The Italian market of sparkling wines: latent variable models for brand positioning, customer loyalty, and transitions across brands' preferences

Abstract

The Italian market of sparkling wines has undergone a strong expansion driven by what can be defined as the "Prosecco phenomenon". It has extended the consumption reaching new and more complex segments with a wide offer of appellations, brands, and prices. We aim to evaluate the Italian market of sparkling wines to figure out the competitive associations among the major brands. We propose two different analyses to disentangle distinctive groups of brands. First, using information on scanner purchases of sparkling wines recorded by a consumer panel over a two-year period, and appropriate specifications of the latent class model, we cluster homogeneous groups of winery brands for the product attributes they propose to the market. Then, we analyze consumers' brand preferences in a dynamic perspective by employing a hidden Markov model to identify segments of brands perceived as similar. These results shed light on the loyalty behavior and its evolution over time in the market.

Keywords: sparkling wines, Prosecco, brand positioning, customer loyalty, latent class analysis, hidden Markov model

Introduction

The Italian market of sparkling wines has undergone a strong expansion driven by what can be defined as the "Prosecco phenomenon". In the last decade, the strong growth of the Prosecco market has been accompanied by an expansion of the supply aimed at reaching new markets and meeting the needs of a new and large circle of consumers. The supermarket shelf of sparkling wines has therefore been enriched with multiple variations of product and price: a consumer can choose among production processes (Charmat vs. Champenoise), appellations, sugar residual content (dry, extra dry, brut etc.), blend (cuveé), cru, rather than opting for green or organic version. The increase in competition has led the wineries to include sparkling wines in their supply, to create new brands and to try to reposition their brand in new market segments. Consequently, wineries have extended their assortment following a multi-brand strategy such as line extension, family brand and umbrella brands in merging wineries.

In 2018, the Italian market of sparkling wines reports a production of 6,7 million hectoliters, representing approximately 15.9% of the overall wine production. The domestic consumption is approximately 2.8 million hectoliters, corresponding to 12.8% of total consumption, while exports reach 3.9 million hectoliters (Corriere Vinicolo, 2019). The Italian sparkling wine production is dominated by Prosecco (approximately 4 million hectoliters in 2018; Compound Annual Growth Rate - CAGR 2018/2013 of 12.5%) having produced a strong pull effect on this market. The Italian domestic supply of sparkling wines is differentiated between the two productions or fermentation processes (Charmat and Champenoise or Traditional in Italy) and appellations. The Charmat wine (92% of total sparkling production) includes the major appellations such as Prosecco, Asti, Brachetto, while the traditional method accounts appellations such as Franciacorta, Trento, Oltrepo Pavese or Alta Langa which production is approximately

the 4-5% of the domestic one. There is a significant share of sparkling wines with no appellations.
Accordingly, the sparkling market growth has extended the consumption reaching new and more complex segments. While in the past the sparkling wine consumption was mostly seasonal and pulled by Christmas holidays, nowadays, the purchase occasions are larger and distributed along the year. More specifically, the wide offer of appellations, brands and prices has strongly increased the market penetration which is around 64% of Italian wine drinkers (Wine Intelligence, 2018) having different loyalty and consumption features.
This paper aims to evaluate the market of sparkling wines to identify the competitive relations among the main winery brands, showing loyalty and variety seeking by customers. Using information on purchases of sparkling wines recorded by a consumer panel over a two-year period, we identify homogeneous groups of brands (or brand portfolios). These results shed light on customers' preferences since they draw patterns of associations among brands and product features. Brands assigned to the same group are perceived as similar by customers. Then we analyze consumers' preferences dynamics looking at how they switch across brands in repeated purchases during the observational period. These results shed light on the loyalty behavior in the market. The goals are reached by applying to the data appropriate specifications of Latent Class (LC) models (Lazarsfeld & Henry, 1968; Clogg & Goodman, 1984; Pennoni, 2014) and by considering a Hidden Markov Model (HMM, Bartolucci et al., 2013) tailored for categorical data to capture unobserved customer's perceptions and to evaluate their evolution over time.
We apply the LC model, specifically, we estimate multilevel LC models (Vermunt, 2003) that allow us to identify homogeneous groups of brands in the market, exploiting all information derived from the consumer panel. The data is hierarchical: level-one units are purchases performed by sampled households in the two-year period, while level-two units are brands. The estimation of a multilevel latent class (MLLC) model that considers the fact that each customer can make more than one purchase in the reference period, allows us to identify homogeneous groups of brands in the market of sparkling wines. The brands in the same group are homogeneous for the type of products proposed to the market. This result sheds light on the competitive relations among the brands.
Previous works have already emphasized the benefits of the LC methodology to market analysis (Magidson & Vermunt, 2002), especially segmentation and dynamic segmentation (Bassi, 2013). This approach has indubitable advantages over traditional clustering methods (Bassi, 2007 and 2009). LC analysis attempts to explain the observed association between the factors that make up a multiway contingency table (Goodman, 1974a and 1974b) by introducing unobservable underlying classes (clusters). LC analysis explicitly considers the categorical nature of the observed variables, moreover LC clustering is a model-based clustering approach with parameters estimated via maximum likelihood. Classical cluster analysis, although vastly applied in marketing research, is a descriptive statistical technique and suffers from lack of robustness. LC clustering is simple and flexible at the same time, for example, it easily treats variables measured on different scales; moreover, restrictions can be imposed and tested on the parameters.
HMMs (Bartolucci et al., 2013) extend the latent class models to analyze longitudinal data, assuming the existence of a latent process which affects the distribution of the response variables. The latent process is assumed to follow a Markov chain with a certain number of states. HMMs are especially suitable to model customers' behavior and choices since they identify segments of clients (Paas et al. 2007; Pennoni et al., 2018) and allow to model the transition of customers from one latent state to another to capture the evolution over time (see, among others, Poulsen, 1990; and Netzer et al., 2008). In this

work, by employing HMM, we provide latent segments of brand preferences and we analyze the dynamics of subsequent purchases over time in the reference period; specifically, we identify groups of brands that are perceived as similar by the customers, we describe how customers switch across different brands, and predict possible acquisition patterns over time. These analyses add important information on customers' loyalty in this market.

The paper is organized as follows. Section 1 presents a review of the existing literature on wine market segmentation and consumer behavior with reference to sparkling wine. Section 2 illustrates the data and reports preliminary descriptive analyses. Section 3 introduces the proposed models. Section 4 provides estimation results. Finally, Section 5 discusses our findings and contains some concluding remarks.

1. Literature review

The literature on wine segmentation and branding is quite wide going back to nineties and before, studies on sparkling wine market are growing. The market of sparkling wines is young but it shows peculiarities at both production and consumption levels.

The literature on wine segmentation is wide (Szolnoki & Hoffmann, 2014; Stoddard & Clopton, 2015; Wolf et al., 2018) going from traditional approaches that follow socio-demographic criteria, behavioral and generational segmentation, psychographic variables such as lifestyles' segmentation and involvement attributes.

Wine segmentation is often associated with the consumer's involvement (Aurifeille et al., 2002) which plays a key role in the sparkling wine consumption (Charters et al., 2011; Morton et al., 2013; Verdonk et al., 2017). Following Taylor et al. (2018), the involvement is a combination of personal and social motivations that affect wine purchase through a complex interaction of intrinsic and extrinsic motivations. The intrinsic motivations refer to wine knowledge, to hedonic aspects (pleasure, enjoyment, relax, hobby, etc.), to social interactions (status symbol, power); extrinsic motivations are wine attributes (grape variety, origin, alcohol, price, winery brand, taste, aroma/bouquet, medals and awards, food pairing, etc., Taylor et al, 2018, p. 707). Ogbeide (2014) adopted the concept of enduring (stable and durable over time) involvement in the Australian wine market while showing that moderate and low involvement represents the majority of the market (58% and 27% of consumers, respectively).

Behavioral, generational and lifestyles' segmentations have been largely applied in wine markets worldwide while attracting the interest of large wine companies. For instance, the Project Genoma (Constellation Brands, 2014) segmented the American wine drinkers in six clusters (price driven, everyday loyal, overwhelmed, image seekers, engaged newcomers, enthusiasts) according to bottle price, wine involvement, age and gender, wine habits (where drinking and how much wine to drink, type of wine, etc.). A review of wine segmentation researches can be found in Stoddard and Clopton (2015) and Wolf et al. (2018).

