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Abstract

This paper proposes a new estimation model to capture the complex effect of age on organization survival. Testing various theoretical propositions on organizational mortality, we study the survival of French agricultural cooperatives in comparison with other firms with which they compete. The relationship between age and mortality in organizations is analyzed using a Bayesian Generalized discrete-time semi-parametric hazard model with correlated random effects, incorporating unobserved heterogeneity and isolating the various effects of time. This analysis emphasizes the specificity of the temporal dynamics of cooperatives in relation to their special role in agriculture.

Keywords: bayesian estimation, bayesian model selection, cooperatives, generalized additive model, survival analysis

JEL Classification: C11, C41, Q13, L25

Une approche flexible de l'influence de l'âge sur la mortalité organisationnelle. Comparer la durée de vie des coopératives et des entreprises non-coopératives à partir d'un modèle Bayésien additif généralisé de survie à temps discret

Résumé

Cet article propose une nouvelle méthode d'estimation des effets complexes de l'âge sur la survie des organizations. Testant différentes propositions théoriques sur la mortalité organisationnelle, nous étudions la survie des coopératives agricoles françaises en comparaison avec les autres entreprises en compétition. La relation entre âge et mortalité est estimée par un modèle Bayesian généralisé additif semi paramétrique à temps discret et effets aléatoires corrélés, prenant en compte l'hétérogénéité inobservée et isolant les diférents effets du temps. Notre analyse met en évidence la spécificité de la dynamique temporelle des coopératives en relation avec leur rôle particulier dans l'agriculture.

Mots-clés: estimation bayesienne, sélection de modèle bayésien, coopératives, modèle additif généralisé, analyse de survie

Classification JEL: C11, C41, Q13, L25

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1. Introduction

The survival of firms is a major subject of study in economics, industrial organization or organizational ecology, with a large number of works, using various approaches, addressing this issue (Geroski, 1995; Geroski *et al.*, 2010; Hannan, 1998, 2005; Jovanovic, 1982, 2001; Martimort, 1999; Mata and Portugal, 1994; Simons and Ingram, 2004). The literature on organizational mortality has identified four different effects of age on firm mortality (Hannan, 1998; Le Mens *et al.*, 2011). The first effect, the *liability of newness* (P1), is a negative effect of age on mortality. According to standard industrial organization approach, the market acts as a selection for initially non-performing organizations that could not later adapt themselves (Geroski, 1995). For organizational ecology, the new roles and functions of these new organizations come at some cost; the firm faces constraints on capital which may limit its development capacity; it is more fragile due to the non-stability of inner social interactions (the problem of organizational learning); and, finally, it has not gained full legitimacy, lacking stable relationships with customers. The second effect of age, the *liability of adolescence* (P2), emphasizes the existence of an increased mortality rate after the first years (Brüderl and Schusseler, 1990). Organizations have some "immunity" endowments (Hannan, 1998), that enable them to live for a certain period after their creation. Rational actors will put an end to an organization only if they have had enough information on its negative performance.[1] During the first years, the founders are more determined to make an effort to save the organization, the probability of death taking the form of an inverted U. P2 suggests an increase in mortality and a negative effect of age on the mortality rate. The third effect of age, the *liability of obsolescence* (P3), is a positive effect of age on the mortality rate due to environmental change. The notion of structural inertia is used to explain this effect: founders leave their mark on the organization. This makes its transformation costly and increases mortality (Hannan *et al.*, 2006). Since the distance between the initial and the current environment increases with the age of the organization (Barron *et al.*, 1994), the mortality rate should increase with each successive time period. Age is not a causal factor, but an indicator of the gap between the current environment and the environment at the time of foundation. Hannan (1998) points out, however, that initial endowments and resources of companies protect them from bankrupt in a particular environmental context, but can also potentially protect them when this environment changes. They may lead to the reduction or even the elimination of this effect in relation to others. The final effect of age, the *liability of senescence* (P4), emphasizes a positive effect of age on mortality due to the effects of bureaucratization. This effect is typical in industrial organization (Martimort, 1999). An older organization is characterized by greater

[1] See the equation developed by Schary (1990) to explain firm exit in a sector.

difficulty in controlling the activity of its employees or members, who may relax their innovation efforts. In organizational ecology, bureaucratization leads to greater organizational inertia. The old organizations function by tending to rely on traditional solutions which, in time, limit effective collective action (Barron *et al.*, 1994).

The result of the combination of these four effects is relatively unknown (Coad, 2017). Hannan *et al.* (2007) propose an integration of these different effects to emphasize a positive impact of age on mortality in organizational ecology (domination of P3 and P4 over P1 and P2), and a negative effect, followed by a positive effect, in industrial organization (domination of P1 and P4 over P2 and P3). Different structures within the sectors may appear (Hannan, 2005): if there is a dominance of P1 and P2, the first entrants dominate the sector for long periods; in the case of dominance of P3 and P4, we see waves of Schumpeterian creative destruction. As pointed out by Le Mens *et al.* (2011), mixed empirical results highlight, for some, the increased mortality of young organizations, for some, the fact that this mortality occurs after a certain time, and, for others, that older organizations have the greatest chance of dying. The study of agricultural cooperatives is particularly relevant to test these effects because the agri-food industry and wholesale trading are characterized by a multiplicity of organizational structures: cooperatives and non-cooperatives, small and large companies, *etc.* (Boone and Ozcan, 2014; Maietta and Sena, 2008; Simons and Ingram, 2003, 2004; Sykuta and Cook, 2001).

Cooperatives are of particular interest to economists because of their unique ownership structure and the incentives associated with this structure (Fulton and Giannakas, 2013). The presence of cooperatives in agriculture is also a the subject of intense debate. Are these structures relics of the past, surviving due to the ideologies that generated them in the 19th century (social Catholicism, Republicanism, *etc.*),[2] but destined to disappear and to be replaced by more effective organizations, more suited to deal with market pressure (Cross *et al.*, 2009)? Or, conversely, are they a modern structure, consistent with the new demands of a globalized agriculture, capable of organizational innovation (Chaddad and Cook, 2004)? The distinctive features of cooperatives as *members-owned businesses* (Birchall, 2013) can give them special survival comparative advantages. With regards to the literature (Boone and Ozcan, 2014, 2016; Burdin, 2014; Frenken, 2014; Kitts, 2009; Monteiro and Stewart, 2015; Risch *et al.*, 2014; Rousselière and Joly, 2011), an important empirical contribution is the identification of the various effects of time, a distinctive feature of the cooperative *vs.* the non-cooperative enterprise.

Our main contributions to the overall work involving the study of the various effects of time on the mortality of organizations are twofold. First, at the empirical level, we rely on confidential and nearly-exhaustive data of the Annual Business Surveys 1984-2006, provided by the French Ministry of Agriculture.[3] To our knowledge, this is one of the first analyses of the French agri-

[2]Refer to Gueslin (1998) for the case of France and to Beltran (2012) for Spain.

[3]The statistical methodology of French Annual Business surveys changed in 2007. Therefore, we cannot

cultural cooperative sector, one of the most developed and innovative in the world (Bijman and Iliopoulos, 2014; Charriere and Aumond, 2016). Contrary to previous studies using the same database (Carrere *et al.*, 2011; Rousselière and Joly, 2011), thanks to our time-varying model, we underline the lower importance of unobserved heterogeneity on the survival of cooperatives, suggesting that unobserved variables may have a smaller impact. Second, we propose an original contribution to panel data econometrics and survival models in particular (Singer and Willett, 2003), which allows us to identify the factors determining the survival of cooperatives, and to distinguish the latter from other organizational structures. To isolate these effects, we estimate an original Bayesian generalized additive discrete-time semi-parametric hazard model with correlated random effects, incorporating unobserved heterogeneity. This is the first attempt in the literature on organizational mortality to estimate a smooth effect of time on survival. This model belongs to the more general family of GAMM (Generalized Additive Mixed Models). As discussed in the conclusion, this framework can be easily extended to take into account other survival features.

