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Quality Labels and Firm Survival in the French Cheese Industry*

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Abstract

EU regulation on quality food products (PDO labeling) is expected to sustain competitiveness within the agricultural sector. This paper examines the impact of this policy on the survival of cheese firms over the period 1990-2006 in France. We show that such a policy (Appellation d'Origine Controlée) reduces exiting risk for smaller firms. However, smaller firms still have a lower survival rate compared to larger ones that cannot be compensated by the quality label effect.

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1 Introduction

In line with the successive reforms of the Common Agricultural Policy, the European Union (EU), gradually eliminates price support in favor of non-distortional measures that are decoupled from production. In the same time, the EU also develops an EU quality policy in order to fit consumer concerns about the attributes of food products, such as quality and geographical characteristics (Marette (2005)). This policy aims at sustaining the economic viability of businesses that were hurt by the gradual decrease in public support but that provide such quality goods. Accordingly, the EC regulation introduced in 1992 (European-Commission (1992) and European-Commission (2006)) on the protection of geographical indications and designations of origin is expected to sustain competitiveness and profitability within the agricultural sector through the diversification of agricultural production. In particular, the development of product differentiation schemes PDO (Protected Designations of Origin) and PGI (Protected Geographical Indications) aims at providing high-quality reputation food products. The PDO label certifies both a high product quality and the product's geographical origin. Its quality is inherent to a limited geographical area characterized by geological, agronomic, climatic, and historical factors. It also depends on specific manufacturing process and human factor requirements. Some countries have adopted this kind of quality policy for many years. For instance, the Appellation d'Origine Controlée (AOC) regulation in France and the Denominazione di Origine Controllata (DOC) in Italy were created in 1935 and 1963, respectively.[1]

Public intervention through public label regulation is proved to enhance social welfare (cf. Moschini et al. (2008); Marette and Crespi (2003) and Lence et al. (2007)). Public labels certify the quality of a product that cannot be otherwise observable (credence goods) and recognized as such by consumers (Akerlof (1970)). By restoring information to consumers, the development of product differentiation schemes gives producers more incentive to produce high-quality products.[2]

The success of the PDO label in creating value added for agro-food producers has been studied through the measurement of the willingness to pay of consumers for these quality labels (Deselnicu et al. (2011)). However, the empirical research on PDO has not yet determined which suppliers have an incentive to adopt this type of public certification. Our goal is to assess empirically the ability of such a public quality policy to sustain the competitiveness of firms and to determine which firms have benefited from it. To achieve this, we provide an empirical analysis

[1]AOC recognition follows the creation of the INAO (National Institute for Appellation of Origin) in 1935 in the wine and liquor sector and has been extended to cheese in 1955. A specific regulation for Roquefort cheese allowed the creation of the first AOC cheese in 1925. Since 1992, AOC also applies to all agricultural and food products.

[2]cf. Bonroy and Constantatos (2008) for a more general discussion on labeling profitability.

of the French AOC label, which is older than its EU equivalent, the PDO.[3] We investigate how the AOC policy affects the survival of cheese firms in France in addition to their firm characteristics such as its size, age or relative efficiency.

The adoption of PDO by producers is voluntary and confers a collective reputation to the certified producers.[4] The profitability of acceding to this collective reputation depends on the trade-off between the return they can get from the label and the extra costs they have to incur to certify their products or to comply to the PDO technology (Bouamra-Mechemache and Chaaban (2010)). In the absence of (or with low) certification costs, producers may have the incentive to produce a high quality product. However, if that cost is too high, then this incentive is reduced and producers may opt to produce a low quality (generic) product. Collusion on quantity can then be a tool to overcome the quality provision concern. Actually, when certification costs are high, collusion allows for individual profits that may compensate for PDO certification costs and for the costs generated by the PDO technical requirements. In that case, PDO emergence is more likely to occur in a monopoly-type industry structure than in a perfect competition one; the intermediate structures leading to an intermediate quality likelihood (Lence et al. (2007)). It turns out that the profitability of labeling is determined by various factors such as supply control conditions (Lence et al. (2007)) and market structure (Hayes et al. (2004)). For instance, Carriquiry and Babcock (2007) show that monopolists are more likely to invest on quality because they can get the full return from their investment in reputation. Langinier and Babcock (2008) suggest that a high number of producers may benefit from sharing the certification cost but suffer from the loss of profit due to intensive competition. In addition, PDO labels segment the market into PDO and non PDO sub markets. This market segmentation affects market structure. It relaxes the market competition pressure for firms producing PDO products and allows firms to survive on the market.

This paper makes a number of contributions. First, while the theoretical literature on the profitability of a public quality label is extensive, empirical findings are scarce. We fill this gap by analyzing how a PDO-like label can contribute to the success of firms that voluntarily enter into such a quality certification scheme.

Second, we use two original data sets that cover the period 1990–2006 and which provide very detailed information at the firm-level on the characteristics of firms and products in the French dairy sector. The first one is an annual firm survey that covers firm-level data, while the second

[3]In 2010, AOC labeled products included 48 cheese and 40 other food products (among which there were 13 AOC labels for fruits and vegetables, 13 for olive and olive oil, and 6 for meat). There is in addition 394 PDO wine for which a specific European regulation applies. Because cheese represents the main products under the AOC label, we focus on the cheese sector.

[4]The INAO is in charge of PDO certification in France and decides whether or not a PDO label can be created. Then, all firms within the specific PDO area can get the label as far as they fulfill the requirements imposed in the PDO specification.

is an exhaustive annual survey of all dairy plants. It provides information on individual production at a detailed product category level. Such information, which is quite difficult to obtain at the individual level, enabled us to distinguish between AOC and non-AOC dairy plants. We use the information to assess for the first time the impact of AOC labelling on firm performance. The performance of dairy firms is measured by 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, such as profitability and growth, and provides a better understanding of industrial strategies (cf. Dunne et al. (1988)).

Third, our empirical strategy relies on discrete-time duration models that specify duration dependence in a flexible way. We propose a semiparametric approach, introducing some parametric restrictions while retaining some flexibility in modeling the survival. The empirical modeling thus assumes a parametric form for the effect of the determinants on survival, but allows the form of the underlying survival function to be unspecified and controls for unobservable heterogeneity. To ensure the validity of our empirical strategy and check the absence of selection bias, we first check if the decision of a firm to enter the AOC labeling scheme is independent from the variables that explain the differences in firm survival. Adjusting for differences in this set of covariates thus removes biases in the comparison between AOC and non-AOC firms, allowing for a causal interpretation of those adjusted differences in survival.

