UNIVERSITÀ POLITECNICA DELLE MARCHE

DIPARTIMENTO DI SCIENZE ECONOMICHE E SOCIALI

THE IRRESISTIBLE RISE OF THE CRAFT-BREWING SECTOR IN ITALY: CAN WE EXPLAIN IT?

ROBERTO ESPOSTI, MATTEO FASTIGI AND ELENA VIGANÒ

QUADERNO DI RICERCA n. 414
ISSN: 2279-9575

January 2016

THE IRRESISTIBLE RISE OF THE CRAFT-BREWING SECTOR IN ITALY:

Can We Explain it?

di Roberto Esposti[1], Matteo Fastigi[1], Elena Viganò[2]

Abstract

This paper empirically investigates the emergence of microbreweries in Italy over the last 20 years (period 1993-2014). This rise is expressed by the increasing number of entries in the sector actually accompanied, in most recent years, by an increasing number of exits. The paper proposes an empirical investigation of this entry-exit dynamics through a sequence of survival models. Three orders of possible determinants are considered. Beyond idiosyncratic characteristics, the other two order of factors are the exogenous evolution of the beer market and the specific geographical and local context. Estimation results show that, whereas market force and individual features unquestionably affects entry and exit choices, geographical and local factors are of limited relevance, especially for the entry process.

Keywords: Market entry and exit, Craft brewing, Beer industry, Survival analysis

JEL Classification codes: L11, L66, Q13, R12

---

[1] *Università Politecnica delle Marche. Department of Economics and Social Sciences - Ancona (Italy). E-mail (corresponding author): r.esposti@univpm.it*

[2] *University of Urbino, Department of Economics, Society, Politics – Urbino (Italy)*

Contents

The Irresistible Rise of the Craft-Brewing Sector in Italy:
Can We Explain it?

1. Introduction

In the last decades the beer industry has been interested by the so called "craft beer revolution", whose origin can be dated back to the 1970s in the United States (Flack, 1997; Carroll and Swaminathan, 2000). Evidently craft brewing is not a new phenomenon as it rather belongs to the centuries-old history of beer production both in America and in Europe. But only recently craft beers emerged as a new market segment within the relatively mature beer industry. This emergence satisfies the demand of an increasing amount of consumers for old-style, local, tastier and more full-bodied beers after years of standardization and mass-production. However, while craft brewing boasts a very long and prominent tradition in many European beer-producing countries, this is definitely not the case of Italy (and of other wine producing countries), where the brewing industry was only born with industrial and mass production in the last century and has no significant tradition in craft producing. Nonetheless, and quite surprisingly, from the mid 1990s this market segment started to appear also in the Italian market with the rapid growth of the number of small and very small craft or micro-breweries. Eventually, in the last decade the number of these breweries and the popularity (and consumption) of craft beers boomed across the country (Garavaglia, 2010 and 2015; Fastigi, 2015).

This paper aims at empirically investigating this emergence of craft brewing in Italy over the last 20 years (period 1993-2014). The main objective is to assess which are the main drivers of this surprisingly success as well as the dynamics of this market segment. In fact, the increasing number of entries in the sector has been actually accompanied, in most recent years, also by an increasing number of exits. Therefore, the paper proposes an empirical investigation of this entry-exit dynamics within this emerging market adopting typical concepts and methods of the so called Event History Analysis (EHA), that is, through a sequence of survival models. Compared to the quite wide empirical literature on market entry and exit (Geroski, 1991; Dunne et al., 2013), the paper presents two main original features. First of all, it deals with a very peculiar phenomenon, the growth of an infant branch (at least in Italy) within a quite mature industry. Secondly, as typical in the agro-food sector (Bontemps et al., 2013), the rise of microbreweries in Italy tends to show a spatial concentration. It can be argued that space apparently matters in determining the recent dynamics within the craft brewing segment and this occurs because geographical and local factors have a major influence both on entries, due to agglomeration economies of different nature, and on exits, because of congestion effects (or localized diseconomies). However, the role of these geographical and local factors is often neglected in empirical studies on market entry-exit dynamics since it is implicitly considered as a sort of spaceless process.

Section 2 provides a short introduction on the evolution of beer production and consumption worldwide and discusses the main characteristics of craft brewing and its emergence within the Italian market over the last two decades. Section 3 then presents a stylized and general model of entry and exit to be then adapted to the specific case under study. Three orders of possible drivers are considered to explain entry-exit dynamics. Beyond idiosyncratic characteristics, the two orders of factors are the exogenous evolution of the beer market and, as anticipated, the specific geographical and local context. Section 4 presents the adopted dataset and the empirical investigation as a sequence of nonparametric, semiparametric and parametric survival models applied to both entry and exit dynamics. The respective econometric implications and estimation results are then discussed and reported, respectively, in section 5. Section 6 draws some general concluding remarks.

2. The Emergence of Craft Brewing

2.1. *Evolution of beer production and consumption worldwide: a short overview*

The origin of brewing dates back to thousands of years ago. However, only in the last two centuries this activity took the form of one of the major food industries. This occurred when technological innovations (in particular, the transition from top to bottom fermentation)[1] allowed the standardization of a new type of beer (light, perfectly clear and transparent: the *lager beer*) produced in large-scale plants that soon became extremely popular and dominant both in the European and the USA markets (Gourvish, 1998; Hornsey, 2003; Poelmans and Swinnen, 2011).

---

[1] Top fermentation indicates a process where yeasts, during fermentation, rise to the surface and form the skim-yeast. In bottom fermentation the yeast sinks to the bottom thus making the final product more clear and transparent. Top fermentation is conducted at a higher temperature than bottom fermentation and consequently its duration is shorter thus generating a further difference in beer's flavors (Jelinek, 1946).

This progressive shift from traditional craft brewing to industrial and mass beer production had some major consequences. First of all, it drastically reduced the number of breweries. In the USA, this number declined from several thousand of firms by the end of the 19th century to 43 in 1983 (Swaminathan, 1998). Nonetheless, during the 20th century the production of beer increased greatly and by the end of 2013 the world beer production reached 197 billion litres. At the same time, also the geography of beer production progressively changed. After a century of undisputed leadership, in 2002 USA production was overtaken by China that also surpassed the aggregate EU27 production in 2008 (Table 1). The largest world brewing company, however, remains the Belgian Anheuser-Busch InBev that, in 2014, concentrated 21% of the overall world beer production (http://www.barthhaasgroup.com).

The size and geography of beer consumption have changed, too. At the world level, beer consumption is by far higher than any other alcoholic drink, in terms of both quantity and value (Colen and Swinnen, 2011). While in 1960 world beer consumption was twice the consumption of wine (in quantity), by 2005 it had grown up to more than six times the wine level (153 billion litres for beer, 24 billion litres for wine and 18.5 billion litres for other spirits). In 2013, global beer consumption reached 189 billion litres (about 1% more than 2012), its 28th consecutive annual increase (http://www.kirinholdings.co.jp). Also in value terms, although beer is sold, on average, at cheaper prices than wine or spirits, in 1990 beer and spirits consumption was almost equivalent; by 2005, however, the value of beer consumed worldwide had become about 130 billion US$, the spirits stayed at about 90 billion US$ and wine at about 65 billion US$.

Despite this global tendencies, however, it is worth noticing that beer consumption dynamics is quite different among group of countries. In emerging countries, i.e. those with still relatively low average income but experiencing intense economic growth (such as Russia, Brazil, China and India) beer consumption is regularly increasing– Deconinck and Swinnen, 2011; JunFei et al., 2011; Arora et al., 2011). On the contrary, in developed countries (i.e., those whose average per-capita income already reached 30,000 international dollars) per-capita beer consumption is, in fact, decreasing. Furthermore, a negative correlation between trade openness and the share of beer on total alcoholic consumption is empirically observed in countries with a strong beer tradition (such as Belgium, Germany, Czech Republic and United Kingdom). The opposite occurs in countries that are traditional wine (Italy, Spain, France) or spirits (Russia) consumers. These results support the hypothesis that increasing economic integration and globalization are inducing a progressive convergence of alcoholic consumption patterns across countries as also evident in Table 2 (Aizenman and Brooks, 2008; Bentzen et al., 2010; Leifman, 2001).

Table 1: Evolution of the global beer consumption and production from 2001 to 2013: country ranking

Country	**Per-capita beer consumption (litres per year) (2012)**	**2001**		**2007**		**2013**	
		Production (1.000 hl)	**Ranking**	**Production (1.000 hl)**	**Ranking**	**Production (1.000 hl)**	**Ranking**
China	32	227.000	2	393.137	1	506.500	**1**
United States	77	233.000	1	232.839	2	224.093	**2**
Brazil	68	84.000	4	96.000	5	135.500	**3**
Germany	106	108.500	3	103.970	4	94.365	**4**
Russia	74	63.000	6	115.000	3	88.600	**5**
Mexico	60	62.307	7	81.000	6	82.500	**6**
Japan	43	71.300	5	62.804	7	57.200	**7**
United Kingdom	68	56.802	8	51.341	8	42.420	**8**
Poland	98	24.140	11	35.500	9	39.560	**9**
Spain	68	27.710	9	34.350	10	32.700	**10**
Czech Republic	149	17.881	17	19.897	17	18.605	**22**
France	30	18.866	16	15.096	24	18.500	**24**
Belgium	74	15.039	19	18.565	20	18.069	**25**
Italy	**29**	**12.782**	**22**	**13.520**	**27**	**12.688**	**30**

Source: http://www.barthhaasgroup.com/en/.

Table 2: Share (%) of beer, wine and other spirits on total alcoholic consumption in selected countries (in litres of pure alcohol) – in bold the highest share by country

Country	**1961**			**2000**			**2010**		
	Beer	**Wine**	**Oth.**	**Beer**	**Wine**	**Oth.**	**Beer**	**Wine**	**Oth.**
Poland	27,66	12,24	60,10	49,29	21,19	29,52	**55,14**	9,35	35,51
Germany	57,14	17,32	25,54	55,46	24,63	19,91	**53,61**	27,83	18,55
Czech Republic	69,01	19,05	11,94	56,58	13,84	29,58	**53,51**	20,48	26,00
United States	47,05	11,15	41,79	56,27	14,25	29,48	**50,00**	17,29	32,71
Spain	11,04	65,39	23,58	37,68	37,05	25,27	**49,74**	20,12	28,19
Belgium	71,28	15,06	13,67	57,26	35,62	7,03	**49,10**	36,33	14,38
Russia	14,61	17,14	68,26	21,44	6,92	71,64	**37,59**	11,42	50,99
United Kingdom	80,95	4,32	14,73	49,26	25,97	18,37	**36,94**	33,82	21,83
Italy	**2,08**	**89,60**	**8,26**	**17,71**	**76,24**	**6,05**	**22,95**	**65,57**	**11,48**
France	11,25	74,41	14,33	15,26	63,02	19,88	**18,80**	56,41	23,08

Source: Elaboration on Colen and Swinnen (2011) and World Health Organization .

Among the changes experienced by the brewing sector in the last century, however, of major interest here is the so called craft beer revolution, which started in the 1970s in the United States and whose motivation is the (re)discovery of traditional beer styles as opposed to the large-scale, industrial and mass (i.e., highly standardized) production and the consequent increasing use of less qualitative and cheaper cereals such as corn and rice. Providing a common definition of craft beer is not easy as it may vary across countries. In the United States, a craft brewery is defined as a (very relatively) small (annual production less than about 7 million hectoliters), independent (less than 25 percent of the craft brewery can be owned or controlled by an alcoholic beverage industry member that is not itself a craft brewery) and traditional (the majority of its production has flavors deriving from traditional or innovative brewing ingredients and their fermentation) beer producer.

In general, microbrewers often reinterpret traditional beer styles by characterizing them in an original and somehow innovative way. During the last decades, in fact, their main ability has been to vary the quantity, quality and variety of hops, to use various and sometime novel combination of raw or malted cereals or to modify the beer flavors and taste with the addition of fruit, spices, etc. As a result, microbreweries usually obtain a darker, stronger and more flavourful beer than industrial beers (Tremblay and Tremblay, 2005). Therefore, craft beers are more differentiated products and their market success depends less on price and more on the capacity of capturing the consumers' changing tastes.[2]

2.2. *Craft brewing in Italy*

As typical of most traditional and major wine producing countries, Italy has not a notable brewing tradition. Up to twenty years ago, Italy had very few industrial beer producers, mainly located in the North-Eastern part of the country due to the German and Austrian historical influence. Unlike several other European countries, Italy has not a prominent and centuries-old craft brewing tradition and this production remained negligible until the end of last century. This makes the present Italian craft brewing experience quite peculiar because it takes the form of a fast-growing novel segment within a largely mature beverage sector. Previous works have already analyzed such peculiarity by mostly emphasizing the role of market evolution, and especially the

---

[2] This can explain the empirical evidence suggesting a lower price elasticity of craft beer demand than that of industrial beer (Kleban and Ingeborg, 2011).

change in consumers' tastes and preferences (Garavaglia, 2015), but they did not explicitly assess the role of the different drivers in the observed firm dynamics and, in this respect, disregarding the geographical and local dimension of this emerging segment. This latter assessment is, in fact, the main objective and novelty of the present paper.

In Italy, the craft beer movement began growing in mid 1990s, mostly in the Central and Northern regions. This grow was fostered by some legislative and institutional innovations. In particular, in 1995 the Legislative Decree n. 504 introduced some simplifications and innovations into the complex bureaucratic procedures concerning beer production, and this explains why 1996 is usually considered the year in which the Italian craft brewing sector was born.[3] The first Italian microbreweries had a very small productive capacity and their beers were neither pasteurized nor filtered. Some of these pioneers are now world-renowned. Compared to other European countries, in Italy the lack of tradition, in fact, left room to creativity and experimentalism and this makes the Italian experience somehow closer to the US craft brewing renaissance.

This creativity, combined with the Italian artisan ability, soon made Italian craft beers more and more respected and popular among beer experts, both in Italy and abroad and many of them are now recognized worldwide especially for their original tastes and styles. In 2014 the Italian craft beer sector produced 378.000 hl, with a growth of 18% with respect to 2013 and reaching 2,8% of the total national beer production (http://www.assobirra.it/). At the same time, the number of microbreweries is increasing year after year. It reached almost 800 units by the end of 2014 with a continuously growing pace of entries but also a growing number of exits at least in the last years signaling that a sort or turnover process has also began (Figure 1).

