Quality Labels and Firm Survival in the Food Industry

Christophe Bontemps
Zohra Bouamra-Mechemache
Michel Simioni

Toulouse School of Economics (Gremaq, INRA)

Paper prepared for presentation at the EAAE 2011 Congress
Change and Uncertainty
Challenges for Agriculture,
Food and Natural Resources

August 30 to September 2, 2011
ETH Zurich, Zurich, Switzerland

Quality Labels and Firm Survival in the Food Industry

Christophe Bontemps, Zohra Bouamra-Mechemache and
Michel Simioni*

February 15, 2011

Abstract

Both industry and firm characteristics influence the survival of a firm in an industry over time. Aging, size, structure are factors often discussed in the literature, but public intervention effects - through public quality labeling for example - may also have an effect that is examined here. We use data on French firms producing cheese under public quality label or not over the period 1990-2006. We perform a nonparametric estimation using Kaplan-Meier estimators as well as proportional hazard rate models to assess the impact of such factors on firms survival.

Our results confirm existing findings on firm survival determinants. We also shed light on the effect of public intervention into that industry. More precisely, our focus on public quality labeling in the French cheese industry shows that quality label reduces the risk of exiting for firms and more particularly for small firms. In other words, public intervention in this industry is well designed to increase the competitiveness of small firms enabling the coexistence on the market of both small and large firms.

*Christophe Bontemps and Zohra Bouamra-Mechemache are at the Toulouse School of Economics (Gremaq,INRA), Michel Simioni is at the Toulouse School of Economics (Gremaq,INRA and IDEI). We gratefully acknowledge financial support from the department of agricultural economics from INRA. We thank Jad Chaaban and the participants of the Agricultural & Applied Economics Association 2010 AAEA,CAES & WAEA Joint annual meeting, Denver, for comments. We are grateful to ï¿½lise Maigne for her impressive and efficient work on the raw dataset.

1 Introduction

In line with the successive reforms of the Common Agricultural Policy that tends to eliminate price support and use non distortional measures that are decoupled from production in the European Union, the European Commission (EC) has developed an EU quality policy. Its objective is to valorize and protect agricultural and food products through the diversification of agricultural production in order to 'achieve a better balance between supply and demand on the markets' (European-Commission (1996)).Public intervention, though, may enhance social welfare by providing public labels that certifies the quality of the product. In particular, smaller firms that can find it too expensive to signal individually the quality of their products can collectively signal it by sharing the cost of quality signal through public quality label. Some countries have adopted this kind of regulation for many years. For instance, the AOC (Appellation d'Origine Controllée) regulation in France and the DOC (Denominazione di Origine Controllata) in Italy have been respectively created in 1935 and in 1963.

Our goal is to assess the ability of such a public policy for quality to sustain the competitiveness of firms and determine which firms have benefited from it. From the theoretical literature on geographical indication (GI), we know that public labels are an efficient tool to provide quality. In a perfect competitive market with free entry, Moschini et al. (2008) show that an equilibrium exists where GI producers benefit from positive externalities linked to the sharing of GI certification cost, which makes possible the production of GI. The perfect competitive setting for GI products may not always be the adequate market structure to consider given the specificity of the territory, the input and process requirements required in the certification regulation. This is at least the case in the average run where entry adaptation is difficult and even impossible (Hayes et al. (2004)). Moreover, perfect competition applies when the GI geographical area is large enough and when there is no land constraint so that the GI products do not cover much of the local agricultural production and production cannot be controlled. One might thus consider the profitability of GI in a context of non competitive markets where production is somehow controlled and where this supply control may enhance the development of geographical indication market (cf. Marette and Crespi (2003) and Lence et al. (2007)). If the quality label meets the consumer needs, the innovation in production and marketing developed by the operators for labeled products may lead to a successful activity for those operators.

While the theoretical literature on the profitability of public quality label is extensive, empirical findings are scarce. This paper tries to fill this gap by analyzing how GI-like label can contribute to the success of firms that voluntary enter into such a quality certification scheme. To accomplish this, we provide an empirical analysis of the French AOC label, which is older than its EU equivalent PDO (Protected Designation of Origin).

