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Movers and stayers in the farming sector: accounting for unobserved heterogeneity in structural change

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Summary. The paper investigates whether accounting for unobserved heterogeneity in farms' size transition processes improves the representation of structural change in agriculture. Considering a mixture of two types of farm, the mover–stayer model is applied for the first time in an agricultural economics context. The maximum likelihood method and the expectation–maximization algorithm are used to estimate the model's parameters. An empirical application to a panel of French farms from 2000 to 2013 shows that the mover–stayer model outperforms the homogeneous Markov chain model in recovering the transition process and predicting the future distribution of farm sizes.

Keywords: EM algorithm; Farms; Markov chain; Mover–stayer model; Structural change; Unobserved heterogeneity

1. Introduction

In most developed countries, the number of farms has decreased sharply and their average size has increased continually over recent decades. Structural change has long been a subject of considerable interest to agricultural economists and policy makers. Previous studies aimed in particular to understand the mechanisms underlying this process to identify the key drivers that influence the observed trends, and to generate prospective scenarios. This paper makes a methodological contribution to the literature. More specifically, the aim of the research was to investigate whether a mixture modelling approach could account for unobserved heterogeneity in the size transition process of farms and, in doing so, to improve the estimation and prediction of structural change in agriculture.

As Zimmermann *et al.* (2009) showed in their review, it has become quite common in agricultural economics to study the way that farms experience size change by applying the so-called Markov chain model (MCM) to aggregate series of farm numbers by size categories (see Huettel and Jongeneel (2011), Zimmermann and Heckelei (2012) or Ben Arfa *et al.* (2014) for recent examples). Although the MCM framework is essentially a statistical modelling approach, Stokes (2006) showed that a Markovian transition process may be derived from a structural model of intertemporal profit maximization, giving theoretical grounds to using the MCM. Basically, this model states that a farm's size at a given date is the result of a probabilistic process which depends on only its size in the previous period since, in general, a first-order Markov process is

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assumed. In its simplest version, the MCM framework assumes stationarity and homogeneity, i.e. it assumes that transition probabilities are invariant over time and that all farms move from one category to another according to the same unique stochastic process, conditionally on their initial size. Although MCMs were first developed in this simplest form, two directions have been investigated to improve the modelling framework when applied to farming. Firstly, assuming that farms' transition probabilities may vary over time, non-stationary MCMs have been developed to investigate the effects of time varying variables such as agricultural policies on farm structural changes (see Zimmermann *et al.* (2009) for a review). Secondly, assuming that the transition process may differ depending on farm and/or farmer characteristics, some studies have accounted for farm heterogeneity in modelling structural change. However, to date, to the best of our knowledge, only observed heterogeneity (such as regional location, type of farming, legal status or age group) has been considered, implying that all farms sharing the same observed characteristics follow the same stochastic process (see Zimmermann and Heckelei (2012) for a recent example).

We argue that structural change in agriculture may also pertain to individual characteristics or behaviours of farms and/or farmers which are not observable in practice. From a theoretical point of view, this unobserved heterogeneity may originate from several sources that relate to, for example, the imperfect functioning of land and/or credit markets, or farmer preferences. 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 be faced with the same land supply: because land is mostly released on retirement, a farmer who is surrounded only by young colleagues will not find plots to buy or rent. Even if land offers exist, farmers may have different abilities to negotiate with landowners, may face unequal conditions to access credit or simply may not be willing to extend their business for personal reasons. In any case, such types of rationale may not be fully linked to 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 they share the same observed characteristics, farms with an equal initial size may not experience structural change at the same speed or to the same extent. Therefore, as farm level data have become more widely available, accounting for unobserved heterogeneity in farms' size transition processes may allow the underlying data-generating process to be recovered in a more efficient way than with a simple homogeneous MCM. In this paper, we investigate whether or not this is so by comparing two alternative modelling frameworks, namely the homogeneous MCM, which does not account for heterogeneity, and the mover-stayer model (MSM), which accounts for unobserved heterogeneity.

The MSM extends the MCM framework by considering two types of agent following two different transition processes: the 'movers' who follow a first-order Markovian process and the 'stayers' who never experience a transition. Because it derives from the MCM, the MSM exhibits the same mathematical simplicity and stability properties that have made Markovian approaches attractive for modelling dynamic random phenomena in economics (Meyn and Tweedie, 2009). However, since it has been shown that economic transition processes are often not 'purely' Markovian (Bickenbach and Bode, 2001), the MSM enables relaxation of the homogeneity assumption underlying the MCM. The MSM has thus allowed evidencing the presence of unobserved heterogeneity in several economic issues such as social (Singer and Spilerman, 1974, 1976), labour (Blumen *et al.*, 1955; Fougere and Kamionka, 2003, 2008) or income mobility (Shorrocks, 1976; Dutta *et al.*, 2001), financial rating (Frydman and Kadam, 2004) or firm size dynamics (Cipollini *et al.*, 2012).

There are two reasons why there have been so few studies that explicitly account for farm heterogeneity. Firstly, most previous studies focus on specific farm types such as dairy farming

or hog production. The researchers may therefore have assumed that such groups are sufficiently homogeneous to justify discarding heterogeneity issues. Secondly, studies that investigate the potential drivers of structural change in farming emphasize the role of economic factors such as market or policy variables. The researchers have therefore plainly left heterogeneity issues in the background, considering heterogeneity as a control variable rather than a variable of key interest. Although our implementation of the MSM compares with similar studies in other strands of economics, the primary contribution of our work is to demonstrate that unobserved heterogeneity is also present in the process of farm structural change, and that the MSM also constitutes a relevant model in this specific sector. In our case, the agents studied are farms and we investigate how their size, measured in economic terms, evolves over time. ‘Mover’ farms change size according to a first-order Markovian process, whereas ‘stayer’ farms always remain in their initial size category. In our view, considering this stayer type of farmers is justified because, since structural change in agriculture is a long-term process and because of the potential sources of unobserved heterogeneity that were listed above, some farms may experience no size change at all or no sufficiently large size changes to move to another size category for a sufficiently long period of time to qualify as stayers. To establish our result, we compare the respective strength of both the MCM and the MSM by using a panel of 17285 commercial French farms observed during the period 2000–2013. We estimate transition probability matrices (TPMs) and perform short- to long-term out-of-sample projections of farm size distributions for both models, which allow us to compare their respective performance, firstly, in predicting farms’ size transition probabilities and, secondly, in performing farm size distribution forecasts over time.

The paper is structured as follows: in the first section we introduce the way in which the homogeneous MCM can be generalized into the mixed MCM (MMCM) and how the specific MSM is derived. In the next two sections, we describe the method that is used to estimate MSM parameters and the two measures, namely the likelihood ratio and the average marginal error (AME), used to compare the respective performances of the MCM and the MSM. We then report our application to France, starting with a description of the data that are used and following with a presentation of the results. Finally, we conclude with some considerations on how further to extend the approach that is described here.