At the same time, especially in the last five years, the sector is experiencing an increasing heterogeneity in terms of brewery typologies (Figure 2). Based on the Brewers Association's taxonomy, the Italian microbreweries can be categorized into four different typologies: 1) *craft brewery* ('birrificio artigianale'), whose sales are mostly off-site; 2) *brew pub*, whose sales are mostly on-site, that is, within its own bar/pub/restaurant; 3) *beer firm*, whose production is, at least in part, brewed by another brewery acting as a outsourcer; 4) *agricultural craft brewery*, a novel category introduced within the Italian regulation in 2010 by Ministerial Decree n. 212. This norm acknowledges as "agricultural products" a list of typically industrial food products or beverages whenever their production is closely jointed with agricultural activity. With reference to beer production, agricultural craft brewing implies that at least 51% of the raw materials used for brewing is produced from the farm itself (Fastigi, 2015).

3. Entry, Survival and Exit in an Emergent Market Segment

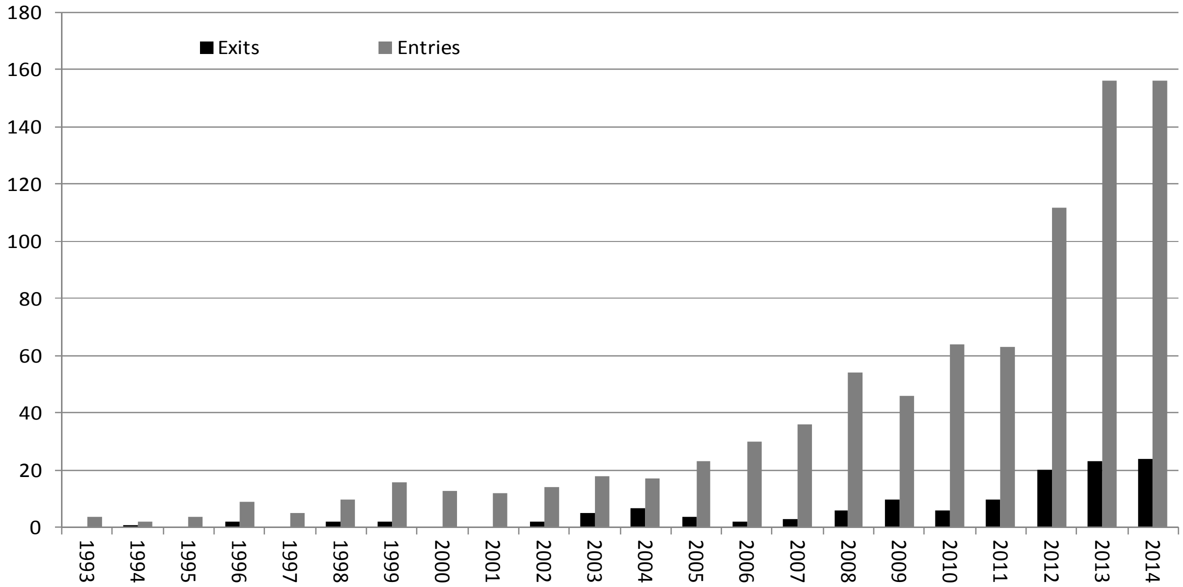
Most literature, either theoretical or empirical, on market entry and exit shares the idea that firms take entry/exit decisions on the basis of the current value of the expected future profits thus assuming agents' rationality in terms of profit maximizing behavior (Geroski, 1991; Pakes and Ericson, 1998; Clementi and Palazzo, 2013; Dunne et al., 2013). Such behavior actually takes the form of a sequence of choices or "entry programme" (Geroski, 1991): to enter or not the market; how much to invest and to produce; how and what to produce (technology and product quality); stay or not in the market (i.e., exit or not). Here we follow this general approach and also assume that, in this sequence of firm's choices and states, exit is an absorbing state, that is, firm's exit is irreversible.[4] Consequently, it is also assumed that the two extreme (initial and final) choices of the abovementioned sequence, that is, entering and exiting the market can be considered as independent choices. Though entry is evidently needed before exiting, once a firm has entered, the decision (and the probability) to stay or not within the market can be represented as an independent choice (and stochastic process). This remains true even if the determinants of the two choices (e.g., geographical location) may be at least partially the same. Therefore, the aim here is to stylize a model for these two sequential but independent choices.

---

[3] In fact, few producers were already active (see section 4).

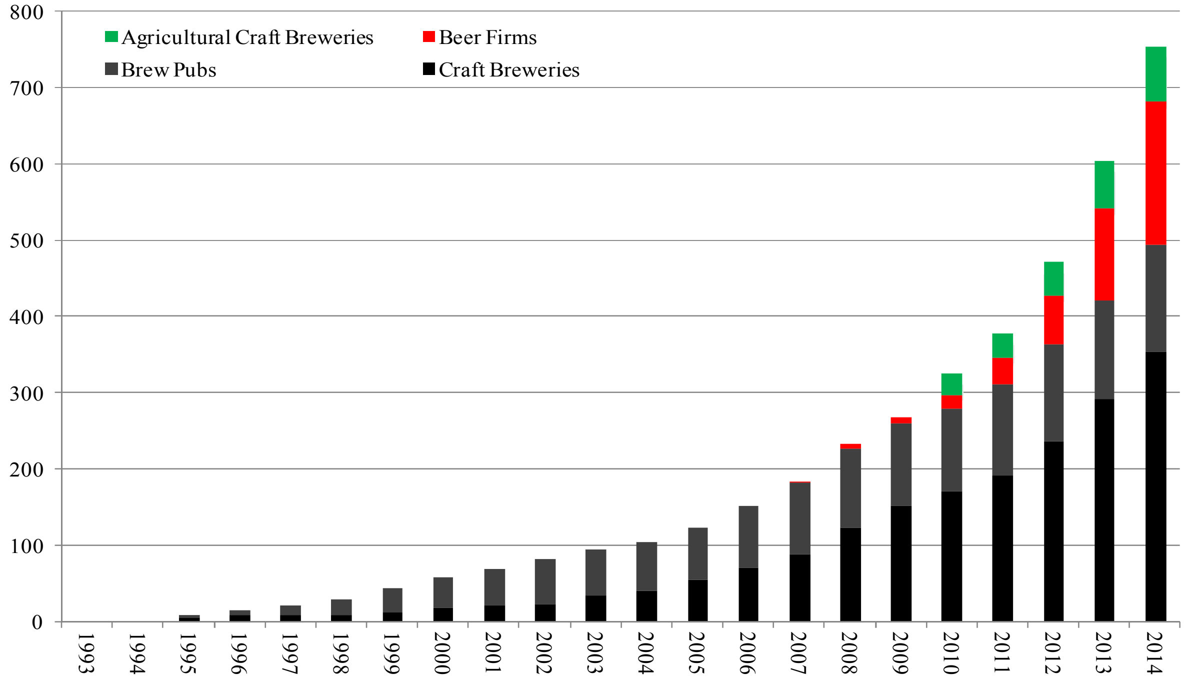
[4] This assumption is consistent with the dataset under consideration here as will be clarified in detail in section 4.1.

Figure 1: Entries and exits in the Italian craft brewing sector (1993–2014)



Source: Elaboration on data from www.microbirrifici.org

Figure 2: Number of microbreweries in Italy by category (1993–2014)



Source: Elaboration on data from www.microbirrifici.org.

3.1. *A stylized model*

Let assume there is a set *M* of *m* potential entrants (potential craft breweries). At time t, the i-th potential entrant will enter the market only if the present value of the expected future market profits (Π_{it}) exceeds the costs of entry ($C_{EN,it}$). Π_{it} evidently incorporates the expectations about future revenue and production costs (therefore, output and input prices and productivity), while $C_{EN,it}$ also includes all those costs summarized under the general, and generic, concept of *entry barriers*. It is thus possible to define the *entry value function* $V_{EN,it} = \Pi_{it} - C_{EN,it}$. Such function can vary over time (i.e., it can be $V_{EN,it} \neq V_{EN,it+1}$) and also admits heterogeneity, as it can be $V_{EN,it} \neq V_{EN,jt}, \forall i, j \in M$. Moreover, though based on $V_{EN,it}$, the entry choice is stochastic as it also depends on an unobservable stochastic term, ε_{it}, whose statistical distribution is left undetermined for the moment, but for which we assume $E(\varepsilon_{it}) = 0$. Therefore, it is $E(V_{EN,it} + \varepsilon_{it}) = V_{EN,it}$.

Firm's entry choice can be thus represented as a dichotomous random variable EN_{it} taking value 1 if entry occurs and value 0 otherwise:

$$(1)\ EN_{it} = \begin{cases} 1\ if\ \ E(V_{EN,it} + \varepsilon_{it}) = V_{E,it} > 0 \\ 0\ if\ \ E(V_{EN,it} + \varepsilon_{it}) = V_{E,it} \leq 0 \end{cases}$$

Therefore, at any time t, there will be a set N_t of n_t incumbent firms with $n_t<m$ and $N_t \in M, \forall t$. At time *t*, these firms come across the decision to stay or not in the market, that is, to exit or not. Following the same argument of the entry choice, the i-th incumbent will exit the market only if the present value of the expected future market profits (Π_{it}) is lower than the value of exit ($C_{EX,it}$). $C_{EX,it}$ includes the expected residual value of the firm once it is liquidated or its residual resources (mostly capital) are sold but also, and above all, the *opportunity cost* (this explains the maintained notation $C_{EX,it}$) of staying in the craft beer market rather moving to other sectors or activities. We can thus define the *exit value function* as $V_{EX,it} = \Pi_{it} - C_{EX,it}$. Again, it can vary over time ($V_{EX,it} \neq V_{EX,it+1}$), it admits heterogeneity ($V_{EN,it} \neq V_{EN,jt}, \forall i, j \in M$) and the exit choice is stochastic such that $E(V_{EX,it} + u_{it}) = V_{EX,it}$ where $E(u_{it}) = 0$.

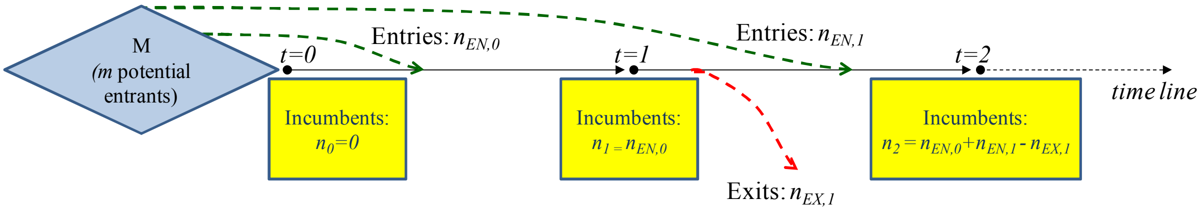
Firm's exit choice can be thus represented as a dichotomous random variable EX_{it} taking value 1 if exit occurs and value 0 otherwise:

$$(2)\ EX_{it} = \begin{cases} 1\ if\ E\left(V_{EX,it} + u_{it}\right) = V_{EX,it} < 0 \\ 0\ if\ E\left(V_{EX,it} + u_{it}\right) = V_{EX,it} \geq 0 \end{cases}$$

At any point in time *t*, some firms entry the market, $n_{EN,t} \leq m$, while others exit it, $n_{EX,t} \leq n_t$. *M* and N_t are called *risk sets* as they contain all the units for which the two events can potentially occur,. Evidently, if the observation period starts (i.e., at *t=0*) when the market segment does not exist yet, N_0 is an empty set, thus $n_0 = 0$, and $n_{EX,0} = 0$. Therefore, at any time *t* the number of incumbents will be $n_t = \sum_{s=t}^{0}\left(n_{EN,t-s} - n_{EX,t-s}\right)$ while, as exit is irreversible, the number of potential entrants is $\left(m - \sum_{s=t}^{0} n_{EN,t-s}\right)$. As the interest here is on a still nascent segment, let assume is here that $m >> \sum_{s=t}^{1} n_{EN,t-s}, \forall t$ so that the number of potential entrants can be regarded as constant over time: $m_t = m_{t+1} = m, \forall t$. Figure 3 illustrates the entry and exit process now depicted.

As in most empirical studies on entry-exit dynamics, here the interest is in investigating the determinants of firm's entry/exit choices. In practice, the interest is in investigating $E\left(EN_{it} \middle| \mathbf{X}_{it}\right)$ and $E\left(EX_{it} \middle| \mathbf{X}_{it}\right)$ where $\mathbf{X}_{it}$ is the vector of possibly time-varying and individual-specific variables (or covariates) affecting the entry and exit choice.

Figure 3 – Graphical representation of the modelled entry/exit process



3.2. *The drivers of entry and exit*

It is common in the entry/exit literature to distinguish three orders of variables affecting the entry/exit decision (Geroski, 1991: 59): external (or exogenous) structural factors (for instance, market size or production technology), external transitory factors (for instance, a temporary price rise), internal (or endogenous) factors (for instance, an investment made in past years or other idiosyncratic transitory determinants).[5] Most of these determinants remains valid across different contexts (countries and sectors) but others reflect the peculiar features of specific industries. The food sector, in particular, is often considered a mature industry and this maturity is often regarded as the main reason for the lower entry and exit rates compared to other manufacturing activities and, in particular, to new and fast growing sectors (Caves; 1998; Disney et al., 2003; Bontemps et al., 2013). The case of microbreweries in Italy, however, is itself quite peculiar. Though the beer industry can be considered, in Italy as elsewhere, a mature sector, microbrewing is really a novelty within the national context and its dynamics seems closer to the experience of novel sectors rather than of mature industries.

With respect to this peculiar case, here we want to pay more attention on an aspect that often remains neglected in this literature, that is, the role of space. With space here we refer to the fact that the observed market dynamics has a clear spatial characterization as entries and exits tend to concentrate in specific territories. This is evidently not surprising since in Italy (as in many other European countries) many craft activities especially in the food sector tend to show such territorial characterization and specialization. How space plays this role, however, is not necessarily obvious and has been seldom make explicit in this kind of empirical studies.

Also depending on the available information, therefore, here we revisit the abovementioned distinction in three orders of entry/exit determinants: the *idiosyncratic characteristics* of the entering/exiting firms; the *structural and transitory features of the Italian beer market*; spatial characteristics intended both as the geographical localization of the entering/exiting firms and the features of the local social and economic environment or *local milieu*. As will be discussed more in detail in next section, these determinants influence both the current value of expected future profits (Π_{it}) and the entry and opportunity costs ($C_{EN,it}$ and $C_{EX,it}$). Thus, the entry and the exit value functions can be expressed as $V_{EN,it} = f(\mathbf{MK}_t, \mathbf{ID}_{it}, \mathbf{SP}_{it})$ and $V_{EX,it} = g(\mathbf{MK}_t, \mathbf{ID}_{it}, \mathbf{SP}_{it})$, where $\mathbf{MK}_t$, $\mathbf{ID}_{it}$, $\mathbf{SP}_{it}$ are the vectors of market, idiosyncratic and spatial determinants, respectively, and it is $\mathbf{X}_{it} = (\mathbf{MK}_t', \mathbf{ID}_{it}', \mathbf{SP}_{it}')'$.

