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**Heterogeneity in spatial interaction effects on farm survival and growth:  
evidence from Brittany**

Legrand D. F. Saint-Cyr<sup>\*1</sup>, Hugo Storm<sup>2</sup>, Thomas Heckelei<sup>2</sup>, Laurent Piet<sup>1</sup>

\*Corresponding author: SMART, AGROCAMPUS OUEST, INRA, 4 allée Adolphe Bobierre, CS 61103, F-35011 Rennes cedex; [legrand.saintcyr@agrocampus-ouest.fr](mailto:legrand.saintcyr@agrocampus-ouest.fr)

<sup>1</sup>SMART, AGROCAMPUS OUEST, INRA, 35000, Rennes, France

<sup>2</sup>University of Bonn, Germany

## **Abstract**

Accounting for spatial interdependency is relevant when assessing policy changes in farming because of potential interactions between farms. However, impacts of neighbouring farm characteristics may vary according to farmers' motivations. To identify specific impacts of neighbouring farm size both on farm survival and growth, we use a mixture modelling framework that allows accounting for heterogeneity in interactions between farms. An application to a panel of farms in Brittany over 2003 to 2014 shows that interactions between farms are rather competition for land than positive technology adoption spill overs, leading to a negative impact of neighbouring farm size on the probability to survive. The results also show that neighbouring farm size has a positive but indirect effect on farm growth through its impact on farm survival. These results prove that more attention should be paid to heterogeneity in spatial interactions in farming for a better understanding of farm size dynamics.

**Keywords:** Farms interdependence, Finite mixture model, Unobserved heterogeneity, Spatial interaction

**JEL classification:** C23, D22, Q12

## I. 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 (Bollman, Whitener, and Tung, 1995; Eastwood, Lipton, and Newell, 2010). Understanding the factors affecting farmers' decision to exit farming and farm growth has been a concern of agricultural economists and policy makers for quite some time. For example, Weiss (1999) investigated farm survival and growth in Upper Austria; Breustedt and Glauben (2007) examined the exit process of Western European farmers; Dong, Hennessy, and Jensen (2010) studied the exit decision of finisher hog production in North America. In France, Aubert and Perrier-Cornet (2009) studied factors that influence survival and growth of small farms while Bakucs, Bojnec, and Ferto (2013) investigated the relationship between size and farm growth. Among others, these studies identified important aspects of structural change in farming and showed that farm survival and growth processes may help understanding farm dynamics in different farming contexts. More recently, Storm, Mittenzwei, and Heckeley (2015) empirically investigated the effects of direct payments on exit rates of Norwegian farms and showed that spatial interdependence between farms is an important factor in farmers' decisions to keep their production activities. They show that accounting for spatial interdependency of farms may be highly relevant for an aggregate assessment of policy changes in agriculture.

The objective of this paper is to analyze spatial farm interdependence in the French farming sector. The paper adds to the existing literature in three ways. First, we account for spatial interdependency between farms in both farmers' decisions to continue their production activities over time and farm growth process. Indeed, neighboring farm characteristics may influence farm survival as well as farm growth since these two processes are related to each other given the regulation of the land market in some countries, particularly in France. Accounting for interdependence in both farmers' decisions to survive and farm growth process may therefore improve the analysis of structural change in farming. Some studies have already investigated both farm growth and survival in France and in other farming contexts (see Aubert and Perrier-Cornet (2009) and Weiss (1999) for examples). However, none of these studies have so far taken into account the potential spatial interdependence between farms, to the best of our knowledge.

Second, we extend the existing methods by using a mixture modeling approach to investigate spatial interdependency between farms. Generally, studies in this strand of the literature estimate mean effects of neighboring farm characteristics on farmers' decision to exit farming or to increase their operated farm size. The results from these studies are therefore based on the assumption that all farms have the same probability to survive or all farms will behave alike given the investigated characteristics. In our case for example some farms may be more or less sensitive to the characteristics of their neighbors (e.g. direct payment received, farm size, etc.), due to some specific individual characteristics. If all of these characteristics were observed, controlling for them would lead to more efficiently estimate the impacts of neighboring farm characteristics. Otherwise, the resulting parameters may be biased and

inconsistent due to unobserved farm heterogeneity (Kyriazidou, 1997; Pennings and Garcia, 2004). One way to tackle this issue is to use modeling frameworks that allow controlling for unobserved farm heterogeneity. Various modeling approaches such as fixed and random effect, random parameter and mixture models can be used to control for unobserved heterogeneity (Greene, 2012). Holloway, Lacombe, and LeSage (2007) reported also some strategies that could be adopted in order to control for unobserved heterogeneity in modeling spatial dependence. Among these strategies, they argued that the mixture modeling framework seems to be the most attractive since it is simple and intuitive. According to these authors, one of the main advantages of a mixture modeling approach is that it allows the data itself to sample select and designate observations into the most appropriate designations corresponding to a particular form of spatial dependence. The mixture modeling approach can gather farms with similar behaviors and therefore help to identify specific impacts of neighboring characteristics

Third, we develop the mixture modeling approach in order to handle panel data to capture potential dynamics effects in farmers' decisions. Some studies in the literature have already used panel data to study farmers' decisions to exit farming and farm growth process (see Bakucs, Bojnec, and Ferto (2013) for a recent example). However, to the best of our knowledge, we are the first to investigate spatial farm interdependence both using a panel data and controlling for unobserved heterogeneity. The fundamental advantage of a panel data set over a cross section is that it will allow a more flexibility in modeling differences in behavior of individuals (Greene, 2012). We can therefore expect that using a mixture modeling approach could gather farms with similar behaviors and thus reveal different impacts of neighboring farm characteristics on farmers' decision to exit farming or to increase their production capacity.

This paper is structured as follows. In the next section, we provide theoretical arguments supporting the empirical application of this study. Sections 3 and 4 present the modeling approach and the estimation procedure, respectively. Section 5 reports the application to a panel of French farms located in Brittany, starting with a description of the data used and explanatory variables investigated following by a presentation of the main results. Finally, we conclude with some considerations on possible improvements of this study for further research.

