Accounting for farm heterogeneity in the assessment of agricultural policy impacts on structural change

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Abstract

This study aims at investigating the impact of agricultural policies on structural change process in the French farming sector. As farms may behave differently, a mixture modeling approach is applied in order to account for unobserved farm heterogeneity. A multinomial logit specification is used for the transition probabilities and the parameters of the model are estimated by maximum likelihood method using the expectation-maximization (EM) algorithm. An empirical application to an unbalanced panel over 2000-2013 shows that the French farming sector consists of a mixture of two types of farms with transition processes very different. The results also show that the impact of subsidies from the First and the Second Pillars of the Common Agricultural policy (CAP) depends on the type membership of farms. I thus argued that agricultural policy assessment should pay more attention on potential unobserved heterogeneity in farms' behavior.

Key words: Agricultural policy, EM algorithm, Farm structural change, Mixed Markov model, Unobserved heterogeneity

JEL classification: Q12, C15, D92

Introduction

The farming sector has faced important structural change over the last decades. In particular, the number of farms has decreased sharply and their average size has increased continually in most developed countries, implying some changes in the farm size distribution. Such changes may have important consequences for equity among farmers, productivity and efficiency of farming (Weiss 1999). Structural change has been therefore the subject of considerable interest among agricultural economists and policy makers over the last decades. In this respect, studies aim in particular at understanding the mechanisms underlying this process in order to identify the key drivers that influence the observed trends, and to generate prospective scenarios.

Many theoretical studies pointed out potential impacts of agricultural policy on farm size changes (see for example Goddard et al. (1993); Harrington and Reinsel (1995)) . Empirically, it has become quite common in the agricultural economics literature to study the way farms experience size change over time and the impact of time-varying variables including agricultural policies by applying the so-called Markov chain model (Zimmermann, Heckelei, and Dominguez 2009). Empirical investigations however generally found limited impacts of public programs on structural change in agriculture (Ben Arfa et al. 2015). Such results may be explained by the fact that impacts of agricultural policies as well as effects of some other structural characteristics (market conditions, technical change process, etc.) are usually investigated at a macro level using aggregate data when applied Markov chain models. Indeed, focusing on agricultural policies, impacts of public supports on transition probabilities of farms across category of sizes are generally investigated using transition probability matrices estimated for the overall population of farms (see Huettel and Jongeneel (2011); Zimmermann and Heckelei (2012); Ben Arfa et al. (2015) for recent examples). Even using micro level data, yearly transition probability matrices are computed for the overall population of farms first; then, effects of exogenous variables are estimated on transition probabilities of farms (see for example Rahelizatovo and Gillespie (1999)).

This study aims at investigating the impacts of some public supports from the First and the Second Pillars of the Common agricultural Policy (CAP) on structural change in the French farming sector using individual farm level data. The paper adds to the existing literature on farm structural change in two ways: i) assuming that structural change in farming may result from individual farmer's decisions, a discrete choice approach is used to model the transition process of farms and to study the impacts of some agricultural policy measures on farm size changes at the individual farm level; ii) as farmers' choices of optimal farm size may not be fully linked to observed farmer and farm characteristics, a mixture modeling framework is applied in order to take account potential unobserved farm heterogeneity. As policy instruments may affect farm size changes differently, we expect that accounting for both observed and unobserved farm heterogeneity may lead to better represent the structural change process in farming and therefore to estimate agricultural policy impacts in a more efficient way than the usual modeling approaches.

This paper is structured as follows. In the next section, I provide theoretical arguments supporting the empirical application of this study. Section presents the proposed model, the methods of specification and estimation of the parameters. In section , we present some the methods for the model assessment. Section reports the application to a panel of French farms, starting with a description of the data used and explanatory variables investigated following by a presentation of the main results. Finally, I conclude with some considerations on possible improvements of this study for further research.

Theoretical background

Structural change has been subject of considerable interests in the agricultural economics literature. In this case, Markov Chain (MCM) model has become a quiet common modeling approach since it has been shown that such a model is convenient to represent transition process of farms across category of sizes (Bostwick 1962; Padberg 1962; Krenz 1964). More recently, Stokes (2006) showed that a Markovian transition process may derived from a structural model of inter-temporal profit maximization, given theoretical grounds to using the MCM. Basically, this model states that the size of a farm at a given time period is the result of the probabilistic process which only depends on its size in the previous period. In general, a first-order Markov process is assumed and empirical studies used aggregate data since such data are most often easier to obtain than individual level data. Since, Lee, Judge, and Takayama (1965) and Lee, Judge, and Zellner (1977) have shown that robustly estimating a MCM from aggregate data is possible, such a modeling approach has been then widely used to study farm size dynamics and the impacts of some recent agricultural policies, with increasing improvements of the estimation methods (see Zimmermann, Heckelei, and Dominguez (2009) for a review).

However, as argued Freshwater and Reimer (1995), the best way of analysing agricultural policies is to do this at the individual farm level. Indeed, structural change in farming may results from farms' individual behavior. If it is the case, analysing of transition process of farms should take into account potential heterogeneity between farms since not all farms will behave alike, conversely to the basic assumption of the MCM using aggregate data. The implicit homogeneity assumption of the MCM states that all farms have the same probability to change the category of sizes over time given their initial category. Even some improvements in order to take into account effects of time-varying variables, the homogeneity assumption still remains since the model considers that all farms will behave alike at a certain level of a specific exogenous variable. One may however supposed that the impact of public supports for example may vary across farms since the response of farms to such stimuli may depend on some individual characteristics, which may be considered as sources of farm heterogeneity (Howley 2015).

Farm heterogeneity may come from several sources. One of the most important sources of farm heterogeneity is farmers' motivation. The responses of farmers to some incitations such as supports from some public programs or the market conditions may highly depend on their motivation. Not all farmers will increase their operated farm size even if, for example, they received the same amount of subsidies because of less or even non-financial/pecuniary motives (**?**) or potential farming lifestyle values (Hallam 1991). Howley, Dillon, and Hennessy (2014) argued that goals of some farmers such as maintaining farming lifestyle may be as important, or even more important than a profit maximization. Farmers' motivation may also depends on some others characteristics and socio-economic environment of farms. For example, at a certain age, more specifically closed to retirement, farmers may be less motivated to enlarge their farm. Such a situation may depend on potential existence of family members for farm succession (Potter and Lobbley 1992). Some environmental constraint may also play an important role on farmers' behavior. For example, when considering size as measured in terms of the operated area, farmers may not all have the same opportunities to enlarge their farm simply because they may not face the same land supply: as land is mostly released at retirement time, a farmer surrounded by young colleagues only will not find plots to buy or rent. Even if land offers exist, farmers may have different abilities to negotiate with land owners or may face unequal conditions to access credit. Similarly, investigating potential impact of economic environment of farms, Dong, Hennessy, and Jensen (2010) also showed that farmers who expected a sell contract are less likely to exit the farming.

Considering all the potential sources of heterogeneity mentioned above among others, farms may response differently to some incitations (agricultural policy, market condition, ect.). If all sources of farm heterogeneity were observed, it would be able to control for their impact on the responses of farms using for example crossed effects between farm characteristics and the exogenous variables under investigation. However, not all sources of heterogeneity can be observed by the researcher or some of them cannot be fully linked to some observable variables related to human capital such as education, to land market such as land prices, to credit market such as the interest rate, etc. As a result, even if sharing the same observed characteristics, farms with an equal initial size and received the same amount of subsidies may not experience structural change at the same speed and/or to the same extent. Ignoring unobserved heterogeneity in the estimation procedure may thus lead to inconsistent parameters and therefore to some unrealistic or erroneous impacts of exogenous variables, specially when aggregated at the population level (Pennings and Garcia 2004; Holloway, Lacombe, and LeSage 2007). Accounting for unobserved heterogeneity may thus lead to more accurately estimate the impact of the causative factors of structural change in farming.

Modelling approach

In this study, a mixture modeling approach is applied in order to capture unobserved farm heterogeneity. Mixture models have a long story in the literature and has been proved to have several advantages over others techniques also used in order to account for unobserved heterogeneity (see Greene and Hensher (2003); Garver, Williams, and Taylor (2008)). While Markov has been the subject of considerable applications in several strands of the economic literature, Saint-Cyr and Piet (2014) are the first to applied this approach in the context of the farming sector, to the best our Knowledge.[1] They showed that such kinds of models is more accurate in representing farm size dynamics since this modeling framework allows capturing unobserved heterogeneity in the farm transition process. In the following section, we improve Saint-Cyr and Piet (2014) modeling approach by relaxing the pure stayer assumption and allowing transition probabilities to vary over time, as they suggested in their concluding remarks..

The mixed of Markov chain model

Let by N the total number of farms in the population and K the total number of farm size categories (choice alternatives). As farm category of sizes are observed at discrete times, generally 1-year interval, a discrete-time process is assumed. Denote by y_{it} the category of sizes of a specific farm i ($i \in N$) at time t ($1 \leq t \leq T$). The indicator $y_{i1} = j$ ($\forall j = 0, 1, 2, \cdots, K$) if farm i is in category j at time $t = 1$. The category $j = 0$ may indicate entry in or exit from farming. Since farms may enter and leave the farming sector at different time points, the length of the vector $\mathbf{y}_i$ may vary across farms ($i.e$, $T_i \leq T$). Over a time period T, the size evolution of a specific farm i can be represented by the vector $\mathbf{y}_i = (y_{i0}, y_{i1}, \cdots, y_{iT_i})$ where each element of $\mathbf{y}_i$ indicates the farm size category at each time point t ($t \in T_i$). As structural change in farming results from individual movements of farms across category of sizes, this process can thus be described within individual farm's behavior.

In the agricultural economics literature, transition process is generally supposed to follow a first order Markov process specially in the context of farm size changes over time (Zimmermann, Heckelei, and Dominguez 2009). It is thus assumed that farm category of sizes at any time t (y_{it}) only depends on its immediately previous location, that is, its category of sizes at time $t-1$ (y_{it-1}). The Markov assumption implies that the observed random variables $(y_{i1}, y_{i2}, \cdots, y_{iT_i})$ are not independent from each other and $\mathbf{y}_i$ can be described by the probability function (Dias and Willekens 2005):

$$(1) \quad f(\mathbf{y}_i) = \prod_{t=1}^{T_i} P(y_{it}|y_{it-1})$$

where $P(y_{it}|y_{it-1})$ is the probability that farm i chooses a specific category of sizes at time t given its location at time $t-1$, so-called transition probability. In this framework, farm i enters the farming sector if it makes a transition from category $j=0$ to any other category $j \neq 0$ ($\forall j \in K$), that is, $y_{it} = j$ given $y_{it-1} = 0$. Conversely, farm i leaves the farming sector if a transition to category $j=0$ is observed.