Thach and Olsen (2004, 2006, 2015) segmented the US wine market following lifestyle, behavioral approaches. The lifestyle segmentation identified five themes (relaxed, dining ambience, fun and entertainment, social aspiration and travel) according to the occasion and place of drinking wine lifestyle. The behavioral segmentation reports low, moderate and high spenders according to the median bottle price purchase showing differences in gender and age. Liu et al. (2014) identified three segments on Chinese wine market (extrinsic/intrinsic attribute-seeking customers and the alcohol attribute-seeking customers) through a behavioral (or benefit) segmentation. Bruwer and Li (2007) and Bruwer et al. (2017) figured out four lifestyles segments in the Australian wine market:

basic, experimenter, enjoyment oriented and conservative wine drinker, looking at the demographic criteria (gender, education, etc.), wine knowledge and involvement (connoisseurs vs. no expert wine drinker), frequency of consumption (regular vs. occasional), place of consumption (home vs. restaurants), type of wine (still red/white/rosé and/or sparkling), place of purchase (supermarket. vs specialty shops).
King et al. (2012) segmented the Australian market as well in groups of white wine drinkers while identifying four wine styles according to the grape variety (New Zealand Sauvignon, Australian Sauvignon, Riesling and Chardonnay). Wine styles are compared using demographic variables and wine attributes. Geraghty and Torres (2009) identified three lifestyle segments in the Irish wine market: casual buyer, value seeking buyer, and traditionalists, using wine attributes (grape variety, wine style, winery brand), age, gender, education and monthly wine expense. Brunner and Siegrist (2011) found six segments in the Swiss wine market (price-conscious, knowledgeable, image-oriented, indifferent, basic and social wine consumers) by including price, knowledge, motivations and lifestyles. Szolnoki and Hoffmann (2014) made a behavioral segmentation of the German wine purchasers according to their marketing channel. They identified six groups of customers (discount store, food-retail, supermarket, cellar-door, wine shop and multichannel customers) by investigating socio demographic and behavioral variables.
Generational segmentation has received a growing attention, in the last decade. The interest of the wine industry is mostly focused on Millenials or Gen Y, which will pull the present and future wine consumption. Generations are defined by age cohorts (Millennials, after 1980; Generation X, 1964–1980; Baby Boomers, 1945–1964; Silent Generation, before 1945). Past researches investigated generational purchase and consumption differences in New Zealand (Fountain & Lamb, 2011), in the US wine market (Wolf et al., 2005, Qenani-Petrela et al., 2007, Olsen et al., 2007; Barber et al., 2008), in European and extra-European countries such as France, Germany, UK, Canada and US (Mueller et al., 2011), in US and Spanish Millennial consumers (De Magistris et al., 2011). In Italy, Agnoli et al. (2011, 2018) analyzed the behavior of Millennials in drinking wine and alcoholic beverages. Castellini and Samoggia (2018) have deeply investigated Millenials, evaluating their purchase and consumption habits as well as wine the neophobia.
The segmentation process was also applied to organic and biodynamic wine (Castellini et al., 2014; Castellini et al., 2017; Sultan et al., 2018), and, more generally, to sustainability-oriented and health-oriented wine consumption to figure out socio-demographic and behavioral differences in this segment (Pomarici & Vecchio, 2014).
Among wine attributes, the brand plays an important role in wine consumption while acting as a signal of quality for customers (Viot & Passebois-Ducros, 2010) and reducing the risk in purchase decisions (Brochado & Oliveira, 2018). However, the increasing number of brands, going from collective brands (appellations, organic, biodynamic, fair trade, etc.) to winery trademarks, have diminished the brand awareness while enlarging the brand repertoire of each wine drinker (Brochado & Oliveira, 2018). While country or regional origin, such as appellations, are expression of country or regional specificities (terroir, grape variety, history and culture, know-how), the plethora of winery brands are hardly recognized by consumers. For instance, in the Italian wine market there is a jungle of brands from strong producer brands (large wine companies) to weak producer brands (small size local wineries), from merchant brands to private labels or reserve brands within supermarket chains (Rossetto & Galletto, 2019).
In this scenario, the notion of brand does not always reflect factors building equity such as brand awareness, brand associations, brand loyalty and perceived quality (Viot & Passebois-Ducros, 2010; Spielmann, 2014; Brochado & Oliveira, 2018).

Customer's loyalty constitutes the largest component of brand's equity (Keller, 2003). While there is not a common or unique definition of brand loyalty, many authors agree that brand loyalty is a multidimensional construct defined either as behavioral or attitudinal dimension or a combination of them (Cengiz & Cengiz, 2015). The attitudinal loyalty is a purchase intention or, more simply, an intention to recommend the brand to others (without necessarily making repeated purchases). The literature on wine brand loyalty is focused on the behavioral approach, that is, consumers repeat the same purchase over time since they have acquired experience and built their own habits in consumption. Early, Uncles et al. (1994) found that few consumers are "monogamous" (100% loyal) or "promiscuous" (no loyalty to any brand); instead, consumers show a polygamous loyalty to brands (Cooil et al., 2007). More realistically, Rust et al. (2004) argued that customers may leave and return and be either serially monogamous or polygamous among a number of brands (brand repertoire). Accordingly, the firm and retail strategies to control the churn rate may impact the consumer repeated purchases while affecting the wallet of brand repertoire of each buyer as well as the polygamous loyalty. Bianchi (2015) found a strong relation between brand satisfaction and brand loyalty on Chilean wine consumers using a structural equation model. Brochado and Oliveira (2018) show that brand loyalty is the most influential dimension of brand equity for Portuguese green wine.

Many authors evaluated the role of the brand in market segmentation through the analysis of consumers' preferences heterogeneity, which arises from a plethora of attributes, both extrinsic (brand, packaging, vintage, region, wine maker, food/wine pairing, medals/awards, recommendations by others) and intrinsic ones (grape variety, alcohol content, color, taste, texture, bouquet and aromatic complexity, drinkability, smoothness, long aging, etc.) (Ellis & Caruana, 2018). The wide heterogeneity of wines offers to the consumers the opportunity to change the traditional purchase behavior while looking for variety. This behavior is known as variety-seeking behavior (Van Trijp et al., 1996), where a consumer switches from a brand to another because the value comes from the switch itself (Meixner & Knoll, 2012), from the need of "stimulation", curiosity or diversity to avoid the "satiation", from a social norm found in some individualistic cultures. The variety-seeking behavior is found in some product categories such as wine having a pronounced hedonic component since consumers switch among sensory attributes (Inman, 2001, Levaggi & Brentari, 2014).

So far, the literature is mostly about wine and, especially, still wines. Let us now focus on sparkling wines, on which research has been enriched, recently. The literature on sparkling wines refers to three main research areas. One is related to technical aspects such as production process (e.g., yeasts, effervescence, etc.) and sensorial profile (taste and aroma) (Culbert et al., 2017). Consumers' studies are mostly focused on the purchase, perception and, more recently, there is a growing attention in how sensorial features affects consumer behavior in general (Vecchio et al., 2018).

Charters et al. (2011) have deeply analyzed the consumer's behavior for Champagne as well as for other sparkling wines in Anglophone countries. Sparkling wines are perceived as separate products than still wines (Charters, 2005). Bubbles constitute the distinctive trait of these wines, which are often metaphorically associated with positive emotions and dynamism (Charters et al., 2011). This mental and emotive parallelism plays a central role in contributing the consumption of sparkling wines in special occasions, in holidays or relaxed circumstances and among young generations (Sheahan, 2005; Charters, 2005; Morton et al., 2013).