The remainder of this paper is structured as follows. Section 2. provides a review of the existing literature, emphasizing the specificity of cooperatives with respect to four potentially different effects of time on mortality. In section 3., we present our database and justify the focus on the cohort of enterprises created after 1984. We develop eventually our Bayesian econometric framework for estimating the form of the survival function in section 4.. In section 5., we present and discuss the results which underline the specificity of the temporal dynamics of cooperatives. Our main conclusions are summarized in section 6..

2. Earlier works on the impact of time on the survival of cooperatives

The dynamics of survival of cooperatives is a combination of the four effects described above. According to P1, their ability to mobilize non-market resources (*e.g.* free labor from members in case of difficulty, or indivisible reserves), to rely on their members' commitment (Cechin *et al.*, 2013; James and Sykuta, 2006; Nunez-Nickel and Moyano-Fuentes, 2004), or the fact that their founders follow other goals than strictly economic ones, suggest a low mortality rate in the early years (Pérotin, 2004), especially because of the lower entry rate. Indeed, it may be harder for a cooperative to enter the market because founders may have more difficulties to access resources or bank loans and, therefore, face harsher credit constraints (Simons and Ingram, 2004; Chaddad *et al.*, 2005). Because the *liability of newness* may be related to the small size at the entry, Boone and Ozcan (2016) show that cooperatives outlive corporations if investments size at founding is large.

From a different perspective, agricultural cooperatives appear to be victims of the *liability of*

include data from more recent surveys in our longitudinal analysis.

adolescence (Hansmann, 1999). This corresponds to the end of the original ideology of "end of honeymoon", described by Pérotin (2004). Cooperatives can, indeed, run the first few years at a lower cost, by incorporating adjustment mechanisms in the payroll in the case of workers' cooperatives, in exchange for contributions of raw materials in the case of agricultural cooperatives). Similar to non-profit organizations, cooperatives benefit from the strong involvement and enthusiasm of their founders. Pérotin (2004) highlights that the effect of adolescence is much more pronounced for cooperatives than for other companies: the initial selection is more stringent and it is easier to temporarily adjust costs in order to increase their chances of survival. Due to their enthusiasm, cooperative's members do not close the cooperative upon the first observation of poor performance. For example, in the simple case of a supply agricultural cooperative, Fulton (2001) underlines that in case of low commitment and high price, members may exit the cooperative or force the board to a merger with another cooperative or an Investor-Owned Firm (IOF) (Banerjee *et al.*, 2001). Cazzufi and Moradi (2012) show that due to the positive effect of membership size on survival, exit can be related to a decrease in commitment.

Regarding the effect P3, studies show that cooperatives can be victims of changing institutional contexts. According to Nunez-Nickel and Moyano-Fuentes (2004) and Simons and Ingram (2003, 2004), cooperatives are more sensitive to (un)favorable changes in the regulatory environment, but have a greater ability to adapt to macroeconomic fluctuations. Staber (1992) pointed out that agricultural marketing cooperatives are highly resistant to recessions. In France, cooperatives may be sensitive to changes in public policies that affect them: the 1992 reform of the cooperative status, the 2003 reform of the common agricultural policy favoring producer organizations, the reform of milk quotas (Hovelaque *et al.*, 2009), the impact of international trade treaties, *etc.* Cooperatives have a special role in agricultural industries, compared to other organizational forms, and have been supported by public policies (Valentinov, 2007; Iliopoulos, 2013). The favorable policy treatment, that cooperatives have enjoyed, is partially due to the belief that cooperatives have a pro-competitive effect (Fulton and Giannakas, 2013). Iliopoulos (2013) extends this argument and summarizes four main reasons for this:

1. *countervailing market power*: agricultural cooperatives provide individual farmers with an institutional mechanism that increases their bargaining power against upstream and downstream partners in food supply chains, and corrects for excess supply induced prices;

2. *market failure*: agricultural cooperatives address various forms of market failures, acting as a competitive yardstick that improves market performance;

3. *linking supply and offer*: agricultural cooperatives improve the coordination of supply with demand for farm commodities, leading to prices more consistent with production costs;

4. *community development*: agricultural cooperatives are instrumental for achieving community development goals and for facilitating the integration of low-income producers

into community life.

Previous researches show, for example, a positive impact of operational funds on the performance of French cooperative in the fruits and vegetable sector (Camanzi *et al.*, 2011). Therefore, we may underscore a relative low long term mortality for the whole population of cooperatives, in comparison to non cooperative enterprises.

Finally, according to Holström (1999), on the long run, agricultural cooperatives appear to be victims of P4. The accumulation of procedures or the lack of leadership could lead to pronounced effects of organizational inertia, especially in large cooperatives Fulton (2001). The results of Kitts (2009) show the same trend for community-based organizations. However, the control methods used in cooperatives in relation to the needs of their members appear *a priori* to be more flexible forms of organization. They have, as shown in large cooperative groups, the ability to find original solutions to the risks of bureaucratization, *e.g.* Italian cooperative consortia, the variable-geometry unions in agricultural cooperatives, the Mondragon industrial complex, *etc.* (Cook and Chaddad, 2004; Hansmann, 1996).

The methodology that we use here aims to identify not only the general relationship between age and mortality, but also to identify the presence or absence of each of the four potential effects listed above. This is an important difference with respect to previous studies, that use less flexible methods, or evaluate only the effect of legal status on mortality (Burdin, 2014; Monteiro and Stewart, 2015; Frenken, 2014). Particular attention is given to the specificity of cooperatives in seeking a unique temporal dynamic, and to the specific characteristics and contextual elements affecting them.

3. Presentation of the data

Provided by the French Ministry of Agriculture for the years 184-2006, the Annual Business Survey provides information on the economic and financial activity of French enterprises. This survey constitutes a unique longitudinal database on firms. Its pertinence to our study lies in the fact that it is a mandatory and comprehensive survey, which, unlike non-mandatory surveys, does not suffer from non-random non-response and general errors related to sampling. From the data at our disposal, we can reconstruct for each unit a *time of presence* in the database. Depending on the circumstances, these times of presence in the database can be associated with life cycle units. All units are subject to right-censored survival time, in the sense that we have a partial observation of their survival for a time during the observation period. Their survival time is at least equal to their presence time in the population at risk. This problem is addressed routinely by survival models. Enterprises for which the date of birth is unknown raise another problem. They are also subject to left truncation, because they are not identified prior to the first available date in the investigation. Here, information on these units cannot be associated with age. As a result, and following Singer and Willett (2003) and Rabe-Hesketh and Skrondal (2012), these units are excluded from the analysis.

The legal status of companies are grouped into four broad categories: (i) cooperatives, (ii) private limited liability corporations (type A), (iii) public limited liability corporations (Type B), (iv) and other types (other natural or legal persons and legal persons under public law). The descriptive statistics of French enterprises used in the present analysis are reported in Table 5 of Appendix A.1. There are 1,631 cooperatives in the data set, each observed on average 10.21 times, and 7,644 non cooperative enterprises, with an average of 8.91 observations each. 54% of the cooperatives in the dataset were still functioning in 2006. This rate is 46% for private limited liability companies, and only 19% for public limited liability companies.

Different studies have highlighted the need for control variables in order to isolate pure age effects. Regional affiliation have been found as having a significant impact on the survival of businesses, which may benefit from local conditions favorable to their development (Basile *et al.*, 2017; Fritsch *et al.*, 2006; Gagliardi, 2009; Kalmi, 2013; Simons and Ingram, 2004). For our study, we used the geographic division of agricultural cooperatives regional federations. This information is used only as a control variable, as this division becomes part of a particular history and specific to agricultural cooperation.

An industry effect has also been noted: if the activity takes place in a growing sector, then the chance of survival is higher (Mata and Portugal, 1994; Tsvetkova *et al.*, 2014). The industries have, therefore, been recoded into five sets: the Wholesale and Distribution, the Milk and Dairy Products, Meat and Poultry, the Beverage industries, and Others. These last sector is, by definition, much more heterogeneous and difficult to interpret. Cooperatives are more present in the Wholesale industry, and relatively less present in the Meat and Poultry industry.