Suppose now that the observed random sample of farms is divided into G homogeneous types instead of just one, each type gathers farms with similar behaviors, the density function of $\mathbf{y}_i$ as a discrete mixing distribution with G support points can thus be rewritten (McLachlan and Peel 2004):

$$(2) \quad f(\mathbf{y}_i) = \sum_{g=1}^{G} \pi_g f_g(\mathbf{y}_i)$$

where $f_g(\mathbf{y}_i)$ is the probability function describing the evolution of farm type g as specified in equation (1); and π_g, the mixing proportions, are non-negative and sum up to one. In the statistics literature, π_g is called the mixing distribution and $f_g(\mathbf{y}_i)$ is called the mixed function (Train 2009). As we defined a finite number of farm types, the mixed model can be also called a 'latent class model' with G latent transition processes. The density function of $\mathbf{y}_i$ is thus conditional on the mixing distribution and we can represent the evolution of farm size as (Vermunt 2010):

$$(3) \quad f(\mathbf{y}_i) = \sum_{g=1}^{G} P(g_i = g) \left[\prod_{t=1}^{T_i} P(y_{it} = k | y_{it-1} = j, g_i = g) \right]$$

Under the mixed Markov model farm size evolution has thus two set of probabilities. From the left hand size, the first term equation 3 are probabilities that farm i belongs to a specific farm type g while the second term are probabilities of making transitions across category of sizes given farm i belongs to type g.

Specifying transition probabilities

As that categories of sizes are mutually exclusive, finite and exhaustive, a discrete-choice model is used to specify transition probabilities of farms. The discrete choice model assumes that farmers' choice of initial category of sizes as well as to make some transitions across category of sizes can be represented by a random utility model (Train 2009). The farmer's utility may represent in our case the net benefit that arise from choosing or moving to a specific category of sizes at a given time t.

Denote by U_{ijkt} the utility of farm i arising upon moving from category of sizes j to another one k at time t. Under the basic behavioral assumption, it is supposed that farmers choose the category which maximized their utility. Therefore, a move from j to k (*i.e*, $y_{it} = k|y_{it-1} = j$) will be observed if and only if $U_{ijkt} \geq U_{ijlt}$ $(\forall j,k,l \in K)$. We consider that farms staying in the same category two consecutive times make a transition from j to j. Under a mixture assumption, farm utility level is conditional on its type specific g. A farm belonging to a specific type g will thus make a transition from a specific category of sizes j to another one k if and only if $U_{ijkt|g} \geq U_{ijlt|g}$ $(\forall g \in G)$, where $U_{ijkt|g}$ is the utility of farms given belonging to the specific type g.

As this study is interested in determining the impacts of some exogenous variables on farm size change, transition probabilities (*i.e*, the utility arising from moving across category of sizes) are specified as a function of some public supports and other causative factors. Under mixture assumption, the utility that would accrue to farm i upon moving from category j to another one k at time t given belonging to type g can be expressed as:

$$\begin{aligned} P(y_{it}=k|y_{it-1}=j,g_i=g,\mathbf{x}_{it-1}) =& P(U_{ijkt|g} \geq U_{ijlt|g}) \\ p_{ijkt|g} =& f(\mathbf{x}_{it-1},\boldsymbol{\beta}_g,\varepsilon_{ijkt|g}), \quad \forall t \in T_i; j,k,l \in K; g \in G \end{aligned} \tag{4}$$

where $\mathbf{x}_{it-1}$ are explanatory variables; $\boldsymbol{\beta}_g$ and $\varepsilon_{ijkt|g}$ are parameters to estimate and an *iid* random error term given type g, respectively. Generally, explanatory variables are lagged 1-year since farmers' decisions for entering the farming sector as well as for expansion, or contraction are likely dependent upon information available during the previous period.

Since farmers may face multiple choices at each occasion, it is econometrically convenient to used a multinomial specification (Greene 2006).[2] Assuming that the error terms $\varepsilon_{g,ijkt}$ are randomly drawn from a Gumbel distribution (type I extreme value), the conditional probability of making a transition from a specific category of sizes j to the category k at time t is given by:

$$P(y_{it}=k|y_{it-1}=j,g_i=g,\mathbf{x}_{it-1}) = \frac{\exp(\boldsymbol{\beta}'_{jk|g}\mathbf{x}_{it-1})}{\sum_{l=1}^{K}\exp(\boldsymbol{\beta}'_{jl|g}\mathbf{x}_{it-1})} \quad (\forall j,k=1,2,\cdots,K) \tag{5}$$

where $\boldsymbol{\beta}_{jk|g}$ is a vector of parameters specific to each type of farm g and each couple jk of transitions. Assuming permanence in a same category of sizes two consecutive years as the reference lead to state $\boldsymbol{\beta}_{jj|g} = 0 \quad \forall g=1,2,\cdots,G$ and $\forall j=1,2,\cdots,K$ for identification.

Estimation procedure

The parameters of the model are estimated using the maximum likelihood estimation method. Let $\mathbf{y}=(\mathbf{y}_1,\mathbf{y}_2,\cdots,\mathbf{y}_n)$ the observed random sample of farms obtained from the mixture density, where the vector $\mathbf{y}_i=(y_{i0},y_{i1},\cdots,y_{iT_i})$ gathering farmer's choices (or farm's locations) over the time period $T \geq T_i$. According to equation (3) and the model specification, state that:

$$P(y_{it}=k|y_{it-1}=j,g_i=g,\mathbf{x}_{it-1}) = p_{ijkt|g} = P(\mathbf{x}_{it-1};\boldsymbol{\beta}_{jk|g})$$

Under a mixture assumption, the log-likelihood (LL) function for the parameters ($\boldsymbol{\beta}$) of the model, conditional on observing $\mathbf{y}$, writes:

$$(6) \qquad LL(\boldsymbol{\beta}) = \sum_{i=1}^{N} \ln \left\{ \sum_{g=1}^{G} \pi_g \prod_{t=1}^{T_i} \prod_{j,k}^{K} \left[P(\mathbf{x}_{it-1}; \boldsymbol{\beta}_{jk|g}) \right]^{d_{ijkt}} \right\}$$

where $\boldsymbol{\beta} = (\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \cdots, \boldsymbol{\beta}_G)$ is a matrix of parameters with $\boldsymbol{\beta}_g = \left\{ \boldsymbol{\beta}_{jk|g} \right\}$ $\forall g \in G$ and $j,k = 1,2,\cdots,K$; the indicators $d_{ijkt} = 1$ if farm i moves from j to category k at time t (*i.e*, $y_{it} = k|y_{it-1} = j$) and zero otherwise. Since farm type is unknown beforehand and given some numerical difficulties associated to the maximization of the above expression, the expectation-maximization (EM) algorithm is generally used to estimate the parameters of such a model (McLachlan and Krishnan 2007).[3] The EM algorithm developed by Dempster, Laird, and Rubin (1977) simplifies the complex log-likelihood in equation (6) in a set easily solvable log-likelihood functions by introducing a so-called 'missing variable'.

Let v_{gi} be a discrete unobserved variable indicating the type membership of each farm. The random vector $\mathbf{v}_i = (v_{1i}, v_{2i}, \cdots, v_{Gi})$ is thus g-dimensional with $v_{gi} = 1$ if farm i belongs to type g and zero otherwise. Assuming that v_{gi} is unconditionally multinomial distributed with probability π_g, the complete likelihood for $(\boldsymbol{\beta}, \boldsymbol{\pi})$, conditional on observing $\mathbf{y}_c = (\mathbf{y}, \mathbf{v})$, therefore writes:[4]

$$(7) \qquad L_c(\boldsymbol{\beta}, \boldsymbol{\pi}) = \prod_{i=1}^{N} \prod_{g=1}^{G} \left\{ \pi_g \prod_{t=1}^{T_i} \prod_{j,k}^{K} \left[P(\mathbf{x}_{it-1}; \boldsymbol{\beta}_{jk|g}) \right]^{d_{ijkt}} \right\}^{v_{gi}}$$

where $\boldsymbol{\pi} = (\pi_1, \pi_2, \cdots, \pi_G)$ vector gathering share of each type of farms to estimate. The complete log-likelihood is thus obtained as:

$$(8) \qquad LL_c(\boldsymbol{\beta}, \boldsymbol{\pi}) = \sum_{i=1}^{N} \sum_{g=1}^{G} v_{gi} \ln \left\{ \pi_g \prod_{t=1}^{T_i} \prod_{j,k}^{K} \left[P(\mathbf{x}_{it-1}; \boldsymbol{\beta}_{jk|g}) \right]^{d_{ijkt}} \right\}$$

In this case, v_{gi} is called the 'posterior' probability that farm i belongs to the g-th type with $\mathbf{y}_i$ have been observed, that is $P(v_{gi} = 1|\mathbf{y}_i)$, while π_g is a 'prior' probability of the mixture McLachlan and Peel (2004). This log-likelihood can be then divided into two components:

$$
\begin{aligned}
&LL_1 = \sum_{i=1}^{N}\sum_{g=1}^{G} v_{gi}\ln\pi_g \\
(9)\qquad &LL_2 = \sum_{i=1}^{N}\sum_{g=1}^{G} v_{gi}\sum_{t=1}^{T_i}\sum_{j,k}^{K} d_{ijkt}\ln\left\{P(\mathbf{x}_{it-1};\boldsymbol{\beta}_{jk|g})\right\}
\end{aligned}
$$

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

(i) Initialization: Arbitrarily choose initial values $\mathbf{\Phi}^0 = (\boldsymbol{\phi}_1^0, \boldsymbol{\phi}_2^0, \cdots, \boldsymbol{\phi}_G^0)$ where $\boldsymbol{\phi}_g^0 = (\pi_g^0, \boldsymbol{\beta}_{jk|g}^0)$ $\forall j,k = 1,2,\cdots,K$ and $\forall g = 1,2,\cdots,G$ for the parameters of the model, with some parameters set to zero for identification as previously mentioned in section .