2. Modelling a transition process by using the Markov chain framework

Consider a population of N agents that is partitioned into a finite number J of categories or ‘states of nature’. Assuming that agents move from one category to another during a certain period of time r according to a stochastic process, we define the number $n_{j,t+r}$ of agents in category j at time $t+r$ as

$$n_{j,t+r} = \sum_{i=1}^J n_{i,t} p_{ij,t}^{(r)} \quad (1)$$

where $n_{i,t}$ is the number of agents in category i at time t , and $p_{ij,t}^{(r)}$ is the probability of moving from category i to category j between t and $t+r$. As such, $p_{ij,t}^{(r)}$ is subject to the standard non-negativity and summing to 1 constraints for probabilities:

$$\begin{aligned} p_{ij,t}^{(r)} &\geq 0, & \forall i, j, t, \\ \sum_{j=1}^J p_{ij,t}^{(r)} &= 1, & \forall i, t. \end{aligned} \quad (2)$$

Then, since we focus on the issue of accounting for heterogeneity, similarly to work that

has been done by others (Major, 2008; Cipollini *et al.*, 2012), we restrict our analysis to the stationary case where the r -step TPM $\mathbf{P}_t^{(r)} = \{p_{ij,t}^{(r)}\}$ is time invariant, i.e. $\mathbf{P}_t^{(r)} = \mathbf{P}^{(r)}$ for all t . In matrix notation, equation (1) can then be rewritten as

$$\mathbf{n}_{t+r} = \mathbf{n}_t \times \mathbf{P}^{(r)} \quad (3)$$

where $\mathbf{n}_{t+r} = \{n_{j,t+r}\}$ and $\mathbf{n}_t = \{n_{j,t}\}$ are row vectors.

Using individual level data, the observed r -step transition probabilities can then be computed from a contingency table as

$$p_{ij}^{(r)} = \nu_{ij}^{(r)} / \sum_j \nu_{ij}^{(r)} \quad (4)$$

where $\nu_{ij}^{(r)}$ is the total number of r -step transitions from category i to category j during the period of observation and $\sum_j \nu_{ij}^{(r)}$ the total number of r -step transitions out of category i .

2.1. The simple Markov chain model

Assuming that the transition process of agents is Markovian first order, Anderson and Goodman (1957) showed that the maximum likelihood estimator of the one-step TPM corresponds to the observed transition matrix, i.e. $\hat{\mathbf{\Pi}} = \mathbf{P}^{(1)}$. Under the assumption of stationarity, the r -step TPM $\hat{\mathbf{\Pi}}^{(r)}$ is then obtained by raising the one-step transition matrix to the power r :

$$\hat{\mathbf{\Pi}}^{(r)} = \hat{\mathbf{\Pi}}^r \quad (5)$$

The MCM approach thus assumes that agents in the population are homogeneous, i.e. they all move according to the same stochastic process that is described by $\hat{\mathbf{\Pi}}$. However, in general, whereas $\hat{\mathbf{\Pi}}$ is a consistent estimate of $\mathbf{P}^{(1)}$, $\hat{\mathbf{\Pi}}^{(r)}$ proves to be a poor estimate of $\mathbf{P}^{(r)}$ (Blumen *et al.*, 1955). In particular, the main diagonal elements of $\hat{\mathbf{\Pi}}^{(r)}$ largely underestimate those of $\mathbf{P}^{(r)}$. This means that, in general, $\hat{\pi}_{ii}^{(r)} \ll p_{ii}^{(r)}$. In other words, the simple MCM tends to overestimate agents' mobility because of the homogeneity assumption.

2.2. Accounting for unobserved heterogeneity: the mixed Markov chain model

One way to obtain a one-step TPM that leads to a more consistent r -step estimate consists in relaxing the assumption of homogeneity in the transition process underlying the MCM approach.

Following Poulsen (1983), Frydman (2005) proposed to ground the source of population heterogeneity on the rate of agents' movement; agents may move across categories at various speeds, each according to one of several types of transition process. This usually constitutes unobserved heterogeneity because observing the set of transitions that an agent actually experienced does not, in general, unambiguously reveal which stochastic process generated this specific sequence and hence the agent's type.

Implementing this idea leads to considering a mixture of Markov chains to capture the population heterogeneity. It is considered that the population is divided into a discrete number G of homogeneous types or groups of agents instead of just one, each agent belonging to one and only one of these types. Assuming that each agent type is characterized by its own elementary Markov process, the general form of the MMCM then consists in decomposing the one-step transition matrix as

$$\Phi = \{\phi_{ij}\} = \sum_{g=1}^G \mathbf{S}_g \mathbf{M}_g \quad (6)$$

where $\mathbf{M}_g = \{m_{ij,g}\}$ is the TPM defining the one-step Markov process followed by type g agents, and $\mathbf{S}_g = \text{diag}(\mathbf{s}_{i,g})$ is a diagonal matrix that gathers the shares of type g agents in each category.

Since every agent in the population must belong to one and only one type g , the constraint that $\sum_{g=1}^G \mathbf{S}_g = \mathbf{I}$ must hold, where \mathbf{I} is the $J \times J$ identity matrix.

Since we consider only the stationary case here, it is assumed that neither \mathbf{M}_g nor \mathbf{S}_g varies over time. Then, the r -step TPM for any future time period r can be defined as the linear combination of the r -step processes:

$$\Phi^{(r)} = \sum_{g=1}^G \mathbf{S}_g \mathbf{M}_g^r. \quad (7)$$

With the MCM and MMCM modelling frameworks as defined above,

- (a) the MMCM reduces to the MCM if $G = 1$, i.e. only one type of agents is considered or, equivalently, the homogeneity assumption holds, and
- (b) the aggregate overall MMCM process that is described by $\Phi^{(r)}$ as defined by equation (7) may no longer be Markovian even if each agent type follows a specific Markov process.

2.3. A simple implementation of the mixed Markov chain model: the mover–stayer model

In this paper, we stick to the simplest version of the MMCM, namely the MSM that was first proposed by Blumen *et al.* (1955). In this restricted approach, only two types of homogeneous agents are considered: those who always remain in their initial category (the stayers) and those who follow a first-order Markovian process (the movers). Formally, this leads to rewriting equation (6) in a simpler form as

$$\Phi = \mathbf{S} + (\mathbf{I} - \mathbf{S}) \mathbf{M}. \quad (8)$$

With regard to the general formulation (6), this corresponds to setting $G = 2$ and defining $\mathbf{S}_1 = \mathbf{S}$ and $\mathbf{M}_1 = \mathbf{I}$ for stayers, and $\mathbf{S}_2 = \mathbf{I} - \mathbf{S}$ and $\mathbf{M}_2 = \mathbf{M}$ for movers. Thus, following equation (7), the MSM overall population r -step TPM can be expressed as

$$\Phi^{(r)} = \mathbf{S} + (\mathbf{I} - \mathbf{S}) \mathbf{M}^r. \quad (9)$$

3. Estimation method

Various methods have been used to estimate the MSM parameters ranging from a simple calibration method (Goodman, 1961), minimum χ^2 (Morgan *et al.*, 1983) and maximum likelihood (Frydman, 1984) to Bayesian inference (Fougere and Kamionka, 2003). Frydman (2005) was the first to develop a maximum likelihood estimation method for the general MMCM. In the following section, we present the corresponding strategy in the simplified case of the MSM, which consists of two steps: firstly, under complete information, i.e. as if the population heterogeneity were perfectly observable; secondly, under incomplete information, i.e. accounting for the fact that population heterogeneity is not actually observed.