The article is organized as follows. The next section reviews the determinants of firm survival. Section 3 provides an overview of the data set 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

The relation between firm performance and firm survival has been empirically shown in the literature. The measurement of performance through total factor productivity has been showed to affect survival (Bellone et al. (2006) and Foster et al. (2008)). In addition, low 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 influence a firm's duration in the industry. Substantial rates of entry and exit are recurrently found in a number of countries. In this section, the main findings are summarized. We use these findings to construct an empirical strategy for testing the determinants of firm dynamics in the French cheese sector.

Table 1 about here

Table 1 summarizes the determinants of firm survival found in the literature. Firm age 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 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 old firms, but its impact is stronger on the dynamics of new firms. According to Aldrich and Auster (1986), different factors may explain that fact. First, small-sized firms may have more difficulty raising capital. Second, tax law can be more detrimental on small firms than on large firms. Third, public regulation may affect small firms more than large firms. In addition, large firms may be favored in a competitive labor market. Considering that the failure rate increases with the size of the irretrievable outlay needed to move from minimal-scale (or fringe entry) to optimal-scale operations, the size of the irretrievable outlays also affects firm survival. Thus, small firms may have a high failure rate as they may find it difficult to reach a minimum size at which they will be able to operate efficiently. Another explanation of the size-based impact on survival is related to labor and capital costs. If these two costs are high, this could be detrimental to newer, smaller firms that may have more difficulty in developing their activities than do older, larger firms. In addition to age and size, the structure of the firm may also affect a firm's dynamics. As shown by Disney et al. (2003), when an establishment is part of a group, it increases its survival rate relative to that of a single establishment. This supports the suggestion that establishments that are part of a group can learn from other establishments in the group and get better market information compared to that obtained by single establishments.

The survival rates for firms are also shaped by entrepreneurial factors including managerial abilities. Entrepreneurship characteristics, such as human capital as well as specific education and skills or the personal characteristics of the founder of the firm, have been shown to be a key determinant of firm survival and of small businesses in particular (Vivarelli and Santarelli (2007)). Innovation ability is another factor that influence the hazard rate (Helmers and Rogers (2010)). Evidence from the UK industry shows that innovation through trade-marking decreases the probability of exit in almost all economic sectors while the impact of innovation through patenting is less clear and heterogeneous depending of the sector.

Last, public intervention may be a key factor for the agricultural and food industry. For instance, government payments in the United States have been shown to increase slightly the survival of farm businesses, particularly that of bigger farms (Key and Roberts (2006)). In this article, we focus on the impact of government intervention on agro-food firms through the PDO labeling regulation, and we analyze how this public labeling scheme, that can be voluntary and collectively used by groups of producers, has contributed to the development of dairy firms and to the current structure of the dairy industry.

Firm dynamics also depends on the characteristics of the industry under consideration. Comparison between different industries in different countries reveals common industry determinants for survival patterns. Both firm entry and concentration depend on the depth of the incumbents' commitments and, more generally, on trade barriers, which have an impact on survival duration. Trade barriers in an industry can arise from high minimum efficiency scale (MES), capital intensity, advanced technology, or product differentiation and innovation. On the one hand, a high MES implies a relatively large amount of resources that are needed to reach the MES level. If firms cannot achieve this level of resources, they may not be able to survive on the market. On the other hand, firms that have entered the market will be less sensitive to market exit if they have incurred large resource expenditures. A high level of innovative activity in an industry may make entry more risky and may increase failure risk (Jensen et al. (2008)). However, the reverse could be also true if there is a self-selection process used by a firm before making an entry decision. Moreover, some knowledge spill-over may be available to firms that are close to innovative firms. Agglomeration or regional advantages may compensate for the negative effects of higher costs and of competition from other firms in the same area. Falck (2007) and Fritsch et al. (2006) empirically show the importance of these regional effects on survival. The distribution of innovations between new and incumbent firms is reported to change over an industry's life cycle (Agarwal and Gort (2002)). These changes affect the probability of survival for firms within three phases: lower survival rate occurs in the early phase of their life cycle, when innovation is high and market entry risky. A higher survival rate occurs in the next phase when the market is mature and competitiveness has increased as a result of limitations in innovation and technical change rates. Finally, during obsolescence of initial endowment phase, the failure rate increases again

We analyze the impact on firm dynamics of the most relevant factors identified above, i.e., age, size, size disadvantage (whether its level of output is below the MES), and single or multi-establishment firm. Using the example of the French cheese industry, we study the impact of adopting the AOC label.[5] When adopted by firms, AOC labeling may result in higher costs linked to quality requirements and certification costs. It results that firms that adopt PDO labeling may suffer from a higher cost disadvantage, everything else being unchanged, which may drive them out of business. On the other hand, with the PDO label, they may benefit from a high-quality signal and a higher reputation for their products which could compensate for their cost disadvantage. We try to disentangle this trade-off by assessing the impact of the AOC label on firm survival and by measuring the relative importance of the selected relevant factors.

3 Data and Descriptive Statistics

We use exhaustive firm and dairy plant surveys covering the period 1990–2006 provided by the French Administrative Direction of Statistics (INSEE). The first data set reports economic and administrative information at the firm level (EAE) while the second set reports productions at the plant level for dairy firms (EAL).[6] 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 labeled products in the total production of cheese is approximately 17% (and 20% in value). In France, AOC cheese seems to benefit from a price premium compared to non AOC (branded or not branded) cheese. The price of AOC cheese is on average 58% higher than for non AOC cheese in 2009-2010.[7] For the French camembert cheese, the price premium linked to the AOC characteristic is of the same order of magnitude as for the brand characteristic but the willingness to pay for the AOC characteristics seems to be higher under a private retailer brand compared to a firm national brand (Hassan and Monier-Dilhan (2006) and Bonnet and Simioni (2001)). We focus in this study on AOC cheese made from cow (30 AOC) and sheep (3 AOC) milk which represents 97% of the milk used in the processing of AOC cheese.[8] Each observation provides information on firms that might be constituted of different

[5]The data used do not allow us to analyze the impact of firms' branding strategy. It is true that there are strong national brands either on AOC or non AOC cheese that may impact the survival in addition to the AOC label. This may be partly captured by the size as it should concern well known large companies.

[6]EAE stands for *Enquête Annuelle d'Entreprise* while EAL is the *Enquête Annuelle Laitière*, both provided by INSEE.