Many papers dealing with the topic focus on the market of French Champagne, an iconic sparkling wine present on the most prestigious shelves worldwide. The image and brand reputation of Champagne tends to overcome any other categorization when buying this

wine in both Europe (Müeller, 2006; Vignes & Gergaud, 2007, Cerjak et al., 2016) and in newer wine markets like the United States (Judica & Perkins, 1992) and Australia (Verdonk et al, 2017). The peculiarities of Champagne therefore imply that its market cannot be considered jointly with that of “regular” sparkling wines as in new wine markets it constitutes a separate product category (Charters, 2009; Thach & Olsen, 2006). Going to Italian sparkling market, Thiene et al. (2013) segregated sparkling wine consumers into groups through a LC regression model of stated willingness to pay WTP applied to data collected in a survey. They figured out consumer patterns and different WTP for Prosecco appellations. Onofri et al. (2015) applied a probit regression model on homescan data, testing the relationships between the probability of purchasing Prosecco as appellation and consumer features. Contini et al. (2015) employed a LC regression model to homescan data, evaluating mass trade retail strategies on consumer's preferences. They evaluated the effect of wine attributes including still versus sparkling wines. Vecchio et al. (2018) figured out that consumers appreciate differently the sparkling production process (Charmat better than Champenoise) while being positively influenced by the brand (Champenoise better than Charmat). Trestini et al. (2018) investigated the sparkling wine German market looking at the positioning of Prosecco appellations while checking the consumer perception on Prosecco’s appellations. Rossetto and Gastaldello (2018) employed a Dirichlet model on the Italian sparkling wine market, classifying appellations by loyalty and variety-seeking purchase behavior. They figured out a high loyalty in Prosecco’s consumers in the upper price segment, while deep discount price strategies may hurt Prosecco’s loyalty in the long run.
The literature on sparkling wines has been mostly focused on market segmentation and consumer behavior analysis. Researches are mostly done on data survey, collected through questionnaires, or data collected at the point of sale such as POS data.
In this paper, we follow a different approach. First, we apply a MLLC methodology to the data to evaluate the consumer behavior. The data are recorded by a panel of consumers (homescan data) and the aim is to estimate homogenous groups of consumers as brand choices, behavioral and socio-demographic variables, while showing unobservable latent classes. Then, we perform the analysis proposing a HMM to evaluate brand preferences in a dynamic perspective over time. LC models have been largely applied in segmenting wine market (Lockshin and Cohen, 2011; Scarpa et al., 2009; Corsi et al., 2012; Thiene et al., 2013; Contini et al., 2015; Bruwer et al., 2017; Pomarici et al., 2017; Gonçalves et al., 2019); however, up to our knowledge, the proposed HMM has never been applied in the literature for the analysis of sparkling wines.

2. The available scanner data

We analyze homescan data (Nielsen, 2017) that cover the purchase of sparkling wine in retail stores in Italy. A panel of 9,000 Italian households is considered along with their purchases over a two-year period: 2015 and 2016, which are repeated over time. Data are representative of the Italian population with reference to the area of residence, family size, monthly per capita income, age of purchasers, type of the family, as better specified in the next paragraph. Families are provided by an optical reader to scan all purchases through the European Article Number (EAN) barcode.
In our analyses, we consider only the market of sparkling wines for a total of 22,362 purchases in unspecialized stores, i.e., hypermarkets, supermarkets, minimarkets and discounts, so our data refer to the portion of the entire panel that made at least one purchase in the reference period: 5,155 households. The dataset is quite rich with detailed

information on purchases: date, place, in-store promotion and attributes of the chosen wine: such as sugar content, appellations (Protected Denomination of Origin, PDO), the winery brand and its location, and the price. With reference to the households, we know where the family lives, the size (# components), the income range (very low, if less than 583 Euros per capita/month; low, when below the sample average, fixed to 959 Euros per month; medium, if above the average but lower than 1,476 Euros per capita per month; high otherwise), and the type of family. Families are classified in seven categories as follows: "pre families" when members are singles or couples with no children and the purchasers is younger than 35 years; "new families" with babies younger than six; "maturing families" with children under 17 (babies and teenagers); "established families" when children are between 11 and 17; "post families" when members are singles between 35 and 54 with no children under 18; "older couples", the purchaser is over 55 and there are no children under 18; "older singles" that are 55 years old and over. Families make from 1 to 230 purchases in the reference period: light buyers (households making one or two purchases) contribute to 66% and 30% as purchases and sales, respectively; conversely, heavy buyers (households purchasing more than twice) generate 33% and 70% of purchases and sales. These results do not confirm the heavy-half principle (light buyers are 50% and buy 20% of bottles) because the strong seasonality enlarges the share of occasional buyers.
Table 1 lists some descriptive statistics with reference to wine attributes and households features. Since the sparkling wine market is fragmented among brands, the homescan sample was rearranged according to winery brand market share; then, first 40 brands for market size were selected. The other 240 brands are aggregated in a residual category that covers 20% of the market (Table 2).
Farris et al. (2010) showed that the market share can be decomposed into the product of three indicators of brand performance measure (BPM), as in equation (1)

$$\frac{a_m}{a_p} = \frac{c_m}{c_p}\frac{a_m}{a_{pm}}\frac{q_{pm}}{q_p}, \qquad (1)$$

with a_m purchases of brand m, a_p purchases of product p, c_m the number of clients of brand m, c_p the number of clients of product p, a_{pm} purchases of product p by clients of brand m, q_{pm} the average quantity of product p purchased by clients of brand m, q_p the average quantity of product p purchased in the market.
The first indicator measures market penetration, i.e., how many customers in the market purchased at least once in the reference period the brand (purchasers of a brand over purchasers of the product category). The second indicator is the share of requirements, a measure of brand loyalty (purchases of the brand over total category purchases by buyers of the brand) and the third and last index refers to the intensity of usage (average category purchases by customers of a brand, compared with average purchases by customers in the category). This decomposition of the market share is very useful to compare brands and to identify strengths and weaknesses of the brand.

Table 1 - Descriptive statistics of purchases and households

Variable	*Mean/Percentage*	*Variable*	*Percentage*
Price per litre	6.02 (s.d. 6.05)	***Family size***	
Product		1	11.87
Champagne	1.38	2	36.44
Classical method	8.70	3	24.63
Charmat Dry	33.26	4	20.21

Charmat Brut	56.65	5+	6.85
Colour		***Area***	
White	94.24	1 – North West	33.84
Red	3.74	2 – North East	21.61
Rose	2.02	3 – Centre	22.90
Type of wine		4 – South	21.66
Brut	35.29	***Age of purchaser***	
Extra dry	19.32	<=34	4.46
Dry	11.88	35-44	16.83
Sweet	33.51	45-54	27.17
Denomination		55-64	24.11
No denomination	44.43	>=65	27.44
Prosecco Docg	12.17	***Type of family***	
Prosecco Doc	17.94	Pre	2.59
Franciacorta Docg	5.85	New	6.01
Asti Docg	5.08	Established	10.02
Trento Doc	4.31	Maturing	11.52
Brachetto d'Acqui Docg	3.16	Post	21.41
Oltrepo Pavese Docg	1.97	Old couples	41.61
Dolomiti Doc	2.17	Old singles	6.96
French appellations	1.61	***Income***	
Other	1.32	Very low	15.21
		Low	27.32
		Medium	37.10
		High	20.36

Table 2 contains, for the 40 analyzed brands, the BPMs that show non-negligible differences among brands. Excluding the residual category, the brand leader Gancia covers 7% of purchases and it reports the highest market penetration as well and a high share of requirements. The brands Fontanafredda, Toso and Togni appear to gain the most loyal customers. The last column of the table reports Prosecco in winery wine assortment. The BPMs and price do not significantly change among companies that have or do not have Prosecco wine in their assortment. In other words, brand loyalty and other market performances seem not to be affected by the presence of Prosecco wine among the offered products.

Identification of competitive associations among the brands operating in the market of sparkling wine, however, requires further and deeper analyses. A study of brand positioning requires the estimation of more complex models (as in the following of the paper) in order to identify competitive relationships as products offered and customers' preferences.