Size has also been found as playing an important role (Esteve-Pérez *et al.*, 2004; Geroski *et al.*, 2010; Boone and Ozcan, 2016): large companies can indeed benefit from economies of scale, and from an opportunity to diversify their activities. Diversification reduces the risk of closure because poor conditions in a market can be offset by better conditions in another. For other authors (Jovanovic, 1982; Ericson, 1995), size is an indicator of differences in efficiency between firms. These differences stem from experience, managerial skills, technology, and organization. Large companies may have an advantage in fund-raising, can benefit from better taxation rules, and can more easily recruit the most qualified workers. New entrants to industries with high capital intensity have more difficulty surviving because of the significant level of resources needed to achieve the minimum threshold size (Fritsch *et al.*, 2006). Size can be expressed in different ways: turnover, number of employees, investments, *etc.* For ease of interpretation, annual turnover, tangible and intangible investments are expressed in thousands of euros. The number of employees is expressed in employees at the end of the fiscal year (December 31). A large size is the sign of a strong capacity to mobilize resources and also of a favorable place *a priori* in the context of competition between organizations for the same resources (Carroll and Hannan, 2000). It increases, other things being equal, the chances of survival of the organization, the *liability of smallness*, (Freeman *et al.*, 1983). We also control for the intensity of exports, express as a share of total turnover. Esteve-Pérez *et al.* (2008) show that exporting SMEs (Small and Medium Enterprises) face a significantly lower probability of failure than non-exporters.

Finally, we expect mixed effects of sectoral diversification strategies on the survival of cooperatives (Trechter, 1996). On one hand, diversification may have a positive impact on performance and, therefore, on survival; on the other hand, it also expresses an increasing heterogeneity among members, that may threaten the efficiency of governance (Hansmann, 1996). The sectoral diversification strategies are measured by the Evenness index (Shannon, 1948):

$$E = \frac{H}{\ln(S)} = \frac{-\sum_{i=1}^{S}(p_i \cdot \ln(p_i))}{\ln(S)} \tag{1}$$

where H is the Shannon-Wiener index, S is the number of categories, and p_i is the share of the category i among all the categories. This diversity index ranges from 0 (for an enterprise present in only one sector) and 1 (present in all sectors). The value of the Evenness diversification index is relatively close for cooperatives and non-cooperative corporations with a mean between 0.05 and 0.07.

To our knowledge, most of previous studies did not control for the possible correlation between explanatory variables and unobserved heterogeneity. To address the issue of time-varying variables, one can include them in the model with their value at creation. As emphasized by various authors (Carroll and Hannan, 2000; Cefis and Marsili, 2005; Le Mens *et al.*, 2011; Rousselière and Joly, 2011), the characteristics of the organization at creation strongly influence its fate. Another option is that time-varying variables are included with a lag of one year. Note, that this method leads to drop the establishments that exited in the first year of existence, omitting thereby a lot of valuable information (Fackler *et al.*, 2013). We choose an alternative specification of correlated random effects, following Mundlak (1978), Wooldridge (2010), and Blanchard *et al.* (2014). The correlated random effects model for non-linear estimations relaxes the assumption of strict exogeneity of covariates. The individual effect depends on the mean observation per individual for each covariate, and permits to partially correct for the unobserved heterogeneity (Bache *et al.*, 2013). Our model becomes a discrete time survival analysis with correlated random effects, as proposed by Blanchard *et al.* (2014).

An important difference with respect to previous works on the *shadow of death* (Blanchard *et al.*, 2014; Griliches and Regev, 1995; Carreira and Teixeira, 2011) is that we don't include efficiency measurement into the econometric model. The *shadow of death* is defined as a pattern of pre-exit decreased productivity. However, there is no consensus in the literature on what the cooperative maximizes and, therefore, on any efficiency index. It can be, for example, the utility or welfare of its members (as in Fulton and Giannakas (2001) or Giannakas and Fulton (2005)), or its profit with a patronage refunded to its members (as in Agbo *et al.* (2015)). For example, Cazzufi and Moradi (2012) show a negative impact of profits on survival for cooperatives.[4]

4. A Generalized Additive Discrete Time Survival Analysis Model with unobserved heterogeneity

The survival analysis (Singer and Willett, 2003) is based on the estimation of the determinants of the hazard (or failure or mortality) for a given unit. There is an ongoing debate in the literature on the advantages and disadvantages of the use of continuous-time and discrete-time models for survival analysis. For example, Carroll and Hannan (2000, p.110) advocate the use of a continuous-time model in order to accumulate empirical results. Authors in organizational ecology largely favor this approach and have a preference for the piece-wise continuous model.[5] Unfortunately, continuous-time survival methods assume that all survival times are unique, and that there are no pairs of individuals with identical or tied survival times (Rabe-Hesketh and Skrondal, 2012). On the contrary, discrete time survival methods allow many subjects to share the same survival time, due to recording reasons. A firm disappears only because the firm is not recorded in the survey the next year. In this case, the discrete time analysis framework has been shown to be more efficient Allison (2010).

Our proposition to use a Generalized Additive Discrete Time Survival Model can be viewed as a compromise between discrete time and continuous time modeling, taking into account the uncertainty about the exact moment of exit. It also goes beyond the traditional approaches to duration analysis, split between non-parametric approaches (such as the canonical Kaplan-Meier model) and (semi-)parametric approaches (based on complementary log-log) (Jenkins, 1995). In this section, we expose our model, which is the Bayesian version of the Additive Discrete Time Survival Model with frailty described in Tutz and Schmid (2016).

The standard cloglog (complementary loglog)model (Jenkins, 1995) can be conceived as a proportional hazard model with discrete-time, *i.e.* as the discrete-time analogue of the Cox model. For an observation i of an enterprise j, the hazard model, with a proportional hazard model structure, leads to the factorization (Rabe-Hesketh and Skrondal, 2012):

$$h(z|X_{ij}) = h_0(t) \cdot \exp(\beta_1 \cdot x_{1ij} + \cdots + \beta.x_{pij} + \cdots + \beta_P \cdot x_{Pij}) \quad (2)$$

[4] See Soboh *et al.* (2009) for a more complete review on the objective functions of cooperatives.

[5] Laird and Olivier (1981) had already demonstrated that the piece-wise exponential model for continuous time is mathematically equivalent to a Poisson model for discrete time. Tutz and Schmid (2016) note also that applying a Cox model to discrete data leads to a modification of the partial log-likelihood (Cox, 1972), equivalent to the estimation of a conditional logistic regression model.

where $h(z|X_{ij})$ is the hazard (or failure or mortality) of observation i of enterprise j at time z,[6] $h_0(z)$ is the baseline hazard, X is the vector of P explanatory variables x_p, and β_p the estimated coefficient of x_p.

When we observe the survival time only by intervals, we observe that an integer value $T_{ij} = t$ if $z_{t-1} < Z_{ij} < z_t$, with Z_{ij} the continuous survival time. The hazard in discrete time is given by:

$$\begin{aligned} h_{tij} &= h(t|X_{ij}) = P(T_{ij} = t|X_{ij}, T_{ij} > t-1) = \frac{P(Z_{ij} > z_{t-1}|X_{ij}) - P(Z_{ij} > z_t|X_{ij})}{P(Z_{ij} > z_{t-1}|X_{ij})} \\ &= 1 - \frac{P(Z_{ij} > z_t|X_{ij})}{P(Z_{ij} > z_{t-1}|X_{ij})} = 1 - \frac{S(z_t|X_{ij})}{S(Z_{t-1}|X_{ij})} \\ &= 1 - \left(\frac{S_0(z_t)}{S_0(Z_{t-1})}\right)^{\exp(\beta_1 \cdot x_{1ij} + \dots + \beta_P \cdot x_{Pij})} \end{aligned} \quad (3)$$

with S_0 the baseline survival function.

From equation (3), we get:

$$\ln(1 - h_{tij}) = \exp(\beta_1 \cdot x_{1ij} + \dots + \beta_P \cdot x_{Pij}) \times [\ln(S_0(z_t)) - \ln(S_0(z_{t-1})] \quad (4)$$

We then obtain the transformation complementary log-log of hazard, hereafter cloglog:

$$\ln\left[-\ln(1 - h(t|X_{ij}))\right] = \beta_1 \cdot x_{1ij} + \dots + \beta_P \cdot x_{Pij} + \alpha_t \quad (5)$$

with $\alpha_t = \ln\left[\ln(S_0(z_t)) - \ln(S_0(z_{t-1})\right]$ the time-specific constant.

