Heterogeneity and spatial interdependence in farm survival: evidence from Brittany

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Abstract

Accounting for spatial interdependence is relevant for the analysis of structural change in farming because of potential interactions between farms. To identify specific farms' relationships considering farm survival, a mixture modelling framework that enables capturing heterogeneity in spatial interdependence between farms is developed. An application to a panel of farms in Brittany in France from 2004 to 2014 shows that relationships between farms are more in terms of competition for land than positive spill overs of new technology adoption, leading to a negative impact of neighbouring farms' size on the probability to survive for a majority of farms.

Keywords: EM algorithm, Farm interdependence, Mixture model, Spatial interactions, Unobserved heterogeneity

JEL Classification: C23, D22, Q12

1 Introduction

The farming sector faced considerable structural change over the last decades. In most developed countries, the total number of farms decreased significantly and their average size increased, implying changes in the distribution of farm sizes. Understanding the factors that affect farmers' decisions to enter or exit farming has been a concern of agricultural economists and policy makers for quite some time. Several studies investigated farm survival or farmers' exit decisions in different farming contexts (see Weiss (1999), Breustedt and Glauben (2007), Dong et al. (2010) for examples). Among others, these studies identified important aspects of structural change in farming and showed that farm survival may help understand farm size dynamics. More recently, Storm et al. (2015) empirically investigated the effects of direct payments on exit rates of Norwegian farms and showed that the spatial interdependence between farms is an important factor in farmers' decisions to maintain their production activities. The authors showed that accounting for spatial interdependence between farms may be highly relevant for an aggregate assessment of policy changes in agriculture. Understanding the relationships that may exist between farms may thus give a better insight into the ongoing structural change in farming.

The study presented in this adds to the existing literature especially in two ways. Firstly, we extend the existing methods by using a mixture modelling approach to investigate spatial interdependence between farms. Generally, studies in this strand of the literature estimate mean effects of neighbouring farms' characteristics on farmers' decision to exit farming. However, some farms may be more or less sensitive to the characteristics of their neighbours, due to some specific individual characteristics. The resulting parameters based on homogeneity assumption may thus be biased and inconsistent because of the presence of unobserved farm heterogeneity (Pennings and Garcia 2004). One way to tackle this issue is to use modelling frameworks that allow controlling for unobserved farm heterogeneity. Various modelling approaches such as fixed and random effect, random parameter and mixture models can be used to control for unobserved heterogeneity (Greene 2012). Among these strategies, the mixture modelling framework has the advantage to allow the data themselves to sample select and gather observations characterised by similar relations between dependent and independent variables. Therefore, the mixture modelling approach can group farms with similar behaviours and thus could help identify specific impacts of neighbouring farm's characteristics.

Secondly, we develop the mixture modelling approach in order to handle panel data to capture potential dynamic effects in farmers' decisions. To the best of our knowledge, we are the first to investigate spatial farm interdependence both using panel data and controlling for unobserved heterogeneity. The fundamental advantage of a panel dataset over a cross section one is that the former allows greater flexibility in modelling differences in the behaviour of individuals (Greene 2012). We can therefore expect that this approach could enable grouping farms with similar behaviours and thus reveal different impacts of neighbouring farms' characteristics on farmers' decision to exit farming.

This paper is structured as follows. The next section provides theoretical arguments supporting the empirical application of this study. Section 3 presents the modelling approach and the corresponding estimation procedure. The data used for our empirical application and explanatory variables for the model specification are presented in Section 4. Section 5 reports the main results. The last section concludes with some considerations on possible improvements of this study for further research.

2 On heterogeneity in spatial interdependence between farms

Neighbouring farms' characteristics may have important impacts on own farm size and/or on farmers' decision to exit farming. According to Storm et al. (2015), a farm will survive if its willingness to pay (WTP) for land is greater than the WTP for land of its neighbours. As the WTP for land of a farm depends on the farm characteristics, the farmer's decision resulting from the difference in his/her WTP for land is therefore related to his/her neighbouring farms' characteristics. In this study, we argue that the impact of neighbouring farms' characteristics also depends on the own characteristics of the farmer under consideration. Focusing on the neighbouring farms' specific characteristic that is size, we extend Storm et al. (2015)'s theoretical background providing some additional elements supporting this proposition.