---

[5] Most literature on market entry, survival and exit follow the general (and generic) analogy between market and natural selection: as in any ecological systems the capacity of any single individual to be born and survive depends at the same time on the external environment and on the own individual characteristics (fitness to that environment) (Geroski, 1991).

In next sections we more deeply discuss which factors may really have a role in the Italian craft brewing experience, that is, which variables to include in vectors $\mathbf{MK}_t$, $\mathbf{ID}_{it}$, $\mathbf{SP}_{it}$ by explicitly linking them to the underlying theoretical framework outlined in previous section.

3.2.1. Market drivers

The first order of determinants are the (exogenous) market drivers. In the present case, the market segment under investigation is novel with no or very few small-size incumbents. Therefore, some of typical determinants affecting expected future profits, thus entry and exit, like market concentration and power and consequent entry barriers are, in fact, of limited relevance. In the case of microbreweries in Italy, market profitability and costs associated to entry and exit actually depend and vary according to the overall market changes that motivate the birth of this new segment. These market changes are, in fact, a combination of two long-term processes. On the one hand, the already mentioned convergence of Italian alcoholic drink consumption towards the international standards that implies a reduction of the wine share in favor of beer, thus with a regular demand growth of this latter. At the same time, more than in wine market, the last years have shown a remarkable change in the consumers' attitude towards beer consumption.

In this respect, a significant role in the diffusion of microbreweries in Italy is played by the increasing attention on the traditional or pre-industrial ways of production. It is a major change in consumers' attitude as mass and undifferentiated consumption are progressively replaced or contrasted, especially in food and beverages, by highly differentiated consumption behaviors (Bourdieu, 1984; Johnston and Baumann, 2010). The success of microbreweries may also be partially originated from what Harvey (2004) calls an effect of post-modernity, namely the increasing need of consumers to affirm an identity (individual or collective) as a defense of own local traditions and peculiarities against the globalization of markets and tastes (Carroll and Swaminathan, 2000; Schnell and Reese, 2003; Pratt, 2007). In this context, we can represent the emergence of craft brewing in Italy as a combination of small producers that start an home-made and mostly self-consumed beer production just for leisure or imitation, then creatively improve their handcraft skills and eventually, under changing market dynamics, either turn into a real business activity or simply disappear.

Two variables are here considered to capture the influence on entry/exit dynamics of the peculiar evolution of such a novel segment within a mature sector. The first is the beer demand growth in the Italian market at the time of entry or exit. At time *t* this variable simply is $d_t = \partial D_t / \partial t$ where D_t express beer demand. Here we actually assume that the entry/exit decision is taken by observing the average demand growth rate in the last three years, i.e., $d_t = \left(\sum_{s=1}^{3} \partial D_{t-s} / \partial t \right) \Big/ 3$. We can thus formulate an intuitive hypothesis about the role of this variable on market entry and exit: the higher the demand growth the higher (lower) the incentive to enter (exit) the market.

> *Hypothesis n.1 (Demand growth)*: it is $\partial E(EN_{it}) / \partial d_t > 0$ and $, \partial E(EX_{it}) / \partial d_t < 0$ where $E(EN_{it})$ and $E(EX_{it})$ express the expected value of the probability of market entry and exit of the i-th firm at time *t*, respectively.

The second variable expressing the market environment affecting entry and exit decisions has to do with the sector life cycle. In particular, we may assume that within an infant industry or market segment the impact of the number of incumbents, n_t, on the rate of entry and exit differs throughout its grow, that is, according to n_t itself. During the expansion or boom of the segment, imitation will induce increasing entries and restrain exits. When the segment reaches maturity, competition and congestion will reduce entries and encourage exits. As life cycles admit both a booming and a maturity stage, we will observe increasing entries and low exits in the early period while it will be the opposite in the later years of the segment life. Therefore, we can formulate the following hypothesis:

> *Hypothesis n.2 (Life cycle)*: if the market segment experiences a booming phase, it is $\partial E(EN_{it}) / \partial n_t > 0$ and $\partial E(EX_{it}) / \partial n_t < 0$. If the market segment experiences maturity, it is $\partial E(EN_{it}) / \partial n_t < 0$ and $\partial E(EX_{it}) / \partial n_t > 0$. If the period of observation includes both phases, it is $\partial E(EN_{it}) / \partial n_t > 0$ and $\partial E(EX_{it}) / \partial n_t < 0$ for $n_t < \overline{n}$, and $\partial E(EN_{it}) / \partial n_t < 0$ and $\partial E(EX_{it}) / \partial n_t > 0$ for $n_t > \overline{n}$, where $\overline{n}$ indicates the threshold market density when competition and congestion effects start prevailing.

It follows that the vector of market determinants is $\mathbf{MK}_t' = (d_t, n_{t-1})$.[6] Notice that for these variables the *i* index does not appear simply because they are invariant across firms. Therefore, they do not admit heterogeneity in the entry and exit behaviour as the

---

[6] To avoid endogeneity, in the empirical application n_t is replaced by n_{t-1}.

firm's choice only depend on the external market context which is the same for all potential entrants and incumbents.

3.2.2. Individual characteristics

Beyond market drivers, we should admit heterogeneous entry and exit behaviour across microbreweries (either potential entrant or incumbent) as expected profits and entry/exit costs depend on individual firm's characteristics and consequent choices. However, some of these individual factors, for instance entrepreneurial capacity, are in fact unobservable and the main empirical challenges is to define those observable variables that can be somehow expression of these factors. Here we distinguish between two observable sources of heterogeneity: market positioning and learning. This latter, in fact, can be itself hardly observable but can be proxied by the firm's age under the assumption that learning requires time and occurs over time; thus, more time spent in the market implies more learning.

Market positioning is expressed by those strategic decisions taken by the entrants, and maintained by the incumbents, in terms of which type of brewery to be ($type_i$), which kind of beer ($beer_i$) and how many beers ($number_i$) to produce and sell. Notice that these variables lack the time index as they are assumed to be time-invariant choices. Though in principle these strategic decisions can be modified by incumbents during their life, in the case under analysis here it is generally true that once the entrant decides the choice is maintained until the exit or the end of the observational period.

We can hardly formulate ex-ante hypotheses about how $type_i$ and $beer_i$ affect $E(EN_{it})$ and $E(EX_{it})$, though we can argue that agricultural breweries producing bottom fermentation beers have a higher probability of entry and a lower chance of exit probably due to lower entry costs and higher expected profitability, respectively. It seems more intuitive to formulate an hypothesis about the impact of $number_i$ on entry/exit dynamic. A larger gamma (that is, higher $number_i$) implies a higher expected profitability not only because it is often associated to a large size (which is, unfortunately, not directly observable), but also because it shows a more sophisticated and, arguably, successful marketing strategy. Therefore, we can formulate the following:

Hypothesis n.3 (Diversification): production diversification facilitates market entry, $\partial E(EN_{it})/\partial number_i > 0$, and favors market survival, $\partial E(EX_{it})/\partial number_i < 0$.

The second source of heterogeneity is learning proxied by age to be intended here with two different meanings: the years spent before entering the market to observe and study it (t_{ENi}); the years spent within the market after entry and before exit ($t_{EX,i}$). The first kind of learning expresses, within a booming sector, the combined effect between the impulse to imitation and the "wait and see" strategy of late entrants. One may argue that compared to passive imitation, "wait and see" may represent a better entry strategy unless it implies higher entry costs due to the stronger contrasting strategies and market power of the incumbents. Thus we can formulate the following hypothesis:

> *Hypothesis n.4 (Imitation)*: imitation behaviour prevails if we observe $\partial E(EN_{it})/\partial t_{EN,i} < 0$. Otherwise ($\partial E(EN_{it})/\partial t_{EN,i} > 0$) the "wait and see" strategy is prevalent.

We can also formulate an hypothesis about the learning process of the incumbents, that is, after entry. Literature on this aspect identifies two different kinds of learning (Pakes and Ericson, 1998). One is *passive learning*, where the firms' increasing age naturally and almost unconsciously (in other words, passively) brings about larger and better knowledge and therefore competitiveness. The alternative kind of learning is *active exploration* where learning depends on explicit firm's decisions and investments (in human capital rather than information and knowledge, for instance); thus it is costly and, above all, it is not necessarily related to age. In fact, entrants may be more aggressive compared to incumbents on this ground in order to gain more chances to survive and prevail in the market. Such conceptually straightforward distinction between these two forms of learning can be expressed in a testable hypothesis as follows:

> *Hypothesis n.5 (Learning)*: if passive learning prevails, it is $\partial E(EX_{it})/\partial t_{EX,i} < 0$. Otherwise, under active forms of learning it is $\partial E(EX_{it})/\partial t_{EX,i} = 0$ (or even $\partial E(EX_{it})/\partial t_{EX,i} > 0$).

It follows that the vector of individual determinants here considered is $\mathbf{ID}_{it}' = \left(type_i, beer_i, number_i, t_{EN,i}, t_{EX,i}\right)$.

3.2.3. Spatial factors

A third and final group of entry/exit determinants are those related to the spatial economic and social environment in which the i-th entering or exiting brewery operates. These spatial determinants are somehow intermediary variables between time-variant homogenous market drivers and the time-invariant individual characteristics expressing heterogeneity. *Strictu sensu*, these variables are invariant across individuals only if they belong to the same “space”. At the same time, they can vary over time whenever they capture spatial features that changes over time. Therefore, in principle, these variables may have both *i* and *t* indexes.

In fact, we can distinguish between two different kinds of spatial characteristics. On the one hand, we have those features do not varying over time simply because they are immutable characteristics of the spatial context where the i-th firm operates (therefore, these variables have only the *i* index). These are the *geographical features* and we consider here the region/province (reg_i) and the altitude (alt_i) where the i-th craft brewery is located. In this respect, we can argue that geography matters in explaining the craft brewing experience in Italy both for the different regional consumers’ attitude and for the different availability of suitable cereal production. By looking at the spatial distribution of craft breweries in Italy, we can formulate the following hypothesis:

> *Hypothesis n.6 (Geography)*: craft breweries tend to concentrate in some (North-Eastern and Central, NEC) regions more than in others, therefore $\partial E(EN_{it})/\partial reg_i \neq 0$ and $\partial E(EX_{it})/\partial reg_i \neq 0$; at the same time, breweries tend to concentrate in rural (thus, often mountainous or hilly) areas, therefore $\partial E(EN_{it})/\partial alt_i > 0$ and $\partial E(EX_{it})/\partial alt_i < 0$.

On the other hand, a second kind of spatial features concerns the evolution of the local social and economic context where the i-th brewery operates. These are time-varying features (therefore, these variables have a *t* index) generally expressing the presence of local/agglomeration economies or diseconomies, that is, localized positive or negative externalities that favor or discourage the entry and the survival of craft breweries. It is worth reminding that both economic and sociological literature emphasizes that the Italian industrialization process has been largely based on systems of small and medium enterprises localized in semi-peripheral areas (Bagnasco, 1988; Becattini, 1979; Esposti and Sotte, 2003; Trigilia, 2005; Becattini and Coltorti, 2006). The 'local milieu', intended as institutional, cultural, social and economic context, contributes to create value and economic development (Granovetter, 1973; 1985; Carboni, 2009). The institutional, social and economic relations within the local milieu condition economic agents’ behavior and create opportunities or impose restrictions upon the extension of the market (Magatti, 2002). In fact, these relations may generate either local economies or diseconomies.

The former are localized advantages in terms of lower costs (e.g., larger availability of a critical production factor), higher productivity (e.g., due to better knowledge and skills) and larger local demand thus higher output prices. These advantages are often summarized by the concept of *social capital* that, especially in food production, concerns the strength of traditions, of productive vocations, of local identity that may reinforce that sort of “neolocalism” that is reconnecting the consumption behavior and choices of people to their local community and economy (Shortridge, 1996; Flack, 1997; Shortridge and Shortridge, 1998). Local diseconomies, on the contrary, mostly take the form of congestion effects. Higher density of economic activities (especially in the same sector or market) may compete for the same local production factors or compete for the same local consumers’ demand, thus inducing higher production costs and/or lower revenues.

In the specific case of craft brewing this local milieu can be intended as a combination of the overall socio-economic development (here expressed by the local unemployment rate at the time of i-th firm’s entry in the market, un_{it}) and of more sector-specific features. In this respect, here we consider the following local features: the agricultural vocation/specialization expressed by the percentage of agricultural workers on total population at the time of entry of the i-th brewery (agr_{it}); the food/beverage vocation/specialization expressed by the percentage of workers in both the food ($food_{it}$) and beverage (bev_{it}) industry on total manufacturing employment at the time of entry of the i-th brewery; the craft brewing vocation/specialization expressed by number of microbreweries already active in the local context at the time of entry of the i-th brewery (con_{it}).

With respect to this role of the spatial environment, we can thus formulate the following hypotheses:

Hypothesis n.7 (Local development): a well developed social and local context facilitates the creation of new craft breweries and their survival in the market: $\partial E(EN_{it})/\partial un_{it} < 0$ and $\partial E(EX_{it})/\partial un_{it} > 0$.

Hypothesis n.8 (Local milieu): if local economies prevails on local diseconomies (or congestion effects), variables expressing local vocation/specialization increase entries and survival, therefore $\partial E(EN_{it})/\partial agr_{it}, \partial food_{it}, \partial bev_{it}, \partial con_{it} > 0$ and $\partial E(EX_{it})/\partial agr_{it}, \partial food_{it}, \partial bev_{it}, \partial con_{it} < 0$.

It follows that the vector of spatial determinants is $\mathbf{SP}_{it}'=\left(reg_{\mathrm{i}},\mathrm{alt}_{i},un_{it},agr_{it},food_{it},bev_{it},con_{it-1}\right)$.[7]

4. The Empirical Application

4.1. The sample and the dataset

The entry and exit dynamics within the Italian microbrewery sector is here investigated over the 1993-2014 period. 2014 being the last fully observed, 1993 is the first year that officially register the presence of commercial microbreweries in Italy. The main trends in entry/exit dynamics have been already anticipated in section 2.2 (see also Figures 1 and 2). At the end of the observation period (end of 2014) there were 754 operating commercial microbreweries in Italy. Most of them entered the market in the last 5 years with an increasing entry rate: about 150 new microbreweries entered the market in the period June 2014 to December 2014. At the same time, over the whole period 112 Italian microbreweries exited the market but also exits concentrated in the last years. This implies that, in fact, the sample under observation over the 1993-2014 period is made of 866 units.[8]

Beside the year of entry and of exit (if occurred), for each brewery we also observe: the localization (region, province and municipality) of the production plant, the type of brewery according to the regulation (craft brewery, beer pub, beer firm or agricultural craft brewery) and the type of beer produced (numbers of different beers and top or bottom-fermentation beers). The source of all these data on individual breweries is the website www.microbirrifici.org, the portal of Italian microbrewing. This set of variables is combined with official statistical information (Italian National Institute of Statistics, ISTAT) providing data on variables expressing the spatial features (see previous section). Finally, data about the evolution of Italian beer

---

[7] To avoid endogeneity, in the empirical application con_t is replaced by con_{t-1}.