## **II. On farm heterogeneity**

Neighboring farm characteristics may have important impacts on own farm size and/or on farmers' decision to exit farming. Storm, Mittenzwei, and Heckelei (2015) argued that a farm will survive if its WTP for land is greater than the WTP for land of its neighbors. As the WTP for land of farms depends on farm characteristics, farmers' decision resulting from the difference in their WTP for land is therefore related to their neighboring farm characteristics. In this study, we state that the impact of neighboring characteristics of farms depends on farmer characteristics. Focusing on neighboring farm size, we extend Storm, Mittenzwei, and Heckelei (2015)'s theoretical background providing some additional elements supporting this statement.

The existing literature distinguishes two types of effects of neighboring farm size originating from technology adoption. On the one hand, neighbors can be viewed as a

competitor especially for plots (Weiss, 1999). In this case, farmers surrounded by larger farms may be pushed to close their 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 neighbors therefore have a higher WTP for land leading to a negative impact on the probability to survive. On the other hand, neighbors can be considered as source of motivation and example to adopt new technologies (Case, 1992; Holloway, Shankar and Rahmanb, 2002). In this case, neighboring farm size positively influence farm survival because farmers surrounded by larger farms are more likely to profit from the innovation of larger neighboring farms (Harrington and Reinsel, 1995). This may imply an increase of the WTP for land for those farms since new technology adoption generally required acquisition of land for to reduce cost per unit of output.

However, these neighboring interactions might not be equally important for all farms. Instead we expect that the effect of neighboring farm size is rather heterogeneous across farms and crucially depends on the type and characteristics of a farm and the farmer. One of the most important sources of farm heterogeneity that may shape farmer's behavior is their motivation. Neighboring farm size is more likely to have an impact (positive or negative) on farms which are mainly motivated by profit maximization. In the context of free market competition, such business-oriented farms are constrained either to innovate or to exit, leaving resources to be acquired by the innovative farms (Harrington and Reinsel, 1995; Jackson-Smith, 1999). 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 the technology and land, managerial capacity, risk perception, risk tolerance, etc. (Bowman and Zilberman, 2013; Conradt et al., 2014; Trujillo-Barrera, Pennings and Hofenk, 2016).

Nevertheless, not all farmers give priority to the commercial aspect of the farming activities (Maybery, Crase and Gullifer, 2005; Howley, Dillon and Hennessy, 2014). Some non-competitive farms may keep their activity because of less or even non-financial/pecuniary motives (Harrington and Reinsel, 1995), perhaps enjoying the farming lifestyle (Hallam, 1991) or maintain production at sub-optimal levels (Howley, 2015). It may be the case of some environmentally oriented farms (Willock et al., 1999) or certain hobby farms (Daniels, 1986; Holloway, 2002). For such kinds of farms, new technology is evaluated for different aspects others than financial viability before adoption (Mzoughi, 2011). Then, the technology will be adopted only if it is considered as conformed to some predefined criteria. On overall, one can thus expect a lower or even no specific impact of neighboring farm size on the probability to survive or to increase operated size for those farms characterized by less or non-pecuniary motives.

Based on these considerations we hypothesize that there are two different types of farms that respond differently to neighboring farm size. Two questions arise from this: which farms are more likely to be in one of these specific types? And, what is the dominant type of effects in the French farming sector, particularly in Brittany? The response to the first question is theoretical while the second one requires empirical investigations.

### III. Modeling approach

We separately investigate neighboring farm size impacts on farm survival and growth process in farming. For farm survival, a probit model is applied. Following Storm, Mittenzwei and Heckelei (2015), the probit model can be motivated by a latent regression where the latent variable represents the difference between farmers' and their neighbors' willingness to pay (WTP) for land. The latent variable  $y_{it}^*$  underlying the probit model determines the outcome of farmer's decision to survive two consecutive years. As yearly information about farmers' decisions is available, the observed outcome can be thus obtained as:

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

where  $y_{it}$  is the observed outcome at time  $t$  which takes values:  $y_{it} = 1$  if farm survive two consecutive years and  $y_{it} = 0$ , otherwise. The latent variable at time  $t$  is thus given by:

$$y_{it}^* = \mathbf{x}_{it-1}\boldsymbol{\beta} + e_{it}, \quad t = 1, 2, \dots, T_i \leq T \quad (2)$$

where  $\boldsymbol{\beta}$  are parameters to estimate;  $\mathbf{x}_{it-1}$  are own and neighboring farm characteristics; and  $e_{it}$  is an *iid* normal error terms. The disturbances are T-variate normally distributed with  $T \times T$  positive definite covariance matrix  $\Omega$ . The typical element of  $\Omega$  is denoted  $\sigma_{ts}$  and the standard deviations  $\sigma_t$ . The data on  $\mathbf{x}_{it-1}$  are assumed throughout to be strictly exogenous, which implies that  $Cov[\mathbf{x}_{it}; e_{js}] = \mathbf{0}$  across all individuals  $i$  and  $j$  and all periods  $t$  and  $s$  (Greene, 2004).

Farm growth processes of farms staying in is represented by a linear model. The total land used at any specific time  $t$  is thus given by:

$$y_{it} = \mathbf{x}_{it-1}\boldsymbol{\theta} + u_{it}, \quad t = 1, 2, \dots, T_i \leq T \quad (3)$$

where  $\boldsymbol{\theta}$  are vectors of parameters to estimate;  $\mathbf{x}_{it-1}$  are own and neighboring farm characteristics; and  $u_{it}$  is an *iid* normal error terms. In both models, the explanatory variables are lagged for one year to reflect the response delay of the adjustment to exogenous variables. Neighboring farm characteristics are introduced in the specification of the models to capture spatial effects and interdependence between farms.

As argued in the previous section, neighboring farm size may influence farmers' decisions in various ways. To capture heterogeneity in farmers' responses to their neighboring characteristics, we apply a mixture modeling approach, which allows capturing unobserved heterogeneity. The mixture modeling approach supposes that the farm population is divided into more than one homogeneous types; each type of farms is characterized by a specific effect of the exogenous variables, including neighboring farm size, on farmers' decisions. Let  $\mathbf{y} = (\mathbf{y}_1^T, \dots, \mathbf{y}_n^T)$  denotes 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  $f(\mathbf{y}_i)$  writes (McLachlan and Peel, 2004):

$$f(\mathbf{y}_i) = \sum_{g=1}^G \pi_g f_g(\mathbf{y}_i) \quad (4)$$

where  $\pi_g$  is the proportion of farms belonging to type  $g$  with  $g = 1, 2, \dots, G$ , *i.e.* non-negative quantities that sum to one; and  $f_g$  is type- $g$  density as described by equations (2) and (3) for farm survival and growth process, respectively.