The performance of dairy firms is measured through their life duration on the market or "survival". It is one of the most widely used empirical measure of performance (Foster et al. (2008)). Firm survival has been shown to be strongly related to other performance measures as profitability and growth and gives a better understanding on industrial strategies (cf. Dunne et al. (1988)). These results were obtained using standard statistical tools in survival analysis. This methodology has been widely used to analyze how industry or firm characteristics can influence firms survival, but not to analyze public intervention, which may be a key driver of agricultural and agro-food firms. For instance, government payments in the United States have been showed to increase slightly the survival of farm businesses and particularly of bigger farms (Key and Roberts (2006)). In this article, we rather focus on the impact of government intervention on agrofood firms and we analyze how AOC quality label has contributed to the development of dairy firms and to the current structure of the dairy industry.

The article is organized as follows. The next section review the determinants of firm survival. Section 3 provides an overview of the dataset and discusses its strengths and weaknesses for measuring firm survival. Section 4 presents the methodology used to estimate firm survival and Section 5 provides the main estimation findings. The final section discusses conclusions and implications for future research.

2 Determinants of Firm Survival

he relation between performance and survival has been empirically shown in the literature. Measure of performance through total factor productivity affects survival (Bellone et al. (2006) and Foster et al. (2008)). Lower performance is observed some years before their failure (Kiyota and Takizawa (2006)). Different factors may explain survival. Various "stylized facts" have been drawn from the empirical literature on firm survival, entry and exit. These facts apply in many countries and for many industrial sectors (Geroski (1995) and Caves (1998)). Both industry and firm characteristics influences firms' duration length. Substantial rates of entry and exit is recurrently found in a number of countries. In this section, the main findings are summarized. We use these findings to construct the empirical strategy when testing the determinants of cheese firm dynamics.

The age of firms is an important feature of firm survival. New firms face high risk of failure during the first years of their existence (newness). Their capacity to survive depends on their ability to gather market information and to modify their strategy to the post-entry environment. Firm mortality then declines over time. The oldest firms may suffer from erosion of technology and products (obsolescence) over time so that their failure rate may be high (aging). However, they may also benefit from strong trademarks that help them increase their longevity. Firm size is also a major determinant of survival (smallness). This factor is relevant both for new and older firms but its impact is stronger on the dynamics of new firm. Different factors may explain this fact. First, small-sized firms may have more difficulty to raise capital. Second, tax law can be more detrimental compared to larger firms. Third, public regulation affects more smaller firms. In addition, large firms may be favored in the competition on the labor market. Considering that the failure rate is increasing with the size of irretrievable outlay needed to move from minimal or fringe entry to optimal-scale operation, the size of irretrievable outlays also affects the survival of firms. It results that small firms may have a higher failure rate as they will find it more difficult to reach the minimum efficiency size at which they will be able to operate. Another explanation of the size impact on survival is related to the costs of labor and capital. If they are high, this could be detrimental to new/small firms that will have more difficulty to develop their activities and favor older/larger firms. In addition to age and size, the structure of the firm may also affect firms' dynamic. As shown by Disney et al. (2003), when an establishment is part of a group, it increases its survival rate relative to a single establishment. This result supports the idea that establishments that are part of a group can learn from other establishments of the group and get better market information compared to single establishments.

The dynamics of firms also depend on the characteristics of the industry under consideration. Comparison between different industries in different countries reveals common industry determinants for survival patterns. Both entry and concentration depend on the sunkness of incumbents' commitment and more generally on trade barriers, which has an incidence on survival length. Trade barriers in an industry can arise from high minimum efficiency scale (MES), capital intensity, advanced technology or product differentiation and innovation.

In the next section, we analyze the impact on firm dynamics of the most relevant factors identified above, age, size, MES and single establishment firm. On the example of the French cheese industry, we study the impact of some form of innovation through public labeling (AOC).

3 Data and Descriptive Statistics

We use firm and plant surveys covering the period 1990-2006 provided by the French Administrative Direction of Statistics (INSEE). The first main set of information reports economic and administrative information at the firm level (EAE) while the second set is reporting production, activities and more detailed information on the industrial process at the plant level for dairy firms (EAL). [1] The first set is available only for firms with more than 20 employees, while the second set is exhaustive at the France level.