[7]Data for cheese sold in supermarkets, hypermarkets and hard discount, which represents around 85% of total sales (CNAOL and INAO (2010)). Note in addition that the price premium for PDO (the EU equivalent for AOC) is 23 % for food products (Deselnicu et al. (2011)).

[8]Data from EAL do not allow the identification of AOC among firms producing cheese from goat milk. AOC cheese from goat milk have been developed in the 1990s and concerns 13 AOC cheeses but only 3% of AOC cheese sales.

plants.

The survival analysis was 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 an AOC label or not. The final data set provides information on all firms involved in cheese production.[9] Among the firms observed in the period, cheese production may or may not be the main activity of the firm. When firms have other activities, cheese is most often the main one; other activities typically include dairy products other than cheese. We choose to do the analysis at the firm level rather than at the plant level because an AOC strategy is decided at the firm level and not at the plant level.[10] Moreover, firm level analysis enables us to take into account firm characteristics that may influence firm survival. Entry and exit data correspond to the creation and closing of a firm. Firms are considered to be active as long as at least one of its plants is active (i.e., is producing cheese).

Table 2 about here

We compute the time spell corresponding to the survival of the surveyed firms and define entrant, exitor, one-year-only and stayer as in Disney et al. (2003) (see Table 2). By design, these periods are evaluated as intervals, measured in years, over the period 1990–2006. Indeed, our data indicate whether a firm was present in the sample for a given year. But, if a firm disappeared from the sample in the following year, the exact time (day or week) the exit occurred is not known. In this case the transition times are said to be grouped and discrete-time hazard models are used to analyze such data. Thus, the minimum time unit is one year, with a maximum of 17 years. On average, a firm survives 8 years in the industry, over the period considered (see also Figure 7 in appendix).

Table 3 about here

The pattern of entry and exit in our sample is summarized in table 3.[11] Compared to other studies, the cheese sector in France exhibits a low rate of turnover with only 8% of firms in the market a given year exiting the market and only 5% entering, meaning that the French

[9] 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.

[10] For firms less than 20 employees, the firm and the plant levels coincide. For larger firms, a firm chooses its portfolio of productions and the locations of the production (which correspond to the plant level).

[11] We do not provide trends in the panel of AOC producing cheese. Indeed, many AOC firms produce also other cheeses that are not AOC labeled. Moreover, the share of AOC in the firm's production differs from one to the other and the choice of different thresholds to define when a firm is considered as an AOC firm may induce very different trends. More information is available upon request to the authors.

cheese sector becomes more concentrated over time, i.e., the number of firms in the market decreases over time. Between 1990 and 2006, the number of firms decreased by 40% from 924 to 559. Entry and exit rates in the French cheese sector are in the range of values found in the literature for manufacturing industries. For instance, Caves (1998) reports entry and exit rates in several countries and found entry rates varying from 3% to 13% and exit rates from 5% to 13%. These values are higher in the study of Disney et al. (2003) who found an entry rate of 18.5% and exit rate of 16.5% in the food, drink, and tobacco sector in the U.K. in the period 1986–1991. Similarly, Fritsch et al. (2006) reports that the survival rate after two years for start-up firms in the food sector is around 72%.[12] In addition, reported entry and exit rates in these articles suggest that the food sector is among the industries showing the lowest entry and exit rates. Another feature is that entry and exit rates are both relatively low, which is consistent with the report of Geroski (1995) (stylized fact 3) who states that net entry rates and penetration are modest fractions of gross entry rates and penetration. Moreover, the net exit rate is quite low (3%), which suggests that the French cheese sector is in a rather mature stage of its life cycle (Agarwal and Audretsch (2001) and Jensen et al. (2008)). Now, we consider the covariates we can observe and that can affect the survival of the dairy firms. In tables 4 and 5, we define several variables of interest in the analysis performed here. These variables include the main determinants of firm survival found in the literature. We define time-varying as well as time-constant variables for the purpose of this analysis.

Table 4 about here

Table 4 presents definitions of the time-constant variables created and used in the first step of the survival analysis presented below. We consider that a firm is an AOC firm whenever at least one of its plants produces an AOC labeled cheese during the whole period. Half of the observed firms were AOC firms for at least one year. *Old* indicates whether the firm was or was not present before the beginning of the period under scrutiny.[13] $MESD$ indicates whether a firm has or has not reached the minimum efficiency scale as defined by the median firm production, by cheese category, during the whole period.[14] The cheese industry is mainly composed of small firms ($SmallD$). We observe a large majority of firms with less than 20 employees on their first annual report (78%). On the contrary, big firms ($BigD$) are those with more than 100 employees;

[12]The study of Disney et al. (2003) analyzes the pattern of industries using plant data while the one of Fritsch et al. (2006) considers only very small firms. These features may explain their high values; the smaller the production unit, the higher the turnover.

[13]The information on the precise age of the firm is not available for all firms that were present before the beginning of the period under scrutiny.

[14]The partitioning of firms according to cheese production category shows that one third devote their main production to hard cheese, 22% to semi-hard cheese, and 18% to soft cheese; the remaining firms producing blue, processed, fresh, and other cheeses.

they are a bit less numerous than firms of medium size ($MediumD$). Unfortunately, the data at hand do not provide detailed information about the precise age and size of firms.[15] We use also a categorical variable, $SizeD$, defined according to the number of employees. That variable is also used in the Kaplan-Meier analysis of section 5. Table 5 presents the time-varying variables used in the second step of the survival analysis. These variables are defined according to a firm's time-constant variables in table 4, but now vary with time, with the noticeable exception of the variable *Old*. We do not report the annual summary statistics of those variables[16]. On average the share of AOC production relative to the total cheese production of the firm each year is quite stable (around 45%). 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%. Note that, as mentioned above, the total number of firms has decreased during the same period.

Table 5 about here

4 Empirical Methodology

Over the period covered by the surveys (1990–2006), three different time spells can be described: (1) a complete time interval in which a firm enters the sample before 1990 and exits before 2006; (2) a right-censored time interval in which a firm enters after 1990 and is still active in 2006; and (3) a left-truncated time interval in which a firm entered before 1990 and either exits before 2006 or is still active in 2006. We identify this latter type of time interval because the surveys indicate if a firm was active or not before 1990. However, for most of the firms that were active before 1990, we do not know when they were created. Fortunately, left truncation will not affect the maximum likelihood estimators presented below. As shown 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.