3.1. Likelihood maximization under complete information

Under complete information the status of each agent k , either stayer (denoted S) or mover (denoted M), is perfectly known *ex ante* and can be recorded through a dummy variable $Y_{k,S}$ where $Y_{k,S} = 1$ if agent k is a stayer and $Y_{k,S} = 0$ if agent k is a mover. The log-likelihood of the MSM for the entire population is then

$$\log(L) = \sum_{k=1}^N Y_{k,S} \log(l_{k,S}) + \sum_{k=1}^N (1 - Y_{k,S}) \log(l_{k,M}) \quad (10)$$

where the first sum on the right-hand side is the overall log-likelihood that is associated with stayers and the second sum is the overall log-likelihood that is associated with movers.

At the individual level, conditionally on knowing that k was initially in size category i :

- (a) the likelihood that agent k is a stayer, $l_{k,S}$, is given by s_i , the share of agents who never move out of category i during the entire observation period;
- (b) the likelihood that agent k is a mover is (Frydman and Kadam, 2004)

$$l_{k,M} = (1 - s_i) \prod_{i \neq j} m_{ij}^{\nu_{ij,k}} \prod_i m_{ii}^{\nu_{ii,k}} \quad (11)$$

where $\nu_{ij,k}$ is the number of transitions from category i to category j made by agent k and $\nu_{ii,k}$ is the total number of times that agent k stayed in category i . On the right-hand side of equation (11), the first product is thus the probability that agent k moves out of category i , whereas the second product is the probability that agent k stays in category i from one period to the next, even though k is a mover.

Substituting $l_{k,S}$ and $l_{k,M}$ in equation (10), the log-likelihood of the MSM for the entire population can be expressed as

$$\log(L) = \sum_i n_i \log(1 - s_i) + \sum_i n_{i,S} \log\{s_i / (1 - s_i)\} + \sum_{i \neq j} \nu_{ij} \log(m_{ij}) + \sum_i \nu_{ii,M} \log(m_{ii}) \quad (12)$$

where n_i and $n_{i,S}$ are respectively the numbers of agents and stayers who were initially in category i , $\nu_{ij} = \sum_k \nu_{ij,k}$ is the total number of transitions from category i to category j , $\nu_{ii,M} = \sum_k (1 - Y_{k,S}) \nu_{ii,k}$ is the total number of times that movers stayed in category i and m_{ij} and m_{ii} are the elements of the transition probability matrix \mathbf{M} of movers.

3.2. The expectation–maximization algorithm under incomplete information

Since in practice it is unlikely to know beforehand which farms actually behave as stayers among those who remain in their starting category during the observation period, equation (12) cannot be used to estimate the MSM parameters directly. Because the transition process is assumed to be stochastic, even movers may remain in their initial category for a long time before moving, so they may not appear as movers but as stayers during the observed period. In this case, Fuchs and Greenhouse (1988) suggested that the MSM parameters could be estimated by using the expectation–maximization (EM) algorithm that was developed by Dempster *et al.* (1977): rather than observing the dummy variable $Y_{k,S}$, the EM algorithm allows its expected value $E\{Y_{k,S} | X_k(0) = i\}$ to be estimated, i.e. the probability for each farm k to be a stayer, given farm k 's initial category i and observed transition sequence.

Following Frydman and Kadam (2004), the four steps of the EM algorithm are defined in the case of the MSM as follows.

- (a) *Initialization*: arbitrarily choose initial values s_i^0 for the shares of stayers and m_{ii}^0 for the main diagonal entries of the TPM of movers, \mathbf{M} .
- (b) *Expectation*: at iteration p of the algorithm, compute the probability that farm k is a stayer, $E^p\{Y_{k,S} | X_k(0) = i, \theta^p\}$, where $\theta^p = (s_i^p, m_{ii}^p)$ is the vector of iteration p values of the parameters to be estimated. If at least one transition is observed for farm k then set $E^p\{Y_{k,S} | X_k(0) = i, \theta^p\} = 0$; otherwise this probability is given by, according to Bayes's law

$$E^p\{Y_{k,S} | X_k(0) = i, \theta^p\} = \frac{l_{k,S}}{l_{k,S} + l_{k,M}}. \quad (13)$$

Replacing $l_{k,S}$ and $l_{k,M}$ in this equation, we obtain

$$E^P\{Y_{k,S}|X_k(0)=i, \theta^P\} = \frac{s_i^P}{s_i^P + (1-s_i^P)(m_{ii}^P)^{\nu_{ii,k}}}. \quad (14a)$$

Then compute

(i) the expected value of the number of stayers in category i , $E^P(n_{i,S})$, as

$$E^P(n_{i,S}) = \sum_k E^P\{Y_{k,S}|X_k(0)=i, \theta^P\} \quad (14b)$$

(ii) and the expected value of the total number of times that movers remain in category i , $E^P(\nu_{ii,M})$, as

$$E^P(\nu_{ii,M}) = \sum_k [1 - E^P\{Y_{k,S}|X_k(0)=i, \theta^P\}] \nu_{ii,k}. \quad (14c)$$

(c) *Maximization*: update s_i^P and m_{ii}^P by maximizing equation (12) using the expected values of $n_{i,S}$ and $\nu_{ii,M}$ obtained at iteration p . The new parameters are thus given by

$$\begin{aligned} s_i^{p+1} &= \frac{E^P(n_{i,S})}{n_i}, \\ m_{ii}^{p+1} &= \frac{E^P(\nu_{ii,M})}{\nu_i + E^P(\nu_{ii,M})}. \end{aligned} \quad (14d)$$

(d) *Iteration*: return to expectation step (b) using s_i^{p+1} and m_{ii}^{p+1} and iterate until the parameters converge.

When convergence is reached, the optimal values s_i^* and m_{ii}^* are considered to be the search values for estimators \hat{s}_i and \hat{m}_{ii} . Then, \hat{m}_{ij} derives from \hat{m}_{ii} as

$$\hat{m}_{ij} = \frac{\nu_{ij}}{\nu_i} (1 - \hat{m}_{ii}) \quad \forall i \neq j \quad (15)$$

where $\nu_i = \sum_{j \neq i} \nu_{ij}$ is the total number of transitions out of category i .