The model can be adapted to account for unobserved heterogeneity with an additional term u_j:

$$h(t|X_{ij}) = h_0(t) \cdot \exp(\beta_1 \cdot x_{1ij} + \dots + \beta_P \cdot x_{Pij} + u_j) \quad (6)$$

with $u_j \sim N(0, \psi)$. u_j can be interpreted as the impact of potential unobservable variables (such as management skills of managers) or omitted variables (such as imitation strategies of enterprises established nearby). The unobserved heterogeneity term, specific to each observed enterprise j, is usually assumed to follow a normal distribution.[7]

In the case of the correlated random effects model, we relax the hypothesis of strict exogeneity of u with the distribution $D(u_j|X_{ij}) = D(u_i|\bar{X}_{ij})$: [8]

$$\ln\left[-\ln(1 - h(t|X_{ij}))\right] = \beta_1 \cdot x_{1ij} + \dots + \beta_P \cdot x_{Pij} + \beta_{a1} \cdot \bar{x}_{1ij} + \dots + \beta_{aP} \cdot \bar{x}_{Pij} + \alpha_t + u_j \quad (7)$$

[6]Note, that in our case t is equivalent to the age of the enterprise.
[7]Various ways to model the unobserved heterogeneity are developed in Nicoletti and Rondinelli (2010).
[8]In the standard random effects model, we have $D(u_j|X_{ij}) = D(u_j)$.

where bars indicate the mean of each time-varying variable.

The cloglog of the Generalized Additive Mixed Model (GAMM) is a straightforward application of the cloglog with mixed effects to the Generalized Additive Model (GAM) framework developed by Wood (2006):

$$\ln\left[-\ln(1-h(t|X_{ij}))\right] = \beta_1 \cdot x_{1ij} + \cdots + \beta_P \cdot x_{Pij} + \beta_{a1} \cdot \bar{x}_{1ij} + \cdots + \beta_{aP} \cdot \bar{x}_{Pij} + f(t) + u_j \quad (8)$$

with $f(.)$ a smooth function of the time variable t. Time is introduced as a non parametric term using thin plate regression splines. The smooth function $f(.)$ is modeled as follows:

$$f(t) = \gamma_0 + \gamma_t \cdot t + \sum_{k=1}^{K} \mu_w \cdot w_k(t) \quad (9)$$

with $\mu_w \sim N(0, \sigma^2)$ and $w_k(.)$ the thin plate regression spline function. According to Wood (2003), $w_k(.)$ is the default approach to smooth terms because they are the optimal smoother of any given basis dimension/rank. The interest of the smooth term is that it addresses the issue of unstable estimations when, as t increases, only few observations are at risk and estimates become unstable. In this case the result are jumps in the estimated function that occur when the hazards are plotted against time (Tutz and Schmid, 2016).[9]

Finally, we can extend our model using smooth terms for various covariates:[10]

$$\begin{aligned}\ln\left[-\ln(1-h(t|X_{ij}, Z_{i,m}))\right] = {} & \beta_1 \cdot x_{1ij} + \cdots + \beta_P \cdot x_{Pij} + \beta_{a1} \cdot \bar{x}_{1ij} + \cdots + \beta_{aP} \cdot \bar{x}_{Pij} \\ & + f_1(t) + \sum_{m=1}^{M} f_m(B_{im}) + u_j \quad (10)\end{aligned}$$

where $f_1(.)$ is a smooth function of time variable t, and $f_m(.)$ are the smooth functions of covariates B.

We can calculate two different indicators in order to assess the importance of unobserved heterogeneity. The first one is the estimated residual intra-class correlation among the latent responses for two observations of the same enterprise:

$$\rho = \frac{\psi}{\psi + \pi^2/6} \quad (11)$$

with ψ the variance of u_j. The second indicator is the median hazard ratio (Rabe-Hesketh and

[9] Note, that in conjunction to GAMM modeling, the use of Bayesian estimation is an additional way to address this issue, where median and robust parameters are used to measure central tendency (Buerkner, 2017).

[10] Note, that our strategy can be easily extended to capture risk factors that may change with time, as proposed by Kauermann *et al.* (2005) using smooth interaction terms (Wood, 2003).

Skrondal, 2012):

$$HR_{median} = \exp\left\{\sqrt{2 \cdot \psi} \cdot \Phi^{-1}(3/4)\right\} \tag{12}$$

with Φ^{-1} the normal inverse function. HR_{median} is the median relative change in the hazard when comparing two observations with the same covariates, but corresponding to two different cooperatives (Austin *et al.*, 2017).

Estimations are conducted with package Brms for R (Buerkner, 2017), based on Stan, a C++ program performing Bayesian inference and optimization (Gelman *et al.*, 2015). Bayesian modelling accounts for uncertainty and sparse data (Gelman *et al.*, 2014a). The Bayesian estimator does not generally allow analytical solutions. Recourse to draws from the posterior parameter distribution are required. Stan is a highly efficient program for high-dimensional and multilevel models with correlated parameters using the No-U-Turn Sampler (NUTS) algorithm (Buerkner, 2017). The NUTS algorithm (Hoffman and Gelman, 2014) removes autocorrelation quicker than frequentist and Bayesian alternative algorithms.[11] In order to increase the effective sample size (ESS), different chains based on different draws may be estimated.

We used weakly informative priors (Independent Cauchy prior distribution with center 0 and scale 2.5 on population parameters and a half Student-t prior with 3 degrees of freedom on the group level parameter), following Gelman (2006) and Buerkner (2017). These weakly informative priors are a good compromise between a fully informative prior and a non-informative prior (that corresponds to traditional frequentist analysis and often leads to unstable estimates), and can be used as routine in real world applications (Gelman *et al.*, 2008).

There are different strategies to include time effects in a survival analysis: year dummies (Bontemps *et al.*, 2013), smooth polynomial representations of time (Monteiro and Stewart, 2015), *i.e.* linear, quadratic and cubic effects, log of age, or incorporating period effects (Kitts, 2009; Varum and Rocha, 2010). In his survey on firm age effects, Coad (2017) notes that as individual firms change over time, adding a cohort effect distorts the representation of firm-level ageing viewed at the population level. Period effects can be included in order to control for potential macroeconomic (crisis) or institutional effects (change of economic regulations) on the survival dynamics of the enterprise (Varum and Rocha, 2010). In our case, the periods correspond to various changes in the cooperative regulation.[12]

For Singer and Willett (2003), the completely general specification of time with dummy variables lacks parsimony and yields fitted hazard functions that can fluctuate erratically across consecutive time periods, due to nothing more than simple sampling variation (Fahrmeir and Wagenpfeil, 1996).

[11] Autocorrelation produces samples that are unrepresentative of the true underlying posterior distribution.

[12] Years 1992 and 1996 refer to new French legislation on agricultural cooperatives, and 2003 to the change in the Common Agricultural Policy.

A three step approach is advocated by Cefis and Marsili (2005) or Bontemps *et al.* (2013) in order to select the appropriate specification: identification of a suitable parametric distribution using a non-parametric bivariate model, identification of temporal variables and control variables to isolate the effect of age on survival, and, lastly, estimation of a semi-parametric multivariate model complementary log-log. Following Singer and Willett (2003), and because of the inconsistency of stepwise model selection (Kass and Raftery, 1995), we used instead a one-stage approach based on Bayesian model selection (BMS) (Ando, 2010; Raftery, 1995). The Widely Applicable Information Criterion (WAIC) implemented in Vehtari *et al.* (2017) is a fully Bayesian method for estimating point-wise out-of-sample prediction accuracy from a fitted Bayesian model using the log-likelihood evaluated at the posterior simulations of the parameter values (Gelman *et al.*, 2014b). Our benchmark estimation is compared to alternative specifications, a lower WAIC highlighting a better fit. We can also calculate the Akaike weights that are analogous to posterior probabilities of models, conditional on expected future data (McElreath, 2016):

$$w_i = \frac{\exp(-\frac{1}{2}\Delta\,WAIC_i)}{\sum_{j=1}^{m}\exp(-\frac{1}{2}\Delta\,WAIC_j)} \tag{13}$$

with $\Delta\,WAIC_i$ the WAIC difference between the model i and the model with the lowest WAIC.