4.1 Nonparametric Approach

We use the Kaplan-Meier (Kaplan and Meier (1958)) estimator following the philosophy of the nonparametric analysis, i.e., of letting the data speak for themselves by making no assumption about the functional form of the survival.The Kaplan-Meier estimator can be used to compare survival curves across the values of the covariates. Testing a difference between the estimated

[15]We could not use a continuous size variable, because we only have the number of employees for the subsample of firms having more than 20 employees. We code this variable according to the size classes defined by the French administrative direction of statistics (INSEE). We then define three classes in order to have enough firms in each class.

[16]They are available from the authors upon request.

survival functions is also possible using statistical tests. However, these tests do not provide strong evidence that the considered covariate influences survival because other factors may be correlated with both this covariate and with survival. Thus, the effects of the covariates cannot be modeled explicitly using this estimator.

4.2 Semiparametric Approach

To overcome the limitations mentioned above, we propose a semiparametric approach, introducing some parametric restrictions while retaining some flexibility of the nonparametric framework in modeling survival. The most widely used semiparametric model in continuous-time survival analysis is the so-called proportional hazard model (Cox (1972)).[17] 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 the hazard function given by:

$$h(\tau|\mathbf{x}_i) = h_0(\tau) \times \exp\left(\mathbf{x}_i'\gamma\right), \tag{1}$$

where $\mathbf{x}_i$ is a vector $(k \times 1)$ of the covariates, γ is a vector $(k \times 1)$ of the parameters, and $h_0(\tau)$ is the baseline hazard function (the hazard when each covariate $\mathbf{x}_i^j = 0$) whose functional form is not specified. It follows that continuous-time hazards are proportional; in the sense that the hazard ratio:

$$\frac{h(\tau|\mathbf{x}_i)}{h(\tau|\mathbf{x}_h)} = \exp\left((\mathbf{x}_i' - \mathbf{x}_h')\gamma\right),$$

does not depend on time. Note that an exponentiated parameter represents the hazard ratio for a one unit change in the corresponding covariate, controlling for the other covariates.

The equivalent of the continuous-time proportional hazard model defined in equation (1) in discrete-time is the complementary log-log model (see Cameron and Trivedi (2005) or Rabe-Hesketh and Skrondal (2008) for a proof) defined as:

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

where $h_{i,s}$ denotes the discrete-time hazard function for firm i at year s, $d_{1,t}$, …, $d_{J,s}$ are dummy variables for years 1, …, J, J referring to the last time period observed for any firm in the

[17] See the overview of recent industrial organization literature on firm survival by Manjón-Antolin and Arauzo-Carod (2008).

sample, with $d_{t,s} = 1$ if $s = t$, 0 otherwise, and the complementary log-log transformation is defined as:

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

The parameters γ in equation (2) are identical to the parameters in the underlying continuous-time proportional hazards model defined by equation (1). This 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 equation (1). The solution is to incorporate multiplicative, unobserved heterogeneity that is 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 equation (1), unobserved heterogeneity is thus accounted by the inclusion of the multiplicative term ν_i, which is assumed to be positive, i.e.,

$$h(\tau|\mathbf{x}_i) = h_0(\tau) \times \exp\left(\mathbf{x}_i'\gamma\right) \times \nu_i.$$

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 at 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 now becomes:

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

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. The usual generating distribution functions are the gamma and the Gaussian distributions. The first distribution function is often chosen in continuous-time duration models, not only for analytical convenience but also for theoretical reasons (see Abbring and Van Den Berg (2007)). Instead, in discrete-time duration analysis, the assumption of a Gaussian distribution can be computationally convenient. Moreover, a recent simulation study by Nicoletti and Rondinelli (2010) shows that an incorrect Gaussian assumption for the distribution of the unobserved heterogeneity does not bias the duration dependence or the covariate coefficient estimates. This suggests that choosing a Gaussian distribution can be viewed as a sensible choice when estimating discrete-time duration models.

Parameters in equation (2), 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:

$$\begin{aligned} h_{i,s} &= \text{Prob}[T_i = s|\ T_i \geq s,\ \mathbf{x}_i] \\ &= \text{Prob}[y_{i,s} = 1|\ \mathbf{x}_i], \end{aligned} \tag{5}$$

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 (4)). 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 by using, for instance, a Gauss-Hermitte quadrature (see, among others, Judd (1998)) or simulation methods (see, among others, Train (2009)). Finally, note that a natural choice for parameterizing the probability $\text{Prob}[y_{i,s} = 1|\ \mathbf{x}_i]$ would be to use a logit link in equation (2) (or in equation (4) when frailty is assumed in the discrete-time duration model) as usually done in binary choice models. This model is most appropriate when events can only occur at regular, discrete times as noted by Jenkins (2005).[18]

5 Results

Before assessing the impact of AOC labeling on firm's survival, the issue of firm selection between entering or not into the AOC scheme should be addressed.[19] More specifically, the independence between the firm decision to enter into the AOC labeling scheme and the variables that explain the differences in firm survival has to be checked. If the entry decision is independent from our selected explanatory variables, then the differences in performance between AOC and non-AOC firms with the same values for these covariates are due to the status of the firm. Our empirical

[18] In our application, exit of a firm can occur at any point of time during the year. Ties occur because this event is measured coarsely by considering the year where it happens. Thus, the logit model does not seem appropriate for our data.

[19] For a complete discussion on the issue of selection on observables, see Imbens and Wooldridge (2009).

strategy could be viewed as assuming that beyond the chosen observed covariates, there are no (unobserved) firm characteristics associated with both the survival and the status of the firm. However, our empirical strategy corrects this assumption by introducing unobserved heterogeneity when estimating hazard rate, through a multiplicative term capturing the impact of omitted variables on the hazard rate. Figure 1 displays the estimated densities of propensity scores for AOC and non-AOC firms. Propensity scores are estimated using a probit model where the probability of being an AOC firm is explained by $Medium_t$, Big_t, MES and Old. Densities are then estimated using the nonparametric Nadaraya-Watson estimator. Clearly, the two estimated densities overlap, indicating that the probit model has poor predictive performances. This result is confirmed when considering two usual measures of predictive performances of binary response models, the correct classification rate and the area under the receiver operators characteristics (ROC) curve whose values are 62.48% and 0.64 respectively.[20] In other words, this result indicates that no selection on the observables seems to occur, allowing the investigation of AOC labeling on firm performances after having controlled for the chosen covariates.