Under the mixture approach above, the conditional density for the observed data for farm  $i$  is:

$$f(\mathbf{y}_i | \mathbf{X}_i; \boldsymbol{\varphi}) = \sum_{g=1}^G \pi_g f_g(\mathbf{y}_i | \mathbf{X}_i; \boldsymbol{\varphi}_g) \quad (5)$$

where  $\boldsymbol{\varphi} = \boldsymbol{\varphi}_1, \boldsymbol{\varphi}_2, \dots, \boldsymbol{\varphi}_G$  are parameters and  $f_g$  is the density function for the probit model or the linear model specific for each type- $g$  of farms.

#### IV. Estimation procedure

The mixture models described in the previous section are estimated by maximum likelihood. Assuming independence across time, the log-likelihood (LL) function for the parameters  $\boldsymbol{\varphi}$  of the model, conditional on observing  $\mathbf{y}$  writes:

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

where  $f(\mathbf{x}_{it-1}; \boldsymbol{\varphi}_g)$  are the cumulative density functions for the probit model or and the linear model; respectively given by:

$$f(\mathbf{x}_{it-1}; \boldsymbol{\beta}_g) = [F(\mathbf{x}_{it-1}; \boldsymbol{\beta}_g)]^{y_{it}} [1 - F(\mathbf{x}_{it-1}; \boldsymbol{\beta}_g)]^{(1-y_{it})} \quad (7)$$

and

$$f(\mathbf{x}_{it-1}; \boldsymbol{\theta}_g) = \frac{1}{\sqrt{2\pi\sigma_g^2}} \exp \left\{ -\frac{1}{2\sigma_g^2} (y_{it} - \mathbf{x}_{it-1} \boldsymbol{\theta}_g)^2 \right\} \quad (8)$$

where  $[F(\mathbf{x}_{it-1}; \boldsymbol{\beta}_g)]$  is the probability of survival of farm  $i$  at time  $t$  given that it belongs to the specific type  $g$ ; and  $y_{it}$  is the observed outcomes as defined in section 3.

As the type of farms is unknown beforehand, the expectation-maximization (EM) algorithm is used to estimate the parameters of the models. The EM algorithm simplifies the

complex log-likelihood in equation (6) in a set easily solvable log-likelihood functions by treating farm type as missing information (McLachlan and Krishnan, 2007). Using a non-parametric mixing distribution approach, the complete log-likelihood is thus writes (Train, 2008):

$$LL_c = \sum_{n=1}^N \sum_{g=1}^G v_{ig} \ln \left\{ \pi_g \prod_{t=1}^{T_i} f(\mathbf{x}_{it-1}; \boldsymbol{\varphi}_g) \right\} \quad (7)$$

In this case,  $v_{ig}$  is called the 'posterior' probability that farm  $i$  belongs to the  $g$ -th type with  $\mathbf{y}_i$  has been observed, that is  $P(v_{ig}=1|\mathbf{y}_i, \mathbf{x}_{it-1}, \boldsymbol{\varphi})$ , while  $\pi_g$  is a 'prior' probability of the mixture (McLachlan, G., and D. Peel, 2004). The above expression can be then divided into two components:

$$LL_1 = \sum_{n=1}^N \sum_{g=1}^G v_{ig} \ln \pi_g \quad (8)$$

$$LL_2 = \sum_{n=1}^N \sum_{g=1}^G v_{ig} \sum_{t=1}^{T_i} \pi_g \ln f(\mathbf{x}_{it-1}; \boldsymbol{\varphi}_g) \quad (9)$$

As the farm type is not observed, the posterior probability that farm  $i$  belongs to type  $g$  ( $v_{ig}$ ) has to be estimated from the observations. The EM algorithm therefore consists in the four following steps:

i) **Initialization:** Arbitrarily choose initial values  $\boldsymbol{\Psi}^0 = (\pi_1^0, \dots, \pi_G^0, \boldsymbol{\varphi}_1^0, \dots, \boldsymbol{\varphi}_G^0)$  for the parameters of the models.

ii) **Expectation:** At iteration  $p + 1$  of the algorithm, compute the expected probability that farm  $i$  belongs to a specific type  $g$  while observing  $\mathbf{y}_i$  and given parameters  $\boldsymbol{\varphi}^{(p)}$ . This conditional expectation probability, that is, the posterior probability  $v_{ig}^{(p+1)} = v_{ig}(\mathbf{y}_i; \boldsymbol{\varphi}^{(p)})$  can be obtained according to the Bayes' law:

$$v_{ig}^{(p+1)} = \frac{\pi_g^{(p)} \prod_{t=1}^{T_i} f(\mathbf{x}_{it}; \boldsymbol{\varphi}_g^{(p)})}{\sum_{h=1}^G \pi_h^{(p)} \prod_{t=1}^{T_i} f(\mathbf{x}_{it}; \boldsymbol{\varphi}_h^{(p)})} \quad (10)$$

Replacing  $v_{ig}$  by its expected value in equation (7) leads to the conditional expectation of the complete data log-likelihood.

iii) **Maximization:** Update  $\boldsymbol{\varphi}^{(p)}$  by maximizing the complete log-likelihood conditional on the observations. The model parameters are thus updated as:

$$\boldsymbol{\varphi}^{(p+1)} = \operatorname{argmax}_{\boldsymbol{\varphi}} \sum_{n=1}^N \sum_{g=1}^G v_{ig}^{(p+1)} \sum_{t=1}^{T_i} \ln f(\mathbf{x}_{it-1}; \boldsymbol{\varphi}_g) \quad (11)$$

The maximization process of the above equation is straightforward. The parameters of the model  $\hat{\boldsymbol{\varphi}}^{(p)}$  are updated considering  $v_{ig}(\mathbf{y}_i; \boldsymbol{\Psi}^{(p)})$  as weight factors for each observation. Then, the prior probabilities of belonging to a specific type are updated as:

$$\pi_g^{(p+1)} = \frac{\sum_{i=1}^N v_{gi}^{(p+1)}}{\sum_{i=1}^N \sum_{h=1}^G v_{ih}^{(p+1)}}, \forall g \in G \quad (12)$$

iv) **Iteration:** Return to expectation step ii) using the updated parameters ( $\pi_g^{(p+1)}$  and  $\boldsymbol{\varphi}^{(p+1)}$ ) and iterate steps ii) and iii) until convergence of the observed log-likelihood given by equation (5).