5. Results

Based on weakly informative priors, our benchmark model is based on 4 chains and 2,000 iterations of which the first 1,000 are a warm-up to calibrate the sampler, leading to a total of 4,000 posterior samples.[13] The Stan algorithm is highly efficient as the autocorrelation of the Markov chains disappear quickly (refer to Figure 1 for the estimations of the age parameter). We obtain therefore a large ESS.

The potential scale reduction factor on split chains, $\hat{R}$, and ESS are reported for the parameters of interest in Tables 6 and 7 of Appendix A.2. At convergence, $\hat{R} = 1$ (Gelman *et al.*, 2014a).[14] The WAIC is minimal for the GAMM cloglog model and generates a posterior probability of 1 (see Table 1). As expected, a time dummies approach to time effect lacks parsimony, but surprisingly less than other approaches, such as the use of log, linear, cubic, or quadratic effects of age. This suggests that the impact of age on mortality can not be summarize in our case by polynomial representations, but requires a more flexible approach.

The results for the GAMM cloglog model are reported in Table 2 for cooperatives and in Table 3 for non-cooperative enterprises. For cooperatives, results underline a negative impact of the

[13]Each model took approximatively two days to run for cooperatives, and four days for non cooperative enterprises on a modern computing server dedicated to econometric analysis.

[14]If $\hat{R}$ is considerably greater than 1 (*i.e.*, $\hat{R} > 1.1$) the chains have not yet converged and it is necessary to run more iterations and/or set stronger priors (Buerkner, 2017).

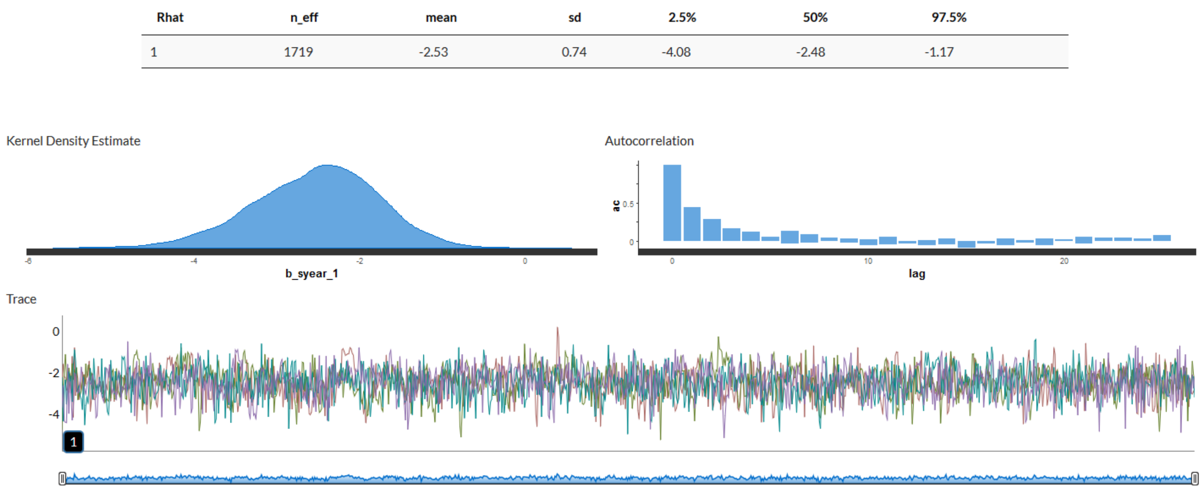

Figure 1: Diagnostics of age parameter

Table 1: WAIC for various models with different specifications of age effects

	WAIC		dWAIC	Weight
	estimate	std. error		
GAMM (smooth effect of age)	6992.78	161.66	0.00	1.00
Age dummies	7015.43	162.25	22.65	0.00
ln (age)	7057.71	165.97	64.93	0.00
cubic effect of age	7065.13	166.09	72.35	0.00
quadratic effect of age	7079.15	166.32	86.37	0.00
linear effect of age	7084.55	166.32	91.77	0.00

number of employees, turnover, and tangible investment on mortality. The number of past legal statuses has opposite effects on cooperatives (increases the hazard probability) and on non-cooperative enterprises (decreasing the hazard probability, although not significantly). These results are in line with the empirical findings of Boone and Ozcan (2016).

In Table 4, we report the various measures of unobserved heterogeneity. ρ is equal to 0.229 for cooperatives and 0.264 for non-cooperative enterprises, underlining the importance of unobserved variables for the survival of non-cooperatives. As reported in Table 8 of Appendix A.3, the difference is significant according the robust Bayesian estimation test developed by Kruschke (2013). Concerning the other measure, HR median permits a comparison of the magnitude of this general contextual effect with that of model covariates (Austin *et al.*, 2017). As shown by the values of HR_{median}, the hazard ratio which compares the observation with the larger hazard to the observation with the smaller hazard from two different cooperatives, exceeds 1.594 in 50% of the samples. For non-cooperative enterprises, this median hazard ratio is 1.756. As reported in Tables 6 and 7 of Appendix A.2, these magnitudes are larger than for the independent variables.

As shown by Allison (1999) and Williams (2009), direct comparison of the coefficients of non-

Table 2: GAMM cloglog for cooperatives

Parameter	mean	s.d.	2.5%	50%	97.5%
Intercept	-2.047	0.208	-2.451	-2.051	-1.640
PER2	0.247	0.126	-0.002	0.250	0.492
PER3	-0.568	0.116	-0.797	-0.567	-0.342
PER4	-0.643	0.149	-0.944	-0.645	-0.356
NPLS	0.425	0.076	0.281	0.423	0.584
EMPLOYEES	-0.004	0.001	-0.007	-0.004	-0.002
TURNOVER	-0.001	0.000	-0.002	-0.001	-0.000
TANGIBLE	-0.049	0.013	-0.077	-0.049	-0.025
INTANGIBLE	-0.016	0.135	-0.352	0.015	0.157
Group-means variables					
mean(EMPLOYEES)	-0.000	0.001	-0.003	-0.000	0.002
mean(TURNOVER)	0.002	0.000	0.001	0.002	0.003
mean(TANGIBLE)	0.023	0.012	-0.002	0.024	0.045
mean(INTANGIBLE)	-1.384	0.530	-2.571	-1.342	-0.506
ψ	0.489	0.231	0.036	0.491	0.946
Smooth terms					
s(AGE)	-2.533	0.740	-4.079	-2.479	-1.170
s(EVENNESS)	-0.074	0.291	-0.716	-0.066	0.530
s(EXPORT)	-0.508	0.414	-1.450	-0.461	0.191
sd(s(AGE))	5.545	1.934	2.898	5.171	10.399
sd(s(EVENNESS))	1.273	1.303	0.042	0.860	4.993
sd(s(EXPORT))	3.140	2.232	0.401	2.598	8.739
log-posterior	-4043.039	84.158	-4177.733	-4053.388	-3851.257

Notes: Regional and sector fixed effects included, s.d. stand for standard deviations.

linear models across groups can be invalid and misleading. Differences in the degree of residual variation across groups can produce apparent differences in slope coefficients that are not indicative of true differences. A valid alternative is to compare predicted probabilities (Long, 2009).[15] In Figures 2 and 3, we report the median of the predicted probabilities as a measure of central tendency. The age effect on mortality has been estimated as a smooth effect. Figure 4 represents this effect for the 4 categories of enterprises. The age dependence in mortality is different for the various organizational forms. After the first three years, mortality increases with age for non-cooperative enterprises (with a higher hazard for public than private corporations with limited liability, and the highest hazard for enterprises with other legal status), with a highest point between years 19 and 21. For cooperatives, the probability of mortality is the lowest at the age of 3 and 13, and the highest for years 7 and 19, suggesting a combination of the various liabilities.

We report the marginal effects of age on mortality. We see that the marginal effect is positive for the first two years, between 5 and 8 years, and finally between 15 and 20 years, underlining

[15]See Bouchard and Rousselière (2016) for an application to survival analysis.