[8] For the sake of completeness, it is worth reminding that, in fact, two of the four microbreweries that were already active in 1993 actually entered the market before that year. According to the information we collected, the entrance in the market can be dated back to 1983 and 1988, respectively. Nonetheless, these cases do not seem to have statistical relevance and, therefore, also following Bontemps et al. (2013), we treat these two observations as they entered the market in the first year of observation, that is, 1993. Moreover, though the entry/exit analysis is here carried out as a single-event case (i.e., the event of entry and exit can happen only once), there are still two microbreweries that entered early in the market, exited after few years and then entered again. In fact, we treat these repeated-entry cases as independent observations, so the two microbreweries enter the sample as four distinct observations.

consumption are taken from the Italian association of beer producers (www.assobirra.it).

The whole set of variables here considered and the respective information about data sources and coverage are summarized in Table 3. They are divided into three typologies as discussed and explained in section 3.2: time-variant variables (d_t and n_t), time-invariant and individual-specific variables ($type_i$, $beer_i$, $number_i$, $t_{EN,i}$, $t_{EX,i}$, reg_i, alt_i), time-variant and site-specific variables ($un_{it}, agr_{it}, food_{it}, bev_{it}$ and con_{it}). In fact, with the only exclusion of con_{it}, within this latter group all variables are time invariant. Since they express structural (i.e, almost constant in the short and medium run) characteristics of the local economies, the respective value is taken at the beginning of the period with the most intense entry rate, that is, in 2011.

The assumption here maintained is that all these variables are exogenous with respect to the hazard rate (or survival) functions to be estimated (see next section). This seems largely plausible for variables depending on the market evolution and on the local environment while it could be questionable for individual-specific variables whenever they are time-variant and may express strategic choices that depend on entry/exit decision. Nonetheless, here most of the idiosyncratic variables considered are time-invariant and aims at expressing permanent (i.e., unchanging) features and choices of each individual microbrewery.

4.2. The entry and exit models

To empirically investigate the entry and exit dynamics we specify and estimate models known in the econometric literature as Event History or Duration or Survival Models (SM). Here, for simplicity, we adopt this latter denomination. SM aim at quantitatively analyzing and explaining, for a given individual, the elapsed time before a given event occurs. More generally, SM represent form and causes of a transition (the event) between two states of units observed over a finite time interval (Blossfeld et al., 2007; Hosmer and Lemeshow, 2008; Cleves et al., 2010). Here the two states are “in” or “out” the beer market and two possible transitions are admitted: from “out” to “in” (entry), from “in” to “out” (exit). The latter stage is absorbing, thus no further transition (re-entry) is possible.

Table 3: Entry and exit determinants (variables) used in the econometric analysis

Variable	Symbol	Geographical level	Year	Source
Market determinants				
Demand growth: avg. rate in the 3 years before entry	d_t	Country	1993-2014	www.assobirra.it
Life cycle: number of active microbreweries	n_t	Province	1993-2014	www.microbirrifici.org
Idiosyncratic determinants				
Type of microbrewery: agricultural brewery dummy	$type_i\_agr$			www.microbirrifici.org
Type of microbrewery: craft brewery dummy	$type_i\_crf$			www.microbirrifici.org
Number of different beers produced	$number_i$			www.microbirrifici.org
Bottom-fermentation beer production (dummy)	$beer_i$			www.microbirrifici.org
Learning: years from the beginning of the market before entry	$t_{EN,i}$			www.microbirrifici.org
Learning: years from entry in the market before exit	$t_{EX,i}$			www.microbirrifici.org
Spatial determinants				
Geographical:				
Geography: regional dummies[a]	reg_i	Region		www.microbirrifici.org
Geography: "Inner mountain" dummy	$alt1_i$	Municipality		www.microbirrifici.org ISTAT
Geography: "Inner hills" dummy	$alt3_i$	Municipality		www.microbirrifici.org ISTAT
Geography: "Plain areas" dummy	$alt5_i$	Municipality		www.microbirrifici.org ISTAT
Local:				
Local development: unemployment rate	un_{it}	Province	2011	ISTAT (Population Census)
Local milieu: % agricultural workforce (permanent employees only) on total population	agr_{it}	Municipality	2010	ISTAT (Agricultural and Population Censuses)
Local milieu: % employees of the food industry on employees of the whole manufacturing	$food_{it}$	Province	2011	ISTAT (Industry and Services Census)
Local milieu: % employees of the beverage industry on employees of the whole manufacturing	bev_{it}	Province	2011	ISTAT (Industry and Services Census)
Local milieu: Number of active microbreweries in the area	con_{it}	Province	1993-2014	www.microbirrifici.org

[a] To facilitate results' interpretation in comparative terms, of the 20 Italian regions one is excluded from the analysis (Friuli-Venezia-Giulia). Thus, the estimated models includes 19 regional dummies

In practice, these two transitions can be interpreted as independent events and can be studied separately. As often done in this empirical literature (Ozturk and Kilic, 2012), therefore, two separate models (an entry model and an exit model) are specified and estimated. This imply that, in principle, the drivers of entry and exit can be themselves different although, in fact, here we will consider as determinants the variables listed in Table 3 for both the entry and the exit model. But their impact on entry and exit is independent and, therefore, very likely differs (see section 3.2).

Let *t* be a discrete random variable indicating the timing of the event (when the event occurs). The probability that the event occurs at a given time t_1 during the observation period from time *0* to time *t** (where *t** is the end of the observation period) is expressed by the probability density function $f(t) = \Pr(t = t_1)$. The respective cumulative density function will thus be $F(t) = \sum_0^{t_1} f(t)$ and it expresses the probability that the event occurred from the initial period of observation up to time t_1. The same kind of information on the stochastic nature of the event, though in complementary way, can be provided through the so called *Survival Function S(t)*, expressing the probability that the event did not occurred from *0* up to t_1. Therefore, it is: $S(t) = 1 - F(t) = 1 - \sum_0^{t_1} f(t)$. Evidently, if the period of observation is finite from time *0* to *t** (as always occurs in empirical study) it can still be that $F(t^*)<1$ and $S(t^*)>0$. This problem of censoring is typical in this kind of analysis and will be discussed later.

Rather than (as using *F(t)* or *S(t)*), however, it is more practical to specify a SM with the *Hazard Rate Function*, *h(t)*, which can be simply defined as the ratio $h(t) = \frac{f(t)}{S(t)} = \left(f(t) \Big/ 1 - \sum_0^{t_1} f(t) \right)$.[9] Given the definition of $f(t)$ and $S(t)$ it follows that, in the continuous domain, it is $f(t) = -\frac{\partial S(t)}{\partial t}$. Therefore, it also follows that $h(t) = -\frac{\partial \ln S(t)}{\partial t}$ (Blossfeld et al., 2007; Hosmer and Lemeshow, 2008; Cleves et al., 2010).[10] SM are typically expressed in terms of *h(t)* and aim at investigating how it varies over time and if and how it is affected by covariates **X**. Therefore, we can distinguish between the unconditional hazard rate, $h(t)$, and the conditional hazard rate, $h(t|\mathbf{X})$. In the present case, as mentioned, two models are considered. One

---

[9] Consequently, the cumulative hazard rate function can be expressed as $H(t) = \sum_0^{t_1} h(t)$.

[10] Though *h(t)* depends on the probability that the event (or transition) occurs at a given time, strictly speaking it is not a probability as it may assume a >1 value.

concerns the event of entry for the generic i-th potential entrants, $h\left(t_{EN,i}\left|\mathbf{X}_{it}\right.\right), \forall i \in M$; the second model concerns the exit of the i-th incumbent microbrewery, $h\left(t_{EX,i}\left|\mathbf{X}_{it}\right.\right), \forall i \in N_{t_{EX,i}}$.

To empirically estimate these hazard rate functions we need empirical specifications of $h\left(t_{EN,i}\left|\mathbf{X}_{it}\right.\right) = g_{EN}\left(\mathbf{X}_{it}\boldsymbol{\beta}_{EN}, t_{EN,i}\right)$ and $h\left(t_{EX,i}\left|\mathbf{X}_{it}\right.\right) = g_{EX}\left(\mathbf{X}_{it}\boldsymbol{\beta}_{EX}, t_{EX,i}\right)$, where $\boldsymbol{\beta}_{EN}$ and $\boldsymbol{\beta}_{EX}$ are two vectors of unknown parameters to be estimated and where $\mathbf{X}_{it} = \left(\mathbf{MK}_t', \mathbf{ID}_{it}', \mathbf{SP}_{it}'\right)'$ with the exclusion of $t_{EN,i}$ and $t_{EX,i}$ than are now separately specified. In practice, an empirical specification of these hazard rate functions implies some arbitrary assumption on $g_{EN}(\cdot)$ and $g_{EX}(\cdot)$. One key assumption concerns whether and how the hazard rate depends on duration, that is, on $t_{EN,i}$ and $t_{EX,i}$, respectively. The major issue in this respect is whether to impose that the influence of duration on the hazard rate is homogenous across individuals or to admit heterogeneity, that is, such influence differs between units *i* and *j*, where $i, j \in M$ and $\forall i, j \in N_{t_{EX,i}}$ respectively. As such heterogeneity is captured by covariates (at least the individual and site-specific variables), the issue becomes whether we can assume that $h\left(t_{EN,i}\left|\mathbf{X}_{it}\right.\right) = h\left(t_{EN,j}\left|\mathbf{X}_{jt}\right.\right), \forall i, j \in M$ with $t_{EN,i} = t_{EN,j}$, and that $h\left(t_{EX,i}\left|\mathbf{X}_{it}\right.\right) = h\left(t_{EX,j}\left|\mathbf{X}_{jt}\right.\right), \forall i, j \in N_{t_{EN,i}}$ with $t_{EX,i} = t_{EX,j}$.

According to this assumption, two different kinds of SM models are distinguished. Models imposing homogeneity are called Proportional Hazard (PH) models. Models admitting heterogeneity are called Accelerating Failure Time (AFT) models. In fact, unobserved heterogeneity (also called *frailty* in this literature) could be still admitted also in PH models by stratifying the sample (*stratified PH models*) or by introducing random individual effects (*frailty PH models*). However, in the former solution the stratification may be arbitrary, while in the latter the interpretation of the results in terms of heterogeneous behaviour is not necessarily univocal. In this respect, AFT models represent a feasible and suitable alternative (Keiding et al., 1997).

The proportionality of the PH models depends on their assumption that the hazard rate ratio (i.e., the ratio between the hazard rates of two generic units) is constant as they move over time following the same pattern, that is, in parallel. Thus, the general expression of PH models is the following:[11]

---

[11] Note that there is no "error" term as the randomness is implicit to the survival process (Hosmer and

(3) $h\left(t_{EN,i}/\mathbf{X}_{it}\right)=h_0\left(t_{EN,j}\right)g_{EN}\left(\mathbf{X}_{it}\boldsymbol{\beta}_{EN}\right)$ and $h\left(t_{EX,i}/\mathbf{X}_{it}\right)=h_0\left(t_{EX,j}\right)g_{EX}\left(\mathbf{X}_{it}\boldsymbol{\beta}_{EX}\right)$

that imply these underlying survival functions:

(4) $S\left(t_{EN,i}/\mathbf{X}_{it}\right)=S_0\left(t_{EN,j}\right)\exp\left[g_{EN}\left(\mathbf{X}_{it}\boldsymbol{\beta}_{EN}\right)\right]$ and $S\left(t_{EX,i}/\mathbf{X}_{it}\right)=S_0\left(t_{EX,j}\right)\exp\left[g_{EX}\left(\mathbf{X}_{it}\boldsymbol{\beta}_{EX}\right)\right]$

For the sake of empirical tractability, it is usually assumed that $g_{EN}\left(\mathbf{X}_{it}\boldsymbol{\beta}_{EN}\right)=\exp\left(\mathbf{X}_{it}\boldsymbol{\beta}_{EN}\right)$ and $g_{EN}\left(\mathbf{X}_{it}\boldsymbol{\beta}_{EX}\right)=\exp\left(\mathbf{X}_{it}\boldsymbol{\beta}_{EX}\right)$. $h_0\left(t_{EN,j}\right)$ and $h_0\left(t_{EX,j}\right)$ are called *baseline hazards* and express how the hazard rate varies over time. By construction, this variation is homogeneous across units as it only depends on duration and not on covariates $\mathbf{X}_{it}$. An explicit (i.e. parametric) specification of the baseline hazard rates $h_0\left(t_{EN,j}\right)$ and $h_0\left(t_{EX,j}\right)$ is needed if we are interested in investigating how duration affects the hazard rate, thus survival. This is definitely the case here as we stressed that, due to entry strategies and learning processes, $t_{EN,j}$ and $t_{EX,j}$ are expected to affect the entry and the exit rates. However, if we were only interested in investigating how all the other determinants (i.e., $\mathbf{X}_{it}$) affect the entry and exit rates (therefore, the interest is in estimating $\boldsymbol{\beta}_{EN}$ and $\boldsymbol{\beta}_{EX}$) a very useful specification of (3) is the *Cox PH model*, also called *semiparametric PH model* just because the parametric specification does not apply to $h_0\left(t_{EN,j}\right)$ and $h_0\left(t_{EX,j}\right)$ which actually remains unspecified.

With respect to the Cox PH model, (3) can be modified in two directions. Firstly, it can be assumed that the hazard rate does not depend on $\mathbf{X}_{it}$, therefore the Cox PH model can be estimated as a unconditional hazard rates $h\left(t_{EN,i}/\mathbf{X}_{it}\right)=h_0\left(t_{EN,j}\right)$ and $h\left(t_{EX,i}/\mathbf{X}_{it}\right)=h_0\left(t_{EX,j}\right)$. As for terms $h_0\left(t_{EN,j}\right)$ and $h_0\left(t_{EX,j}\right)$ there is no parametric specifications, this is also called *nonparametric estimation* of the hazard rate function. In empirical works, the nonparametric estimate of the survival functions (and of the respective hazard rate functions) is usually obtained through the Kaplan-Meier estimation (Blossfeld et al., 2007; Hosmer and Lemeshow, 2008; Cleves et al., 2010). Though this is not informative on the impact of covariates on entry and exit rates, it is still very useful to analyse the shape taken by $h_0\left(t_{EN,j}\right)$ and $h_0\left(t_{EX,j}\right)$ over the duration time, and to test the proportionality hypothesis by performing this nonparametric estimation on sub-samples (groups of units) and assessing whether the estimated functions are parallel, as implied by PH models, or not.