(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 $\mathbf{\Phi}^p$. This conditional expectation probability, that is, the posterior probability $v_{gi}^{(p+1)} = v_{gi}(\mathbf{y}_i;\mathbf{\Phi}^p)$, can be obtained according to the Bayes' law:

$$
(10)\qquad v_{gi}^{(p+1)} = \frac{\pi_g^p \prod_{t=1}^{T_i}\prod_{j,k}^{K}\left[P(\mathbf{x}_{it-1};\boldsymbol{\beta}_{jk|g}^p)\right]^{d_{ijkt}}}{\sum_{h=1}^{G}\pi_g^p \prod_{t=1}^{T_i}\prod_{j,k}^{K}\left[P(\mathbf{x}_{it-1};\boldsymbol{\beta}_{jk|h}^p)\right]^{d_{ijkt}}}
$$

Replacing v_{gi} by its expected value in equation (8) leads to the conditional expectation of the complete data log-likelihood.

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

$$
(11)\qquad \boldsymbol{\beta}^{(p+1)} = argmax_{\boldsymbol{\beta}}\sum_{i=1}^{N}\sum_{g=1}^{G} v_{gi}^{(p+1)}\sum_{t=1}^{T_i}\sum_{j,k}^{K} d_{ijkt}\ln\left[P(\mathbf{x}_{it-1};\boldsymbol{\beta}_{jk|g})\right]
$$

The maximization process of the above equation is straightforward. The transition probability parameters ($\hat{\boldsymbol{\beta}}^p$) are updated considering $v_{gi}(\mathbf{y}_i;\mathbf{\Phi}^p)$ as a weighted factor for each observation (Pacifico and Yoo 2012). Then, the posterior probabilities of belonging to a specific type are updated as follows :

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

(iv) Iteration: Return to expectation step (ii) using $\boldsymbol{\pi}^{(p+1)}$ and $\boldsymbol{\beta}^{(p+1)}$ and iterate until convergence of the observed log-likelihood given by equation (6). At convergence, the resulting parameters are considered as the optimal values ($\hat{\boldsymbol{\Phi}}$).

A problem which often occurs in a mixture analysis with several components is that some solutions may be suboptimal. Indeed, the non-concavity of the log-likelihood function in equation (6) does not allow the identification of a global maximum in the mixture model, even for discrete mixtures of multinomial logit (Hess, Bierlaire, and Polak 2006). Given the potential presence of a high number of local maxima, the EM solutions may be highly dependent on the initial values of $\boldsymbol{\Phi}^0$. Various techniques are used in the literature to avoid suboptimal solutions (see Baudry and Celeux (2015) for a short review). In this study, the EM algorithm are run with various initial values of parameters (randomly chosen) and the starting values providing the largest likelihood at convergence are chosen as the best ones.

Model assessment and elasticities

As there exist no background on the exact total number of farm types in the population, some selection criteria are used to choose an optimal number of types. Given the total farm type chosen, transition probability and structure elasticities are derived for each type of farms and also for the overall population, respectively.

Choosing optimal number of farm types

The total number of components for a mixture model can be chosen either by a priori assumptions or via information statistics. In the latter case, statistics are generally based on the value of $-2LL_G(\mathbf{y};\hat{\mathbf{\Phi}})$ of the model, where matrix $\hat{\mathbf{\Phi}}$ represents the maximum likelihood estimates adjusted for the number of free parameters in the model with a total of G homogeneous types. The basic principle under these information criteria is parsimony, that is, all other things being the same, the model with fewer parameters is chosen (Andrews and Currim 2003). The selection of the total number of homogeneous types is generally based on the following criterion:

$$(13) \quad C_G = -2\left\{LL_G(\mathbf{y};\hat{\mathbf{\Phi}})\right\} + \kappa N_G$$

where $LL_G(\mathbf{y};\hat{\mathbf{\Phi}})$ is the overall population log-likelihood value computed with the resulting estimated parameters for the model specified with G types; N_G is the total number of free parameters in the model and κ a penalty constant. Different values of κ lead to the two well known information criteria: Akaike Information Criterion (AIC) with $\kappa = 2$ and the Bayesian Information Criterion (BIC) using $\kappa = \log N$ with N the total number of observations. Other information criteria can be also derived such as the Consistent Akaike Information Criterion (CAIC) stating $\kappa = \log N + 1$ and the modified AIC (AIC3) which uses $\kappa = 3$ as penalizing factor (Andrews and Currim 2003; Dias and Willekens 2005). For these heuristic criteria, smaller values mean more parsimonious models.

There is no general consensus in the literature for using a specific type of criteria to choose an optimal number of components for a mixture model. However, some studies suggest that the CAIC and AIC3 may be more useful in the context of mixture models since these criteria penalize more severely the addition of parameters (Andrews and Currim 2003; Dias and Willekens 2005).

Probability elasticities

Since choice probabilities are function of observed variables, the model tests whether the investigated exogenous variables have significant impacts on the probability to enter the farming sector in a specific category of sizes and or to move across categories. As the estimated coefficients indicate marginal effects on the log-odds ratios in equation **??**, the impacts of the explanatory variables are difficult to interpret directly (Greene 2006). In this case, the impacts of explanatory variables are usually evaluate in terms of elasticities. The probability elasticities measure the effect of a 1% change in the ith explanatory variable (Zepeda 1995). In the mixture model these probability elasticities may depend on farm type. Yearly transition probability elasticities for farms belonging to a specific type g are obtained as:

$$(14)\quad \boldsymbol{\delta}_{jkt|g} = \frac{\partial p_{jkt|g}}{\partial \mathbf{x}_{t-1}} \times \frac{\mathbf{x}_{t-1}}{p_{jkt|g}}, \qquad \forall j,k \in K \quad \forall g \in G$$

where $\boldsymbol{\delta}_{jkt|g}$ is a vector gathering elasticities at the means of the explanatory variables in vector $\mathbf{x}_{t-1}$; and $p_{jkt|g}$ is the probability to move from category j to category k at time period t given belonging to type g. The first term of the above equation thus represents the marginal effects of explanatory variables and is given by (Greene 2006):

$$(15)\quad \frac{\partial p_{jkt|g}}{\partial \mathbf{x}_{t-1}} = p_{jkt|g}\left(\boldsymbol{\beta}_{jk|g} - \sum_{l=1}^{K} \boldsymbol{\beta}_{jl|g} p_{jlt|g}\right)$$

where $\boldsymbol{\beta}_{jk|g}$ is the vector of estimated parameters.

Replacing the marginal effects in equation (14) leads to express the probability elasticities of transitions as:

$$(16)\quad \boldsymbol{\delta}_{jkt|g} = \left(\boldsymbol{\beta}_{jk|g} - \sum_{l=1}^{K} \boldsymbol{\beta}_{jl|g} p_{jlt|g}\right) \mathbf{x}_{t-1}$$

Given the constraint $\boldsymbol{\beta}_{jj|g} = 0$ for identification, the probability elasticities for the reference pair of transitions jj is thus obtained as:

$$(17)\quad \boldsymbol{\delta}_{jjt|g} = \left(- \sum_{l=1}^{K} \boldsymbol{\beta}_{jl|g} p_{jlt|g}\right) \mathbf{x}_{t-1}$$

Farm structure elasticities

Since this study concerns structural change in farming, one could be interested to know whether a specific chosen explanatory variable has significant impact on the distribution of farms across category of sizes. Yearly structure elasticities are thus derived for each category of sizes. The elasticity of farm structure measures the percentage change in the total number of farms in a specific category j at time t for a 1% change in the investigated explanatory variable (Zepeda 1995).

Under the mixture modeling framework, the total number of farms in a specific category k at time t can be obtained as:

$$(18) \quad n_{kt} = \sum_{j=1}^{G} \pi_g \sum_{j}^{K} n_{jt-1} p_{jkt|g}, \qquad \forall k \in K, \forall t \in T$$

where π_g is the probability of belonging to type g; n_{jt-1} is the total number of farms located in category of sizes j at time $t-1$; and $p_{jkt|g}$ the probability for farm i to make a transition from category of sizes j to category k at time t. The farm structure elasticities are then given by:

$$(19) \quad \boldsymbol{\eta}_{kt} = \frac{\partial n_{kt}}{\partial \mathbf{x}_{t-1}} \times \frac{\mathbf{x}_{t-1}}{n_{kt}}$$

Only transition probabilities in equation (18) depend on exogenous variables ($\mathbf{x}_{t-1}$). The farm structure elasticities can be therefore obtained using the corresponding probability marginal effects in equation (15). The farm structure elasticities with respect to the explanatory variables at any specific time t are then derived as:

$$(20) \quad \boldsymbol{\eta}_{kt} = \left(\sum_{g=1}^{G} \pi_g \sum_{j=1}^{K} n_{jt-1} \frac{\partial p_{jkt|g}}{\partial \mathbf{x}_{t-1}} \right) \frac{\mathbf{x}_{t-1}}{n_{kt}}$$

where the marginal effects at the means of the corresponding explanatory variable may be replaced by their values.

Empirical application

For the empirical application, an unbalanced panel from the "Réseau d'Information Comptable Agricole" (RICA) database is used. In this section, the data are describe followed by the selection of the explanatory variables, specially focusing on the main programs from Common Agricultural Policy (CAP). Finally, the results are discussed.

Data

Online available RICA data from 2000-2013, the French implementation of the Farm Accountancy Data Network (FADN), are used. FADN is an annual survey which is defined at the European Union (EU) level and is carried out in each member state. The information collected at the individual level relates to both the physical and structural characteristics of farms and their economic and financial characteristics. It is the only database providing information about the total subsidies received by farms from the Common Agricultural Policy (CAP) (see http://ec.europa.eu/agriculture/rica/index.cfm to learn more about FADN). In France, RICA is produced and disseminated by the statistical and foresight office of the French ministry for agriculture. It focuses on 'medium and large' farms and constitutes a stratified and rotating panel of approximately 7,000 farms surveyed each year. Some 10% of the sample is renewed every year so that, on average, farms are observed during 5 consecutive years. However, some farms may be observed only once, and others several, yet not consecutive, times. Some farms remained in the database over the whole of the studied period, *i.e.*, fourteen consecutive years. Each farm in the dataset is assigned a weighting factor which reflects its stratified sampling probability, allowing for extrapolation at the population level (see http://www.agreste.agriculture.gouv.fr/ to learn more about RICA France).