The proportion of AOC in the total production of cheese amounts to around 17%. We focus in this study on AOC cheese made from cow (30 AOC) and sheep milk (3 AOC) which represents 97% of milk used in the processing of AOC cheese. Each observation gives us information on firms that might be constituted of different plants.

The survival analysis is performed on the 1430 firms observed during the period 1990-2006, for which we were able to identify if the firm was producing cheese with AOC label or not. The final dataset provides information on all firms involved in cheese production.[2] Among those 485 firms observed on the period, cheese production may or not be the main activity of the firm. When firms have other activities, cheese is most often the main one. Other activities include dairy products other than cheese. We choose to do the analysis at the firm level rather than at the plant level. An analysis at the firm level is more relevant as AOC like strategy is decided at the firm level and not at the plant level. Moreover, it enables us to take into account firm characteristics that may influence firm survival as its number of plants or its product mix. Entry and exit data thus correspond to the creation and destruction of firms. Firms are considered to be active as long as at least one of its plant is active (i.e. produces cheese).

We compute the time spells corresponding to the survival of the surveyed firms using the previously described data sets. By construction these time spells are evaluated as intervals measured in years over the period 1990-2006. Indeed, our data indicate that a firm was present in the sample during a given year. But, when a firm disappeared in the following year, the exact time (day or week) the exit has occurred is not known. In this case the

[1]EAE stands for *Enquête Annuelle d'Entreprise* while EAL is the *Enquête Annuelle Laitière*, both provided by INSEE (Institut National de la Statistique et des Etudes Economiques.)

[2]Accounting data are not available for plants that are reported in EAL and that are not linked with firms present in the EAE baseline. These plants are reported as small firms of less than 20 employees.

transition times are said to be grouped and discrete-time hazard models are used to deal with such data. Thus the minimum value of a time spell is one year, and its maximum value is 17. One average, a firm survives 8 years in the industry, for the period considered.

Now consider the covariates that can affect the survival of dairy firms. These variables are time-varying variables. The variable $AOCshare_t$ represents the share of AOC production relative to the total cheese production of the firm in year t. On average, the share of AOC production is quite stable (around 45%). Old_t is a dummy variable that indicates whether the firm was present or not before the beginning of the period under scrutiny. The dummy variable MES_t indicates whether a firm has reached or not the minimum efficiency scale defined as the median firm production by category of cheese in year t. We finally consider size variables. The cheese industry is mainly composed of small firms ($Small_t$). We observe a large majority of firms with less than 20 employees on their first annual report (78%). On the contrary, big firms (Big_t) are those with more than 100 employees, they are a bit less numerous than firms of medium size ($Medium_t$). The share of large firms increases over the period from 9% in 1990 to 14% in 2006, while the share of small firms decreases from 79% to 67%.

4 Empirical Methodology

By the definition of the period covered by the surveys (1990-2006), three different time spells can be observed: (1) Complete time spell when a firm enters the sample before 1990, and exits before 2006, (2) right-censored time spell when a firm enters after 1990, and is still alive in 2006, and (3) left-truncated time spell when a firm entered before 1990, and exits before 2006 or is still alive in 2006. We can identify this latter type of time spell because the surveys indicate if a firm was active or not before 1990. But, for most of the firms that were active before this year, we do not know when they have been created. Fortunately, left truncation will not affect the maximum likelihood estimators presented below. A showed by Rabe-Hesketh and Skrondal (2008), the correct contribution to the likelihood of a left-truncated firm under delayed entry is obtained by discarding the periods preceding 1990.