Following Frydman (2005), the standard errors that are attached to the MSM parameters can be computed directly from the EM equations by using the method that was proposed by Louis (1982). Since the log-likelihood function that is given by equation (12) is twice differentiable with respect to the model parameters, both the Fisher information matrix and the missing information matrix can be straightforwardly derived (see McLachlan and Krishnan (2007) for more details). The standard errors that are attached to the overall 1-year TPM Φ can then be derived by applying the standard delta method to equation (8) (Oehlert, 1992). Finally, because it is more complicated to apply the delta method to equation (9) because it involves powers of matrices, we used a bootstrap sampling method to compute standard errors attached to the r -step TPMs $\mathbf{M}^{(r)}$ and $\Phi^{(r)}$ (Efron, 1979; Efron and Tibshirani, 1986).

4. Model comparison

Two types of analysis were conducted to assess whether or not the MSM outperforms the MCM.

4.1. Likelihood ratio test

The likelihood ratio test allows a comparison of the in-sample performance of the two models in recovering the data-generating process. As stated by Frydman and Kadam (2004), the likelihood

ratio statistic for the MSM is given by

$$\text{LR} = \frac{L_{\text{MCM}}(\hat{\Pi})}{L_{\text{MSM}}(\hat{S}, \hat{M})} \quad (16)$$

where L_{MCM} and L_{MSM} are the estimated maximum likelihoods for the MCM and the MSM respectively. The asymptotic distribution of $-2\log(\text{LR})$, under H_0 , is χ^2 with $(G-1) \times J$ degrees of freedom. In the case of the MSM, the likelihood ratio tests the hypothesis that the process follows an MCM ($H_0: \hat{S} = \mathbf{0}$) against the hypothesis that it is a mixture of movers and stayers ($H_1: \hat{S} \neq \mathbf{0}$). The observed log-likelihood for both models can be derived from equation (10), by imposing $Y_{k,S} = 0$ for all agents k for the MCM and by replacing $Y_{k,S}$ by its optimal expected value $E^*(Y_{k,S})$ for the MSM.

4.2. Average marginal error

The estimated parameters were used to compute the corresponding r -step TPMs, i.e. $\hat{\Pi}^{(r)} = \hat{\Pi}^r$ for the MCM and $\hat{\Phi}^{(r)} = \hat{S} + (\mathbf{I} - \hat{S})\hat{M}^r$ for the MSM. These r -step TPMs were then used to perform out-of-sample short- to long-term projections of farm distributions across size categories according to equation (1) (see below).

On the one hand, TPMs from both models were compared with the observed TPM, providing a second in-sample assessment in addition to the likelihood ratio test. Following Frydman *et al.* (1985) who compared percentage differences between predicted and observed transition probabilities, we compute an AME for each model based on the formulation of Cipollini *et al.* (2012) of the expected marginal distribution. The AMEs for the transition probability matrices are thus obtained as

$$\text{AME}_{\text{TPM}} = \frac{1}{JJ} \sum_{i,j} \sqrt{\left\{ \left(\frac{\hat{p}_{ij}^{(r)} - p_{ij}^{(r)}}{p_{ij}^{(r)}} \right)^2 \right\}} \quad (17)$$

where $\hat{p}_{ij}^{(r)}$ and $p_{ij}^{(r)}$ are the predicted and observed TPM entries respectively:

- (a) $\hat{p}_{ij}^{(r)} \equiv \hat{\pi}_{ij}^{(r)}$ under the MCM whereas $\hat{p}_{ij}^{(r)} \equiv \hat{\phi}_{ij}^{(r)}$ under the MSM;
- (b) $p_{ij}^{(r)}$ derives from equation (4).

On the other hand, AMEs were similarly computed for both the MCM and the MSM projections of farm size distributions with respect to those actually observed, providing an out-of-sample comparison of the models. The AMEs for the projected farm size distributions at time $t+r$ are thus obtained as

$$\text{AME}_{\text{FSD}}(t+r) = \frac{1}{J} \sum_j \sqrt{\left\{ \left(\frac{\hat{n}_{j,t+r} - n_{j,t+r}}{n_{j,t+r}} \right)^2 \right\}} \quad (18)$$

where $\hat{n}_{j,t+r}$ are the predicted proportions of farms in size category j at time $t+r$ by using either $\hat{\pi}_{ij}^{(r)}$ for the MCM or $\hat{\phi}_{ij}^{(r)}$ for the MSM, and $n_{j,t+r}$ are the observed counterparts.

In contrast with some dissimilarity indices (Jafry and Schuermann, 2004) or the matrix of residuals (Frydman *et al.*, 1985), the AME provides a global view of the distance between the predicted TPM or population distribution across size categories and the observed ones. It can be interpreted as the average percentage of deviations on predicting the observed TPM or population distribution across size categories. Thus, the higher the AME, the greater the difference between the computed TPM or distribution and the observed one is. The better model is therefore the model that yields the lowest AME.

5. Data

In our empirical application, we used the 2000–2013 ‘Réseau d’information comptable agricole’ (RICA) data, which is the French strand of the Farm Accountancy Data Network. The network is an annual survey defined at European Union level and carried out in each member state. The information that is collected at individual level relates to both the physical and the structural characteristics of farms and their economic and financial characteristics. To comply with accounting standards that may differ from one country to the next, the European Union level questionnaire was adapted for France, but the results were unchanged whether the original or adapted version of the questionnaire was used.

In France, the RICA data are produced and disseminated by the Ministry for Agriculture’s Statistical and Foresight Office. It focuses on ‘medium and large’ farms (see below) and constitutes a stratified and rotating panel of approximately 7000 farms surveyed each year. About 10% of the sample is renewed every year so, on average, farms are observed during five consecutive years. However, some farms may be observed only once, and others several but not consecutive times. Some farms remained in the database over the entire period that was studied, i.e. 14 consecutive years. Each farm in the data set is assigned year-specific weighting factors that reflect its annual stratified sampling probabilities, allowing for extrapolation at the population level when the database is used in its cross-sectional dimension. However, when the database is used as a panel, as here, these extrapolation weights should not be used because they are not relevant in the intertemporal dimension.

Because we considered all 17285 farms in the 2000–2013 sample, whatever the type of farming, we chose to concentrate on size as defined in economic terms. In accordance with European Union regulation (CE) N°1242/2008, European farms are classified into 14 economic size (ES) categories, evaluated in terms of total standard output (SO) expressed in euros. As mentioned above, in France, the RICA survey focuses on medium and large farms, i.e. those whose SO is greater than or equal to €25000; this corresponds to ES category 6 and above. Since size categories are not equally represented in the sample, we aggregated the nine ES categories that are available in the RICA survey into five categories: strictly less than €50000 of SO (ES category 6); from €50000 to less than €100000 of SO (ES category 7); from €100000 to less than €150000 of SO (the lower part of ES category 8); from €150000 to less than €250000 of SO (the upper part of ES category 8); €250000 of SO and more (ES categories 9–14).