Table 3: GAMM cloglog for non cooperative enterprises

Parameter	mean	sd	2.5%	50%	97.5%
Intercept	-0.593	0.089	-0.774	-0.592	-0.424
PER2	-0.006	0.034	-0.073	-0.005	0.060
PER3	-0.482	0.036	-0.550	-0.483	-0.409
PER4	-0.903	0.048	-0.995	-0.902	-0.809
NPLS	-0.034	0.021	-0.078	-0.034	0.006
EMPLOYEES	-0.000	0.000	-0.001	-0.000	0.000
TURNOVER	-0.000	0.000	-0.001	-0.000	-0.000
TANGIBLE	-0.005	0.001	-0.008	-0.005	-0.003
INTANGIBLE	0.004	0.002	0.000	0.004	0.007
PRIVATE_LIMITED	-0.767	0.070	-0.905	-0.767	-0.634
PUBLIC_LIMITED	-1.098	0.068	-1.232	-1.098	-0.966
Group-means variables					
mean(EMPLOYEES)	-0.001	0.000	-0.001	-0.001	-0.000
mean(TURNOVER)	0.001	0.000	0.000	0.001	0.001
mean(TANGIBLE)	0.009	0.002	0.006	0.009	0.013
mean(INTANGIBLE)	-0.003	0.007	-0.017	-0.003	0.009
ψ	0.590	0.041	0.511	0.591	0.672
Smooth terms					
s(AGE)	-2.082	0.488	-3.041	-2.075	-1.129
s(EVENNESS)	-0.058	0.093	-0.281	-0.046	0.121
s(EXPORT)	-0.099	0.102	-0.355	-0.077	0.053
sd(s(AGE))	4.665	1.817	2.097	4.357	9.070
sd(s(EVENNESS))	0.397	0.448	0.010	0.259	1.582
sd(s(EXPORT))	0.574	0.481	0.059	0.433	1.845
log-posterior	-27520.232	142.561	-27796.239	-27523.007	-27224.345

Notes: Regional and sector fixed effects included, s.d. stand for standard deviations.

some specific effects of liability of newness, adolescence and obsolescence.

Finally, we compare the marginal effects of period on mortality. There is a small increase in mortality for the second period only for the cooperatives (after the change in the cooperative legislation), while the other period effects are slightly similar. On the opposite, there is a huge decrease for other forms (private limited, public limited and others) for the last two periods. The 1992-1995 period was characterized by important changes in cooperation regulation which create incentives to merger between cooperatives (Filippi *et al.*, 2012).

6. Discussion and conclusion

Our work aimed to propose an original estimation method, that is more flexible than conventional survival regressions proposed in the literature on firm age, and able to disentangle the various effects of time (age and period), while being in line with the principles of parsimony. We

Table 4: Impact of unobserved heterogeneity

	ψ	ρ	Median hazard ration HR_{median}
cooperatives	0.489	0.229	1.594
non cooperatives	0.590	0.264	1.756

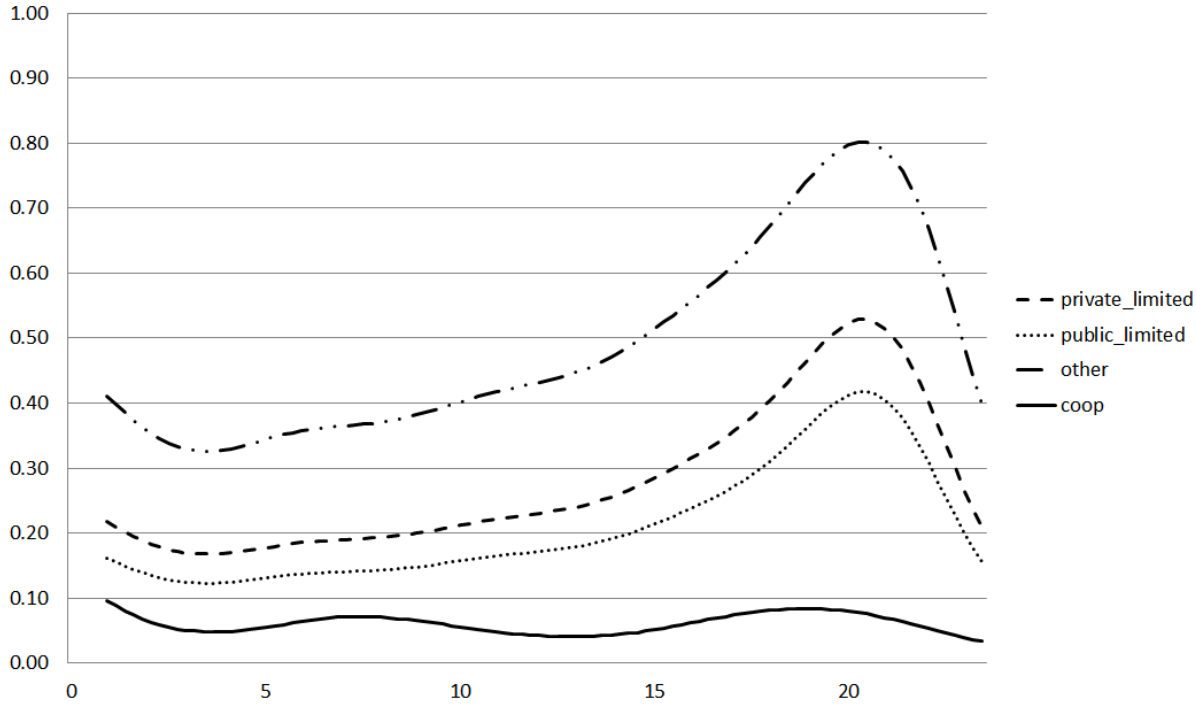

Figure 2: Smooth effect of age on mortality
Notes: Probability of failure on the vertical axis; age in years on the horizontal axis.

tested the relationship between age and mortality in firms in the food and wholesale industries characterized by a diversity of organizational structures. To do this, in the absence of adequate distribution of a survival function a priori, we estimated a Bayesian semi-parametric discrete-time model with smooth terms, taking into account unobserved heterogeneity and time-varying covariates.

The Bayesian GAMM presented in this paper is a very flexible framework and can be straightforwardly extended. It can also accommodate variable selection using Lasso prior on the population-level effects (Park and Casella, 2008) or spatial analysis, being therefore an alternative to classical models based on the inclusion of contextual variables (*e.g.* (Basile *et al.*, 2017)). Indeed, one can consider the possibility of spatial autocorrelation, which is only imperfectly captured by our region variable. Federations may play a role in the differences in survival (Herbel *et al.*, 2015). A process of imitation between comparable firms, or, conversely, of competition for the same resources (Simons and Ingram, 2004) may also be a source of isomorphism at local level (Nilsson *et al.*, 2012). Also, as noted in the theoretical models of interaction between cooperatives and non-cooperatives in agricultural and food markets (Drivas and Gian-