The starting point for modeling the survival of firms using the previously defined time spells, is the discrete-time hazard function. Let T be the period of exit and $\mathbf{x}_i$ a vector $(k \times 1)$ of covariates. The discrete-time hazard function is defined as the probability of exit of a firm at any discrete time t, given that firm i has not exited yet i.e.

$$h_{i,t} = \text{Prob}[T_i = t |\ T_i \geq t, \mathbf{x}_i]. \quad (1)$$

To analyse firm survival, the most widely used semiparametric model in continuous-time is the so-called proportional hazard model (Cox (1972)).[3] This model assumes a parametric form for the effect of the covariates on survival, but allows the form of the underlying survival function to be unspecified. Thus the survival time of each firm i is assumed to follow a hazard function given by

$$h(\tau|\mathbf{x}_i) = h_0(\tau) \times \exp(\mathbf{x}_i'\gamma) \quad (2)$$

[3]See the overview of the recent Industrial Organization literature on firm survival by Manjón-Antolin and Arauzo-Carod (2008).

where γ is a vector $(k \times 1)$ of parameters. $h_0(\tau)$ is the baseline hazard function (the hazard when each covariate $\mathbf{x}_i^j = 0$) whose functional form is not specified. The equivalent of the continuous-time proportional hazard model in discrete-time is the complementary log-log model defined as

$$\text{cloglog}(h_{i,t}) \equiv \ln\{-\ln(1 - h_{i,t})\} \tag{3}$$

and the corresponding model as

$$\text{cloglog}(h_{i,s}) = \alpha_1 d_{1,s} + \alpha_2 d_{2,s} + \ldots + \alpha_J d_{J,s} + \mathbf{x}'_{i,s}\gamma \tag{4}$$

where $d_{1,t}, \ldots, d_{J,s}$ are dummy variables for years $1, \ldots, J$, J referring to the last time period observed for any firm in the sample, with $d_{t,s} = 1$ if $s = t$, 0 otherwise. The parameters γ in equation (4) are identical to the parameters in the underlying continuous-time proportional hazards model defined by equation (2). It means that the complementary log-log model coefficients have a direct relative risk interpretation as noted above. Similarly, the time-specific constants α_t can be written as function of the baseline hazard function $h_0(\tau)$. By estimating these parameters freely for each time-point, no assumption is done regarding the shape of this baseline hazard function within the time intervals. Thus, the complementary log-log model retains some of the flexibility of the nonparametric approach.

The problem of unobserved heterogeneity stems frequently from incomplete specification in (2). The solution is to incorporate multiplicative unobserved heterogeneity uncorrelated with regressors. This individual unobserved heterogeneity component is known in the survival analysis literature as "frailty". It is a multiplicative term and thus measures a proportional increase or decrease in the hazard rate relative to that of an average firm. In the proportional hazard model defined in (2), unobserved heterogeneity is thus accounted by the inclusion of the multiplicative term ν_i, which is assumed to be positive, i.e.

$$h(\tau|\mathbf{x}_i) = h_0(\tau) \times \exp(\mathbf{x}_i'\gamma) \times \nu_i \tag{5}$$

The random variable ν summarizes the impact of "omitted variables" on the hazard rate, whether the missing regressors are intrinsically unobservable or simply unobserved in the data set to hand. Alternative interpretations are proposed in terms of errors of measurement in recorded regressors or recorded survival times.

The corresponding discrete-time complementary log-log model with frailty becomes now:

$$\text{cloglog}(h_{i,s}) = \alpha_1 d_{1,s} + \alpha_2 d_{2,s} + \ldots + \alpha_J d_{J,s} + \mathbf{x}'_{i,s}\gamma + \varepsilon_i \tag{6}$$

where $\varepsilon_i = \log(\nu_i)$. Usually, it is assumed that ε_i, or, equivalently, ν_i, is generated according to a given parametric distribution function. Usual generating distribution functions are the Gamma and the Gaussian distributions.

Parameters in equation (4), i.e. when no frailty is assumed, can be estimated using maximum likelihood techniques applied to a binary choice model with a complementary log-log link. Indeed, by construction, each firm's survival story is broken into a set of discrete time units that can be treated as distinct observations. Then, a binary choice model that predicts whether exit did or did not occur in each time unit can be estimated. More formally, it can be easily shown that

$$\begin{aligned} h_{i,s} &= \text{Prob}[T_i = s |\ T_i \geq s,\ \mathbf{x}_i] \\ &= \text{Prob}[y_{i,s} = 1 |\ \mathbf{x}_i] \end{aligned} \tag{7}$$

where $y_{i,s}$ is an indicator for the exit occurring at time s for firm i. Unobserved heterogeneity can be accounted for by including random effects ε_i, $i = 1, \ldots, n$, in this binary choice model framework (see equation (6)). If a specific parametric distribution is assumed for these random effects, calculating the marginal likelihood function involves now a one-dimensional integral that can be computed numerically.