In order to consider all farms in the sample whatever their type of production, the study concentrates on farm size as defined in economic terms. In accordance with the EU regulation (CE) N°1242/2008, European farms are classified into fourteen economic size (ES) categories, evaluated in terms of total standard output (SO) expressed in Euros. As mentioned before, in France, RICA focuses on 'medium and large' farms, those whose SO is greater than or equal to 25,000 Euros; this corresponds to ES category 6 and above. According to the EU regulation (CE) N°1242/2008, the nine ES categories available in RICA are aggregated into three categories: strictly less than 100,000 Euros of SO (ES6); from 100,000 to less than 250,000 Euros of SO (ES7); 250,000 Euros of SO and more (ES8 to

ES14). It should be noted that, according to the EU regulation (CE) N°1242/2008, the two last categories correspond to only large farms. The large sized farms are divided in two classes to have at least 3 category of sizes in the population. In the following, I refer to the defined farm size categories as medium, large and very large, respectively. As RICA being a rotating panel, farms which either enter or leave the sample in a given year cannot be considered as actual entries into or exits from the agricultural sector. Because of that constant population is assumed and only transitions between the category of sizes as defined in this study will be investigated.

For the estimations, the sample is restricted to farms which were present in the database for at least two consecutive years in order to observe at least one transition. The corresponding unbalanced panel then comprised 13,325 farms out of the 15,841 farms in the original database (84.12%), leading to 89,229 (farm$\times$year) observations and 75,904 individual 1-year transitions (including staying in the same category of sizes) from 2000 to 2013. Table 1 shows that farms are more likely to remain in their initial category of sizes two consecutive years. More than 90% of farm remain in their initial category whatever the category of size considered. It should be noted that remaining in the initial category does not means that farms do not increase or decrease size, but the change is not sufficient to fall into a different category of sizes as defined in this study.

Explanatory variables

Several theoretical and empirical studies provide various factors that may play an important role on structural change in farming (see for example Goddard et al. (1993); Boehlje (1992); **?**)). These studies distinguish several categories among factors that could affect farm structural change. In the following, the selected causative factors of structural change are presented, focusing on some recent public support programs. The selection of the explanatory variables is based on the objective of the study and their availability in the database.

As the aim of this paper is to investigate the impacts of agricultural policies on farm structural change, subsidies received by farms from some public support programs are used as explanatory variables of transition probabilities. Considering all farms all together, this study analyzes the impacts of public support programs mainly originate from the Common Agricultural Policy (CAP). Indeed, subsidies from the CAP in France and other countries in the European Union are divided into two main components called Pillars. The aims of the support programs from these two Pillars are different from each order. Theoretically, no consensus has been found for the real effects of such public programs (Zimmermann and Heckelei 2012). Given the conflicting influences on farm structure, Goddard et al. (1993) argued that the impact of public supports to farms may depends on how programs are designed for that commodity. The impacts of public supports from the two Pillars of the CAP are thus separately investigated on the transition probabilities of farms.

Subsidies to farms from the First Pillar of the CAP are considered first. The subsidies to farms from the First Pillar are divided in coupled and decoupled subsidies. Despite the fact that decoupled subsidies were introduced in order to reduce the impacts on level of activity of farms, it has been shown that this kind of supports appear to increase the farm size on the long run (Harrington and Reinsel 1995). Indeed, decoupled subsidies may become coupled since the first ones are based on historical production. Therefore, farmers had better to increase their operate farm size if they expected more subsidies in the future. According to the literature, a positive impacts of subsidies from the First Pillar of the CAP is expected one farm growth, gathering coupled and decoupled subsidies. As the amount of subsidies from the First Pillar is highly correlate to farm size, we divided the total subsidies received by total area used.

The impact of public support programs to farms from the Second Pillar of the CAP is also analyzed. In respect of the CAP, policy instruments from the Second Pillar are devoted to promote rural development. According to the potential impacts on farm size changes, subsidies from the Second Pillar could be divided into two components. The first component would include all subsidies allocated for the agri-environment and climate change programs. These kinds of supports may have a negative impacts on farm growth since agri-environment measures supposed to facilitate change in farming systems towards more resilient styles of production, better able to cope with future climate-related stress (Dwyer 2013). The second component of the Second Pillar would gather subsidies allocated for farm's investments, climatic damage and production diversification. Such kinds of support programs are more likely to favour farm size stagnation and growth by reducing risk. Gathering all kinds of subsidies from the Second Pillar of the CAP, a positive impact is thus expected on farm size stagnation.

Several factors other than agricultural policy have proved to affect structural change in farming (see Harrington and Reinsel (1995); Zimmermann, Heckelei, and Dominguez (2009)). In this study, only factors related to farm path dependency and economic environment of farms are considered. The reason for only considering these factors is because of data limitations. Indeed, proxies for other factors that may play an import role on farm size change, such as market condition, technical change, ect., are not available at the individual farm level in the RICA database. Nevertheless, as factors that affect transition process of farms may relate to each other (Goddard et al. 1993), proxies used may also capture impacts of some other causative factors of farm size change.

Following Zimmermann and Heckelei (2012), the total initial stocks is used as a proxy of path dependency. Initial stocks is supposed to negatively affect farm size declined since high initial stocks are assumed to result from former investment. Conversely to Zimmermann and Heckelei (2012), we do not used initial size in term of capacity of production as proxy of path dependency because farms are categorized on their capacity of production (see section) and this variable is quiet correlated to the total initial stocks.

We use the Gross Operating Surplus (GOS) minus the total amount of subsidies received and the debt rate of farms to reflect the economic environment of farms. The GOS represents the financial capacity of a farm and as such is a very important indicator to obtain credit from a bank which can be used for new investments. The GOS could also relate to the self-financing capacity of farms. A positive effect of the Gross Operating Surplus is thus expected on the probability of farm to grow. Debt rate is also expected to have a positive impact on farm growth since credit generally enables firms to obtain necessary resources Goddard et al. (1993).

Finally, some farm and farmer characteristics such as age, managerial capacity of farmers and legal status, localisation, specialisation of farms are also used in the specification of the transition probabilities. Farm and farmer characteristics may allow controlling for observed heterogeneity and are introduced in the model specification using dummy variables. Table 2 presents the description and summary statistics for the all chosen explanatory variables.

Before starting with the results, it should be noted that, given some potential sources of unobserved heterogeneity as mentioned in section , the impacts of the investigated explanatory variables may vary according to the types that a farm belong to.

Results

The mixed Markov model is applied to the RICA data described above. It is assumes that farms do not move from medium to very large size and vice versa since only few movements between these two category of sizes are observed (see Table 1). That is a common procedure in the agricultural economic literature when using Markov modeling approach (see Ben Arfa et al. (2015) for a recent example). The main results are presented and discussed in this section.

Type membership and transition probability matrices

According to the information criteria presented in section , a mixture of two types of farms seems to be the most appropriated data generating process. I chose two types as the optimal number specifically for two reasons: first, the criteria BIC and CAIC indicate that two types is the optimal number of farm types; second, even the other criteria (AIC and AIC3) indicate a higher optimal number of farm types, the results show that the improvement of these criteria is relatively small when specifying more than two types of farms (see Figure 1). This means that increasing the total number of homogeneous types in the population increase much more the total number of parameters to estimate than the representativeness of the data generating process. A mixture of two types of farms is thus preferable to represent farm size dynamics in the French farming sector.

Table 3 reports the estimated type shares and the resulting transition probability matrices (TPMs) for the two types of farms. As expected, the resulting TPMs are quite different from each other. The average posterior probabilities of belonging to a specific type indicate that a majority of farms tends to remain in their initial category of sizes indefinitely (at least during the whole period of observation). Indeed, about 68% of the sample consists of farms who predominantly stay in their initial category of sizes. Conversely, farms belonging to the second type, about 32% of the sample, are more likely to change category of sizes two consecutive years than farms in the first type. In the following, I refer to farms in the first type as 'stayers' and those in the second farm type as 'movers'.

For the stayers farm type, the categories are almost all absorbing states (see Table 3.a). The probability to remain in the same category of sizes two consecutive years for those farms are close or over 0.99. This result means that these farms have about 99% of chance to remain in the same category of sizes during a long time period. The transition probability matrix of the 'movers' type is also strongly diagonal meaning that even farms which are likely to change category of sizes also have a high probability to remain in their initial category two consecutive years (table 3.b). However, the probability to remain in the same category of sizes for movers is around 0.85 meaning that farms in this type have about 15% more chance to change their category of sizes than those in the stayers type. In both farm types, large sized farms represent the largest category with about 43% of the total number of farms. These larger proportions of large sized farms in both types of farms could be explained by the fact that this category of sizes is the largest in the sample (see Table 1).

Some summary statistics for various farm and farmer characteristics for both stayers and movers farm types are then computed in order to identify the profile of farms in each type. The summary statistics reported in Table 4 show that farmers who are close retirement and farms specialized in crops or operated under individual legal status are more likely to behave like a stayer. Contrary, farms whose most of part is located in area without natural handicap (mountains, piedmont plains, etc.) and farms whose farmers have received at least a minimum agricultural training are more likely to behave as a mover. However, the probability of belonging to a specific type is not very correlated to the farm and farmer characteristics considered in the model specification. Indeed, the statistics are quiet similar for all observed characteristics of farms and farmers in both types. The difference in the distribution of these characteristics between the two types of farms is very low. The difference in the proportion of farms with a specific observed characteristic in the two types is lower than 1% for almost all characteristics considered in the study. For example, the proportion of farmers over 55 years old in the stayers type and in the movers type are 17.80% and 17.50%, respectively. The descriptive statistics thus show that unobserved heterogeneity cannot be sufficiently controlled by some observed farms and/or farmer characteristics and accounting for both kinds of heterogeneity may therefore lead to more efficiently estimate the impacts of explanatory variables, including agricultural policies.

The transition probability matrix for the overall population of farms can be easily derived by summing the two types of TPMs weighted by their respective shares in the population. The resulting 1-year TPM for the overall population is reported in Table 5. The transition probabilities show that, on overall, farms are more likely to remain in their initial category two consecutive years which is a common features in the agricultural economics literature (see for example (Hallberg 1969; Stokes 2006; Piet 2011)). Indeed, the overall population TPM is strongly diagonal. The probability to remain in the same category of size two consecutive years is around 0.94. This high probability to remain in the same category of sizes is due to the high proportion of the stayers type in the population. Consequently, considering an homogeneous population to describe farm size dynamics as well as to investigate the impact of some explanatory variables on transition probabilities may be not sufficiently informative. Analysis under a mixture approach may be more informative by separating the impacts of explanatory variables, including agricultural policies, on different behaviors of farms in the population (stayers and movers in this case).

