maize fodder on the probability of observing an investment spike. There is also no significant effect of the municipality's variables, namely dairy cow density and dairy farm density in the i -th farm's municipality. In addition, the higher the labour to capital ratio, the higher the probability of investing substantially, suggesting the need to substitute labour for capital.

The result on dairy herd size indicates that each additional dairy cow on farm i decreases the probability of observing an investment spike by 0.032% on this farm i . Such a negative effect contradicts with previous literature findings on technology adoption, that bigger farms innovate more (Barham et al., 2004; Feder et al., 1985; Laple et al., 2017). In our sample it seems that what matters is production intensity, captured through livestock density and milk specialisation. More production-intensive farms are more likely to invest large amounts, suggesting that innovative investments are influenced more by farm technology type (highly intensive farms vs. less intensive farms) than by farm size.

However, although the direct effect of dairy herd size is negative, the total (own plus neighbours') effect is not significant. In fact, among the X explanatory variables, only milk specialisation has a significant indirect (i.e. neighbours') effect on the probability of observing an investment spike. This effect is negative, indicating that the degree of specialisation of farm i 's neighbouring farms in milk production decreases the probability that farm i invests heavily. Overall, the total (direct plus indirect) effect is also negative, suggesting that the probability of a farm making an investment spike is driven more by the specialisation degree of the farm's neighbours than by its own degree of specialisation. The negative impact of the neighbouring farms' specialisation on other farms' investment may be due to farmers fearing strong competition from highly specialised farms and thus curbing their own investment behaviour, as suggested by local experts.

Finally, regarding the control variables, as expected, the greater the number of occurrences of a farm in the sample, the higher the probability of observing an investment spike for this farm. Own milk price also has a significant effect on a farm's probability of an investment spike; the effect being positive. This is in accordance with the theory of investment behaviour that investment is driven by output price (Elhorst, 1993; Femenia et al., 2017; Sckokai and Moro, 2009). Both variables used to control for the effect of the end of the dairy quota policy have a

positive effect on own farm's investment suggesting, as expected, that quota removal lifts the constraints on a farm's expansion (Ang and Oude Lansink, 2014; Levi and Chavas, 2018).

The estimation of the SLX probit model was also performed on two alternative dependent variables, where the investment spike is defined with two different thresholds β (15% and 25%). Results (not shown here) confirm the findings described above.

Table 4: Results of the SLX probit model: marginal effects

	Direct effects (Y, X)		Indirect effects (WY, WX)		Total effects	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
<i>Investment age (Y)</i>						
Investment age 1 year old	-1.17686***	0.19512	0.11152*	0.05011	-1.06534***	0.20145
Investment age 2 years old	-0.05353***	0.01166	-0.03588	0.05389	-0.08941	0.05514
Investment age 3 years old	-0.07025***	0.01307	0.00041	0.05738	-0.06984	0.05885
Investment age 4 years old	-0.03672***	0.01418	0.01880	0.05974	-0.01792	0.06140
Investment age 5 years old	-0.04710***	0.01610	0.01380	0.06784	-0.03330	0.06972
Investment age 6 years old	-0.04900***	0.01609	0.11815	0.05018	0.06915	0.05270
<i>Other explanatory variables (X)</i>						
Dairy herd size	-0.00032***	0.00016	0.00080	0.00077	0.00048	0.00079
Livestock density	0.00020*	0.00009	-0.00030	0.00030	-0.00010	0.00031
Milk specialisation	0.07492*	0.02275	-0.22781**	0.07294	-0.15289***	0.07641
Labour to capital ratio	137.69652*	54.666	0.81132	98.97394	138.50784	113.06729
Reliance on fodder maize	-0.00347	0.02795	-0.02864	0.10225	-0.03211	0.10600
Dairy cow density	-0.0037	0.03677			-0.0037	0.03677
Farm cow density	1.47643	2.16637			1.47643	2.16637
<i>Control variables</i>						
Number of occurrences	0.00837***	0.00177			0.00837***	0.00177
Milk price	0.00061***	0.00012			0.00061***	0.00012
Dummy year 2008	0.03633*	0.01137			0.03633***	0.01137
Rate of growth of milk quota	0.03691***	0.01882			0.03691***	0.01882

Notes: *, **, ***: significance at the 10, 5, 1% level.