5 Results

Table 1 shows the estimation results for four discrete-time proportional hazard models. In the first column of this table, we present the estimates of a complementary log-log model that does not include any potential unobserved individual heterogeneity (model 1). Dummies denoted by year== j, $j = 2, \ldots, 16$, are created to represent the years where a firm may be present in the sample. In the second column, estimates of the same model but now incorporating different effects of $AOCshare_t$ with respect to the size of the firm (small, medium, or big) (model 2) are reported. Models 3 and 4 correspond to models 1 and 2, respectively, but now including an unobserved individual heterogeneity term. The latter is assumed to follow a Gaussian distribution. The relative importance of unobserved individual heterogeneity for the two models is indicated by the estimates for ρ. This parameter measures the share of individual variation in the hazard rate that is due to variation in the unobserved factors. Tests can be performed to assess if this share is significant or not. Thus, if the null hypothesis of $\rho = 0$ cannot be rejected, we can conclude that frailty is unimportant. Estimates of models 3 and 4 are given in the third and four columns of table 1, respectively.

Both for models 3 and 4, the tests for unobserved individual heterogeneity, i.e. the likelihood ratio tests of the null hypothesis of $\rho = 0$, allow us to reject the null hypothesis that unobserved individual heterogeneity is not relevant. Accounting for unobserved individual heterogeneity significantly increases the respective likelihoods. Moreover, the share of individual variation in the hazard rate due to variation of unobserved factors accounts for nearly 83% of the total variation in the hazard rate for the two model specifications. In other words, ignoring unobserved individual heterogeneity would not be a good idea when discussing the impacts of the covariates on hazard rate. For instance, comparison of the estimates of models 1 and 2 (without frailty) with those of models 3 and 4 (with frailty) reveals that, even if qualitative results for fraitly models do not differ from those for no fraitly ones, the estimates of the coefficients of the covariates in the models with frailty are much larger in absolute value than those of non frailty models, as expected (Jenkins (2005)). Therefore the following analysis will focus on the estimation results of models 3 and 4.

Models 3 and 4 differ in how the effect of the share of AOC in total cheese production is modeled. A direct effect of $AOCshare_t$ on the rate of hazard is considered in the first model while $AOCshare_t$ interacts with the size of the firm in the second. To choose between the two models, we note that the likelihood ratio test rejects the null hypothesis that the effect of $AOCshare_t$ is the same whatever the size of the firm. Results in table 1 show that while increasing the volume of AOC labeled production significantly reduces the probability of failure (model 3), cross effect estimates from model 4 are significant only for small firms. Engaging in AOC production increases thus significantly the survival of small firms while