The existing literature distinguishes two types of effects of neighbouring farms' size originating from technology adoption. On the one hand, neighbours can be viewed as competitors especially for the acquisition of plots (Weiss 1999). In this case, a farmer surrounded by larger farms may be constrained to close his/her operation since larger farms are more likely to adopt new technologies earlier given their potentially greater access to information and better financial capacity (Goddard et al. 1993). Larger neighbours therefore have a higher WTP for land, leading to a negative impact on the probability to survive, for the farm under consideration. On the other hand, neighbours can be considered as a source of motivation and example to adopt new technologies (Case 1992, Holloway et al. 2002). In this case, neighbouring farms' size positively influences the survival of the farm under consideration, because a farmer surrounded by larger farms is more likely to benefit from the innovation of larger neighbouring farms (Harrington and Reinsel 1995). This may imply an increase in the WTP for land for those neighbouring farms since new technology adoption generally requires acquisition of land for an optimal use of the technology.

However, these interactions among neighbours may depend on the farm under consideration. Indeed, we expect that the effect of neighbouring farms' size is rather heterogeneous across farms under consideration, and crucially depends on the type and characteristics of the farm and the farmer considered. Among others, farmer's motivation, which may shape their behaviours, is one of the most important sources of farm heterogeneity. Indeed, neighbouring farms' size is more likely to have an impact (positive or negative) on farmers who are mainly motivated by profit maximisation. In the context of a free market competition, such business-oriented farms are constrained either to innovate or to exit, leaving resources to be acquired by more innovative competitors in the latter case (Harrington and Reinsel 1995). The persistence of commercial farms thus depends on their competitiveness, that is, on their capacity to innovate. However, this capacity differs across farms and depends on a variety of factors such as accessibility to technology and land, managerial capacity, risk perception, attitudes towards risk, etc. (Conradt et al. 2014, Trujillo-Barrera et al. 2016).

Based on these considerations, we hypothesise that there are at least two different types of farms that respond differently to neighbouring farms' size: a negative response because of competition for land, or a positive response resulting from positive spill overs of new technology adoption. The main question addressed in the present analysis is: which type of relationship between farms is the prevailing one? Investigating such a question may help understand farm size dynamics in specific farming contexts.

3 Specifying and estimating a mixture model for farm survival

Regarding farm survival, a probit model is applied. A latent regression underlies the probit model, where the latent variable represents the utility that is obtained from staying in or exiting the farming sector. Farmers' utility may be affected by their own WTP for land as well as their neighbours' WTP for land. The latent variable y^*_{it} underlying the probit model determines the outcome of the farmer's decision to stay in business in two consecutive years. As yearly information about farmers' decisions is available, the observed outcome can be thus obtained as:

$$\begin{aligned} y_{it} &= 1 \quad \text{if} \quad y^*_{it} > 0, \quad \forall t \in T_i \\ y_{it} &= 0 \quad \text{if} \quad y^*_{it} \leq 0 \end{aligned} \tag{1}$$

where y_{it} is the observed outcome at time t for farm i which takes values: $y_{it} = 1$ if the farm survives two consecutive years, and $y_{it} = 0$ otherwise; T_i is the length of time that farm i is observed. The latent variable at time t is in turn given by:

$$y^*_{it} = \mathbf{x}_{it-1}\boldsymbol{\beta} + \epsilon_{it}, \qquad t = 1, 2, \cdots, T_i \leq T \tag{2}$$

where $\boldsymbol{\beta}$ are the parameters to estimate, $\mathbf{x}_{it-1}$ are own and neighbouring farm characteristics. The disturbances ϵ_{it} are T-variate, normally distributed with $T \times T$ positive definite covariance matrix $\boldsymbol{\Sigma}$. The typical element of $\boldsymbol{\Sigma}$ is denoted σ_{ts} and the standard deviations σ_t. The data on $\mathbf{x}_{it-1}$ are assumed to be strictly exogenous, which implies that

$\mathrm{Cov}[\mathbf{x}_{it-1}; \epsilon_{js}] = 0$ across all individuals i and j and all periods t and s (see Greene (2004) for more details).