Impact of explanatory variables

The parameters of transition probabilities are estimated under the mixture Markov assumption. For each type of farms, a multinomial logit regression is estimated using the posterior probability of belonging to a specific type as a weighted factor as described in section . As mentioned in section , for each initial category of sizes the alternative to remain in the same category of sizes two consecutive years is used as the reference. The estimated coefficients for the odds ratios are reported in Table 6. As expected, the results show that the impacts of the explanatory variables are different given the type of farms considered. Even the same sign is most often observed for some parameters, the coefficient values are generally different meaning that the impacts of explanatory variables depend on the type membership of farms. On overall, subsidies per hectare from the First and the Second Pillars, initial stocks, total Gross Operating Surplus and debt rate of farms have a positive impact on the probability to grow and negatively affect farm size declined whatever the farm type considered. These results are consistent to the literature and confirm the expectations. Several studies showed that subsidies from some support programs of the Common Agricultural Policy (CAP) are likely to favour farm growth (see Ben Arfa et al. (2015) for a recent example). Zimmermann and Heckelei (2012) found that stocking density positively affect farm growth. Contrary to the later authors, the results also support that initial stocks decrease the probability of farms to decline. Furthermore, it should be noted that subsidies from the Second Pillar are more likely to increase the probability of farms to grow only for medium sized farms. These kinds of subsidies generally decrease the probability to decline. This result confirms our expectation that subsidies from the Second Pillar of the CAP are less likely to encourage farm growth than public supports from the First Pillar.

The results also show that farms are more likely to decrease category of sizes when farmers are over 55 years, in both types of farms. Individual legal status as well as specialisation in crop productions have the same impacts on farm growth. These results can be explained by the fact that: first, farmers may be less motivated to increase their capacity of production when they are close of retirement because they should be more interested to the farm succession (Potter and Lobbley 1992) or by the fact that younger farmers are more likely to seek to increase agricultural activity, as they would be less financially secure than their older counterparts (Howley, Dillon, and Hennessy 2014); second, farms involving under individual legal status may face much more economical constraints (capital, access to credit, etc.) than corporate farms which may constrain new investments or such farms may just have less financial motives than corporate farms (Boehlje 1992); third, it may be more difficult for farms specialized in crop productions to increase their operated farm size over time because of the regulation of the land market, specially in France, since increasing the production capacity for crop farms may generally need to increase the total land used more than for livestock production systems. Conversely to the previous farm and farmer characteristics, the probability to grow increase if the most part of the farm is located in an area without natural handicap or if farmers have received a minimum agricultural trainings. The later result confirm the positive impact of the managerial capacity on farm size growth (Boehlje 1992; Goddard et al. 1993).

Because of the coefficient values from the multinomial logit model are difficult to interpret (Greene 2006), the probability elasticities for the main explanatory variables are derived. As the study specially investigates impacts of agricultural policies on farm size changes, more attention is paid on the impact of subsidies received by farms from the two Pillars of the CAP. The results are then compared to those obtained under the assumption of homogeneous farm population.

Tables 8, 9 and 10 respectively report the probability elasticities for farms to grow, decline and remain in the same category of sizes two consecutive years. The results show that the impact of subsidies both from the First and the Second Pillars of the CAP on the probability of farms to grow or decline is higher for farms belonging to the stayers type than for farms in the movers one. For example, a 1% increase of subsidies from the First Pillar (in 1000 Euros) will increase the probability of farms in the stayers type to move from medium sized to large about 0.57 but only 0.17 for the movers type. The impact of coupled and decoupled subsidies is thus about 70% higher for farms in the stayers than for the movers ones. This result may be explained by the fact that the stayers type could gather farms who have some liquidity constraints and aids from government programs may have an income multiplier effect for those farms (Latruffe et al. 2010).

Nevertheless, the results also show that for the stayers type of farms the subsidies from the First Pillar of the CAP only have a positive impact on growth of medium sized farms. Indeed, large and very large sized farms in this type are more likely to remain in their category of sizes when increased their amount of subsidies. It could be the fact that farms in the stayers type may be less motivated to increase their operated farm size at a certain level for some of the reasons mentioned in section . In particular, they may have less financial motives and therefore may have a lower optimal size than farms in the movers type. As the subsidies received will increase the total profit, the probability for these farms to become very large may decrease with the amount of subsidies received.

Structure elasticities are then computed at the mean effects of subsidies from each Pillar. Since it is impossible to take into account entry and exit in farming and constant population were assumed, the structure elasticities are computed on proportion of farms by category of sizes. The structure elasticities thus represent the variation of farm proportion in a specific category of sizes that will occur by 1% change of the total amount of subsidies received by farms. Figure 2 and 3 present the resulting structure elasticities for both the homogeneous and the mixture model. The figures show that the resulting structure elasticities from the homogeneous model and the mixture one are quite different. Overall, the homogeneous model tends to overestimate the impacts of subsidies from both the first and the Second Pillars of the CAP. For example, the homogeneous model predicts that a 1% increase of subsidies from the First Pillar will decrease the proportion of medium sized farms by about 2.72% while the mixture model predicts a decrease only about 1.82% (see Figure 2). Likewise, the homogeneous model predicts a about 0.67% increase of the proportion of very large sized farm if subsidies from the Second Pillar increase by 1% (see Figure 3) while this proportion is only about 0.41% for the mixture model. These results confirmed that ignoring unobserved heterogeneity in modeling farm size dynamics can lead to different level of agricultural policy impacts on structural change and thus to misleading conclusions.

Concluding remarks

This paper provides a new approach for modeling structural change in agriculture. Using individual level data, a mixture of homogeneous types of farms is considered in order to incorporate unobserved heterogeneity in farm transition process. A discrete choice modeling approach is used to describe farm size choices by the farmers as decision makers. A multinomial logit specification of the transitions probabilities were applied and the expectation-maximization algorithm allowed estimating parameters of the mixed Markov model. Transition probability elasticities as well as structure elasticities are derived to analyze the impacts of some exogenous variables on farm size change in the French farming sector, specially focusing on the impact of some agricultural policies.

Using a sample of farms from the 'Réseau d'Information Compatable Agricole' (RICA) from 2000 to 2013, the results showed that French farms can be divided in two types: 'stayers' who are more likely to remain in their initial category of sizes and 'movers' who change category of sizes more frequently than the farms in the stayers type. The results also showed that the population of French farms consists of a higher proportion of farms that behave like stayers which leads to a strongly diagonal transition probability matrix for the overall population. Descriptive statistics showed that the probability to belong to the stayers type or the movers one are not very correlated with the observed farm and/or farmer characteristics meaning that unobserved heterogeneity cannot be fully controlled by the observed heterogeneity.

The results also showed that the impacts of some explanatory variables of structural change in farming, including subsidies from the First and the Second Pillars of the Common Agricultural Policy (CAP), depends on the type that farms belong to. Aggregated at the population level, structure elasticities showed that mixture model leads to different results and overall the homogeneous model tends to overestimate the impacts of subsidies both from the First Pillar and the Second Pillars on farm size change over time. These results are relevant for policy assessment since they confirmed that ignoring potential unobserved heterogeneity in farmer behavior may lead to incorrect parameters and therefore to misleading conclusions.

This study has some limitations that may motivate further research. In the current paper, the estimations were performed under constant population assumption since we could not take into account entries and exits in the French farming sector because some data limitations. Accounting for entry and exits could be an obvious way to analyze the impact of agricultural policy on total number of farms by category of sizes. The results could be also improved considering other explanatory variables than those used in this application since it has been proved that several other factors may play an important role on structural change in farming.

Notes

[1]Mixture models have been so far applied to the study of economic issues such as labor mobility (Blumen, Kogan, and McCarthy 1955; Fougere and Kamionka 2003), bounds rating (Frydman and Kadam 2004; Frydman and Schuermann 2008), income or firm size dynamics (Dutta, Sefton, and Weale 2001; Cipollini, Ferretti, and Ganugi 2012).

[2]It should be noted that, the multinomial logit model is often used in the agricultural economics literature to specify transition probabilities even using aggregate data (see Zimmermann and Heckelei (2012) for a recent example). Storm (2014) used this specification method to generate individual transition probabilities for farms in a Monte Carlo simulation.

[3]The likelihood does not yield to an explicit solution for the model parameters. The EM algorithm transforms the maximization of a log of sums into a recursive maximization of the sum of logs (McLachlan and Krishnan (2007) pp. 15).

[4]This assumption means that the distribution of the complete-data vector $(\mathbf{y}_c)$ implies the appropriate distribution for the incomplete-data vector $(\mathbf{y})$ (see McLachlan and Peel (2004) pp.48).

References

Andrews, R.L., and I.S. Currim. 2003. "Retention of latent segments in regression-based marketing models." *International Journal of Research in Marketing* 20:315–321.

Baudry, J.P., and G. Celeux. 2015. "EM for mixtures-Initialization requires special care.", pp. .

Ben Arfa, N., K. Daniel, F. Jacquet, and K. Karantininis. 2015. "Agricultural Policies and Structural Change in French Dairy Farms: A Nonstationary Markov Model." *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 63:19–42.

Blumen, I., M. Kogan, and P.J. McCarthy. 1955. *The industrial mobility of labor as a probability process*, vol. VI. Cornell Studies in Industrial and Labor Relations.

Boehlje, M. 1992. "Alternative models of structural change in agriculture and related industries." *Agribusiness (1986-1998)* 8:219.

Bostwick, D. 1962. *Yield probabilities as a Markov process*. Marketing Economics Division, Economic Research Service, US Department of Agriculture.

Cipollini, F., C. Ferretti, and P. Ganugi. 2012. "Firm size dynamics in an industrial district: The mover-stayer model in action." In A. Di Ciaccio, M. Coli, and J. M. Angulo Ibanez, eds. *Advanced Statistical Methods for the Analysis of Large Data-Sets*. Springer Berlin Heidelberg, pp. 443–452.

Dempster, A.P., N.M. Laird, and D.B. Rubin. 1977. "Maximum likelihood from incomplete data via the EM algorithm." *Journal of the Royal Statistical Society* 39:1–38.

Dias, J.G., and F. Willekens. 2005. "Model-based clustering of sequential data with an application to contraceptive use dynamics." *Mathematical population studies* 12:135–157.