Table 1: **Complementary log-log model**

Models	Model 1		Model 2		Model 3		Model 4	
	Coef.	($s.e.$)	Coef.	($s.e.$)	Coef.	($s.e.$)	Coef.	($s.e.$)
year==2	0.131	0.135	0.132	0.135	1.043***	0.236	1.096***	0.243
year==3	0.136	0.139	0.135	0.139	1.619***	0.326	1.694***	0.337
year==4	0.001	0.149	0.001	0.149	1.915***	0.394	2.010***	0.407
year==5	0.586***	0.132	0.589***	0.132	2.946***	0.454	3.065***	0.470
year==6	0.225	0.158	0.233	0.158	3.023***	0.524	3.182***	0.544
year==7	-0.025	0.177	-0.017	0.177	3.013***	0.565	3.189***	0.587
year==8	0.854***	0.143	0.864***	0.143	4.227***	0.603	4.421***	0.627
year==9	-0.348	0.231	-0.337	0.231	3.285***	0.662	3.483***	0.685
year==10	-0.219	0.236	-0.204	0.236	3.475***	0.672	3.685***	0.697
year==11	0.088	0.217	0.105	0.217	3.958***	0.689	4.168***	0.714
year==12	-0.485	0.286	-0.469	0.286	3.497***	0.726	3.705***	0.749
year==13	-0.166	0.263	-0.149	0.264	3.944***	0.734	4.169***	0.759
year==14	-0.290	0.287	-0.272	0.287	3.926***	0.755	4.161***	0.781
year==15	-0.046	0.271	-0.029	0.271	4.331***	0.770	4.569***	0.796
year==16	0.067	0.264	0.079	0.264	4.493***	0.775	4.717***	0.801
$AOCshare_t$	-0.678***	0.097			-1.020***	0.196		
$Medium_t$	-1.042***	0.135	-1.270***	0.167	-2.134***	0.264	-2.617***	0.329
Big_t	-1.261***	0.178	-1.369***	0.195	-2.703***	0.380	-3.007***	0.428
MES_t	-0.198**	0.076	-0.192*	0.076	-0.651***	0.158	-0.671***	0.160
Old_t	0.253***	0.077	0.270***	0.077	0.432*	0.181	0.471*	0.184
$AOCShareSmall_t$			-0.764***	0.101			-1.228***	0.210
$AOCSharMedium_t$			0.169	0.319			0.433	0.504
$AOCShareBig_t$			0.060	0.587			0.350	0.921
Constant	-2.323***	0.111	-2.316***	0.111	-4.456***	0.471	-4.550***	0.489
$\widehat{\rho}$					0.829	0.038	0.839	0.036
Log-Likelihood	-2913.766		-2909.557		-2896.871		-2891.482	
LRT of $\rho = 0$:								
Chi2-value					33.790		36.151	
P-value					0.000		0.000	
LRT of the same effect of $AOCshare_t$ whatever the size of the firm								
Chi2-value							10.779	
P-value							0.005	

Notes : ***, ** and * indicate the significance of the estimated parameters at the 1%, 5% and 10% levels.

there is no such evidence for larger firms. This does not suggest that AOC labeling is not profitable for larger firms. It may be a useful tool among others (brand strategy, production diversification, etc...) for large firms to increase their profits but it is not a key determinant for their profitability while smaller firms rely more on AOC to stay competitive on the market. Notice that being a larger firm increases significantly the probability to survive. When larger, firms are able to benefit from economy of scale and economy of scope, they can also increase their investments to develop their brands, differentiate their products or increase their production capacity. The labeling policy can be seen as a public intervention tool for small firms that are less likely to be able to invest to make their products known by consumers. Finally, results show that even if AOC labeling is key driver of firm survival, efficiency (producing at or above the minimum efficiency scale) remains a highly significant determinant of profitability and survival.

In order to visualize the effect of AOC labeling and its interaction with other covariates, we proceed now with the prediction of the hazard rate using the frailty model 4. We start with predicting

$$z(s) = \widehat{\alpha}_1 d_{1,s} + \widehat{\alpha}_2 d_{2,s} + \ldots + \widehat{\alpha}_J d_{J,s} + \mathbf{x}'\widehat{\gamma} + \varepsilon \tag{8}$$

for given values of the covariates $\mathbf{x}$ and of the unobserved heterogeneity term ε, using the estimated coefficients $(\widehat{\alpha}_j, \widehat{\gamma}_j)$ of models with frailty. Then the hazard rate can be predicted as

$$h(s) = 1 - \exp\left(-\exp\left(z(s)\right)\right) \tag{9}$$

using the reciprocal of the complementary log-log transformation defined in equation (3). In order to investigate more precisely the impact of PDO labeling policy, we fix the values of the covariates and consider an hypothetical small firm which has been created before 1990 and which produces cheese with a small proportion of PDO cheese and above the minimum efficiency rate (case 1a) . We analyze what will be the impact on its survival when this hypothetical firm is more oriented toward AOC labeled production (case 1b). Then we perform the same analysis for two other hypothetical firms which differ by their size (medium size firm in case 2 and large firm in case 3). In all cases, predictions are derived assuming that the frailty term is set equal to its mean value.

Figure 1 shows that the probability to survive for such an hypothetical firm after 10 years is quite small (less than 20%), while those of larger firms is more than 80% and remains relatively high even after 15 years. Predictions show no significant differences in the survival rate between medium and large firms the 8 first years and only a small difference after that period. When the hypothetical small firm becomes more AOC label oriented (case 1b), its predicted survival rate is increased but the firm achieves a survival rate that remains below the rate for larger firms. Labeling strategy does not compensate the size effect on the survival rate. However, for medium and large firms, we get a opposite but rather small effect of the label on survival.