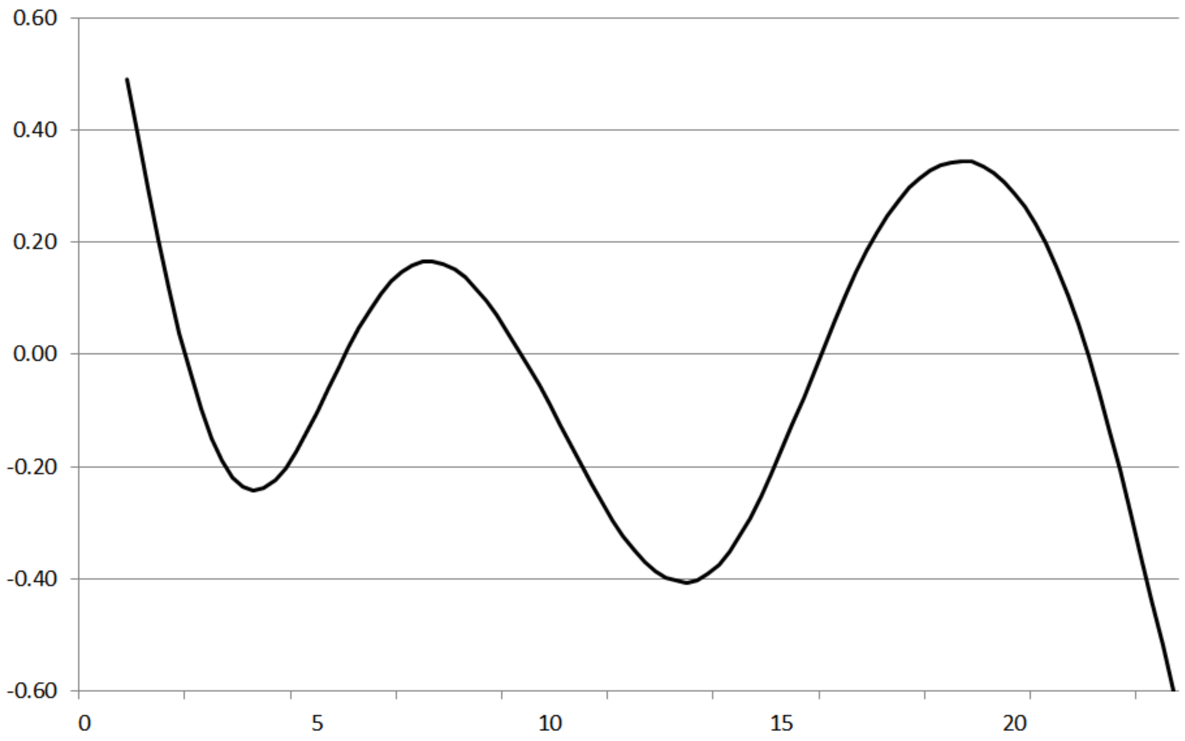

Figure 3: Marginal effect of age on cooperatives' mortality
Notes: Probability of failure on the vertical axis; age in years on the horizontal axis.

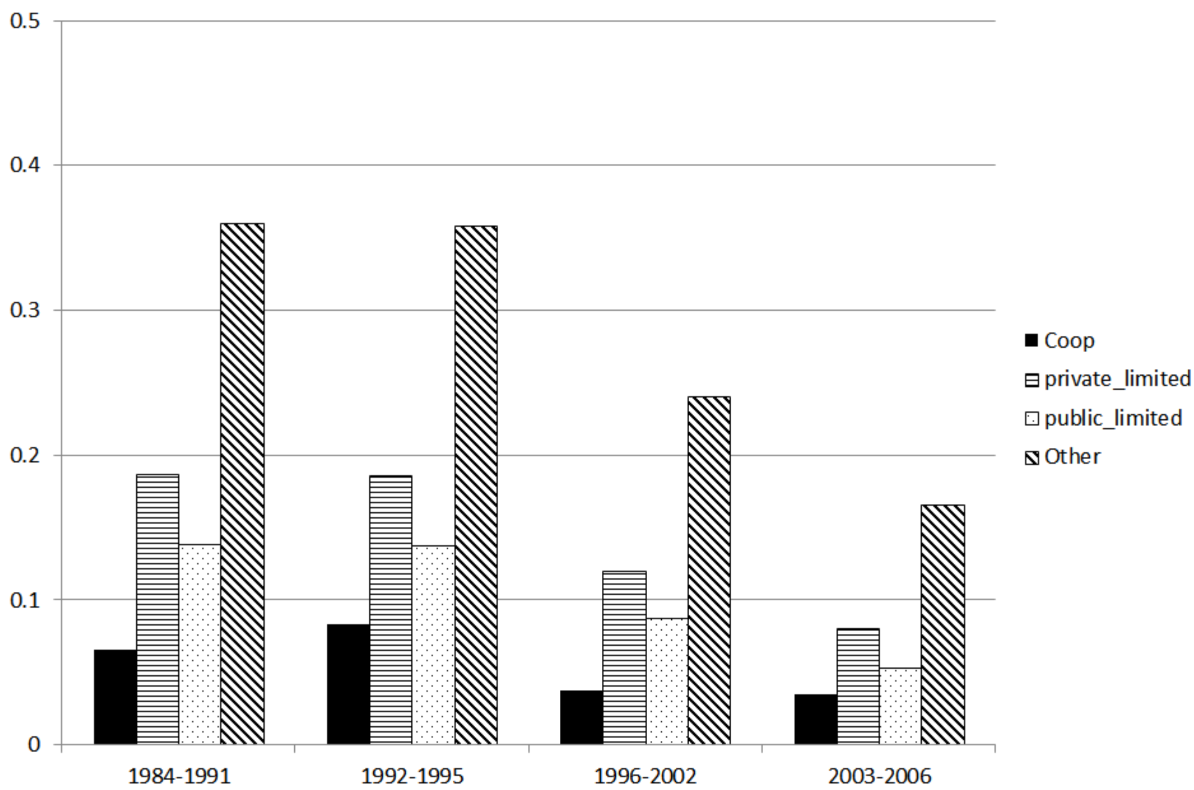

Figure 4: Effect of period on mortality
Notes: Probability of failure on the vertical axis; age in years on the horizontal axis.

nakas, 2010), a strong interaction between these different forms exists with respect to strategic choices (*e.g.* differentiation in terms of quality of products offered by agricultural cooperatives from their business competitors). Similarly, on the empirical level, the development of cooperatives happened to compensate for the exit of non-cooperative corporations (Simons and Ingram, 2004). In other contexts, "cooperative beehiving" has been observed. Hakelius *et al.* (2013) characterized this process as the phenomenon of members who de-associate themselves from large cooperatives and form smaller entities. These new dynamics of spatial autocorrelation can be addressed using smooth terms for latitude and longitude (Fahrmeir and Kneib, 2011).

Our GAMM model captures a smooth effect of age on mortality, that is different for cooperative and non cooperative enterprises, while periods seem to have the same effects on the mortality of both firm types. We find evidence of the liabilities of newness, adolescence, and obsolescence. The marginal effects of age being positive for the first two years, between years 5 and 8, and years 15 and 20. The effect for years 5-7 is also highlighted by Coad (2017), after which firm performance tends to stabilize, at least in relative terms. In our case, we observe one additional peak, suggesting the necessity for cooperatives to adapt themselves to a changing context. This effect is corroborated by a small increase in the mortality during the 1992-1995 period, which included important changes in the French legislation for cooperatives. A striking result is the higher importance of unobserved heterogeneity for non cooperative enterprises than for their cooperative counterparts. Unobserved variables (such as managerial ability or specific human capital of the direction) seem to have a greater impact on the survival of non cooperatives enterprises, than on that of cooperative enterprises characterized by a democratic and more collective governance (Diaz-Foncea and Marcuello, 2013; Pozzobon and Zylbersztajn, 2013).

Cooperatives appear to be highly resistant to the change in the social and economic environment, leading Nunez-Nickel and Moyano-Fuentes (2004) to consider the cooperative ownership structure as a buffer for structural and conjectural shocks or economic depressions. Cooperatives may be less profitable than investor-owned firms, but operate more efficiently, present a stronger financial position (Soboh *et al.*, 2012), and have a stabilizing effect on employment (Delboni and Reggiani, 2013) and price (Muller *et al.*, 2017) with respect to shocks. In line with our empirical findings, this "stability argument" (Chevallier, 2011) for public policy goes beyond the traditional pro-competitive argument for the promotion of cooperatives in developed economies.