Dong, F., D.A. Hennessy, and H.H. Jensen. 2010. "Contract and exit decisions in finisher hog production." *American Journal of Agricultural Economics* 92:667–684.

Dutta, J., J.A. Sefton, and M.R. Weale. 2001. "Income distribution and income dynamics in the United Kingdom." *Journal of Applied Econometrics* 16:599–617.

Dwyer, J. 2013. "Transformation for sustainable agriculture: what role for the second Pillar of CAP?" *Bio-based and Applied Economics* 2:29–47.

Fougere, D., and T. Kamionka. 2003. "Bayesian inference for the mover-stayer model in continuous time with an application to labour market transition data." *Journal of Applied Econometrics* 18:697–723.

Freshwater, D., and B. Reimer. 1995. "Socio-economic policies as causal forces for the structure of agriculture." *Canadian journal of agricultural economics*, pp. .

Frydman, H. 2005. “Estimation in the mixture of Markov chains moving with different speeds.” *Journal of the American Statistical Association* 100:1046–1053.

Frydman, H., and A. Kadam. 2004. “Estimation in the continuous time mover-stayer model with an application to bond ratings migration.” *Applied Stochastic Models in Business and Industry* 20:155–170.

Frydman, H., and T. Schuermann. 2008. “Credit rating dynamics and Markov mixture models.” *Journal of Banking and Finance* 32:1062–1075.

Garver, M.S., Z. Williams, and G.S. Taylor. 2008. “EMPLOYING LATENT CLASS REGRESSION ANALYSIS TO EXAMINE LOGISTICS THEORY: AN APPLICATION OF TRUCK DRIVER RETENTION.” *Journal of Business Logistics* 29:233–257.

Goddard, E., A. Weersink, K. Chen, and C.G. Turvey. 1993. “Economics of Structural Change in Agriculture.” *Canadian Journal of Agricultural Economics/Revue canadienne d’agroeconomie* 41:475–489.

Greene, W.H. 2006. *Econometric analysis*, 6th ed. Pearson Education India.

Greene, W.H., and D.A. Hensher. 2003. “A latent class model for discrete choice analysis: contrasts with mixed logit.” *Transportation Research Part B: Methodological* 37:681 – 698.

Hallam, A. 1991. “Economies of Size and Scale in Agriculture: An Interpretive Review of Empirical Measurement.” *Review of Agricultural Economics* 13:155–172.

Hallberg, M.C. 1969. “Projecting the size distribution of agricultural firms. An application of a Markov process with non-stationary transition probabilities.” *American Journal of Agricultural Economics* 51:289–302.

Harrington, D.H., and R.D. Reinsel. 1995. “synthesis of forces driving structural change.” *Canadian Journal of Agricultural Economics*, pp. .

Hess, S., M. Bierlaire, and J. Polak. 2006. “A systematic comparison of continuous and discrete mixture models.” Working paper.

Holloway, G., D. Lacombe, and J.P. LeSage. 2007. “Spatial Econometric Issues for Bio-Economic and Land-Use Modelling.” *Journal of Agricultural Economics* 58:549–588.

Howley, P. 2015. “The Happy Farmer: The Effect of Nonpecuniary Benefits on Behavior.” *American Journal of Agricultural Economics*, pp. .

Howley, P., E. Dillon, and T. Hennessy. 2014. “It s not all about the money: understanding farmers labor allocation choices.” *Agriculture and Human Values* 31:261–271.

Huettel, S., and R. Jongeneel. 2011. “How has the EU milk quota affected patterns of herd-size change?” *European Review of Agricultural Economics* 38:497–527.

Jafry, Y., and T. Schuermann. 2004. “Measurement, estimation and comparison of credit migration matrices.” *Journal of Banking & Finance* 28:2603–2639.

Krenz, R.D. 1964. “Projection of Farm Numbers for North Dakota with Markov Chains.” *Agr. Econ. Res.* 16:77–83.

Latruffe, L., S. Davidova, E. Douarin, and M. Gorton. 2010. “Farm expansion in Lithuania after accession to the EU: The role of CAP payments in alleviating potential credit constraints.” *Europe-Asia Studies* 62:351–365.

Lee, T., G. Judge, and A. Zellner. 1977. *Estimating the parameters of the Markov probability model from aggregate time series data*. Amsterdam: North Holland.

Lee, T.C., G.G. Judge, and T. Takayama. 1965. “On estimating the transition probabilities of a Markov process.” *Journal of Farm Economics* 47:742–762.

McLachlan, G., and T. Krishnan. 2007. *The EM algorithm and extensions*, vol. 382. John Wiley & Sons.

McLachlan, G., and D. Peel. 2004. *Finite mixture models*. John Wiley & Sons.

Pacifico, D., and H.I. Yoo. 2012. “lclogit: a Stata module for estimating latent class conditional logit models via the expectation-maximization algorithm.” *UNSW Australian School of Business Research Paper*, pp. .

Padberg, D.I. 1962. “The Use of Markov Processes in Measuring Changes in Market Structure.” *J. Farm Econ.* 44:189–199.

Pennings, J.M., and P. Garcia. 2004. "Hedging behavior in small and medium-sized enterprises: The role of unobserved heterogeneity." *Journal of Banking & Finance* 28:951–978.

Piet, L. 2011. "Assessing structural change in agriculture with a parametric Markov chain model. Illustrative applications to EU-15 and the USA." Paper presented at the XIIIth Congress of the European Association of Agricultural Economist, Zurich (Switzerland).

Potter, C., and M. Lobbley. 1992. "AGEING AND SUCCESSION ON FAMILY FARMS: The Impact on Decision-making and Land Use." *Sociologia Ruralis* 32:317–334.

Rahelizatovo, N.C., and J.M. Gillespie. 1999. "Dairy farm size, entry, and declining production region." *J. Agr. Appl. Econ.* 31:333–347.

Saint-Cyr, L.D., and L. Piet. 2014. "Movers and Stayers in the Farming Sector: Another Look at Heterogeneity in Structural Change." In *2014 International Congress, August 26-29, 2014, Ljubljana, Slovenia*. European Association of Agricultural Economists, 183068.

Stokes, J.R. 2006. "Entry, exit, and structural change in Pennsylvania's dairy sector." *Agr. Resource Econ. Rev.* 35:357.

Storm, H. 2014. "Methods of analysis and empirical evidence of farm structural change." Dissertation.

Train, K.E. 2009. *Discrete choice methods with simulation*. Cambridge university press.

Vermunt, J. 2010. "Longitudinal Research Using Mixture Models." In K. van Montfort, J. H. Oud, and A. Satorra, eds. *Longitudinal Research with Latent Variables*. Springer Berlin Heidelberg, pp. 119–152.

Weiss, C.R. 1999. "Farm growth and survival: econometric evidence for individual farms in upper Austria." *American Journal of Agricultural Economics* 81:103–116.

Zepeda, L. 1995. "Asymmetry and nonstationarity in the farm size distribution of Wisconsin milk producers: An aggregate analysis." *American Journal of Agricultural Economics* 77:837–852.

Zimmermann, A., and T. Heckelei. 2012. "Structural change of European dairy farms: A cross-regional analysis." *Journal of Agricultural Economics* 63:576–603.

Zimmermann, A., T. Heckelei, and I.P. Dominguez. 2009. "Modelling farm structural change for integrated ex-ante assessment: Review of methods and determinants." *Environmental Science and Policy* 12:601–618.

Figures

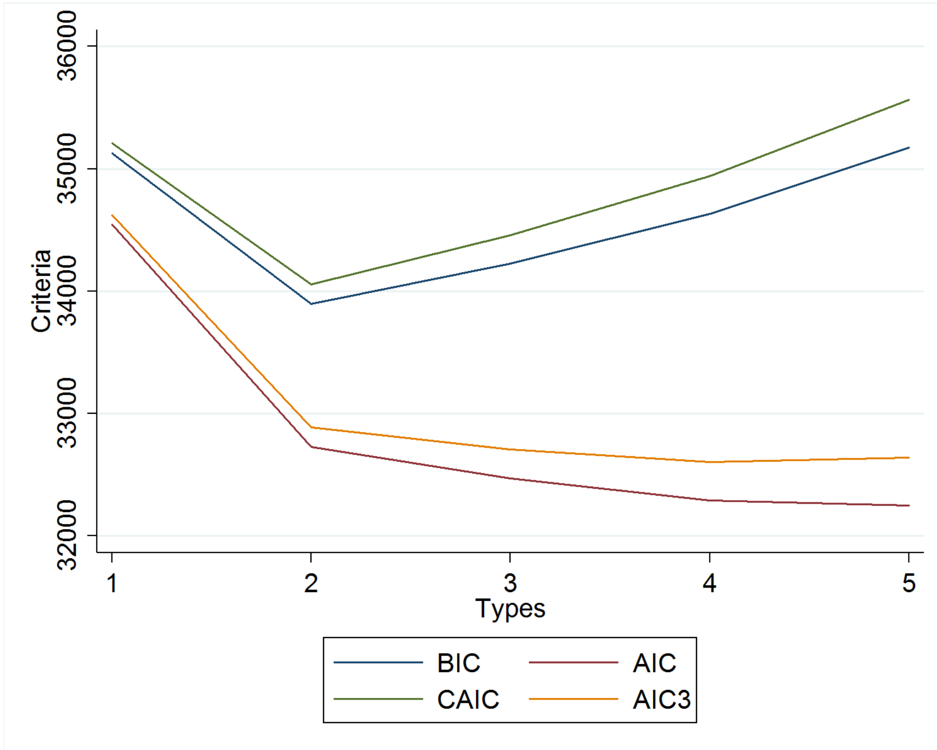

Figure 1. Comparison of model-fit statistics for different numbers of types.