Table 2 - Market share decomposition by brand

41 Brands	*Market share %*	*Penetration %*	*Share of requirements %*	*Heavy usage*	*Average price*	*Prosecco*
Others	20.86	40.76	33.42	1.51	6.00	Yes
Gancia	7.59	20.72	21.84	1.66	4.36	Yes
Togni	5.27	14.10	22.48	1.64	3.45	No
Cantina Soave	4.97	9.72	18.46	2.74	4.13	No
Campari	4.91	13.81	21.46	1.64	5.08	Yes
Martini	4.88	13.95	20.63	1.68	5.68	Yes
F.lli Martini	3.83	11.70	16.54	1.95	3.83	Yes
Contri	3.55	9.72	21.79	1.66	2.63	Yes
Berlucchi	3.09	9.10	16.79	2.00	14.29	No
Cantine Riunite	2.97	7.02	16.89	2.48	6.26	Yes
Cantina Valdobbiadene	2.89	6.54	16.51	2.65	6.97	Yes

Ferrari	2.84	8.77	16.74	1.91	16.30	No
Valdo	2.29	5.63	16.12	2.50	7.29	Yes
Mionetto	2.27	4.29	19.79	2.65	9.44	Yes
Cavit	2.22	4.89	14.18	3.17	5.19	Yes
Duchessa Lia	1.78	6.01	15.57	1.88	5.50	Yes
Villa Sandi	1.68	4.83	15.35	2.23	7.30	Yes
Fontanfredda	1.67	4.91	25.83	1.30	7.58	No
Carpenè	1.39	3.53	18.83	2.07	8.42	Yes
Pirovano	1.35	3.76	14.85	2.40	3.48	Yes
Bosca Cora	1.32	3.28	21.36	1.86	3.50	No
La Marca	1.22	3.72	11.42	2.84	5.50	Yes
Schenk	1.18	2.87	20.11	2.01	4.23	Yes
Cielo	1.18	1.82	19.48	3.27	3.46	No
La Versa	1.09	2.48	11.59	3.73	4.63	No
Toso	1.02	2.00	25.22	2.00	3.13	Yes
Bosca Tosti	1.02	3.36	13.98	2.14	4.44	Yes
Zonin	1.02	3.30	12.12	2.51	6.40	Yes
Cesarini Sforza	0.91	2.21	12.94	3.15	8.93	No
Cavicchioli	0.89	1.73	10.99	4.61	4.10	Yes
Santero	0.87	3.01	15.2	1.87	4.17	Yes
La Delizia	0.86	1.61	20.89	2.52	3.75	No
Le Fade	0.85	2.08	11.32	3.59	5.86	Yes
Concilio vini	0.73	1.82	9.30	4.27	4.64	No
Moet	0.70	2.35	15.22	1.93	45.86	No
Conad (private label)	0.56	1.67	18.13	1.84	6.41	Yes
Cormons	0.52	1.16	7.54	5.84	5.14	No
Mezzacorona	0.50	1.55	15.01	2.12	9.79	No
Serena wines	0.45	0.97	14.18	3.21	4.78	Yes
Astoria	0.44	1.51	6.93	4.17	7.83	Yes
Pernod Ricard	0.37	1.36	15.47	1.72	29.63	No

3. Proposed models

3.1 Latent class model

Latent class (LC) analysis assumes the existence of one or more latent variables not directly observable when considering the association among the observed responses. It can be applied when these are categorical or continuous. LC models were introduced by Lazarsfeld (1950) and Lazarsfeld and Henry (1968) to express latent concepts from dichotomous survey items, then they were extended to nominal variables by Goodman (1974a, 1974b), who also developed the maximum likelihood estimation method for the model parameters that nowadays serves as the basis for many software with this purpose. Later, these models were further extended to include observable variables of mixed scale type, like ordinal, continuous and counts.

Let Y_{ijl}, $i = 1,\ldots,n_j, j = 1,\ldots,J, l = 1,\ldots, L,$ denote the response of individual or level-1 unit i within group or level-2 unit j on item l; $s_l = 1,\ldots,S_l$, a particular level of item l; U_{ij} be a latent variable with K classes, where k denotes a latent class, $k = 1,\ldots,K$; $\mathbf{Y}_{ij}$ be the full vector of responses of unit i in group j; and $\underline{s}$ as a generic response pattern.

The probability of the observed response pattern is defined as follows:

$$P(\mathbf{Y}_{ij} = \underline{s}) = \sum_{k=1}^{K} P(U_{ij} = k) P(\mathbf{Y}_{ij} = \underline{s} \mid U_{ij} = k) = \sum_{k=1}^{K} P(U_{ij} = k) \prod_{l=1}^{L} P(Y_{ijl} = s_l \mid U_{ij} = k) \quad (2)$$

As specified in equation (2), the probability of observing a particular response pattern is a weighted average of a class-specific probability $P(Y_{ijl} = s_l \mid U_{ij} = k)$ where the weight is referred to the probability that unit *i* in group *j* belongs to latent class *k*. As the local independence assumption implies, indicators Y_{ijl} are conditionally independent. This model is also quoted in the reference literature as traditional LC cluster model.

3.2. Multilevel latent class model

Multilevel latent class modelling (MLLC, Vermunt, 2003) is based on the assumption that some model parameters can vary across groups or clusters or level-2 units. Differently from the above LC cluster model, MLLC modelling does not assume that the parameters are the same for the whole population. The multilevel approach allows for variation across level-2 units for the intercept (threshold) of each indicator and makes it possible to examine how level-2 units influence the level-1 indicators that define latent class membership (Vermunt, 2003). In the MLLC model a group-level discrete latent variable is introduced so that the parameters are allowed to differ across latent classes and groups:

$$P(\underline{\mathbf{Y}}_{ij} = \underline{s}) = \sum_{h=1}^{H} \left\{ P(W_j = h) \prod_{i=1}^{n_j} \left[\sum_{k=1}^{K} P(X_{ij} = k \mid W_j = h) \prod_{l=1}^{L} P(Y_{ijl} = s_l \mid X_{ij} = k) \right] \right\} \quad (3)$$

where W_j denotes the latent variable at the group level, assuming value *h*, with *h* = *1,…,H*; X_{ij} the latent variable at the individual level, assuming value *k*, with *k* = *1,…,K*; n_j the size of group *j*. Equation (3) is obtained with the additional assumption that n_j members' responses are independent of one another conditional on group class membership.

A natural extension of the multilevel LC model involves including level-1 and level-2 covariates to predict membership, like an extension of the LC model with concomitant variables (Dayton & McReady, 1988). In the terminology of MLLC modelling, the categories of the latent variable for level-1 units are called clusters, while the categories of the latent variable for level-2 units are called classes.

3.3. Hidden Markov model

The availability of scanner panel data contributes to a deeper analysis of the consumers' markets (Guadagni & Little, 1983). We propose to analyze such data by means of a HMM (Bartolucci et al., 2013) to tackle the observed customers' dynamics and to estimate their latent preferences. The latent process follows a Markov chain with states defining the customers' segments and accounting for the state dependence towards a certain brand: the behavior of customers differs across segments and it is the same within each segment (see, among others, Wedel & Kamakura, 2000). At each purchase occasion, the customer

can choose the same brand or switch to another and repeated purchases are indicators of the latent perceived differences of each customer across brands. The main assumption is that the latent process fully explains the observed customer behavior. By employing the HMM, we estimate latent typologies of brands that are judged to be similar by customers, their initial allocation and their transition across segments over time.
The latent Markov model introduced by Wiggins (1955, 1973) was proposed in marketing by Ehrenberg (1965). Recently, due to important inferential developments, HMMs are applied in many fields (see Bartolucci et al., 2013 and the references therein). The corresponding version of the HMM which does not relay on latent variables is called Markov chain model, and it is also referred as a transition model, since it provides estimates of the transitions between observable states.
In the following, we consider the repeated purchases of the customers at different occasions and we allow the time of the purchase occasions to vary from consumer to customer, that is $t_i = 1,\dots,T_i$ for $i = 1,2,\dots,n$. We deal with a categorical response variable representing the quality of the purchase, namely the denominations of the wine. We model jointly the responses for each customer assuming that their probability distribution depends on a latent stochastic process of first-order having a finite number of states. Therefore, we observe a vector of categorical response variables having c categories coded from 0 to c-1 denoted as $\boldsymbol{Y}_t = (Y_1,\dots,Y_T)$ where each t is the purchase period specific of each customer (in the following the subscript i is omitted from t to simplify the notation). We note that in the data presented in Section 2, the purchase occasions may vary from 1 to 230 and the denominations of the wine (the categories of the response variable) are 41. We assume the existence of a time-varying latent stochastic process $\boldsymbol{U} = (U_1,\dots,U_T)$ with state space $\{1,\dots,k\}$ where k is the number of latent states affecting the distribution of the response variables. We assume that the response vectors of each customer are conditionally independent given the latent process (local independence assumption) and each response variable is conditionally independent given the latent process at the same occasion.
The measurement model is related to the conditional response probabilities given by