The explanatory variables are lagged one year to reflect the response delay of the adjustment to exogenous variables. Neighbouring farms' characteristics are introduced in the specification of the models to capture spatial effects and interdependence between farms. In this analysis, spatial interdependence between farms are captured using explanatory variables defined at certain geographical level, instead of defining spatial weighting matrix which is the methodology generally applied in the literature because of data limitations. This approach is convenient for our estimation procedure and has already been applied to account for spatial dependence in other strands of the economic literature (see Teillard et al. (2012) for recent example).

As argued in the previous section, neighbouring farms' size may influence farmers' decisions in various ways. To capture the heterogeneity in farmers' responses to their neighbouring farms' characteristics, we apply a mixture modelling approach, which allows capturing unobserved heterogeneity. The mixture modelling approach supposes that the farm population is divided into more than one homogeneous group; each type of farms is characterised by a specific effect of the specified exogenous variables on farmers' decisions. Let $\mathbf{y} = (\mathbf{y}_1^T, \cdots, \mathbf{y}_n^T)$ denote the observed random sample where $\mathbf{y}_i$ is the sequence of choices or states of farm i over a certain period of time. Under a mixture approach, the density $f(\mathbf{y}_i)$ is written as (McLachlan and Peel 2004):

$$f(\mathbf{y}_i) = \sum_{g=1}^{G} \pi_g f_g(\mathbf{y}_i) \tag{3}$$

where π_g is the proportion of farms belonging to type g with $g = 1, 2, \cdots, G$, and f_g is type-g density as described by equations (2). Since the unobserved types have to be exhaustive and mutually excluding, the π_g proportions are non-negative and sum up to unity.

Under such a mixture approach, the conditional probability density for the observed data for farm i is:

$$f(\mathbf{y}_i|\mathbf{X}_i; \mathbf{\Psi}) = \sum_{g=1}^{G} \pi_g f(\mathbf{y}_i|\mathbf{X}_i; \mathbf{\Phi}_g) \tag{4}$$

where $\mathbf{\Psi} = (\pi_1, ..., \pi_G, \mathbf{\Phi}_1, ..., \mathbf{\Phi}_G)$ are the parameters to be estimated; and the probability density function specific to farm type g, given by:

$$f(\mathbf{y}_i|\mathbf{X}_i; \mathbf{\Phi}_g) = f(\mathbf{x}_{it-1}; \boldsymbol{\beta}_g) = \left[F(\mathbf{x}_{it-1}\boldsymbol{\beta}_g)\right]^{y_{it}} \left[1 - F(\mathbf{x}_{it-1}\boldsymbol{\beta}_g)\right]^{(1-y_{it})} \tag{5}$$

where $F(\mathbf{x}_{it-1}; \Phi_g)$ is the cumulative density function for and farm type g and y_{it} is the observed outcome.

The mixture model described above is estimated using the maximum likelihood method. Assuming that, for each model, observations are independent within farm types given $\mathbf{x}_{it-1}$, the log-likelihood (LL) function for the parameters $\mathbf{\Psi}$ of the model, conditional on observing $\mathbf{y}_i$, is written as:

$$LL(\mathbf{\Psi}) = \sum_{i=1}^{N} \ln \left\{ \sum_{g=1}^{G} \pi_g \prod_{t=1}^{T_i} f(\mathbf{x}_{it-1}; \mathbf{\Phi}_g) \right\} \tag{6}$$

As the type of farms is unknown beforehand, the expectation-maximisation (EM) algorithm is used to estimate the parameters of the models. The EM algorithm simplifies the complex log-likelihood in equation (6) into a set easily solvable log-likelihood functions by treating the unobserved farm type as a missing information (McLachlan and Krishnan 2007).