A focus on small firms helps understanding the impact of the label for different characteristics of the firm (cf. figure 2). We examine two extreme situations (compared to case 1) , one where the firm is no more efficient but created after 1990 (case 4) and the worst one where the firm is no more efficient and created before 1990 (case 5). While age and efficiency

Figure 1: Predicted Survival rates for the frailty model: effect of size on survival rate

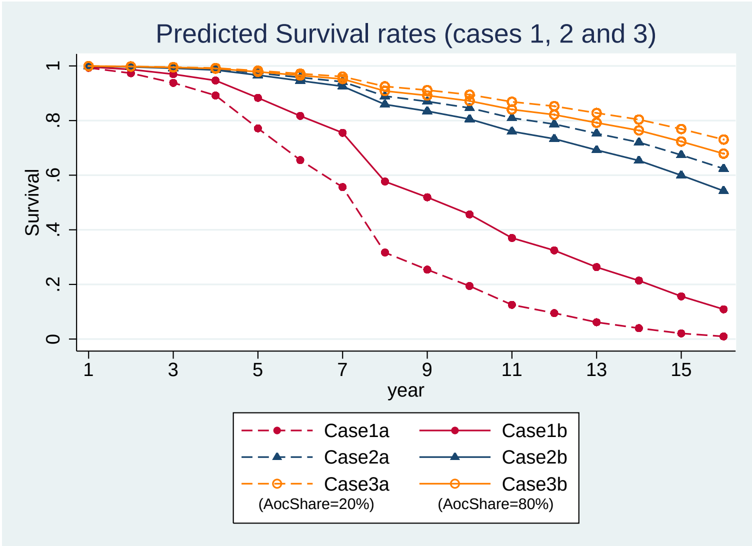
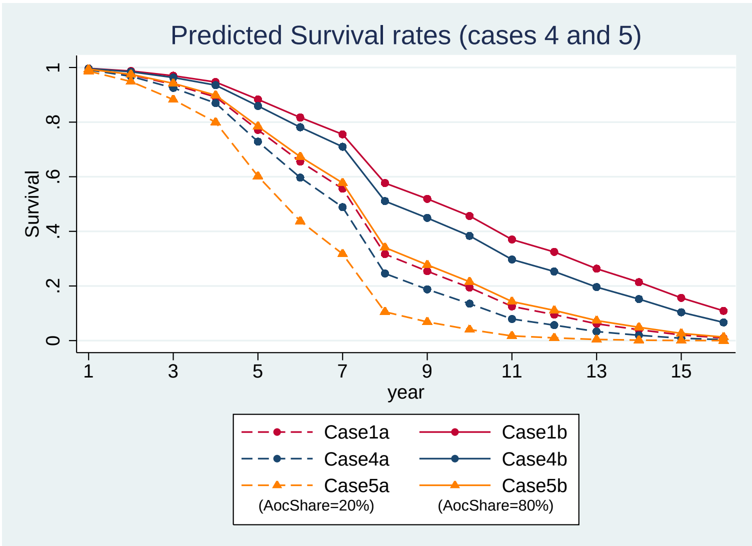


Figure 2: Predicted Survival rates for the frailty model: effect of firm characteristics on small firms



but also AOC policy do not seem to influence the survival rate the first 3 years, the pattern of survival is greatly influenced after 3 years. When the hypothetic old firm becomes less efficient (moving from case 1a to case 5a), its predicted survival rate is significantly reduced. In addition, when such a firm becomes younger (moving from case 5a to case 4a), the age effect compensates the efficiency effect. AOC labeling increases the survival rate up to 30% and up to 40% in the worst situation. A second feature of the label is that it influences less the survival rate after 12 years. After this survival length, the patterns of survival rates with or without AOC converge. This suggests that the AOC labeling policy is an effective tool to maintain the activity of small firm businesses at the medium run but not in a longer run.