Lemeshow, 2008).

The other direction to modify the Cox PH model is to provide an explicit/parametric specification of $h_0(t_{EN,j})$ and $h_0(t_{EX,j})$. These are the *parametric PH models*. With respect to the Cox PH model, this parametric specification imposes an *ex ante* arbitrary restrictions and, therefore, should be carefully evaluated on the basis of the nonparametric estimation of the unconditional hazard rate functions. Moreover, this arbitrary specification implies that different parametric PH models can be, in fact, adopted. In this respect, the most used specifications are the Exponential, Weibull and Gompertz PH models. As anticipated, they differ for specification of $h_0(t_{EN,j})$ and $h_0(t_{EX,j})$ implying further parameters to be estimated, in addition to $\boldsymbol{\beta}_{EN}$ and $\boldsymbol{\beta}_{EX}$, also called ancillary parameters. The value of these parameters affect the shape of the hazard rate with respect to duration time (i.e., t_{EN} and t_{EX}). A detailed analysis of these PH model specifications is beyond the scope of the present paper (for a technical treatment see Blossfeld et al., 2007, Hosmer and Lemeshow, 2008, Cleves et al., 2010). Just to make an example, the easiest specification is the Exponential PH model that takes the following form:

(5) $h(t_{EN,i}/\mathbf{X}_{it}) = \beta_0 \exp(\mathbf{X}_{it}\boldsymbol{\beta}_{EN})$ and $h(t_{EX,i}/\mathbf{X}_{it}) = \beta_0 \exp(\mathbf{X}_{it}\boldsymbol{\beta}_{EX})$

where the baseline hazard simply is a constant term to be estimated, $h_0 = \beta_0$. Therefore, such specification imposes a constant hazard rate over t_{EN} and t_{EX} which evidently is a strong assumption in the present case given the discussion in section 3.2. Weibull and Gompertz PH models are more general (in fact, the former admits the Exponential PH model as a special case) but still imposes monotonic baseline hazard rates, that is, always increasing or decreasing depending on the value of the respective ancillary parameters (p and γ, respectively).

To move to more general parametric specifications of the hazard rate, we need to adopt an AFT specification. The main advantage of these SM is that they allow for large heterogeneity across units not only because the hazard rate depends on covariates but also because the hazard rate ratio itself can vary over time.[12] Evidently, this argument applies to observed heterogeneity as resulting from the differences $\mathbf{X}_{it}$ within the sample, therefore from the individual and site-specific variables. In general terms, AFT specifications admit that t_{EN} and t_{EX} themselves depend on $\mathbf{X}_{it}$, $\boldsymbol{\beta}_{EN}$ and

---

[12] The term "Accelerating" refers to the fact that a variation of any covariate can either increase (accelerate) or decrease (decelerate) the positive impact of duration time on the survival function.

$\boldsymbol{\beta}_{EX}$. The commonly used AFT model specifications share the following expression of this dependence:

(6) $t_{EN,i} = \exp(\mathbf{X}_{it}\boldsymbol{\beta}_{EN})\exp(\varepsilon_{EN,i})$ and $t_{EX,i} = \exp(\mathbf{X}_{it}\boldsymbol{\beta}_{EX})\exp(\varepsilon_{EX,i})$

that is more often expressed in the logarithms as $ln(t_{EN,i}) = \mathbf{X}_i\boldsymbol{\beta}_{EN} + \varepsilon_{EN,i}$ and $ln(t_{EX,i}) = \mathbf{X}_i\boldsymbol{\beta}_{EX} + \varepsilon_{EX,i}$. $\varepsilon_{EN,i}$ and $\varepsilon_{EX,i}$ are two random terms whose distributional assumption leads to the consequent AFT model specification.[13] As in the PH models, also the AFT specification depends on ancillary parameters to be estimated: a constant term for the Exponential AFT model; p for the Weibull AFT model; σ for the Lognormal AFT model; γ for the Loglogistic AFT model; σ and κ for the Generalized Gamma AFT model. As before, these parameters decide of the shape of the hazard functions over time (t_{EN} and t_{EX}). In the case of the Lognormal, Loglogistic and Generalized Gamma AFT models, however, these parameters can take values implying non-monotonic hazard functions.[14]

Following this discussion, it should be clear that the AFT models do not include a baseline hazard (i.e., independent on $\mathbf{X}_{it}$ and, thus, homogeneous across individuals) (Blossfeld et al., 2007, Hosmer and Lemeshow, 2008, Cleves et al., 2010). Just to make an example, the Weibull AFT model implies the following hazard rate functions:

(7) $h(t_{EN,i}/\mathbf{X}_{it}) = p_{EN}\, t^{p_{EN}-1}\exp(-p_{EN}\mathbf{X}_{it}\boldsymbol{\beta}_{EN})$ and $h(t_{EX,i}/\mathbf{X}_{it}) = p_{EX}\, t^{p_{EX}-1}\exp(-p_{EX}\mathbf{X}_{it}\boldsymbol{\beta}_{EX})$

where p_{EN} and p_{EX} are the respective ancillary parameters to be estimated.[15]

4.3. Econometric issues

In present work we estimate a battery of alternative specifications of the entry and exit models. For both cases, we firstly compute the Kaplan-Meier nonparametric estimation of the hazard rate and survival functions. Then, we estimate the Cox, Exponential, Weibull and Gompertz PH models. Finally, we estimate the Exponential, Weibull, Lognormal, Loglogistic and Generalized Gamma AFT models. For all parametric models, $\boldsymbol{\beta}$ and ancillary parameters are estimated. As the hazard rate

---

[13] With a normal distribution we obtain the Lognormal AFT model; with a logistic distribution, the Loglogistic AFT model; with a extreme-value distribution, the Weibull AFT model and the Exponential AFT model as a specific case; with a gamma distribution, the Generalized Gamma AFT model.

[14] The Generalized Gamma, in particular, is extremely flexible in this respect allowing for many different shapes and admits the Exponential, the Weibull and the Lognormal shapes as special cases.

[15] Specifications in (7) collapse to the Exponential AFT case when $p_{EN} = p_{EX} = 1$.

functions of entry and exit are different (though dependent on the same set of covariates $\mathbf{X}_{it}$), the estimated parameters (included the ancillary ones) are specific for the two cases: $\boldsymbol{\beta}_{EN}$ and $\boldsymbol{\beta}_{EX}$, $\beta_{0,EN}$ and $\beta_{0,EX}$, p_{EN} and p_{EX}, σ_{EN} and σ_{EX}, γ_{EN} and γ_{EX}, κ_{EN} and κ_{EX}.

Parameters are estimated via Maximum Likelihood Estimation (MLE) (Blossfeld et al., 2007, Hosmer and Lemeshow, 2008, Cleves et al., 2010. In fact, the semiparametric Cox PH model is estimated via a partial likelihood function as it only involves parameters and not the baseline hazard that remains unspecified and it is excluded from the estimation procedure (Cox, 1972).[16] Therefore, the Cox PH model is estimated via Maximum Partial Likelihood Estimation (MPLE). It is worth emphasizing that these likelihood functions, and respective MLE procedures, take the peculiar nature of survival data into account: during the observation period, any entrant exits from the entry risk set M (that is, the set of potential entrants) and enters the exit risk set (that is, the set of incumbents) N_t whose size is, for this reason, time variant; at the same time, any exiting microbrewery also exits the respective risk set N_t. Therefore, the MLE accounts for the fact that, as the observation period is finite, some units belonging to the risk set (that is, the set of units for which the event can occur) experience the event outside the observation period (right-censoring).

Nonetheless, the present sample, as well as many other survival data, still incur other problems of censoring and truncation that can hardly properly managed within the adopted estimation approaches.[17] Left-censoring occurs in SM whenever units potentially belonging to the risk set experiences the event before the observation period. Left-censoring, therefore, is more problematic because it implies that not only some events are not observed but also the risk set misses some observations. Evidently, MLE can not take missing observations into account and, therefore, useful information for the proper identification and estimation of SM's parameters is lost (Blossfeld et al., 2007, Hosmer and Lemeshow, 2008, Cleves et al., 2010). Nonetheless, in the present case left censoring can be excluded for both the entry and the exit models. As already anticipated, here the observation period starts in 1993, that is, when the sector was still not existent and, therefore, entries and exits before this year (i.e., left censoring) can be reasonably excluded or are negligible.

---

[16] All estimations (Kaplan-Meier, MPLE and MLE) are performed with software STATA12.

[17] Censored and truncated observations are those units for which, due to how the sample is constructed and respective data collected, we do not observe the event and, therefore, we can not fully observe the influence of time and $\mathbf{X}_{it}$ on the event itself.

According to this argument data censoring and truncation does not jeopardize the validity of the estimation approaches here adopted for the exit model. Unfortunately, the same does not hold true in the case of the entry model as in this case either left or right truncation is likely to occur and the size of this truncation is unknown but presumably not negligible. Here, the entry model incurs truncation simply because the actual risk set for the entry analysis (the set *M* of potential entrants) is, in fact, unobservable. What we actually observe, and we call the *observed risk set* (M_{Obs}), is the set obtained merging all the incumbents' sets, i.e., $M_{Obs} = N_1 \cup N_2 \cup ..... \cup N_{t*}$. In such circumstance, we can not exclude that some potential entrants do not enter during the observation period and, therefore, these observations are missed simply because they never enter the risk set. This is a typical case of right truncation (Hosmer and Lemeshow, 2008).

But also left truncation can not be excluded. According to how the observed risk set is defined, here we implicitly assume that all microbreweries that actually entered in the markets were potential entrants from the very beginning, that is, from the initial year observation. In fact, they might have become potential entrants later but they are attributed a duration time that is still the period between the initial observation year and the time of entry.[18] In the case of right truncation we simply do not observe the covariates $\mathbf{X}_{it}$ of these unobserved units. In the case of left truncation we do not observe when observed units actually enter the risk set. So, they are partially unobserved (i.e., unobserved for some time during the period of observation) and we attribute their $\mathbf{X}_{it}$ to a duration which can be, in fact, overestimated.

In the case of the entry model, as both right and left truncation depend on unobserved units, this kind of issues can be hardly handled (either corrected or just assessed) within the estimation approaches here adopted.[19] In practice, we can not exclude that actual ML estimates are biased with the respect to the ML estimates that would be obtained if these unobserved unites were actually observed. The presence of this potential bias in the case of the entry model, therefore, suggests particular caution in interpreting the respective estimation results.

---

[18] This is a case of left truncation (Hosmer and Lemeshow, 2008) because at any point in time the minimum duration is the period between the beginning of the observation period and that point.

[19] For more details on possible solutions to right and left truncation see Klein and Moeschberger (1997).

5. Estimation Results

In the present section the econometric estimates concerning entries and exits in the Italian microbrewery sector (1993-2014) are presented following the same sequence of results. Firstly, the nonparametric estimates of the hazard rate and survival functions are presented and discussed in order to visually recognize how entry and exit are affected by duration, that is, the time spent by a given unit in the risk set. In addition, by computing these nonparametric estimations on groups of units, i.e. sub-samples, it is possible to visually assess whether the estimated functions move in parallel and, therefore, the PH hazard assumption may be valid or not.

Secondly, parametric estimates are presented and discussed in order to explicitly assess the role of covariates (see Table 3) on entry and exit processes. In particular, the respective estimated coefficients and significance tests performed on them allow formally testing the hypothesis put forward in section 3.2 and, therefore, the relative importance of the market determinants, of individual characteristics and of the spatial features (geographical and local factors). For the sake of completeness and comparison in order to better identify the robust evidence, the Cox PH model is initially estimated. As mentioned, not only this specification imposes proportional hazard but its estimation disregards the baseline hazard and, therefore, the possible influence of duration (or life time) on entry and exit hazard rate themselves. As a matter of fact, specifying the hazard rate and including it in the estimation not only explicitly estimates this influence but also affects these estimated coefficient of the other determinants. Thus, it provides a more complete picture on the determinants. This is achieved with the other PH models. All admitted specifications (see section 4.3) are considered and respective estimations performed. However, we do not report and discuss here estimates for all those specifications but only of the best performing models. These are selected according to the computed AIC.[20] These values are presented in Table 4 where it emerges that the Gompertz and the Weibull specifications are adopted for the entry and the exit PH models, respectively.

Finally, the assumption of the PH is removed in order to admit heterogeneity across units depending on how duration interacts with the individual-specific covariates. Also in this case, all specifications mentioned in the previous section are estimated though results are presented only for the Weibull AFT and the Lognormal AFT models, respectively, following the AIC (Table 4). In any case, following this

---

[20] All further model estimations for both the entry and the exit models are available upon request.

model selection criterion we should conclude that in the case of the entry model the best specification is the Gompertz PH model while it is the Lognormal AFT in the case of the exit model. Thus, in the two cases the PH assumption is implicitly accepted and rejected, respectively.

Table 4: Model specification selection: AIC of the alternative PH and AFT entry and exit model specifications (in bold the selected models)

Model specification:	Entry	Exit
PH		
Exponential	1864.62	646.28
Weibull	-89.98	**618.24**
Gompertz	**-503.23**	633.77
AFT		
Exponential	1864.62	646.28
Weibull	**-89.28**	618.24
Lognormal	586.00	**615.95**
Loglogistic	142.57	618.49
Generalized Gamma	620.98	616.78

5.1. Market entry

5.1.1. Nonparametric estimation: entry dynamics

Figure 4 displays the nonparametric Kaplan-Meier estimation of the (unconditional) survival function and the respective smoothed hazard rate estimate for market entry. Both estimated functions clearly express what already evident from Figures 1 and 2: the entry rate in the Italian microbrewery sector has constantly increased over the whole period and it is still is in its exponential or booming stage though some initial evidence of slowdown seems to emerge in very last few years of observation. In this respect, these functions are not particularly informative on the underlying market dynamics compared to the exit model (see below) that seems to be more insightful in this respect. This is at least partially due to the already mentioned severe limitation affecting the entry analysis: the underlying risk set is never actually observed, the assumption being that $M_t = M_{t+1} = M = M_{Obs}, \forall t$ with the consequent right and left truncation. The estimated survival function displayed in Figure 4, after all, is a further consequence of such truncation as function goes to 0 by the end the observation period just because the observed risk set (M_{Obs}) corresponds with the merge of all incumbents' sets.