4 Empirical application

For our empirical application, we used data provided by the 'Mutualité Sociale Agricole' (MSA), the French authority for farmers' healthcare and social security. The MSA database contains information about all individuals who declare carrying out a non-salaried farming activity in France, and about their farm. Information is collected annually and is available for farmers who were active on January 1st of each year, from 2004 to 2014. The database can be actually considered as almost exhaustive for the French farm population[1], so we can assume that a farm: i) survived if it remained in the MSA database over the whole period of observation; ii) started business if it entered the database after 2004; iii) quit farming if it was not in the database before 2014. In this empirical application, we restricted our investigation to farms located in Brittany (Western France), which is one of the largest agricultural regions in France.

The analysis of the spatial interdependence between neighbouring farms in their decisions to survival requires special attention because the database exhibits two main limitations for such a study. Firstly, the MSA database contains only a few variables that can be used to explain farm survival. We thus choose to concentrate on the possible impacts of the limited set of available variables. Other databases are merged with the MSA to provide additional information especially at different special scales. The most important farm characteristic that may play a role in the probability to survive is farm size in terms of total UAA (*area*) and farm total agricultural profit (*agri_profit*). The age of the farm holder (*age*), dummies indicating that the farm production specialisation is pig and/or poultry (*pig/poultry*), and a dummy indicating that the legal status of the farm is a corporate farm in opposition to partnerships or individual farms (*corporate*), are also included in the model specification. Theses variables are introduced to capture farm observed heterogeneity. Age square and area square are used to capture non-linear effect of the farm holder age. As a farm's WTP for land may decrease at retirement time despite high agricultural profits, we control for the impact of retirement time by using an interaction term between farm agricultural profit and a dummy indicating that the farmer is close to retirement time (*agr_profit_ × _retirement*). According to the MSA, the minimum age for retirement in France is 60 years old but farmers' behaviour may change earlier. Since some studies have indeed shown that farmers' succession is prepared between 5 and 10 years in advance, we choose to retain 55 years old and above as the indicator of retirement closeness (Gaté and Latruffe 2016).

Secondly, the MSA database contains no information about the precise geographical location of the farmstead and farm plots. It is therefore impossible to determine the actual distance between farms. Only the municipality where the farmstead is located is available in the database. As municipalities in France are relatively small and given the dispersion of farm plots on French farms, farms may compete for land in their own

[1] The database is considered as 'almost' exhaustive because only it does not survey small farms which do not contribute to the MSA as well as corporate farms employing only salaried workforce.

municipality and even in neighbouring municipalities (Piet and Cariou 2014, Latruffe and Piet 2014). We thus use average farm characteristics at the municipality level to capture the effects of neighbouring farms' size on a farm's survival. At a first spatial scale, we consider farms located in the same municipality as the farm under consideration. Brittany counts 1,270 municipalities with an average area of 21 square km. From this, we calculate the average farm size by municipality *(average_mun_area)* and use it as a proxy for neighbouring farms' size. We also calculate, using the MSA database, the average age of farm holders (*average_mun_age*), the share of farms specialised in pig and/or poultry (*mun_pig/poultry_share*) and the share of corporate farms (*mun_corporate_share*) at the municipality level.

Following Storm and Heckelei (2016), we also include the same variables calculated at a larger spatial scale than the municipality. This allows distinguishing the effects of farm interactions that take place on a smaller spatial scale from spatial correlation arising from unobserved spatially correlated regional characteristics at a larger scale. Specifically, we calculate the average characteristics and shares for small agricultural regions (SAR), which is a geographical unit that may contain one or more municipalities. The SAR level is a zoning that was specifically designed to define units with homogeneous conditions in terms of agricultural systems, soil and climate. The mean size of a French SAR is 22.4 ± 13 square km (Teillard et al. 2012). Based on the INSEE 2007 classification, there exist 25 SAR in Brittany, that is, about 50 municipalities by SAR on average. The variables (farm area, age of farm holder, pig/poultry specialisation and corporate legal status) are defined here at the SAR level as: *average_sar_area*, *average_sar_age*, *sar_pig/poultry_share* and *sar_corporate_share*.