Figure 1 about here

We now evaluate the effect of each variable described in table 4 separately using the nonparametric Kaplan-Meier estimator of survival function. This descriptive analysis is a preliminary exploration of firm survival in the period, and is completed by a multivariate analysis, measuring the effect of the complete set of covariates, allowing interactions between the covariates.

5.1 Kaplan-Meier Survival Estimates

Figure 2a displays the Kaplan-Meier estimates of the survival function in the whole sample. We focus on the main determinants identified in the literature (see section 2) and analyze the impact of the age and size of the firm on firm survival. In addition, to test the role of productivity, we estimate the Kaplan-Meier probabilities for firms producing above or under the minimum efficiency scale level. Figures 2b-d present the estimated survival curves and their respective 95% confidence intervals.

Figure 2 about here

[20]The ROC curve for a binary classification problem plots the true positive rate as a function of the false positive rate. The points of the curve are obtained by sweeping the classification threshold from the most positive classification rule to the most negative. For a fully random classification, the ROC curve is a straight line connecting the origin to $(1, 1)$ and the area under this curve, or AUROC, is equal to 0.5. Any improvement over random classification results in an ROC curve at least partially above the straight line. With a perfect classification, AUROC $= 1$.

We obtain no clear results when considering the age effect, but older firms seem to have a higher failure rate than young firms for some time intervals (figure 2b). On the contrary, firm size is a key determinant of cheese firm survival. The survivor curve of the large firms is less steep than the survivor curve of small firms (figure 2c). While there is a clear difference between small (<20 employees) and medium-size or large firms, the survival patterns were not very different between the medium-size and large firms.[21] Finally, exceeding the minimum efficiency scale significantly increases the survival of firms (figure 2d).

Table 6 about here

Statistical tests can be used to confirm the qualitative results found above and used to substantiate the validity of the differences previously observed between survivor curves. We use log-rank tests within the family of tests proposed by Harrington and Fleming (1982). The null hypothesis is that two (or more) survival curves that have been estimated by the Kaplan-Meier estimator are equal to each other. The test outcomes (values of the statistics and their p values) are given in table 6. They show that the aforementioned differences between the survivor curves are not only visually apparent but also statistically significant. Thus efficiency scale, age, and size are important factors that determine the risk of exit at any time. These results are consistent with the main findings of the literature on firm survival that were discussed in section 2.

Figure 3 about here

One feature of the French cheese industry is the existence of a AOC labeling policy. Here, we use the same methodology to asses the impact of AOC labeling on firm survival. Figure 3a reports the estimated survival curves for two cohorts of firms, producing or not producing AOC-labeled cheese. The two curves display slightly diverging patterns, AOC firms having a lower probability of exit than non-AOC firms. The log-rank test (table 6) confirms that this difference is significant. A closer investigation of this effect is provided in figures 3b, 3c, and 3d where we distinguish firms according to size category.[22] We find a large and statistically significant effect of AOC labeling when considering small firms (<20 employees) while this effect does not show up for larger firms (see table 6). These results support our hypothesis that the AOC

[21] In addition, because of the existence of large groups in the French dairy cheese sector, we analyzed whether survival probability differs when a firm is part of a group. We also investigated whether holding several plants has an influence on survival. Both of these two determinants positively affect the survival rate. However, as they are highly correlated with the variable $Size$, they also capture a size effect, with larger firms facing a lower probability of exit, whatever the duration. We do not report the detailed results. They are available upon request

[22] We cross the AOC factor with other factors (age, MES) and fail to detect any significant effect.

quality scheme positively affects the survival of small cheese makers in the French dairy industry.

The Kaplan-Meier estimates of firm survival have the advantage of providing a good descriptive analysis of survival without specifying any functional form for the survival pattern and they highlight the differences between firm cohorts (AOC, age, type, etc.). However, this approach is limited when survival is investigated on firm sub-cohorts and the effect of variables on the hazards of firms becomes difficult. In order to overcome this problem, and give more structure to the estimation, we now investigate the effects of covariates on the hazard in the multivariate framework presented in section 4.2.

5.2 SemiParametric Results

To analyze more formally what is behind the findings discussed above, we now turn to a semi-parametric analysis. Table 7 shows the estimation results for four discrete-time proportional hazard models. In the first column of the table, we present 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. The covariates are the time-varying variables presented in table 5. In the second column of table 7, 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 include 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 parameter ρ, which measures the share of individual variation in the hazard rate that is due to variation in the unobserved factors.[23] 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 7, respectively.

Table 7 about here

For both 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.[24] Accounting for unobserved individual heterogeneity

[23]Formally, let σ_ε^2 denote the variance of the ε term in (4). Then, $\rho = \sigma_\varepsilon^2/(\sigma_\varepsilon^2 + \pi^2/6)$ where the denominator captures the total heterogeneity in the hazard rate.

[24]This test is a boundary test that takes into account that the null distribution is not the usual chi-square distribution with 1 degree of freedom but is an equi-proportionate mixture of a chi-square variate with 0 degrees

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 the 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 the qualitative results for the frailty models do not differ from those for no frailty 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) and Gullstrand and Tezic (2008)). 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 firm's share of AOC in total cheese production is modelled. 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, regardless of the size of the firm. Results in table 7 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. Thus, engaging in AOC production increases significantly the survival of small firms but 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 (e.g., brand strategy, production diversification) for large firms to increase their profits, but it is not a key determinant for their profitability. On the contrary, the AOC labelling scheme seems to affect the survival of smaller cheese makers by equipping them with a reputable signalling tool that is well recognized by French consumers. Notice that being a larger firm increases significantly the probability to survive. Larger firms may be able to benefit from economies of scale and scope and invest more to develop their brands, differentiate their products, or increase their production capacity. The AOC labeling policy can be seen as a public intervention tool for small firms that are less able to invest in order to make their products known by consumers. Finally, results show that even if AOC labeling is a key driver of firm survival, firm efficiency (producing at or above the minimum efficiency scale) remains a highly significative determinant of profitability and survival.

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of freedom, which is a point mass at zero and a chi-square variate with 1 degree of freedom; see Self and Kung-Yee (1987).

To better visualize the effect of AOC labeling and its interaction with other covariates, we proceed with the prediction of the hazard rate using frailty model 4. We start with predicting:

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

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

$$h(s) = 1 - \exp\left(-\exp\left(z(s)\right)\right),$$

using the reciprocal of the complementary log-log transformation defined in equation (3).