Beside this descriptive evidence on the entry dynamics, however, the nonparametric estimation of the survival function is helpful to provide support in favor of the PH assumption implying that for all units (thus for all groups of units), their hazard rate moves over time following parallel patterns (and the hazard rate ratio remains constant). Figure 5 displays the Kaplan-Meier nonparametric estimation of the survival function on sub-samples. These are evidently distinguished on the basis of individual-specific variables and, in particular, the geographical location, the type of brewery, the type of beer produced.

On the former aspects we consider the sub-sample of units localized in the regions of North-East-Centre (NEC) of Italy that are typically considered exemplary of that Italian economic development pattern based on localized systems of specialized small-medium enterprises (Becattini and Coltorti, 2006). Visual inspection clearly indicates that no significant difference emerges among the two groups in terms of survival function. This is confirmed by the 95% confidence bands that are largely overlapping.

Higher support in favor of significant heterogeneity in the survival function emerges in the case of sub-samples distinguished on the basis of production typologies. The difference between agricultural microbreweries and the others craft breweries is, in fact, evident but not particularly large while, on the contrary, it seems remarkable comparing bottom-fermentation and top-fermentation beer productions. The respective 95% confidence bands do not overlap over the whole period. According to this comparison, the conclusion is that at least with respect to these individual characteristics a significantly heterogeneous baseline hazard occurs and this violates the PH assumption.

5.1.2. Determinants of market entry: PH and AFT model estimates

Table 5 reports the estimates of the entry model according to the three specifications that are worth discuss and compare. In interpreting these estimation results, it should be taken in mind that for both the entry and the exit models the estimated relationship is the hazard rate function and, therefore, the dependent variable is the hazard rate. Consequently, the sign and magnitude of the estimated coefficients have to be interpreted in terms of impact on the hazard rate of entry and exit respectively. All models allow testing the hypotheses put forward in section 3.2 though, in fact, the Cox PH model not only assumes proportional hazard, thus constant hazard ratios, but also provides a partial parametric estimation as it does not include the parameters possibly entering the baseline hazard specification. This complete parametric representation is achieved with the Gompertz PH model thus allowing to explicitly test the role of duration on the hazard rate function and, consequently, the hypothesis about the microbrewery life cycle (Hypothesis n. 4). In this latter respect, the Weibull AFT allows for a more flexible impact of duration on the hazard rate by interacting with the observables and, thus, admitting heterogeneity across units.

Having these differences clearly in mind, it is firstly helpful to concentrate on robust results, those that are confirmed across the three specifications of the entry model. For the sake of comparison, it is worth reminding that in Weibull AFT specification the interpretation of the estimated coefficients' sign is the opposite compared to the PH models: a negative coefficient analogous to a positive coefficient in the two PH specifications and implies an increase in the entry hazard rate survival time (a lower entry time).

The two variables expressing market determinants are statistically significant, concordant in all three specifications and generally confirm the hypotheses. In particular, Hypothesis n.1 is accepted as it emerges that hazard rate increases (thus, entry time decreases) when demand growth is higher though the magnitude of this effect strongly declines in the AFT specification. This result can be interpreted as a confirmation that the market signal to which the rise of microbrewery responds is, among others, the increase in beer demand itself maybe because it signals, in fact, some more specific (and here unobserved) changes in the composition of this demand. Estimates concerning the sector life cycle (Hypothesis n.2) indicate that the hazard rate decreases (entry time increases) when the number of microbreweries operating in the market increases. This is consistent with the fact, though the sector seems to be still in its booming (or exponential) stage of the life cycle (see Figures 1, 2 and 4), it is probably close to reach maturity and, therefore, the numerosity already reached the threshold that makes congestion effects prevail. Also in this case, however, the AFT specification strongly reduces the impact of this variable on the entry time compared to PH specifications.

Also the idiosyncratic determinants seem to have a major role in affecting the entry time. In particular, the two dummies expressing the microbrewery typology are statistically significant and concordant across all model specifications though, again, with a much lower magnitude in the AFT case. Agricultural and craft breweries (i.e., those typologies that more closely express the idea of home-made or self-produced beers), both show a lower hazard rate, thus longer entry time. This confirms the interpretation proposed in section 3.2.2 and also indicated by the nonparametric estimation represented in Figure 5: the rise of agricultural microbrewery is pretty recent. In practice, it is concentrated in the last five years of the observation period, that is, after the introduction of the respective regulation in Italy. Considering the risk has been here identified (as the merge of all incumbents' sets), the consequence of this recent and intense rise of agricultural microbreweries is a higher entry rime (thus, lower hazard rate) of this typology.

For the other hypotheses concerning the individual characteristics, estimation results provide mixed evidence. First of all, the number of different beers and the dummy capturing the bottom-fermentation production are statistically significant in the Cox PH model but not in the other two specifications thus confirming the semiparametric model may miss, and misrepresent, some of the actual drivers of the entry dynamics. Secondly, these statistically significant parameters fully confirm expectations as entry time is lower for more diversified microbreweries as expected (Hypothesis n.3). The result concerning the bottom-fermentation production indicates a shorter entry time compared to top-fermentation production and it can be explained by the fact that during the progressive rise of craft beers' production and consumption in Italy we also observe a shift from the more typically home-made and self-crafted bottom-fermentation beers to more commercial-oriented beers, thus closer to industrial production.

A final set of potential entry determinants are the spatial variables, either geographical or local factors. As anticipated, the literature on agro-food emerging sectors and on the Italian industrial development pays major attention to this spatial dimension. Therefore, the respective coefficient estimates reported in Table 5 represent the most interesting and original results of the present study. In this respect, however, results are somehow surprising and deserves careful and cautious interpretation. If we limit the attention the Cox PH model estimates, estimates confirm that geography matters though not always in the expected directions. The entry time is higher for units located in the NEC regions and in mountainous areas (Hypothesis n.6). The obvious interpretation is that in these relatively remote or less integrated territories starting a new business is less likely or deserves a more cautious evaluation. The local socio-economic environment matters, as well, but also in this case ex-ante hypotheses are not always accepted. The degree of local development (as expressed by a low unemployment rate) does not facilitate entry (Hypothesis n.7) while congestion effects prevail on agglomeration economies as the specialization in food production and the local concentration of microbreweries are themselves factors that increase the entry time. A sort of agglomeration economy, however, remains in the case of specialization in beverage production which may evidently concern, in Italy, the presence of local wine production (Hypothesis n.8).

Nonetheless, also this critical relevance of the spatial factors in explaining the entry dynamics actually vanishes when we move from the semiparametric to the parametric models, both PH and AFT. These two specifications are very concordant in indicating that no geographical or local factor is, in fact, a statistically significant determinant of the entry time. This can be interpreted as a further confirmation that the incomplete representation of the entry process provided by the Cox PH specification may eventually overemphasize the role of some individual-specific factors (spatial features, in the present case) while, in fact, the real underlying driver is time duration itself either homogenously (as in parametric PH models) or heterogeneously (as in AFT specifications) across units.

This is clearly confirmed by the fact that the additional parameters of the parametric specifications (the ancillary parameters) are strongly statistical significant. Their magnitude is a further expression of the currently booming entries in the Italian microbrewery sector.[21] In the Gompertz PH model, parameter γ is statistically greater than 0 and close to unity thus indicating that entry time increases as duration itself increases. The Weibull AFT model confirms this impact of duration on the hazard rate through the very high (close to 9) value of parameter p. Therefore, as could be expected for the fact that entries are so strongly concentrated in the last years of the observation period, the prevalence of a "wait and see" strategy is accepted (Hypothesis n.4) though it is, again, at least partially the consequence of how the entry risk set is defined.

In addition, this result confirms the acceleration effect, that is, that duration reinforces the impact of determinants (either positive or negative) on the hazard rate and, therefore, this generates heterogeneity across units due to the individual-specific determinants. Eventually, whenever this impact of duration on the entry time is admitted in the model, the apparently major role of space vanishes and only the market and individual determinants maintain their role.

---

[21] Constant terms themselves are significant but this should not be associated any particular meaning as they only serve to scale the baseline hazard (in the PH specifications).

5.2. Market exit

5.2.1. Nonparametric estimation: exit dynamics

The entry model estimates presented above provides a limited, and quite predictable, information on the market dynamics within the growing Italian microbrewery sector. The prevailing, though slowing down, booming stage represents the major explanatory driver of the entry dynamics. Also the apparently relevant spatial factors become negligible with respect to this generalized expansion. In addition, as already stressed, right and left truncation may have severe implications and suggests caution in the interpretation of the econometric estimates.

On the contrary, the exit model is expected to provide more insightful evidence on the actual processes underlying the explosive growth of the Italian microbrewery. In particular, it allows to assess whether the firm turnover has actually increased in the last years within this sector and to investigate the nature and the drivers of this increase. Figure 6 displays the Kaplan-Meier nonparametric estimation of the survival function and the respective hazard rate function. Unlike the entry model, the survival function does not evidently decline to zero, as many microbreweries are still incumbent at the end of the observation period.

The quite low estimated hazard rates are consistent with a booming sector: among the microbreweries that entered the market over the 1993–2014 period the probability that they are still incumbent after 15 years from entry is higher than 60%.[22] Nonetheless, it is interesting to notice that the survival function does not decline linearly as clearly demonstrated by the non-monotonic hazard function. This latter grows in the first years after entry and achieves the maximum value at the sixth year. Then it declines and grows again to reach another peak after 13 years in the market.

Evidently, despite the apparently regular growth of the number of microbreweries in the Italian market, the entry/exit dynamics and, therefore, the firm turnover is more multifaceted and suggests more complex behavior and choices. Heterogeneous exit behavior might be part of this complexity. In fact, sub-samples distinguished in terms of geographical localization (NEC regions vs other regions) or type of beer produced (bottom-fermentation vs top-fermentation production) do not show significantly different survival functions as confirmed by the 95% confidence bands that are largely overlapping. The only significant heterogeneity of the survival function concerns the microbrewery typology (agricultural microbreweries vs other typologies) though, in fact, the number of observed market exits is very limited (thus, not particularly meaningful) in the case of agricultural microbrewery.

5.2.2. Determinants of market exit: PH and AFT model estimates

Table 6 reports the estimates of the exit models according the three adopted specifications. For the sake of comparison, it is worth reminding that, as for the Weibull AFT specification in the case of the entry model, here the Lognormal AFT specification implies opposite interpretation of the estimated coefficients' sign compared to the PH models. All parameter estimates are consistent in sign across the specifications though, again, the magnitude is smaller in the AFT model. Starting with the market determinants, the increase of market demand does not impact on exit according to the expectation (Hypotheses n.1) as the chance of exiting the market actually increases with an higher beer demand growth. The interpretation can be that a more intense demand growth, while increasing entries, also induces more turnover within the sector. None can be said, on the contrary on Hypothesis n.2, that is, the impact of numerosity of incumbents as the respective coefficient is not statistically different from zero. Evidently, exit dynamics does not depend on this numerosity as the booming stage of the life cycle increases the incumbents and this also increases the turnover thus offsetting the reduction in the exit probability associated with this intensive market growth.

The individual determinants, if statistically different from zero, are consistent in terms of their influence on exit hazard rate (thus, exit time). Agricultural microbreweries show higher capacity to remain in the market and diversification itself (as expressed by the number of different beers produced) increases the survival time thus confirming Hypothesis n.3. These are, actually, the only determinants that significantly increase the survival rate thus confirming that in the rise of the Italian microbrewery sector, agricultural microbreweries with diversified production seem to be the winning players.

Unlike the entry model, the estimates of the exit model suggest that the spatial determinants play a significant role and this evidence seems robust across model specifications. Geography matters as, although altitude does not play any role in the exit dynamics, coefficients associated to regional dummies are statistical significant in

---

[22] Since microbreweries older than 15 years are very few (just 26), the nonparametric estimation of the hazard

several cases (Hypothesis n.6). The survival rate is lower (i.e., exit hazard rate higher) is some regions and this evidence concerns all parts of Italy: the North-Western part (Lombardy), NEC regions (Emilia-Romagna, Toscana) and the Centre-Southern part (Abruzzo and Sicily). The interpretation of these regional effects, however, may actually differ. In Centre-Southern regions the overall economic conditions, as well as a "beer culture" still not very developed, may be less favorable for the survival of new microbreweries while, on the contrary, in Northern or NEC regions the congestion effects due to already high microbreweries' concentration may imply a more intense turnover within the sector.

Local factors, on the contrary, are not significant drivers of survival. No clear evidence emerges in terms of influence of the local socio-economic development (Hypothesis n.7) and of local agglomeration economies or diseconomies (Hypothesis n.8) on the rise and success of microbreweries. The only exception concerns the agricultural specialization which seems to decreases the survival rate of microbreweries. However, rather than express some localized congestion effect, this result expresses the fact that a higher presence of agricultural employment, in Italy as well as in most countries, is not an indicator of agricultural specialization but rather of a limited overall economic development. In this context, while agricultural microbreweries may more easily rise from a prevalence of the agricultural activity over other sectors, this does not imply in any case a higher degree of success within the market.

A final set of estimated parameters are those associated to the fully parametric specifications (ancillary parameters): these are the constant terms (β_0), and the p and σ parameters that express the baseline hazard in the case of the Weibull PH model, and the acceleration effect of duration in the case of the Lognormal AFT model, respectively. Constant terms are significant but, as mentioned, this should not be associated any particular meaning. The estimated parameter p of the Weibull PH suggests that the hazard functions increases with duration therefore the chance of exit increases as survival in the market proceeds. However, parameter value is between 1 and 2 and, thus, the implied hazard rate pattern is not far from being constant (Cleves et al., 2010).

A different result about how the entry hazard rate changes with duration is observed in the Lognormal AFT model. It is worth reminding that such functional specification admits non-monotonic hazard function with coexisting period of

---

function is not available from the fifteenth year onwards.

increasing and declining hazard rates (Cleves et al., 2010). Here, the estimated parameter σ (statistically equal to 1) indicates an hazard rate function that after a short period of increase tends to very slowly decline and, in fact, to remain almost constant. This latter evidence would indicate a complex, but fully coherent, learning process with an initial period, after entry, of active exploration than followed by a longer period of passive learning (Hypothesis n.5). It seems also consistent with the non-monotonic nonparametric estimation of the exit hazard rate displayed in Figure 6.