At convergence, the resulting parameters ( $\hat{\boldsymbol{\varphi}}^{(p)}$ ) are considered as optimal. Because of the potential presence of a high number of local maxima (Hess, Bierlaire and Polak, 2006), the EM algorithm is run with various initial parameter values (randomly chosen) and the resulting values with the largest likelihood at convergence are chosen.

## V. Empirical application

For our empirical application, we use data from the "Mutualite Sociale Agricole" (MSA), the French authority for farmer healthcare and social security. The MSA database contains information about all individuals who declare a non-salaried farming activity in France and their farms. Information is collected annually and is available for farmers who were active on January 1st of each year from 2002 to 2014. The database can be actually considered as almost exhaustive so we can assume that a farm: i) survived if it remained in the database over the whole period of observation; ii) started business if it entered the database after 2002; iii) quit farming if it exited the database before 2014.

However, using the MSA data requires some preliminary works to adapt the database to analyze interdependence between farms. The data have first to be consolidated at the farm level because the MSA collects information about farm holders. Only data from 2004 to 2014 that is operated farms from 2003 to 2013 in the consolidation because of inconsistency regarding information for the two first years of the database. We restrict our application on farms located in Brittany, which is one of the largest agricultural regions in France.

### 5.1. Dependent and explanatory variables

For the analysis of farm survival, the dependent variable takes the value 1 if farm survive and 0 otherwise. Since we considered all farm whatever their production system, a farm survives if it remains present in the database two consecutive years, that is, if farm holders contribute to the MSA in the later year. Farm growth is represented by the evolution of the total land used in hectare over the period of observation. The analysis of spatial interdependence between farms

in the process of farm survival and growth requires special care because the MSA database exhibit two main limitations.

First, the MSA database contains only few variables that can be used to explain farm survival and growth in Brittany. We thus choose to concentrate only on the possible impacts of the limited set of available variables. All explanatory variables are derived from information collected by the MSA on farm holders. The most important farm characteristics that may play a role for the probability to survive are farm size in terms of total land used (*area*) and farm total agricultural benefit (*agri\_ben*). Both explanatory variables are expected to positively influence the probability to survive and increase operated farm size because such farm characteristics may increase the farm's willingness to pay (WTP) for land. While the total land used is rather a proxy of path dependency, the total agricultural benefit indicates whether or not farming is a profitable activity. As farm WTP for land may decrease at retirement time despite high agricultural benefits, we control for retirement time impact by using a cross effect of farm agricultural benefit and a dummy indicating that the farmer is over 54. According to the MSA, the minimum age for retirement in France is 60, but farmers' behavior may change a bit earlier. Age of farm holder (*age*) and dummies indicating farm specialization in pig and/or poultry production (*soil-less*) and legal status of farms (*corporate*) are also included in the model specification.

Second, the MSA database contains no information about the precise geographical location of the farm-stead or plots. It is therefore impossible to determine the distance between farms. Only the municipality where the farm-stead is located is available in the database. As municipalities in France are relatively small and given farm plots dispersion, farms may compete for land over a whole municipality and even over neighboring municipalities. We thus use farm characteristics at the municipality level to capture effects of neighboring farm size on farm survival and growth. For this study, we considered only farms located in a same municipality as neighbors. Brittany counts 1,270 municipalities with an average area of 21 km<sup>2</sup>. We then derived the average farm size by municipality (*mun\_area*) as a proxy of neighboring farm size. We also derived the average age of farm holders (*mun\_age*), the share of farms specialized in pig and/or poultry (*mun\_soil-less*) and share of corporate farms (*mun\_corporate*) at the municipality level. Following Storm and Heckeley (2016), we include that same variables calculated at a larger spatial scale. The aim is to distinguish the effects of actual farm interaction, take place on a smaller spatial scale, and spatial correlation arising from unobserved spatially correlated regional characteristics at a larger scale. Specifically, we calculate the average characteristics within *small agricultural areas (saa)*, which is a geographical unit that may contain one or more municipalities. Table 1 presents summary statistics for all the explanatory variables.

Additionally, we used the rate of unemployment by small employment area (*unempl\_rate*). The unemployment rate shows the possibility to access to non-farm activities and is thus supposed to have a direct effect on the probability of farms to remain in farming but an indirect effect on farm growth because of its impact on farm survival. Given the land market regulation in France, the more farms exit the farming sector the higher the possibility to increase operated farm size for the remaining farms. A time trend is also used to capture time effect on

farm survival and growth. We used the same set of explanatory variables to explain both farm survival and growth. Since the dependent variable is the total land used in the second model, the logarithm of the total land is used to facilitate convergence of the model. All explanatory variables are lagged one year because it is supposed that farmers take their decisions based on available information.

## **5.2. Results**

We estimate the finite mixture models in order to divide farms in sub-populations on the basis of similarity of their behaviors and identify – among others – different impacts of neighboring farm size. The mixture probit model and the mixture linear model are estimated separately. Based on the discussion in section 2, we estimate the model specifying different numbers of types from one to three. First, we focus on farm survival from the finite mixture probit model; then, we analyze the impact of neighboring farm size on farm growth process from the finite mixture normal regression model.

### **5.2.1. Farm survival segments in Brittany**

The mixture probit model casts the farm population of Brittany into three mean types, differing with respect to the effect of neighboring farm size (see Table 2). Across all farms the effect of neighboring farm size is negative but insignificant. However, the first and the second types of farms are characterized, respectively, by a significant positive and negative impact of neighboring farm size on the probability to survive. In the third type the effects is considerably smaller and insignificant. The negative influence of neighboring farm size on the probability to survive is found for the majority of farms (about 54%) while a positive impact is observed only for about 18% of farms. Computed z-scores show that these opposite effects are significantly different at a level of 1% (see Table 3). According to the discussion in section 2, the two first types could gather specially business oriented farms where farm holders are meanly motivated by profit maximization. The resulting negative impact of neighboring farm size on the probability to survive indicates that farms in this type are especially competitors for land. As competitiveness is most often related to farm size, the larger are your neighbors the more competitive they are. Because farms compete for a fixed asset of land, business oriented farms are thus constraint to close their activity if they are not competitive. Conversely, farms that are positively affected by the size of their neighbors are farms benefiting from positive spillovers. Since larger farms are more likely to adopt new technology, farms surrounded by large neighbors could have more access to information about new technology.