Source: Agreste, RICA France 2000-2013 – authors' calculations

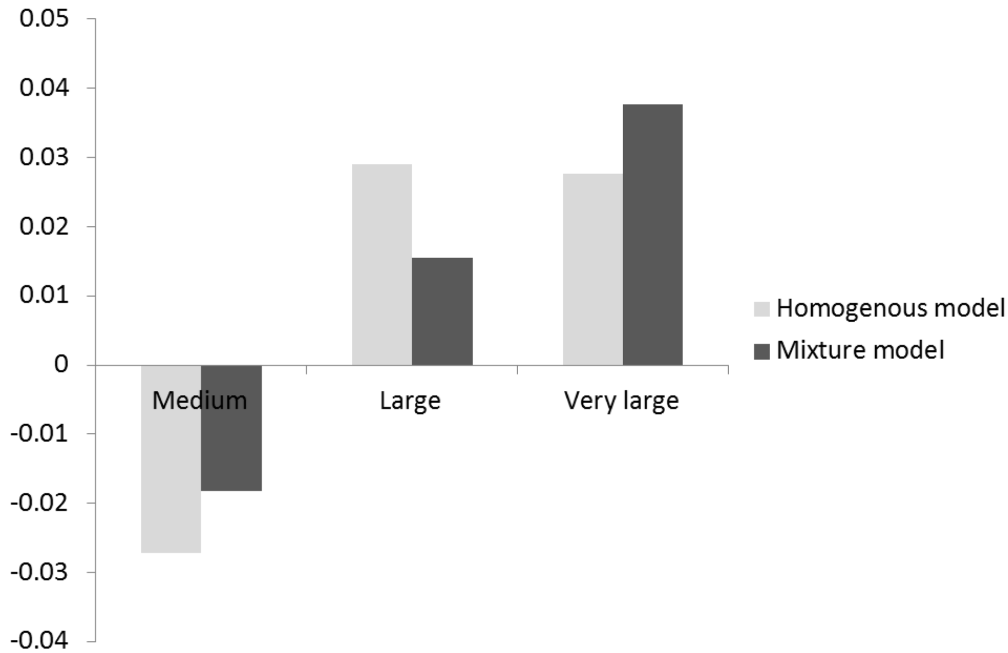

Figure 2. Yearly structure elasticities of subsidies from the First Pillar of the CAP for the homogeneous and the mixed Markov models.

Source: Agreste, RICA France 2000-2013 – authors' calculations

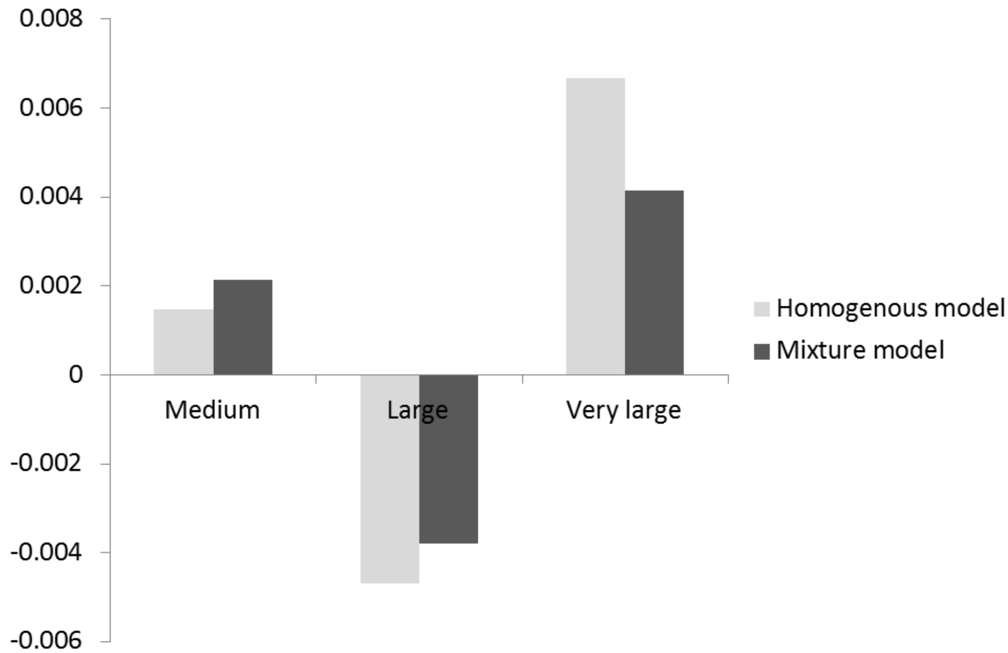

Figure 3. Yearly structure elasticities of subsidies from the Second Pillar of the CAP for the homogeneous and the mixed Markov models.

Source: Agreste, RICA France 2000-2013 – authors' calculations

Tables

Table 1. Farm 1-year interval transitions across category of sizes, 2000-2013

		ES class			
		25-100	100-250	≥ 250	Total transitions
ES class	25-100	26,034	1,310	27	27,371
	100-250	1,257	32,425	1,055	34,737
	≥ 250	31	840	12,925	13,796

Note: ES in 1,000 Euros of standard output (SO).

Source: Agreste, RICA France 2000-2013 – authors' calculations

Table 2. Descriptive statistics and definition of the explanatory variables (n=75,904)

Variable	Mean	Std. Dev.	Min.	Max.
pillar1/hectare	1.667	1.073	0.000	10.692
(Subsidies per hectare from the 1st pillar)				
pillar2/hectare	0.420	0.718	-0.001	11.202
(Subsidies per hectare from the 2nd pillar)				
in_stocks	91.547	128.361	0.000	1,814.976
(Total initial stocks)				
output/AWU	85.651	52.594	-364.297	646.905
(Total output per AWU)				
GOS/utans	26.053	38.480	-421.569	561.165
(GOS per non-salaried UTA)				
debt_rate	39.678	26.679	0.000	366.400
(Total debt/liabilities)				
close_retirement	0.177	0.381	0.000	1.000
(over 55 years old[a])				
crops	0.451	0.498	0.000	1.000
(Specialized in crops)				
individual	0.513	0 .500	0.000	1.000
(Operate under individual legal status)				
well_located	0.599	0.490	0.000	1.000
(Most part in area without natural handicap)				
agri_skills	0.936	0.246	0.000	1.000
(Has agricultural trainings)				

pillar1/hectare, *pillar2/hectare*, *in_stock* and *GOS/utans* in 1,000 Euros;
[a]In order to take into account anticipation of farmers, 55 years old is used instead of 62 which is the legal age of retirement in France.

Source: Agreste, RICA France 2000-2013 – authors' calculations

Table 3. Estimated farm type shares and 1-year transition probability matrices (TPMs)

		Shares	ES class		
		68.15%	25-100	100-250	≥ 250
ES class	25-100	40.10%	0.992(0.014)	0.008(0.014)	0.000(.)
	100-250	42.92%	0.007(0.009)	0.986(0.012)	0.007(0.007)
	≥ 250	16.98%	0.000(.)	0.011(0.019)	0.989(0.019)

a) Stayers TPM

		Shares	ES class		
		31.85%	25-100	100-250	≥ 250
ES class	25-100	36.90%	0.858(0.113)	0.142(0.113)	0.000(.)
	100-250	43.12%	0.091(0.076)	0.828(0.080)	0.081(0.074)
	≥ 250	19.98%	0.000(.)	0.151(0.100)	0.849(0.100)

a) Movers TPM

Note: ES in 1,000 Euros of standard output (SO); standard deviations in parenthesis

Source: Agreste, RICA France 2000-2013 – authors' calculations

Table 4. Descriptive statistics for observed farm characteristics by type membership.

Variable	Stayers type		Movers type	
close_retirement	0.822	(0.382)	0.825	(0.380)
crops	0.453	(0.498)	0.447	(0.497)
individual	0.516	(0.500)	0.506	(0.500)
well_located	0.599	(0.490)	0.600	(0.490)
agri_skills	0.933	(0.249)	0.940	(0.238)

Standard deviations in parenthesis

Source: Agreste, RICA France 2000-2013 – authors' calculations

Table 5. Overall population 1-year transition probability matrix.

		ES class		
		25-100	100-250	≥ 250
ES class	25-100	0.951(0.045)	0.049(0.045)	0.000(.)
	100-250	0.034(0.029)	0.935(0.027)	0.031(0.025)
	≥ 250	0.000(.)	0.055(0.038)	0.945(0.038)

Note: ES in 1,000 Euros of standard output (SO); standard deviations in parenthesis

Source: Agreste, RICA France 2000-2013 – authors' calculations

Table 6. Estimated parameters of farm probabilities to grow two consecutive years for the homogeneous and the mixed Markov models.

Odds ratios	Variables	Homogeneous		Stayers type		Movers type	
p12/p11	*intercept*	-3.912***	(0.208)	-6.804***	(0.385)	-2.998***	(0.193)
	pillar1/hectare	0.274***	(0.044)	0.417***	(0.071)	0.141***	(0.042)
	pillar2/hectare	-0.119	(0.071)	0.229**	(0.080)	-0.206**	(0.070)
	in_stocks	0.003 ***	(0.001)	0.004***	(0.001)	0.013***	(0.001)
	GOS/utans	0.010***	(0.002)	0.005*	(0.002)	0.011***	(0.002)
	debt_rate	0.010***	(0.001)	0.010***	(0.001)	0.015***	(0.001)
	close_retirement	0.307**	(0.100)	1.046***	(0.214)	0.150	(0.096)
	crops	-0.387***	(0.081)	-0.254	(0.137)	-0.363***	(0.072)
	individual	-0.783***	(0.074)	-1.412***	(0.115)	-0.714***	(0.068)
	well_located	0.283***	(0.083)	0.641***	(0.134)	0.249***	(0.070)
	agri_skills	0.285*	(0.146)	0.362	(0.264)	0.314*	(0.137)
p23/22	*intercept*	-4.782***	(0.242)	-4.697***	(0.342)	-4.400***	(0.263)
	pillar1/hectare	0.169***	(0.044)	-0.536***	(0.057)	0.311***	(0.039)
	pillar2/hectare	0.055	(0.053)	-0.049	(0.089)	0.024	(0.058)
	in_stocks	0.003***	(0.000)	0.001	(0.001)	0.005***	(0.000)
	GOS/utans	0.006***	(0.001)	0.003**	(0.001)	0.008***	(0.001)
	debt_rate	0.012***	(0.001)	0.009***	(0.002)	0.014***	(0.001)
	close_retirement	0.096	(0.096)	-0.030	(0.150)	0.164	(0.099)
	crops	-0.436***	(0.081)	0.220	(0.122)	-0.750	(0.083)
	individual	-0.520***	(0.082)	-0.040	(0.119)	-0.716***	(0.083)
	well_located	0.200*	(0.087)	0.180	(0.146)	0.167***	(0.083)
	agri_skills	0.222	(0.184)	-0.201	(0.240)	0.384***	(0.210)

Note: Standard errors in parenthesis; ***, ** and * are significant at 0.1%, 1% and 5%, respectively.