5. Concluding remarks

This article investigates the spatial determinants of farmers' investment, in particular the role of neighbourhood effects. We take the specific case of dairy farmers in a region of Western France during the period 2005-2014. Our first contribution is to the literature on investment since it allows, for the first time, a better understanding of how farmers' investment decisions are influenced by their neighbourhood. Here large investment decisions are considered, namely investment spikes, allowing us to link our approach to the literature on adoption of innovation. Our analysis relies on a spatial lag of the X (SLX) probit model. Our second contribution is to the literature on innovation adoption, since we not only account for neighbourhood effects arising from neighbours' simultaneous decisions but also for neighbourhood effects arising from the previous decisions of neighbours. To do this, we include in the explanatory variables dummies proxying investment age.

Moran's I results do not reveal the existence of neighbourhood effects due to simultaneous decisions of neighbours in the occurrence of farms' investment spikes. However, results of the SLX probit model show the existence of neighbourhood effects due to the previous decisions of neighbours, confirming that farmers take account of their neighbours' decisions when they make substantial investment decisions. Indeed, the results indicate that the probability of observing an investment spike on a farm increases if investment spikes occurred on neighbouring farms in the year before. By contrast, neighbours' decisions in less recent years do not affect a farm's own decisions. Interestingly, the positive effect of neighbours' last year investment does not compensate for the negative effect of own farm's last year investment. This latter negative effect can be explained by adjustment costs faced by farmers when implementing a large investment.

From a policy point of view, our investigation suggests that neighbourhood effects are a positive multiplier in farms' large investment decisions, as found by Läßle et al. (2017) for the case of sustainable technology adoption in the Irish dairy sector. Increasing farmers' direct interactions or indirect information sharing could thus provide incentives to invest. However, interactions should not relate solely to which investments to implement, but also to how to implement them in such a way that adjustment costs are limited. Demonstration events and extension services are therefore crucial. This is particularly true in a period of changing economic conditions such as those faced by our sample's dairy farmers: our estimation results confirm that the progressive elimination of the EU's dairy quota policy triggered farms' large investments.

There are limitations to our study due to data constraints. Firstly, we proxied neighbourhood effects by geographic proximity but we do not know exactly how farmers communicate with each other; for example, which network they mostly use. Network proximity would be a more complete measure of neighbourhood effects, especially in a developed country where communication channels are well developed and allow for distances to be ignored. Conley and Topa (2002) consider, for example, a social economic distance instead of a physical distance. Secondly, we did not include information about farmers' education, experience, or age due to a lack of data, although such information may play an important role in the adoption of innovation as shown, for example, by Foltz and Chang (2002).

This is the first study to consider the role of neighbourhood effects on farmers' investment behaviour. Further research could go beyond the neighbourhood effects studied here, which are Manski (1993)'s endogenous effects of social norms. Manski (1993) suggested two other types of effects of social norms, namely exogenous effects and correlated effects. Exogenous (or contextual) effects of social norms imply that the propensity of an individual to behave changes in some way with the exogenous characteristics of the social group that the individual belongs to. For example, certain socio-economic groups are more likely to do certain things, such as rich people being more likely to play golf. In the case of farms' investment decisions, organic farms could be one such social group. As for the correlated effects of social norms, they mean that individuals belonging to the same social group tend to behave similarly because they face similar institutional environments. In the case of farms' investment decisions, this would mean studying, for instance, the role of the downstream sector (e.g. having a contract with a specific dairy) and upstream sector (e.g. being distant from machinery salesmen or farmers' associations for shared machinery). One possibility would be to build the spatial weight matrix based on the relative economic distance matrix defined by Elhorst and Halleck Vega (2017) or on the social economic distance defined by Conley and Topa (2002).