Contrary to the two first types of farms, the impact of neighboring farm size is highly non-significant for about 28% of the farm population in Brittany. According to the discussion in section 2, this type could gather farms characterized by less or even no pecuniary motives. It could be also the case of business oriented farms that already reach their optimal economic size. The probability of survival for such farms may be therefore independent from the size of their neighbors. The results also show that the effect of the average farm size at the small agricultural area on the probability to survive of this type of farms is not significant contrary to the two first

types. This could mean that the farming context may have no specific influence on the persistence of such farms in the sector. This result is confirmed by the positive impact of the time trend meaning that the probability to survive increases for those farms which is not surprising given the discussion in section 2. The inverse trend is observed for farms that compete for land. This negative trend could be explained by the evolution of farm size and the regulation of the land market over the last decades. The larger neighbors become the higher is the competition for land for farms and the more difficult it becomes to innovate since new adoptions generally require more land.

Figure 1 represents the probability that average farm remains active to consecutive years from 2003 to 2013 for varying average farm area at the municipality level. The figure shows that overall the probability to survive is lower for competitors for land and this probability decreases with neighboring farm size (farm type 2). The opposite effect is observed for farms that benefit from positive spillovers (farm type 1). The figure also shows that the probability to survive is higher and does not vary with the neighboring size farm for farms having possible non-pecuniary motives (farm type 3)

The impacts of observed farm and farmer characteristics on the probability to survive vary according to the type specific that a farm belongs to. Overall, a positive impact is observed for age of farm holders, operated farm size, total agricultural benefit as well as for the fact that farm is specialized in soil-less production system (pig and/or poultry) or is operated under corporate legal status. However, the first type of farms is characterized by a negative impact of age of farms holders and total agricultural benefit. While the second result is more difficult to interpret, the negative impact of age of farm holders could be explained by the fact that young farmers may be more likely to adapt their production capacity using new technology. This result is conformed regarding the positive impact of the average age of farm holder at the municipality level on the probability of farm to survive. The younger are your neighbors the more competitive they could be because of a possible relative higher motivation or capacity to innovate by adopting new technology.

As expected, the results show that farms in Brittany are more likely to be divided into three types with a specific impact of neighboring farm size. In comparison to a pooled probit, the finite mixture model performs better as considering all the criteria reported in Table 1. More specifically, the finite mixture probit model is more accurate in predicting farm survival in Brittany. The superiority of the mixture model specifically comes from the specificity. Indeed, the mixture model does about 15% better in predicting farm exit in Brittany than the pooled estimation.

The descriptive statistics reported in Table 4 show that farms that are more likely to behave like competitors are rather corporate and larger farms than those in the other types. This result is conformed to our discussion in section 2 since such farms are more likely to be business oriented and thus mainly motivated by profit maximization. Conversely, individual farmers with smaller operated farm sizes are more likely to benefit from positive spillovers of new technology adoption.

### 5.2.2. Farm growth processes in Brittany

Contrary to our expectation, the mixture normal regression model does not allow identifying opposite impacts of neighboring farm size on own operating size. Even though the results show that the farm population in Brittany can be divided into more than one homogeneous type, farm size is found to be positively related to neighboring farm size for all types (see table 5). The positive impact of neighboring farm size on own size may indicate a sample selection, that is, farmers are constrained to continually adjust their operated farm size while remaining in the farming sector. However, the level of the impacts of neighboring farm size is specific for each type of farms meaning that the motivation of farmers could be different. The results show that this impact is relatively small for farm types 1 and 3 (see figure 2). This could mean that those farms are less motivated by profit maximization and thus are less sensitive to their neighboring farm size.

Descriptive statistics show that farms in type 1 and 2, with a relative high impact of neighboring farm size, are relatively larger than those in type 3. These two types contain also a higher percentage of corporate farms. According to the results discussed in the previous section, this could mean that those farms are constrained either to innovate, by increasing their operating size, or leave the farming.

## VI. Concluding remarks

This paper applies a modeling approach that allows identifying heterogeneous effects of neighboring farm size on farm survival and growth. The results show that the relationship between farms in Brittany is rather a competition for land than positive spillovers of new technology adoption leading to a negative impact of neighboring farm size on the probability to survive for a majority of farms. The results also show that while neighboring farm size may have no specific impact on the probability of certain farms to remain active two consecutive years, it seems that all farms tend to adjust their operated size over time since the impact is always positive on farm growth. These results confirm that neighboring farm size may differently influence farm survival and growth and suggest that farms should not be considered as isolated entities and agricultural policies should take into account potential relationship between farms.

The results from this work could be improved in two different ways. First, the impact of neighboring farm size was investigated by using an average farm size at the municipality and small agricultural area levels. As farms may compete for land in other municipalities, investigate impact of neighboring farm size using the exact location of farms could lead to better results. Second, some other factors such as subsidies received by farms and their neighbors may have a significant impact on farm survival and growth as it has been shown by previous studies. Incorporating such variables in the analysis of spatial interdependencies between farms may lead to a better understanding of neighboring farm size impact.

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## Tables and figures

Table 1: Definition and descriptive statistics of explanatory variables (n=344617)

Variable	Code	Mean	Std. Dev	Min	Max
Age of farm holder	<i>age</i>	48.45	9.12	18.50	99.00
Total land used	<i>Area</i>	48.82	41.20	0	580.30
Total agricultural benefit	<i>agri_ben</i>	10.78	12.72	-313.92	465.72
Dummy if has pig/poultry	<i>soil-less</i>	0.18	0.38	0	1
Dummy if corporate farm	<i>corporate</i>	0.46	0.49	0	1
<b>Municipality level (<i>mun</i>)</b>					
Average farm holder age	<i>mun_area</i>	48.82	13.60	0	227.29
Average farm size	<i>mun_age</i>	48.45	2.33	25.00	88.00
Share of pig/poultry farms	<i>mun_soil-less</i>	0.18	0.13	0	1
Share of corporate farms	<i>mun_corporate</i>	0.46	0.14	0	1
<b>Small agricultural area level (<i>saa</i>)</b>					
Average farm holder age	<i>saa_area</i>	48.82	7.66	13.92	70.61
Average farm size	<i>saa_age</i>	48.45	1.12	44.30	51.28
Share of pig/poultry farms	<i>saa_soil-less</i>	0.18	0.07	0.01	0.29
Share of corporate farms	<i>saa_corporate</i>	0.46	0.08	0.24	0.70
<b>Employment area level</b>					
Unemployment rate	<i>unempl_rate</i>	7.03	1.21	3.70	9.90