6 Concluding remarks

In this paper, we assess the ability of quality labeling policy to sustain the competitiveness of agro-food firms involved in such a policy and determine which firms have benefited from it. We more specifically analyze how AOC quality label has contributed to the development of dairy firms and to the current structure of the dairy industry. This analysis relies on a detailed database on French dairy firms that combines accounting data as well as production data. The performance of dairy firms is measured through their life duration on the market or survival. We use recent tools in statistical analysis of duration data to estimate the impact of various determinants of firm performances including AOC labeling. These tools allow for incorporating unobserved heterogeneity in the specification of the hazard rate.

Our results confirm existing findings in the literature on firm survival determinants. We find that the size effect is the main determinant of firm survival in the dairy industry. In addition, the AOC labeling effect is less pronounced than the size effect. However, when it interacts with firm size, the benefit of being more specialized in AOC production shows up for small firms only. In other words, encouraging AOC production reduces the risk of exiting for small firms. Public intervention in this industry is well designed to increase the competitiveness of small firms enabling the coexistence on the market of both small and large firms. AOC labeling can act as a differentiation tool in the market where small niche firms are able to survive thanks to a reduced price competition. This generates a lower hazard rate for this firms that it would be without the implementation of the quality label. We can then presume that without the label policy, the market would be more concentrated. Further work and more detailed data on the dairy markets would be needed to better understand how the label policy affects the dairy market structure.

References

Auriol, E. and Schilizzi, S. (2003). Quality signaling through certification.

Bellone, F., Musso, P., Quere, M., and Nesta, L. (2006). Productivity and market selection of french manufacturing firms in the nineties. *Revue de L'OFCE*, pages 319 – 349.

Caves, R. E. (1998). Industrial organization and new findings on the turnover and mobility of firms. *Journal of Economic Literature*, 36(4):1947 –.

Cox, D. (1972). Regression models and life-tables (with discussion). *Journal of the Royal Statistical Society, Series B*, 34:87–220.

Disney, R., Haskel, J., and Heden, Y. (2003). Entry, exit and establishment survival in uk manufacturing. *Journal of Industrial Economics*, 51(1):91–112.

Dunne, T., Roberts, M. J., and Samuelson, L. (Winter, 1988). Patterns of firm entry and exit in u.s. manufacturing industries. *The RAND Journal of Economics*, 19(4):495–515.

European-Commission (1996). Council regulation (ec) no 510/2006 of 20 march 2006 on the protection of geographical indications and designations of origin for agricultural products and foodstuffs. Official Journal of the European Union.

Foster, L., Haltiwanger, J., and Syverson, C. (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?. *American Economic Review*, 98(1):394 – 425.

Geroski, P. (1995). What do we know about entry? *International Journal of Industrial Organization*, 13(4):421 –.

Hayes, D. J., Lence, S. H., and Stoppa, A. (2004). Farmer-owned brands. *Agribusiness*, 20(3):269 – 285.

Jenkins, S. (2005). *Survival Analysis*. Institute for Social and Economic Research, University of Essex. unpublished Lecture Notes manuscript.

Key, N. and Roberts, M. J. (2006). Government Payments and Farm Business Survival. 88(2):382–392.

Kiyota, K. and Takizawa, M. (2006). The shadow of death: Pre-exit performance of firms in japan. Discussion papers 06033, Research Institute of Economy, Trade and Industry (RIETI).

Lence, S., Marette, S., Hayes, D., and Foster, W. (2007). Collective marketing arrangements for geographically differentiated agricultural products: Welfare impacts and policy implications. *American Journal of Agricultural Economics*, 89:947 – 963.

Manjón-Antolin, M. and Arauzo-Carod, J. M. (2008). Firm survival: Methods and evidence. *Economica*, 35:1–24.

Marette, S. and Crespi, J. M. (2003). Can quality certification lead to stable cartels? *Review of Industrial Organization*, 23(1):43 – 64.

Moschini, G., Menapace, L., and Pick, D. (2008). Geographical indications and the competitive provision of quality in agricultural markets. *American Journal of Agricultural Economics*, 90(3):794 – 812.

Rabe-Hesketh, S. and Skrondal, A. (2008). *Multilevel and Longitudinal Modeling Using Stata, 2nd Edition.* in Stata Press books. StataCorp LP.