As the RICA survey is a rotating panel, farms that either enter or leave the sample in a given year cannot be considered as actual entries into or exits from the agricultural sector. Thus, we could not work directly on the evolution of farm numbers but rather on the evolution of population shares by size categories, i.e. the size distribution in the population. Table 1 presents the year-by-year evolution by size categories of farm numbers in the sample as well as for the extrapolated population. It also reports the average ES in thousands of euros of SO both at the sample and at the extrapolated population levels.

Fig. 1 shows that the share of smaller farms (below €100000 of SO) decreased from 56% to 46% between 2000 and 2013 whereas the share of larger farms (above €150000 of SO) increased from 28% to 38%, and the share of intermediate farms (€100000 to less than €150000 of SO) remained stable at 16%. As a consequence, as can be seen from Table 1 and Fig. 1, the average economic size of French farms was multiplied by more than 1.25 over this period. Table 1 also reveals that the size distribution became more heterogeneous since the standard deviation of economic size was multiplied by almost 1.5, which is a feature that has already been observed for the population of French farms as a whole and in other periods (Butault and

Table 1. Distribution by ES and average ES for the sample studied, 2000–2013†

Year	Numbers of farms by the following ES categories ($\times 10^3$ €)					Total	Average ES (standard deviation)
	0–50	50–100	100–150	150–250	≥ 250		
2000	790	2234	1629	1762	1342	7757	168.88 (179.01)
	87924	129691	59857	67367	41457	386296	134.46 (151.72)
2001	746	2231	1625	1817	1382	7801	170.98 (180.88)
	84442	123900	57583	67741	41890	375556	136.75 (155.04)
2002	713	2128	1663	1818	1443	7765	177.57 (198.12)
	81228	118571	58104	65448	42344	365695	140.99 (184.50)
2003	690	1975	1562	1693	1393	7313	176.27 (193.55)
	78249	113662	56961	64946	42859	356677	141.08 (176.08)
2004	707	1940	1538	1707	1437	7329	177.67 (188.47)
	75481	109118	56118	64252	43419	348388	142.63 (169.30)
2005	741	1927	1516	1711	1467	7362	178.03 (181.95)
	72896	104906	54811	64112	44007	340732	144.55 (161.46)
2006	756	1922	1488	1688	1491	7345	181.21 (209.21)
	70516	101035	54202	63443	44740	333936	146.99 (171.49)
2007	774	1845	1552	1694	1511	7376	182.27 (191.10)
	68286	97435	54032	62390	45491	327634	150.08 (172.33)
2008	780	1866	1511	1721	1587	7465	185.49 (200.25)
	66201	94098	52412	62889	46338	321938	153.47 (185.00)
2009	778	1816	1517	1734	1624	7469	188.43 (205.95)
	64243	90970	51137	63151	47278	316779	156.14 (186.03)
2010	652	1885	1537	1770	1608	7452	190.53 (199.03)
	62429	88104	51320	62062	48267	312182	157.88 (174.96)
2011	638	1856	1468	1791	1658	7411	194.89 (207.58)
	60743	85444	49285	63292	49381	308145	162.11 (189.23)
2012	651	1797	1396	1794	1679	7317	200.28 (249.45)
	59152	82943	47911	63953	50626	304585	166.69 (227.41)
2013	658	1769	1361	1804	1701	7293	202.41 (240.15)
	57668	80638	46821	64414	51939	301480	169.49 (225.53)

†For each year, the first row reports figures at the sample level and the second row reports figures for the extrapolated population. Source, Agreste, RICA France 2000–2013—authors' calculations.

Delame, 2005; Desriers, 2011). Lastly, Table 1 reveals that these observations apply at sample level also, even though the sample is skewed towards larger sizes with regard to the population as a whole.

To assess which model performed better, we compared the MCM and the MSM on the basis of both in-sample estimation and out-of-sample size distribution forecasts. To do so, we split the RICA database into two parts:

- observations from 2000 to 2010 were used to estimate the parameters of both models;
- observations from 2011 to 2013 were used to compare actual farm size distributions with their predicted counterparts for both models.

In doing so we assumed that, in the case of the MSM, 11 years are a sufficiently long interval for a robust estimation of the movers' transition process.

Before proceeding with the results, it should also be noted that, because we worked with panel subsets of the full sample and therefore could not account for extrapolation weights in the estimations as explained above, the transition probabilities that are reported in the next section can only be viewed as *conditional* on having been observed over a specific number of consecutive years during the entire period under study. Projected population distributions that

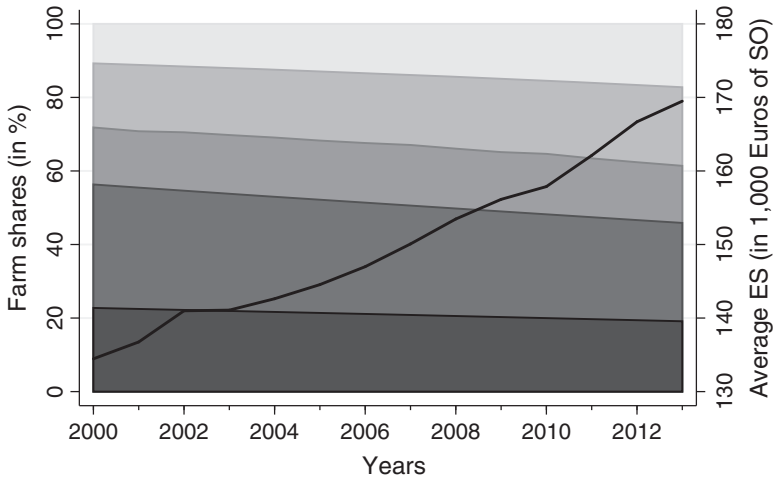


Fig. 1. Extrapolated population shares by farm size categories and average ES ($\times 10^3$ €) (source, Agreste, RICA France 2000–2013—authors' calculations): ■, 0–50; ■, 50–100; ■, 100–150; ■, 150–250; ■, ≥ 250 ; —, average ES

were obtained from these transition probabilities should therefore be interpreted with due care from an empirical point of view. They were performed here to compare the forecasting power of the models studied, for which the above *caveat* applies to the same extent.

6. Results

In this section, we first report the results of in-sample estimations, i.e. the estimated 1-year TPMs for the MCM and the MSM. We then compare the models based on in-sample results to assess which model performs better in recovering the underlying transition process from both a short-term and a long-term perspective. Lastly, we compare the models' ability to forecast future farm size distributions on the basis of out-of-sample observations.

6.1. In-sample estimation results

The MCM and MSM parameters were estimated by using 10 subsamples according to the minimum length of time that farms remain in the database. For brevity, here we report only those for the balanced subsample, i.e. using the 2000–2010 balanced panel consisting of 2170 individual farms and 21700 observed transitions over the 11 years. However, when any of the unbalanced panels were considered, the results, and hence conclusions, remained similar to those reported here.

Table 2 reports the estimated 1-year TPM under the MCM assumption. As is usual, the matrix is strongly diagonal, meaning that its main diagonal elements exhibit by far the largest values and that probabilities rapidly decrease as we move away from the main diagonal. This means that, overall, farms are more likely to remain in their initial size category from one year to the next. This does not mean no size change at all but, at least, no change that is sufficient to move to another category as we defined them.