Source: MSA, Bretagne 2003-2013 - authors' calculations

Table 2: Estimated parameters for the probit models

Code	Pooled	Mixture Probit		
		Type 1	Type 2	Type 3
<i>intercept</i>	0.0358	1.3314**	-0.8903*	-60.2809***
	0.3396	0.4774	0.3875	1.3082
<i>trend</i>	0.0062**	-0.0222***	-0.0286***	0.1037***
	0.0028	0.004	0.0033	0.0092
<i>age</i>	0.0104***	-0.0258***	0.0066*	3.2279***
	0.0025	0.0036	0.0027	0.0328
<i>age2</i>	-0.0003***	2.10e-05	-0.0001***	-0.040***
	2.23e-05	3.26e-05	2.51e-06	0.0004
<i>area</i>	0.0042***	-0.0173***	0.0092***	0.0007
	0.0002	0.0004	0.0002	0.0008
<i>area2</i>	9.64e-06***	0.0001***	2.40e-05***	4.37e-05***
	1.09e-06	2.29e-6	1.30e-06	6.01e-06
<i>agri_ben</i>	0.0009**	-0.0499***	0.004***	0.0508***
	0.0004	0.0007	0.0004	0.0045
<i>agri_benXret</i>	-0.0185***	-0.0283***	-0.0162***	-0.0515***
	0.0006	0.0008	0.0006	0.0046
<i>soil-less</i>	0.0228**	0.2074***	0.0281*	0.2085***
	0.0105	0.0167	0.0119	0.0333
<i>corporate</i>	0.3093***	1.2208***	0.2897	-0.0157
	0.0091	0.0144	0.0101	0.0319
<i>mun_area</i>	-0.0003	0.0049***	-0.0013**	-0.0001
	0.0004	0.0005	0.0004	0.0012
<i>mun_age</i>	0.0051***	-0.001	0.0053*	0.0202***
	0.0018	0.0025	0.0021	0.0061
<i>mun_soil-less</i>	0.0104	-0.0373	0.0062	-0.1104
	0.0354	0.0504	0.0407	0.1149
<i>mun_corporate</i>	-0.0545	-0.4082***	-0.0202	-0.0499
	0.0358	0.0497	0.0409	0.114
<i>saa_area</i>	0.0018***	0.0026**	0.0032***	-0.0022
	0.0007	0.001	0.0008	0.0024
<i>saa_age</i>	0.0181**	0.0435***	0.026***	0.1549***
	0.0071	0.0099	0.0081	0.0232
<i>saa_soil-less</i>	0.1488**	1.0079***	0.1223	0.1305
	0.0709	0.0993	0.0816	0.2306
<i>saa_corporate</i>	0.1402**	0.4428***	0.1994**	0.0997
	0.0677	0.0962	0.0770	0.221
<i>unempl_rate</i>	0.0104***	0.0311***	0.0164***	0.0797***
	0.0033	0.0046	0.0038	0.0105
Shares		17.90%	54.20%	27.90%
Number of obs	317177		317177	
Correct predictions	92.73%		93.85%	
Log pseudo-likelihood	-76323		-73696	
AIC	152684		147470	
BIC	152886		147886	
AIC3	152703		147509	

Note: \*, \*\* and \*\*\* are significance at 5%, 1% and 0.1% levels, respectively; standard errors in shaded lines.

Source: MSA, Bretagne 2003-2013 - authors' calculations

**Table 3: z-scores tests of the difference between estimated parameters of farm types from the finite mixture probit model**

Variables	z-scores (1-2)	p-value	z-scores (1-2)	p-value	z-scores (1-2)	p-value
<i>intercept</i>	-3.61	0.00	-44.24	0.00	-43.53	0.00
<i>trend</i>	-1.22	0.22	12.49	0.00	13.50	0.00
<i>age</i>	7.18	0.00	98.55	0.00	97.84	0.00
<i>age_2</i>	-2.49	0.01	-107.10	0.00	-106.99	0.00
<i>area</i>	55.92	0.00	19.68	0.00	-9.86	0.00
<i>area_2</i>	-26.93	0.00	-1.59	0.11	11.02	0.00
<i>agri_ben</i>	67.28	0.00	22.27	0.00	10.43	0.00
<i>agri_benXret</i>	11.67	0.00	-4.94	0.00	-7.58	0.00
<i>soil-less</i>	-8.75	0.00	0.03	0.98	5.11	0.00
<i>corporate</i>	-53.11	0.00	-35.38	0.00	-9.14	0.00
<i>mun_area</i>	-8.95	0.00	-3.81	0.00	0.91	0.36
<i>mun_age</i>	1.90	0.06	3.21	0.00	2.31	0.02
<i>mun_soil-less</i>	0.67	0.50	-0.58	0.56	-0.96	0.34
<i>mun_corporate</i>	6.03	0.00	2.88	0.00	-0.25	0.80
<i>saa_area</i>	0.52	0.60	-1.87	0.06	-2.19	0.03
<i>saa_age</i>	-1.37	0.17	4.42	0.00	5.24	0.00
<i>saa_soil-less</i>	-6.89	0.00	-3.49	0.00	0.03	0.98
<i>saa_corporate</i>	-1.98	0.05	-1.42	0.16	-0.43	0.67
<i>unempl_rate</i>	-2.45	0.01	4.25	0.00	5.68	0.00

Source: MSA, Bretagne 2003-2013 - authors' calculations

**Table 4: Main characteristics of type of farms from the finite mixture probit model**

Variables	means			t-tests		
	Type1	Type2	Type3	(1-2)	(1-3)	(2-3)
<i>age</i>	49.25	48.27	47.77	39.52	60.86	21.35
<i>area</i>	43.91	50.49	48.04	-63.66	-37.70	22.22
<i>agri_ben</i>	8.80	11.02	11.36	-77.33	-78.59	-9.54
<i>soil-less</i>	0.17	0.18	0.19	-17.96	-25.60	-9.20
<i>corporate</i>	0.43	0.48	0.45	-35.74	-11.45	21.80
<i>mun_area</i>	48.19	48.30	48.58	-3.16	-10.66	-7.85
<i>mun_age</i>	48.46	48.25	48.31	36.31	25.23	-9.63
<i>mun_soil-less</i>	0.18	0.18	0.19	-16.35	-21.09	-6.06
<i>mun_corporate</i>	0.46	0.46	0.47	8.35	-13.38	-21.35