In order to investigate more precisely the impact of AOC labeling policy, we fix the values of the covariates and consider an hypothetical small firm which was created before 1990 and which produces cheese with a small proportion of AOC cheese (20%) and below the minimum efficiency scale. Given the parameter estimates, this firm has the lowest survival rate. It will serve as a baseline to analyze the impact of AOC labeling and its interaction with other covariates.[25] The number of possible combinations of covariate is high, leading to a high number of potential simulations. We choose to focus on the combinations that stress the cross effects of AOC labeling with the size and efficiency effects.

Figure 4 focuses on small firms and helps in understanding the impact of the label for different firm characteristics. It presents the predicted survival curves for the baseline firm and two other firms (plain lines). The first one differs from the baseline in the variable MES while the second one differs in MES and OLD. While age, efficiency but also AOC policy do not seem to influence the survival rate in the first 3 years, the pattern of survival is greatly influenced after 3 years. Compared to the baseline, the predicted survival rate is higher for a hypothetical firm which is more efficient (above the MES). The highest survival rate is achieved for a firm which in addition has been created after 1990. Comparing these three hypothetical firms with cases where firms are more specialized in AOC production (changing the share of the firm's AOC production from 20% to 80%; dotted lines), the ranking of the survival curves remains unchanged. In these simulations, specialization in AOC production increases the survival rate by up to 25%. In addition, it is noteworthy that, in our simulated framework, the variable AOC and MES have an effect of the same order of magnitude on the baseline firm's survival. Finally, the simulations suggest that the AOC effect on survival remains strong over time except for the baseline. For the baseline, the dotted and the plain curves converge toward zero with time. This suggests that the AOC labeling policy is an effective tool in maintaining the activity of small

[25] In all cases, predictions are derived assuming that the frailty term is set equal to its mean value.

firms over the medium term, at least for young and more efficient firms.

We perform the same simulation analysis on a hypothetical medium-size firm in figure 5. We do not report simulations for a large firm as they are almost identical to the medium size firm case. For a medium (or big)-size hypothetical firm, the survival rates are higher than for the small firm case in figure 4. While the ranking of survival curves are unchanged compared to the small firm case, the magnitude of the MES and OLD effects is lower. In addition, the gap in survival between the baseline and the two other simulated firms increases over time.

Figures 4 and 5 about here

In figure 6, we compare the AOC effect for different size classes. This figure clearly highlights the size effect which is the main determinant of firm survival in the French cheese sector. It shows that the probability of survival after10 years for an hypothetical small firm is quite small (less than $<20\%$), while that for large/medium firms is more than 80% and it remains relatively high even after 15 years. Predictions show no differences in the survival rate between the medium and large firms in the 8 first years, and a small difference after that period. When the hypothetical small firm becomes more AOC label oriented, its predicted survival rate is increased, but remains far below the rate for a larger firm. Thus a labeling strategy seems unable to compensate for the size effect on the survival rate.

Figure 6 about here

6 Concluding Remarks

In this paper, we assess the ability of a quality labeling policy to sustain the competitiveness of agro-food firms involved with such a policy and determine which firms have benefited from it. We focus on AOC quality labeling and investigate how AOC labeling has contributed to the development of dairy firms and to the current structure of the dairy industry. The analysis uses a unique and detailed database on French dairy firms that comprises accounting and production data. The performance of dairy firms is measured on the basis of their duration on the market or survival. We use recent statistical methods to analyze duration data in order to estimate the impact of AOC labeling as well as other determinants of firm survival. These methods allows for controlling unobserved heterogeneity. We show that this feature was important in our data and emphasize the need to control for it in order to get consistent estimation. Our results show that the voluntary use of AOC labeling does contribute to increase the survival of firms in the dairy industry. We also find that the AOC labeling effect is less pronounced than the size effect.

As in many sectors, the size effect is the main determinant of firm survival in the dairy industry. However, when the AOC effect interacts with the firm size effect, we show that the benefit of being more specialized in AOC production does exist for small firms but does not exist for larger firms. Encouraging AOC production reduces thus the risk of exiting only for small firms. Public intervention in this industry is thus well designed to increase the competitiveness of small firms by enabling the coexistence in the market of both small and large firms. AOC labeling conveys a collective reputation based on traditional and less capital intensive methods. Small firms that voluntary engage in AOC production can share the cost of labeling and benefit from minimum reputation without incurring large advertising/R&D expenditures. However, AOC is less important for larger firms' survival than for small firms. Larger firms can make a better use of capital intensive technology and benefit from scope or scale economies or from other quality signalling tools (branding). In this way, AOC labeling can act as a differentiation tool in the market, a tool by which small niche firms are able to survive because of reduced price competition. This generates a lower hazard rate for firms. We can presume that without the label policy, the decrease in the number of small firms would be even higher. Further work and more detailed data on dairy markets are needed to better understand how such a label policy affects dairy market structure.

Appendix

Figure 7 about here

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Tables

Table 1: Determinants of Firm Survival

Determinant	Impact on survival
Firm characteristics	
Newness	-
Aging	+/−
Obsolescence	-
Smallness	-
Capital and labor cost	−/+
Establishment is part of a group	+
Productivity	+
Industry characteristics	
Barrier to entry	−/+
Innovativeness	−/+
Early stage in life cycle	−/+
Agglomeration and technological spill over	+

Table 2: Definition of Firm Entry and Exit Types at Different Times (t)

	$t-1$	t	$t+1$
Exitor	Observed	Observed	Not observed
Entrant	Not observed	Observed	Observed
One-year-only	Not observed	Observed	Not observed
Stayer	Observed	Observed	Observed

Table 3: Number of Firms as well as Stayer, Entrant, Exitor, and One-Year-Only Firms

Year	**Firms**	**Stayers**		**Entrants**		**Exitors**		**One-Year-Only**	
	N	*N*	%	*N*	%	*N*	%	*N*	%
1990	924	823	89	30	3	71	8	0	0
1991	872	771	88	21	2	85	10	5	1
1992	809	725	90	25	3	64	8	5	1
1993	783	685	87	39	5	62	8	3	0
1994	753	621	82	32	4	102	14	2	0
1995	707	589	83	63	9	59	8	4	1
1996	674	610	91	25	4	41	6	2	0
1997	653	518	79	21	3	117	18	3	0
1998	642	518	81	99	15	28	4	3	0
1999	652	573	88	38	6	41	6	0	0
2000	643	569	88	34	5	43	7	3	0
2001	614	577	94	13	2	24	4	0	0
2002	607	562	93	17	3	28	5	0	0
2003	596	546	92	15	3	36	6	1	0
2004	585	528	90	24	4	38	6	5	1
2005	570	519	91	21	4	32	6	2	0
2006	559	540	97	19	3	.	.	.	.
Mean	693	607	87.6	34	5	54	8	2	0.3