$$\phi_{y|u} = P(\boldsymbol{Y_t} = \boldsymbol{y_t}|U_t = u), \tag{4}$$

where $t = 1,\dots,T$, $u = 1,\dots,k$ and $y = 0,\dots,c$-1. The manifest probability of the observed responses, is computed through the recursions known in the literature of this class of models (Bartolucci et al., 2013).
We assume that the latent process follows a first-order Markov chain: for all $t > 2$, the latent variable U_t is assumed conditionally independent on $U_1,\dots,U_{t-2}$ given U_{t-1}. The initial probabilities of the latent process, denoted as π_u with $u = 1,\dots,k$, define the allocation of the customers in each segment at the beginning of the period. The transition probability is the conditional probability that the customer is in any of the k latent brands' segments in the next period, given the customers' segment in the current period and it is denoted as $\pi_{tu|\bar{u}}$ with $t = 2,\dots,T$, and $u, = 1,\dots,k$. The whole transition probabilities are stored in a matrix denoted as Π, that is a quadratic stochastic matrix defined transition matrix.
Given a sample of n independent customers providing the response vectors $\boldsymbol{y}_i = \boldsymbol{y}_{1,\dots,}\boldsymbol{y}_n$, the model log-likelihood has the following expression:

$$l(\boldsymbol{\theta}) = \sum_{i=1}^{n} \log P(\boldsymbol{y}_i), \tag{5}$$

where $\boldsymbol{\theta}$ is a random vector of all free parameters and $P(\boldsymbol{y})$ is the manifest probability of the responses. The Expectation-Maximization (EM) algorithm (Dempster et al., 1977) is based on the complete data likelihood, that is the likelihood we could compute knowing the latent states of each customer at each time occasion. In order to estimate the model parameters, the EM algorithm alternates the two steps until convergence by calculating the expected value of the complete data log-likelihood and then maximizing it. The appropriate number of latent states, when not known in advance, is estimated from the model through a penalized-likelihood criterion, such as the Bayesian Information Criterion (Schwartz, 1978) that is a measure of relative goodness of fit, since it adds a penalty to the model maximum log-likelihood according to the number of parameters and the number of units. The chosen model is that with the lowest value of the index. The information criteria have been compared by Bacci et al (2014), showing that for HMMs the most common decision criteria perform reasonably well.

4. Results

4.1 Results of the multilevel latent class model

The MLLC model figures out six clusters of homogeneous purchases and five classes of brands (Vermunt & Mgidson, 2013). Tables 3 and Table 4 list the results of the best fitting MLLC with the lowest BIC index (Lukočienė et al., 2010) and the lowest estimated proportion of classification errors. The magnitude of clusters and classes is reported. Each cluster is identified by wine attributes such as the average price per liter, the type of product, the color and sugar content, and the appellation (Table 3). The brand loyalty, calculated as the proportion of repeated purchases over all purchases of brands, enters into the model as active covariate to describe homogeneous groups of brands and it results in different means among groups; household demographic characteristics are used as descriptors of the groups of brands since they provide the profile of the average buyer for each group. These variables have all statistically different distributions in the five groups of brands.

The upper part of Table 3 retrieves the probabilistic relationships between clusters and classes. The other figures in the table define the profiles of the purchases in the six clusters. Table 4 describes the five classes of brands.

Table 3 - *MLCM model estimation results: cluster profiles*

	Size	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**	**Cluster 6**
Size	%	32.93	30.78	13.38	10.67	6.63	5.60
		Conditional probabilities*					
Class 1	36.19	13.19	29.07	**36.84**	1.60	**18.29**	1.02
Class 2	29.05	**96.74**	3.23	0.02	0.00	0.00	0.00
Class 3	19.52	0.29	**98.98**	0.20	0.46	0.07	0.00
Class 4	10.00	0.00	0.00	0.00	**99.99**	0.00	0.00
Class 5	5.24	0.01	0.01	0.01	0.01	0.01	**99.93**
Attributes				**Mean**			
Price per liter		6.94	4.26	3.29	13.98	6.52	34.32
Product		**Conditional probabilities***					
Champagne		0.00	0.03	0.00	0.00	0.00	**81.90**
Traditional method		0.40	0.69	0.00	**97.87**	0.00	**17.93**
Charmat Dry		0.00	0.45	**100**	0.00	**98.99**	0.00
Charmat Brut		**100**	**98.84**	0.00	2.13	1.01	1.80
Color							

White	**99.42**	**96.76**	**98.59**	92.51	69.41	**98.20**
Red	0.00	0.08	1.17	0.00	**30.50**	0.00
Rosé	0.68	**3.16**	0.24	**7.48**	0.08	1.80
Sugar content						
Brut	18.68	**68.56**	0.00	**90.82**	0.00	**97.32**
Extra dry	**40.03**	**26.59**	0.00	8.78	0.00	2.65
Dry	**40.23**	4.83	0.00	0.40	0.01	0.03
Sweet	1.06	0.02	**99.99**	0.00	**99.99**	0.00
Appellation						
No appellation	4.79	**69.48**	**90.19**	1.24	13.71	0.82
Prosecco "Superior"	**37.45**	7.50	0.97	0.07	0.00	0.01
Prosecco	**57.13**	10.35	0.00	0.27	0.24	0.01
Franciacorta	0.00	0.00	0.00	**46.35**	**16.59**	7.95
Asti	0.01	0.67	6.03	0.00	**31.98**	0.00
Trento	0.00	0.01	0.00	**51.37**	0.00	0.00
Brachetto	0.00	0.00	0.00	0.00	**28.56**	0.00
Oltrepo	0.00	**3.77**	2.08	0.39	**2.75**	0.00
Dolomiti	0.00	**7.01**	0.00	0.00	0.00	0.00
France appellations	0.02	0.05	0.04	0.00	0.00	**91.21**
Others appellations	0.41	1.15	0.69	0.31	**6.15**	0.00

**Numbers in bold indicate values higher than the mean value in the overall sample*

Cluster 1 is the largest segment, containing 32.93% of purchases, all of Prosecco wine, which is confirmed by product, sugar content and, especially, the appellation. Cluster 2 includes 30.78% of purchases. In this segment, the price is low (4.26 euro/liter), the typical product is a white, Charmat Brut sparkling wine, with no appellation, except a lower share of wines, mostly from varietal grapes (e.g. Chardonnay), labelled as Dolomiti (Alps area) and Oltrepo Pavese (hilly area). This cluster includes low spending purchases of brut and extra dry Charmat wines. Cluster 3 (13.38% of purchases) shows the lowest average price (3.29 euro/liter) for purchasing white and sweet wine with no appellation. This segment covers drinkers that prefer low cost and sweet sparkling wines. Cluster 4 (10.67% of purchases) reports a high average price (13.98 euro/liter) of brut, white or rosé sparkling wines produced through the traditional or Champenoise method such as Franciacorta DOP and Trento DOP appellations. Cluster 5 (6.63% of purchases) includes average price purchases of sweet and red sparkling wines such as Brachetto DOP as well as white Charmats such as Asti. Finally, cluster 6 is the segment of Champagne purchases showing the highest average price and the lowest size.