6. Concluding remarks

The recent intense rise of microbrewing in Italy represents a very interesting case of emergence of a new sector and market. Powerful and versatile econometric tools put forward by the so called survival analysis (or EHA) now allows for a sophisticated and comprehensive investigation of the determinants of this dynamics. In particular, geographical and local factors are often emphasized in explaining the trajectories of emerging sectors in Italy especially concerning relatively mature industries based on small-size firms. Microbrewery could be considered just another successful example of this “Italian way” to local economic and industrial development. In fact, there is no local tradition of beer production in Italy and, therefore, this local bottom-up factor of success may be seriously questioned. Empirical results confirm that, at least in this specific case, the spatial factors are largely overemphasized. Local factors do not play a significant role and no evidence in favor of major local agglomeration economies or diseconomies seems to emerge.

The key drivers of the Italian microbrewery boom do not seem to have a spatial specificity. Market growth plays a role both on entries and exits thus, in fact, resulting in a greater impulse to market turnover and leading the sector towards maturity out from the previous intense booming stage. Eventually, however, the main determinants actually depend on the individual choices and characteristics of microbreweries. On the one hand, a large part of the boom observed in the last years should be ascribed to agricultural microbreweries. Whether this latter aspect is attributable to successful production solutions and changing consumer preferences or to the favorable conditions granted by the recent Italian legislations deserves further and more careful investigation. Nonetheless, this success of agricultural microbreweries seems associated to an higher degree of product diversification and, therefore, to a stronger market-orientation of these more recent entries in the market.

A final consideration concerns the appropriate entry and exit model specifications especially for the underlying dynamics they implicitly assume. In general terms, while a PH specification seems to be valid in the entry case, a suitable exit modelling requires a AFT model as it is evidently needed to fully capture the heterogeneity across units especially in terms of how duration affect the exit decision and, therefore, of the underlying economic processes (mostly learning). Results suggest that the hazard rate of both entry and exit is not independent from the time duration spent by microbreweries as potential entrants and incumbents and this dependence is not necessarily monotonic. This indicates that a microbrewery life-cycle hypothesis can be put forward as a consequence of individual market strategies and learning processes. These latter aspects may deserve further investigation and empirical evidence.

References

Aizenman, J. and Brooks, E. (2008). Globalization and taste convergence: The cases of wine and beer, *Review of International Economics* 16: 217-233.

Arora, A., Bhaskar, A., Minten, B., Vandeplas, A. and Swinnen, J. F. M. (2011). Opening the Beer Gates: How Liberalization Caused Growth in India's Beer Market. In Swinnen, J. F. M. (ed.), *The Economics of Beer*. Oxford: Oxford University Press, 308-332.

Bagnasco, A. (ed.) (1988). *La Costruzione Sociale del Mercato*. Bologna: Il Mulino.

Becattini, G. (ed.) (1979). *Dal Settore Industriale al Distretto Industriale. Alcune Considerazioni sull'Unità di Indagine dell'Economia Industriale*. Bologna: Il Mulino.

Becattini, G. and Coltorti, F. (2006). Areas of Large Enterprise and Industrial Districts in the Development of Post-war Italy: A Preliminary Survey. *European Planning Studies* 14(8): 1105-1138.

Bentzen, J. and Smith, V. (2010). Developments in the Structure of Alcohol Consumption in OECD Countries. Paper for the pre-AARES conference workshop. Adelaide.

Blossfeld, H.-P., Golsch, K., Rohwer, G. (2007). *Event History Analysis with Stata*. New York: Psychology Press.

Bontemps, C., Bouamra-Mechemache, Z., Simioni, M. (2013). Quality labels and firm survival: some first empirical evidence. *European Review of Agricultural Economics* 40(3): 413-439.

Bourdieu, P. (ed.) (1984). *Distinction: A Social Critique of the Judgement of Taste*. Cambridge: Harvard University Press.

Carboni, C. (ed.) (2009). *La Governance dello Sviluppo Locale. Città e Territori in Italia nell'Epoca della Globalizzazione*. Bologna: Il Mulino.

Carroll, G. R. and Swaminathan, A. (2000). Why the microbrewery movement? Organizational dynamics of resource partitioning in the U.S., *American Journal of Sociology* 106: 715-762.

Caves, R.E. (1998). Industrial organization and new findings on the turnover and mobility of firms. *Journal of Economic Literature* 36: 1947-1982

Clementi, G.L. and Palazzo, B. (2013). Entry, Exit, Firm Dynamics, and Aggregate Fluctuations. NBER Working Paper No. 19217, Cambridge, MA.

Cleves, M.A., Gould, W.W., Gutierrez, R.G. and Marchenko, Y.V. (2010). *An Introduction to Survival Analysis Using Stata*. 3rd Edition. College Station, TX: Stata Press.

Colen, L. and Swinnen, J. F. M. (2011). Beer-drinking nations: The determinants of global beer consumption. In Swinnen, J. F. M. (ed.), *The Economics of Beer*. Oxford: Oxford University Press, 124-140.

Cox, D.R. (1972). Regression models and life-tables (with discussion). *Journal of the Royal Statistical Society, Series B* 34: 187-200.

Deconinck, K. and Swinnen, J. F. M. (2011). From vodka to baltika: A perfect storm in the Russian beer market. In Swinnen, J. F. M. (ed.), *The Economics of Beer*. Oxford: Oxford University Press, 287-307.

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

Dunne, T., Klimek, S.D., Roberts, M.J., Yi Xu, D. (2013). Entry, Exit and the Determinants of Market Structure. *The RAND Journal of Economics* 44(3): 391–583.

Esposti, R., Sotte, F. (2002). Institutional Structure, Industrialization and Rural Development. An Evolutionary Interpretation of the Italian Experience. *Growth and Change* 33 (1): 3-41.

Fastigi, M. (2015). Un settore economico in fermento: il caso dei birrifici artigianali in Italia. Ph.D. Dissertation, Department of Economics and Social Sciences, Università Politecnica delle Marche, Ancona (Italy).

Flack, W. (1997). American microbreweries and neolocalism: “Ale-ing” for a sense of place. *Journal of Cultural Geography* 16: 37-53.

Garavaglia, C. (2010). Birra, identità locale e legame territoriale, *Agriregionieuropa*. http://agriregionieuropa.univpm.it/content/article/31/20/birra-identita-locale-e-legame-territoriale.

Garavaglia, C. (2015). Entrepreneurship and entry of small firms into a mature industry; the case of microbreweries in Italy. AAWE Working Paper No. 179 – Economics, American Association of Wine Economists, New York.

Geroski, P. (1991). *Market dynamics and entry*. Cambridge (UK): Blackwell Publishers.

Goldammerm, T. (ed.) (1999). *The Brewer's Handbook*. Clifton: KVP Pulishers.

Gourvish, T. R. (1998). Concentration, diversity and firm strategy in European brewing, 1945–90. In Wilson, R. G. and Gourvish, T. R. (eds), *The Dynamics of the International Brewing Industry since 1800*. London: Routledge, 80–92.

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology* 78: 1360-1380.

Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *American Journal of Sociology* 91: 481-510.

Harvey, D. (ed.) (2004). *The Condition of Postmodernity: An Enquiry into the Origins of Cultural Change*. Cambridge: Blackwell.

Hosmer, D.W., Lemeshow, S. (2008). *Applied Survival Analysis. Regression Modelling of Time to Event Data*. 2nd Edition. New York: John Wiley & Sons.

Hornsey, I. S. (ed.) (2003). *A History of Beer and Brewing*. Cambridge: The Royal Society of Chemistry.

Jelinek, B. (1946). Top and bottom fermentation systems and their respective beer characteristics. *Journal of the Institute of Brewing* 52(4): 174-181.

Johnston, J. and Baumann, S. (eds) (2010). *Foodies: Democracy and Distinction in the Gourmet Foodscape*, New York: Routledge.

JunFei, B., JiKun, H., Rozelle, S. and Boswell, M. (2011). Beer battles in China: The struggle over the world's largest beer market. In Swinnen, J. F. M. (ed.), *The Economics of Beer*. Oxford: Oxford University Press.

Keiding, N., Andersen, P.K. and Klein, J.P. (1997). The role of frailty models and accelerated failure time models in describing heterogeneity due to omitted covariates. *Statistics in Medicine* 16(1-3):215-24.

Kleban, J. and Ingeborg, N. (2011). The U.S. craft brew industry. *Proceedings of the International Academy for Case Studies* 18: 33-38.

Klein, J.P. and Moeschberger, M.L. (1997). *Survival Analysis Techniques for Censored and Truncated Data*. New Yrok: Springer-Verlag.

Leifman, H. (2001). Trends in population drinking. In Norström T. (ed.), *Alcohol in Post-War Europe: Consumption, Drinking Patterns, Consequences and Policy Responses in 15 European Countries*. Stockholm: National Institute Of Public Health.

Magatti, M. (Ed.) (2002). *Mercato E Società: Introduzione Alla Sociologia Economica*. Roma: Carocci.

Ozturk, S. And Kilic, D. (2012). Patterns and Determinants of Entry and Exit in Turkish Manufacturing Industries. *International Journal of Arts and Commerce* 1(5): 107-118.

Pakes, A. and Ericson, R. (1998). Empirical Implications of Alternative Models of Firm Dynamics. *Journal of Economic Theory* 79: 1-45.

Poelmans, E. and Swinnen, J. F. M. (2011). A brief economic history of beer. In Swinnen, J. F. M. (ed.), *The Economics of Beer*. Oxford: Oxford University Press.

Pratt, J. (2007). Food values. The local and the authentic. *Critique of Anthropology* 27, 285-300.

Schnell, S. M. and Reese, J. F. (2003). Microbreweries as tools of local identity. *Journal of Cultural Geography* 21: 45-69.

Shortridge, J. R. (1996). Keeping tabs on Kansas: Reflections on regionally based field study. *Journal of Cultural Geography* 16: 5-16.

Shortridge, B. G. and Shortridge, J. R. (eds) (1998). *The Taste of American Place*. Lanham: Rowman and Littlefield.

Swaminathan, A. (1998). Entry into new market segments in mature industries: Endogenous and exogenous segmentation in the U.S. brewing industry. *Strategic Management Journal* 19: 389-404.

Tremblay, V. J. and Tremblay, C. H. (eds) (2005). *The U.S. Brewing Industry: Data and Economic Analysis*. Cambridge: MIT Press.

Trigilia, C. (ed.) (2005). *Sviluppo Locale. Un Progetto per l'Italia*. Roma-Bari: Laterza.

Figure 4: Market entry: Kaplan-Meier survival function (left) and smoothed hazard rate function (right)

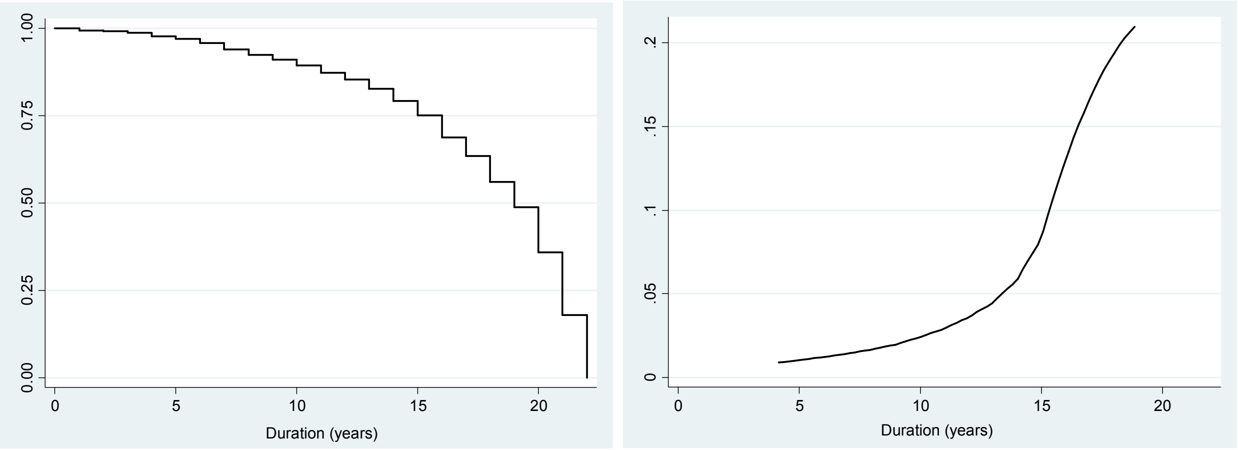


Figure 5: Market entry: Kaplan-Meier survival function for different subgroups of microbreweries

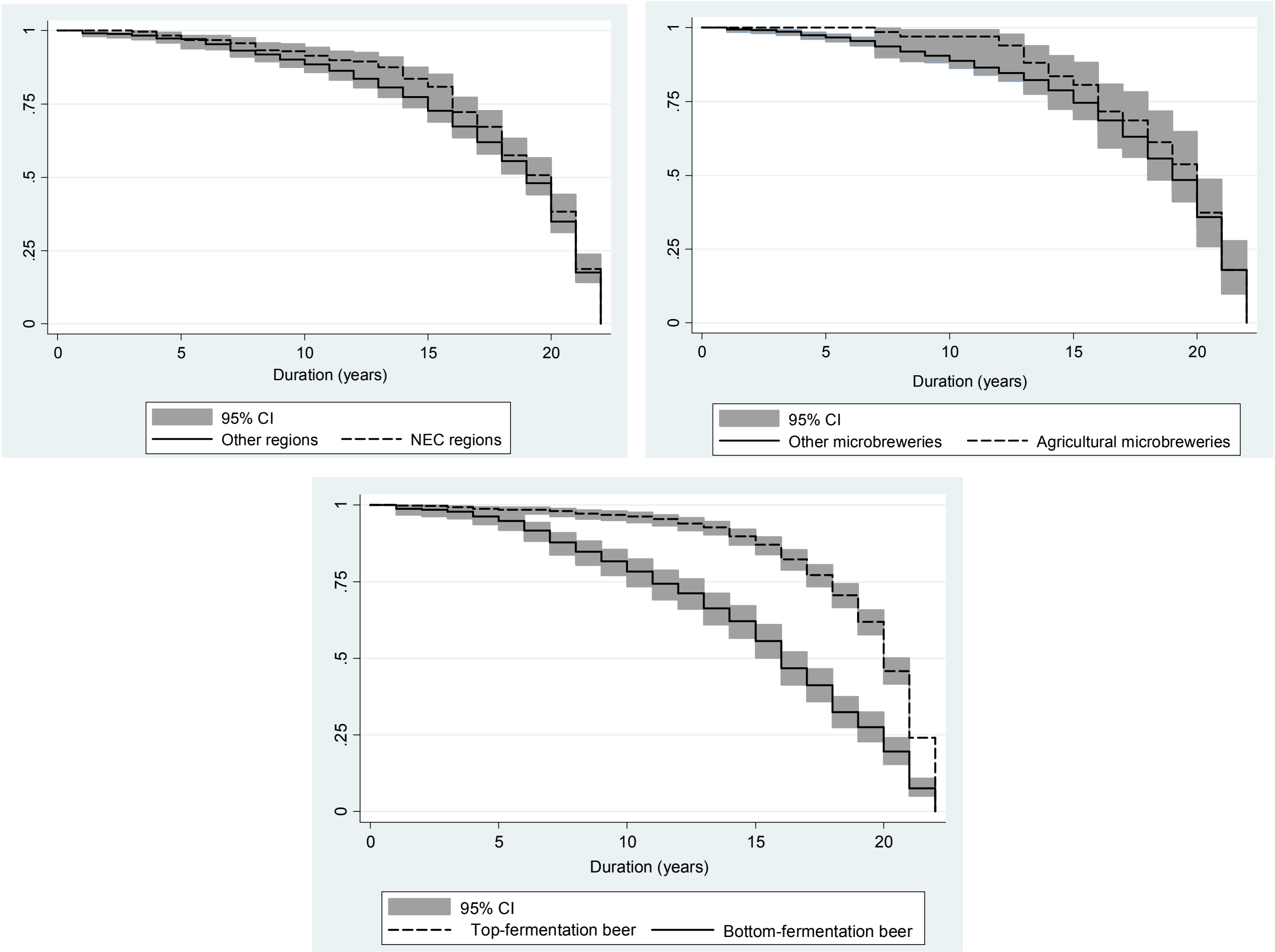


Figure 6: Market exit: Kaplan-Meier survival function (left) and smoothed hazard rate function (right)