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A Appendix

A.1 Descriptive Statistics

Table 5: Descriptive statistics for cooperative and non cooperative enterprises

Variable	Cooperatives: 16,667 obs.				Non-cooperatives: 68,176 obs.			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
AGE : Age (in years)	8.26	6.79	0	23	5.36	5.66	0	23
PER1: period 1984-1991	0.38	0.48	0	1	0.34	0.48	0	1
PER2: period 1992-1995	0.15	0.36	0	1	0.18	0.38	0	1
PER3: period 1996-2002	0.30	0.46	0	1	0.31	0.46	0	1
PER4: period 2003-2006	0.17	0.38	0	1	0.17	0.38	0	1
NPLS: # legal statuses in the past	0.04	0.30	0	7	0.44	0.88	0	8
EMPLOYEES: # employees (in 1,000) at the end of the year	73	144	0	2,400	118	283	0	7,950
TURNOVER: Turnover (in K €)	136	311	0.07	6,782	106	356	0.06	14,571
TANGIBLE: Tangible investment (in K €)	3.57	13.63	0	580.75	3.89	27.17	0	4,384
INTANGIBLE: Intangible investment (in K €)	0.03	0.88	0	89.31	0.115	5.30	0	1,100
EVENNESS: Index of sectoral diversity	0.07	0.08	0	0.42	0.05	0.06	0	0.43
EXPORTS: Exports as % of turnover	0.10	0.16	0	0.99	0.09	0.18	0	1
OTHER: Other legal status					0.02	0.13	0	1
PRIVATE_LIMITED: Private limited liability corporations (« SARL »)					0.27	0.44	0	1
PUBLIC_LIMITED: Public limited liability corporations (« SA »)					0.72	0.45	0	1

A.2 Convergence diagnostics

Table 6: $\hat{R}$ and ESS for cooperatives

Parameter	$\hat{R}$	ESS
Intercept	1.0	976
PER2	1.0	4000
PER3	1.0	4000
PER4	1.0	4000
NPLS	1.0	1057
EMPLOYEES	1.0	1215
TURNOVER	1.0	4000
TANGIBLE	1.0	4000
INTANGIBLE	1.0	1734
Group-means variables		
mean(EMPLOYEES)	1.0	4000
mean(TURNOVER)	1.0	4000
mean(TANGIBLE)	1.0	4000
mean(INTANGIBLE)	1.0	4000
ψ	1.0	105
Smooth Terms		
s(AGE)	1.0	1719
s(EVENNESS)	1.0	1274
s(EXPORT)	1.0	1635
sd(s(AGE))	1.0	1561
sd(s(EVENNESS)	1.0	1156
sd(s(EXPORT))	1.0	1125

Table 7: $\hat{R}$ and ESS for non cooperative enterprises

Parameter	$\hat{R}$	ESS
Intercept	1.0	1352
PER2	1.0	4000
PER3	1.0	3329
PER4	1.0	4000
NPLS	1.0	554
EMPLOYEES	1.0	4000
TURNOVER	1.0	4000
TANGIBLE	1.0	4000
INTANGIBLE	1.0	4000
PRIVATE_LIMITED	1.0	2153
PUBLIC_LIMITED	1.0	1991
Group-means variables		
mean(EMPLOYEES)	1.0	4000
mean(TURNOVER)	1.0	4000
mean(TANGIBLE)	1.0	4000
mean(INTANGIBLE)	1.0	4000
ψ	1.0	313
Smooth Terms		
s(AGE)	1.0	1142
s(EVENNESS)	1.0	1511
s(EXPORT)	1.0	1393
sd(s(AGE)	1.0	901
sd(s(EVENNESS)	1.0	1324
sd(s(EXPORT)	1.0	950

A.3 Bayesian estimation of the difference in unobserved heterogeneity for cooperatives and non cooperative enterprises

Table 8: Robust Bayesian estimation of Rho difference

parameter	mean	median	mode	HDI%	HDIlo	HDIup
ρ_{coop}	0.2204	0.2204	0.2203	95	0.2178	0.2232
$\rho_{noncoop}$	0.2639	0.2639	0.2639	95	0.2635	0.2643
$diff$	-0.0434	-0.0434	-0.0436	95	-0.0461	-0.0406
var_{coop}	0.0859	0.0859	0.0858	95	0.0839	0.0879
$var_{noncoop}$	0.0135	0.0135	0.0135	95	0.0132	0.0138
$diff$	0.0724	0.0724	0.0723	95	0.0703	0.0743
nu	120.8136	113.1463	98.9419	95	47.2221	208.3972
log10nu	2.0544	2.0536	2.0749	95	1.7481	2.3511
effSz	-0.7068	-0.7068	-0.7066	95	-0.7522	-0.6591

A.4 Hazard ratios

Table 9: Hazard ratios for various explanatory variables

	Cooperatives	Non-cooperatives
PER2	1.281	0.994
PER3	0.567	0.953
PER4	0.526	0.405
NPLS	1.530	0.967
EMPLOYEES	0.996	1.000
TURNOVER	0.999	1.000
TANGIBLE	0.952	0.995
INTANGIBLE	0.984	1.004
PRIVATE_LIMITED		0.464
PUBLIC_LIMITED		0.334

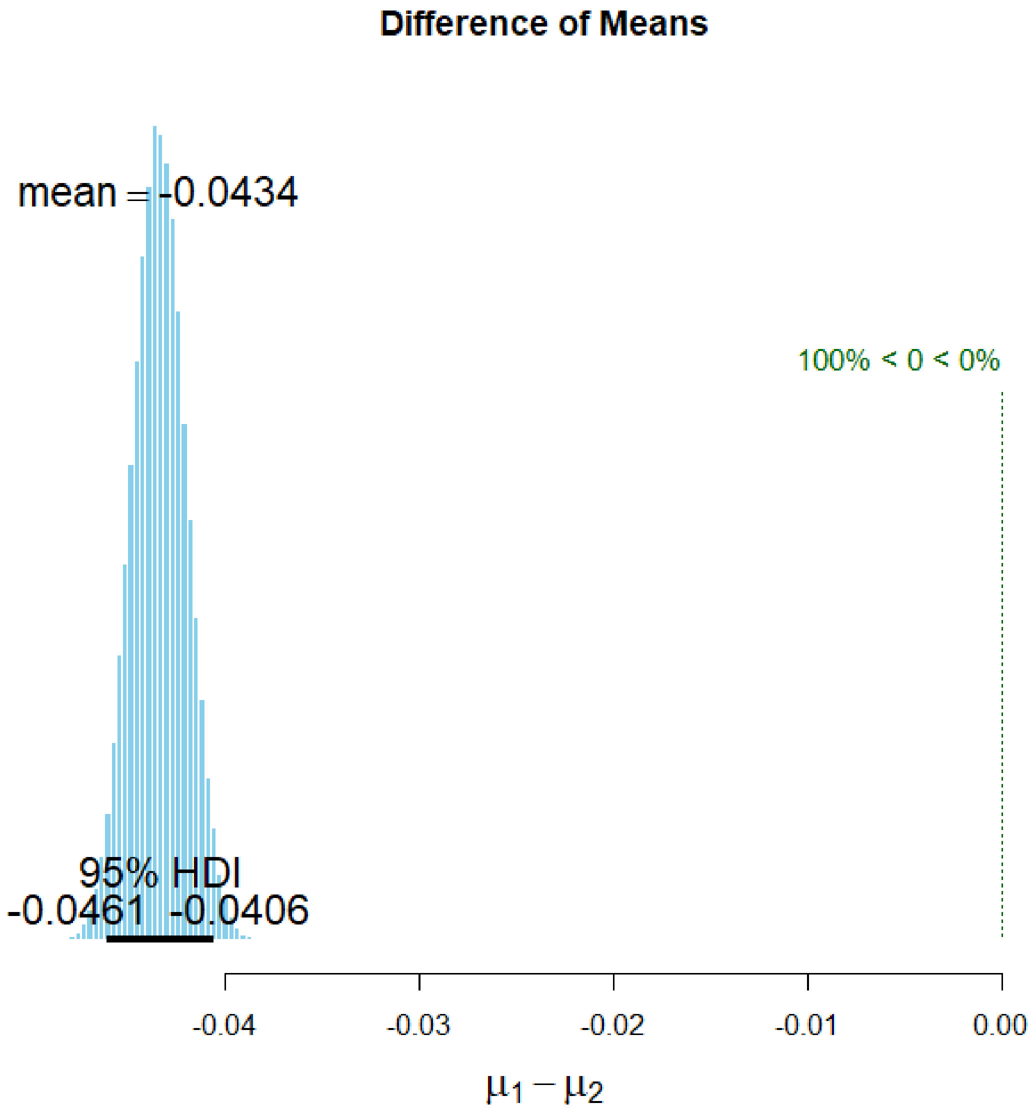

Figure 5: Rho difference between cooperatives and non cooperatives using BEST test (Kruschke, 2013)

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