Source: MSA, Bretagne 2003-2013 - authors' calculations

Table 5: Estimated parameters for the linear models

Code	Pooled	Mixture normal regression		
		Type 1	Type 2	Type 3
<i>Intercept</i>	4.0651	-147.2279***	-59.9425***	-17.5979***
	5.6072	1.0430	14.6292	1.0048
<i>Trend</i>	0.2524***	0.0197*	0.4053***	-0.0964***
	0.0475	0.0087	0.1218	0.0087
<i>age</i>	-0.711***	-0.0976***	0.0854	0.0025
	0.0386	0.0110	0.1563	0.0066
<i>age2</i>	0.0003	0.0008***	-0.0093***	-0.0002***
	0.0004	0.0001	0.0017	0.0001
<i>ln_area</i>	5.6571***	52.6593***	4.8363***	9.4797***
	0.0372	0.0431	0.0325	0.0176
<i>agri_ben</i>	0.3538***	0.0040***	0.3598***	0.0100***
	0.0100	0.0011	0.0151	0.0012
<i>agri_benXret</i>	0.1108***	-0.0138***	-0.1086***	0.0123***
	0.0143	0.0017	0.0300	0.0030
<i>soil-less</i>	-9.7902***	0.2651***	-18.2485***	0.1193***
	0.1809	0.0317	0.4210	0.0355
<i>corporate</i>	27.1756***	0.4472***	24.545***	0.9315***
	0.1238	0.0234	0.3401	0.0366
<i>mun_area</i>	0.8599***	0.0085***	1.2661***	0.0034**
	0.0072	0.0011	0.0167	0.0012
<i>mun_age</i>	0.7470***	0.0309***	1.3864***	0.0031
	0.0306	0.0058	0.0816	0.0052
<i>mun_soil-less</i>	12.267***	-0.5257***	21.3584***	0.9872***
	0.6074	0.1031	1.5000	0.1132
<i>mun_corporate</i>	-31.8797***	-0.3832***	-50.9605***	0.7515***
	0.6083	0.1049	1.5183	0.1081
<i>saa_area</i>	0.0585***	-0.0113***	0.0718*	0.0080***
	0.0122	0.0023	0.0331	0.0021
<i>saa_age</i>	-0.4408***	-0.1048***	0.0917	0.1777***
	0.1172	0.0216	0.3054	0.0209
<i>saa_soil-less</i>	-4.3395***	0.2592	-25.2777***	0.3612
	1.2088	0.2054	2.9371	0.2179
<i>saa_corporate</i>	-5.6855***	-0.8635***	8.6827**	0.2063
	1.1420	0.2066	2.9053	0.2046
<i>unempl_rate</i>	0.2425***	0.1176***	0.4492***	-0.0651
	0.0519	0.0095	0.1371	0.0104***
<hr/>				
<i>Lnsigma</i>	3.4262	1.3233***	3.7508***	1.1468***
	0.0032	0.0038	0.0046	0.0039
<hr/>				
Shares		43.72%	27.68%	28.60
Number of obs.	294288		294288	
Log pseudo-likelihood	-1425877		-1036676	
AIC	2851794		2073434	
BIC	2852005		2073868	
AIC3	2851814		2073475	

Note: \*, \*\* and \*\*\* are significance at 5%, 1% and 0.1% levels, respectively; standard errors in shaded lines.

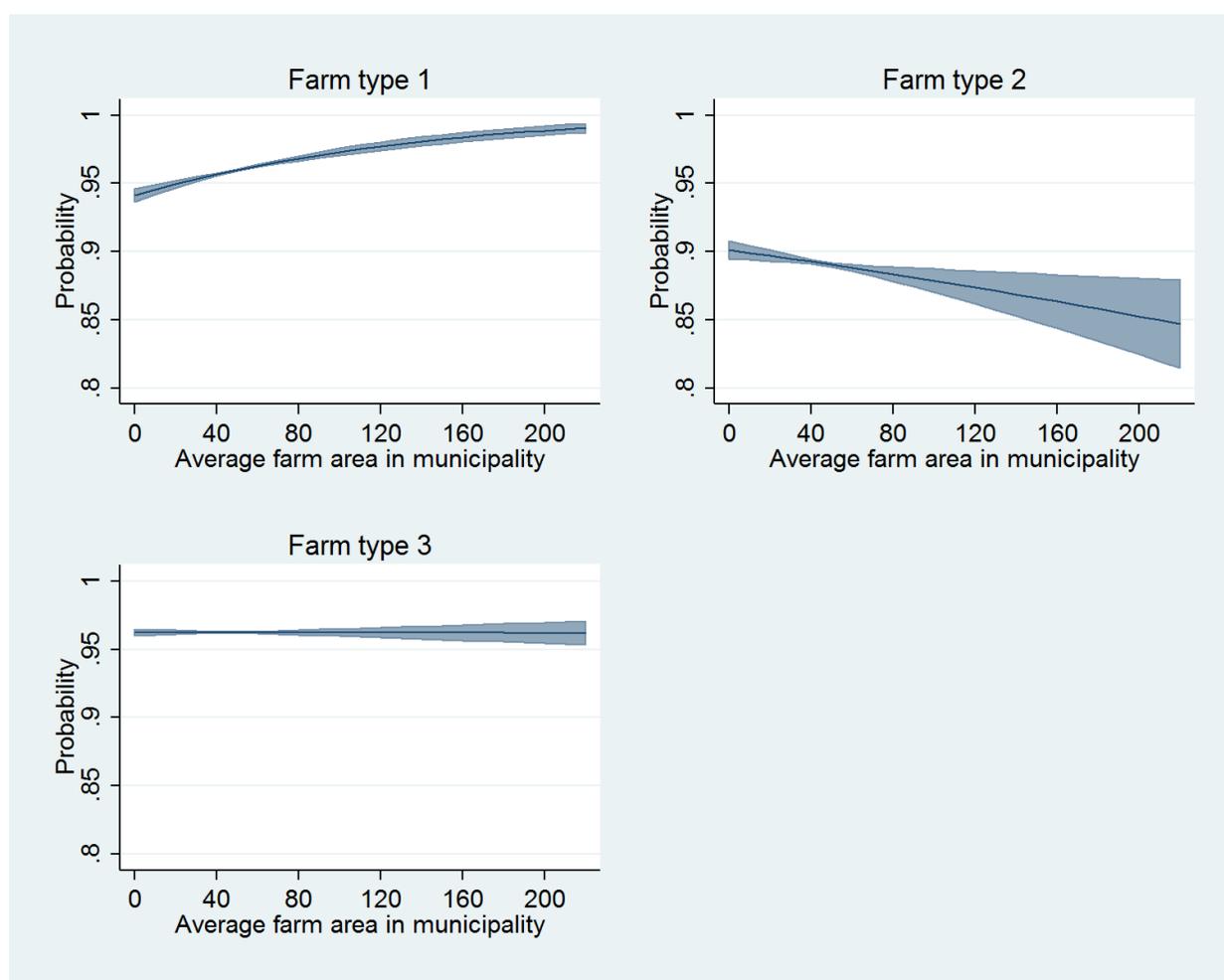
Source: MSA, Bretagne 2003-2013 - authors' calculations