Table 3 reports the estimated shares of stayers, Table 4 reports the TPM of movers and Table 5 reports the corresponding 1-year TPM for the entire population under the MSM assumption. Two main results can be seen from Tables 3–5. Firstly, the estimated stayer shares (Table 3)

Table 2. Estimated 1-year TPM under the MCM ($\hat{\Pi}$)[†]

Date t ES class ($\times 10^3$ €)	TPM for the following date $t+1$ ES classes ($\times 10^3$ €):				
	0–50	50–100	100–150	150–250	≥ 250
0–50	<i>0.917</i> (0.024)	<i>0.079</i> (0.007)	<i>0.002</i> (0.001)	<i>0.002</i> (0.001)	<i>0.001</i> (0.001)
50–100	<i>0.030</i> (0.002)	<i>0.898</i> (0.013)	<i>0.065</i> (0.004)	<i>0.005</i> (0.001)	<i>0.002</i> (0.001)
100–150	<i>0.002</i> (0.001)	<i>0.062</i> (0.004)	<i>0.854</i> (0.014)	<i>0.080</i> (0.004)	<i>0.002</i> (0.001)
150–250	<i>0.001</i> (0.000)	<i>0.004</i> (0.001)	<i>0.054</i> (0.003)	<i>0.886</i> (0.012)	<i>0.055</i> (0.003)
≥ 250	<i>0.000</i> (0.000)	<i>0.001</i> (0.001)	<i>0.003</i> (0.001)	<i>0.048</i> (0.003)	<i>0.948</i> (0.014)

[†]Log-likelihood, $\log(L_{\text{MCM}}) = -8689.36$: estimated parameters are in italics; standard errors are in parentheses. Source, Agreste, RICA France 2000–2010—authors' calculations.

show that the probability of being a stayer is close to or above 30% whatever the category that is considered; it reaches almost 50% for farms below €50 000 of SO and is even higher than 60% for farms over €250 000 of SO. This means that, according to the MSM and depending on the size category, at least 30% of the farms are likely to remain in their initial category for at least another 10 years. Secondly, the TPM (Table 4) reveals that, even though movers are by definition expected to move from one category to another in the next 10 years, nevertheless, the highest probability for them is to remain in the same category from one year to the next. Since the average time that is spent by movers in a particular category is given by $1/(1 - m_{ii})$, it can be seen from Table 4 that movers in the intermediate ES class ($1/(1 - 0.793) = 4.8$) were likely to remain in the same category for almost 5 years, whereas those above €250 000 of SO ($1/(1 - 0.875) = 8$) were likely to remain for 8 years before moving. In other words, farms that remained in a particular category for quite a long time (theoretically even over the entire observation period) were not

Table 3. Estimated stayer shares \hat{s}_i [†]

ES class ($\times 10^3$ €)	Stayer share \hat{s}_i
0–50	<i>0.494</i> (0.036)
50–100	<i>0.422</i> (0.021)
100–150	<i>0.291</i> (0.016)
150–250	<i>0.371</i> (0.017)
≥ 250	<i>0.650</i> (0.021)

[†]Log-likelihood, $\log(L_{\text{MSM}}) = -8384.08$: estimated parameters are in italics; standard errors are in parentheses. Source, Agreste, RICA France 2000–2010—authors' calculations.

Table 4. Mover transition probability matrix \hat{M}^\dagger

Date t ES class ($\times 10^3$ €)	Matrix for the following date $t+1$ ES classes ($\times 10^3$ €):				
	0–50	50–100	100–150	150–250	≥ 250
0–50	<i>0.837</i> (0.041)	<i>0.154</i> (0.012)	<i>0.004</i> (0.002)	<i>0.004</i> (0.002)	<i>0.001</i> (0.001)
50–100	<i>0.055</i> (0.004)	<i>0.815</i> (0.022)	<i>0.118</i> (0.006)	<i>0.009</i> (0.002)	<i>0.003</i> (0.001)
100–150	<i>0.002</i> (0.001)	<i>0.089</i> (0.005)	<i>0.793</i> (0.020)	<i>0.113</i> (0.005)	<i>0.003</i> (0.001)
150–250	<i>0.002</i> (0.001)	<i>0.007</i> (0.001)	<i>0.087</i> (0.004)	<i>0.816</i> (0.020)	<i>0.088</i> (0.004)
≥ 250	<i>0.001</i> (0.001)	<i>0.003</i> (0.001)	<i>0.007</i> (0.002)	<i>0.114</i> (0.007)	<i>0.875</i> (0.027)

\dagger Log-likelihood, $\log(L_{\text{MSM}}) = -8384.08$: estimated parameters are in italics; standard errors are in parentheses. Source, Agreste, RICA France 2000–2010—authors' calculations.

Table 5. Overall population 1-year TPM $\hat{\Phi}^\dagger$

ES class ($\times 10^3$ €)	TPM for the following date $t+1$ ES classes ($\times 10^3$ €):				
	0–50	50–100	100–150	150–250	≥ 250
0–50	<i>0.917</i> (0.019)	<i>0.078</i> (0.011)	<i>0.002</i> (0.001)	<i>0.002</i> (0.001)	<i>0.001</i> (0.001)
50–100	<i>0.032</i> (0.003)	<i>0.893</i> (0.012)	<i>0.068</i> (0.005)	<i>0.005</i> (0.001)	<i>0.002</i> (0.001)
100–150	<i>0.002</i> (0.001)	<i>0.062</i> (0.004)	<i>0.854</i> (0.014)	<i>0.080</i> (0.005)	<i>0.002</i> (0.001)
150–250	<i>0.001</i> (0.000)	<i>0.005</i> (0.001)	<i>0.055</i> (0.004)	<i>0.884</i> (0.012)	<i>0.055</i> (0.004)
≥ 250	<i>0.000</i> (0.000)	<i>0.001</i> (0.001)	<i>0.003</i> (0.001)	<i>0.040</i> (0.005)	<i>0.956</i> (0.009)

\dagger Log-likelihood, $\log(L_{\text{MSM}}) = -8384.08$: estimated parameters are in italics; standard errors are in parentheses. Source, Agreste, RICA France 2000–2010—authors' calculations.

necessarily stayers but could be movers who had not yet moved. Together, these two results yield a 1-year TPM for the whole population that is also highly diagonal (Table 5).

6.2. In-sample model comparison

Both models show that, at the overall population level, farms were more likely to remain in their initial size category from year to year, confirming that structural change in the agricultural sector is a slow process which would be worth investigating in the long term. In this respect, although the 1-year TPMs look very similar across both models, the resulting long-term transition model differs between the MCM, given by equation (5), and the MSM, given by equation (9). It is therefore important to assess which model performs better in recovering the true underlying transition process.