Table 4 - *MLLC model estimation results: brand's class profiles*

	Class 1	Class 2	Class 3	Class 4	Class 5
41 Brands	Tosti, Bosca Cora, Campari, Conad (private label), Contri, Duchessa Lia, Fontanafredda, F.Martini, Gancia, La Versa, Martini e Rossi, Santero, Togni, Toso, Others	Astoria, Cant. Riunite, Carpenè, La Delizia, La Marca, Le Fade, Mionetto, Cant. Valdob-biadene, Serena Wines, Valdo, Villa Sandi, Zonin	Cant. Soave, Cavicchioli, Cavit, Cielo e Terra, Concilio vini, Cormons, Pirovano, Schenk	Berlucchi, Cesarini Sforza, Ferrari, Mezzacorona	Moet Chandon Pernod Ricard
Inactive Covariates			**Means**		
Loyalty %	42.06	43.40	50.88	32.10	19.75
Price	5.13	6.86	4.31	13.98	34.51

Prosecco	66.67	100	50.00	0.00	0.00
Household profile	**Conditional probabilities***				
Area of residence					
1 – North West	29.34	**35.14**	**49.47**	**39.28**	**36.97**
2 – North East	19.06	**28.48**	**26.83**	17.05	15.13
3 – Centre	**23.06**	24.80	14.99	**23.81**	**26.05**
4 – South	**27.74**	11.58	8.71	19.85	21.85
Age of the purchaser					
<=34	**5.04**	3.68	3.12	3.45	**7.98**
35-44	16.44	**18.58**	15.51	**17.05**	**23.11**
45-54	26.44	**29.92**	26.96	26.31	**29.41**
55-64	24.68	22.73	**26.24**	20.65	13.45
>=65	27.40	25.09	**28.16**	**32.52**	26.105
Family size (# comp.)					
1	11.14	**12.51**	11.42	**16.38**	**16.81**
2	35.17	**39.58**	**37.56**	36.48	**40.34**
3	**25.23**	21.43	**27.17**	23.39	23.11
4	20.94	**21.31**	16.50	19.06	13.03
5+	**7.52**	5.17	**7.34**	4.69	6.75
Type of family					
- Pre	**2.92**	2.22	1.51	2.38	**5.04**
- New	**6.45**	4.73	**6.21**	5.30	5.46
- Established	9.13	**12.90**	10.22	10.11	7.56
- Maturing	10.69	**12.75**	**13.41**	10.60	10.50
- Post	**22.00**	21.17	18.70	20.46	**32.35**
- Old couples	**42.51**	38.99	**42.09**	41.29	31.51
- Old singles	6.30	**7.24**	**7.86**	**9.87**	**7.56**
Income					
- Very low	**18.30**	9.73	11.77	10.78	8.02
- Low	**28.15**	26.37	**28.06**	22.47	21.10
- Medium	36.76	**38.94**	35.03	**38.98**	37.55
- High	16.80	**24.96**	**25.15**	**27.77**	**33.33**

**Numbers in bold indicate values higher than the mean value in the overall sample*

The combination of clusters of purchases and classes of brands describes the sparkling wine market. Specifically, the brand class segmentation together with purchase clusters allow us to picture each segment (Thach & Olsen, 2006; Bruwer et al., 2017; Geraghty & Torres, 2009; Brunner & Siegrist, 2011). Each segment includes brands that are homogeneous for proposed products, appellations, consumer's loyalty; more likely, these brands have a very similar positioning in the market, i.e., they are perceived as alternative by the customers and, therefore, they are competitors.

Class 1 identifies the largest group of brands that are associated to purchases in clusters 3 and 5 accounting together for 33% of purchases. Brands in Class 1 are mostly supplied by big and historical wine companies, some of them are located in Piedmont region where sweet sparkling such as Asti and Brachetto are produced. Some companies have also acquired in their assortment the Prosecco as a strategy to exploit Italian and, especially, foreign markets. The heterogeneous category of "others", that collects Clusters 3 and 5, covers a wide range of households located in Center or South Italy where the age of purchaser is low or medium-high, the family size is three components or more, families are young couples or older couples with no young children, income is lower than the average. By combining the wine attributes and family features we can call this wide segment as "Sweet popular drinkers" since they buy low price sparkling wines, they are attracted by sweet bubbles to celebrate holidays (e.g. Christmas, Easter) and other anniversaries, they do not pay attention to appellations. Purchasers on this segment do not show high loyalty, suggesting a switch among brands over time.

Class 2 includes twelve brands offering Prosecco wine only and located in the area of production (North-eastern Italy). The Prosecco's wineries include a wide range of producers for size and assortment, covering all Prosecco's appellations. The typical Prosecco is Charmat extra dry, the price is approximately 7.0 Euros per liter and its consumption overlaps the production area. This segment can be defined as "Prosecco amateurs", which collects approximately 33% of purchases. The purchaser is between 15 and 54 years, the households include singles and couples as well as big families (four components) corresponding to families with children or adult boys/girls and old singles. The family income is medium-high. The loyalty index is quite far from one in classes 1 and 2, showing that consumers move easily from a Prosecco's brand to other brands.

Class 3 corresponds to the purchases in cluster 2, which accounts approximately for 31% of the sparkling wine purchases. Brands accruing to this class come from big wineries offering white Charmat sparkling wines produced from varietal grapes (e.g. Chardonnay, Muller Thurgau, Pinot, Garganega, etc.) without a specific appellation, except two small ones (Dolomiti and Oltrepo). Wineries are located in North-eastern Italy and Lombardy and half of them have Prosecco in their assortment. This segment looks not very different from that of "sweet and basic drinkers" but consumption is shifted to old consumers with low income. The typical purchaser is over 55 years old, families have two or three components with adult boys/girls or they are old couples. This segment of "brut popular drinkers" represents consumers who do not choose sweet bubbles and buy low price wines because of a low budget available. This segment shows the highest loyalty index; however, this result should be reinterpreted considering the large assortment supplied by each winery, which covers many grape varieties (e.g. Chardonnay, Pinot, etc.) and prices. In this segment, the variety-seeking behavior is within each winery brand or it can be induced by discount strategies (Ellis & Thompson, 2018).

Class 4 includes a short list of winery brands producing traditional or Champenoise sparkling wines, located in the production area of appellations Franciacorta and Trento. This segment, with size approximately 11%, refers to purchases in cluster 4 of traditional, brut sparkling wines. The average price is 13.98 Euros per liter, almost doubled than Prosecco segment. This segment of "knowledgeable drinkers" includes consumers that come from North-West and Center Italy. The typical purchaser is between 35 and 44 years old, or older than 64, while households are mostly old singles with a medium-high income. The loyalty to these brands is low, suggesting that these consumers switch easily to other sparkling wines brands or they drink these wines in special occasions.

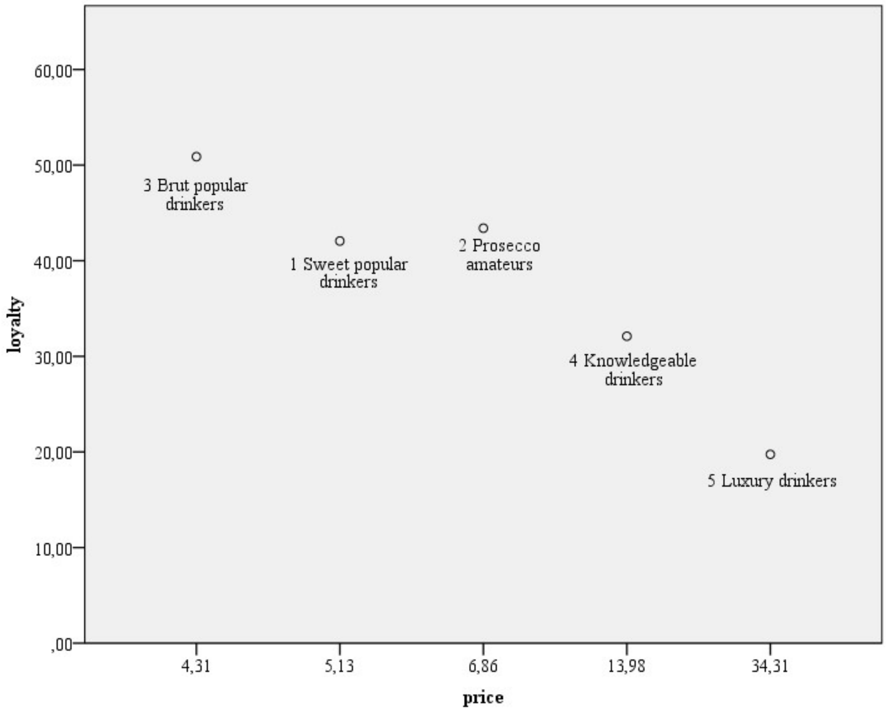
Lastly, class 5 refers to French Champagnes and it corresponds to cluster 6, involving less than 6% of total purchases. The age of purchasers is wide going from young people to 40s and 50s, while families are singles or couples with no children. The income is high. This segment of "luxury drinkers" is not loyal; most likely, these consumers buy many sparkling wines while restricting the consumption of Champagne to special occasions.