Table 5: Main characteristics of types from the finite mixture of normal regression

Variables	means			t-tests		
	Type1	Type2	Type3	(1-2)	(1-3)	(2-3)
Age	47.3	45.551	51.226	52.219	-97.306	-132.963
Area	54.521	79.304	12.849	-130.848	749.653	-107.485
agri_ben	12.285	12.593	6.438	-6.11	109.407	100.638
soil-less	0.148	0.242	0.179	-56.042	-19.48	33.515
Corporate	0.469	0.767	0.211	-154.652	134.212	287.649
mun_area	49.36	51.933	43.805	-46.601	98.916	-185.247
mun_age	48.183	48.206	48.561	-2.491	-37.264	-32.498
mun_soil-less	0.186	0.194	0.166	-14.623	36.044	46.559
mun_corporate	0.466	0.48	0.438	-23.204	45.846	62.992

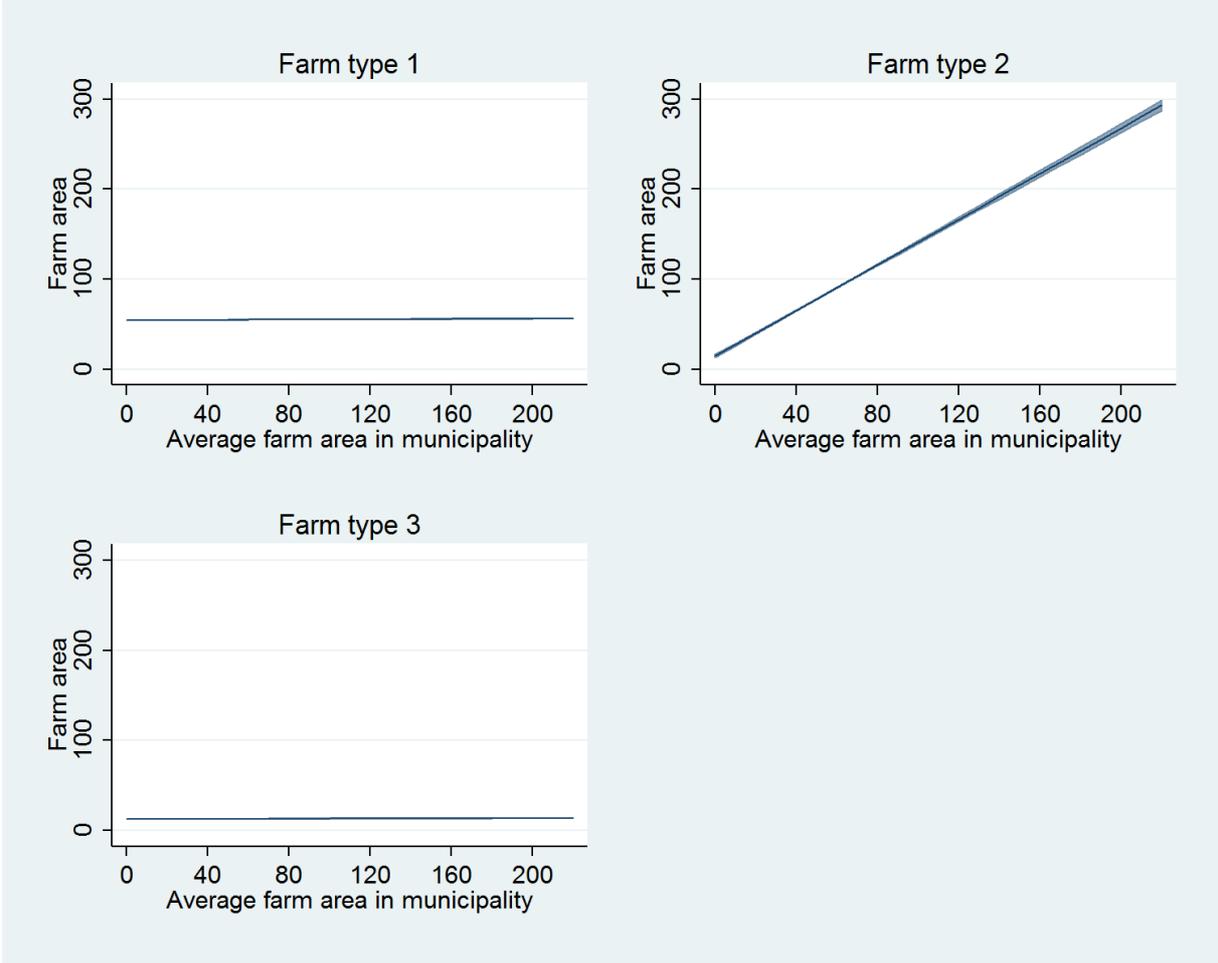
Source: MSA, Bretagne 2003-2013 - authors' calculations

Figure 1: The probability to survive for varying average farm area in municipality by type of farms (predicted margins with 95% CIs)



Source: MSA, Bretagne 2003-2013 - authors' calculations

Figure 2: Total land used for varying average farm area in municipality by type of farms (predicted margins with 95% CIs)



Source: MSA, Bretagne 2003-2013 - authors' calculations