The first assessment method that was used, i.e. the likelihood ratio test, reveals that the MSM yields a better fit than the MCM: the value of the test statistic as defined by equation (16) is $-2\log(\text{LR}) = -2(-8689.36 + 8384.08) = 610.56$, which is highly significant since the critical value of a χ^2 -distribution with $(G - 1) \times J = 5$ degrees of freedom and the 1% significance level is $\chi_{0.99}^2(5) = 15.09$. This leads to the rejection of the H_0 assumption that the stayer shares are all 0, and thus to the conclusion that the MSM allows the data-generating process to be recovered more efficiently than does the MCM. The MSM should therefore also lead to a better approximation of transition probabilities in the long term.

The second assessment method that was used allows this very point to be evaluated. Estimated parameters for both models were used to derive the corresponding 10-year TPMs, namely $\hat{\Pi}^{(10)} = \hat{\Pi}^{10}$ for the MCM and $\hat{\Phi}^{(10)} = \hat{S} + (\mathbf{I} - \hat{S})\hat{M}^{10}$ for the MSM. These estimated long-term matrices were then compared with the observed matrix $\mathbf{P}^{(10)}$, which is derived from equation (4). It appears from a visual inspection of the panels of Tables 6 and 7 that the MSM 10-year matrix more closely resembles the matrix that is actually observed than the MCM 10-year matrix. In particular, we find as expected that the diagonal elements of $\hat{\Pi}^{(10)}$ largely underestimate those of $\mathbf{P}^{(10)}$ whereas those of $\hat{\Phi}^{(10)}$ are far closer. This means that the MCM largely tends to overestimate the farms' mobility in the long term, with regard to the MSM. The AMEs that are reported in Table 8 confirm the MSM's superiority over the MCM in modelling the long-term transition process. The AME for the overall predicted 10-year TPM is around 0.95 for the MCM whereas it is about 0.78 for the MSM. This means that the MSM is about 17 percentage points closer to the observed TPM than is the MCM in the long term. However, the AMEs also confirm that the improvement arises principally from the main diagonal elements: when only these are considered, the MSM performs about five times better than the MCM ($0.292/0.057 = 5.1$), whereas both models are almost comparable for off-diagonal elements, with the MCM this time performing slightly better ($0.657/0.724 = 0.9$).

6.3. Out-of-sample projections

In-sample estimation results lead us to conclude that accounting for unobserved heterogeneity in the rate of farms' movement, as the MSM does, avoids overestimating their mobility across size categories. The MSM should therefore also lead to a more accurate prediction of the farms' size distribution in the long term without hampering its short-term prediction.

To validate this point, we performed out-of-sample short- to long-term projections of farm size distribution by using the parameters estimated for both models. To do this, farm size distributions in 2011, 2012 and 2013 were predicted from a short- to long-term perspective,

Table 6. Observed 10-year TPM†

Date t ES class ($\times 10^3$ €)	TPM for the following date $t + 1$ ES classes ($\times 10^3$ €):				
	0–50	50–100	100–150	150–250	≥ 250
0–50	0.715	0.235	0.029	0.014	0.007
50–100	0.107	0.641	0.199	0.038	0.015
100–150	0.020	0.146	0.536	0.268	0.030
150–250	0.010	0.032	0.096	0.630	0.232
≥ 250	0.005	0.021	0.020	0.124	0.830

†Source, Agreste, RICA France 2000–2010—authors' calculations.

Table 7. Predicted 10-year TPMs for both models†

Date t ES class ($\times 10^3$ €)	TPMs for the following date $t + 1$ ES classes ($\times 10^3$ €):				
	0–50	50–100	100–150	150–250	≥ 250
<i>(a) MCM predicted 10-year TPM $\hat{\Pi}^{(10)}$</i>					
0–50	<i>0.476</i> (0.028)	<i>0.361</i> (0.020)	<i>0.106</i> (0.008)	<i>0.043</i> (0.006)	<i>0.014</i> (0.004)
50–100	<i>0.141</i> (0.011)	<i>0.467</i> (0.015)	<i>0.240</i> (0.011)	<i>0.116</i> (0.007)	<i>0.036</i> (0.004)
100–150	<i>0.044</i> (0.004)	<i>0.234</i> (0.011)	<i>0.338</i> (0.013)	<i>0.281</i> (0.011)	<i>0.103</i> (0.007)
150–250	<i>0.015</i> (0.002)	<i>0.082</i> (0.005)	<i>0.193</i> (0.010)	<i>0.428</i> (0.013)	<i>0.282</i> (0.013)
≥ 250	<i>0.005</i> (0.001)	<i>0.026</i> (0.003)	<i>0.068</i> (0.005)	<i>0.245</i> (0.013)	<i>0.656</i> (0.018)
<i>(b) MSM predicted 10-year TPM $\hat{\Phi}^{(10)}$</i>					
0–50	<i>0.690</i> (0.017)	<i>0.140</i> (0.010)	<i>0.097</i> (0.007)	<i>0.053</i> (0.005)	<i>0.020</i> (0.003)
50–100	<i>0.060</i> (0.007)	<i>0.684</i> (0.010)	<i>0.126</i> (0.007)	<i>0.090</i> (0.005)	<i>0.040</i> (0.003)
100–150	<i>0.041</i> (0.004)	<i>0.119</i> (0.007)	<i>0.586</i> (0.012)	<i>0.164</i> (0.009)	<i>0.090</i> (0.006)
150–250	<i>0.018</i> (0.002)	<i>0.062</i> (0.004)	<i>0.117</i> (0.006)	<i>0.676</i> (0.010)	<i>0.127</i> (0.009)
≥ 250	<i>0.005</i> (0.001)	<i>0.021</i> (0.002)	<i>0.048</i> (0.003)	<i>0.093</i> (0.005)	<i>0.833</i> (0.008)

†Estimated parameters are in italics; bootstrap standard errors are in parentheses (1000 replications). Source, Agreste, RICA France 2000–2010—authors' calculations.

Table 8. AME_{TPM} between the predicted 10-year TPMs $\hat{\Pi}^{(10)}$ and $\hat{\Phi}^{(10)}$ and the observed TPM $\mathbf{P}^{(10)}$ †

Model	Overall matrix	Main diagonal elements	Off-diagonal elements
MCM	<i>0.949</i> (0.044)	<i>0.292</i> (0.010)	<i>0.657</i> (0.036)
MSM	<i>0.781</i> (0.034)	<i>0.057</i> (0.007)	<i>0.724</i> (0.035)

†Bootstrap standard errors are in parentheses (1000 replications). Source, Agreste, RICA France 2000–2010—authors' calculations.