The positioning on the market according to loyalty and price is reported in Figure 1. Brands in classes 2 (brut popular drinkers) and 3 (sweet popular drinkers) share the same average price but show very different levels of loyalty. Brands in group 4 (knowledgeable drinkers) have the opposite positioning of those in group 3: high vs. low price and low vs. high loyalty.

The relationship among classes and clusters describes product customers' preferences referring to each group. Buyers of brands in class 1 are quite heterogeneous since they buy sweet wines but are also interested in other Charmats as Prosecco; customers of brands in class 3 choose wine with no appellation or Oltrepo Pavese and Dolimiti

appellations; customers of brands in class 4 prefer Franciacorta and Trento, customers of brands in classes 2 buy mostly Prosecco but they are interested in sweet sparkling wines. Customers of brands in class 5 buy Champagne.
Prosecco amateurs account for a large share of purchases while showing the most loyal behavior, however, this does not automatically transfer to single brands that produce this type of wine. In other words, Prosecco consumers are loyal to this product but no to a specific brand. There are other factors that affect the loyalty to a specific brand or group of similar brands.

Figure 1- *Positioning of the five groups of brands by price and loyalty*



4.2 Results of the Hidden Markov model

The dynamics of consumers' behavior has been further analyzed to explore more deeply loyalty to brands in the market of sparkling wine as illustrated in Subsection 3.3. The structure of the data is showed in Table 5, where we list the purchases of five customers and the chosen brands among the 41 typologies illustrated in Table 2. The overall number of purchases varies from 1 to 203 and they are not equally spaced over the two years period. We estimate the HMM with the observed data for a number of latent states ranging from 1 to 14 by adapting suitable functions[1] from the R (R Core Team, 2020) package LMest (Bartolucci et al., 2017). The results in terms of log-likelihood at convergence, number of parameters and BIC values are reported in Table 6. The lowest value of the BIC index is reached with $k = 13$, indicating the best model in terms of goodness of fit and parsimony.

[1] *The code is available from the second author upon request.*

Table 5 - *Example of data structure*

Customer id	Purchase occasion	Brand
1	1	Other brands
2	1	Campari
2	2	Gancia
2	3	Gancia
2	4	Martini
3	1	Duchessa Lia
3	2	Duchessa Lia
4	1	Other brands
5	1	Bosca Cora
5	2	Gancia

Table 6 - *Maximum log-likelihood, BIC values, number of parameters of the hidden Markov models with a number of latent states ranging from 2 to 14*

Model	$\hat{l}$	BIC	Number of Parameters
M_2	-66,758	133,883	43
M_3	-64,542	129,424	48
M_4	-62,320	125,110	55
M_5	-60,613	121,775	64
M_6	-59,752	120,145	75
M_7	-58,392	117,537	88
M_8	-58,462	117,805	103
M_9	-57,529	116,084	120
M_{10}	-56,227	113,643	139
M_{11}	-55,864	111,983	160
M_{12}	-60,613	113,293	183
M_{13}	-54,537	110,853	208
M_{14}	-54,507	111,023	235

Table 7 shows the estimated segments with the corresponding brands according to the selected HMM. The values correspond to the estimated conditional probabilities as in equation (4). Table 8 shows the estimated initial probabilities according to which 20% of customers are allocated in segment 11 at the initial period of the survey. The other customers are most likely to be allocated in segments 3 (18%), 10 (17%), 9 (14%) and 5 (12%).

Table 7 – *Segments defined according to the estimated conditional probabilities of the selected hidden Markov model (M_{13})*

Segments	Brands
1	Schenk (0.90)
2	Cantina Soave (0.62), Valdobbiadene (0.36)
3	Astoria (0.07), Berlucchi (0.47), Bosca Tosti (0.15), Other brands (0.30)
4	Bosca Cora (0.90)
5	Campari (0.76)
6	Cielo (0.16), Cavicchioli (0.14), Cavit (0.30), Cesarini Sforza (0.13), Concilio Vini (0.11), Cormons (0.09)
7	Fontanafredda (0.14), Gancia (0.65), La Versa (0.09), Le Fade Luca Ricci (0.07)
8	Cantine Riunite (0.20), Santero (0.04), Serena Wines (0.37), Togni (0.37), Toso (0.07), Valdo (0.16), Zonin (0.07)
9	Other brands (0.96)

10	Carpanè Malvolti, Conad, Contri (0.23), Duchessa Lia (0.12), Ferrari (0.19), Fratelli Martini (0.25)
11	Mezzacorona (0.09), Mionetto (0.45), Moet (0.13) Hennessy, Pernod Ricard, Pirovano (0.26)
12	Martini & Rossi (0.78)
13	La Delizia (0.29), La Marca (0.24), Villa Sandi (0.43)

Table 8 - *Estimated initial probabilities of the selected hidden Markov model (M_{13})*

Latent state	$\hat{\pi}_u$
1	0.01
2	0.09
3	0.18
4	0.03
5	0.12
6	0.02
7	0.10
8	0.06
9	0.14
10	0.17
11	0.20
12	0.04
13	0.02

The segments defined in Table 7 are different from the five classes identified by the MLLC. Those classes refer to brands that are homogeneous for the type of wines that they propose to the market, these 13 states refer instead to brands that are perceived as similar, maybe even substitutes, by the customers. This result indicates that brands proposing the same product might not be perceived as similar by the customers and the other way round. For example, the brands Soave and Valdobbiadene are perceived as equivalent by the customers', or at least, the same customers buy both of them.

Table 9 reports the estimated averaged transition matrix. The estimated transition probabilities on the main diagonal of Table 9 (in bold) can be considered as a measure of loyalty to the brands in each segment. The estimated averaged transition matrix shows active transitions from a state to another on the horizontal axis (time *t*) and passive transitions meaning that a state (group of brands) receives customers from other groups (new customers into the group) on the vertical axis (time *t-1*). Specifically, the transition probabilities outside the main diagonal, indicate the probability of segment switching and show competing brands across segments as well as the evolution of the customers' preferences; their estimates can help to define marketing actions. For instance, the customers have a fairly high probability of remaining in segment 8 (Cantine Riuninte, Santero, Serena Wines, Togni, Toso, Valdo, Zonin) from one purchase to the next, since the estimated value on the diagonal of the transition matrix is very high (0.98). Interestingly, customers in the third segment (Astoria, Berlucchi, Bosca Tosti, Other brands), are less stable than customers in other segments since the persistence is only 0.41. At the beginning of the period, customers allocated in this segment are 18%. After the first purchase they switch towards brands in the other segments except segment 1. More specifically, these customers move towards segments 2 (0.15) (Cantina Soave, Valdobbiadene) and 10 (0.14) (Carpanè Malvolti, Conad, Contri, Duchessa Lia, Ferrari, Fratelli Martini). Brands in segment 10 are the most attractive in this market, since non-negligible transitions probabilities toward this segment are estimated from segments: 4 (Bosca Cora), 5 (Campari) and 6 (Cielo, Cavicchioli, Cavit, Cesarini Sforza, Concilio Vini, Cormons). Other competitive brands are Campari (segment 5) and brands in segment 7 (Fontanafredda, Gancia, La Versa, Le Fade). On the other hand, customers of segment 7 tend to buy also Martini & Rossi. By looking at the upper part of the transition matrix, over the main diagonal, we observe that the transitions mainly occur towards segments 7, 8, 9, 10 and 12 with prevalence for segment 10.