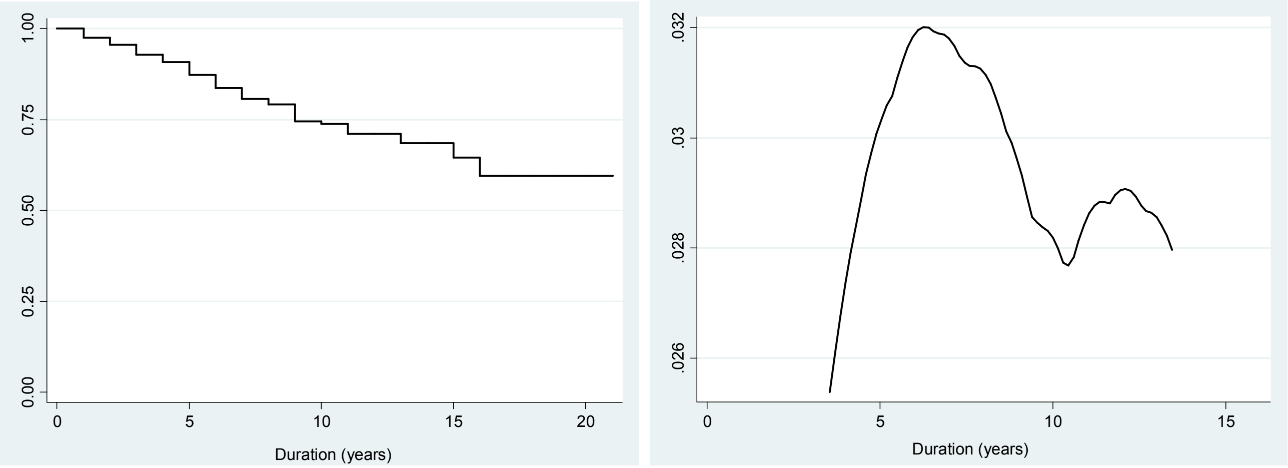


Figure 7: Market exit: Kaplan-Meier survival function for different subgroups of microbreweries

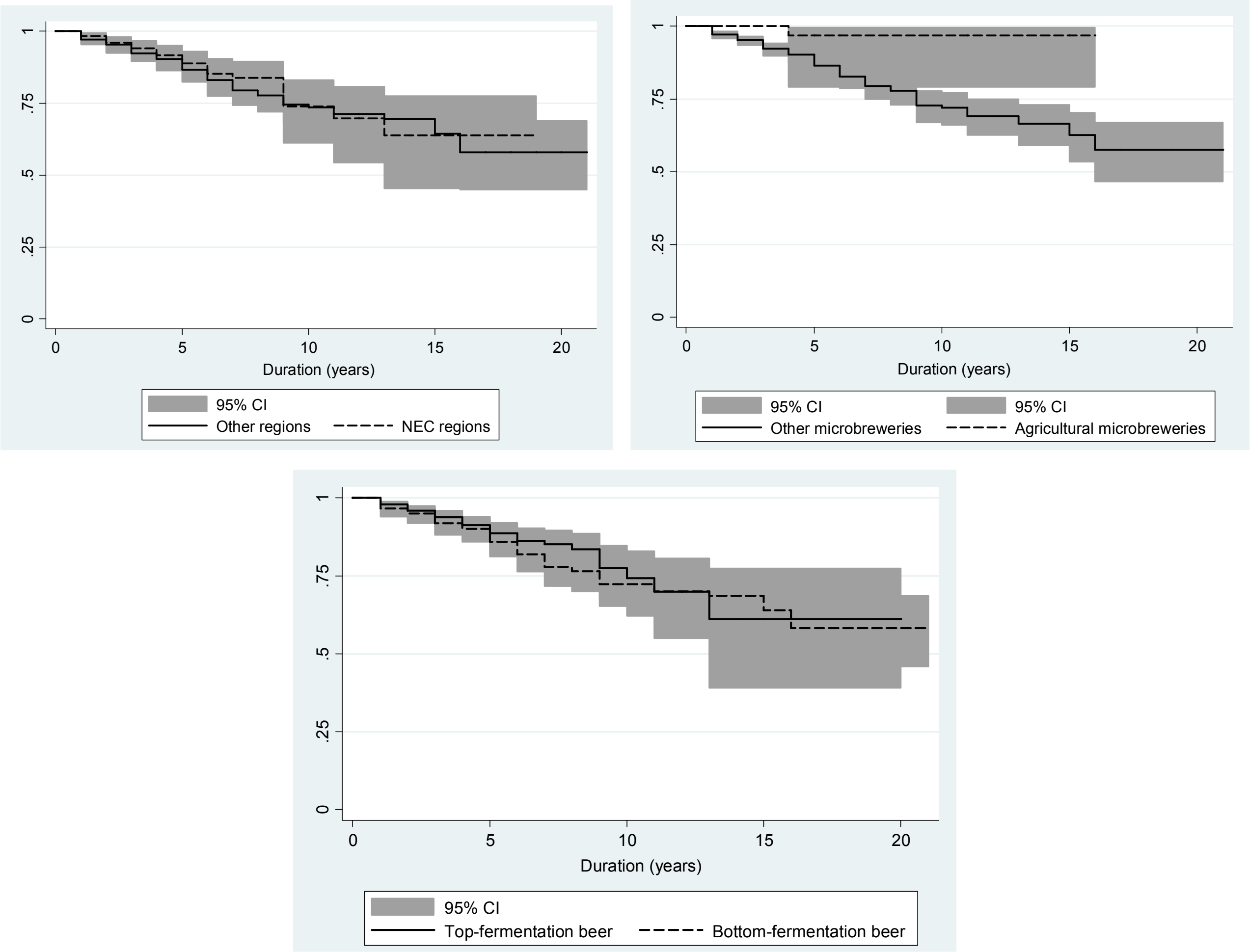


Table 5: The entry model: parameter estimates of the Cox, Gompertz PH and Weibull AFT models (estimated standard error in parenthesis)

Variable	COX (PH)		GOMPERTZ (PH)		WEIBULL (AFT)	
Market determinants						
d_t	0.194*	(0.033)	0.144*	(0.025)	-0.017*	(0.003)
n_t	-0.024*	(0.009)	-0.012*	(0.000)	0.001*	(0.000)
Idiosyncratic determinants						
$type_i\_agr$	-0.616*	(0.151)	-0.436*	(0.150)	0.044*	(0.017)
$type_i\_crf$	-0.511*	(0.096)	-0.387*	(0.097)	0.038*	(0.011)
$number_i$	0.042*	(0.005)	0.006	(0.007)	0.000	(0.001)
$beer_i$	0.311*	(0.084)	0.120	(0.082)	-0.011	(0.009)
Spatial determinants						
Geographical						
Altitude dummies:						
$alt1_i$	-0.313*	(0.130)	0.050	(0.126)	-0.006	(0.014)
$alt3_i$	-0.082	(0.092)	-0.118	(0.093)	0.011	(0.010)
$alt5_i$	-0.085	(0.142)	-0.109	(0.133)	0.011	(0.015)
Regional dummies:						
Valle d'Aosta	-0.331	(0.559)	-0.686	(0.556)	0.066	(0.063)
Piedmont	-0.195	(0.234)	-0.371	(0.238)	0.039	(0.027)
Lombardy	-0.365	(0.227)	-0.361	(0.229)	0.032	(0.026)
Veneto	-0.563*	(0.243)	-0.336	(0.246)	0.032	(0.028)
Trentino Alto Adige	-0.393	(0.313)	-0.530	(0.311)	0.055	(0.035)
Liguria	-0.195	(0.316)	-0.135	(0.310)	0.014	(0.035)
Emilia-Romagna	-0.873*	(0.250)	-0.395	(0.251)	0.040	(0.028)
Tuscany	-0.639*	(0.242)	-0.316	(0.241)	0.031	(0.027)
Umbria	0.076	(0.316)	-0.308	(0.312)	0.028	(0.035)
Marche	-0.628*	(0.266)	-0.198	(0.265)	0.020	(0.030)
Abruzzo	-0.284	(0.310)	-0.315	(0.307)	0.026	(0.034)
Molise	0.104	(0.485)	-0.395	(0.478)	0.042	(0.054)
Lazio	-0.088	(0.286)	-0.357	(0.277)	0.026	(0.031)
Campania	0.759	(0.427)	-0.613	(0.431)	0.053	(0.048)
Basilicata	0.105	(0.569)	0.055	(0.571)	0.008	(0.064)
Apulia	0.162	(0.385)	-0.653	(0.376)	0.058	(0.042)
Calabria	0.743	(0.512)	-0.441	(0.511)	0.037	(0.057)
Sicily	-0.068	(0.461)	-0.377	(0.456)	0.029	(0.051)
Sardinia	0.195	(0.438)	-0.469	(0.430)	0.043	(0.048)
Local						
un_{it}	-0.087*	(0.027)	0.019	(0.025)	-0.001	(0.003)
agr_{it}	-0.008	(0.006)	-0.006	(0.006)	0.001	(0.001)
$food_{it}$	-0.020*	(0.007)	-0.005	(0.007)	0.000	(0.001)
bev_{it}	0.101*	(0.040)	0.067	(0.051)	-0.006	(0.006)
con_{it}	-0.100*	(0.009)	-0.001	(0.010)	0.000	(0.001)
$\beta_{0,EN}$			-9.791*	(0.448)	2.439*	(0.038)
γ_{EN}			0.849*	(0.025)		
p_{EN}					8.892*	(0.271)

*Statistically significant at 5% confidence level

Table 6: The exit model: parameter estimates of the Cox, Weibull PH and Lognormal AFT models (estimated standard error in parenthesis)

Variable	**COX (PH)**		**WEIBULL (PH)**		**LOGNORMAL (AFT)**	
Market determinants						
d_t	0.283*	(0.119)	0.354*	(0.128)	-0.113*	(0.040)
n_t	-0.002	(0.044)	-0.001	(0.001)	0.001	(0.001)
Idiosyncratic determinants						
$type_i$ _agr	-2.173*	(1.046)	-2.222*	(1.047)	1.636*	(0.613)
$type_i$ _crf	0.171	(0.270)	0.189	(0.271)	-0.030	(0.186)
$number_i$	-0.258*	(0.039)	-0.282*	(0.041)	0.197*	(0.026)
$beer_i$	0.072	(0.246)	0.068	(0.249)	-0.148	(0.165)
Spatial determinants						
Geographical						
Altitude dummies:						
$alt1_i$	-0.069	(0.354)	-0.085	(0.353)	-0.011	(0.247)
$alt3_i$	0.249	(0.275)	0.216	(0.276)	-0.270	(0.189)
$alt5_i$	0.333	(0.396)	0.385	(0.399)	-0.327	(0.257)
Regional dummies:						
Valle d'Aosta	-4.082	(2.075)	-1.646	(1.964)	1.349	(1.187)
Piedmont	1.870	(0.809)	2.039*	(0.808)	-1.168*	(0.505)
Lombardy	2.024*	(0.770)	2.164*	(0.767)	-1.391*	(0.490)
Veneto	0.983	(0.855)	1.085	(0.856)	-0.450	(0.528)
Trentino Alto Adige	0.994	(0.960)	1.045	(0.958)	-0.690	(0.614)
Liguria	1.830	(0.967)	2.024*	(0.968)	-1.077	(0.637)
Emilia-Romagna	2.363*	(0.805)	2.547*	(0.803)	-1.637*	(0.515)
Tuscany	1.709*	(0.843)	1.828*	(0.841)	-1.330*	(0.526)
Umbria	1.876	(0.959)	1.931	(0.957)	-1.134	(0.643)
Marche	1.360	(1.036)	1.534	(1.038)	-0.621	(0.646)
Abruzzo	2.085*	(0.967)	2.256*	(0.976)	-1.185	(0.635)
Molise	2.311	(1.485)	2.572	(1.498)	-1.711	(0.934)
Lazio	1.782	(1.012)	1.974	(1.021)	-1.098	(0.623)
Campania	2.271	(1.253)	2.425	(1.267)	-1.230	(0.814)
Basilicata	2.163	(1.523)	2.349	(1.541)	-1.164	(1.071)
Apulia	2.246	(1.195)	2.383	(1.218)	-1.435	(0.736)
Calabria	0.805	(1.636)	1.060	(1.654)	0.126	(1.027)
Sicily	3.433*	(1.404)	3.777*	(1.455)	-2.208*	(0.849)
Sardinia	1.775	(1.298)	1.939	(1.324)	-0.944	(0.818)
Local						
un_{it}	-0.043	(0.071)	-0.047	(0.074)	0.014	(0.045)
agr_{it}	0.033*	(0.015)	0.034	(0.016)	-0.020*	(0.010)
$food_{it}$	-0.025	(0.021)	-0.030	(0.021)	0.007	(0.013)
bev_{it}	0.016	(0.111)	0.030	(0.113)	0.077	(0.076)
con_{it}	-0.048	(0.044)	-0.049	(0.044)	0.021	(0.028)
$\beta_{0,EX}$			-4.970*	(1.006)	2.863*	(0.582)
p_{EX}			1.565*	(0.135)		
σ_{EX}					1.033*	(0.080)

*Statistically significant at 5% confidence level