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Appendix 1: Results of the non-spatial probit model estimated each year: coefficients

	2006	2007	2008	2009	2010	2011	2012	2013	2014
<i>Investment age (Y)</i>									
Investment age 1 year old	-	-4.91255	-5.08163	-7.33735	-4.85757	-4.65951	-4.82358	-4.94731	-4.97371
Investment age 2 years old	-	-	0.00323	-0.25565**	-0.46411***	-0.45460***	-0.38121***	-0.26929***	-0.23152
Investment age 3 years old	-	-	-	-0.66301***	-0.16273	-0.19507	-0.56508***	-0.36557***	-0.41005**
Investment age 4 years old	-	-	-	-	-0.21682	-0.27154**	-0.20304	-0.28943***	-0.11878
Investment age 5 years old	-	-	-	-	-	-0.40555***	-0.21822	-0.54962***	-0.01523
Investment age 6 years old	-	-	-	-	-	-	-0.20154	-0.44702***	-0.31502**
<i>Other explanatory variables (X)</i>									
Dairy herd size	-0.00536*	-0.00210	-0.00364	-0.00332	-0.00280	-0.00306	0.00096	-0.00159	0.00686***
Livestock density	0.00029	0.00088	0.00074	0.00056	0.00011	0.00028	0.00038	-0.00027	0.00160
Milk specialisation	0.45226*	0.00911	0.52617***	0.51956**	0.09898	-0.11257	-0.06607	0.07078	-0.31860
Labour to capital ratio	-1203.21416	508.47198*	1407.24148***	1718.34427	816.32559***	738.1532**	3077.48166***	2183.86235***	6876.31581***
Reliance on fodder maize	0.22054	0.27055	0.55296**	0.20607	-0.42631	0.37547	0.060962	0.11145	-0.78447
Dairy cow density	-0.50630	-0.29326	0.80650***	0.24210	-0.80478*	-0.09451	-0.23900	-0.11649	0.01295
Dairy farm density	5.48854	25.53906	-41.71528***	-21.477841	22.45626	11.49690	27.02154	-17.70319	-13.44942
<i>Control variables</i>									
Number of occurrences	0.02561	-0.00276	0.01905	0.03474	0.06488***	0.03662	0.07144***	0.07402***	0.05830**
Milk price	0.00016	-0.00169	0.00168	0.00323***	0.00121	0.00157	0.00093	-0.00164	-0.00329
Rate of growth of milk quota	0.03761	0.14666*	1.66213***	0.10844	0.92145**	0.69018*	0.64377794**	-0.03835	0.09072
Intercept	-2.00094*	-0.83015	-3.83853***	-2.52285***	-2.35761***	-2.43766***	-2.53320***	-0.55877505	-0.58270
Log-Likelihood	-574.23062	-639.11225	-771.83662	-795.92518	-602.32078	-602.32078	-669.17094	-584.003572	-385.92311
LR test	44.36435	70.13235	150.67446	175.61059	114.057412	114.057412	113.528072	87.3814471	68.02617
Moran's I	0.00210	-0.00779	0.01748***	0.00048	-0.00274	-0.00311	0.00163	0.01453**	-0.00613

Notes: *, **, ***: significance at the 10, 5, 1% level.

Appendix 2: Results of the non-spatial probit model estimated for the pooled sample: coefficients

	Coefficient	Standard error
<i>Investment age (Y)</i>		
Investment age 1 year old	-5.24745682	24.9270562
Investment age 2 years old	-0.18063396***	0.05020276
Investment age 3 years old	-0.24735028***	0.05722879
Investment age 4 years old	-0.07058377	0.05985053
Investment age 5 years old	-0.08936631	0.06806766
Investment age 6 years old	-0.06794521	0.06850298
<i>Other explanatory variables (X)</i>		
Dairy herd size	-0.00063454	0.00071123
Livestock density	0.00071737*	0.00040099
Milk specialisation	0.12593287	0.092617
Labour to capital ratio	626.528045***	143.222575
Reliance on fodder maize	-0.01861549	0.12048116
Dairy cow density	-0.12637196	0.15220741
Farm cow density	3.05067642	9.27748022
<i>Control variables</i>		
Number of occurrences	0.03378292***	0.00765278
Milk price	0.00228592***	0.00049881
Dummy year 2008	0.17879209***	0.04052872
Rate of growth of milk quota	0.16978577***	0.04336643
Intercept	-2.67218262***	0.20619301

Notes: *, **, ***: significance at the 10, 5, 1% level.