Table 4: Time-Constant Variables

Variable	Unit	Definition	Mean	Sd
AOC	dummy	= 1 if Firm is producing AOC cheese	0.50	0.50
Old	dummy	= 1 if firm created before 1990	0.62	0.49
MESD	dummy	= 1 if firm's production is above the Minimum Efficiency Scale of its specific cheese industry	0.54	0.50
SmallD	dummy	= 1 if number of employees < 20 is the first observation	0.78	0.42
MediumD	dummy	= 1 if 20 ≤ number of employees< 100 in the first observation	0.12	0.33
BigD	dummy	= 1 if number of employees ≥ 100 in the first observation	0.10	0.30
SizeD	0, 1 or 2	= 0 if $SmallD = 1; 1$ if $MediumD = 1$; and 2 if $BigD = 1$		

Table 5: **Time-varying variables**

Variable	Definition
$AOCshare_t$	Share of AOC production relative to the total cheese production of the firm in year t (0 if not producing)
MES_t	= 1 if Firm's production is above the Minimum Efficiency Scale of its specific cheese industry in year t
$Small_t$	= 1 if 20 ≤ number of employees < 100 in year t
$Medium_t$	= 1 if number of employees ≤ 20 and < 100 in year t
Big_t	= 1 if number of employees ≥ 100 in year t

Table 6: Log-rank tests

Null hypothesis	Log-rank statistics	*p* value
$\{H_O$: No impact of $MESD\}$	86.34	0.000
$\{H_O$: No impact of $SizeD\}$	23.66	0.000
$\{H_O$: No impact of $Old\}$	8.57	0.003
$\{H_O$: No impact of $AOC\}$	29.68	0.000
$\{H_O$: No impact of $AOC\}_{forSmallfirms}$	40.81	0.000
$\{H_O$: No impact of $AOC\}_{forMediumfirms}$	0.81	0.368
$\{H_O$: No impact of $AOC\}_{forBigfirms}$	0.72	0.397

Table 7: **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 $\rho = 0$:								
Chi-square 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								
Chi-square value							10.779	
p value							0.005	

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

Figures

Figure 1: Prediction scores of AOC labelling

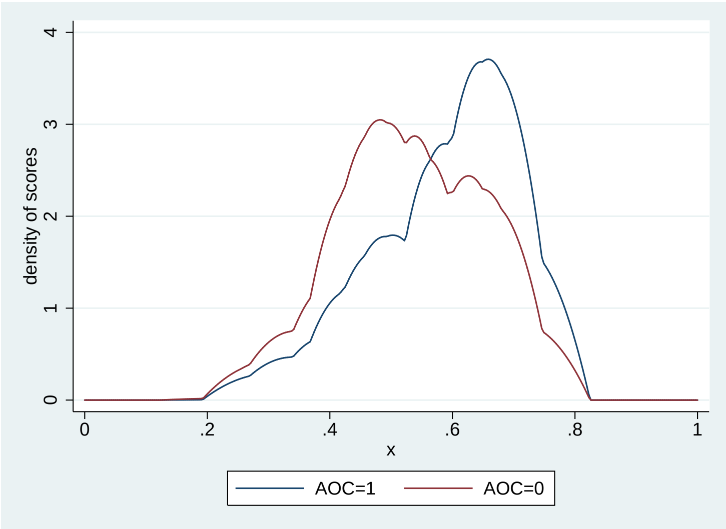
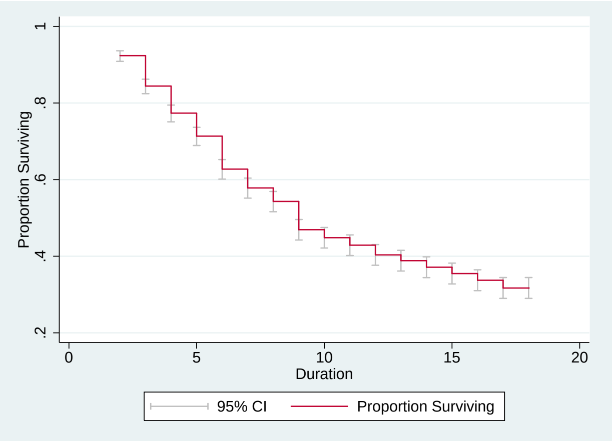
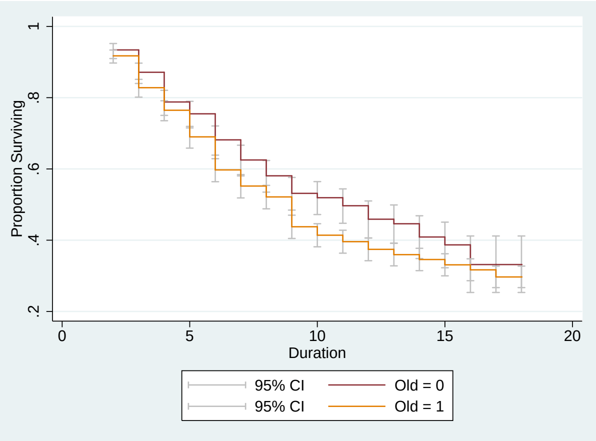