Table 9 - *Estimated averaged transition matrix of the selected hidden Markov model (M_{13}): elements in bold in the main diagonal of the matrix indicate persistence in the same latent state, elements in italic out of the main diagonal indicate a probability of transition greater than 0.10.*

Time *t-1*	Time *t*												
	1	2	3	4	5	6	7	8	9	10	11	12	13
1	**0.67**	0.01	0.01	0.00	0.01	0.00	0.00	*0.12*	*0.12*	0.05	0.00	0.00	0.01
2	0.00	**0.63**	0.00	0.00	0.07	0.10	0.03	0.01	0.07	0.07	0.01	0.01	0.01
3	0.00	*0.15*	**0.41**	0.02	0.08	0.02	0.05	0.01	0.07	*0.14*	0.01	0.02	0.01
4	0.00	0.09	0.00	**0.51**	0.10	0.00	0.04	0.03	0.09	*0.12*	0.00	0.02	0.00
5	0.00	0.00	0.00	0.00	**0.45**	0.04	*0.13*	0.04	0.03	*0.23*	0.01	0.06	0.01
6	0.00	0.00	0.00	0.00	0.00	**0.78**	0.05	0.01	0.03	*0.12*	0.00	0.01	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	**0.60**	*0.12*	0.04	0.00	0.04	*0.16*	0.04
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.98**	0.02	0.00	0.00	0.00	0.00
9	0.01	0.02	0.01	0.00	0.01	0.02	0.02	0.05	**0.72**	0.09	0.03	0.00	0.03
10	0.00	0.00	0.00	0.00	0.00	0.00	*0.19*	0.07	0.04	**0.55**	0.04	0.06	0.04
11	0.01	0.00	0.00	0.00	0.00	0.00	0.00	*0.25*	0.07	0.00	**0.67**	0.00	0.00
12	0.01	0.00	0.00	0.00	0.00	0.00	0.00	*0.27*	0.01	0.00	*0.11*	**0.60**	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.01	*0.11*	0.06	0.00	*0.12*	0.09	**0.60**

5. Discussion and conclusions

The analyses on the Italian retail sparkling wine market using MLLC and HMM shed light on consumer behavior and competitive relationships among brands.
The MLLC model segmented the sparkling wine market among brands and purchases while profiling each segment according to wine attributes and household features. Methodologically, the MLLC segmentation approach is applied to purchase scanner data that catch information on wine and purchaser. The wine segmentation literature following behavioral, generational or lifestyle approaches (Thach & Olsen 2006; Bruwer et al., 2007; Geraghty & Torres, 2009; Fountain & Lamb, 2011; Mueller et al., 2011; Castellini & Samoggia, 2018) work on sociodemographic variables, usage, product and buying preferences, way of living, etc., using survey data collected usually through interviews (questionnaires). Scanner data, such as AC Nielsen data, have been used in the Italian wine literature to segment the price of Sicilian wines (Di Vita et al., 2015), to estimate the demand of table wines (Torrisi et al., 2006) or to figure out differences in Prosecco appellations (Onofri et al., 2015).
The MLLC model figured out five brand clusters: sweet popular drinkers, brut basic drinkers, Prosecco amateurs, knowledgeable drinkers and luxury drinkers.
Sweet popular drinkers and brut basic drinkers are quite similar and account, together, for 50% of the purchases. These results are also found in Rossetto and Gastaldello (2018), confirming that a high market share is covered by a wide range of brands meeting consumers' preferences (sweet vs. brut) and budget constraints while not paying attention to the regional origin. The Prosecco amateurs segment covers almost one third of the market where the purchases come from a large range of families as size and age but with a higher income. Knowledgeable drinkers and luxury drinkers account for 11% and 6% of purchases, respectively. These are niche sparkling markets devoted to traditional or

Champagne brands, which are purchased by expert consumers or drunk in special occasions.

The loyalty increases as the price grows except for the sweet popular drinkers' segment which loyalty is lower than that of brut popular drinkers and Prosecco amateurs. This result has a twofold meaning. From the consumer side, the sweet sparkling wines are, usually, drunk in few special occasions (Christmas or special celebrations such as birthdays, anniversaries, etc.), while brut wines are consumed in more occasions since they can be easily paired with food. From the producer perspective, sweet sparkling wines are a part of a line extension strategy that includes other sparkling (e.g. brut, extra dry) and still wines. The brands included in sweet and brut popular segments are trademarks of large companies or wineries controlled by holdings, and they offer a complete range of wines, including Prosecco, to cover the popular sparkling wine segment.

The Prosecco amateurs' segment has acquired a significant loyalty while reaching a market share of approximately 30%, lower than the one in brut popular segment as reported by Rossetto and Gastaldello (2018). Differently from sweet and brut popular segments, the Prosecco amateurs include brands that are supplied by Prosecco's specialized wineries. The Prosecco amateurs segment shows a consumer profile similar to that found by Onofri et al. (2015).

According to Rossetto and Gastaldello (2018), knowledgeable drinkers and luxury drinkers show a low loyalty suggesting a variety-seeking behavior in these segments.

Respect to generation, the scanner data cannot give information on the age of drinkers. However, Prosecco amateurs are likely to include Gen X and Gen Y (Millennials), as it is suggested by the age of purchaser (35-54 years) and families having adult boy/girls (established/maturing families).

The parameters of the estimated HMM provide useful hints in interpreting the variety-seeking behavior of sparkling wine consumers. Specifically, this model allows us to analyze the patterns in choosing brands along the time, which are pictured by 13 latent states. Each segment corresponds to a group of brands perceived as similar and chosen in repeated purchases. Interestingly, there are quite differentiated segments: some having one or few brands (usually, light consumers) and others colleting many brands (heavy consumers). The estimated transition probabilities suggest that variety-seeking behavior is among brands producing wines different for price positioning, method of production (Charmat vs. Champenoise), area of production and appellation. The transition matrix allows us to figure out the high loyalty of some brands (segments 8 and 9), low loyalty in others (segments 3 and 5), and movements across groups of brands (segments 10, 8, 3 and 5). In particular, segments such as 10 and 8 attract customers from others segments, while 3, 4 and 5 are segments that loose customers.

The advantage of the proposed HMM is mainly that it works on real market data trying to figure out patterns in choosing brands while other studies on variety-seeking behavior are aimed to assess time invariant effects (Ellis & Thompson, 2018). A close approach is found in Meixner and Knoll (2012) for the analyses on food market. The HMM enables us to model the dynamics in the market, to infer the customer position in each segment and to which segments customers move.

This research work is done on purchases occurring in the large scale retail channel or supermarket channel (approximately 40% off-trade channel as value, Euromonitor, 2017) while excluding direct sales from the winery, specialized shops, online sales and the Ho.Re.Ca channel. The supermarket channel offers a brand assortment, which is roughly targeted on no expert consumers, while discounting strategies, especially during winter holidays, strongly affect the purchases. Secondly, the sales of sparkling wine are occasional e mostly concentrated on Christmas holidays. Though, the Prosecco has

partially changed this seasonality while extending consumption along the year and to other occasions such as aperitif, dining, etc.
In our database, customers are required to record how many liters of sparkling wine were purchased in promotion; unfortunately, this information is missing in more than half of the records and it is, in our judgment unreliable, since it is voluntarily inserted by the panelist, not provided by the scanned code of the product. Therefore, the type of promotion is not available, as well as the amount of the discount.
Exploratory analyses on our data have shown that seasonality affects all brands and all types of customers in the same way: purchases grow during the Christmas season and, in lower magnitude, in the Easter season. However, this aspect needs for sure further research.
We restrict the analysis to the sparkling market only. From the consumer side, this market is separated from the still one as it is reported by many authors (Charters et al., 2011; Verdonk et al, 2017), that is, consumer preferences for sparkling and still wines are different. From the producer side, the exclusion on still wines may be a limit for this research, especially for large wineries having a wide assortment and building strategies jointly for still and sparkling wines.
Practical implications for producers and distributors can be drawn from this research. First of all, the segmentation of sparkling wine purchasers tells to producers the features and magnitude of the target segment as well as the loyalty and price positioning of their brands. Secondly, the dynamic segmentation allows producers to better target their marketing strategies according to the consumer's loyalty vs. the tendency of buying other brands and the brand portfolio chosen in a time spam. In particular, purchase movements in and out the target may suggest strategies aimed at not losing or catching new purchasers. Analogously, supermarkets may fit their brand assortment and promotional strategies according to purchasers' behavior.
Future research can be developed along various lines. It will be interesting to perform a dynamic segmentation of customers and brands over a longer time span to explore the stability of the clusters in the long period. For our analyses we could rely on purchases collected over two years, it would be very interesting to observe purchase behavior for a longer reference period. Another line of research should include the effects of the covariates related to the characteristics of the point of sale as in-store promotions and marketing strategies at brand level.

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