Source: Agreste, RICA France 2000-2013 – authors' calculations

Table 7. Estimated parameters of farm probabilities to decline two consecutive years for the homogeneous and the mixed Markov models.

Odds ratios	Variables	Homogeneous		Stayers type		Movers type	
p21/p22	*intercept*	-1.471***	(0.195)	-4.509***	(0.326)	0.228	(0.185)
	pillar1/hectare	-0.224***	(0.037)	-0.377***	(0.066)	-0.161***	(0.035)
	pillar2/hectare	-0.053	(0.040)	0.045	(0.063)	-0.083	(0.043)
	in_stocks	-0.009***	(0.001)	0.002*	(0.001)	-0.013***	(0.001)
	GOS/utans	-0.014***	(0.002)	-0.013***	(0.002)	-0.014***	(0.002)
	debt_rate	-0.005***	(0.002)	0.008***	(0.002)	-0.009***	(0.001)
	close_retirement	-0.327***	(0.081)	-1.068***	(0.127)	-0.163	(0.085)
	crops	-0.158*	(0.075)	-0.379**	(0.122)	-0.104	(0.071)
	individual	0.802***	(0.075)	0.761	(0.122)	0 .675***	(0.070)
	well_located	-0.485***	(0.075)	0.013	(0.130)	-0.539***	(0.073)
	agri_skills	-0.105	(0.149)	0.536*	(0.249)	-0.526***	(0.141)
p32/p33	*intercept*	-1.066***	(0.252)	-2.434***	(0.375)	0.469*	(0.244)
	pillar1/hectare	-0.060	(0.038)	-0.355***	(0.067)	-0.122**	(0.040)
	pillar2/hectare	-0.201**	(0.067)	-0.139	(0.097)	-0.203**	(0.071)
	in_stocks	-0.004***	(0.001)	0.001	(0.001)	-0.006***	(0.001)
	GOS/utans	-0.007***	(0.001)	-0.01***	(0.002)	-0.007***	(0.001)
	debt_rate	-0.006***	(0.002)	-0.003	(0.003)	-0.009***	(0.002)
	close_retirement	-0.131	(0.099)	-1.111***	(0.159)	-0.073	(0.105)
	crops	-0.266**	(0.098)	-1.170***	(0.190)	-0.037	(0.084)
	individual	0.431***	(0.099)	1.914***	(0.154)	0.147	(0.091)
	well_located	-0.261*	(0.102)	0.055	(0.233)	-0.212*	(0.096)
	agri_skills	0.018	(0.188)	-0.659**	(0.257)	-0.013	(0.171)

Note: Standard errors in parenthesis; ***, ** and * are significant at 0.1%, 1% and 5%, respectively.

Source: Agreste, RICA France 2000-2013 – authors' calculations

Table 8. Yearly probability elasticities of farm growth for the homogeneous and the mixed Markov models.

Probability	Variables	Homogeneous		Stayers type		Movers type	
Medium/Large (p12)	*pillar1/hectare*	0.363	(0.058)	0.574	(0.098)	0.171	(0.051)
	pillar2/hectare	-0.058	(0.035)	0.118	(0.041)	-0.090	(0.031)
	i*in_stocks*	0.111	(0.031)	0.155	(0.045)	0.381	(0.026)
	GOS/utans	0.103	(0.021)	0.056	(0.024)	0.103	(0.020)
	debt_rate	0.298	(0.027)	0.323	(0.043)	0.393	(0.026)
	close_retirement	0.241	(0.078)	0.855	(0.175)	0.105	(0.068)
	crops	-0.149	(0.032)	-0.101	(0.055)	-0.128	(0.026)
	individual	-0.594	(0.057)	-1.115	(0.091)	-0.491	(0.048)
	well_located	0.118	(0.034)	0.277	(0.058)	0.093	(0.026)
	agri_skills	0.248	(0.127)	0.329	(0.241)	0.246	(0.106)
Large/V. large (p23)	*pillar1/hectare*	0.304	(0.075)	-0.955	(0.102)	0.522	(0.062)
	pillar2/hectare	0.020	(0.019)	-0.018	(0.031)	0.012	(0.020)
	in_stocks	0.231	(0.028)	0.085	(0.056)	0.421	(0.028)
	GOS/utans	0.155	(0.028)	0.095	(0.034)	0.218	(0.024)
	debt_rate	0.480	(0.049)	0.372	(0.069)	0.558	(0.055)
	close_retirement	0.086	(0.077)	-0.020	(0.123)	0.137	(0.076)
	crops	-0.197	(0.037)	0.103	(0.057)	-0.326	(0.037)
	individual	-0.227	(0.033)	-0.019	(0.047)	-0.338	(0.036)
	well_located	0.136	(0.055)	0.118	(0.095)	0.125	(0.049)
	agri_skills	0.208	(0.169)	-0.192	(0.225)	0.384	(0.186)

Note: Standard errors in parenthesis

Source: Agreste, RICA France 2000-2013 – authors' calculations

Table 9. Yearly probability elasticities of farm declined for the homogeneous and the mixed Markov models.

Probability	Variables	Homogeneous		Stayers type		Movers type	
Large/Medium (p21)	*pillar1/hectare*	-0.397	(0.065)	-0.669	(0.118)	-0.312	(0.058)
	pillar2/hectare	-0.019	(0.014)	0.016	(0.022)	-0.029	(0.015)
	in_stocks	-0.751	(0.107)	0.148	(0.062)	-1.070	(0.079)
	GOS/utans	-0.366	(0.042)	-0.344	(0.052)	-0.368	(0.055)
	debt_rate	-0.224	(0.062)	0.342	(0.092)	-0.386	(0.057)
	close_retirement	-0.264	(0.065)	-0.878	(0.104)	-0.133	(0.064)
	crops	-0.067	(0.034)	-0.178	(0.057)	-0.024	(0.031)
	individual	0.315	(0.028)	0.300	(0.048)	0.264	(0.026)
	well_located	-0.312	(0.048)	0.008	(0.085)	-0.33	(0.045)
	agri_skills	-0.102	(0.136)	0.504	(0.233)	-0.483	(0.124)
V. Large/Large (p32)	*pillar1/hectare*	-0.106	(0.067)	-0.643	(0.121)	-0.206	(0.069)
	pillar2/hectare	-0.073	(0.024)	-0.054	(0.038)	-0.063	(0.023)
	in_stocks	-0.794	(0.150)	0.209	(0.114)	-1.171	(0.110)
	GOS/utans	-0.379	(0.055)	-0.530	(0.097)	-0.325	(0.051)
	debt_rate	-0.269	(0.080)	-0.167	(0.168)	-0.383	(0.071)
	close_retirement	-0.100	(0.076)	-0.886	(0.127)	-0.051	(0.073)
	crops	-0.127	(0.047)	-0.601	(0.098)	-0.015	(0.035)
	individual	0.089	(0.020)	0.421	(0.033)	0.026	(0.016)
	well_located	-0.191	(0.075)	0.043	(0.182)	-0.138	(0.063)
	agri_skills	0.016	(0.167)	-0.612	(0.239)	-0.011	(0.138)

Note: Standard errors in parenthesis

Source: Agreste, RICA France 2000-2013 – authors' calculations

Table 10. Yearly probability elasticities of farms to remain in the same category of sizes for the homogeneous and the mixed Markov models.

Probability	Variables	Homogeneous		Stayers type		Movers type	
Medium/Medium (p11)	*pillar1/hectare*	-0.021	(0.004)	-0.006	(0.001)	-0.031	(0.010)
	pillar2/hectare	0.003	(0.001)	-0.001	(0.001)	0.012	(0.004)
	in_stocks	-0.008	(0.003)	-0.003	(0.001)	-0.088	(0.008)
	GOS/utans	-0.008	(0.002)	-0.001	(0.000)	-0.025	(0.006)
	debt_rate	-0.020	(0.002)	-0.004	(0.001)	-0.087	(0.007)
	close_retirement	-0.013	(0.004)	-0.008	(0.002)	-0.018	(0.012)
	crops	0.007	(0.001)	0.001	(0.000)	0.020	(0.003)
	individual	0.023	(0.002)	0.005	(0.000)	0.064	(0.005)
	well_located	-0.007	(0.002)	-0.003	(0.001)	-0.018	(0.005)
	agri_skills	-0.013	(0.007)	-0.003	(0.002)	-0.042	(0.018)
Large/Large (p22)	*pillar1/hectare*	0.003	(0.003)	0.008	(0.001)	-0.027	(0.009)
	pillar2/hectare	0.000	(0.001)	0.000	(0.000)	0.003	(0.002)
	in_stocks	0.008	(0.002)	-.002	(0.001)	0.018	(0.006)
	GOS/utans	0.001	(0.002)	0.000	(0.000)	-0.002	(0.004)
	debt_rate	-0.010	(0.003)	-0.006	(0.001)	-0.021	(0.008)
	close_retirement	0.007	(0.003)	0.005	(0.001)	0002	(0.009)
	crops	0.008	(0.001)	0.000	(0.001)	0.025	(0.003)
	individual	-0.014	(0.002)	-0.003	(0.001)	-0.028	(0.005)
	well_located	0.005	(0.002)	-0.001	(0.001)	0.018	(0.005)
	agri_skills	-0.003	(0.008)	-0.002	(0.002)	0.018	(0.019)
V.Large/V.Large (p33)	*pillar1/hectare*	0.007	(0.004)	0.004	(0.001)	0.038	(0.012)
	pillar2/hectare	0.004	(0.001)	0.000	(0.000)	0.010	(0.003)
	in_stocks	0.028	(0.004)	-0.002	(0.002)	0.104	(0.007)
	GOS/utans	0.015	(0.002)	0.004	(0.000)	0.035	(0.004)
	debt_rate	0.017	(0.005)	0.002	(0.002)	0.069	(0.012)
	close_retirement	0.006	(0.005)	0.007	(0.001)	0.009	(0.013)
	crops	0.006	(0.002)	0.006	(0.001)	0.002	(0.005)
	individual	-0.008	(0.002)	-0.013	(0.002)	-0.006	(0.004)
	well_located	0.011	(0.004)	0.000	(0.002)	0.023	(0.010)
	agri_skills	-0.001	(0.011)	0.006	(0.002)	0.002	(0.025)

Note: Standard errors in parenthesis

Source: Agreste, RICA France 2000-2013 – authors' calculations