[Table 1 about here.]

Additionally, we use the rate of unemployment in employment regions (*unempl_rate*). The unemployment rate captures the opportunities for off-farm activities and is thus supposed to have a direct effect on the probability for farms to remain in farming. A time trend is used in addition. It may capture potential effects of, for example, technical change in farming that may influence farm survival. Descriptive statistics are reported in Table 1.

5 Results

Table 2 reports the estimated parameters for both a pooled estimation where unobserved heterogeneity is not considered and the mixture probit model. Estimated parameters of the pooled probit thus constitute a mean effect of the considered farms' own characteristics and neighbouring farms' characteristics on the probability to survive from one year to the next, while the mixture model identifies impacts which are specific to the endogenously determined homogeneous farm types.

[Table 2 about here.]

The results from the homogeneous model are consistent with our expectations. Overall, a positive impact is observed for the age of farm holders, the operated farm size (land), and the total agricultural profit. The results show a non-linear impact both for the age of farm holders and the total farm area. The negative impact of the square of age means that older farm holders are less likely to remain active over years. The effect the square of farm area is lower which may suggest that very large may face some constraints that tend to decrease their probability to survive in comparison to smaller farms. A positive effect is also observed for farm specialisation in pig and/or poultry and for farms operated under a corporate legal status. This result is in agreement with our expectations: the probability to survive of farm specialised in pig/and or poultry production may be less related to competition for land, while corporate farms may be in a better place to compete because of lower financial and credit constraints. Farm agricultural profit is also found to positively affect farm survival, but farm holders close to retirement time tend to leave the farming sector although this activity is profitable may be because they expect to receive good pension at this time. The average farm size at the municipality level is not significant which may suggest that ignoring farm heterogeneity is not appropriate to analyse the impact of neighbouring size. However, the probability to survive is positively related to the average farm size at the small agricultural region level, which indicates unobserved spatial correlation between regional characteristics.

The mixture probit model distinguishes three optimal types in the studied farm population, especially differing with respect to the effect of neighbouring farms' size. Across all farms, the effect of neighbouring farms' size is negative but insignificant. However, the first and the second types of farms are characterised by a significant positive and, respectively, negative impact of neighbouring farms' size on the probability to survive. In the third type, the effect is considerably smaller and not significant. The negative influence of neighbouring farms' size on the probability to survive is found for the majority of farms (about 54%) while the positive impact is observed only for about 18% of farms. Computed z-scores (not reported here) show that these opposite effects are significantly different at a 1% level. The different effects of neighbouring farms' size observed for the various groups may explain the insignificant impacts for the overall population, that is to say when such unobserved heterogeneity is not considered.

Referring to the discussion in Section 2, the two first types could mostly consist of business oriented farms where farm holders are mainly motivated by profit maximisation. The resulting negative impact of neighbouring farms' size on the probability to survive for type 2 may indicate that farms in this type are rather competitors for land, while the opposite effect for farms in type 1 may originate from positive spill overs of new technology adoption for these farms. Contrary to the two first farm types, the impact of neighbouring farms' size is highly non-significant for the third type which accounts for about 28% of the farm population in Brittany. This initially unexpected type could comprise farms characterised by prevailing non-pecuniary motives. It could be also the case of business oriented farms that have already reached their optimal economic sizeHowley (2015). The probability of survival for such farms may be therefore independent from the size of their neighbours. This result is in line with the impact of the average farm size at the small agricultural region, which has no significant effect on the probability to survive of this third farm type, contrary to the two first types. This suggests that the farming context has no specific influence on the persistence of such (third type) farms in the sector. This interpretation is confirmed by the positive impact of the time trend, meaning that the probability to survive increases for those (third type) farms over time, while the inverse trend is observed for farms that compete for land. This result is consistent with the evolution of farm size over the years: the larger the neighbours and the higher the competition for land, then the more difficult it becomes to innovate since new adoptions generally require more land.