Figure 2: Kaplan-Meier survival analysis

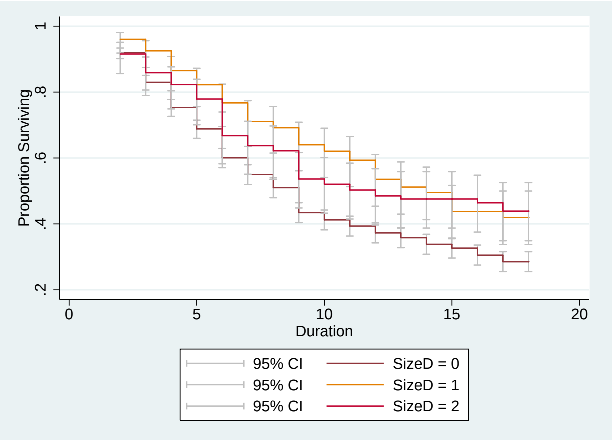
(a) all sample



(b) by Age



(c) by Size



(d) by MESD

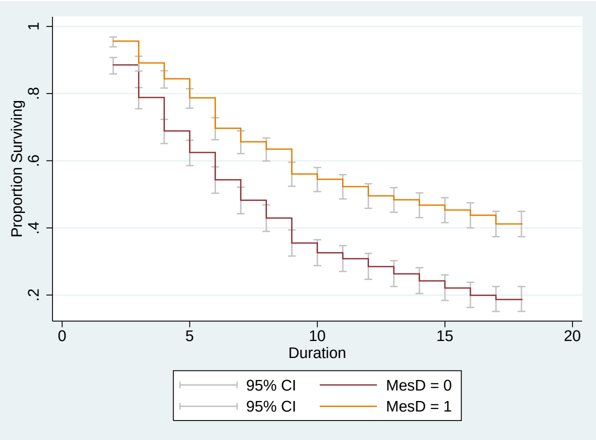
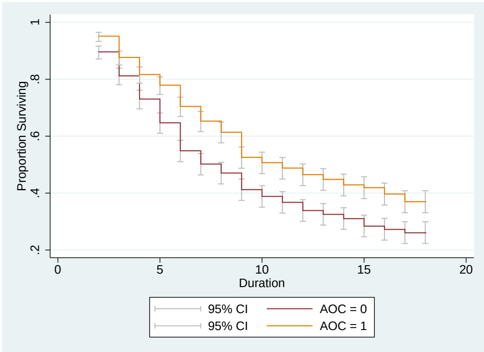


Figure 3: AOC effect and firm survival with regard to the size of the firm

(a) all firms



(b) small firms (c) medium firms (d) large firms

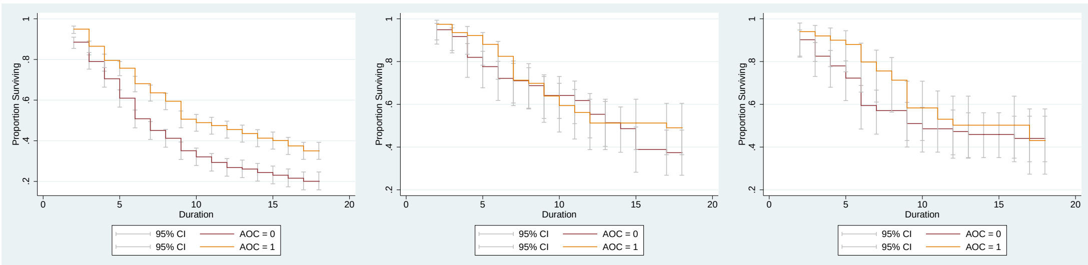


Figure 4: Predicted survival rates for the frailty model: Effect of firm characteristics on small firms

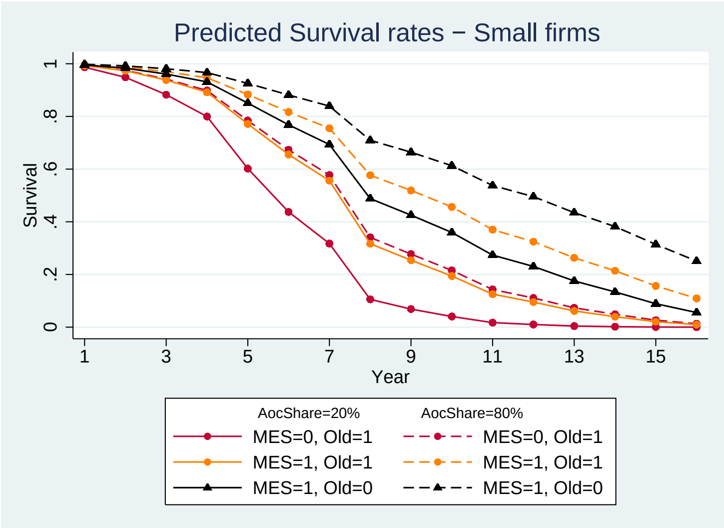


Figure 5: Predicted survival rates for the frailty model: Effect of firm characteristics on medium firms

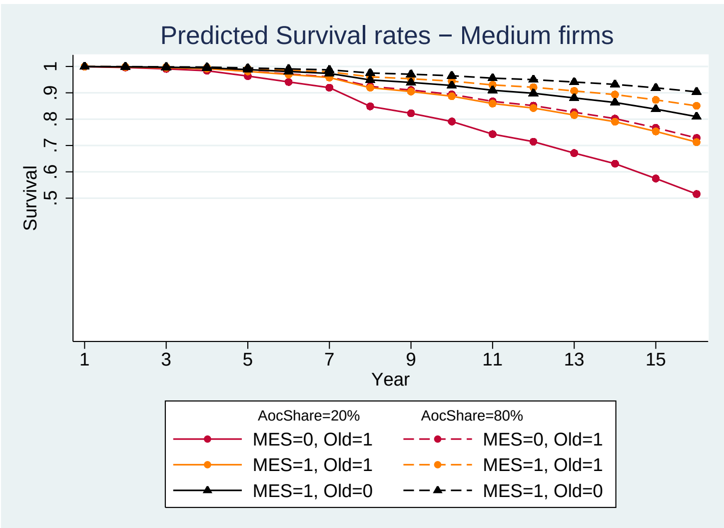


Figure 6: Predicted survival rates for the frailty model: Effect of size on survival rate

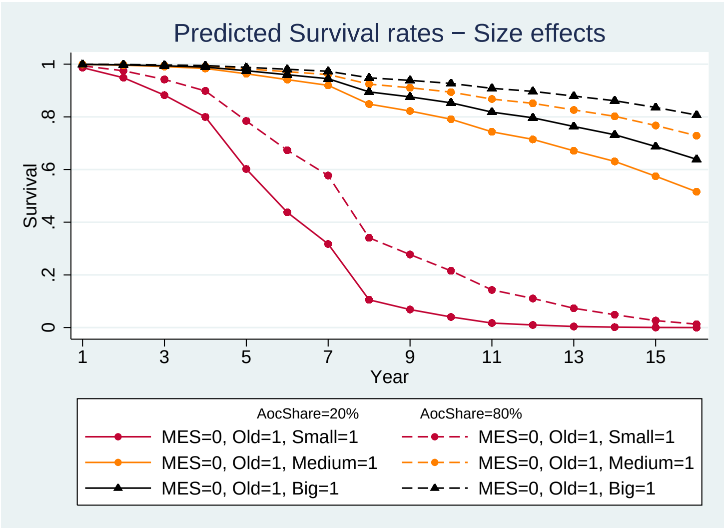


Figure 7: Density of firms' survival