by applying the estimated r -step TPMs (for $1 \leq r \leq 11$) to the corresponding observed distributions from 2000 to 2012. In other words, distributions in 2011, 2012 and 2013 were predicted: by applying the estimated 1-year TPMs ($\hat{\Pi}$ for the MCM and $\hat{\Phi}$ for the MSM) to the observed distributions in 2010, 2011 and 2012 respectively; by applying the estimated 2-year TPMs ($\hat{\Pi}^{(2)} = \hat{\Pi}^2$ for the MCM and $\hat{\Phi}^{(2)} = \hat{\mathbf{S}} + (\mathbf{I} - \hat{\mathbf{S}})\hat{\mathbf{M}}^2$ for the MSM) to the observed distributions in 2009, 2010 and 2011 respectively; and so forth. This process was continued by applying the estimated r -step TPMs ($\hat{\Pi}^{(r)} = \hat{\Pi}^r$ for the MCM and $\hat{\Phi}^{(r)} = \hat{\mathbf{S}} + (\mathbf{I} - \hat{\mathbf{S}})\hat{\mathbf{M}}^r$ for the MSM) to the observed distributions in 2011– r , 2012– r and 2013– r and varying r up to 11. Then, the resulting distributions for both models were compared with distributions actually observed in 2011, 2012 and

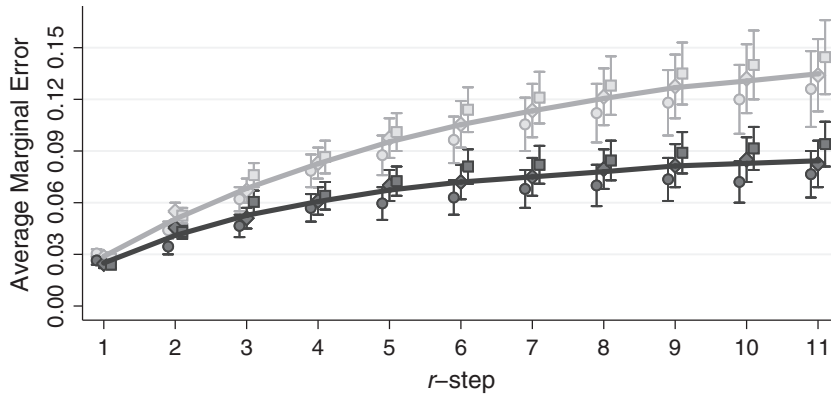


Fig. 2. $AME_{FSD}(t+r)$ between the out-of-sample projections of farm size distributions and the actually observed distributions for the MCM model (—, Q3–Q1; ○, 2011; ◇, 2012; □, 2013; —, 2011–2013 average) and the MSM (—, Q3–Q1; ●, 2011; ◆, 2012; ■, 2013; —, 2011–2013 average) (see the text for an explanation on how short- to long-term projections were obtained; the interquartile ranges Q3–Q1 were obtained from the 1000 bootstrap replications; source, Agreste, RICA France 2000–2013—authors’ calculations)

2013 (see Table 1). The corresponding AMEs that are reported in Fig. 2 summarize the results that were obtained for the 1000 bootstrap replications. Four conclusions can be drawn from Fig. 2. Firstly, as expected, the accuracy of both models decreases when increasing the time horizon of projections: the computed AMEs are significantly smaller in the short term than they are in the medium and long term for both models. Secondly, both models are almost comparable in the short run, confirming that adopting the MSM modelling framework does not degrade year-by-year forecasts with regard to the MCM. Thirdly, the MSM performs significantly better than the MCM in both the medium term and the long term. For example, the average AME for the MCM (0.088) is 1.3 times that of the MSM (0.068) for 5-year interval projections and is 1.5 times for 11-year interval projections (0.121 for the MCM compared with 0.082 for the MSM). Fourthly, Fig. 2 also shows that the accuracy and robustness of farm size distribution predictions decrease more rapidly for the MCM than for the MSM when increasing the time horizon of projections since the AMEs as well as the interquartile ranges of the 1000 bootstrap replications increase more rapidly for the MCM than for the MSM.

7. Concluding remarks

To our knowledge, this is the first paper in applied statistics to investigate whether accounting for unobserved heterogeneity in farms’ size transition processes improves the representation of structural change. Existing literature on structural change in agriculture has so far accounted only for observed heterogeneity. Considering a mixture of two types of farm, the so-called MSM is applied for the first time in an agricultural economics context. Our results show that, with regard to the MCM and even using the simple MSM framework, accounting for unobserved farm heterogeneity allows closer estimates of both the observed transition matrix and farms’ distribution across size categories in the long term to be derived, without degrading any short-term analysis. This result is consistent with findings in other strands of economic literature, i.e. by relaxing the assumption of homogeneity in the transition process, which is the basis of the MCM, the MSM gives a better representation of the underlying structural change process. Moreover, checks of robustness show that these conclusions remain valid when

using different boundaries for size interval definitions and/or using different numbers of size categories.

However, this modelling framework remains a somewhat restricted and simplified version of the more general MMCM that we presented as an introduction to the MSM. Extending the MSM further could therefore lead to even more economically sound, and statistically more accurate, models for the farming sector. We briefly mention here some of the extensions that we believe are promising. Firstly, more heterogeneity across farms could be incorporated by allowing for more than two unobserved types. For example, accounting for different types of movers could provide a better representation of the structural change process in the farming sector by allowing farms that mainly tend to enlarge to be separated from farms that mainly tend to shrink. Secondly, the relatively strong assumption of a ‘pure stayer’ type could be relaxed because it appears unlikely that some farms ‘never move at all’, i.e. will not change size category over their entire lifespan even if they do not do so for a relatively high number of consecutive years. In other words, an ‘almost stayer’ type could be hypothesized rather than a pure stayer type. In this respect, the robustness of the MSM to the number of years during which farms are observed could be investigated. Indeed, by considering 11 years to perform in-sample estimations, our results show that movers may stay for 5–8 years in a given category before experiencing a sufficiently large (positive or negative) size change to reach another category. We can then infer that, the shorter the observation period, the higher the number of farms that would be inappropriately considered as pure stayers. From a methodological point of view, this leads to the conclusion that sufficiently long panel data need to be available if the MSM is to be empirically implemented. This could be seen as a shortcoming of the MSM with regard to the MCM but it is consistent with farm structural change being a long-term and slow process.

The empirical application in this study showed that accounting for unobserved farm heterogeneity is important when analysing structural change in farming, and that a mixture modelling framework such as the MSM is relevant to do this. However, although we could put forward some theoretical explanations for unobserved heterogeneity, to our knowledge, there is, as yet, no formal framework in agricultural economics that could help to identify the potential sources of this heterogeneity and to guide the empirical measurement of how they may affect farms’ transition processes. We hope that the results that are presented here and the limitations that were mentioned will contribute to encouraging the development of such theoretical frameworks for a better understanding of structural change under the assumption of heterogeneous farm populations.

Our final recommendations are that, when implemented for thorough empirical studies, the modelling framework proposed should be extended to account for entries and exits, that factors driving homogeneous group membership—including observed heterogeneity variables—should be investigated and that a non-stationary version of the MMCM model should be developed. Since this should allow the transition process to be recovered more efficiently, it would surely prove to be very useful for analysing the factors that drive structural change in the farming sector, including agricultural policies, not only from a size distribution perspective, but also with regard to the evolution of farm numbers.

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