[Figure 1 about here.]

The descriptive statistics for farm types (not reported here) show that the probability of belonging to a specific type does not correlate to the farm and farmer characteristics considered in the model specification. There is no significant difference in the distribution of these observed characteristics between the three types of farms. This result means that the unobserved heterogeneity cannot be sufficiently controlled for by the observed farms and/or farmer characteristics considered.

Figure 1 reports the probability that an average farm remains active from year to year from 2003 to 2013 with respect to the average farm size calculated at the municipality level. Three panels are provided, one for each type of farms. The figure shows that, overall, the probability to survive is lower for competitors for land and this probability decreases with neighbouring farms' size (farm type 2). The opposite effect is observed for farms that benefit from positive spill overs of new technology adoption (farm type 1). Figure 1 also shows that the probability to survive is higher and does not vary with the neighbouring farms' size for farms having mainly non-pecuniary motives or already that reached their optimal size (farm type 3).

In addition to the fact that the mixture probit model enables identifying specific impacts of neighbouring farm size, it presents some other advantages in comparison to the pooled estimation where unobserved heterogeneity is not considered. The results show that the finite mixture model performs better in terms of all criteria reported at the bottom of Table 2 (correct predictions, log-likelihood, and AIC, BIC, AIC3 information criteria). Furthermore, the finite mixture probit model is more accurate in predicting farm survival in Brittany. The superiority of the mixture model in particular comes from the specificity value. Indeed, the mixture model performs about 15% better in predicting farm exit in Brittany than the pooled estimation.

6 Concluding remarks

The study conducted in this paper underlines the importance of accounting for unobserved farm heterogeneity in spatial interdependence between farms when analysing farm structural change. This was made possible by a modelling approach that enables endogenously grouping farms within specific homogeneous types. This approach allows identifying specific relationships between farms via the impact of neighbouring farms' size, measured at the municipality level, on farm survival. The application to a panel of French farms located in Brittany shows that the relationship between farms in this region is rather in terms of competition for land than in terms of positive spill overs of new technology adoption. This results in a negative impact of neighbouring farms' size on the probability to survive for a majority of farms. However, for a about 18% of the farm population, the neighbouring farms' size has no significant impact on the probability to survive, which could suggest the existence of potential non-pecuniary motives for these farms.

The results from this study confirm that neighbouring farms' size may differently influence farm survival. This suggests that farms should not be considered as isolated entities and that agricultural policies should take into account potential relationships between farms. Moreover, the results also show that unobserved heterogeneity in farming cannot be fully linked to some observable farms' and/or farmers' characteristics.

While this study clearly adds to the existing literature, the analysis could be improved especially in two different ways. Firstly, the impact of neighbouring farms' size is investigated here by using the average farm size at the municipality as a proxy. However, farms may compete for land in other municipalities in addition to their own municipality. Hence, investigating the impact of neighbouring farms' size using a spatial weighting matrix constructed at the municipality level or, if possible, at the farm level (using appropriate data sources that include the exact location of farms), could help estimate more efficiently the impact of neighbouring farms' characteristics. Secondly, some other factors, such as subsidies received by the farms and their neighbours, may have a significant impact on farm survival as it has been shown by previous studies. Including such variables in the analysis may thus improve the understanding of structural change in farming.

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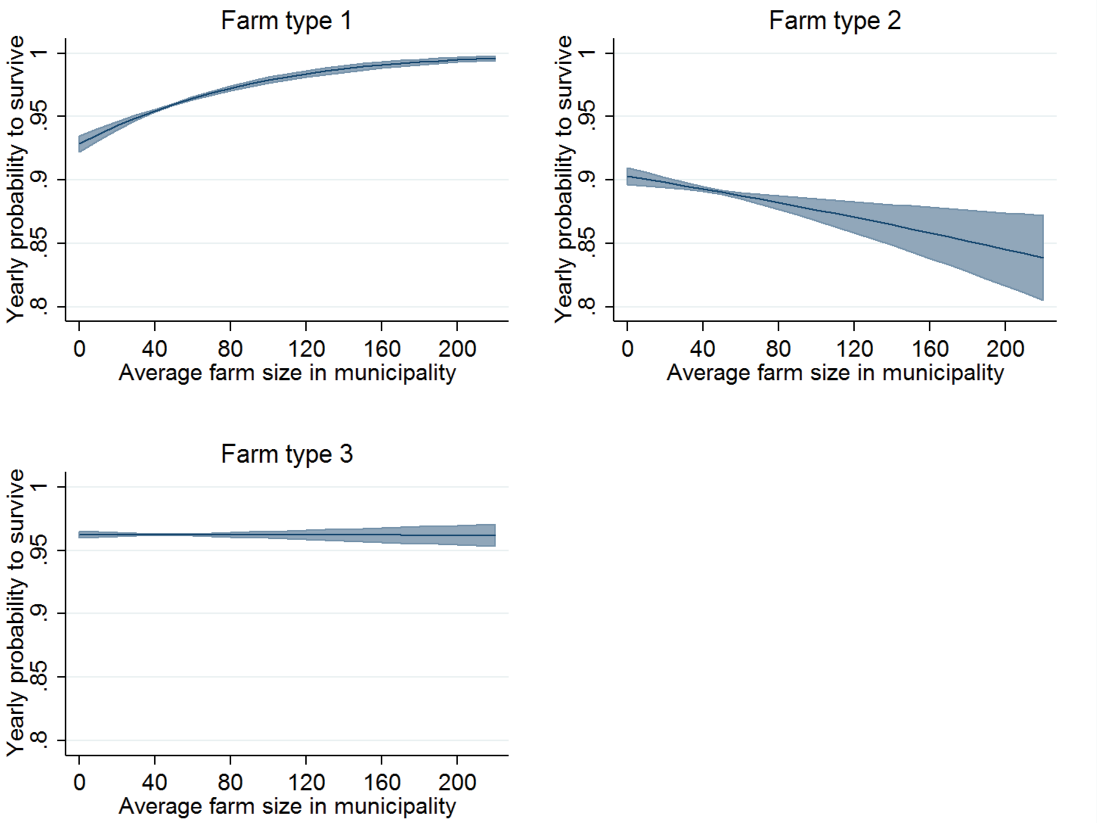
Figure 1: Probability to survive for varying municipality-level average farm sizes by unobserved farm types (predicted margins with 95% confidence intervals)



Source: MSA COTNS database, Bretagne 2004-2014 - authors' calculations

Table 1: Definition and descriptive statistics of explanatory variables (n=344,617)

Variable	Code	Mean	St.Dev.	Min	Max
Farm level					
Age of the farm holder (years)	*age*	48.45	9.12	18.50	99.00
Total UAA (ha)	*area*	48.82	41.20	0.00	580.30
Total agricultural profit (1,000 Euros)	*agri_profit*	10.78	12.72	-313.92	465.72
Pig/poultry specialisation dummy (1 if yes)	*pig/poultry*	0.18	0.38	0.00	1.00
Corporate farm dummy (1 if yes)	*corporate*	0.46	0.49	0.00	1.00
Municipality level (mun)					
Average farm holder age	*average_mun_age*	48.45	2.33	25.00	88.00
Average farm size	*average_mun_area*	48.82	13.60	0.00	227.29
Share of pig/poultry farms (%)	*mun_pig/poultry_share*	18.00	13.00	0.00	100.00
Share of corporate farms (%)	*mun_corporate_share*	46.00	14.00	0.00	100.
Small agricultural region level (sar)					
Average farm holder age	*average_sar_age*	48.45	1.12	44.30	51.28
Average farm size	*average_sar_area*	48.82	7.66	13.92	70.61
Share of pig/poultry farms	*sar_pig/poultry_share*	18.00	7.00	1.00	29.00
Share of corporate farms	*sar_corporate_share*	46.00	8.00	24.00	70.00
Employment regional level					
Unemployment rate (%)	*unempl_rate*	7.03	1.21	3.70	9.90

Source: MSA COTNS database, Bretagne 2004-2014 - authors' calculations

Table 2: Estimated parameters for both the pooled and the mixture probit model for farm survival

Variable code	Pooled	Mixture		
		type 1	type 2	type 3
intercept	0.0358	1.3314**	-0.8903*	-60.2809***
	(0.3396)	(0.4774)	(0.3875	(1.3082)
time_ trend	0.0062**	-0.0222***	-0.0286***	0.1037***
	(0.0028)	(0.0040)	(0.0033)	(0.0092)
age	0.0104***	-0.0258***	0.0066*	3.2279***
	(0.0025)	(0.0036)	(0.0027)	(0.0328)
age_ square	-0.0003***	2.10e-05	-0.0001***	-0.040***
	(2.23e-05)	(3.26-05)	(2.51e-06)	(0.0004)
area	0.0042***	-0.0173***	0.0092***	0.0007
	(0.0002)	(0.0004)	(0.0002)	(0.0008)
area_ square	9.64e-06***	0.0001***	2.40e-05***	4.37e-05***
	(1.09e-06)	(2.29e-6)	(1.30e-06)	(6.01e-06)
agri_ profit	0.0009**	-0.0499***	0.004***	0.0508***
	(0.0004)	(0.0007)	(0.0004)	(0.0045)
agri_ profit_ × _ retirement	-0.0185***	-0.0283***	-0.0162***	-0.0515***
	(0.0006)	(0.0008)	(0.0006)	(0.0046)
pig/poultry	0.0228**	0.2074***	0.0281*	0.2085***
	(0.0105)	(0.0167)	(0.0119)	(0.0333)
corporate	0.3093***	1.2208***	0.2897	-0.0157
	(0.0091)	(0.0144)	(0.0101)	(0.0319)
average_ mun_ age	0.0051***	-0.0010)	0.0053*	0.0202***
	(0.0018)	(0.0025)	(0.0021)	(0.0061)
average_ mun_ area	-0.0003	0.0049***	-0.0013**	-0.0001
	(0.0004)	(0.0005)	(0.0004)	(0.0012)
mun_pig/poultry_ share	0.0104	-0.0373	0.0062	-0.1104
	(0.0354)	(0.0504)	(0.0407)	(0.1149)
mun_ corporate_ share	-0.0545	-0.4082***	-0.0202	-0.0499
	(0.0358)	(0.0497)	(0.0409)	(0.1140)
average_ sar_ age	0.0181**	0.0435***	0.026***	0.1549***
	(0.0071)	(0.0099)	(0.0081)	(0.0232)
average_ sar_ area	0.0018***	0.0026**	0.0032***	-0.0022
	(0.0007)	(0.0010)	(0.0008)	(0.0024)
sar_ pig/poultry_ share	0.1488**	1.0079***	0.1223	0.1305
	(0.0709)	(0.0993)	(0.0816)	(0.2306)
sar_ corporate_ share	0.1402**	0.4428***	0.1994**	0.0997
	(0.0677)	(0.0962)	(0.0770)	(0.2210)
unempl_ rate	0.0104***	0.0311***	0.0164***	0.0797***
	(0.0033)	(0.0046)	(0.0038)	(0.0105)
Type shares		17.90%	54.20%	27.90%
Number of observations	317,177		317,177	
Correct predictions	92.73%		93.85%	
Log pseudo-likelihood	-76,323		-73,696	
AIC	152,684		147,470	
BIC	152,886%		147,886	
AIC3	152,703		147,509	

Note: *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively; standard errors in parentheses.

Source: MSA COTNS database, Bretagne 2004-2014 - authors' calculations